State Dependence in Access to Credit

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Abstract

We present a simple theory and an empirical test for state dependence in firm access to credit. We estimate a first-order Markov model of credit restriction with sample selection that makes it possible to estimate state dependence in the presence of feedback effects and observed and unobserved heterogeneity. The results, based on a representative sample of Italian firms, show that state dependence in access to credit is a statistical and economically significant: experiencing a credit restriction in the past has a negative impact on the outcome of the current loan application and the decision to apply for a new loan.

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1 Introduction

A well established result of the modern theory of banking is that credit markets can be characterized by credit rationing phenomena in equilibrium (Jaffee and Russell, 1976; Keeton, 1979; Stiglitz and Weiss, 1981). In the 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 increase interest rates, excluding some borrowers from access to credit and discouraging others from applying for a loan. The standard microeconomic models analyze credit rationing in a static partial equilibrium framework, ignoring the degree of persistence of credit rationing at the firm level and its impact on the borrower's decision to apply for a new loan.[1]

Similarly, the empirical literature explores the determinants of the likelihood of loan applications, credit denials and discouragement (amongst others, see Alessandrini et al., 2009; Han et al., 2009; Becchetti et al., 2011), but it does investigate whether and to what extent firms can be "locked" in a state of credit constraints over time.[2]

In this paper, we make two contributions to the literature. First, we present a simple theory of state dependence in access to credit based on the hypothesis of imperfect bank screening technology. Second, building on the approach proposed by Cappellari and Jenkins (2004), we introduce a first-order Markov model with sample selection that allows us to estimate state dependence consistently in the presence of feedback effects and unobserved heterogeneity.

Borrowers are considered credit-constrained if they are restricted by banks in access to credit (in terms of quantity or price) or if she is discouraged from applying for a loan, in anticipation of a likely future credit restriction (Jappelli, 1990). Then, access to credit is state-dependent if borrowers whose loan applications have been fully or partly restricted by banks at time $t-1$ are, other things being equal, more likely to be restricted (state dependence in credit restriction) and/or discouraged from applying for a loan (discouragement effect) at time t than other borrowers.

A way to rationalize state dependence in access to credit is the borrower net worth channel explored by the literature on financial accelerator and credit cycle (Bernanke and Gertler, 1989; Greenwald and Stiglitz, 1993; Kiyotaki and Moore, 1997; Carlstrom and Fuerst, 1997). An adverse shock to the borrower's productivity or to the credit supply reduces the value of collateralizable assets. When credit markets are imperfect and when applying for a loan is costly, a lower value of collateral hinders access to credit. Credit-constrained borrowers have to cut back investment, and the resulting decline in net worth further reduces their ability and willingness to borrow. In these models state dependence in access to credit is triggered by

[1] A review of credit rationing theories is provided by Parker (2002) and Freixas and Rochet (2008), while Kon and Storey (2003) present a theory of discouraged borrowers.

[2] Two partial exceptions are Levenson and Willard (2000, p. 91), who explicitly argue that "credit rationing has a duration dimension", and Jiménez et al. (2012), who investigate whether credit supply restrictions are binding looking at the probability that a firm can successfully apply for a loan, conditional on a previous rejection.

temporary shocks in the financial or non-financial sectors of the economy and may propagate into large aggregate output fluctuations, locking firm into long-lasting credit traps. If financial frictions are more marked for small and informationally opaque borrowers, these firms are not only more likely to be unconditionally credit-constrained, but also more likely to be locked in a credit restriction state (Gertler and Gilchrist, 1993, 1994).

A complementary explanation of state dependence in firm access to credit rests upon the hypothesis that the bank screening technologies are faulty and sticky. In the next section we advance a highly simplified information-based theory of state dependence in credit constraints.[3] Here we provide the basic intuition. We assume that banks make lending decisions on the basis of a noisy credit-worthiness test of borrowers' likelihood of repayment and that the screening technology is characterized by a certain degree of memory. This implies that the present expected quality of a borrower that has already applied to that bank depends on the results of previous credit-worthiness tests. Since the credit-worthiness test takes on the lowest values for rejected borrowers, the likelihood that the current credit-worthiness test confirms the result of the previous test is higher for rejected than for non-rejected (and new) applicants. In addition, if loan application is costly, previously rejected borrowers may be discouraged from applying for a loan in the future, anticipating the higher probability of credit denial. In our theory of screening failures, firm state dependence in access to credit is not engendered by an external shock, but it is a feature of credit markets also in tranquil periods. Also, contrary to the asset-based theory of state dependence, our model predicts that small and informationally opaque borrowers – whose credit-worthiness test is noisier and application costs are higher – could have a lower likelihood of being locked in a credit rejection state (although, unconditionally, they have a higher probability of being rejected), while are more likely of being discouraged from applying for a loan once they have experienced a credit restriction in the past.

We test these predictions on a representative sample of Italian manufacturing firms, surveyed by the National Institute of Statistics (ISTAT). This survey provides detailed information on firm loan demand and access to credit, location and several other firm characteristics on a quarterly basis from 2008:q2 to 2009:q4.

Modeling state dependence in the context of access to credit poses two main challenges. First, the use of standard binary response models is inappropriate given that firms demanding credit might be a non-random sample of population (Popov and Udell, 2012; Presbitero et al., 2014). Ignoring the modeling of credit demand would produce inconsistent estimators of the transition probabilities into a credit restriction state. In addition, the economic significance of state dependence in access to credit would be understated by not considering the discouragement effect of past credit restrictions on current loan applications. Second, the empirical model needs to wipe out the persistence effects due to fundamental differences in individ-

[3] Multi-period models of credit markets study how bank's assessment of borrowers change over time, but do not address the problem of state dependence in firm access to credit (Lang and Nakamura, 1989; Ghosh and Ray, 2001; Scalera and Zazzaro, 2001).

ual observed and unobserved characteristics. Third, the model has to deal with the possible presence of feedback effects that may generate from past credit restrictions on present firm characteristics, such as firm size and export orientation.

We take into account both the unobserved heterogeneity and selection bias by introducing a new first-order Markov model for transition probabilities from $t-1$ to t between three possible states. In each period t a firm can: (i) apply for credit and receive the requested amount; (ii) apply for credit and not receive the requested amount or receive it at more onerous terms (we label this outcome credit restriction and these firms as restricted applicants); or (iii) not to apply for credit. We specify two binary outcome equations: one for the bank lending decision and the other for the firm credit demand at time t. We model initial conditions since the separation between the group of firms at risk of credit restriction 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 supply in the initial condition. The first-order Markov model is estimated on a dataset of pooled transitions, where the observation unit is the firm observed for every possible pair of consecutive periods. This approach allows us to eliminate possible confounding feedback effects by using lagged values of covariates (Cappellari and Jenkins, 2004).

In line with our theory, in the empirical analysis we address three main questions. First, we test for the degree of state dependence in credit restriction at the firm level (i.e. the probability that credit supply is restricted at time t conditional on having experienced a restriction in $t-1$) and for the strength of the discouragement effect (i.e. the probability that a firm does not apply for credit at time t given that its application has been restricted in $t-1$), washing out other sources of persistence due to observed and unobserved heterogeneity. Second, we assess whether and to what extent state dependence in credit restriction and the discouragement effect are heterogeneous with respect to firm size. Third, in the last part of the paper, we examine whether state dependence in access to credit is a phenomenon which is triggered by major global liquidity shocks or whether it is a more pervasive occurrence in credit markets, persisting in tranquil periods.

Our main results are the following. *First*, we find evidence that state dependence in access to credit is a statistical and economically significant phenomenon in the Italian credit markets. *Second*, consistent with the predictions of our information-based model of state dependence in access to credit, we find that small firms are more likely to escape from a credit restriction state, but they are also more likely to be discouraged from applying for a new loan after experiencing a credit restriction. *Third*, we find that the bankruptcy of Lehman Brothers in September 2008 produced not only a crunch in the credit supply, as documented in other studies on Italy and other European countries (Puri et al., 2011; Jiménez et al., 2012; Popov and Udell, 2012; Iyer et al., 2014; Presbitero et al., 2014), but also exacerbated the persistence of credit restrictions for Italian firms. However, we also find that state dependence in access to credit is not limited to times of crisis, as firms can be locked in a state of credit restriction even in tranquil periods.

The rest of the paper is organized as follows: in Section 2 we present a simple two-period model of credit market with adverse selection and imperfect screening technology accounting for state dependence in access to credit. In Section 3 we introduce the first order Markov model with sample selection and our measures of state dependence in credit denial and discouragement effect. In Section 4 we present the dataset and the variables. In Section 5 we discuss the estimation results. The final Section concludes.

2 A two-period credit market with imperfect screening

2.1 Firms: projects and application costs

Consider a two-period credit market with universal risk neutrality and a riskless interest rate normalized to zero. In each period, firms are randomly endowed with a one-period investment project with probability q. The cost of investment is 1 unit of money. Projects are of two types: good (g) and bad (b). Good projects, in proportion θ, are positive net present value (NPV), yielding a return Y_g in the case of success, with probability π_g, and zero otherwise; bad projects are negative NPV, yielding a return Y_b in the case of success with probability $\pi_b < \pi_g$ and zero otherwise:

$$\pi_g Y_g > 1 > \pi_b Y_b \tag{1}$$

Firms have no wealth and no access to saving technologies (Ghosh and Ray, 2001), such that they have to apply for a loan of 1 to execute the investment both in the first and second period. In addition, firms can apply to only one bank per period at an effort cost $c > 0$, due to, for example, documentation requirements (balance sheet, business plan, etc.) and time spent on negotiating with loan officers.

Without loss of generality, assume that with the same probability q, firms that do not obtain access to credit in the first period can store the investment project and resubmit a loan application to a bank in $t = 2$, bearing again the cost c. To simplify the analysis, we assume that firms cannot switch bank from one period to another or, which is the same, that the decision of the bank on the firm's loan application in $t = 1$ and the signal s_1 received by banks about borrowers' credit-worthiness are publicly observable due to the presence, for example, of credit bureaus. The alternative, more realistic hypothesis that borrowers can change bank in $t = 2$ would complicate the model substantially by introducing two more types of borrowers (new and old) and another choice on the part of borrowers in $t = 2$ (whether to apply to the same bank contacted in $t = 1$ or switch to another bank). However, the results would remain qualitatively the same, insofar as we introduce the much milder assumption that banks contacted by new borrowers in $t = 2$ attribute a certain probability to the event that new borrowers were rejected by other banks in $t = 1$.

2.2 Banks: information and screening technology

The supply of deposits is perfectly elastic at the riskless (zero) interest rate. Banks can have some market power in the loan market and fund projects which yield an expected return no lower than $\rho \geq 1$. The type of project of which a loan applicant is endowed is publicly unobservable. As the b-projects have negative NPV, banks cannot charge an interest rate higher than Y_g. Otherwise they would make negative profits with certainty. In addition, assume that the share of firms endowed with a good project is low enough such that a firm selected at random from the population of firms is not worth financing on the part of the bank at the interest rate $r = Y_g$:

$$[\theta \Delta \pi + \pi_b] Y_g < \rho \tag{2}$$

where $\Delta \pi = \pi_g - \pi_b$.

However, each bank is endowed with an imperfect screening technology which returns a continuous, noisy signal $s \in S$ about the project type from which the bank draws an indicator of the applicant's credit-worthiness that may assume values $CW = G, B$. In particular, the screening technology is such that:

$$\Pr(G_t | g, s_t) = f(s_t) > \theta \tag{3}$$

$$\Pr(G_t | b, s_t) = g(s_t) < \theta \tag{4}$$

for any $s \in S$ and where $t = 1, 2$. If we assume that the densities $f(s)$ and $g(s)$ satisfy the monotone likelihood ratio property (MLRP), then the banks' optimal lending rule can be specified as follows.

Lemma 1. *Banks reject applications for which the credit-worthiness indicator is B and applications for which the indicator is G but the intensity of the signal s is sufficiently low, $s < \tilde{s}(\hat{p}_g)$, where $\tilde{s}$ increases with $\hat{p}_g$.*

Proof. From (2), loan applications are rejected if

$$\Pr(g | CW, s) \leq \hat{p}_g = \frac{\rho - \pi_b Y_g}{\Delta \pi Y_g} \tag{5}$$

From Bayes's rule, and recalling the MRLP and the boundary assumptions on $\Pr(G_t | g, s_t)$ and $\Pr(B_t | b, s_t)$, then: (i) $\Pr(g_t | G_t)$ is non-decreasing with s; (ii) $\Pr(g_t | B_t)$ is non-increasing with s and is strictly lower than θ. This means that the signal s is informative for banks and that they neither fund firms whose credit-worthiness indicator is B nor firms for which $CW = G$, but the intensity of the signal s is low enough such that the bank's expected profits at $r = Y_g$ are negative, i.e. such that $\Pr(g | G, \tilde{s}) \leq \hat{p}_g$ as in (5). □

Assume that the screening technology is imperfect and that, in the case of repeated screening of the same borrowers, it has memory.[4] To be precise, for the sake of calculation, and

[4] In this model we assume that the stickiness of the credit-worthiness signal is due to technological reasons: for

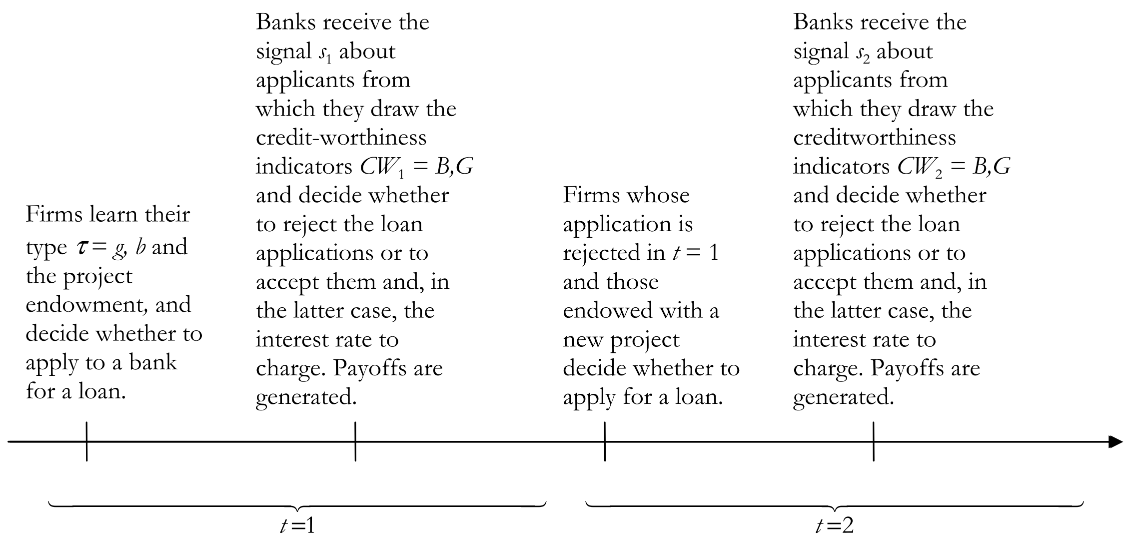

Figure 1: The credit game: the sequence of events

without any loss of generality, assume that:

$$s_t = \begin{cases} \mu_s + \epsilon & \text{if} \quad t = 1 \\ \mu_s + \epsilon & \text{if} \quad t = 2 \quad \text{and} \quad D_1 = 0 \\ (1-\lambda)\mu_s + \lambda s_1 + \epsilon & \text{if} \quad t = 2 \quad \text{and} \quad D_1 = 1 \end{cases} \tag{6}$$

where $\mu_s > \tilde{s}(\hat{p}_g)$ is the average value of s, $\epsilon \in [-x, x]$ is a zero-mean uniform random variable, D_t is an indicator variable taking value 1 for firms that apply for credit in t and 0 otherwise, and $\lambda > 0$ denotes the degree of memory of the screening technology. According to (6), the credit-worthiness test is such that good (bad) firms that apply to the bank for the first time, no matter whether at $t = 1$ or $t = 2$, get (no) access to credit on average.[5] In contrast, for applicants that were already screened by the bank in the first period, the result of their credit-worthiness test is influenced to a certain degree, λ, by the value of signal s_1. To summarize, Figure 1 outlines the sequence of events in the credit market.

2.3 State dependence in credit restriction

Let R_t be an indicator variable taking the value 1 if the loan application is rejected by the bank in t and 0 otherwise. Moving backward, consider the case of a firm which has applied for credit. The following result can be easily proved:

example, the credit scoring algorithm used by the bank includes the previous score among the determinants of the present score. However, the stickiness of s could be easily interpreted as the result of the minimization of screening costs by the bank.

[5]Recall that on average the credit-worthiness signal is higher than the credit rating threshold established by the bank, $\mu_s > \tilde{s}$. Hence, from lemma 1: $\Pr(g_t|G_t, \mu_s) > \hat{p}_g$ and $\Pr(b_t|G_t, \mu_s) < \hat{p}_g$.

Result 1. *Conditional on applying for a loan, the probability of rejection for applicants who apply for credit in $t = 2$ after being rejected in $t = 1$ is greater than the probability of rejection for both applicants who were not rejected in $t = 1$ and new applicants:*

$$\Pr(R_2 = 1|R_1 = 1) > \max\left[\Pr(R_2|R_1 = 0), \Pr(R_2|D_1 = 0) = \Pr(R_1)\right]$$

Proof. From (5) and (6), loan applications are rejected when:

$$\epsilon_t < \epsilon_t^* = \begin{cases} \tilde{s}(\hat{p}_g) - \mu_s & \text{if} \quad t = 1 \\ \tilde{s}(\hat{p}_g) - \mu_s & \text{if} \quad t = 2 \quad \text{and} \quad D_1 = 0 \\ \tilde{s}(\hat{p}_g) - (1-\lambda)\mu_s - \lambda s_{10} & \text{if} \quad t = 2, \;\; D_1 = 1 \quad \text{and} \quad R_1 = 0 \\ \tilde{s}(\hat{p}_g) - (1-\lambda)\mu_s - \lambda s_{11} & \text{if} \quad t = 2, \;\; D_1 = 1 \quad \text{and} \quad R_1 = 1 \end{cases} \tag{7}$$

where s_{10} and s_{11} are the signals received by the bank at time 1 in the event, respectively, of loan acceptance ($R_1 = 0$) and rejection ($R_1 = 1$). Since $s_{11} < \min[\mu_s, s_{10}]$, the probability of being rejected is higher for old applicants who were previously rejected rather than for old applicants who were not rejected at 1 and for new applicants. Finally, $\Pr(R_2|R_1 = 0) \lesseqgtr \Pr(R_1)$ according to whether $s_{10} \gtreqless \mu_s$. □

The degree of state dependence in credit rejection quantifies the variation in the probability of a firm experiencing a credit rejection in $t = 2$ due to the fact that it experienced a credit rejection in the previous period. Since in $t = 1$ firms may, or may not, have applied for credit, we can measure state dependence in credit rejection as the difference between the probability of being rejected in $t = 2$ conditional on having been rejected in $t = 1$ and, alternatively, the expected probability of being rejected in $t = 2$ conditional on having applied for and received credit in $t = 1$ (i.e., conditional on $D_1 = 1$ and $R_1 = 0$) or the unconditional probability of being rejected not having applied for credit in the previous period ($D_1 = 0$). From (7), and recalling that ϵ distributes as a uniform zero-mean random variable, we have:

$$SD_{R_1=0} = \frac{\lambda}{2x}(\mu_{s|s\geq\tilde{s}} - s_{11}) \tag{8}$$

$$SD_{D_1=0} = \frac{\lambda}{2x}(\mu_s - s_{11}) \tag{9}$$

Therefore, the following testable comparative static results can be easily proved.

Result 2. *Conditional on applying for a loan:*

I. *(i) The tighter the bank's credit standards $\hat{p}_g$, (ii) the more imperfect the lending technology (i.e., the smaller is μ_s), and (iii) the noisier the signal s (i.e., the greater is x or the variance of ϵ), then the higher the probability of a firm being credit rejected in $t = 1$ or in $t = 2$ conditional on $D_1 = 0$.*

II. *(iv) The stronger the memory of the screening technology λ; (v) the less imperfect the lending technology (i.e., the greater is μ_s), and (vi) the less noisy the signal s, (i.e. the smaller is x), then the stronger the persistence in the credit restriction state.*

Proof. From (7):

$$\Pr(R_2 = 1|D_1 = 0) = \Pr(R_1 = 1) = \frac{\tilde{s}(\hat{p}_g) - \mu_s + x}{2x},$$

from which, and given that $\mu_s > \tilde{s}(\hat{p}_g)$, items (i)-(iii) follow. As $\mu_{s|s \geq \tilde{s}} > \mu_s$ and $\tilde{s}(\hat{p}_g) > s_{11}$, items (iv)-(vi) follow from (8) and (9). □

Part I of result (2) is consistent with the extant evidence on firm access to credit (Parker, 2002). Smaller and informationally opaque firms are more likely to be restricted in access to credit because it is more difficult for the bank to gather reliable signals about their creditworthiness. In addition, the lower is the return of potential projects Y_g and the stronger is the bank's market power ρ, the tighter are the credit standards used by the bank (i.e. the higher the value of $\hat{p}_g$) and the higher is the probability of firms experiencing restrictions in access to credit. In contrast, part II suggests, first, that informationally opaque firms are less likely to be locked in a credit restriction state than transparent firms and, second, that the use of credit scoring technologies, which are largely based on information about the borrower's past performance, can increase the persistence in credit rationing.

The intuition of these static comparative results is simple. The stickier the screening technology, and less noisy the information about a borrower, the less inclined the bank is to review the results of their past screening tests, and thus the stronger is the degree of state dependence in access to credit. Therefore, whether the restrictions in the availability of credit are more persistent for small than for large firms is ambiguous. Small firms are typically informationally more opaque than large firms and for the former the signal s can be assumed to be more noisy (i.e., the greater the value of x). Accordingly, credit availability could be expected to be *less* state dependent for small than for large firms. However, the degree of stickiness (λ) of the screening technology in small business lending may in principle be lower or higher than in lending to large borrowers: on the one hand, the use of credit scoring technologies tends to be less predominant in lending to small firms; on the other hand, the screening costs are typically greater in small business lending, which is why banks could be pushed to rely more on past information, thus increasing the stickiness of the selection process.

2.4 The discouragement effect

Consider now the demand stage. A firm endowed with an investment project $\tau = g, b$ seeks credit only if the probability of being funded by a bank is sufficiently high compared to its application costs. Let $E(r) = \rho / \left[\Pr(g_t|G_t, s_t > \hat{p}_g)\Delta\pi + \pi_b\right]$ be the expected interest rate should the loan application be accepted. To make the discouragement effect produced by a past credit restriction evident, let us assume:

Assumption 1. $c_\tau < [1 - F(\epsilon_1^*)]\, \pi_\tau [Y_\tau - E(r)]$.

where $[1 - F(\epsilon_1^*)]$ is the probability of receiving the requested loan, with $\epsilon_1^* = \tilde{s} - \mu_s$. According to Assumption 1, application costs are sufficiently low such that in the first period, all firms endowed with an investment project apply for a loan, and thus $\Pr(D_1 = 1) = q$. Similarly, as $s_{10} > \tilde{s}(\hat{p}_g)$, in the second period, all firms endowed with a new project apply to a bank too, and therefore $\Pr(D_2 = 1|D_1 = 0) = \Pr(D_2 = 1|D_1 = 1, R_1 = 0) = q$. Things are different for firms that were credit rejected in $t = 1$. In this case, since the screening technology has memory, the probability of a firm getting access to credit in the second period depends on the score of the credit-worthiness test carried out by the bank on that firm in $t = 1$. As a result, firms whose score was particularly low can be discouraged from applying to a bank, thus making the probability of a firm demanding credit in $t = 2$ dependent on the credit restriction state in period 1. In particular, we can prove the following result.

Result 3. *Firms for which*

$$\epsilon_1 \leq \epsilon_d = Z = \frac{2xc}{\lambda \pi_\tau (Y_\tau - E(r))} - \frac{x - \tilde{s}(\hat{p}_g) + \mu_s}{\lambda} \tag{10}$$

are discouraged from applying for credit in $t = 2$. The probability that a previously credit rejected firm seeks credit is then lower than that of a previously funded firm:

$$\Pr(D_2 = 1|D_1 = 1, R_1 = 1) = q\left[F(\hat{p}_g) - F(Z)\right] < \\ \Pr(D_2 = 1|D_1 = 1, R_1 = 0) = \Pr(D_2 = 1|D_1 = 0) = q \tag{11}$$

Finally, (i) the noisier the signal s (i.e. the greater is the value of x), (ii) the stronger the memory of the screening technology λ, and (iii) the higher the application costs, c, then the stronger the discouragement effect of a credit rejection in $t = 1$ on credit demand in $t = 2$.

Proof. Recalling that the probability of being credit-rejected in $t = 2$ conditional on being rejected in $t = 1$ is $F(\epsilon_{21}^*) = \frac{\tilde{s}(\hat{p}_g) + (1-\lambda)\mu_s - \lambda s_{s11} + x}{2x}$, inequality (10) follows trivially. From (11),

$$[F(\tilde{s}) - F(Z)] = q\frac{\tilde{s}(\hat{p}_g) - Z}{2x}$$

Substituting for Z and differentiating with respect to x and c it is easy to verify that the comparative static results about the discouragement effects of credit rationing on credit demand reported above hold. □

Hence, while for informationally opaque firms credit restriction can be less state-dependent than for transparent firms, Result 3 suggests that their future credit demand react more strongly and negatively to past credit restrictions from banks. On top of that, if we assume realistically that unit loan application costs are higher for small than large firms, again we have a prediction that are the former to be most discouraged from applying for a loan after experiencing a past credit restriction.

3 Empirical strategy

In order to identify state dependence in access to credit, we need to disentangle the influence of experiencing a credit restriction in the past from the influence of observed and unobserved heterogeneity which determines the actual tendency of firms to experience a restriction in credit availability and to stay out of the credit market in any period (Heckman, 1981a). In particular, sources of persistence other than state dependence can arise from firms' observable characteristics, time-invariant unobserved heterogeneity, and correlation in unobservable time-varying effects.

In formulating a dynamic model for credit restrictions, three critical issues arise. First, some firms can non-randomly decide not to apply for a loan, giving rise to a possible source of selection bias when estimating the probability of being credit restricted. Second, since the model is dynamic, the series of credit restriction events needs to be initialized (Heckman, 1981b). If we were to assume that the initial state of firms concerning access to credit is independent of the unobservable time-invariant firm and market characteristics, we could estimate a model for credit demand and supply at time t without specifying equations for the initial conditions of credit demand and supply. However, the exogeneity assumption could be only appropriate when the length of the time-series is adequate for asymptotics. With T fixed and relatively short-length – as in our sample, covering eight quarters –, the assumption of independence between the firm's initial state and its unobservable specific characteristics is barely tenable. Third, standard approaches to the estimation of dynamic models require the assumption of strict exogeneity (conditional on time-invariant unobserved effects) to hold. In practice, past values of the response variable are thought not to influence current values of covariates. In our case, this assumption is likely to be violated since the experience of being restricted in credit availability in the past may affect the current values of some firms' characteristics (for instance, liquidity, production level and even firm size) that, in turn, could influence the bank's decision to accept or reject the current loan applications. The presence of feedback effects does not allow for the identification of state dependence in access to credit and calls for an appropriate *ad-hoc* approach.

In order to address these three concerns, we specify a dynamic probit model for pairs of consecutive periods that accounts for selectivity bias, endogenous initial conditions and allows us to identify the state dependence in presence of unobserved heterogeneity and possible feedback effects. Precisely, in the spirit of Cappellari and Jenkins (2004)[6], we specify a first-order Markov model for credit demand and supply based on a dataset of pooled transitions, where the observation unit is the firm observed for every possible pair of consecutive quarters. Then, we formulate the two-period model for firm transitions between different states in the credit

[6] Cappellari and Jenkins (2004) specify a trivariate dynamic probit model for poverty transitions between two consecutive periods with sample attrition. Their trivariate specification includes a selection equation to control for the bias generated by sample attrition. By accounting for the selection bias generated by the credit demand, we extend their framework so as to include the selection equation in the initial conditions as well.

market in $t-1$ and t. In each period, any firm is in one of the following states: (i) it applies to a bank for a loan and receives the requested amount; (ii) it applies for a loan, but its application is not fully accepted by the bank in terms of quantity and/or interest rate (hereafter, we define such firms as credit restricted); and (iii) it does not apply to any bank for credit. We specify two binary outcome equations at time t, one for credit restriction and one for credit demand. We account for the initial condition problem following the linearized reduced form approach of Heckman (1981b), by specifying two additional equations for credit demand and supply in $t-1$, where $t-1$ is the initial period in the first-order Markov model. Identification of state dependence is achieved by using the lagged rather then the current values of covariates in the outcome equations in t.

The other three estimators for dynamic binary (short)-panel data models proposed in the literature that also allow for the covariates to be only predetermined rather than strictly exogenous suffer from some limitations that make them not easily applicable to our context.[7] First, the approach followed by Biewen (2009) to jointly estimate the parameters of the model for the response variable and predetermined covariates cannot be easily extended to a model with two response variables (credit restriction and loan application) and requires the formulation of a model for feedback effects for all the predetermined covariates, whose number is very large in our case.[8] Second, the approach proposed by Honoré and Lewbel (2002) requires that a continuous exogenous instrument is available, a condition which we are not able to meet in our dataset as present values of all the available firms' characteristics could be in principle influenced by past restriction events. Finally, the semi-parametric estimator of Arellano and Carrasco (2003) considers only a small number of explanatory variables and it is hardly feasible with a set of regressors as large as ours.

Our empirical approach is not without costs. First, by assuming that the process of credit restriction events lasts two periods, we do not fully exploit the longitudinal structure of the dataset, inducing a loss of estimation efficiency. Second, we cannot identify feedback effects, and third, we cannot disentangle the persistence in time-varying unobserved heterogeneity from the persistence due to time-invariant unobserved heterogeneity. Nevertheless, since our main objective is to test for state dependence in access to credit, these shortcomings are not problematic in our context.

In the remainder of this section, we lay out the model specification in the general case of a dynamic probit model with sample selection, then we discuss the first-order Markov model and its estimation, and we illustrate possible measures of state dependence in credit restriction and discouragement effects.

[7] Standard formulations of random effects (Heckman, 1981b; Keane and Sauer, 2009; Wooldridge, 2005) and the fixed-effects models (Chamberlain, 1985; Honoré and Kyriazidou, 2000) for short panels all require the strict exogeneity assumption to hold.

[8] While Biewen (2009) derives his joint model for the response variable and only two binary predetermined regressors, we should consider production, liquidity, size, export, etc. which, in our dataset, are measured as countinuous, binary or ordinal.

3.1 A general framework

We model credit restriction and credit demand for firm i at time t as follows:

$$r_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \gamma R_{it-1}^* + \alpha_i + \varepsilon_{it} \tag{12}$$

$$d_{it} = \mathbf{w}_{it}'\boldsymbol{\delta} + \phi R_{i,t-1}^* + \eta_i + u_{it} \quad \text{for} \quad i = 1, \ldots, N \; t = 2, \ldots, T. \tag{13}$$

In the first equation, r_{it} is the latent propensity to be credit restricted for firm i at time t which we observe as $R_{it} = \mathbf{I}(r_{it} > 0)$, where the function $\mathbf{I}(\cdot)$ indicates whether firm i experiences a restriction of credit availability in t ($R_{it} = 1$) or not ($R_{it} = 0$). Obviously, we can observe R_{it} only if firm i decides to apply for a loan in t. Similarly, in equation (13), d_{it} indicates the latent propensity to apply for credit which is observed as $D_{it} = \mathbf{I}(d_{it} > 0)$. The vector $\mathbf{x}_{it} \equiv (1, x_{1it}, \ldots, x_{Kit})$ includes K time-varying and time-invariant covariates at the firm and market level, while the vector $\mathbf{w}_{it} \equiv (1, x_{1it}, \ldots, x_{Kit}, w_{1it}, \ldots, w_{Mit})$ consists of the K covariates in $\mathbf{x}$ and M suitable exclusion restriction variables affecting the firm decisions to apply for a loan but not directly influencing bank willingness to grant the requested amount of credit.

Since R_{it-1} is not observed for those firms that did not apply in $t-1$, we substitute the lagged restriction outcome R_{it-1} with an "actual-restriction" state variable R_{it-1}^*, that takes value 1 for firms which state they have experienced an actual restriction in credit supply in $t-1$ and zero for non-rejected applicants and for those firms that did not apply for credit in $t-1$, whose rationing outcome would be otherwise unobserved. In practice, we separate firms that were actually screened and negatively valued by banks in $t-1$ (that is, using the terminology of Lemma 1 in Section 2, firms for which banks have drawn from the screening test the indicator B or the indicator G with a signal $s < \tilde{s}$) from those who were not subject to any creditworthiness test by banks, irrespective of whether they had no credit needs or were discouraged from applying for a loan.

In order to assess the impact of state dependence in access to credit, we include R_{it-1}^* in both credit supply and demand equations (12) and (13), to consider the effect of a past credit restriction on the likelihood that the bank will supply credit (i.e. state dependence in credit restriction) and on the firm propensity to apply for a new loan (i.e. discouragement effect).

The terms α_i and η_i capture the time-invariant firm unobserved heterogeneity and ε_{it} and u_{it} are idiosyncratic shocks with zero mean and unit variance. We make further assumptions on the error terms combining the covariance structures in Vella and Verbeek (1999), for the cross-equation dependence due to the presence of sample selectivity, with the proper normalizations due to the presence of binary data and in Keane and Sauer (2009), for the autocorrelation structure in the time-varying unobserved components:[9]

(A1) $\alpha_i + \varepsilon_{it} \sim N(0, \sigma_\alpha^2 + 1)$ and $\eta_i + u_{it} \sim N(0, \sigma_\eta^2 + 1)$ for $t = 2, \ldots, T$.

(A2) $\varepsilon_{it} = \tau_\varepsilon \varepsilon_{it-1} + \omega_{it}$ and $u_{it} = \tau_u u_{it-1} + \xi_{it}$, for $t = 2, \ldots, T$, where ω_{it} and ξ_{it} are white noises.

[9] The following applies for the special case $\alpha_i \equiv \eta_i$ as well.

(A3) $\mathrm{E}\left[\varepsilon_{it}u_{is}\right]=0$ for $t\neq s$ and $\mathrm{E}\left[\varepsilon_{it}u_{it}\right]=\rho$ for $t=2,\ldots,T$.

(A4) $\mathrm{E}\left[\alpha_i\eta_i\right]=\sigma_{\alpha\eta}$.

(A5) $\alpha_i \perp\!\!\!\perp \varepsilon_{it}$, $\eta_i \perp\!\!\!\perp u_{it}$, $\alpha_i \perp\!\!\!\perp u_{it}$, and $\eta_i \perp\!\!\!\perp \varepsilon_{it}$ for $t=2,\ldots,T$.

As the separation between the group of firms at risk of credit supply restriction from those that are not may be non-random from the beginning, estimation of model (12)-(13) requires assumptions on the initial state. The initial restriction outcome also suffers from selection bias in the initial period. Therefore, following Heckman (1981b), the processes are initialized as:

$$
\begin{aligned}
r_{i1} &= \mathbf{z}_{i1}'\boldsymbol{\pi}+\theta\alpha_i+v_{i1} && (14)\\
d_{i1} &= \mathbf{q}_{i1}'\boldsymbol{\lambda}+\psi\eta_i+\vartheta_{i1} \quad \text{for} \quad i=1,\ldots,N && (15)
\end{aligned}
$$

where we observe D_{i1} and R_{i1} according to the same observational rule for D_{it} and R_{it}; $\mathbf{z}_{i1}\equiv(1,z_{1i1},\ldots,z_{Ki1})$ and $\mathbf{q}_{i1}\equiv(1,z_{1i1},\ldots,z_{Ki1},q_{1i1},\ldots,q_{Mi1})$ are vectors of covariates including suitable exclusion restrictions. The distribution of the composite error terms is defined by the following assumptions:

(A6) $\theta\alpha_i+v_{i1}\sim N(0,\theta^2\sigma_\alpha^2+1)$ and $\psi\eta_i+\vartheta_{i1}\sim N(0,\psi^2\sigma_\eta^2+1)$.

(A7) $\mathrm{E}\left[v_{i1}\vartheta_{i1}\right]=\rho$.

(A8) $\mathrm{E}\left[\varepsilon_{it}v_{i1}\right]=\varpi_\varepsilon$ and $\mathrm{E}\left[u_{it}\vartheta_{i1}\right]=\varpi_u$; $\mathrm{E}\left[\varepsilon_{it}\vartheta_{i1}\right]=0$ and $\mathrm{E}\left[u_{it}v_{i1}\right]=0$, for $t=2,\ldots,T$.

In order to estimate the parameters in (12)-(15) plus the covariance and autocorrelation parameters we need to specify the joint distribution of the composite error terms. According to assumptions (A1)-(A8), they follow a $2T$-variate normal distribution with zero mean and covariance matrix

$$
\boldsymbol{\Omega}=\begin{pmatrix}
\theta^2\sigma_\alpha^2+1 & \theta\sigma_\alpha^2+\varpi_\varepsilon\tau_\varepsilon & \theta\sigma_\alpha^2+\varpi_\varepsilon\tau_\varepsilon^2 & \cdots & \theta\psi\sigma_{\alpha\eta}+\rho & \theta\sigma_{\alpha\eta} & \theta\sigma_{\alpha\eta} & \cdots\\
\theta\sigma_\alpha^2+\varpi_\varepsilon\tau_\varepsilon & \sigma_\alpha^2+1 & \sigma_\alpha^2+\tau_\varepsilon & \cdots & \psi\sigma_{\alpha\eta} & \sigma_{\alpha\eta}+\rho & \sigma_{\alpha\eta} & \cdots\\
\theta\sigma_\alpha^2+\varpi_\varepsilon\tau_\varepsilon^2 & \sigma_\alpha^2+\tau_\varepsilon & \sigma_\alpha^2+1 & \cdots & \psi\sigma_{\alpha\eta} & \sigma_{\alpha\eta} & \sigma_{\alpha\eta}+\rho & \cdots\\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\
\theta\psi\sigma_{\alpha\eta}+\rho & \psi\sigma_{\alpha\eta} & \psi\sigma_{\alpha\eta} & \cdots & \psi^2\sigma_\eta^2+1 & \psi\sigma_\eta^2+\varpi_u\tau_u & \psi\sigma_\eta^2+\varpi_u\tau_u^2 & \cdots\\
\theta\sigma_{\alpha\eta} & \sigma_{\alpha\eta}+\rho & \sigma_{\alpha\eta} & \cdots & \psi\sigma_\eta^2+\varpi_u\tau_u & \sigma_\eta^2+1 & \sigma_\eta^2+\tau_u & \cdots\\
\theta\sigma_{\alpha\eta} & \sigma_{\alpha\eta} & \sigma_{\alpha\eta}+\rho & \cdots & \psi\sigma_\eta^2+\varpi_u\tau_u^2 & \sigma_\eta^2+\tau_u & \sigma_\eta^2+1 & \cdots\\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots
\end{pmatrix} \qquad (16)
$$

3.2 First-order Markov model and estimation

The violation of the strict exogeneity assumption does not allow us to identify γ and ϕ in (12) and (13). Therefore, instead of formulating the model as in (12)-(15), we specify a first-order Markov model for credit restriction in access to credit where we take as the observation unit the firm in two consecutive periods: the credit restriction and credit demand outcomes are taken at time t as a function of R^*_{it-1}, and the initial conditions are specified in $t-1$. Under the assumption that not strictly exogenous covariates are predetermined – that is, that their initial observation is exogenous to the system –, we identify state dependence, and avoid confounding due to the presence of feedback effects, by taking the lagged values of the covariates in the credit restriction and demand equations at time t. In symbols, our model is specified as:[10]

$$\begin{aligned} r_{it} &= \boldsymbol{x}'_{it-1}\boldsymbol{\beta} + \gamma R^*_{it-1} + \alpha_i + \varepsilon_{it} && (17)\\ d_{it} &= \boldsymbol{w}'_{it-1}\boldsymbol{\delta} + \phi R^*_{it-1} + \eta_i + u_{it} && (18)\\ r_{it-1} &= \boldsymbol{z}'_{it-1}\boldsymbol{\pi} + \theta\alpha_i + v_{it-1} && (19)\\ d_{it-1} &= \boldsymbol{q}'_{it-1}\boldsymbol{\lambda} + \psi\eta_i + \vartheta_{it-1} \quad i=1,\ldots,N\ t=1,\ldots,T. && (20) \end{aligned}$$

where r_{it}, d_{it}, r_{it-1}, and d_{it-1} are the latent propensities to be credit constraints and applying for a loan in each period, of which we observe the binary indicators R_{it}, D_{it}, R_{it-1}, and D_{it-1} following the same observational rules as (12)–(15). Under assumptions (A1)-(A8), the joint distribution of the composite error terms is a quadrivariate normal with zero mean and an appropriate 4×4 subset of $\boldsymbol{\Omega}$ in (16) as variance-covariance matrix. However, since we are considering a two-period model, all the parameters of the variance-covariance matrix cannot be identified. Therefore, we define a correlation structure for (17)-(20) as $\boldsymbol{\Sigma} = unvech\,(1, \rho_{21}, \rho_{31}, \rho_{41}, 1, \rho_{32}, \rho_{42}, 1, \rho_{43}, 1)$, where diagonal elements have been normalized to unity and the off-diagonal correlations parametrize the dependence in the individual unobserved heterogeneity as follows:

- $\rho_{21} = \theta\psi\sigma_{\alpha\eta} + \rho$ and $\rho_{43} = \sigma_{\alpha\eta} + \rho$ capture the correlation due to the selection bias in $t-1$ and t, respectively (i.e., the correlation between the error terms in (19) and in (20) and in (17) and (18)). Note that these correlations contain the dependence due to both time-invariant ($\sigma_{\alpha\eta}$) and time-varying (ρ) unobserved heterogeneity.

- $\rho_{31} = \psi\sigma^2_\eta + \varpi_u\tau_u$ and $\rho_{42} = \theta\sigma^2_\alpha + \varpi_\varepsilon\tau_\varepsilon$ measure the correlation between the firm's status in $t-1$ and t in credit demand and in credit restriction respectively (i.e., the correlation between the error terms in (18) and (20) and in (17) and (19)). ρ_{31} and ρ_{42} capture the persistence in the unobservables through both the firm's constant unobserved effects (σ_α, σ_η) and the autocorrelations in the error terms (ϖ_ε,ϖ_u,τ_ε, τ_u).

- $\rho_{32} = \psi\sigma_{\alpha\eta}$ and $\rho_{41} = \theta_{\alpha\eta}$ capture the time-invariant sample selection correlation (i.e. the correlations between the error terms in (18) and (19) and in (17) and (20)). Note that this is a consequence of assumption (A8) that can be easily relaxed.

From these definitions, it is clear that in the formulation of the first-order Markov model the persistence due to constant unobserved firms' effects cannot be disentangled from the autocorrelation in the time-varying error components. Notwithstanding, individual unobserved

[10] For simplicity, in (17)-(20) we use the same notation for the regression parameters in (12)-(15)

heterogeneity is accounted for and parametrized by the above correlation structure, and the parameters of interest γ and ϕ remain identified.

Under the assumption of joint normality, the first-order Markov model (17)-(20) is estimated as a quadrivariate probit model where (18) and (20) are selection equations. We estimate the parameter vector $[\boldsymbol{\beta}', \gamma, \boldsymbol{\delta}', \phi, \boldsymbol{\pi}', \boldsymbol{\lambda}', \text{vech}(\mathbf{C})']'$, where $\mathbf{C}$ is the lower triangural Cholesky of $\boldsymbol{\Sigma}$, by Simulated Maximum Likelihood (SML). The contribution of firm i to the log-likelihood is $\ell_i = \ln(P_i)$ with

$$\ell_i = \ln(P_i) = \ln[\Phi_4(\mathbf{a}_i, \mathbf{b}_i, \mathbf{C})] \tag{21}$$

where $\Phi_4(\cdot)$ is the quadrivariate standard normal distribution function. Full expressions for the integral bounds $\mathbf{a}_i$ and $\mathbf{b}_i$ are given in Appendix. The probability $\Phi_4(\cdot)$ is simulated using the GHK algorithm, with 200 replications (Geweke, 1989; Keane, 1994; Hajivassiliou and McFadden, 1998). Standard errors are obtained in the usual way by using a sandwich formula. In the first-order Markov model formulation, the estimation of a quadrivariate probit model on pooled transitions is equivalent to estimating a random effect sample selection dynamic probit with $T = 2$ and linearized initial conditions as in Heckman (1981b), where the use of GHK instead of standard quadrature methods is necessary since unobserved heterogeneity is accounted for by a suitable parametrization of the correlation structure.

3.3 Measuring state dependence in credit restriction and discouragement effect

Other than testing for state dependence in access to credit, we are interested in evaluating the magnitude of state dependence in credit restriction as defined in (8) and (9). We compute state dependence in credit restriction as the average difference between the probability that the loan application has not been fully accepted by banks at time $t-1$ and, alternatively, the probability of credit restriction in t conditional on not having applied for a loan $t-1$ ($\overline{SD}_{R_{t-1}=0}$) or the probability of having requested and obtained credit in $t-1$ ($\overline{SD}_{D_{t-1}=0}$). Using the notation of model (17)-(20):

$$\overline{SD}_{R_{t-1}=0} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Pr(R_{it}=1, D_{it}=1, R_{it-1}=1, D_{it-1}=1)}{Pr(R_{it-1}=1, D_{it-1}=1)} - \frac{Pr(R_{it}=1, D_{it}=1, R_{it-1}=0, D_{it-1}=1)}{Pr(R_{it-1}=0, D_{it-1}=1)}\right] \tag{22}$$

$$\overline{SD}_{D_{t-1}=0} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Pr(R_{it}=1, D_{it}=1, R_{it-1}=1, D_{it-1}=1)}{Pr(R_{it-1}=1, D_{it-1}=1)} - \frac{Pr(R_{it}=1, D_{it}=1, D_{it-1}=0)}{Pr(D_{it-1}=0)}\right] \tag{23}$$

Similarly, we compute the discouragement effect as the average difference between the probability of not applying for credit in t conditional on having experienced a credit restriction in $t-1$ and, alternatively, the probability of not applying for credit in t conditional on having obtained credit in $t-1$ ($\overline{DE}_{R_{t-1}=0}$), or the probability of no application in either t or $t-1$ ($\overline{DE}_{D_{t-1}=0}$):

$$\overline{DE}_{R_{t-1}=0} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Pr(D_{it}=0, R_{it-1}=1, D_{it-1}=1)}{Pr(R_{it-1}=1, D_{it-1}=1)} - \frac{Pr(D_{it}=0, R_{it-1}=0, D_{it-1}=1)}{Pr(R_{it-1}=0, D_{it-1}=1)}\right] \tag{24}$$

$$\overline{DE}_{D_{t-1}=0} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Pr(D_{it}=0, R_{it-1}=1, D_{it-1}=1)}{Pr(R_{it-1}=1, D_{it-1}=1)} - \frac{Pr(D_{it}=0, D_{it-1}=0)}{Pr(D_{it-1}=0)}\right] \tag{25}$$

We can test the statistical significance of state dependence in access to credit by calculating the standard errors for expressions (22)-(25) using the Delta Method.

It is worth noting that these indicators of state dependence – which correspond to the Genuine State Dependence computed by Cappellari and Jenkins (2004) – control for individual heterogeneity, because they are functions of differences in individual probabilities, which are then averaged over the whole sample. These measures differ from aggregate measures of state dependence and discouragement effects (hereafter ASD and ADE), which can be computed taking the differences between the model transition rates:

$$\begin{aligned} ASD_{R_{t-1}=0} = &\left[\frac{\sum_{i=1}^{N} R_{it}R_{it-1}Pr(R_{it}=1, D_{it}=1|R_{it-1}=1, D_{it-1}=1)}{\sum_{i=1}^{N} Pr(R_{it-1}=1, D_{it-1}=1)}\right] + \\ &- \left[\frac{\sum_{i=1}^{N} R_{it}(1-R_{it-1})Pr(R_{it}=1, D_{it}=1|R_{it-1}=0, D_{it-1}=1)}{\sum_{i=1}^{N} Pr(R_{it-1}=0, D_{it-1}=1)}\right] \end{aligned} \tag{26}$$

$$\begin{aligned} ASD_{D_{t-1}=0} = &\left[\frac{\sum_{i=1}^{N} R_{it}R_{it-1}Pr(R_{it}=1, D_{it}=1|R_{it-1}=1, D_{it-1}=1)}{\sum_{i=1}^{N} Pr(R_{it-1}=1, D_{it-1}=1)}\right] + \\ &- \left[\frac{\sum_{i=1}^{N} R_{it}(1-D_{it-1})Pr(R_{it}=1, D_{it}=1|D_{it-1}=0)}{\sum_{i=1}^{N} Pr(D_{it-1}=0)}\right] \end{aligned} \tag{27}$$

$$\begin{aligned} ADE_{R_{t-1}=0} = &\left[\frac{\sum_{i=1}^{N}(1-D_{it})R_{it-1}Pr(D_{it}=0|R_{it-1}=1 D_{it-1}=1)}{\sum_{i=1}^{N} Pr(R_{it-1}=1, D_{it-1}=1)}\right] + \\ &- \left[\frac{\sum_{i=1}^{N}(1-D_{it})(1-R_{it-1})Pr(D_{it}=0|R_{it-1}=0, D_{it-1}=1)}{\sum_{i=1}^{N} Pr(R_{it-1}=0, D_{it-1}=1)}\right] \end{aligned} \tag{28}$$

$$\begin{aligned} ADE_{D_{t-1}=0} = &\left[\frac{\sum_{i=1}^{N}(1-D_{it})R_{it-1}Pr(D_{it}=0|R_{it-1}=1 D_{it-1}=1)}{\sum_{i=1}^{N} Pr(R_{it-1}=1, D_{it-1}=1)}\right] + \\ &- \left[\frac{\sum_{i=1}^{N}(1-D_{it})(1-D_{it-1})Pr(D_{it}=0|D_{it-1}=0)}{\sum_{i=1}^{N} Pr(D_{it-1}=0)}\right]. \end{aligned} \tag{29}$$

By comparing $\overline{SD}$ and $\overline{DE}$ with ASD and ADE, respectively, we can draw indications about the relative importance of state dependence effect and firms' observed and unobserved heterogeneity in explaining the overall persistence in the probability of being credit restricted and of being out of the credit market. The closer $\overline{SD}$ ($\overline{DE}$) is to ASD (ADE), the stronger is state dependence in access to credit.

4 Data and variables

We draw the data from the monthly "survey on manufacturing firms' confidence"run by the ISAE (Institute of Studies and Economic Analysis), now part of the ISTAT (Italian Institute of Statistics). These data were recently re-engineered for comparability with data released by other European institutions, such as the Ifo Business Climate Survey, consistent with maintaining a focus on the traditional sectors of Italian specialization (Malgarini et al., 2005). The representative sample is stratified by geographical area, economic activity and number of employees. The survey covers about 4,000 Italian manufacturing firms with at least five employees, interviewed from March 2008 to March 2010. Data are available at the firm level, on a quarterly basis (releases in March, June, September and December releases).[11] The availability of a survey run at a quarterly frequency is a better setting to investigate state dependence in access to credit than standard structural surveys run on an annual or pluri-annual basis, as many events that can affect the firm entry and exit from the credit restriction and discouragement states may occur over such a long time frame.

The dataset does not allow identification of the banks with which firms have a credit relationship, but provides information about several firm characteristics. Thanks to the availability of data about firm location, at the administrative province level, we link the ISAE/ISTAT dataset with monthly data on bank branch openings and closures (at the bank-province level) compiled by the Bank of Italy, and with data on regional real GDP published by ISTAT.

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:q1 to 2009:q4 (unbalanced). The estimation of the model (17)-(20), presented in Section 3, is based on the sample of pooled transitions. Therefore, we reshape our dataset such 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. In this way, we end up with a sample of $24,080$ observations.

The survey has a specific section on firm access to credit with information on firm demand for credit and bank lending decisions, so that we can distinguish between the demand for and supply of bank credit. We measure demand for credit by an indicator variable (D) which assumes a value of one for firms that directly contacted one or more banks in the previous quarter in order to apply for credit (i.e., we exclude firms stating that they just went to the bank to ask for information).[12]

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

[12] To be precise, the survey section on access to bank credit includes three main questions:

Q43. How do you consider the access to bank credit with respect to three months ago?

1. improved
2. the same as before
3. worsened
4. do not know

Q44. Is your previous judgement the result of direct contact with a bank aimed at requesting/increasing a

Restricted applicants are identified only among firms that applied for a loan in a given quarter and they are identified by a dummy variable for credit restriction that is equal to one for firms that did not obtain the desired amount of bank credit (R).[13] Lacking loan-level data, our variables on loan demand and credit restriction do not refer to a specific bank-firm relationship.

Table 1 summarizes the sample composition by firm state in t and $t-1$ for the complete sample of pooled transitions. The marginal frequency of restricted applicants at time t in our sample (of applicant firms) is 20.1% while the credit restriction frequency in t conditional on having experienced past credit restriction is 34.6%. This means that 80% of restricted applicants in the quarter t come from the pool of firms that were credit restricted in the previous quarter. The conditional frequency of restricted applicants is constantly higher than that of the marginal frequency, even though the two frequencies follow the same pattern over time, characterized by a sharp increase in the (marginal and conditional) shares of credit restricted firms after the Lehman's collapse (Figure 2).

The set of regressors includes variables at the firm- and at the credit market level. Definitions and sample means of covariates are shown in Table 2. The main variable of interest is firm size, measured by the logarithm of the number of employees (*SIZE*). Following standard arguments (and stylized facts) in the banking literature, we assume that small firms are informationally more opaque than large firms, and that banks provide small business lending on a relational basis more than by using hard-information credit scoring technologies. Expressed in terms of our model of state dependence in access to credit, this implies that the bank screening technology for small firms is noisier and less sticky (that is, x is greater and λ is lower). In addition, for small firms loan application costs, c, tend to be higher due to their simplified and professional organizational structure and the limited availability of public information about them. Small businesses can be expected to be less likely to apply for a loan, but more likely to be in a credit restriction state. Further, they are expected to experience a lower persistence in the credit restriction state, but also to be more discouraged from applying for credit following loan rejection (see equation (8)).

The set of firm-level variables includes a dummy for exporter firms (*EXPORT*), identified as firms that sold at least some of theirs products abroad. This variable, taken as a proxy for pro-

line of credit for your firm, or is it just an opinion which has nothing to do with specific contacts with banks?

1. it derives from direct contact with banks (go to Q45)
2. it is an opinion unrelated to direct contacts with banks (no other questions in this section)

Q45. (for firms answering 1. at Q44). Did you get from the bank the requested amount of credit?

1. yes, at the same conditions (no other questions in this section)
2. yes, but at more onerous terms
3. no
4. I just went to the bank to ask for information (no other questions in this section)

We define $D = 1$ if Q44 = 1 and Q45 = 1, 2 or 3; and $D = 0$ if Q44 = 2 or Q45 = 4.

[13] Precisely, we define $R = 1$ if Q45 = 2 or 3; and $R = 0$ if Q45 = 1.

ductivity, is expected to affect positively the demand for credit and negatively the likelihood of credit restriction. The categorical variable *LIQUIDITY* captures firm financial health on the basis of a question about the level of liquidity with respect to operational needs, which respondents can evaluate as good, neither good nor bad, or bad. To the extent that this variable is an indicator of financial needs and riskiness, it is expected to be negatively correlated with the demand for credit and positively with credit availability.[14] We control for differences in access to credit across sectors adding a set of 10 industry dummies (*INDUSTRY*), and we include a dummy variable identifying firms located in southern regions (*SOUTH*), to take into account the effect that differences in the levels of economic and financial development between the North and the South of Italy could have on access to credit.

Finally, a variable measuring the level of orders (*ORDER*) is used as an exclusion restriction in the initial conditions (19)-(20). The survey asks about the level of orders and demand in the current quarter, which can be assessed as low, normal or high. Since we consider a two-period model for each transition, it can be conjectured that this information may affect only the initial decision to apply for a loan and the initial bank response, while it should not provide additional information in the following quarter. In addition, the trend in labor costs during the previous 12 months *LABOR COST* is used as an exclusion restriction for the credit demand equations (18) and (20), as in Presbitero et al. (2014).[15]

As a measure of the structure of the local credit market at the provincial level (NUTS 3), we include the number of branches per 10,000 inhabitants *BRANCHES* and 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. In our theoretical framework, to the extent that ρ and $\hat{p}_g$ increases with the credit market concentration, the probability of credit restriction and HHI are positively correlated.

We control for regional variation in the business cycle, which may affect the demand for and the supply of credit by adding the regional real GDP growth rate (*GDP GROWTH*). We expand the annual GDP data published by ISTAT using quarterly national data on GDP and expenditure components, following Chow and Lin (1971)'s interpolation. Aggregate common shocks are taken into account by adding quarterly time dummies.

Figure 3 shows the frequencies (both marginal and conditional on the credit restriction state in $t-1$) of restricted applicants at time t, by firm 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 *SIZE*, *HHI* and *BRANCHES*. It is worth noting that, consistent with the predictions of the model, when considering firm size and export, the patterns of the marginal and conditional frequencies are reversed: small and non-exporting firms are, on av-

[14]The survey question is: *"Currently, the level of liquidity with respect to operational needs is good, neither good nor bad, or bad?"*

[15]With regard to labor costs the exact survey question is: *"In percentage, how much has the cost of labor changed in the last 12 months?"*

erage, more likely to have their credit application not fully received by the banks, while large exporter firms show a higher degree of state dependence in credit denial.

5 Estimation results and discussion

5.1 The basic model

5.1.1 Identifying state dependence

Table 3 shows our main results and compares the estimates of the first-order Markov model with the ones obtained with alternative estimation techniques for state dependence in access to credit, not considering firm unobserved heterogeneity and sample selection. The first four columns report the estimated parameters of equations (17)–(20) and the correlation coefficients of the first-order Markov model proposed in Section 3 (Model (1) henceforth). Columns 5 and 6 report the estimation results of a probit model with sample selection in which the probability of a firm being credit restricted is jointly estimated with the demand (selection) equation, but in which the initial state of credit restriction is considered exogenous and the effects of unobserved heterogeneity in $t-1$ are neglected. The last column shows the result of a simple probit model estimation of the supply equation (17), in which both the sample selection and the initial conditions are not addressed.

In Model (1), the key parameter γ, associated to R^*_{t-1} in the credit restriction equation, is positive and statistically significant (column 4), suggesting that once a firm has been restricted in access to credit in $t-1$, its probability of experiencing a new restriction in t is, on average, higher than for firms that have not been credit restricted or did not apply for a loan in $t-1$. At the same time, we find that ϕ is negative and statistically significant (column 3): all else being equal, firms which have experienced a loan denial in $t-1$ are less likely to apply for bank credit in t. Taken together, these results indicate a strong dependence in access to credit, expressed in the propensity of banks to keep the negative assessment on firm creditworthiness from one period to the other, and in the discouragement effect on credit restricted applicants.

Formally, we test for state dependence in the demand and rationing equation computing the Wald test statistic for the null hypothesis of ϕ and γ in (18) and (17) being jointly equal to zero. The value of the statistic is 53.96 which, compared with a χ^2_2, indicates that the null hypothesis of absence of state dependence can be rejected.

Looking at the results of the probit model with sample selection (columns 5 and 6) makes it clear that a pooled model, not taking into account the unobserved time-invariant firm heterogeneity, leads to biased results. In particular, the state dependence parameters change substantially when initial conditions are not accounted for. First, previously credit restricted firms look more likely to be restricted again in the next period, but the estimated value of the parameter γ is much lower than the one estimated by the first-order Markov model, hiding the effects of the sample selection in $t-1$.[16] Second, and more noticeably, when ignoring the initial conditions, the coefficient for R^*_{t-1} in the demand equation is significantly positive, suggesting that experiencing a credit restriction in $t-1$ would result in spurring rather than discouraging firms to apply for credit in t.

We test for the exogeneity of the initial conditions computing a LR test for the null hypothesis of $\rho_{31} = \rho_{41} = \rho_{32} = \rho_{42} = 0$. The value of the test is 1173.75, such that the null hypothesis is rejected (the value of the test needs to be compared with a χ^2_4).

The estimated correlation coefficients of Model (1) 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 some firms do not apply for credit as they expect to have a high probability of being restricted by banks and prefer to 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 that would prove extremely large (see column 7).

Interestingly, we also find that the correlation between the error terms in the credit restriction equations (ρ_{31}) is positive and statistically significant, suggesting that there are time-invariant unobservable characteristics which affect the individual probability of being credit restricted. Differently, we do not find a similar effect for the credit demand equations, as ρ_{42} is not statistically different from zero.

From the estimates of the first-order Markov model we can calculate the state dependence in credit restriction and discouragement effects, as presented in Section 3.3. On average, firms experiencing a credit restriction in $t-1$ are 25.2% more likely to be credit restricted again in t than borrowers that were not restricted by banks in $t-1$ ($\overline{SD}_{R_{t-1}=0}$) and 26.4% more likely to be restricted with respect to firms which did not applied for a loan in the previous period ($\overline{SD}_{D_{t-1}=0}$). This difference is statistically significant and large enough to be also economically significant, given that the sample frequency of rationed firms is 20%. Likewise, the discouragement effect proves to be statistically and economically significant, as the probability of not applying for credit conditional on a previous credit restriction is 10% ($\overline{DE}_{R_1=0}$) higher than for non-restricted borrowers and 33.3% higher than for new applicants ($\overline{DE}_{D_1=0}$).

The quantities $\overline{SD}$ and $\overline{DE}$ measure the probability of experiencing a credit restriction or the probability of being discouraged, conditional on credit restriction in the previous period, net of the individual observed and unobserved heterogeneity (Section 3.3). We could gauge how much of the persistence in access to credit is actually due to state dependence, rather than to the firms' observed and unobserved heterogeneity comparing $\overline{SD}$ and $\overline{DE}$ with the

[16] Typically, neglecting initial conditions results in overstating rather than understating the magnitude of state dependence. However, in this case the biases in the demand equation and supply equations in t depend on the correlation between the unobserved heterogeneity and both the initial outcomes.

aggregate measures of state dependence and discouragement effects, ASD and ADE. The latter are displayed at the bottom of Table 4, which reports the average estimated probabilities of being in one of the three possible states at time t, conditional on coming from each state in $t-1$. The comparison clearly shows that most of the persistence in credit restriction and in being out of the credit market is due to state dependence while the persistence explained by firms' heterogeneity is much lower.

5.1.2 Comparing different models: goodness-of-fit

As a first measure of the goodness of fit of Model (1), we compare the the predicted transition rates reported in Table 4 with the sample conditional frequencies displayed in Table 1 and we find an almost perfect coincidence between the two set of probabilities.

To assess the accuracy of the different models we look at the Receiver Operating Characteristic (ROC) 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 model predictions.[17] The AUROC provides a simple test against the null value of 0.5 (a complete uninformative model).

Figure 4 shows the ROC for the probabilities of credit restriction in t (panel a), and of being credit constrained (panel b). For the first–order Markov model, probabilities are assigned according to the state in $t-1$. In panel (a) the probability of credit restriction for the first–order Markov model and for the probit model with sample selection are conditional on applying for credit in t, for comparability with the pooled probit model without sample selection. In panel (b), the probability of being credit restricted is computed as the marginal probability of not applying for loan, $P(D_t = 0)$, plus the joint probability of applying and being restricted by banks, $Pr(D_t = 1, R_t = 1)$. We exclude the simple probit model from this second analysis since, in this model, it is assumed that credit demand and denial are independent.

Figure 4 confirms that the first–order Markov model describes access to credit 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 panels 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 indicate that, for a

[17] 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 us 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 loan application is actually denied) The x-axis is 1-Specificity, where 'Specificity' is the probability of correctly predicting the outcome variable equal to zero (i.e. the loan application is not rejected). It is easy to see that the further the ROC curve is away from the 45 degree line the better the model predicts both states (i.e. credit availability and denial). When the area under the ROC curve is 1, the model predicts everything correctly. For a recent use of the AUROC in a finance context, see Bharath and Dittmar (2010).

given share of true positives, the simple probit models call a larger share of false alarms that 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 AUROCs of the two probit models are almost identical. This suggests that the increase in accuracy comes from the capacity to deal with unobserved heterogeneity, rather than from modeling sample selection.

5.1.3 The other determinants of credit access

In this section we discuss the effect of other variables on the probabilities of loan application and credit restriction, referring to the estimates of Model (1).

We find that small and exporting firms are more likely to apply for a loan and to suffer credit restrictions by banks than large and domestic-oriented firms. This result is not only consistent with the extensive literature on firm financing constraints, but also with the predictions of the model in Section 2, under the assumption that the screening technology used by banks for lending to small and exporting firms is more imperfect and noisy than that used to lend to large and domestic-oriented firms. As expected, firm liquidity needs are positively correlated with the demand for credit, but they do not show any significant association with the probability of experiencing a credit restriction.

Firms facing a low demand for their products have a higher probability of staying out of the credit market, either because they do not demand credit or because they do not obtain it. This finding is consistent with our model, predicting that when project returns (Y) are low bank credit standards ($\hat{p}_g$) are tighter, leading to a higher probability of credit restriction and to a stronger discouragement effect.

Moving on to the credit market structure, we find that the degree of credit market concentration is associated with a lower probability of credit demand and a higher probability of credit restriction, even if the coefficients on HHI are not statistically significant. By contrast, firms located in more financially developed provinces (i.e. where the number of bank branches per capita is higher) are more likely to apply for credit and to have their application accepted. To the extent that a greater presence of branches in the market involves lower application costs for borrowers (i.e., lower c) and lower market power for banks (i.e., lower ρ), these empirical findings speak to the predictions of our theoretical model.

Once firm- and market-specific characteristics are taken into account, our results do not indicate that being located in the less developed southern regions or in regions where GDP growth rate is lower is associated with worse access to credit.

Finally, the coefficients on the time dummies indicate that Italian firms experienced a credit crunch after the Lehman bankruptcy. The point estimates show a significant reduction in the demand for credit but, even accounting for this effect, there is evidence of a large and statistically significant reduction in the likelihood of firms obtaining the required credit, consistent with the existing evidence for Italy (Del Giovane et al., 2011; Gobbi and Sette, 2014; Presbitero et al., 2014) and with the descriptive statistics (Figure 2).

5.2 State dependence, discouragement effect, and firm size

Our information-based theory of state dependence in access to credit predicts that informationally opaque borrowers, having experienced a credit restriction: 1) are more likely to be discouraged from applying again for a new loan, but 2) can be less likely to be locked in a credit restriction state in the future.

We test these two predictions by adding to the baseline specification (Model (1)) the interaction term between the variable R^*_{t-1} in the rationing and demand equations and firm size, as a proxy for firm information opaqueness.

The negative and positive signs of coefficients for the interaction terms in the supply and demand equations indicate, respectively, that small firms are less likely to be locked in a credit restriction state than large firms, but are more likely to be discouraged from applying for credit in the future (Table 5).[18]

Given that in non-linear models the sign and magnitude of marginal effects associated with interaction terms are not directly interpretable (Ai and Norton, 2003), we compute state dependence in credit restriction and the discouragement effect, as indicated in expressions (23)-(24), for different values of firm size. The results are plotted in Figure 5. Consistent with expressions (8)-(9) in Section 2, state dependence in credit restriction is increasing nonlinearly with firm size and is especially low for micro and small enterprises. Consistent with the model (recall that $\mu_{s|s\geq\tilde{s}} > \mu_s$), this nonlinearity is stronger if state dependence is computed with respect to non-applicants (panel b), while state dependence with respect to non-restricted borrowers increases more steadily with firm size (panel a). The discouragement effect is decreasing nonlinearly with firm size (Figure 5, panels c and d).

Variations in the state dependence and discouragement effects due to firm size are economically (and statistically) significant. For a firm with 5 employees, the penalty due to having been credit restricted in t-1 on the current likelihood of credit restriction is 18%, while ti increases to 26.8% for a firm with 25 employees and to 38% for a larger firm with 200 employees (Figure 5, panel a). The variation in the discouragement effect due to firm size is also considerable: DE increases, in absolute terms, from -5% for a firm with five employees to -10% and -17% for a firm with 25 and 200 employees, respectively (Figure 5, panel c).

5.3 State dependence in tranquil and crisis times

During our sample period the Italian economy was severely hit by the global financial crisis triggered by the collapse of Lehman Brothers in the US. Since five out of the seven quarters in

[18] The null hypotheses of absence of state dependence, exogeneity of initial conditions and joint exogeneity are rejected as in Model (1). In addition, estimated coefficients for control variables and estimated average state dependence and discouragement effects are in line with results in Table 3.

our sample are crisis periods, a possible concern with our analysis is that state dependence in access to credit could be due to the global liquidity shock and limited to the crisis period.

To test whether state dependence in credit restriction and the discouragement effect are specific features of malfunctioning credit markets in crisis periods we interact R^*_{t-1} with quarter dummies to allow for the effect of R^*_{t-1} on the probabilities of demanding credit and having the loan application restricted to vary over time. Since Lehman Brothers filed for Chapter 11 in September 2008, we consider the quarters 2008:q4-2009:q4 the post-Lehman period.

The results, reported in Table 6, reject the hypothesis that state dependence in access to credit is an exclusive occurrence in times of crisis. The coefficients on R^*_{t-1} confirm the presence of state dependence in access to credit in tranquil periods, while those on the interaction terms suggest that the discouragement effect decreased during the crisis.

In order to have a clearer picture of the evolution of state dependence in firm access to credit during the sample period, we compute the values of SD and DE quarter by quarter and test for their significance. Figure 6 shows that state dependence in credit restriction and the discouragement effect are present throughout the sample.[19]

The confidence bands in Figure 6 show that the variations in state dependence and discouragement effects from one quarter to the next are generally not statistically significant. However, when we compute the variation in SD and DE by aggregating quarters in pre- and post-Lehman periods[20], we observe that state dependence in credit restriction is 9.7% higher in the post- than in the pre-Lehman period, while the discouragement effect decreases by almost 12.5% after the Lehman collapse (Table 7).

6 Conclusions

The ongoing financial crisis has made it clear once again that financial frictions constitute a key determinant 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 micro foundation of these macro models, the limited empirical evidence on the actual pres-

[19]To be precise, the value of state dependence in the pre-Lehman quarter 2008:q2 is equal to 0.13 and statistically significant (panels a and b). In the same quarter, $\overline{DE}_{R_{t-1}=0} = 0.04$ and it is not not significantly different from 0 (panel c), but the discouragement effect computed with respect to non-applicant firms in $t-1$ amounts to -0.184 and is significant at the 5% level (panel d).

[20]The effect on the state dependence in credit restriction measures of the discrete change between the pre- and post-Lehman Brothers quarters (ΔLB) is calculated by setting to zero/one the quarter dummies for the pre/post-Lehman periods:

$$\frac{\Delta\overline{SD}_{R_{t-1}=0}}{\Delta LB} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\Delta P_{1i}}{\Delta LB} - \frac{\Delta P_{0i}}{\Delta LB}\right]$$

where $P_{1i} = \frac{Pr(R_{it}=1,D_{it}=1,R_{it-1}=1,D_{it-1}=1)}{Pr(R_{it-1}=1,D_{it-1}=1)}$ and $P_{0i} = \frac{Pr(R_{it}=1,D_{it}=1,R_{it-1}=0,D_{it-1}=1)}{Pr(R_{it-1}=0,D_{it-1}=1)}$. We test for the statistical significance of $\frac{\Delta\overline{SD}_R}{\Delta x}$ via delta method. In the same way we derive $\Delta\overline{SD}_{D_{t-1}=0}/\Delta LB$, $\Delta\overline{DE}_{R_{t-1}=0}/\Delta LB$ and $\Delta\overline{DE}_{D_{t-1}=0}/\Delta LB$.

ence of persistence in financial frictions at the firm level is somewhat surprising. This paper sought to fill this gap investigating state dependence in access to credit on a representative sample of Italian manufacturing firms.

We employed a first-order Markov model to estimate state dependence: we took 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 denied in two consecutive periods. Considering that in each period a firm may: (i) be credit restricted, (ii) not demand bank credit, and (iii) have full access to bank credit, we were able to estimate the degree of state dependence in credit restriction and the strength of the discouragement effect.

Our results show that firm access to credit is characterized by state dependence in credit restriction and discouragement effects. State dependence in access to credit varies across firm characteristics. Once credit restricted, small and informationally opaque firms are less likely to apply for credit than large firms (i.e. the discouragement effect is stronger), but they are less subject to state dependence in credit restriction. Finally, we document that state dependence, although heightened by global liquidity shocks, is not an exclusive feature of crisis periods.

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APPENDIX

FIGURES AND TABLES

Figure 2: Restricted applicants, marginal and conditional frequencies, by quarter

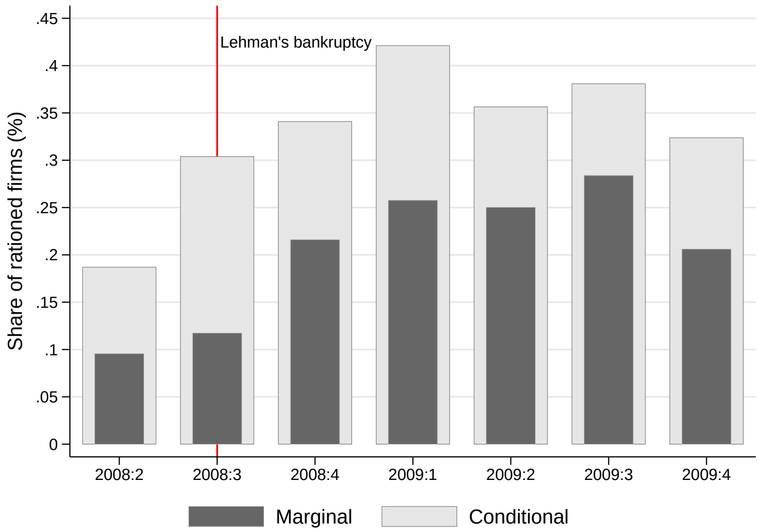


Figure 3: Restricted applicants, marginal and conditional frequencies, by firm and credit market characteristics

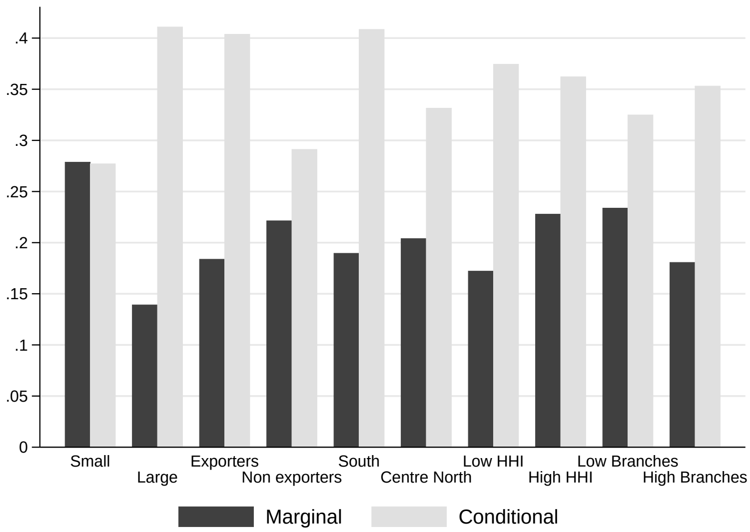
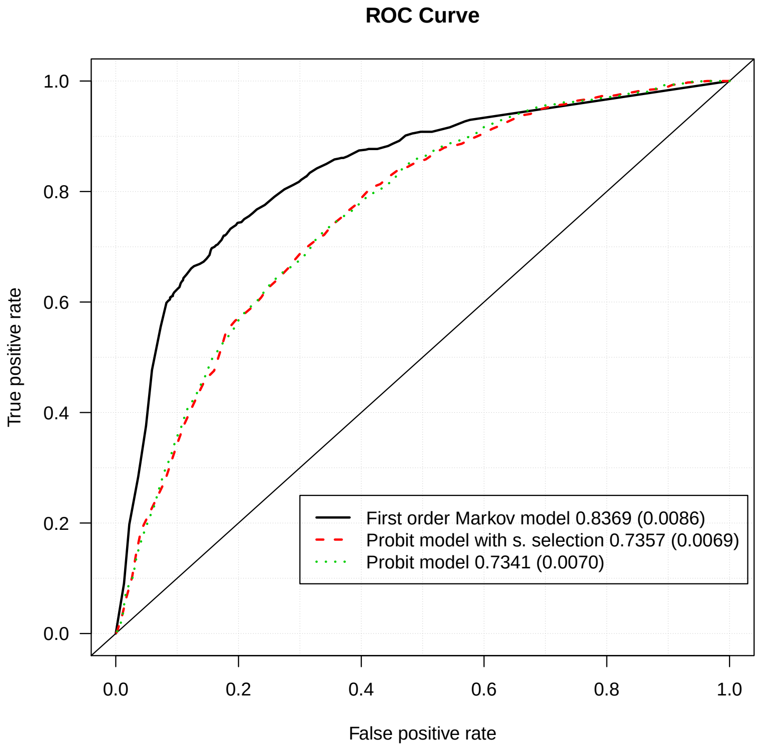
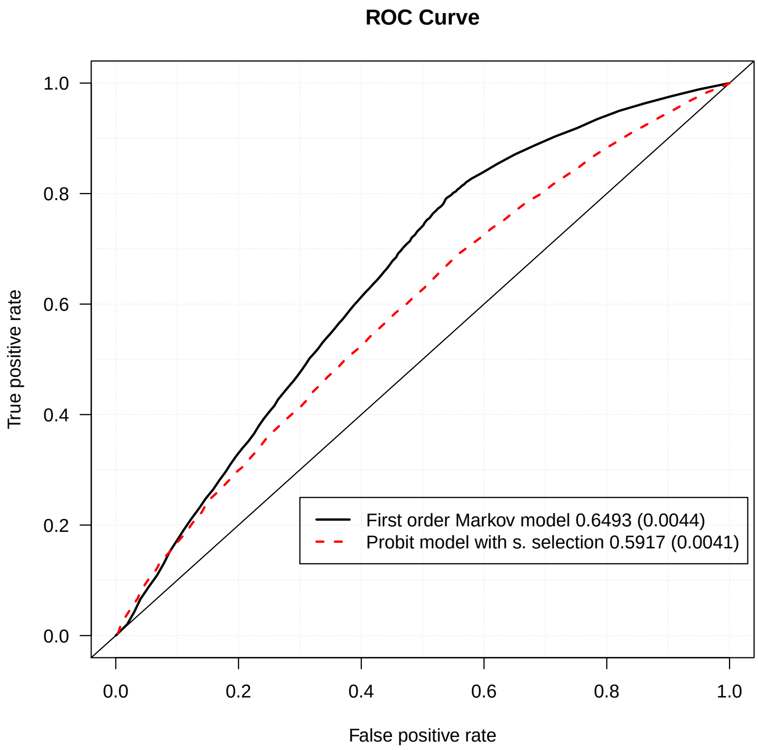


Figure 4: Goodness-of-fit



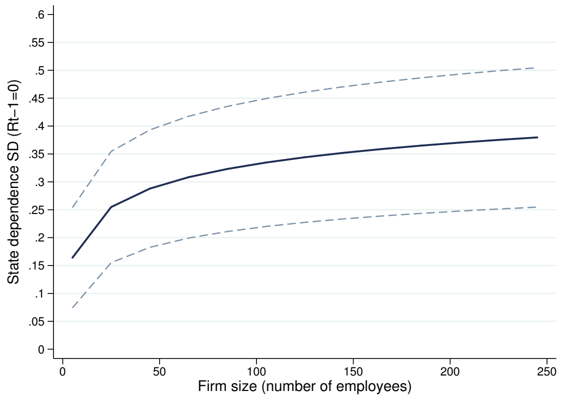
(a) Probability of credit restriction t



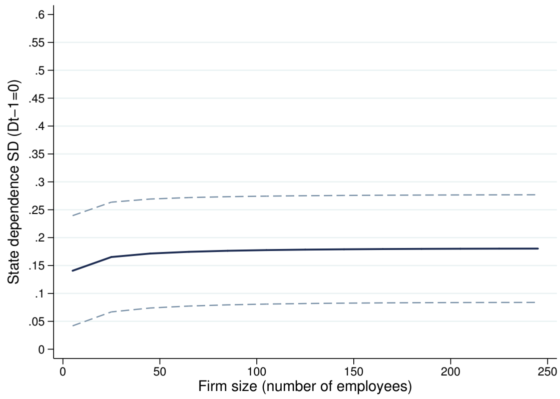
(b) Probability of being credit constrained in t

Notes: elaborations based on results from Table 3.

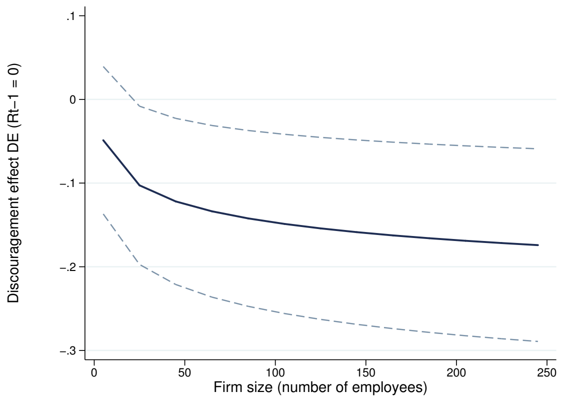
Figure 5: State dependence in access to credit and firm size



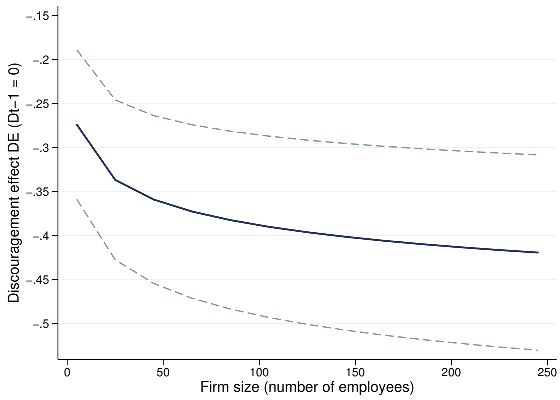
(a) State dependence in credit restriction: $\overline{SD}_{R_{t-1}=0}$



(b) State dependence in credit restriction: $\overline{SD}_{D_{t-1}=0}$



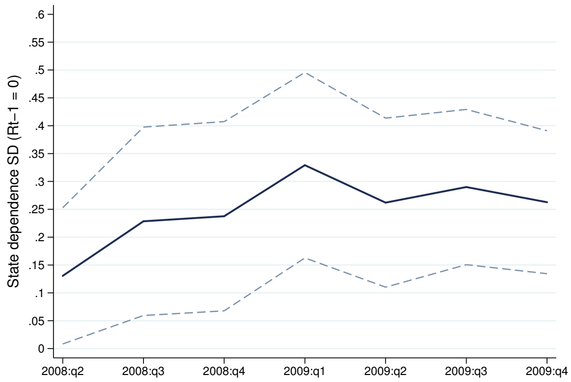
(c) Discouragement effect: $\overline{DE}_{R_{t-1}=0}$



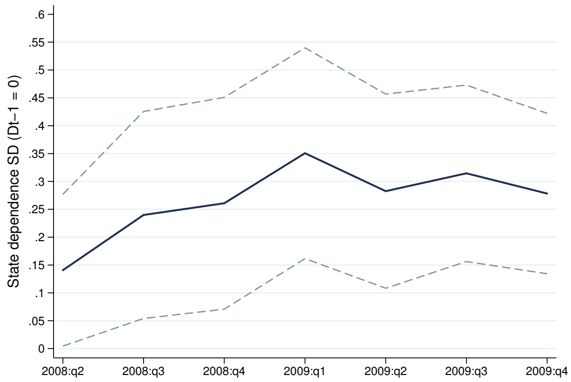
(d) Discouragement effect: $\overline{DE}_{D_{t-1}=0}$

Notes: elaborations based on results from Table 5 (Model 2). The diagrams show the values of $\overline{SD}_{R_{t-1}=0}$, $\overline{SD}_{D_{t-1}=0}$, $\overline{DE}_{R_{t-1}=0}$, and $\overline{DE}_{D_{t-1}=0}$ (solid lines) and the 90% confidence interval (dotted line) for different values of the number of employees. Standard errors are computed via Delta Method.

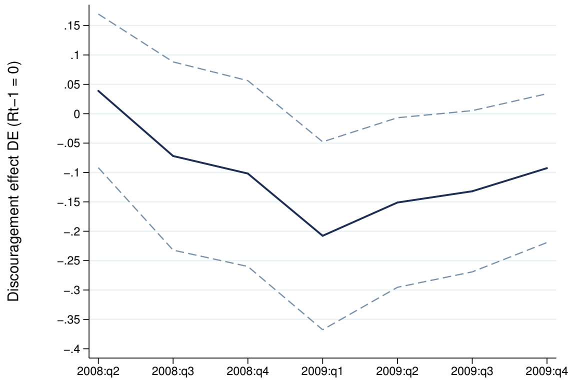
Figure 6: State dependence in access to credit and time



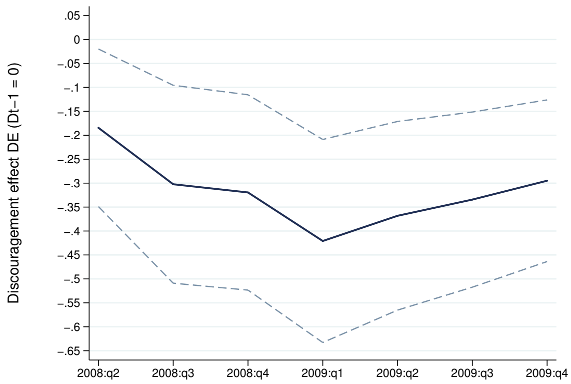
(a) State dependence in credit constraints: $\overline{SD}_{R_{t-1}=0}$



(b) State dependence in credit constraints: $\overline{SD}_{D_{t-1}=0}$



(c) Discouragement effect: $\overline{DE}_{R_{t-1}=0}$



(d) Discouragement effect: $\overline{DE}_{D_{t-1}=0}$

Notes: elaborations based on results from Table 6 (Model 3). The diagrams show the values of $\overline{SD}_{R_{t-1}=0}$, $\overline{SD}_{D_{t-1}=0}$, $\overline{DE}_{R_{t-1}=0}$, and $\overline{DE}_{D_{t-1}=0}$ (solid lines) and the 90% confidence interval (dotted line) for each quarter in the sample. Standard errors are computed via Delta Method.

Table 1: Sample composition by state transitions

We use data from 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 consists 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 $24,080$ pooled transitions.

Quarter $t-1$ \ Quarter t	No demand	Not rationed	Rationed	Obs.
No demand	78.92%	17.13%	3.94%	16,861
Not rationed	53.99%	41.13%	4.87%	5,910
Rationed	46.68%	18.79%	34.53%	1,309
Obs.	17,109	5,566	1,405	24,080

Table 2: Variables: definitions and descriptives

This table shows the description and sample means based on pooled transitions of the variables used in the model estimation. We include covariates both at the firm level and at the local credit market level in the model specification. Statistics based on 24,080 observations.

Variable	Description	Mean
D	Dummy equal to one for firms which report direct contacts with one or more banks in the previous quarter in order to seek credit (i.e., we exclude firms stating that they just went to the bank to ask for information)	28.9
R	Dummy equal to one for firms which stated they did not obtain the desired amount of bank credit provided they contacted one or more banks	20.1
$SIZE$	The logarithm of the firm's number of employees	3.13
$EXPORT$	Dummy equal to one if the firm is an exporter, and zero otherwise	0.471
$SOUTH$	Dummy equal to one if the firm is located in the southerns regions of Italy, and zero otherwise	0.176
HHI	Herfindhal-Hirschman index calculated on bank branches in the province where the firm is located	1.061
$BRANCHES$	Number of branches for 10,000 inhabitants by province	6.273
$GDP\ GROWTH$	Regional real GDP growth rate (ISTAT), expanded using quarterly national data on GDP and expenditure components by Chow and Lin (1971)'s interpolation	0.089
$TIME$	quarter dummies from 2008:q2 to 2009:q4	
$LIQUIDITY$	level of liquidity:	
$GOOD = 1$		0.241
$NEITHER\ GOOD\ OR\ BAD = 2$		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
$ORDER$	level of orders and demand:	
$HIGH = 1$		0.059
$NORMAL = 2$		0.470
$LOW = 3$		0.471
$LABOR\ COST$	percentage change in labor cost per employee in the past 12 months	1.285

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

The first two columns report report the estimated parameters for the initial condition equations (20) and (19). The second 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. The fifth and sixth columns show the estimation results of a probit model with sample selection. The last column shows the results of a simple probit model for 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*. The bottom rows show the values for the state dependence and discouragement effect computed as in (23)-(24) and results of tests for absence of state dependence, expogeneity of initial conditions and joint exogeneity. The test for absence state dependence is a Wald test: under the null, the parameters associated with R^*_{t-1} in (18), (17) 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.

	First order Markov model (1)				Probit with sample selection		Probit model
	eq. (20) D_{t-1}	*eq.* (19) R_{t-1}	*eq.* (18) D_t	*eq.* (17) R_t	D_t	R_t	R_t
R^*_{t-1}			-0.273 (.153) *	0.927 (.137)***	0.605 (.037)***	0.236 (.072)***	1.163 (.055)***
SIZE	0.045 (.008)***	-0.093 (.017)***	0.047 (.008)***	-0.083 (.014)***	0.050 (.008)***	-0.093 (.012)***	-0.099 (.019)***
EXPORT	0.156 (.020)***	-0.067 (.041)*	0.147 (.020)***	-0.126 (.028)***	0.141 (.020)***	-0.122 (.026)***	-0.002 (.043)
HHI	0.004 (.017)	0.020 (.034)	-0.004 (.017)	0.022 (.021)	-0.005 (.018)	0.025 (.022)	0.035 (.039)
BRANCHES	0.012 (.005)**	-0.038 (.009)***	0.011 (.005)**	-0.020 (.007)***	0.013(.005)***	-0.024 (.006)***	-0.032 (.010)***
SOUTH	-0.029 (.023)	0.020 (.044)	-0.027 (.023)	-0.005 (.030)	-0.027 (.024)	-0.010 (.030)	-0.057 (.052)
GDP GR.	-0.025 (.008)***	-0.007 (.015)	-0.012 (.008)	0.005 (.010)	-0.009 (.008)	0.003 (.010)	-0.010 (.017)
TIME							
2008 : $q2$	-0.157 (.032)***	0.007 (.074)					
2008 : $q3$	-0.120 (.033)***	-0.006 (.071)	0.066 (.032)**	-0.019 (.049)	0.080 (.032)**	-0.026 (.044)	0.108 (.078)*
2008 : $q4$	-0.306 (.044)***	0.278 (.086)***	-0.064 (.034)*	0.239 (.095)**	-0.054 (.034)	0.252 (.055)***	0.475 (.079)***
2009 : $q1$	-0.389 (.061)***	0.312 (.116)***	-0.123 (.043)***	0.263 (.091)***	-0.123 (.044)***	0.277 (.062)***	0.418 (.098)***
2009 : $q2$	-0.407 (.069)***	0.273 (.128)**	-0.129 (.061)**	0.232 (.092)**	-0.126 (.061)**	0.242 (.079)***	0.316 (.133)***
2009 : $q3$	-0.464 (.053)***	0.470 (.100)***	-0.278 (.069)***	0.395 (.110)***	-0.277 (.068)***	0.412 (.089)***	0.459 (.149)***
2009 : $q4$			-0.257 (.053)***	0.288 (.071)***	-0.263 (.053)***	0.301 (.069)***	0.223 (.119)**
LIQUIDITY							
NEITHER	0.211 (.022)***		0.224 (.023)***	-0.070 (.106)	0.201 (.022)***	-0.023 (.048)	0.395 (.060)***
BAD	0.493 (.028)***		0.520 (.035)***	-0.120 (.212)	0.389 (.028)***	0.057 (.083)	0.868 (.065)***
LABOR COST	0.016 (.003)***		0.010 (.004)**		0.009(.002)***		
ORDER							
NORMAL	-0.202 (.035)***	0.204 (.079)***					
LOW	-0.227 (.036)***	0.306 (.078)***					
Correlation Coeff.							
ρ_{21}		-0.627 (.156)***					
ρ_{31}		0.429 (.018)***			0		
ρ_{41}		-0.424 (.030)***			0		
ρ_{32}		-0.000 (.128)			0		
ρ_{42}		0.042 (.117)			0		
ρ_{43}		-0.967 (.106)***			-0.954 (.026)***		
Pooled transitions		24,080			24,080		6,971
Censored obs.		17,090			17,090		
Log-likelihood		-33,582.03			-16,931.12		-2,878.50
$\overline{SD}_{R_{t-1}=0}$		0.252 (.060)***					
$\overline{SD}_{D_{t-1}=0}$		0.264 (.065)***					
$\overline{DE}_{R_{t-1}=0}$		-0.100 (.058)**					
$\overline{DE}_{D_{t-1}=0}$		-0.333 (.055)***					
State dependence (χ^2_2)		W=53.962					
Initial conditions (χ^2_4)		LR= 1173.746					
Joint exogeneity (χ^2_6)		LR= 1201.773					

Table 4: Transition matrix of estimated probabilities for model (1) and aggregate state dependence in access to credit

This Table reports in the top panel the estimated transition rates 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). The bottom panel reports the aggregate measures of state dependence (ASD) and discouragement effects (ADE), calculated taking the differences between the estimated transition rates.

Quarter $t-1$ \ Quarter t	No demand	Not rationed	Rationed
No demand	78.98%	17.25%	3.92%
Not rationed	54.24%	40.84%	5.02%
Rationed	46.54%	19.03%	33.97%

Aggregate state dependence and discouragement effect

$ASD_{R_{t-1}}$	$0.340 - 0.052 =$	0.289
$ASD_{D_{t-1}}$	$0.340 - 0.039 =$	0.300
$ADE_{R_{t-1}}$	$0.465 - 0.542 =$	-0.077
$ADE_{D_{t-1}}$	$0.465 - 0.790 =$	-0.334

Table 5: Estimation results: first–order Markov model, Model (2)

This table reports the estimation results of the first–order Markov model for a specification including the interaction of R^*_{t-1} with $log(SIZE)$. Estimation results of initial condition equations are not reported but are available upon request. Results for the constant term, *LIQUIDITY* dummies, and *INDUSTRY* dummies are not reported for brevity. Standard errors are reported in parentheses. The bottom of the table reports the values for the state dependence and discouragement effect and the test statistics for absence of state dependence, exogeneity of initial conditions, and joint exogeneity (see Table 3 for further details).

	Model (2)	
	D_t	R_t
R^*_{t-1}	-0.433 (.152)***	0.680 (.175)***
$SIZE$	0.044 (.008)***	-0.094 (.019)***
$EXPORT$	0.146 (.020)***	-0.120 (.030)***
$SOUTH$	-0.028 (.023)	-0.012 (.033)
HHI	-0.004 (.017)	0.025 (.023)
$BRANCHES$	0.012 (.005)**	-0.022 (.007)***
$GDP\,GR$	-0.011 (.008)	0.004 (.011)
$TIME\,(ref : 2008 : q2)$		
$2008 : q3$	0.068 (.032)**	-0.006 (.051)
$2008 : q4$	-0.062 (.034)*	0.277 (.087)***
$2009 : q1$	-0.122 (.043)***	0.296 (.085)***
$2009 : q2$	-0.128 (.061)**	0.256 (.091)***
$2009 : q3$	-0.275 (.068)***	0.426 (.107)***
$2009 : q4$	-0.254 (.053)***	0.301 (.073)***
$SIZE \times R^*_{t-1}$	0.074 (.032)**	0.088 (.039)**
Correlation coeff.		
ρ_{21}		-0.627 (.175)***
ρ_{31}		0.424 (.018)***
ρ_{41}		-0.417 (.035)***
ρ_{32}		-0.028 (.133)
ρ_{42}		0.056 (.125)
ρ_{43}		-0.941 (.122)***
Log-likelihood	-33,571.98	
$\overline{SD}_{R_{t-1}=0}$	0.248 (.060)***	
$\overline{SD}_{D_{t-1}=0}$	0.261 (.065)***	
$\overline{DE}_{R_{t-1}=0}$	-0.099 (.056)**	
$\overline{DE}_{D_{t-1}=0}$	-0.332 (.054)***	
State dependence (χ^2_4)	W= 61.350	
Initial conditions (χ^2_4)	LR= 1170.852	
Joint exogeneity (χ^2_6)	LR= 1195.518	

Table 6: Estimation results: first–order Markov model, Models (3)

This table reports the estimation results of the first–order Markov model for a specification that includes the interaction terms between of R^*_{t-1} and the quarter dummies. Estimation results of initial condition equations are not reported but are available upon request. Results for the constant term, *LIQUIDITY* dummies, and *INDUSTRY* dummies are not reported for brevity. Standard errors are reported in parentheses. The bottom of the table reports the values for the state dependence and discouragement effect and the test statistics for absence of state dependence, exogeneity of initial conditions, and joint exogeneity (see Table 3 for further details).

	Model (3)	
	D_t	R_t
R^*_{t-1}	-0.739 (.190)***	1.010 (.188)***
$SIZE$	0.046 (.008)***	-0.079 (.024)***
$EXPORT$	0.149 (.020)***	-0.130 (.032)***
HHI	-0.004 (.017)	0.020 (.022)
$BRANCHES$	0.011 (.005)**	-0.019 (.009)**
$SOUTH$	-0.027 (.023)	-0.001 (.033)
$GDP\,GR.$	-0.012 (.008)	0.006 (.009)
$TIME\ (ref: 2008: q2)$		
$2008: q3$	0.054 (.032)*	-0.022 (.055)
$2008: q4$	-0.078 (.034)**	0.222 (.154)
$2009: q1$	-0.156 (.044)***	0.262 (.136)*
$2009: q2$	-0.153 (.062)**	0.233 (.129)*
$2009: q3$	-0.295 (.070)***	0.373 (.146)**
$2009: q4$	-0.264 (.054)***	0.273 (.074)***
$2008: q3 \times R^*_{t-1}$	0.220 (.149)	-0.037 (.185)
$2008: q4 \times R^*_{t-1}$	0.307 (.140)**	-0.113 (.241)
$2009: q1 \times R^*_{t-1}$	0.584 (.127)***	-0.163 (.219)
$2009: q2 \times R^*_{t-1}$	0.425 (.124)***	-0.188 (.185)
$2009: q3 \times R^*_{t-1}$	0.395 (.128)***	0.065 (.194)
$2009: q4 \times R^*_{t-1}$	0.297 (.132)**	0.095 (.172)
Correlation coeff.		
ρ_{21}		-0.638 (.151)***
ρ_{31}		0.439 (.018)***
ρ_{41}		-0.428 (.038)***
ρ_{32}		0.041 (.127)
ρ_{42}		0.023 (.131)
ρ_{43}		-0.980 (.155)***
Log-likelihood	-33,565.57	
$\overline{SD}_{R_{t-1}=0}$	0.564 (.349)**	
$\overline{SD}_{D_{t-1}=0}$	0.574 (.355)**	
$\overline{DE}_{R_{t-1}=0}$	-0.557 (.031)***	
$\overline{DE}_{D_{t-1}=0}$	-0.780 (.042)***	
State dependence (χ^2_{14})	W=86.465	
Exogeneity of initial conditions (χ^2_4)	LR=1206.585	
Joint exogeneity (χ^2_6)	LR=1178.311	

Table 7: Variations in state dependence: Model (3)

This table shows the effect on the measures of state dependence of the discrete change from the Pre-Lehman to the Post-Lehman situation. The quantities are computed following expression (30) and by setting to zero/one the quarter dummies for the Pre/Post-Lehman period. Quantities are computes using the parameter estimates of Model (3) displayed in Table 6. Standard errors are computed by Delta Method.

	Variation in state depedence	s.e.
$\Delta\overline{SD}_{R_{t-1}=0}/\Delta x$	0.097 ***	0.037
$\Delta\overline{SD}_{D_{t-1}=0}/\Delta x$	0.107 ***	0.038
$\Delta\overline{DE}_{R_{t-1}=0}/\Delta x$	-0.125 ***	0.043
$\Delta\overline{DE}_{D_{t-1}=0}/\Delta x$	-0.104 ***	0.040

TECHNICAL APPENDIX — for only publication

TA-I Log-likelihood

The log-likelihood of model (17)-(20) is given by equation (21) for which the full expression of P_i is

$$P_i = \Phi_4(\mathbf{a}_i, \mathbf{b}_i, \mathbf{C}) = \int_{a_{i1}}^{b_{i1}} \int_{a_{i2}}^{b_{i2}} \int_{a_{i3}}^{b_{i3}} \int_{a_{i4}}^{b_{i4}} \varphi_4\left(\varepsilon_{it}, u_{it}, v_{it-1}, \vartheta_{it-1}, \mathbf{C}\right) d\varepsilon_{it} du_{it} dv_{it-1} d\vartheta_{it-1}$$

The integration bounds $\mathbf{a}_i = [a_{1i}, \ldots, a_{4i}]$ and $\mathbf{b}_i = [b_{1i}, \ldots, b_{4i}]$ are set as follows:

$$\begin{aligned}
a_{1i} &= -\boldsymbol{q}'_{it-1}\boldsymbol{\lambda} \text{ if } D_{it-1} = 1, \; -\infty \text{ if } D_{it-1} = 0 \\
b_{1i} &= -\boldsymbol{q}'_{it-1}\boldsymbol{\lambda} \text{ if } D_{it-1} = 0, \; +\infty \text{ if } D_{it-1} = 1 \\
a_{2i} &= -\boldsymbol{z}'_{it-1}\boldsymbol{\pi} \text{ if } R_{it-1} = 1, \; -\infty \text{ if } R_{it-1} = 0 \text{ or missing} \\
b_{2i} &= -\boldsymbol{z}'_{it-1}\boldsymbol{\pi} \text{ if } R_{it-1} = 0, \; +\infty \text{ if } R_{it-1} = 1 \text{ or missing} \\
a_{3i} &= -\boldsymbol{w}'_{it-1}\boldsymbol{\delta} - \phi R^*_{it-1} \text{ if } D_{it} = 1, \; -\infty \text{ if } D_{it} = 0 \\
b_{3i} &= -\boldsymbol{w}'_{it-1}\boldsymbol{\delta} - \phi R^*_{it-1} \text{ if } D_{it} = 0, \; +\infty \text{ if } D_{it} = 1 \\
a_{4i} &= -\boldsymbol{x}'_{it-1}\boldsymbol{\beta} - \gamma R^*_{it-1} \text{ if } R_{it} = 1, \; -\infty \text{ if } R_{it} = 0 \text{ or missing} \\
b_{4i} &= -\boldsymbol{x}'_{it-1}\boldsymbol{\beta} - \gamma R^*_{it-1} \text{ if } R_{it} = 0, \; +\infty \text{ if } R_{it} = 1 \text{ or missing}
\end{aligned}$$