Unnatural Selection At Work: An Analysis of Bank-Firm Relationships in Italy After Lehman *

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Abstract

We analyze the effects of the financial crisis on credit supply, by using highly detailed data on bank-firm relationships in Italy after Lehman's bankruptcy. We control for demand by using firm-specific fixed effects. We find evidence of credit crunch; namely, we document a contraction of credit supply associated to low bank capitalization. Furthermore, and more importantly, we provide evidence of unnatural selection in credit allocation. Under-capitalized banks may have an incentive to allocate credit to impaired borrowers, in order to avoid the realization of losses on their balance sheets. We propose new methods to identify impaired borrowers, based on the lending pattern of financially sound banks, or on the firms' economic fundamentals as proxied by productivity level, or a combination of both. The evidence of 'evergreening' behavior that we find is very robust across identification methods and model specifications. It is the first evidence of this type beyond that supplied for the Japanese crisis of the nineties.

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1 Introduction

It is now largely recognized that credit misallocation played an important role in the prolonged stagnation of the Japanese economy during the 'lost decade' of the nineties. Under-capitalized banks delayed the recognition of losses on their credit portfolio by 'evergreening' loans to otherwise insolvent borrowers; they did so to avoid to increase their own loan loss reserves, which would have further impaired their reported capital and profitability (Peek and Rosengren, 2005).

This phenomenon (which has been dubbed in several ways: evergreening, forbearance lending, zombie lending, unnatural selection in credit markets) has contributed to the long-lasting Japanese stagnation in two ways. First, the weakest firms have been insulated from market forces which otherwise would have forced their bankruptcy or restructuring. Furthermore, there has been a crowding out effect, in the sense that less credit has been available for the growth of healthy and productive firms; also, the entry of new firms has been presumably discouraged (Caballero et al., 2008).[1]

Several observers have emphasized the similarities between the Japanese experience of the nineties and the current financial crisis (Hoshi and Kashyap, 2008; Kobayashi, 2008). In both cases the financial stability of the banking system underwent a dramatic deterioration, initially due to write-downs on structured portfolios and then to the sharp worsening of the macroeconomic environment (e.g., ECB, 2009). It is therefore natural to ask if the type of credit market inefficiencies extensively documented for the Japanese economy could take place in other economies as well.

Indeed, although some specific aspects of the 'lost decade' presumably encouraged the emergence of these allocative distortions (for example loose banking supervision, government pressure on banks and the 'solidarity links' within *keiretsu* conglomerates; Peek and Rosengren, 2005), in principle they may arise in any financially-developed economy. Moreover, the introduction in 2008 of Basle II standards, with their more procyclical capital requirements, may have contributed to the increasing difficulties faced by troubled banks to maintain an adequate capitalization (Panetta et al., 2009). This paper is a first contribution in this direction; it provides evidence based on a unique real-time dataset on the Italian credit market with information at in-

[1] The allocative distortions induced by a 'soft budget constraint' of this type have been documented also for transition economies (Dewatripont and Maskin, 1995).

dividual firm-bank relationship level on credit developments in the aftermath of the Lehman's failure.

Italy is a good case for investigating the arising of 'unnatural selection' for many reasons. First, it is a bank-based economy so that allocation distortions in the credit market are likely to bring a sizable impact.[2] As any other industrialized economy, Italy has been hardly hit by the financial crisis. Although the Italian banking sector has been initially affected only to a limited extent by the crisis, as the exposure of its intermediaries to structured products was relatively modest, this did not prevent an abrupt worsening of the economic outlook and a sharp reduction of the growth of credit to the corporate sector, which came to a substantial halt in recent months, as in rest of the euro area (Bank of Italy, 2009; figure 1). Though the simultaneous contraction of credit demand has been very sharp, there is qualitative evidence from the Eurosystem's quarterly Bank Lending Survey that, starting in the second quarter of 2008, a contraction of credit supply (more precisely, a tightening of credit conditions implemented through a quantitative reduction of the loans being granted) contributed to the credit stallmate. Our goal is to assess if the contraction of loan dynamics has been across the board or if it affected different firms to a different extent; we also tried to verify if the borrowers' selection has been characterized by the type of inefficiencies documented for Japan.[3]

Compared to the previous literature, our contribution represents the first attempt to study unnatural selection beyond Japan and with reference to the current financial crisis. Also, while the existing literature is based on samples containing only large listed firms, our dataset contains information for a comprehensive and representative sample of firms, of small and large size. More importantly, as it will be explained in the following section, this paper differs sharply from previous studies with regard to the way the 'impaired borrowers' are identified.

A further contribution of our work is that we provide what we believe is a

[2] At the end 2008, the ratio of total bank credit to nominal GDP amounted to 60 percent in US, 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).

[3] The literature has emphasized another mechanism through which the impact of a credit crunch may be differentiated across firms. In particular, Bernanke et al. (1996) have documented the presence of a "flight to quality" phenomenon, because of which "borrowers facing high agency costs should receive a relatively lower share of credit extended" during a credit crunch.

robust test of credit crunch. As it is well-known, the difficulties of controlling effectively for changes in the demand of credit, which has decreased sharply as effect of the economic slowdown, make the identification of changes in the credit supply schedule, beyond what can be inferred by surveys on lending standards, extremely complex (Udell, 2009).

The previous literature has suggested several possible solutions.[4] In our case, by observing individual bank-firm transactions, and thanks to the large number of banks from which Italian firms typically borrow (Detragiache et al, 2000), we were able to use fixed effects in order to control for all unobservable firm's characteristics, included the demand of credit.[5]

The remainder of the paper is organized as follows. The next section presents our approach(es) to the identification of 'impaired borrowers', and emphasizes the differences with the existing literature. Section 3 describes the data. Section 4 presents the main evidence of 'unnatural selection', and documents the robustness of our findings across identification schemes and model specifications. Section 5 discusses some extensions of our basic model, exploring the role of some relevant bank and firm variables. Finally, Section 6 draws some conclusions and mentions the areas and extensions of our analysis that we are currently working on.

2 The Methodology

A central issue in the analysis of forbearance lending is the identification of impaired borrowers. To this regard, this paper differs sharply from previous contributions.

Most of the literature, recently surveyed by Peek (2008), identifies these firms by using proxies that reflect current firm's conditions and performances (for example: return on assets, sales, interest coverage ratio, leverage ratio, net working capital). One unsatisfactory feature of all these measures, in our context, is that they do not take into consideration firms' future prospects:

[4] Dell'Ariccia et al. (2008) exploited sectoral differences in the 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).

[5] Note that this is different from having firm-specific fixed effect in a standard panel setup 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.

in other words, by using these measures, it is not possible to distinguish true forbearance lending (which is inefficient, as it is done with the aim of postponing the realization of losses on the credit portfolio, regardless of firm's net present value of the stream of future expected profits) from efficient debt restructuring, whereby a non myopic lender helps a currently distressed borrower go through difficulties which are only temporary. In other words, the analyses based on these proxies do not seem particularly suitable to provide normative implications.

An alternative approach is adopted by Caballero et al. (2008). In their paper, 'zombie' firms are identified as those firms which receive 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. Being not based on indicators of current performances, this approach offers the main advantage of being inherently more forward-looking. Moreover, this identification scheme makes possible to study the impact of this phenomenon on productivity, which clearly would not be possible if the identification were based on productivity measures. One main limitation of this approach, on the other hand, is that it presumes that forbearance lending is related one-to-one to some form of debt forgiveness, which is not necessarily the case.[6] Indeed, the fact that a bank is willing to lend to negative-NPV borrowers represents forbearance lending even if this occurs at high costs.[7]

In this paper we adopt a different approach, which is made feasible by the widespread use of multiple lenders in Italy. Our main identification scheme is built on the notion that, by its definition, 'unnatural selection' in credit allocation does not involve well-capitalized banks. Therefore, we first select the (very large) subsample of firms which borrow from at least one highly-capitalized bank. We then compute, for each of these firms, the growth of total credit received by the pool of well-capitalized banks, and identify as 'impaired borrowers' those at the bottom tail of this distribution. In few

[6] Beyond the Japanese case, one could argue that there is no rationale for the lender top give up claims on the borrower as long as there is some even tiny probability that the borrower will be able to repay back. Franks and Sussman (2005) find, for a sample of UK financially distressed SME's, that, although banks rarely increase interest-rate margins to compensate for the increased default risk, debt forgiveness is virtually absent.

[7] Another more forward-looking measures 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.

words, the idea is that financially sound banks are not inclined to forbearance lending and therefore reduce their supply of credit to firms if and only if such firms are characterized by a negative NPV of future expected profits; throughout this paper, these firms are defined as 'bad' or 'impaired' borrowers.

We believe that this identification scheme is a good way to proceed, as it is based on well-capitalized banks' "revealed preferences", and does not require any aprioristic choice on what is the best proxy of the borrower's current conditions and future prospects. However, in order to verify the robustness of our findings, we replicated the analysis with a couple of alternative identification schemes. The first among these schemes uses the information coming from the lending pattern of more-capitalized banks only to the extent that it is matched with that, totally orthogonal, based on productivity measurements. Namely, in this 'combined' approach we identify as impaired borrowers those firms which simultaneously satisfy two conditions: (i) their credit has been reduced more aggressively by highly-capitalized banks, and (ii) they are among the least productive firms in the sample (in relative terms vs. the sectoral median, to allow for comparison across sectors).

The assumption underlying our 'combined' approach is that productivity, if carefully measured, is a better indicator of the firm's 'economic fundamentals', and therefore a more forward-looking measure, than balance sheet items, thus leading to better-grounded normative implications.

The other alternative identification scheme being used is based entirely on productivity measures; that is, 'bad borrowers' are identified as the least productive firms in the sample.

3 The Data

We use comprehensive 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 variables 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. There are three main sources of data: data on outstanding loans and bank variables come from the Credit Register;

data on firms' inputs, output and other firm characteristics come from the Bank of Italy annual Survey of Italian Manufacturing 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 all individual loans extended in Italy. For each borrower, banks have to report on a monthly basis the amount of each loan, respectively granted and utilized, for all loans exceeding a given threshold.[8] Banks' balance sheet data come from the Banking Supervision Register at the Bank of Italy; they include data on total capital, tier1 capital, total assets, risk weighted assets, interbank assets and liabilities, cash and securities other than shares. The dataset includes also information on bank corporate governance and organization.[9]

The Survey of Italian Manufacturing (SIM) is carried out annually by the Bank of Italy. The data are of unusually high quality, being directly 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. Sample composition is maintained to ensure sample representativeness; since 2002 the Survey has been extended to the services sector. Data drawn from SIM include figures on employment and hours, labor compensation, investment and capital stock, plus qualitative information on a number of variables (for example, in some regressions we used qualitative data on the recent dynamics of credit demand). Data on gross production, purchases of intermediate goods and inventories of finished goods - which are used to measure productivity - are drawn from the Company Accounts Data Service (CADS), which 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 major Italian commercial banks.

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

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

[9] In particular, we are able to identify local small cooperative banks (*BCC*), which are subject to a specific regulatory regime; they have been shown to focus on relationship lending (e.g., Angelini et al., 1998).

4 Stylized facts at the firm-level on the contraction of credit

Credit to non-financial firms fell sharply in Italy in recent months at the aggregate level, as documented in the introduction. In this section we run some preliminary regressions to document some stylized facts on the pattern of credit contraction across different categories of firms. To this aim, we computed total credit received by each firm from all banks, and considered its rate of growth from end-September 2008 to end-March 2009. For the median firm in our sample, credit contracted by 0.8 percent over this period. We regressed such dependent variable on a number of firm characteristics.

The six-months period considered was chosen because it coincides with the aftermath of Lehman's bankruptcy, which induced an unprecedented deterioration of the financial and macroeconomic environment; besides, this is the period when the growth of credit weakened most severely, to come to a substantial halt.[10]

Our regression equation is:

$$\begin{aligned}\Delta cred_i \quad = \quad & \alpha + \beta_1 \cdot size_i + \beta_2 \cdot m\_score_i + \beta_3 \cdot h\_score_i \\ & + \beta_4 \cdot export_i + \beta_5 \cdot tfp_i + \beta_6 \cdot sh\_mainb_i \\ & + \beta_7 \cdot credcom_i + \beta_8 \cdot inv_i + \beta_9 \cdot sector_i + u_i,\end{aligned} \tag{1}$$

where $\Delta cred_i$ is the growth of total credit received by firm i; $size_i$ is a dummy variable which identifies firms with less than 50 employees; m_score_i and h_score_i are dummies which identify firms with, respectively, medium and high risk of default (as signalled by a Zscore value between 4 and 6 and between 7 and 9, respectively);[11] $export_i$ is the share of the firm's exported sales; tfp_i is firm's productivity (as measured by the logarithm of total factor productivity computed on a gross-output basis; see below for details);

[10] A further advantage of using this period is that one indicator of credit demand used in the regressions was obtained from the Bank of Italy Survey conducted in February-March 2009, and such indicator refers precisely to this period (see below).

[11] Zscore is an indicator of the risk profile of a given firm, computed annually by the Company Accounts Data Service using balance sheet variables. It takes values from 1 to 9; firms with a Zscore value ≥ 7 are considered by CADS 'risky'. They are found to be more likely to default within the next two years (see Panetta et al., 2005, and the references cited there).

sh_mainb_i is the share of the firm's total credit received by its main bank; $credcom_i$ is firm's net commercial credit (i.e. net of commercial debt) over total assets; inv_i is firm's fixed investment (net of depreciation allowances) over total assets; $sector_i$ is a set of sectoral dummies at 3-digit level, and u_i is the regression residual which is assumed to be well-behaved. In one estimation of equation (1) we also included a further regressor, $cred\_dom_i$, which is a proxy of the change in firm's credit demand in the period of interest, based on the results of a specific question included in the 2009 Bank of Italy Survey; since this variable is not available for all firms, and therefore reduces somewhat the number of observations, we included it only in one regression as a control of the results of the others.[12]

It is worth clarifying from onset that with these regressions we do not mean to test the hypothesis of 'evergreening', nor the emergence of a credit crunch, for two reasons. First, although variables such as inv_i, $credcom_i$ and $sector_i$ presumably capture cross-firm differences in credit demand to a satisfactory extent, we can further improve our control of demand factors in the rest of our analysis (based on regressions on bank-firm data with firm-level fixed effects). Moreover, since equation (1) is specified at firm level, it is not suitable to study the role of bank characteristics, such as bank capital (the average firm in the sample is borrowing from about eight banks simultaneously). The aim of this exercise is therefore that of uncovering the pattern of credit growth (contraction) across different categories of the firms, something that we cannot achieve through the analysis documented in the next sections, where the use of firms' fixed effect will force the exclusion of firm characteristics as autonomous regressors.

The estimation of (1) was conducted with different estimators. To face the problem that the distribution of our dependent variable - which represents a rate of growth computed on firm-level data - displays not surprisingly a mass of points at -100 and no observations below that threshold, we dropped the bottom 5 per cent of observations in our OLS regressions. As an alternative approach we also estimated a Tobit specification. A similar problem arises at the other tail of the distribution: nil or negligible amounts of total credit at end-September 2008 result in, respectively, infinite or huge positive growth

[12] Firms where asked to assess the change in their demand for credit over the previous 6-month period (the survey was conducted in February-March 2009). For those willing to reply, the five possible answers were: (i) strong decrease, (ii) moderate decrease, (iii) substantial stability, (iv) moderate increase, (v) strong increase. The dummy takes values ranging from 1 in the first case to 5 in the latter.

rates at end-March 2009; in all regressions we dealt with this problem by dropping observations which belong to the top 5 percent of the distribution of the dependent variable.

Results are shown in the first three columns of Table 1. First, the coefficient of firm size is not statistically significant across all regressions. Therefore, contrary to what is commonly suggested in the public debate on the impact of the credit crunch, there is no evidence, at least after controlling for other observable variables, that the contraction of credit supply has been sharper for smaller firms.[13] With regard to the estimated coefficients of m_score_i and h_score_i, there is some evidence, from the OLS regressions, that credit developments have been weaker for firms with a higher risk of default, as expected. Analogously, as to export-propensity, OLS estimates suggest that credit developments have been more favorable for firms which are more export-oriented. Given that these firms have been hit very severely by the collapse of world demand, this is an interesting finding since it reveals that concerns that 'short-termist' banks could possibly reduce credit to these firms, which represent the dynamic and healthy core of the Italian productive system, seem unfounded. However, in principle it cannot be excluded that the estimated coefficient of $export_i$ reflects, at least to some extent, strong credit demand from exporting firms which is not fully captured by the control variables. Indeed, some opposite evidence, suggestive of the possible relevance of 'myopic' lending behavior by banks, is provided by the estimated coefficient for tfp_i,which indicates that credit developments have been weaker for more productive firms. The latter result is very robust across all regressions. While the focus of this paper is not on testing banks' 'myopia', the evidence of unnatural selection documented in the rest of the paper provides an explanation, at least a partial one, of such finding.

Passing on commenting the estimated coefficient of sh_mainb_i, credit dynamics has been weaker for firms which rely more on a single bank, thus presumably developing stronger relationship links with their main lender. This piece of evidence, which is somewhat similar to that found by Peek and Rosengren (2005), it is not straightforward to be interpreted without further analysis. It might reflect the disadvantage of relying mainly on one single bank, in a period characterized by huge funding difficulties for banks

[13] Our sample includes firms with at least 20 employees. Therefore, our results might not apply to very small firms, whose relevance for the Italian economy is not negligible (e.g., 16 percent of employees in industry work in firms with less than 10 employees; see Istat, 2009).

(this interpretation would be consistent with the analysis in Detragiache et al, 2000). As to commercial credit and fixed investment, which are meant to capture credit demand, we just point out that their inclusion or exclusion does not significantly alter the main picture (regressions not shown);[14]. The same holds true for $cred\_dom_i$.

We now turn to the analysis of data on bank-firm relationships, which - by allowing us to control for firm-specific effects - provide a robust framework against which we can test our hypothesis.

5 Testing for unnatural selection

5.1 The basic bank-firm regression framework

The core of this paper is the investigation of bank-firm relationships after the Lehman bankruptcy. We used a panel of roughly 19,000 observations, describing outstanding loans extended by almost 500 banks to roughly 2,500 non-financial firms over the period September 2008-March 2009 (on average, therefore, firms in our sample borrow from eight different banks). Our dependent variable is the change in credit extended by 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 credit because in many cases the amount of credit provided by a single bank to a given firm either 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 negative rate of growth equal to -100 percent (see Table 2, first row).

[14] While the positive coefficient for net investment is as expected, the interpretation of the negative one for commercial credit is more straightforward. We do not attempt to provide any structural interpretation of this coefficient, since this is one of the clearest cases in which the causal relationship between the dependant variable and the regressor can go in either direction. In general, the negative sign is consistent with the fact that the firms which are more trust-worthy could borrow more from banks and suppliers.

Table 2

Descriptive statistics of dependent variable (percent)

Variable (bank-firm level)	Percentiles								
	1st	5th	10th	25th	median	75th	90th	95th	99th
Rate of growth of credit	-100	-100	-100	-63.6	-10.9	16.4	117.5	325.7	23,039
Change of credit over firm's assets	-11.6	-4.6	-2.6	-0.7	0.0	.5	2.6	4.9	12.4

Rather than dropping large tails of the distribution of such dependent variable, which in all likelihood would have resulted in the elimination of many observations with the most interesting information content for our purposes, we chose to divide the change in credit by firm's total assets rather than credit. On one hand, this normalization should not alter the information content of the data. Reassuring evidence to this regard, obtained by consolidating the data at the firm level, comes from the results reported in the fourth column of Table 1.[15] On the other hand, the new dependent variable at the bank-firm level, with firm's total assets as denominator, has a much smoother distribution (see Table 2, second row). This is therefore the dependent variable utilized in the rest of our work.[16]

As a starting point of our analysis on bank-firm relationships, we look at the pattern of credit contraction across different types of bank. In particular, the basic regression model is the following:

$$\begin{aligned} \Delta cred_{b,i} \quad = \quad & \alpha + \beta_1 \cdot low\_cap_b + \beta_2 \cdot hig\_liq_b + \beta_3 \cdot ib\_borr_b \\ & + \beta_4 \cdot large_b + \eta_i + u_{b,i} \ , \end{aligned} \tag{2}$$

where $\Delta cred_{b,i}$ is the change in credit extended by bank b to firm i between September 2008 and March 2009, divided by firm i's total assets in September 2008; low_cap_b is a dummy variable for banks whose (risk-weighted) capital ratio is lower that the sample median, i.e. 13.0 percent;[17] hig_liq_b is a

[15]We computed, for each firm, change in total credit over firm's total assets, and used this variable to estimate equation (1); the pattern of the results was very similar to that of the corresponding second column, obtained by using as dependent variable change in firm's total credit over the level of total credit.

[16]For the sake of robustness, we also replicated our main results by using as dependent variable the change in credit by bank b to firm i, divided by the firm's total credit; the substance of the results did not change (see below in this section).

[17]Although the official regulatory threshold for the total (risk-weighted) capital ratio is 8 percent, it has to be taken into account that the Bank of Italy recommended level is 10

dummy variable for banks whose liquidity ratio (i.e., cash and securities other than shares, divided by total assets) is higher that the sample median, 12.1 percent; ib_borr_b is a dummy variable for banks whose net borrowing position in the inter-bank market is greater than the sample median, -2.6 as a percentage of total assets; $large_b$ is a dummy for banks belonging to the largest five banking groups in Italy (which overall currently extend roughly half of total loans to non-financial firms); η_i is a firm fixed-effect and $u_{b,i}$ is the regression residual.

Equation (2) was estimated with firm-specific fixed-effects; indeed, this is a key feature of the analysis, as it allows us to control for firm's credit demand as well as any other firm's characteristic. Results are reported in Table 3, first column. The main finding refers to the estimated coefficient of low_cap_b, which is statistically significant and negative: the (asset-normalized) change in credit extended by low-capitalized banks is more a percentage point lower (in annual terms) compared to that of other banks. This finding represents convincing evidence that a credit crunch is taking place. Indeed, as already pointed out, not only our regression framework can adequately control for the demand side, but also differences across banks in levels of capitalization are can be considered mostly exogenous in the period being considered, when the banks ability to raise capital has been severely affected.[18]

As to the other regressors, the results confirm the negative contribution to credit developments coming from the five largest banking groups: the (annualized) change in credit disbursed by intermediaries belonging to such groups is roughly half a percentage point lower compared to other banks. The relevance of supply-side factors in explaining credit developments is confirmed also by the evidence for the other variables that capture banks' funding difficulties. The supply of credit has been higher from more liquid banks and banks which collected more funds in the interbank market. In particular, the positive sign of the estimated coefficient for ib_borr_b presumably reflects the

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percent, which appears to be perceived by the intermediaries as the relevant benchmark.

[18]Barakova and Carey (2001) show that banks need an average of 1.6 years to restore their capital after becoming under-capitalized. Kashyap et al. (2008) emphasize two frictions that contribute to this sluggishness: (i) equity issues increase the value of existing debt, thus generating an externality in favor of debtholders and harming existing shareholders; (ii) equity issues may signal forthcoming losses. They also note that under Basel II the pressure to liquidate assets is stronger in crisis periods, when risk and hence risk-weighted capital requirements increase. Repullo and Suarez (2004) emphasize that the market for seasoned offerings is plagued by informational frictions, which may entail prohibitive costs of raising new capital.

good financial conditions of intermediaries which are still able to raise funds in the interbank market.

5.2 The identification of the impaired borrowers and the main result

After uncovering some main determinants, at the bank level, of the change in credit supply, we proceeded to the identification of the impaired borrowers. For constructing our key indicator, we adopted the procedure described in the Section 2, as follows. We identified a pool of more capitalized banks (i.e., the top 25 percent of banks according to the capital ratio, corresponding to banks with capital ratio higher than 16.8) and computed for each firm the total credit received by this group, and its change over the firm's assets. Then, within the subsample of firms which did receive lending from the more capitalized firms (roughly 80 percent of all firms), we identified as 'impaired borrowers' those belonging to the bottom 5 percent of the distribution of firms according to (asset-normalized) change in credit (corresponding to firms whose change in credit from highly-capitalized banks was lower than -6.3 percent; notice that this is a quite a sizable drop, since it is expressed as a percentage of total assets).[19] The advantages of identifying 'bad borrowers' with our scheme have been already discussed at large; the 'cost' of using our scheme is that, by construction, it applies only to firms which borrow from at least one of the banks which are defined as more capitalized. More precisely, when using this identification scheme in regressions, we had to exclude the other firms as well as the more capitalized banks used to identify the 'impaired borrowers'; however, the remaining dataset was still large and diversified enough to allow us to test the hypotheses of interest, by covering roughly 1,900 firms and 360 banks, for a total amount of over 13,000 bank-firm observations.

We re-estimated equation (2) within this subsample. The results are reported in Table 3, second column, and are broadly similar to those obtained over the whole sample, reported in the first column. The only difference is that the coefficients of low_cap_b and hig_liq_b have lost their statistical

[19] While these are the parameters of the 'benchmark' identification scheme used in most of the regressions, we also checked extensively the robustness of our results to the use of different thresholds (quantiles) for the identification of well-capitalized banks or impaired borrowers (see next section).

significance (with p-values around .14 in both cases), while maintaining their sign. With regard to the coefficient of bank capitalization, some insight on the reasons underlying its loss of significance (and sharp reduction of size) will come from the following regressions. We are now ready, in fact, to test our main hypothesis, by investigating the lending behavior of less-capitalized banks towards the 'impaired borrowers' previously identified. We do so by creating a dummy variable imp_bor_i which is equal to 1 for the latter firms, 0 otherwise; this dummy is interacted with low_cap_b, leading to the following regression:

$$\begin{aligned} \Delta cred_{b,i} &= \alpha + \beta_1 \cdot low\_cap_b + \beta_2 \cdot (low\_cap_b \cdot imp\_bor_i) \\ &\quad + \beta_3 \cdot hig\_liq_b + \beta_4 \cdot ib\_borr_b + \beta_5 \cdot large_b \\ &\quad + \eta_i + \varepsilon_{b,i} \ . \end{aligned} \tag{3}$$

The evidence obtained by estimating equation (3) is reported in Table 3, third column. The main result refers to the estimated coefficients of low bank capitalization, β_1, and that of its interaction with the 'impaired borrowers' dummy, β_2. While the contraction of credit in the period of interest remains stronger for credit disbursed by less capitalized banks ($\widehat{\beta_1}$ remains positive and statistically significant), such banks have reduced less their lending to those firms which should be their less attractive customers, i.e. the 'impaired borrowers' ($\widehat{\beta_2}$ is negative and statistically significant).

We explored the robustness of this striking result to the approach used to identify 'impaired borrowers'. We first considered the 'combined' approach, which identifies 'bad borrowers' as firms whose credit was reduced more by highly-capitalized banks and, at the same time, are among the least productive firms in the sample. As to the first criterion, we selected firms which belong to the bottom 10% of the distribution according to change in credit from the top 25 percent of more capitalized banks. As to second criterion, we computed for each firm the log-level of (gross output) total factor productivity, tpf_i:

$$tpf_i = \ln y_i - (\alpha_L \cdot \ln\_l_i + \alpha_K \cdot \ln\_k_i + \alpha_M \cdot \ln\_m_i) \ , \tag{4}$$

where $\ln\_y_i$, $\ln\_l_i$, $\ln\_k_i$ and $\ln\_m_i$ are the logarithm of, respectively, firm's output, hours, capital and intermediate inputs, all measured in real terms, and the α's are the revenue shares of each input.[20] Since the level of productivity may vary widely across sectors, we computed for each firm its difference relative to the sectoral median; we then selected firms which belong to the bottom 25 percent of the distribution according to this variable. As a final step of our 'combined' approach, the firms which belong to both sets (i.e., satisfy simultaneously the two criteria) were identified as 'impaired borrowers'; they represent roughly 3 percent of the sample. The results are reported in Table 3, fourth column, and largely confirm the main finding.[21]

We also used the third identification scheme, based exclusively on productivity levels: bad borrowers were identified as the firms which belong to the bottom 5 percent of the distribution according to productivity levels. Results are reported in Table 3, fifth column. Notice that the use of this scheme for identifying impaired borrowers allows us to use in the regression all the observations, since we do not have to drop firms or banks involved in the benchmark identification scheme. The results, again, confirm the main finding for the new identification scheme and over the whole sample.

We further verified the robustness of our main finding along a number of other dimensions, namely across model specifications, parameters used within the main identification scheme and measures of the dependant variable. Results proved to be extremely robust; they are documented in the next subsection.

5.3 Robustness

One exercise of robustness was related to model specification: we run our main regression after including bank-specific fixed effects, in addition to firm-specific effects. This corresponds to estimating equation (3) by replacing bank characteristics with a set of roughly 360 bank-specific dummies. In such a model one can identify the interaction of interest while at the same time controlling for any possible bank-specific effect. The results are reported in the first column of Table 4 and clearly confirm the finding of unnatural

[20] 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, 1995; for an analysis of these measures with a dataset similar to that used in this work, see Marchetti and Nucci, 2005).

[21] We also applied this combined approach by using different threshold values for criteria (i) and (ii); again the results proved to be very robust.

selection: less capitalized banks lend more to 'impaired borrowers'.

In a second robustness exercise we chose a somewhat different dependent variable, namely we divided change in credit by total firm's credit, rather than total firm's assets; in this case, because of the quite irregular distribution of the dependent variable for the reasons already discussed, we dropped the bottom and top 1 percent of observations. Results are reported in the Table 4, second column.

A third robustness check was related to the definition of low_cap_b. In this exercise, while bad borrowers were identified as in the main ('benchmark') case, the less capitalized banks candidate to do 'evergreening' (i.e., those identified by setting $low\_cap_b =1$) were those belonging to the bottom 25% of the distribution according to the capital ratio (i.e. banks with a capital ratio lower than 10.5), compared to bottom 50% in the benchmark regressions. Results are reported in the Table 4, third column, and again confirm the main findings.

Finally, we tested the sensitivity of the results to changes in the thresholds used in the first ('benchmark') identification scheme. In the version of Table 3, bad borrowers were identified as the firms belonging to the bottom 5 percent of the distribution according to the change in total credit received by the more capitalized banks. We replicated the analysis by referring, respectively, to the bottom 1 and 10 percent of the distribution. In another robustness exercise bad borrowers were identified based on the lending pattern of the more capitalized banks identified as those belonging to the top 50% of the distribution according to the capital ratio (compared to top 25% in the benchmark scheme); in this case low_cap_b was set equal to 1 for banks belonging to the bottom 25% of the distribution (compared to bottom 50% in the benchmark case, otherwise low_cap_b would have been equal to the regression constant).

Results for these three cases are reported, respectively, in the columns 4 through 6 of Table 4 and confirm the main finding.

6 Extensions

In this section we explore some of the aspects and factors underlying the pattern of 'evergreening' which has emerged. In order to do so, we look at a number of bank and firm variables, as well as features of bank-firm relationships which, based on economic theory and institutional features of the Italian banking sector, might play a role in shaping the lending bias in favor of impaired borrowers. We extended our main regression model as follows:

$$
\begin{aligned}
\Delta cred_{b,i} = {} & \alpha + \beta_1 low\_cap_b + \beta_2 (low\_cap_b \cdot imp\_bor_i) \\
& + \mathbf{\Gamma}_1' \mathbf{X}_{b,i} + \mathbf{\Gamma}_2' \mathbf{X}_{b,i} \cdot (low\_cap_b \cdot imp\_bor_i) \\
& + \mathbf{\Phi}_1' \mathbf{Z}_b + \mathbf{\Phi}_2' \mathbf{Z}_b \cdot (low\_cap_b \cdot imp\_bor_i) \\
& + \mathbf{\Psi}_2' \mathbf{W}_i \cdot (low\_cap_b \cdot imp\_bor_i) \\
& + \beta_3 hig\_liq_b + \beta_4 ib\_borr_b + \eta_i + \upsilon_{b,i} \ ,
\end{aligned} \tag{5}
$$

where $\mathbf{X}_{b,i}$ is a vector of variables defined at the individual bank-firm relationship level, $\mathbf{Z}_b$ is a vector of bank characteristics and $\mathbf{W}_i$ a vector of firm characteristics. More precisely, $\mathbf{X}_{b,i} = (mainb_{b,i}, b\_exp_{b,i})$, where $mainb_{b,i}$ is a dummy variable which identifies close firm-bank relationships and is equal to 1 if bank *b's* share of firm i's credit is greater than the corresponding sample median (7.1 percent); $b\_exp_{b,i}$ is a dummy variable which identifies high banks' exposures towards a given firm and is equal to 1 if credit by bank b to firm i as a share of total bank b's credit belongs to the top 5 percent of its distribution (.02 percent); $\mathbf{Z}_b = (coop_b, large_b)$, where $coop_b$ is a dummy variables for cooperative banks; $\mathbf{W}_i = (n\_lend_i, h\_score_i, size_i, \exp ort_i)$, where n_lend_i is a dummy variable which is equal to 1 if the firm's number of lenders is greater that the sample median (12), 0 otherwise.[22] All other variables have been already defined. Equation (5) has been estimated using alternatively all our three identification approaches described above. The results are reported, respectively, in the first, second and third column of Table 5, and appear to be quite robust across the different methods.

First of all, the main finding of unnatural selection (i.e. a positive and statistically significant estimate of β_2) is confirmed across all extended specification, at a very high significance level.

As to firms' characteristics, only interaction terms can be included in the regressions. With regard to the number of lenders, n_lend_i, the prevailing evidence shows that lending to impaired borrowers is lower the higher the number of firm's lenders; this may reflect the fact that a higher number of lenders makes more difficult the explicit or implicit coordination among

[22] The number of lenders is computed by considering all lenders with positive outstanding loans to a given firm at either one of the two dates September 2008, March 2009.

'rescuing' banks. As to credit scoring, bad prospective borrowers with a high Zscore are neither more likely nor less likely to benefit from unnatural selection. This does not seem to be surprising, since - as we explained already in previous sections - on one hand firms with a high Zscore are those with a higher default risk (therefere qualifying, in our hypothesis, as receivers of lending by less capitalized banks), on the other hand several firms, among those characterized by a high Zscore, are probably too severely impaired to induce their borrowers to gamble on their recovery. With regard to firm's size, there is no robust evidence: unnatural selection would favor large firms if impaired borrowers are identified based on productivity only, while firm's size is not a relevant variable under the other two identification schemes. As to the export propensity of firms, there is some prevailing evidence that more export-oriented firms were less likely to benefit from unnatural selection. One possible interpretation is that, on average, their chances of recovery may have been affected more severely by the collapse of world demand induced by the financial crisis.

With regard to bank's exposure to a given firm, the negative (and statistically significant) estimate of the coefficient of $b\_exp_{b,i}$ suggests that, in a period characterized by a sharp deterioration of the economic outlook and a strong increase in the risk of default of borrowers, banks tried to diversify their loan portofolio. Risk mitigation through diversification seems to drive also the estimate of the interaction between $b\_{}_{b,i}$ and $low\_cap_b \cdot imp\_bor_i$: there is some evidence that lending to impaired borrowers has been lower the higher the bank's exposure to the given firm.

As to the variables capturing the intensity of the bank-firms relationships, the picture is not clear-cut. The estimated coefficient of $mainb_{b,i}$ is negative and statistically significant. This result is in line with the evidence obtained with firm-level regressions, reported in Table 1: firms which rely more on a single bank received less credit not only from the other banks but also from their main bank. The interpretation of this outcome is not straitforward as to some extent it might reflect, on accounting grounds, the greater weight of the main bank's credit (and its change) over the firm's assets. Similar considerations can be done with respect to the estimate of β_6. With regard to the role of cooperative banks, there doesn't emerge any clear lending pattern across the different identification schemes; in any case, lending to impaired borrowers has not been either favoured nor discouraged by cooperative banks compared to other banks.

As to the role of banks belonging to the five largest groups, the results confirm their strong negative contribution to credit dynamics, by around one percentage point on an annual basis. On the other hand, their involvement in lending to impaired borrowers does not appear to be significantly different, in either direction, from that of other banks (i.e., the estimate of the interaction between $large_b$ and $low\_cap_b \cdot imp\_bor_i$ is not statistically different from zero).

Finally, the estimated coefficients of the remaining two bank variables included in our basic framework, i.e. liquidity ratio and net borrowing position in the interbank market, have kept their sign and strong statistical significance.

7 Conclusions and directions for research

In this paper we have presented evidence of credit crunch and documented the emergence of 'unnatural selection' (in the sense proposed by Peek and Rosengren, 2005) in the Italian credit market after Lehman's bankruptcy. To this purpose, we have analyzed highly detailed data on bank-firm credit flows. We have shown that banks in poorer financial conditions (i.e., less capitalized) have reduced credit, in the six-month period after September 2008, to their typical borrowers but less so with those identifiable as impaired, based on their economic fundamentals (proxied by productivity) or the pattern of lending received by more financially sound banks (i.e. more capitalized) or a combination of the these two criteria. Results have been shown to be robust not only across bad-borrowers identification schemes, but also along a number of other dimensions, including thresholds used in the identification schemes, model specification and measure of dependent variable.

We have also investigated the potential role of some features of bank-firm relationships, as well as a number of bank and firm characteristics, which, based on economic theory and in the context of the current crisis, might be relevant in shaping the phenomenon of interest.

We are currently investigating the impact or relevance of this misallocation of credit on total credit flows (in the spirit of Peek and Rosengren, 2005, pp. 1163-64). We are also investigating the potential crowding out effects, through lower credit availability, on the performance of sound and productive firms. As argued by Caballero et al (2008), credit misallocation trough unnatural selection induces a congestion which discourages the entry and growth of healthy firms. They have documented this effect for the Japanese economy in the 'lost decade'. To this regard, an obvious extension of our work is to analyze the potential crowding out effects on the employment and investment growth of healthy firms in our sample. In this direction we might find quite useful the data on hiring and investment plans for 2009 included in the results of the latest Survey of Italian Manufacturing (SIM) carried out by the Bank of Italy, described above.

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

Variable description - Bank and credit variables. 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 used are reported in Table A1. Total assets are expressed in millions of euros. The (tier1) capital ratio is computed as the ratio of total (tier1) capital to risk-weighted assets and is expressed in percentage points. Leverage is the ratio of total-assets (non risk weighted) to capital. 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 largest banking groups refer to the set of banks belonging to the five largest banking holding companies. The data for cooperative firms (BCC) refer to small local cooperative banks subject to a specific regulatory regime.

Table A1
Summary statistics on the bank sample
(September 2008)

	Tot. assets	Capital ratio	Tier1 cap. rat.	Leverage	Liquidity ratio	Net interb. liab.
			Five largest banking groups			
No.	63	63	63	63	59	63
25th pctile	2436	8.87	7.41	4.86	4.86	-2.87
median	10553	10.23	9.38	6.46	6.46	3.13
75th pctile	24716	12.57	11.41	8.29	8.29	17.09
mean	30427	12.13	10.39	7.30	7.30	9.56
s.d.	69069	6.56	5.07	3.70	3.70	21.87
			All banks			
No.	488	482	482	488	466	437
25th pctile	287.70	10.48	9.26	7.04	6.53	-5.53
median	716.27	12.96	11.82	8.94	11.21	-2.43
75th pctile	2383.51	16.76	15.90	11.21	17.07	.87
mean	6073.41	15.02	13.82	9.61	12.33	-.64
s.d.	27275.49	8.16	8.26	4.17	8.35	12.55

Variable description - Firm variables. 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: SIM); firm-level man-hours include overtime hours (source: SIM). 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 in buildings, machinery and equipment and vehicles, plus investment in software and patents, (source: SIM), 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 SIM 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 SIM 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 A1

Table A.2
Summary statistics of selected firm variables (percent)
(2007 averages)

Variable	25th pctile	median	75th pctile	mean
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: SIM and CADS.

Table 1
Patterns of Credit Dynamics
at Firm-Level after Lehman

	(1)		(2)		(3)		(4)	
Estimator	OLS		OLS		Tobit		OLS	
Dependent variable	Credit growth		Credit growth		Credit growth		Change in credit over assets	
$Size_i$	.290	(1.419)	.829	(1.521)	.857	(1.658)	-.145	(.256)
M_score_i	-3.507^{**}	(1.521)	-5.400^{***}	(1.689)	1.124	(1.755)	$-.527^{**}$	(.264)
H_score_i	-8.514^{***}	(2.012)	-10.604^{***}	(2.183)	-2.841	(2.351)	-1.254^{***}	(.358)
$Export_i$	4.308^{*}	(2.619)	5.617^{**}	(2.883)	3.990	(3.056)	1.210^{**}	(.473)
Tfp_i	-4.857^{**}	(1.897)	-4.857^{***}	(1.897)	-6.905^{***}	(2.188)	$-.590^{*}$	(.334)
$Mainb_i$	$-.065^{**}$	(.032)	$-.087^{**}$	(.037)	$-.247^{***}$	(.037)	.001	(.005)
$Credcom_i$	$-.144^{***}$	(.039)	$-.133^{***}$	(.043)	$-.147^{***}$	(.045)	$-.015^{**}$	(.007)
$Invn_i$	$.138^{*}$	(.073)	.146	(.091)	$.188^{**}$	(.087)	$.027^{**}$	(.014)
$Cred\_dom_i$	-		4.014^{***}	(.839)	-		-	
Sect. dummies	Yes		Yes		Yes		Yes	
No. observations	2,108		1,724		2,232		2,101	

Note: Each column corresponds to a regression. The dependent variable is defined over the period September 2008-March 2009; regressors data refer to 2007. Parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). Each regression is estimated after dropping the top and bottom 5 percent of the dependent variable (1 percent in the case of the Tobit regression).

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

Table 3
Testing for Unnatural Selection

	(1)	(2)	(3)	(4)	(5)
Sample	Whole	Subsample	Subsample	Subsample	Whole
Scheme for identifying impaired borrowers	-	-	Benchmark	Mixed	TFP
Low_cap_b	-.574***	-.134	-.214**	-.154*	-.597***
	(.070)	(.091)	(.093)	(.092)	(.071)
$Low\_cap_b \cdot imp\_bor_i$	-	-	1.894***	1.137**	.841**
	-	-	(.377)	(.508)	(.362)
Hig_liq_b	.144*	.117***	.115	.118	.147*
	(.085)	(.073)	(.079)	(.079)	(.085)
Ib_borr_b	.217***	.454***	.450***	.454***	.218***
	(.058)	(.073)	(.049)	(.074)	(.058)
$Large_b$	-.269***	-.451***	-.456***	-.452***	-.268***
	(.041)	(.050)	(.049)	(.050)	(.041)
No. firms	2,481	1,926	1,926	1,926	2,481
No. obs.	18,907	13,179	13,179	13,179	18,907

Note: Fixed effect (firm-level) estimation. Each column corresponds to a regression. The dependent variable is defined over the period September 2008-March 2009; regressors data refer to September 2008. Parameter estimates are reported with robust standard errors in brackets (cluster at individual firm level). The subsample referred to in columns 2 through 4 includes only firms which borrow for the pool of more capitalized banks and excludes observations which involve such pool of banks (see text). The identification schemes for impaired borrowers referred to in columns 3 through 5 are as defined in the text.

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

Table 4
Testing for Unnatural Selection:
Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Type of robustness exercise	Model specification	Dependent variable	Low_cap definition	Id. scheme bottom 1% firms	Id. scheme bottom 10% firms	Id. scheme top 50% banks
Low_cap$_b$	-	-.513**	-.910***	-.157*	-.200**	-.942***
	-	(.231)	(.071)	(.092)	(.092)	(.073)
Low_cap$_b$·imp_bor$_i$	1.595***	3.464**	1.512***	2.519***	.771*	1.008**
	(.382)	(1.377)	(.403)	(.804)	(.417)	(.452)
Hig_liq$_b$	-	.131	.254***	.114	.115	.329***
	-	(.198)	(.080)	(.079)	(.079)	(.089)
Ib_borr$_b$	-	1.020***	.368***	.451***	.453***	.332***
	-	(.183)	(.073)	(.074)	(.074)	(.074)
Large$_b$	-	-.907***	-.375***	-.453***	-.454***	-.413***
	-	(.143)	(.050)	(.050)	(.049)	(.049)
Bank dummies	Yes	No	No	No	No	No
No. firms	1,926	1,827	1,926	1,926	1,926	2,114
No. obs.	13,179	12,778	13,179	13,179	13,179	12,856

Note: Fixed effect (firm-level) estimation. Each column corresponds to a regression. The dependent variable is defined over the period September 2008-March 2009; regressors data refer to September 2008. Parameter estimates are reported with robust standard errors below in brackets (cluster at individual firm level). Column (1) refers to a regression with bank dummies. Column (2) refers to a regression whose dependent variable is change in credit over total firm's credit; extreme values of the new dependente variable were eliminated by dropping the bottom and top 1% of the distribution. Column (3) refers to a regression where low_cap$_b$ identifies banks which belong to the bottom 25% of the distribution according to the capital ratio. Column (4) refers to a regression where impaired borrowers are identified as firms which belong to the bottom 1% of the distribution according to the lending pattern from more capitalized banks. Column (5) refers to a regression where impaired borrowers are identified as firms which belong to the bottom 10% of the distribution of firms according to the lending pattern from more capitalized banks. Column (6) refers to a regression where the impaired borrowers are identified based on the lending pattern from the top 50% of more capitalized banks, and low_cap$_b$ identifies banks which belong to the bottom 25% of the distribution according to the capital ratio.

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

Table 5
Unnatural Selection:
Extensions

	(1)	(2)	(3)
Scheme for identifying impaired borrowers	Benchmark	Mixed	TFP
Low_cap_b	-.206** (.091)	-1.176* (.090)	-.563*** (.066)
$Low\_cap_b \cdot imp\_bor_i$	3.235*** (.746)	3.080*** (.845)	4.547*** (.825)
$Mainb_{b,i}$	-.448*** (.077)	-.460*** (.077)	-.465*** (.069)
$Mainf_{b,i}$	-.486*** (.083)	-.467*** (.084)	-.495*** (.079)
$Mainb_{b,i}$*($low\_cap_b \cdot imp\_bor_i$)	-.953* (.515)	-1.800** (.711)	-.858* (.440)
$Mainf_{b,i}$*($low\_cap_b \cdot imp\_bor_i$)	-.081 (.677)	-2.605** (1.185)	-.751 (.660)
$Coop_b$	.262** (.133)	.221 (.137)	-.027 (.116)
$Large_b$*($low\_cap_b \cdot imp\_bor_i$)	-.537*** (.054)	-.518*** (.053)	-.430*** (.047)
$Coop_b$*($low\_cap_b \cdot imp\_bor_i$)	-.680 (1.229)	.850 (1.278)	-.416 (.865)
$Large_b$*($low\_cap_b \cdot imp\_bor_i$)	-.278 (.351)	-.392 (.784)	-.054 (.448)
N_lend_i*($low\_cap_b \cdot imp\_bor_i$)	-1.704** (.782)	-1.828*** (.574)	-.326 (.681)
H_score_i*($low\_cap_b \cdot imp\_bor_i$)	.162 (.797)	.297 (.604)	-.012 (.640)
$Size_i$*($low\_cap_b \cdot imp\_bor_i$)	-1.009 (.766)	-.442 (.703)	-3.508*** (.734)
Exp_i*($low\_cap_b \cdot imp\_bor_i$)	-.170 (.665)	-3.938*** (.615)	-.950** (.454)
Hig_liq_b	.374*** (.087)	.403*** (.086)	.370*** (.088)
Ib_borr_b	.428*** (.071)	.432*** (.071)	.172*** (.056)
No. firms	1,852	1,852	2,373
No. obs.	12,088	12,088	17,209

Note: Fixed effect (firm-level) estimation. Each column corresponds to a regression. The dependent variable is defined over the period September 2008-March 2009; data for regressors refer to September 2008, with the exception of data for h_score, size and exp, which refer to 2007 averages. 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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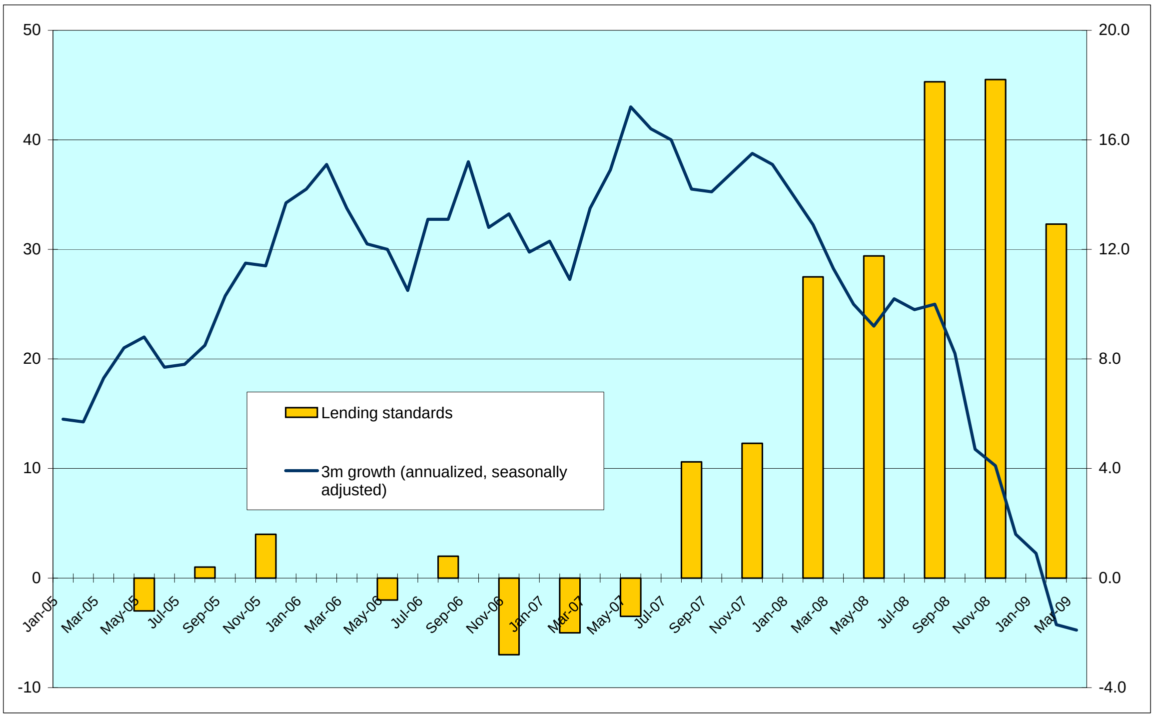
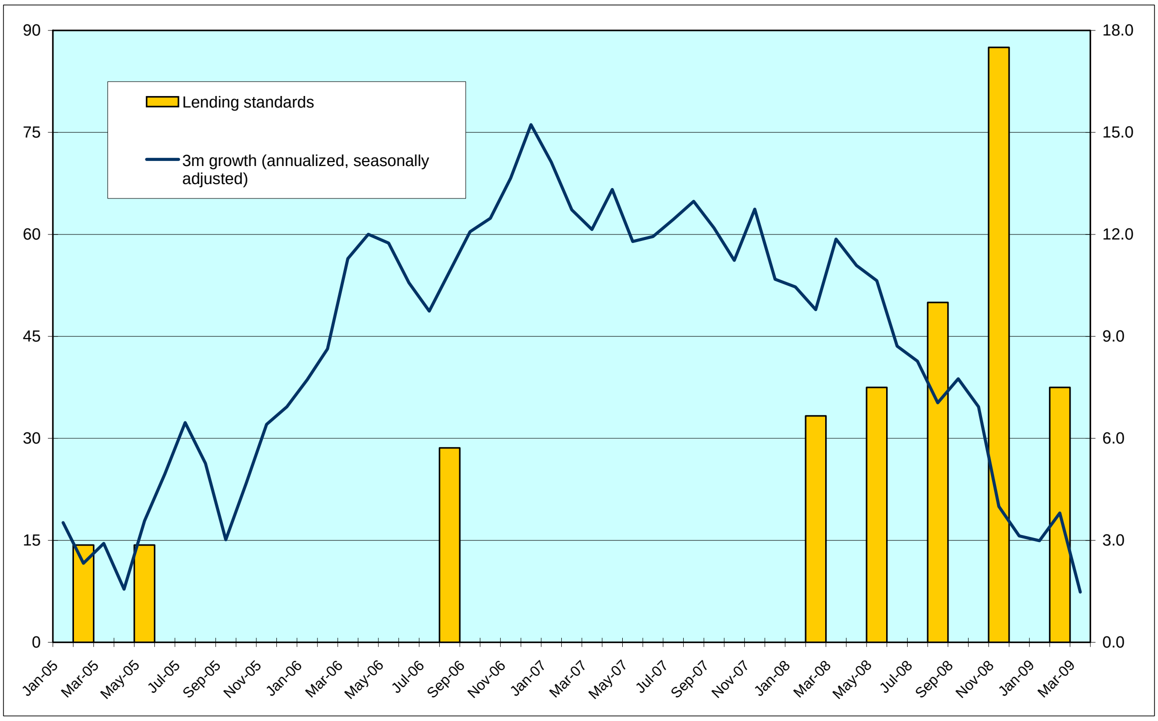
Figure 1

Loans to non financial corporation and lending standards (1)

Euro area



Italy



Source: Bank of Italy and European Central Bank

(1) Lending standards are derived from the quarterly Bank Lending Survey and refers to the tightening through reductions of the amount of the loan or of the credit line (net percentage).