# Credit Crunch, Flight to Quality and Evergreening: An Analysis of Bank-Firm Relationships After Lehman *

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**Abstract**

This paper analyzes the effects of the financial crisis on credit supply by using highly detailed data on bank-firm relationships in Italy after Lehman's collapse. We control for firms' unobservable characteristics, such as credit demand and borrower risk, by exploiting multiple lending. We find evidence of a contraction of credit supply, associated with low bank capitalization and scarce liquidity. The ability of borrowers to compensate through substitution across banks appears to have been limited. We also document that larger low-capitalized banks reallocated loans away from riskier firms, contributing to credit prociclicality. Such a 'flight to quality' has not occurred for smaller low-capitalized banks. We argue that, among other things, this may have reflected evergreening practices. We provide corroborating evidence based on data on borrowers' productivity and interest rates at bank-firm level.

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# 1 Introduction

Since the start of the recent financial crisis there has been an intense debate on whether a credit crunch was taking place, broadly defined as a situation where banks become abnormally reluctant to grant loans to the economy, especially to firms. The debate has attracted not only economists but also politicians and the public at large, for its important implications. A contraction of credit supply is likely to be particularly harmful during a period of weak economic activity as firms' liquidity buffers are low and a dramatic cutback in their investment spending may exacerbate the dampening effects of the recession on production and employment.

One important factor which may lead to a contraction in credit supply is related to the difficulties that banks encounter on the liability side of their balance sheets and, above all, in maintaining an adequate level of capital, whether in connection with prudential regulation or market discipline.[1] Worries intensified after the collapse of Lehman Brothers when credit growth fell dramatically in all the developed economies.

However, despite the intense debate and the massive interventions by public authorities, conclusive evidence of the existence of a credit crunch is still not available.[2] In particular, the need for effective control of developments in credit demand makes the identification of changes in credit supply quite difficult (e.g., Udell, 2009).

An additional factor is that banks' willingness to lend to a given firm may diminish because of an increase in perceived risk and for other good reasons. Basic corporate finance principles suggest that some rationing in financial markets arises as a second best device to face incentive issues: as entrepreneurs should maintain a sufficient stake in the returns on the investment, their debt capacity is limited by their own resources. Disentangling these sources of supply contraction from that associated with capital constraints is difficult, as typically they all get exacerbated during crises.

[1] This is why the label "capital crunch" was initially introduced (see Bernanke et al., 1991).

[2] At an earlier stage of the crisis, when credit growth was deacreasing but still robust, some disputed the very existence of a credit crunch (Chari et al., 2008).

Previous studies have tried to overcome these difficulties in several ways but, due to data limitation, could not properly control for loan demand. Peek and Rosengren (1995), using US bank-level data, document a stronger contraction of credit by undercapitalized banks during the 1990-91 recession. Although highly suggestive, this evidence is not fully persuasive given that differences in bank capital are likely to be associated with differences in borrowers' quality, so that differences in credit growth may simply reflect differences in firms' conditions rather than in banks' conditions. More structural evidence with bank-level data is supplied by Peek and Rosengren (2000), who show that losses in Japan prompted US subsidiaries of Japanese banks to cut back credit in the United States. Woo (2003), based on Japanese data, documents a stronger contraction of credit by undercapitalized banks in 1997, when the indulgence towards banks of government and regulators ceased. A similar approach, based on information on loan rejection rates over the current financial crisis, is followed by Puri, Rocholl and Steffen (2009), who find that German saving banks affiliated with Landesbanken heavily exposed to subprime lending reduced their acceptance rates by more than other saving banks.[3]

In this work we provide robust evidence of a credit crunch, by using highly detailed data on bank-firm relationships after Lehman's collapse, based on a representative sample of Italian firms. The main feature of our empirical analysis is that we control for firm's specific risk and credit demand by exploiting the widespread use in Italy of multiple lenders (Detragiache et al., 2000), which allows us to use fixed effects capturing all firms' unobservable characteristics.[4,5] The period analyzed is the six-month period

[3]Other papers try to exploit firm or sectoral level data, but cannot distinguish 'pure' from other supply factors. Dell'Ariccia et al. (2008) identify loan supply factors by exploiting sectoral differences in dependence on the banking sector; Borensztein and Lee (2002) have used information at the firm level and proxied credit demand with some observable balance sheet items (e.g., net investment and cash-flow). Perhaps most convincingly, Jiménez et al. (2009) go one step further by analyzing individual bank-firm relationships in Spain until December 2008; they show that undercapitalized banks were more likely to reject a given borrower's loan application.

[4]This is different from having firm-specific fixed effects in a standard panel set-up with repeated cross sections, since in that environment fixed effects would capture all time invariant unobservable features which clearly cannot include (time varying) credit demand.

[5]Unlike Jiménez et al. (2009), who also consider individual bank-firm relationships, we look at credit dynamics rather than loan rejections. There are many reasons why loan rejection rates may not reflect only lending policies. For instance, if there is a cost

after Lehman's failure (September 2008-March 2009), when the financial crisis erupted and credit growth collapsed dramatically everywhere (in Italy the 3-month growth of credit to firms fell from 8% to 1%, on a annualized basis; the dynamics of loans has stagnated since then, in Italy as in the rest of the euro area and the other major economies; see Figure 1). This is also when, according to evidence based on bank survey data, credit supply effects were most pronounced.[6]

In the investigation of the credit crunch, Italy is an interesting case to study for two main reasons. It is a bank-based economy, so that distortions in credit supply may have a sizable impact;[7] more generally, because of common economic and banking features, the analysis of credit developments in Italy can help to shed light on developments in the rest of continental Europe. Moreover, because of the data requirements of banking supervision, a unique dataset is available for the Italian economy, which includes timely information on outstanding loans at bank-firm level.

We also investigate whether the (capital) credit crunch had a diversified impact across firms, in particular according to borrower risk. There are several reasons why this may be so. For instance, the higher risk-sensitiveness of the Basle II capital requirements may induce a bias toward less risky borrowers. Other mechanisms, such as evergreening, may work in the opposite direction. According to the latter notion (also known as forbearance lending, unnatural selection or zombie lending), under-capitalized banks may delay the recognition of losses on their credit portfolio by inefficiently rolling over loans to otherwise insolvent borrowers, in order not to cause a further impairment of their reported capital and profitability (Peek and Rosengren, 2005).

Unnatural selection in credit allocation has been largely documented with regard to the long-lasting Japanese stagnation of the 1990s, to which it contributed in several ways (Caballero et al., 2008). Several observers have emphasized the similarities with the current financial crisis (e.g., Hoshi and

associated with the decision to apply for a loan, then the expectation of a tighter (looser) lending policy may discourage (encourage) applicants (one obvious cost is related to the possibility that a bank may get some information on previous rejections from the other lenders, as happens in Italy).

[6] See Del Giovane et al. (2010).

[7] At the end of 2008, the ratio of total bank credit to nominal GDP amounted to 60% in the United States, compared to 112% in Italy (140% in the euro area as a whole, higher than in Italy mainly because of the low level of Italian households' indebtedness).

Kashyap, 2008; Kobayashi, 2008). It is therefore natural to ask if those credit market inefficiencies could take place in other economies beyond the Japanese one. Indeed, the introduction in 2008 of Basle II standards, with their more procyclical capital requirements, may have contributed worldwide to the increasing difficulties faced by troubled banks in maintaining an adequate level of capitalization.[8]

We find substantial differences across lenders in the nexus between poor bank capitalization and the attitude towards borrower's risk. In particular, we show that larger low-capitalized banks reallocated loans away from riskier borrowers. Such 'flight to quality' has not occurred for smaller low-capitalized banks. This finding is consistent with evergreening but also with other explanations (for example, with smaller banks being less affected by Basle II risk-sensitive capital requirements). We provide evidence that suggests evergreening did play a role by using data on borrowers' productivity and interest rates at bank-firm level.

Our contribution to the literature is threefold. We provide robust evidence of a bank capital credit crunch. As to evergreening, our analysis represents the first attempt to our knowledge to study this issue beyond the case of Japan. Furthermore, this paper brings an improvement in the way impaired borrowers are identified. While previous contributions have mainly focused on balance sheet indicators of borrowers' quality, we also consider information on firm's economic fundamentals and competitiveness (based on TFP measures). Crucially, this allows us to disentangle inefficient lending patterns such as evergreening from the opposite phenomenon of 'patience' (namely the extension of credit to economically sound firms which undergo temporary financial difficulties and appear risky). Altogether, we show that an excessive generalized credit tightening and the extension of 'cheap' credit to selected (risky) borrowers may well coexist, both induced by low bank capitalization.[9]

The remainder of the paper is organized as follows. The next section presents a simple model where capital constraints are introduced into a standard model of borrowing capacity. Section 3 describes the data. Section 4 presents the main evidence of a bank capital credit crunch. Section 5 analyzes the heterogeneity of the crunch across firms and banks, in particular

[8] See e.g. Panetta et al. (2009).

[9] It has already been shown for transition economies that credit crunch and soft budget constraint are not mutually exclusive (Berglöf and Roland, 1997).

with respect to borrower risk. Section 6 investigates the role of relationship lending. Finally, Section 7 draws some conclusions.

## 2 The Analytical Framework

In this section we slightly extend a basic corporate finance model of borrowing capacity in order to illustrate the theoretical underpinnings of our empirical analysis. We show how our estimations can identify two interrelated but distinct mechanisms, namely a bank capital crunch and efficient credit rationing.

Let's consider an economy populated by $N$ entrepreneurs, indexed by $i$, each endowed with a risky investment project. The expected return depends on the behavior of the entrepreneur which is not negotiable. The investment is profitable only if the entrepreneur behaves correctly (for example by exerting adequate effort); should he misbehave, he would enjoy some private benefits. Each entrepreneur is endowed with an amount of cash (or equity) equal to $A_i$.[10]

If the total investment required by the project, $I_i$, is larger than $A_i$, the entrepreneur can borrow the difference $(I_i - A_i)$ from a bank.

As the behavior of the entrepreneur cannot be determined by contractual provisions, he will choose an adequate level of effort in equilibrium only if it is advantageous for him to do so (in other words, if the incentive compatibility constraint is satisfied). A standard result is that, for this to be the case, the borrower should keep a sufficient stake in the returns on the investment; more precisely, under quite general conditions it can be shown that there exists a multiplier $k_i > 1$ such that $I_i$ in equilibrium is equal to:

$$I_i' = \min(A_i k_i, I_i^*) \tag{1}$$

where $I_i^*$ is the optimal level of investment (the first-best solution, where all agency frictions are ruled out by assumption). With some approximation, $I_i^*$ can be thought of as loan demand.

The intuition is that, whenever $I_i^* > A_i k_i$, there is some rationing $(I_i^* - A_i k_i)$, and its extent is related to the severity of the agency costs ($k_i$ is a decreasing

[10] More generally, $A_i$ can be interpreted as a measure of balance sheet conditions; a high $A_i$ characterizes a firm with a relatively small debt or relatively high levels of cash, equity or fixed capital which can be used as collateral.

function of the private benefits that the entrepreneur enjoys by misbehaving).[11]

Let's consider now the presence of a (binding) capital constraint. Excluding by assumption the uninteresting case where $I_i^* < A_i$, the capital constraint can be written as:

$$\sum_{i=1}^{N} (I_i - A_i) \leq \gamma C \tag{2}$$

where $C$, bank capital, and $\gamma$ are positive and exogenously given (the left hand side is total lending by the bank). This constraint can be interpreted as representing either the prudential capital regulation ($\gamma = 1/0.08$) or more generally the market discipline which limits the bank's access to financial markets (for the same reasons as outlined above for a generic firm). The solution is readily obtained by assuming so-called type I rationing, namely that lending to each individual borrower is reduced proportionally to the level such that constraint (2) is satisfied with an equality.[12] With this simplifying hypothesis, lending to firm $i$, denoted as $L_i''$ to distinguish it from the unconstrained level $L_i'$, is equal to:

$$L_i'' = L_i' \left(\gamma C / L'\right) = A_i \left(k_i - 1\right) \left(\gamma C / L'\right) \tag{3}$$

with $L' = \sum_{i=1,\ldots,N} L_i'$. Two remarks are in order. First, since $L_i'' < L_i'$, the total rationing imposed on a firm is larger when capital constraints are binding. This additional source of rationing is exactly what the empirical analysis reported in Section 5 seeks to measure. The welfare implications of the two types of rationing are quite different. If banks granted more credit than $L_i'$, they would determine a misalignment of firms' incentives; on the contrary, if banks granted more credit than $L_i''$ then firm's incentives would still be preserved.

The two sources of rationing are likely to move together: when business activity slows down, firms are likely to undergo an erosion of equity and possibly face harsher agency frictions, implying a lower $L_i'$; similarly, the rationing brought by the erosion of bank equity, i.e. the bank capital crunch, is likely to increase during recessions, when banks tend to suffer higher credit losses.

[11] For more details on the notion of equity multiplier see, for example, Tirole (2006).

[12] The opposite case of type II rationing — i.e., some borrowers within a homogeneous group receive credit while others do not — is discussed below.

The rationale of our empirical strategy is suggested by the simple comparison of the two solutions $L_i'$ and $L_i''$. With no shortage of bank capital, lending to a given firm simply reflects its characteristics, such as its equity $A_i$ and agency costs $k_i$. In the alternative case where $\gamma C < \sum_{i=1}^{N} A_i (k_i - 1)$, lending to a firm is also influenced by the lender's characteristics, in particular its capitalization $C$. Taking logs of (3) leads to the regression equation:

$$\ln(L_{i,j}) = \beta_0 + \beta_1 \ln(A_i (k_i - 1)) + \beta_2 \ln(C_j) + \varepsilon_{i,j} \tag{4}$$

where $\beta_0 = \ln\left(\gamma / \left(\sum_{i=1,\ldots,N} A_i (k_i - 1)\right)\right)$ and $\varepsilon_{i,j}$ is an error term. The notation $L_{i,j}$ stands for loans extended to firm $i$ by bank $j$. The null hypothesis of no credit crunch is $H_0 : \beta_2 = 0$, against the alternative $H_1 : \beta_2 > 0$.

By introducing the index $j$ for banks we implicitly dropped the assumption of the existence of a unique bank; this is done not only for the sake of realism, but also for in order to introduce an important methodological feature of our analysis. In principle, estimating (4) requires detailed information not just on balance sheet items $A_i$ but also on variables, such as the agency costs $k_i$, which are hardly observable. Notwithstanding, supposing that there is availability of information on loan dynamics at bank-firm level, an unbiased estimation of the coefficient $\beta_2$ can be obtained by using firm-level fixed effects. The latter can perfectly control for all bank-invariant features related to individual firms' loan demand, credit risk and debt capacity ($I_i^*$, $A_i$, and $k_i$).[13]

The model assumption of bank capital exogeneity needs some clarification. Banks do actively adjust their own capital endowment, presumably by also taking into account current and expected loan demand. However, as documented by the empirical literature, the adjustment of bank capital is not necessarily frictionless (indeed, our test of the bank capital crunch can be seen as a test of capital exogeneity).[14] Broadly speaking, the ability to raise (outside) equity capital is influenced by factors similar to those affecting the

[13] Assuming bank-invariant loan demand is in line with standard hypotheses in banking theory. In principle, one can think of mechanisms that make firms' loan demand specific to individual lenders. However, such factors are arguably of secondary order during a financial crisis, when credit is scarce and it is difficult for firms to select lenders, even if they wished to do so.

[14] Barakova and Carey (2001) show that it takes 1.6 years for banks to restore their capital after becoming under-capitalized. The adjustment is possibly even slower according to Barnea and Kim (2008).

ability to raise debt capital, for both non financial firms and banks.[15]

Finally, it is worth mentioning that there are two potential aspects of a credit crunch which are neglected in the above model but will be investigated in the empirical section. One is that a firm which is rationed by a bank with shortage of capital may be able to compensate by borrowing more from another bank which has an excess of capital. The aggregate effect on credit supply of a shortage of bank capital is thus affected by the ability of firms to substitute across lenders. A second aspect is the possible heterogeneity across firms in the impact of a credit crunch. This heterogeneity may arise for several reasons. First, depending on firms' production technology and banks' monitoring technology, it could be less costly to sacrifice only some borrowers instead of reducing somewhat the credit to all. In addition, banks' lending decisions may be affected by the presence of long-lasting relationships. Third, banks subject to risk-sensitive capital requirements, as with Basel II, might decide to reallocate their loan portfolio towards less risky borrowers in order to save on scarce capital. In the opposite direction, bankers may protect riskier borrowers in order to postpone accounting for credit losses (evergreening). In Section 5 we investigate the heterogeneity of lending to risky borrowers across different types of under-capitalized banks.

# 3 Data

## 3.1 Data definition

We use data on outstanding loans extended by Italian banks to a representative sample of Italian firms in manufacturing and services, merged with data on corresponding bank and firm variables. The data on credit flows refer to the period September 2008-March 2009; the data on bank variables refer to September 2008, those on firm characteristics to 2007 averages. Overall, the dataset includes roughly 19,000 observations on bank-firm relationships, which refer to outstanding loans extended by roughly 500 banks to almost 2,500 non-financial firms (on average, therefore, firms in our sample borrow from 8 different banks).

Our dependent variable is the change in outstanding loans extended by

[15] More specifically, Kashyap and Stein (2004) emphasize that (i) equity issues increase the value of existing debt, thus generating an externality in favor of debtholders and harming existing shareholders; and (ii) equity issues may signal forthcoming losses.

bank $b$ to firm $i$, divided by the firm's total assets at the beginning of the period. We preferred to use this variable rather than the rate of growth of loans because in many cases the amount of credit at bank-firm level at the beginning of the period (September 2008) or at the end (March 2009) was negligible, resulting in a disproportionate number of observations with, respectively, a huge positive rate of growth or a rate of growth equal to -100% (see Table 1, first row).

Table 1
Descriptive statistics of dependent variable (percent)

| Variable (bank-firm level) | Percentiles | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1st | 10th | 25th | median | 75th | 90th | 99th |
| Rate of growth of credit | -100 | -100 | -63.3 | -10.9 | 16.4 | 118.0 | 23,039 |
| Change of credit over firm's assets | -11.6 | -2.6 | -0.7 | 0.0 | .5 | 2.6 | 12.4 |

Rather than dropping large tails of the distribution of the dependent variable in question, which in all likelihood would have resulted in the elimination of observations with the most interesting information content for our purposes, we chose to divide the change in credit by firm's total assets. This normalization should not alter the information content of the data, while delivering a variable with a much smoother distribution (see Table 1, second row). This is therefore the main dependent variable that we use throughout this paper (however, regressions with the rate of growth as the dependent variable were also run, for the sake of robustness; see Tables A3 and A9 in Appendix II).

The risk of firms' defaulting is measured by Zscore, an indicator of the probability of default of a given firm, which is computed annually by the Company Accounts Data Service (CADS) on balance sheet variables (the methodology is described by Altman, 1968, and Altman et al., 1994). It takes values from 1 to 9. Firms with Zscore value between 1 and 3 are considered 'low risk' by CADS, those in the 4-6 range are considered 'medium risk', and those in the 7-9 range are considered 'high risk'; the latter firms are more likely to default within the next two years.

Productivity is computed for each firm as the log-level of (gross output) Solow Residual, $tfp_i$:

$$tfp_i = \ln y_i - (\alpha_L \cdot \ln \_l_i + \alpha_K \cdot \ln \_k_i + \alpha_M \cdot \ln \_m_i) \ , \tag{5}$$

where $\ln\_y_i$, $\ln\_l_i$, $\ln\_k_i$ and $\ln\_m_i$ are the logarithms of, respectively, the firm's gross output, hours, capital and intermediate inputs, all measured in real terms, and the $\alpha$'s are the revenue shares of each input.[16] Since the level of productivity may vary widely across sectors, for each firm we computed the difference relative to the sectoral median, to allow for comparison across sectors.

Further details on the definition of the variables and descriptive statistics can be found in Appendix I.

## 3.2 Data sources

There are four main sources of data: those on outstanding loans come from the Credit Register; bank balance sheet data are drawn from the Banking Supervision Register at the Bank of Italy; data on firms' inputs and outputs (used to measure productivity) and other firm characteristics come from the Bank of Italy annual Survey of Industrial and Service Firms and from the Company Accounts Data Service (CADS).

The Credit Register data are collected by a special unit of the Bank of Italy (*Centrale dei Rischi*) and contain detailed information on virtually all individual loans extended in Italy (see Appendix I).

The Survey of Industrial and Service Firms (SISF) is carried out annually by the Bank of Italy. The data are of very high quality, being collected by officials of the local branches of the Bank of Italy, who often have a long-standing work relationship with the firm's management. The Company Accounts Data Service (CADS - *Centrale dei Bilanci*) is the most important source of balance sheet data on Italian firms. It covers about 30,000 firms and is compiled by a consortium that includes the Bank of Italy and all the major Italian commercial banks.

[16] Gross-output measures of total factor productivity, whenever data are available, are preferable to value-added measures, because of the reduced-form nature of the latter, which may induce potential model misspecification and omitted variable bias when used in regressions (see Basu and Fernald, 1997; for an analysis of these TFP measures with a dataset similar to that used in this work, see Marchetti and Nucci, 2006).

# 4 Evidence for a credit crunch

## 4.1 The main results

The core of this paper is the investigation of loan supply effects, linked to bank balance sheets, in the aftermath of Lehman's bankruptcy, when the growth of credit came to a substantial halt. Within our sample, outstanding loans contracted in nominal terms by -1.1% from September 2008 to March 2009. A first look at the data clearly suggests the importance of balance sheet factors in shaping banks' lending behavior: loans extended by banks belonging to the lowest quartile of the capital ratio distribution decreased by roughly 20%, while credit growth for the other quartiles was positive, in the 5-10% range (Table 2).

Table 2
Growth of loans by bank capitalization (percent)

| Variables | Bank capitalization quartiles | | | | Whole |
|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 4th | sample |
| Share of total loans at Sept. 2008 | 32.2 | 30.7 | 10.0 | 27.1 | 100.0 |
| Growth of loans | -20.8 | 8.4 | 5.2 | 9.3 | -1.1 |

The rest of this section is devoted to a more rigorous analysis of bank capitalization effects on loan supply. Consistently with the model introduced in Section 2, the basic regression for testing the credit crunch hypothesis is the following:

$$\Delta cred_{b,i} = \alpha + \beta_1 \cdot low\_cap_b + \eta_i + u_{b,i} \tag{6}$$

where $\Delta cred_{b,i}$ is the change in outstanding loans extended by bank $b$ to firm $i$ between (end) September 2008 and (end) March 2009, divided by the firm $i$'s total assets in September 2008; $low\_cap_b$ is a dummy variable for low-capitalized banks; $\eta_i$ is a firm-specific fixed-effect and $u_{b,i}$ is the regression residual. More precisely, $low\_cap_b$ is equal to 1 for banks whose total (risk-weighted) capital ratio is lower than 10%. The latter value is that recommended by the Bank of Italy, and — although the official Basle II regulatory threshold is 8% — it appears to be perceived by the market as the relevant benchmark; moreover, it roughly coincides with the 25th percentile

(10.5%) of the sample distribution, and is therefore also a useful reference value in statistical terms.[17]

Equation (6) includes firm-specific fixed-effects; this key feature allows us to control for firms' credit demand as well as their other characteristics. Regression results are reported in the first column of Table 3. The estimated coefficient of $low\_cap_b$ is negative and highly significant, leading to a clear rejection of the null hypothesis that a credit crunch did not occur. We also investigated the role of other balance sheet indicators of banks' funding difficulties — beyond those associated with regulatory requirements — such as the liquidity ratio. We thus included the dummy variable $high\_liq_b$ for banks whose liquidity ratio (i.e., cash and securities other than shares, divided by total assets) was higher that the sample median (12.1%). Results are reported in the second column of Table 3. The supply of credit by more liquid banks is significantly higher, while the estimated coefficient of $low\_cap_b$ remains negative and highly significant.

We also considered, mainly as controls, three variables related to different aspects of banks' organization, which may have been important during the crisis: $large_b$ is a dummy for banks belonging to the major five banking groups (which overall extend roughly half of total loans to non-financial firms, and accounted for most of the credit slowdown); $scoring\_bank_b$ is a dummy, based on survey data, which is equal to 1 for banks whose use of scoring schemes in lending decisions is reported to be either "important" or "very important", and 0 for banks reporting that they make little or no use of credit scoring; $coop_b$ is a dummy variable for cooperative banks, which are subject to a special regulatory regime and have been shown in the literature to focus on relationship lending (e.g., Angelini et al., 1998).

Results of the extended model are reported in the third column of Table 3. The effect of bank capital and liquidity is strenghtened, despite the high significance of the estimated coefficient for $large_b$.[18] Overall, these results show that the findings for $low\_cap_b$ previously reported are not due to possible correlation between low bank capitalization and other banking features, such as the fact of belonging to a major banking group or the reliance on

[17] The use of a dummy for lowly-capitalized banks serves to capture possible non-linearities, since bank capital affects credit supply only when capital constraints are binding.

[18] This finding, as we will see, is not specific to the period under investigation and is possibly related to the ongoing recomposition of market shares in the Italian credit market following the consolidation process of the sector in the first half of the 2000s.

credit scores in lending decisions.[19]

The contraction of loan supply by low-capitalized banks has been significant in both statistical and economic terms. The (asset-normalized) change in credit extended by low-capitalized banks is about two percentage points lower (in annual terms) than that of other banks.[20] It can be estimated that, on an annual basis, this corresponds to roughly 0.7% of the stock of outstanding loans to firms (measured in September 2008); analogously, the effect through liquidity constraints, captured by the coefficient of $high\_liq_b$, corresponds to roughly 0.6% of the stock. Overall, therefore, 'pure' supply effects related to banks' balance sheet conditions amounted to more than 1% of total credit to firms. While this may not seem a huge impact, the macroeconomic effect on output and employment may have been magnified by the fact that many firms, being financially vulnerable at the peak of the recession, were hit by the credit supply shock when the need for external funding was more acute and sharply rising.[21]

Our interpretation of the results is corroborated by looking at loan supply developments in the pre-crisis period. In particular, for comparison purposes, we considered the latest September-March six-month period before the beginning of the turmoil (August 2007), that is September 2006-March 2007, and estimated the extended model with the corresponding data. The results are reported in the fourth column of Table 3: as expected, at normal times the supply of credit is not affected by bank capitalization (or liquidity, for that matter). Overall, the evidence reported for the pre-crisis period strongly confirms the interpretation of our results as evidence of a credit crunch.

[19] The coefficient of $scoring\_bank_b$ is positive and significant, contrary to the common conjecture that substantial use of credit scores would weigh negatively on lending decisions during a recession accompanied by a financial crisis. However, the procyclical implications of credit scoring on loan developments deserve a deeper analysis, which is beyond the scope of this paper. Similar considerations apply to the estimate of the coefficient of $coop_b$, which is typically interpreted as a proxy of relationship lending.

[20] The impact on credit growth at the firm level can be significantly higher, depending on the firm-specific ratio of total assets to credit.

[21] Counterfactual simulations with a large macroeconometric model of the Italian economy suggest that the contraction of credit supply accounted for about a quarter of the 5% decrease in Italian GDP in 2009 (see Caivano et al., 2010); credit restriction is estimated on the basis of the spread between bank lending rates and interbank interest rates over the 3-month horizon (Fair and Jaffee, 1972).

## 4.2 Robustness

The results proved extremely robust in several respects. First, they are substantially unchanged if the original dependent variable is replaced by the rate of growth of loans (Table A3 in Appendix II). Second, the results proved robust to the choice of the threshold value for the definition of $low\_cap_b$ ($low\_cap_b$ was set equal to 1 for banks whose capital ratio is lower than the sample median, i.e. 13.0; Table A4). A third set of robustness checks was related to the definition of credit: we considered granted rather than utilized credit (Table A5).

A further robustness exercise was related to the level at which the capital ratio is computed (individual banks vs. group). Regulatory requirements concern both unconsolidated capital ratios and consolidated ones. Throughout this paper we chose to use unconsolidated ratios, in order to exploit the heterogeneity of behavior and conditions across banks belonging to the same group. For example, the literature on internal capital markets shows that agency frictions among individual firms within industrial or banking groups generates relationships which tend to be similar to those observed among independent market participants (e.g., Shin and Stultz, 1998). Moreover, consolidated balance sheet data are not available at quarterly frequency, so that we would have had to use capital ratios computed on either June or December 2008; given that capital levels were changing during the period of interest, this could add noise to the data. At any rate, consolidated and unconsolidated capital ratios showed an extremely high level of correlation in June 2008 (.87). A final advantage, on statistical grounds, is the much greater variability and granularity of unconsolidated capital ratios.[22] Nonetheless, for robustness purposes (since bank supervision activity tends to focus on consolidated parameters), we regressed our dependent variable (computed with consolidated loan data) on $low\_cap_b$ computed on the basis of consolidated capital ratios and the corresponding distribution. The estimated coefficient remains negative and highly significant (see Table A6).

A final robustness exercise was related to the accounting impact of securitizations on loan data. The data on outstanding loans used throughout the paper do not include securitized loans. In principle this seems appropriate since typically a bank, by securitizing a loan, sells the loan on the market,

[22] The banks of the five major groups (15% of our dataset) account for roughly 60% of total bank-firm observations; over all those observations the five different values of the consolidated capital ratio lie in a very narrow range (9.1-10.4).

transfering the corresponding credit risk to third parties. The loan supply of that bank to the given firm decreases by the corresponding amount. However, in practice, in the period considered here most securitizations were so-called retained-securitizations, whose only purpose was to create securities to be used as collateral in the Eurosystem's refinancing operations but which did not imply any transfer of risk to third parties. In such cases the loan supply at the bank-firm level can be considered unchanged. We therefore adjusted loan data for the effect of securitizations, by re-including loans which were securitized during the period of interest into the stock of outstanding bank-firm loans at the end of March 2009.[23] The results are shown in Table A7 and are virtually unchanged.

A full discussion of all the robustness exercises is provided in Appendix II.

## 4.3 Substitution across banks

We also tried to investigate whether and to what extent borrowers were able to compensate for the contraction of credit supplied by low-capitalized banks by increasing loans from other banks. In principle, in the extreme case of perfect and prompt substitution the crunch would have no effects on production and employment, and there would merely be a recomposition of credit flows within the banking sector.

For each firm in our dataset we thus computed the change of loans extended by all highly-capitalized banks (i.e., banks with a capital ratio $\geq 10\%$) and regressed it on the change of loans extended by all other banks (defined as $cred\_lowcap_i$). If substitution were perfect and this were the only factor driving the relationship being estimated, we would expect a coefficient equal to -1; incomplete substitution would correspond to a coefficient between -1 and 0; a coefficient not statistically different from 0 would imply no substitution, while a positive and significant coefficient would signal complementarity between loans from the two bank categories. As it is not possible to include fixed effects, we included controls in the regression for the main firm characteristics (i.e. risk of default, size, economic sector and region) to capture other factors which might affect the relationship between the dependent variable and the regressor. Results (with and without controls) are

[23] Double-counting is not an issue since virtually all those which bought loans during the period examined are special purpose vehicles or other financial institutions which are not included in our sample of banks.

reported in the first and second columns of Table 4. The estimated coefficient of $cred\_lowcap_i$ is negative and highly significant, with an absolute size much lower than one, thus suggesting that some substitution did take place, but was rather limited (namely, the increase in loans from highly-capitalized banks appears to have compensated on average for only around 30% of the decrease of loans from low-capitalized banks).

Estimating the same regression in the pre-crisis period (September 2006-March 2007) broadly confirms this interpretation of the results. We expect that at normal times, with no credit crunch, the scope for substitution would be smaller, if present at all; in fact, the estimated coefficient of $cred\_lowcap_i$ in the comparable pre-crisis period is much smaller and its statistical significance is lower (third column of Table 4).

Considering again the after-Lehman period, we also found some evidence that the number of lenders affected borrowers' ability to substitute across banks, as one would expect. We computed a new dummy variable, $few\_lenders_i$, for firms that have less than 4 lenders (roughly 31% of the total; firms that have at least 3 represent 22% of the total). The results are reported in the fourth column of Table 4; for the latter category of firms, the estimated coefficient of $cred\_lowcap_i$ is much smaller and not statistically significant, whereas for firms that borrow from at least 4 lenders the estimate is highly significant and very similar in size to that reported earlier.

# 5 Flight to quality and evergreening

## 5.1 Heterogeneity of credit crunch across firms

We now turn to the investigation of a specific aspect of the crunch, namely the occurrence of a flight to quality away from risky borrowers and the heterogeneity of this phenomenon across banks.

We start by analyzing whether (and how) the impact of the crunch was differentiated across different types of firms. We considered four main firm characteristics, namely size, export propensity, risk of default and productivity. The corresponding variables were interacted with $low\_cap_b$, first one at a time and then all together; the results are reported in Table 5. The contraction of loan supply from low-capitalized banks was significantly more pronounced for smaller firms (i.e., firms with less than 50 employees, identified by the dummy $small\_f_i$). As to export propensity, there is no evidence that exporting firms (identified by the dummy $export_i$) were hit more severely by the crunch.[24] With regard to productivity, there is no evidence that more productive firms have been shielded from the crunch ($tfp_i$ is firms' Solow residual, sectorally de-meaned). Finally, and most interestingly for our purposes, there is some evidence that the contraction of credit supply has been stronger for riskier firms ($high\_risk_i$ is a dummy for firms whose Zscore is in the 7-9 range).

The evidence found for $low\_cap_b \cdot small\_f_i$ and $low\_cap_b \cdot high\_risk_i$ brings to mind the notion of the flight to quality described by Bernanke et al. (1996), based on the role of agency costs. Notice however that our findings are slightly different, as in our analysis agency costs are captured by firm-specific fixed effects. The estimated coefficient of $low\_cap_b \cdot small\_f_i$ and that of $low\_cap_b \cdot high\_risk_i$ capture an additional impact on lending to smaller and riskier firms respectively, specific to poor bank capitalization, which is not related to differences in agency costs compared to other borrowers. One possible factor underlying this form of flight to quality linked to bank capital, as mentioned in Section 2, is the effect of the higher risk-sensitiveness of Basel II capital requirements. Other potentially relevant factors include evergreening and 'patience'. The different mechanisms imply differences in lending patterns across banks, according to size and organization.

## 5.2 Flight to quality: Heterogeneity across banks

A first dimension to be investigated is bank size. In the Italian banking sector — as in most developed banking sectors worldwide — small, local banks coexist with large, multi-national banking groups. The divergences in bank's organization and decision-making are likely to affect the attitude towards borrower risk. For example, with regard to evergreening, providing 'cheap' credit to a borrower with a high risk of default, in order to postpone credit losses, is presumably easier for a smaller bank where discretion in lending decisions is higher and the weight of credit scoring is lower than for a larger bank, where lending decisions are based on more automatic procedures. Indeed, by introducing bank size into our analysis of lending patterns to risky borrowers, a clear difference emerges. Consider the following regression:

[24] Given that these firms have been hit hard by the collapse of world demand, this is an interesting finding since it appears to contradict concerns that 'short-termist' banks might possibly reduce credit to these firms, which represent the dynamic and healthy core of the Italian productive system.

$$\begin{aligned} \Delta cred_{b,i} &= \alpha + \beta_1 \cdot low\_cap_b + \beta_2 \cdot (low\_cap_b \cdot high\_risk_i) \\ &+\beta_3 \cdot [low\_cap_b \cdot high\_risk_i \cdot (1 - large_b)] + \beta_4 \cdot large_b \\ &+\eta_i + \varepsilon_{b,i} \ . \end{aligned} \tag{7}$$

The results are reported in the second column of Table 6. Given the specification of this model — namely the presence of the triple interaction term $low\_cap_b \cdot high\_risk_i \cdot (1 - large_b)$ — the coefficient of $low\_cap_b \cdot high\_risk_i$ captures the flight to quality effect (i.e. the reallocation of credit away from riskier borrowers) for larger banks alone. Its coefficient is negative and highly significant; interestingly, this means that the evidence of a reallocation away from riskier borrowers is much stronger for larger banks (both in size and statistical significance) than for the average low-capitalized bank (first column of Table 6).[25] On the other hand, the coefficient of $low\_cap_b \cdot high\_risk_i \cdot (1 - large_b)$ is positive and highly significant, showing that the lending pattern to riskier borrowers by smaller low-capitalized banks is significantly different from that of larger banks — namely, the flight to quality of smaller banks is less pronounced than that of larger banks. Moreover, for such smaller (low-capitalized) banks there is no evidence at all of a flight to quality, since the total reallocation effect towards riskier borrowers by such banks is given by $\widehat{\beta_2} + \widehat{\beta_3}$, which is non-negative.[26] Importantly, all the results are robust to the inclusion in the regression of all double interactions among the variables in the equation (third column of Table 6).[27]

As anticipated throughout the paper, there are at least three possible explanations for the finding that, in striking contrast with larger low-capitalized banks, smaller ones have not reallocated their credit away from riskier borrowers after Lehman.

[25] The first column of Table 5 reports again, for comparison purposes, the regression presented in the fourth column of Table 4.

[26] In mathematical terms, it can readily be seen that, for smaller banks (i.e. those for which $large_b$=0), $\partial \frac{\frac{\partial \text{ change of loans}}{\partial \text{ low\_cap}}}{\partial \text{ high\_risk}} = \widehat{\beta_2} + \widehat{\beta_3}$. Indeed, based on this regression there is evidence of a flight *to risk* for smaller banks, since $\widehat{\beta_2} + \widehat{\beta_3}$=0.504, with the hypothesis of $\widehat{\beta_2} + \widehat{\beta_3} = 0$ being rejected at the 1% statistical level (F-statistic=13.38, with p-value .000).

[27] The positive coefficient for $low\_cap_b \cdot (1 - large_b)$ signals that the effect of capital on lending is more important for larger banks. This may reflect different ownership patterns (which may interfere with banks' ability to adjust their capital promptly) or more careful monitoring by market participants of larger and listed banks.

One explanation is that, compared to larger banks, smaller ones are less affected by the new Basle II risk-sensitive capital requirements and did not reallocate their loan portfolio at all to save on scarce capital. Another potential explanation is evergreening, on the ground that, as already mentioned, reallocation of credit in favor of borrowers with a bad credit score — finalized to avoid or postpone the realization of losses — is presumably easier for smaller banks. A third possible explanation is that smaller banks have better (soft) information on riskier borrowers, compared to larger banks; this would allow smaller banks to keep funding borrowers with bad credit scores that have good economic fundamentals and are just undergoing temporary financial difficulties. If this is so, the lack of 'flight from risk' by smaller banks would be evidence of virtuous 'patience', as opposed to suboptimal myopia (short-termism) on the part of larger banks.[28]

As to the first explanation, when the adoption of Basle II is completed, some technical aspects of the new capital requirements will almost certainly deliver a higher risk-sensitiveness by larger banks (which are more likely to adopt the 'internal rating system'). However, the implementation has been gradual and, in the period under consideration, was still partial.[29] It therefore appears unlikely that the divergences documented above are entirely justified by the effect of Basle II regulation. While the latter effect may be an interesting issue for future research, in the rest of this section we conduct other exercises aimed at disentangling the 'evergreening' explanation from that based on 'patience'.

## 5.3 Corroborating the 'evergreening' explanation

As just argued, the findings of the second and third columns of Table 6 might reflect 'patience' by smaller low-capitalized banks — as opposed to myopia on the part of larger banks — instead of evergreening. Indeed, this is a

[28] This interpretation, however, seems inconsistent with the negative and significant coefficient for $(1 - large_b) \cdot high\_risk_i$, which suggests that the lenience of smaller lenders towards risky borrowers is specific to the lowly capitalized smaller intermediaries.

[29] The sensitivity of new capital requirements to the risk of individual borrowers is maximized under the 'internal ratings-based' (IRB) approach, which is typically chosen by larger banks. Under the alternative system ('standardized' approach), all borrowers that are not rated by the rating agencies are given the same weight in the computation of capital requirements, regardless of the actual individual risk profile. The share of loans covered by the IRB system in the period September 2008-March 2009 for the few (large and small) banks which adopted it varied between roughly 40 and 70%.

general limitation of all balance sheet indicators of borrowers' quality that are used in the evergreening literature, arising from the fact that they do not take into any account firms' future prospects.[30] Thus, by using these measures, it is not possible to distinguish true forbearance lending from efficient debt restructuring, whereby a non myopic lender helps a borrower, who is currently distressed but whose expected profitability is potentially high, overcome temporary difficulties. The latter would typically be the case of a firm which got involved in substantial restructuring, funded by debt, thanks to which it recovers its competitiveness.[31]

A simple but quite powerful method for discriminating between the two alternative explanations is to supplement the information of (financially-focused) balance sheet indicators with that of indicators which are, arguably, better proxies of the firm's economic fundamentals and competitiveness, and therefore more forward-looking measures of its economic prospects, such as productivity.

We therefore replicated the regressions reported in Table 6 by replacing $high\_risk_i$ with a proxy for bad (impaired) borrowers, $imp\_bor_i$, which is equal to 1 if $high\_risk_i$=1 and, at the same time, the firm's Solow residual, sectorally de-meaned, is lower than the sample median. Having identified bad borrowers in this way, any evidence of reallocation of credit towards them (or weaker reallocation away from them) can hardly be interpreted as evidence of 'patience'. The results with $imp\_bor_i$ are reported in Table 7 (whose structure replicates that of Table 6; they strongly confirm, and possibly strengthen, previous evidence. The 'flight from bad borrowers' by

[30] An alternative approach to the identification of impaired borrowers has been adopted by Caballero et al. (2008). In that paper, bad borrowers are identified as those receiving an interest rate subsidy, which in turn is identified by comparing, for any firm and year in the sample, total interest expenses with an estimated lower bound. As it is not based on indicators of current performances, this approach offers the main advantage of being inherently more forward-looking. Another more forward-looking measure adopted is stock returns, as in Peek and Rosengren (2005). The main limitation in this case is that such information can be obtained only for listed firms, which tend to be only large firms. Also, one could argue that during crises stock prices are not as efficiently determined as in normal times.

[31] There is specific evidence that this factor may have been relevant in our context. Bugamelli et al. (2008) document, by analyzing a dataset including our sample of firms, that substantive firms' restructuring occurred in the Italian manufacturing and services sectors in the last decade, as a response to the introduction of the euro and the need to face global competition.

larger banks, captured by the estimated coefficient of $low\_cap_b \cdot imp\_bor_i$ in columns 2-3, has intensified (the size of the coefficient is roughly double that of Table 6). The coefficient of $low\_cap_b \cdot imp\_bor_i \cdot (1 - large_b)$, which captures the difference between the behavior of smaller and larger banks, has remained positive and highly significant; if anything, its size appears to have increased sharply as well. Overall, again, there is no evidence of a 'flight from bad borrowers' by smaller banks (i.e. the hypothesis of $\widehat{\beta_2}+\widehat{\beta_3}=0$ cannot be rejected).[32]

Notice that the findings documented in the second and third columns of Table 7 also lend support to the explanation based on evergreening as against that based on Basle II regulations. In fact, if the lack of a flight to quality for smaller banks (documented in Table 6) were justified only by the differential impact of new capital requirements, including borrowers' productivity in the analysis should leave the results broadly unchanged, since the rating methods used under the IRB approach typically focus on balance sheet variables (such as those summarized in Zscore), and do not take into account measures of firms' productivity and competitiveness. If anything, the use of $imp\_bor_i$ instead of $high\_risk_i$ should attenuate the observed difference between large and small banks, since, in the absence of evergreening, small banks should reallocate their credit away from the 'bad borrowers' identified by $imp\_bor_i$ even if that does not give them the full advantages, in terms of lower risk-weighted capital ratios, brought by Basle II and enjoyed by larger banks. As we saw, on the contrary, the observed difference between larger and smaller banks widened.

Going back to the comparison between the 'evergreening' and the 'patience' explanations, another way of testing the hypothesis that loans to riskier borrowers might actually represent good profit opportunities — with smaller low-capitalized banks being in a better position to detect them — is by looking at interest rate developments at the bank-firm level. This is

[32] A further robustness exercise is the following. Since the aim is to investigate the extension of credit to risky borrowers for the purpose of avoiding losses on pre-existing loans, it is appropriate to include, among the borrowers which may potentially benefit from evergreening, only firms which, at the beginning of the period considered (i.e., September 2008), were actively borrowing from a given bank. To this end, we estimated the regressions reported in Table 6 after dropping the bank/firm observations associated with firms with $imp\_bor_i$ =1 and no outstanding loans from a given bank. After doing this, the dummy $imp\_bor_i$ identifies (only and all) the potential recipients of 'evergreening' loans. The results are substantially unchanged and are reported in Table A7 in Appendix II.

feasible since we have information on average nominal interest rates for each bank-firm relationship over the same period. The rationale for looking at interest rates is that 'genuine' loans (i.e. not associated with evergreening) to riskier but profitable borrowers should be associated with higher interest rates. On the contrary, interest rates on the loans extended by smaller low-capitalized banks to riskier borrowers turned out not to be statistically different from those on other loans. See Table 8, which for the sake of simplicity replicates the structure of Tables 5, with the dependent variable being replaced by interest rates at the bank-firm level (average over the period in question). For our purposes, we do not need to provide a structural interpretation of all the parameters in the regression; we simply notice that the estimated coefficient of $low\_cap_b \cdot high\_risk_i \cdot (1 - large_b)$ is clearly not statistically different from zero (second and third columns of Table 8).

## 5.4 The role of credit scoring

We have provided evidence corroborating the interpretation of our findings based on forbearance lending. When initially putting forward this hypothesis, we mentioned that one reason why evergreening might be easier for smaller banks is the lower weight assigned to credit scoring techniques. It seems natural, therefore, to re-estimate previous regressions after replacing $(1-large_b)$ with $(1-scoring\_bank)$. The results are documented in the fourth and fifth columns of Tables 5, 6 and 7 (which replicate the second and third columns of the corresponding tables). The findings clearly confirm those obtained with $(1 - large_b)$. Namely, banks which rely extensively on credit scoring did reallocate credit away from risky (bad) borrowers, while the others did not (Tables 5 and 6). For the sake of comparing the explanatory power of $(1-large_b)$ with that of $(1-scoring\_bank)$ in capturing the allegedly 'evergreening' effect, we also included all regressors in the same equation. The results, reported in the sixth column of Tables 5 and 6, show that the estimated coefficient of $[low\_cap_b \cdot high\_risk_i \cdot (1-large_b)]$ maintains its high statistical significance, unlike that of $[low\_cap_b \cdot high\_risk_i \cdot (1-scoring\_bank)]$. This suggests that the weight of credit scoring was only one of the factors underlying our findings; additional factors associated with bank size played a role, presumably related to organizational aspects. For example, the importance of agency costs in major groups, documented in the literature (e.g., Stein, 2002), might induce a tendency to centralize decision processes and permanently limit the autonomy of local loan officers, possibly making evergreening more difficult.[33]

# 6 Capital crunch and relationship lending

Finally, we investigated whether and how the capital crunch documented in Section 4 is affected by the intensity of bank-firm relationships. We did so by supplementing the main regressions with the share of credit that a given firm receives from a given bank, $cred\_share_{b,i}$, alone and interacted with $low\_cap_b$. The results for the model without and with controls are reported, respectively, in the first and second columns of Table 9. The estimated coefficients of $low\_cap_b \cdot cred\_share_{b,i}$ and $cred\_share_{b,i}$ are both negative and statistically significant.[34] Overall, therefore, we find no evidence that the crunch has been attenuated by intense bank-firm relationships, or, more in general, that credit supply during the turmoil has been positively affected by relationship lending.[35] This is consistent with the finding by Peek and Rosengreen (2005) that main banks were less likely to increase lending compared to other banks during the 'lost decade' in Japan. At least partially, this pattern may reflect, an attempt by such banks to diversify credit risk in the context of a severe financial crisis.

Notice, however, that our analytical framework is not well suited for an analysis of relationship lending, which is not the aim of this paper. First, the non-negligible category of firms borrowing from a single lender — for which relationship lending is most valuable — is excluded by our analysis, based on the use of firm-level fixed effects which requires multiple lenders. Moreover, for the firms included in our analysis some of the effects of lending relationships might be captured by the fixed effects. For example, the presence of a main bank may provide some kind of 'certification' allowing other intermediaries to lend to the same firm, at lower interest rates, while saving on monitoring costs.[36]

[33] As to Table 7, the estimated coefficient of $low\_cap_b \cdot high\_risk_i \cdot (1 - scoring\_bank_b)$ is negative but mostly not statistically significant, showing that interest rates on the riskier loans extended by low-capitalized banks which make little use of scoring techniques are not higher than those on other loans.

[34] Similar evidence has been obtained by analyzing credit flows to smaller firms, which typically benefit more from relationship lending (third column of Table 8).

[35] Substantially similar results have been obtained by using the rate of growth of loans as the dependant variable (see Table A8).

[36] See Casolaro and Mistrulli (2008). In general, an analysis of the role of relationship

We also investigated the link between the intensity of bank-firm relationships and the patterns of lending to risky borrowers. We run the main regressions reported in Table 7 after including $cred\_share_{b,i}$, respectively alone and interacted with $[low\_cap_b \cdot imp\_bor_i \cdot (1 - large_b)]$ and $[low\_cap_b \cdot imp\_bor_i \cdot (1 - scoring\_bank_b)]$. The results are reported in Table 10; there is no evidence that the (supposedly) 'evergreening' effect is either strengthened or weakened by relationship lending.

# 7 Conclusions

In this paper we have presented evidence of a credit crunch, associated with low bank capitalization and scarce liquidity, over the 6-month period following Lehman's bankruptcy.

We have shown that the dampening effect on credit supply of low-capitalized banks was quite sizeable; moreover, we offer some evidence to the effect that the ability of borrowers to substitute loans from low-capitalized banks with loans from the other banks has been limited, and almost nil in the case of firms that borrow from only a few lenders.

By analyzing the impact of the crunch across different types of firms, we also found that larger low-capitalized banks reallocated their credit away from riskier firms. Quite strikingly, this 'flight to quality' was not observed for smaller low-capitalized banks.

A first explanation for this dichotomy hinges on the potentially different impact of Basle II capital regulations on larger vs. smaller banks; however, the implementation of the new, more risk-sensitive capital requirements was still partial during the period of interest, and appears unlikely to justify all the difference in the observed 'flight to quality'. Another potential explanation hinges on evergreening. The rationale is that evergreening is arguably easier for smaller banks, whose lending decision processes are more flexible and less constrained by credit scores, than for larger banks. A third potential explanation is 'patience' by smaller banks, in the sense described in this paper. In order to disentangle between the two last explanations we used data on borrowers' productivity and interest rates at bank-firm level. The

lending cannot neglect firms' bank-invariant characteristics. De Mitri et al. (2009) conduct an analysis along these lines based on Italian firm-level data (that include our sample); they find a positive link between several measures of relationship lending and firms' credit availability after Lehman.

evidence suggests that evergreening by smaller lenders did take place, pointing to a trade-off vis-à-vis an excessively procyclical lending supply by larger banks.

Overall, this paper innovates by combining two separate strands of the literature on bank capital and lending supply, namely those on the capital crunch and evergreening. Our results indicate that pressure on bank capital may simultaneously produce two opposite lending biases. A generalized excessive tightening (crunch) and some excessive loosening of credit policies towards risky borrowers (evergreening) may well coexist, representing two different facets of banks' response to capital contraints.

Table 3

# Testing for a Credit Crunch

Dependent variable: Change of loans over firm's assets

| Bank variables | (1) | (2) | (3) | (4) Pre-crisis |
|---|---|---|---|---|
| $Low\_cap_b$ | $-.835^{***}$ | $-.867^{***}$ | $-1.086^{***}$ | .036 |
| | (.066) | (.067) | (.076) | (.047) |
| $High\_liq_b$ | - | $.447^{***}$ | $.560^{***}$ | -.078 |
| | - | (.084) | (.144) | (.096) |
| $Large_b$ | - | - | $-.142^{***}$ | $-.090^{*}$ |
| | - | - | (.045) | (.049) |
| $Scoring\_bank_b$ | - | - | $.219^{**}$ | .105 |
| | - | - | (.088) | (.072) |
| $Coop_b$ | - | - | $-.439^{**}$ | -.003 |
| | - | - | (.137) | (.130) |
| No. of firms | 2,558 | 2,558 | 2,546 | 2,358 |
| No. of observations | 19,576 | 19,576 | 17,596 | 16,602 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the change of loans from individual banks over the period September 2008-March 2009, normalized to firm's assets; the regressor data refer to September 2008. In column 4, the dependent variable is defined over the period September 2006-March 2007, and the regressor data refer to September 2006. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level).

$^{*}$Significant at the 10-percent level; $^{**}$significant at the 5-percent level; $^{***}$significant at the 1-percent level.

Table 4

## Substitution across Banks

Dependent variable:

Change of loans from highly-capitalized banks over firm's assets

| Firm variables | (1) | (2) | (3) Pre-crisis | (4) |
|---|---|---|---|---|
| $Cred\_lowcap_i$ | -.306$^{***}$ | -.297$^{***}$ | -.096$^{*}$ | - |
| | (.067) | (.070) | (.051) | - |
| $Cred\_lowcap_i \cdot (1\text{-}Few\_lenders_i)$ | - | - | - | -.316$^{***}$ |
| | - | - | - | (.083) |
| $Cred\_lowcap_i \cdot Few\_lenders_i$ | - | - | - | -.166 |
| | - | - | - | (.107) |
| $Few\_lenders_i$ | - | - | - | -.753$^{**}$ |
| | - | - | - | (.360) |
| Credit risk dummies | No | Yes | Yes | Yes |
| Size dummies | No | Yes | Yes | Yes |
| Sectoral dummies | No | Yes | Yes | Yes |
| Regional dummies | No | Yes | Yes | Yes |
| No. of firms/observations | 2,558 | 2,452 | 2,371 | 2,452 |

Note: OLS estimation with firm-level data. Each column corresponds to a regression. In columns 1, 2 and 4 the dependent variable is the change of loans from highly-capitalized banks, normalized to firm's assets, defined over the period September 2008-March 2009, and the regressor data refer to September 2008; in column 3 the dependent variable is defined over the period September 2006-March 2007 and the regressor data refer to September 2006. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). The credit risk dummies identify firms whose Zscore value is between, respectively, 1 and 3 ('low risk'), 4 and 6 ('medium risk') and 7 and 9 ('high risk') . The size dummies identify four categories of firms: 20-50 employees, 51-200 employees, 201-1000 employees, over 1000 employees. The sector dummies refer to 2-digit sectors. The regional dummies refer to four macro-regions: North-West, North-East, Center and South.

$^{*}$Significant at the 10-percent level; $^{**}$significant at the 5-percent level; $^{***}$significant at the 1-percent level.

Table 5

# Heterogeneity of the Crunch across Firms

Dependent variable: Change of loans over firm's assets

| Bank and firm variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $Low\_cap_b$ | -.744*** | -.799*** | -.964*** | -.808*** | -1.032*** |
| | (.069) | (.143) | (.116) | (.074) | (.201) |
| $Low\_cap_b \cdot Small\_f_i$ | -.384** | - | - | - | -.460** |
| | (.180) | - | - | - | (.211) |
| $Low\_cap_b \cdot Export_i$ | - | -.050 | - | - | .011 |
| | - | (.161) | - | - | (.186) |
| $Low\_cap_b \cdot Tfp_i$ | - | - | .227 | - | .191 |
| | - | - | (.138) | - | (.157) |
| $Low\_cap_b \cdot High\_risk_i$ | - | - | - | -.194 | -.367* |
| | - | - | - | (.168) | (.190) |
| $High\_liq_b$ | - | - | - | - | .583*** |
| | - | - | - | - | (.145) |
| $Large_b$ | - | - | - | - | -.145*** |
| | - | - | - | - | (.045) |
| $Scoring\_bank_b$ | - | - | - | - | .195** |
| | - | - | - | - | (.089) |
| $Coop_b$ | - | - | - | - | -.441*** |
| | - | - | - | - | (.138) |
| No. of firms | 2,558 | 2,558 | 2,558 | 2,452 | 2,440 |
| No. of observations | 19,576 | 19,576 | 19,576 | 18,981 | 17,074 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the change of loans from individual banks, normalized to firm's assets, defined over the period September 2008-March 2009. The regressor data refer to, respectively, September 2008 for bank variables and 2007 averages for firm variables. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). $Small\_f_i$ is a dummy for firms with less than 50 employees; $export_i$ is a dummy for exporting firms (roughly 70% of the total); $high\_risk_i$ is a dummy for firms with a high risk of default (as signalled by a Zscore value between 7 and 9), and $tfp_i$ is a dummy for firms whose total factor productivity (de-meaned at sectoral level) is higher than the median.

*Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

Table 6

# Flight to Quality: Heterogeneity across Banks

Dependent variable: Change of loans over firm's assets

| Bank and firm variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $Low\_cap_b$ | -.808*** | -.805*** | -1.259*** | -.994*** | -1.042*** | -1.551*** |
| | (.074) | (.074) | (.107) | (.083) | (.088) | (.120) |
| $Low\_cap_b \cdot High\_risk_i$ | -.194 | -.639*** | -.483* | -.458** | -.462** | -.729** |
| | (.168) | (.222) | (.263) | (.197) | (.206) | (.294) |
| $Low\_cap_b \cdot High\_risk_i$ | - | 1.143*** | .669** | - | - | .712** |
| $\cdot$ (1-$Large_b$) | - | (.203) | (.304) | - | - | (.340) |
| $Large_b$ | - | -.162*** | .118** | - | - | .314*** |
| | - | (.043) | (.061) | - | - | (.069) |
| $High\_risk_i \cdot$ (1-$Large_b$) | - | - | -.447*** | - | - | -.540*** |
| | - | - | (.142) | - | - | (.151) |
| $Low\_cap_b \cdot$ (1-$Large_b$) | - | - | 1.197*** | - | - | 1.563*** |
| | - | - | (.131) | - | - | (.149) |
| $Low\_cap_b \cdot High\_risk_i$ | - | - | - | 1.253*** | 1.061** | .606 |
| $\cdot$ (1-$Scoring\_bank_b$) | - | - | - | (.327) | (.467) | (.455) |
| $Scoring\_bank_b$ | - | - | - | .187** | .270*** | .101 |
| | - | - | - | (.084) | (.097) | (.100) |
| $High\_risk_i \cdot$ (1-$Scoring\_bank_b$) | - | - | - | - | -.427 | -.142 |
| | - | - | - | - | (.297) | (.291) |
| $Low\_cap_b \cdot$ (1-$Scoring\_bank_b$) | - | - | - | - | .681*** | -.135 |
| | - | - | - | - | (.196) | (.200) |
| No. of firms | 2,452 | 2,452 | 2,452 | 2,440 | 2,440 | 2,440 |
| No. of observations | 18,981 | 18,981 | 18,981 | 17,074 | 17,074 | 17,074 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The estimation period, dependent variable and time reference of regressors are as defined in Table 5; $high\_risk_i$ is a dummy for firms whose Zscore is in the 7-9 range. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). * Significant at the 10-percent level; ** 5-percent level; *** 1-percent level.

Table 7

# Corroborating the ‘Evergreening’ Explanation

Dependent variable: Change of loans over firm’s assets

| Bank and firm variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Low_cap$_b$ | -.792$^{***}$ | -.789$^{***}$ | -1.256$^{***}$ | -.995$^{***}$ | -1.057$^{***}$ | -1.574$^{***}$ |
| | (.068) | (.068) | (.100) | (.077) | (.082) | (.112) |
| Low_cap$_b$ · Imp_bor$_i$ | -.671$^{**}$ | -1.266$^{***}$ | -1.158$^{***}$ | -.992$^{***}$ | -.947$^{***}$ | -1.423$^{***}$ |
| | (.277) | (.360) | (.413) | (.330) | (.342) | (.462) |
| Low_cap$_b$ · Imp_bor$_i$ | - | 1.676$^{***}$ | 1.402$^{***}$ | - | - | 1.657$^{***}$ |
| · (1-Large$_b$) | - | (.346) | (.486) | - | - | (.569) |
| Large$_b$ | - | -.197$^{***}$ | .158$^{***}$ | - | - | .360$^{***}$ |
| | - | (.040) | (.057) | - | - | (.064) |
| Imp_bor$_i$ · (1-Large$_b$) | - | - | -.589$^{***}$ | - | - | -.710$^{***}$ |
| | - | - | (.213) | - | - | (.233) |
| Low_cap$_b$ · (1-Large$_b$) | - | - | 1.212$^{***}$ | - | - | 1.564$^{***}$ |
| | - | - | (.121) | - | - | (.137) |
| Low_cap$_b$ · Imp_bor$_i$ | - | - | - | 1.292$^{***}$ | .645 | -.350 |
| · (1-Scoring_bank$_b$) | - | - | - | (.380) | (.564) | (.563) |
| Scoring_bank$_b$ | - | - | - | .145$^{*}$ | .346$^{***}$ | .154 |
| | - | - | - | (.083) | (.099) | (.100) |
| Imp_bor$_i$ · (1-Scoring_bank$_b$) | - | - | - | - | .003 | .446 |
| | - | - | - | - | (.338) | (.321) |
| Low_cap$_b$ · (1-Scoring_bank$_b$) | - | - | - | - | .836$^{***}$ | .009 |
| | - | - | - | - | (.189) | (.190) |
| No. of firms | 2,452 | 2,452 | 2,452 | 2,440 | 2,440 | 2,440 |
| No. of observations | 18,981 | 18,981 | 18,981 | 17,074 | 17,074 | 17,074 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The estimation period, dependent variable and time reference of regressors are as defined in Table 5; imp_bor$_i$ is a dummy for firms whose Zscore is in the 7-9 range and whose productivity (sectorally de-meaned) is lower than the sample median. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). $^{*}$ Significant at the 10-percent level; $^{**}$ 5-percent level; $^{***}$ 1-percent level.

Table 8

# Evergreening: Robustness on Interest Rates

Dependent variable: Interest rates at the bank-firm level

| Bank and firm variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $Low\_cap_b$ | .031 | .028 | .041 | .039 | .019 | .063 |
| | (.030) | (.030) | (.038) | (.031) | (.032) | (.039) |
| $Low\_cap_b \cdot High\_risk_i$ | -.032 | -.001 | -.034 | .003 | .003 | .014 |
| | (.067) | (.074) | (.084) | (.069) | (.071) | (.089) |
| $Low\_cap_b \cdot High\_risk_i$ | - | -.064 | .019 | - | - | -.169 |
| $\cdot$ (1-$Large_b$) | - | (.093) | (.129) | - | - | (.135) |
| $Large_b$ | - | -.035 | -.054 | - | - | -.068* |
| | - | (.028) | (.038) | - | - | (.040) |
| $High\_risk_i \cdot$ (1-$Large_b$) | - | - | -.070 | - | - | -.010 |
| | - | - | (.083) | - | - | (.085) |
| $Low\_cap_b \cdot$ (1-$Large_b$) | - | - | -.032 | - | - | -.124* |
| | - | - | (.060) | - | - | (.064) |
| $Low\_cap_b \cdot High\_risk_i$ | - | - | - | -.325** | -.310 | -.303* |
| $\cdot$ (1-$Scoring\_bank_b$) | - | - | - | (.151) | (.210) | (.213) |
| $Scoring\_bank_b$ | - | - | - | -.027 | -.003 | .037 |
| | - | - | - | (.049) | (.060) | (.062) |
| $High\_risk_i \cdot$ (1-$Scoring\_bank_b$) | - | - | - | - | -.231* | -.222* |
| | - | - | - | - | (.123) | (.126) |
| $Low\_cap_b \cdot$ (1-$Scoring\_bank_b$) | - | - | - | - | .227* | .291** |
| | - | - | - | - | (.118) | (.122) |
| No. of firms | 2,294 | 2,294 | 2,294 | 2,279 | 2,279 | 2,279 |
| No. of observations | 13,611 | 13,611 | 13,611 | 12,994 | 12,994 | 12,994 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The estimation period, dependent variable and time reference of regressors are as defined in Table 5; $high\_risk_i$ is a dummy for firms whose Zscore is in the 7-9 range. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). * Significant at the 10-percent level; ** 5-percent level; *** 1-percent level.

Table 9

# The Capital Crunch and Relationship Lending

Dependent variable: Change of loans over firm's assets

| Bank and firm variables | (1) | (2) | (3) |
|---|---|---|---|
| $Low\_cap_b$ | -.656*** | -.785*** | -.799*** |
| | (.073) | (.083) | (.083) |
| $Low\_cap_b \cdot Cred\_share_{b,i}$ | -.019** | -.030*** | -.026*** |
| | (.008) | (.008) | (.010) |
| $Cred\_share_{b,i}$ | -.031*** | -.028*** | -.025*** |
| | (.004) | (.004) | (.005) |
| $High\_liq_b$ | - | .434*** | .431*** |
| | - | (.127) | (.128) |
| $Large_b$ | - | -.227*** | -.228*** |
| | - | (.049) | (.049) |
| $Scoring\_bank_b$ | - | .113 | .112 |
| | - | (.088) | (.088) |
| $Coop_b$ | - | -.451* | -.447*** |
| | - | (.140) | (.140) |
| $Low\_cap_b \cdot Cred\_share_{b,i} \cdot Small\_f_i$ | - | - | -.020* |
| | - | - | (.012) |
| $Cred\_share_{b,i} \cdot Small\_f_i$ | - | - | -.012 |
| | - | - | (.010) |
| No. of firms | 2,552 | 2,536 | 2,536 |
| No. of observations | 18,378 | 16,501 | 16,501 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The estimation period, dependent variable and time reference of regressors are as defined in Table 5. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). *Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

Table 10

# Evergreening and Relationship Lending

Dependent variable: Change of loans over firm's assets

| Bank and firm variables | (1) | (2) | (3) |
|---|---|---|---|
| Low_cap$_b$ | -1.307$^{***}$ (.091) | -1.117$^{***}$ (.076) | -1.645$^{***}$ (.103) |
| Low_cap$_b$ · Imp_bor$_i$ | -1.042$^{***}$ (.400) | -.875$^{***}$ (.331) | -1.298$^{***}$ (.445) |
| Low_cap$_b$ · Imp_bor$_i$ · (1-Large$_b$) | .961$^{*}$ (.524) | - | 1.526$^{**}$ (.650) |
| Low_cap$_b$ · Imp_bor$_i$ · (1-Large$_b$)· Cred_share$_{b,i}$ | .025 (.023) | - | -.008 (.031) |
| Large$_b$ | .094 (.058) | - | .296$^{***}$ (.065) |
| Cred_share$_{b,i}$ | -.038$^{***}$ (.004) | -.039$^{***}$ (.004) | -.039$^{***}$ (.004) |
| Imp_bor$_i$ · (1-Large$_b$) | -.358 (.230) | - | -.506 (.264) |
| Low_cap$_b$ · (1-Large$_b$) | 1.233$^{***}$ (.115) | - | 1.583$^{***}$ (.133) |
| Low_cap$_b$ · Imp_bor$_i$ · (1-Scoring_bank$_b$) | - | .142 (.700) | -1.072 (.830) |
| Low_cap$_b$ · Imp_bor$_i$ · (1-Scoring_bank$_b$)· Cred_share$_{b,i}$ | - | .031 (.020) | .050 (.038) |
| Scoring_bank$_b$ | - | .296$^{***}$ (.099) | .150 (.100) |
| Imp_bor$_i$ · (1-Scoring_bank$_b$) | - | .218 (.352) | .540 (.345) |
| Low_cap$_b$ · (1-Scoring_bank$_b$) | - | 1.053$^{*}$ (.194) | 1.053$^{*}$ (.194) |
| No. of firms | 2,444 | 2,426 | 2,426 |
| No. of observations | 17,612 | 15,830 | 15,830 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The estimation period, dependent variable and time reference of regressors are as defined in Table 5. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). $^{*}$ Significant at the 10-percent level; $^{**}$ 5-percent level; $^{***}$ 1-percent level.

# A Appendix I: Data sources, definition of variables and some descriptive statistics

*Bank and credit variables.* The data on outstanding loans come from the Italian National Credit Register, maintained at the Bank of Italy. For each borrower, banks have to report to the Register, on a monthly basis, the amount of each loan, respectively granted and utilized, for all loans exceeding a given threshold.[37] The sample of banks is given by the set of intermediaries reporting a positive amount of credit utilized or extended to at least one firm in the sample of firms on either end-September 2008 or end-March 2009 or at both dates. Data on banks' balance sheets refer to the end of September 2008. Summary statistics on the variables are reported in Table A1. Total assets are expressed in millions of euros. The capital ratio is computed as the ratio of total capital to risk-weighted assets and is expressed in percentage points. The numerator of the liquidity ratio is the sum of the amount of cash and securities other than shares, the denominator is total assets. Net interbank liabilities are expressed as a ratio of total assets. The figures for the five major banking groups refer to the set of banks belonging to the five largest bank holding companies. The data for cooperative firms refer to small local cooperative banks subject to a specific regulatory regime.

*Firm variables.* The data on employment and hours, labor compensation, investment and capital stock are drawn from the Survey of Industrial and Service Firms (SISF), carried out annually by the Bank of Italy. The data on gross production, purchases of intermediate goods and inventories of finished goods are drawn from the Company Accounts Data Service (CADS - *Centrale dei Bilanci*). Total factor productivity (on a gross-output basis) is computed as follows. Gross output is measured as the value of firm-level production (source: CADS) deflated by the sectoral output deflator computed by Istat (the National Statistical Institute). Employment is the firm-level average number of employees over the year (source: SISF); firm-level man-hours include overtime hours (source: SISF). Intermediate inputs are measured as firm-level net purchases of intermediate goods of energy, materials and business services (source: CADS), deflated by the corresponding industry deflator computed by Istat. Investment is firm-level total fixed investment

[37] The threshold was equal to euro 75,000 until December 2008 and was then reduced to euro 30,000.

in buildings, machinery and equipment and vehicles, plus investment in software and patents, (source: SISF), deflated by the industry's Istat investment deflator. Capital is the beginning-of-period stock of capital equipment and non-residential buildings at 1997 prices. To compute it, we applied the perpetual inventory method backwards by using firm-level investment data from SISF and industry depreciation rates from Istat. The benchmark information is that on the capital stock in 1997 (valued at replacement cost), which was collected by a special section of the SISF Survey conducted for that year. The capital deflator is the industry capital deflator computed by Istat. Descriptive statistics on selected firm variables are reported in the Table A2.

Table A1
Summary statistics of bank variables
(percent, unless otherwise indicated)

| Five largest banking groups (62 banks) | 25th pctile | median | 75th pctile | mean |
|---|---|---|---|---|
| Total assets (milions of euro) | 2436 | 10553 | 24716 | 30427 |
| Capital ratio | 8.9 | 10.2 | 12.6 | 12.1 |
| Liquidity ratio | 4.9 | 6.5 | 8.3 | 7.3 |
| All banks (488 banks) | | | | |
| Total assets (milions of euro) | 288 | 716 | 2384 | 6073 |
| Capital ratio | 10.5 | 13.0 | 16.8 | 15.0 |
| Liquidity ratio | 6.5 | 11.2 | 17.1 | 12.3 |

Source: Banking Supervision Register; the data refer to September 2008.

Table A2
Summary statistics of firm variables
(percent, unless otherwise indicated)

| Variable | 25th pctile | median | 75th pctile | mean |
|---|---|---|---|---|
| Number of employees (units) | 45 | 93 | 233 | 357 |
| Real gross output growth | -3.8 | 3.1 | 10.9 | 4.2 |
| TFP growth | -1.6 | .6 | 3.0 | .7 |
| TFP level (log-difference from sectoral median) | -12.7 | 5.1 | 18.8 | .4 |
| Labor revenue-share | 9.6 | 15.5 | 22.9 | 18.4 |
| Capital revenue-share | 4.7 | 8.1 | 12.8 | 10.0 |
| Materials revenue-share | 64.0 | 74.8 | 83.1 | 71.6 |

Source: SISF and CADS; the data refer to 2007.

# A Appendix II: Robustness

This section briefly documents a number of robustness exercises conducted on the results presented in Sections 4 and 5, all of which have been referred to in the main text.

A first set of exercises investigated the robustness, along four different dimensions, of the evidence of a credit crunch reported in Table 3. We replaced the original dependent variable with the rate of growth of loans; the results are reported in Table A3 (extreme values of the dependent variable were eliminated by dropping the top and bottom 5% of the distribution).[38] We computed $low\_cap_b$ based on the median capital ratio (13.0) as the threshold, instead of the 25th percentile; see Table A4 (the size of the coefficient is lower, as expected, since the number of banks involved in the estimation of the effect has doubled, and includes banks with relatively high capital ratios). We changed the definition of credit, by replacing outstanding loans, in the original dependent variable, with total credit lines (utilized and non-utilized); see Table A5 (it may be argued that this is a preferable indicator of credit supply, since their level is chosen mainly by banks, whereas short-term developments of outstanding loans may also reflect the choice of firms, which can increase or decrease the degree of utilization of existing credit lines). We run the baseline regression with consolidated data (both the dependent variable and the regressor $low\_cap_b$); see Table A6. We also adjusted loan data for the accounting effect of securitizations, by re-including loans securitized from October 2008 to March 2009 into the stock of outstanding bank-firm loans at March 2009 (see Section 4.2 for a discussion of the rationale); see Table A7.

A second set of exercises investigated the robustness (with respect to the

[38] This robustness check is important since our choice of the dependent variable might potentially affect the identification of firm-specific effects within our model. Consider, for example, what would happen if "weak" (undercapitalized) banks were specialized, before the crisis, in "weak" firms (hit hardest by the crisis). Given the definition of our benchmark dependent variable (i.e., *absolute* changes in credit), the values of such variable might be of a different order of magnitude across banks exposed to a different degree towards a given firm or category of firms, and in principle our firm-specific fixed-effects might fall short of fully capturing demand effects. In such case, the observations related to the banks most exposed with "weak" firms (associated with the largest absolute changes in credit) might possibly drive the estimate of the coefficient of $low\_cap_b$. The results with the rate of growth of loans as the dependent variable rule out this potential explanation of our results.

dataset) of the evidence on evergreening reported in Table 7. We included, among the borrowers that potentially benefit from evergreening, only firms which, at the beginning of the period considered, were actively borrowing from a given bank. To this purpose, we estimated the regressions reported in Table 7 after dropping the (few) observations associated with firms with $imp\_bor_i$ =1 and no outstanding loans from a given bank at September 2008. By doing so, the dummy $imp\_bor_i$ identifies (only and all) the potential recipients of 'evergreening' loans. See Table A8.

Finally, we checked the robustness of the evidence on relationship lending with respect to the definition of the dependent variable; namely, we replicated the evidence reported in Table 9 after replacing the original dependent variable with the rate of growth of loans. See Table A9.

Table A3

# The Credit Crunch:
# Robustness with respect to the dependent variable

Dependent variable: Rate of growth of loans

| Bank variables | (1) | (2) | (3) | (4) Pre-crisis |
|---|---|---|---|---|
| Low_cap$_b$ | -9.123*** | -9.025*** | -7.572*** | -2.406 |
| | (1.552) | (1.606) | (1.754) | (1.550) |
| High_liq$_b$ | - | -.856 | 7.786** | -2.273 |
| | - | (2.396) | (3.473) | (3.872) |
| Large$_b$ | - | - | 4.302** | -2.753* |
| | - | - | (1.766) | (1.631) |
| Scoring_bank$_b$ | - | - | 9.091*** | 4.285*** |
| | - | - | (2.612) | (2.898) |
| Coop$_b$ | - | - | -8.498** | 8.189 |
| | - | - | (3.811) | (6.426) |
| No. of firms | 2,205 | 2,205 | 2,165 | 2,028 |
| No. of observations | 11,008 | 11,008 | 9,964 | 10,541 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the rate of growth of loans from individual banks over the period September 2008-March 2009; the regressor data refer to September 2008. In column 4, the dependent variable is defined over the period September 2006-March 2007, and the regressor data refer to September 2006. In all the regressions, extreme values of the dependent variable were eliminated by dropping the top and bottom 5% of the distribution. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). *Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

Table A4

# The Credit Crunch:
# Robustness with respect to the threshold for the capital ratio

Dependent variable: Change of loans over firm's assets

| Bank variables | (1) | (2) | (3) | (4) Pre-crisis |
|---|---|---|---|---|
| Low_cap$_b$ | -.463$^{***}$ | -.459$^{***}$ | -.422$^{***}$ | .059 |
| | (.065) | (.065) | (.069) | (.051) |
| High_liq$_b$ | - | .257$^{***}$ | .299$^{**}$ | -.071 |
| | - | (.081) | (.144) | (.096) |
| Large$_b$ | - | - | -.240$^{***}$ | -.087$^{*}$ |
| | - | - | (.045) | (.049) |
| Scoring_bank$_b$ | - | - | .189$^{**}$ | .101 |
| | - | - | (.086) | (.072) |
| Coop$_b$ | - | - | -.249$^{*}$ | -.005 |
| | - | - | (.133) | (.130) |
| No. of firms | 2,558 | 2,558 | 2,546 | 2,358 |
| No. of observations | 19,576 | 19,576 | 17,596 | 16,602 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the rate of growth of loans from individual banks over the period September 2008-March 2009, normalized to firm's assets; the regressor data refer to September 2008. In column 4, the dependent variable is defined over the period September 2006-March 2007, and the regressor data refer to September 2006. Low_cap$_b$ is a dummy for banks whose capital ratio is lower than the sample median (13.0). The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). $^{*}$Significant at the 10-percent level; $^{**}$significant at the 5-percent level; $^{***}$significant at the 1-percent level.

Table A5

# The Credit Crunch:
# Robustness with respect to the definition of credit

Dependent variable: Change of total credit lines over firm's assets

| Bank variables | (1) | (2) | (3) | (4) Pre-crisis |
|---|---|---|---|---|
| Low_cap$_b$ | -1.758*** | -1.821*** | -2.235*** | .009 |
| | (.093) | (.095) | (.107) | (.055) |
| Hig_liq$_b$ | - | .872*** | .989*** | .004 |
| | - | (.129) | (.233) | (.105) |
| Large$_b$ | - | - | -.229*** | -.059 |
| | - | - | (.054) | (.057) |
| Scoring_bank$_b$ | - | - | .336*** | .289*** |
| | - | - | (.101) | (.086) |
| Coop$_b$ | - | - | -.786*** | -.057 |
| | - | - | (.164) | (.143) |
| No. of firms | 2,530 | 2,530 | 2,518 | 2,325 |
| No. of observations. | 19,333 | 19,333 | 17,371 | 16,439 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the change of total credit lines (utilized and non-utilized) from individual banks over the period September 2008-March 2009, normalized to firm's assets; the regressor data refer to September 2008. In column 4, the dependent variable is defined over the period September 2006-March 2007, and the regressor data refer to September 2006. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). *Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

Table A6

# The Credit Crunch:
# Robustness with respect to consolidated bank data

Dependent variable: Change of loans (consolidated) over firm's assets

| Bank variables (consolidated) | Definition of low-capitalized banks<br>Threshold on the consolidated capital ratio:<br>25th percentile (i.e., 11.0) | <br><br>Median (i.e., 13.2) |
|---|---|---|
| $Low\_cap\_cons_b$ | -.213*** | -.209** |
| | (.080) | (.099) |
| No. of firms | 2,557 | 2,557 |
| No. of observations | 14,890 | 14,890 |

Note: Fixed effect (firm-level) estimation with data consolidated at the banking group level. Each column corresponds to a regression. The dependent variable is the rate of growth of loans from banking groups (or individual banks, in the case of banks which do not belong to a group) over the period September 2008-March 2009, normalized to firm's assets; the regressor data refer to September 2008. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). *Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

Table A7

# The Credit Crunch:
# Robustness with respect to the accounting effect of securitizations

Dependent variable: Change of loans over firm's assets

| Bank variables | (1) | (2) | (3) |
| --- | --- | --- | --- |
| $Low\_cap_b$ | -.819*** | -.851*** | -1.069*** |
| | (.065) | (.067) | (.075) |
| $High\_liq_b$ | - | .436*** | .550*** |
| | - | (.084) | (.144) |
| $Large_b$ | - | - | -.137*** |
| | - | - | (.045) |
| $Scoring\_bank_b$ | - | - | .212** |
| | - | - | (.087) |
| $Coop_b$ | - | - | -.441*** |
| | - | - | (.137) |
| No. of firms | 2,558 | 2,558 | 2,546 |
| No. of observations | 19,578 | 19,578 | 17,596 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the change of loans from individual banks over the period September 2008-March 2009, normalized to firm's assets; loan data include securitized loans. The regressor data refer to September 2008. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). *Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

Table A8

# Evergreening:
# Robustness with respect to the dataset

Dependent variable: Change of loans over firm's assets

| Bank and firm variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $Low\_cap_b$ | -.818*** | -.814*** | -1.287*** | -1.020*** | -1.085*** | -1.605*** |
| | (.068) | (.068) | (.100) | (.077) | (.082) | (.112) |
| $Low\_cap_b \cdot Imp\_bor_i$ | -.642** | -1.302*** | -1.078*** | -.973*** | -.898*** | -1.318*** |
| | (.271) | (.347) | (.405) | (.325) | (.337) | (.452) |
| $Low\_cap_b \cdot Imp\_bor_i$ | - | 1.836*** | 1.228** | - | - | 1.406** |
| $\cdot$ (1-$Large_b$) | - | (.347) | (.491) | - | - | (.576) |
| $Large_b$ | - | -.236*** | .143** | - | - | .349*** |
| | - | (.041) | (.057) | - | - | (.065) |
| $Imp\_bor_i \cdot$ (1-$Large_b$) | - | - | -.249 | - | - | -.408 |
| | - | - | (.232) | - | - | (.267) |
| $Low\_cap_b \cdot$ (1-$Large_b$) | - | - | 1.231*** | - | - | 1.584*** |
| | - | - | (.121) | - | - | (.138) |
| $Low\_cap_b \cdot Imp\_bor_i$ | - | - | - | 1.646*** | .686 | -.201 |
| $\cdot$ (1-$Scoring\_bank_b$) | - | - | - | (.436) | (.604) | (.641) |
| $Scoring\_bank_b$ | - | - | - | .115 | .339*** | .154 |
| | - | - | - | (.084) | (.100) | (.102) |
| $Imp\_bor_i \cdot$ (1-$Scoring\_bank_b$) | - | - | - | - | .326 | .576* |
| | - | - | - | - | (.343) | (.336) |
| $Low\_cap_b \cdot$ (1-$Scoring\_bank_b$) | - | - | - | - | .862*** | .025 |
| | - | - | - | - | (.191) | (.193) |
| No. of firms | 2,444 | 2,444 | 2,444 | 2,428 | 2,428 | 2,428 |
| No. of observations | 18,565 | 18,565 | 18,565 | 16,703 | 16,703 | 16,703 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The estimation period, dependent variable and time reference of regressors are as defined in Table 5. Observations with Zscore$\geq$7 and no reported outstanding loans at September 2008 are dropped from the sample. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). * Significant at the 10-percent level; ** 5-percent level; *** 1-percent level.

Table A9

# Relationship Lending and the Credit Crunch: Robustness with respect to the dependent variable

Dependent variable: Rate of growth of loans

| Bank and firm variables | (1) | (2) | (3) |
|---|---|---|---|
| $Low\_cap_b$ | -13.149*** | -9.183*** | -9.164*** |
| | (2.204) | (2.503) | (2.514) |
| $Low\_cap_b \cdot Cred\_share_{b,i}$ | .326*** | .112 | .094 |
| | (.124) | (.144) | (.167) |
| $Cred\_share_{b,i}$ | -.541*** | -.576*** | -.534*** |
| | (.076) | (.080) | (.094) |
| $High\_liq_b$ | - | 7.355** | 7.401** |
| | - | (3.454) | (3.457) |
| $Large_b$ | - | 5.190*** | 5.180*** |
| | - | (1.773) | (1.774) |
| $Scoring\_bank_b$ | - | 9.269*** | 9.271*** |
| | - | (2.618) | (2.617) |
| $Coop_b$ | - | -8.694** | -8.700** |
| | - | (3.788) | (3.785) |
| $Low\_cap_b \cdot Cred\_share_{b,i} \cdot Small\_f_i$ | - | - | .054 |
| | - | - | (.209) |
| $Cred\_share_{b,i} \cdot Small\_f_i$ | - | - | -.144 |
| | - | - | (.163) |
| No. of firms | 2,205 | 2,165 | 2,165 |
| No. of observations | 11,008 | 9,964 | 9,964 |

Note: Fixed effect (firm-level) estimation with data at the bank-firm level. Each column corresponds to a regression. The dependent variable is the rate of growth of loans over the period September 2008-March 2009; the regressor data refer to September 2008. The parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). *Significant at the 10-percent level; **significant at the 5-percent level; ***significant at the 1-percent level.

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