LASTING LENDING RELATIONSHIPS AND TECHNICAL EFFICIENCY. EVIDENCE ON EUROPEAN SMEs

Mariarosaria Agostino, Sabrina Ruberto and Francesco Trivieri*

Department of Economics, Statistics and Finance "*Giovanni Anania*", Ponte Pietro Bucci, Cubo 1C, University of Calabria, 87036, Rende (Cosenza), Italy.

ABSTRACT

Linking the theoretical predictions of the research on lending relationships with those of the literature on managerial incentives, we investigate whether the duration of credit relationships impacts on firms' technical efficiency. Our hypothesis is that the *balance* between costs and benefits of enduring banking relationships might have heterogeneous effects on managers' incentives related to higher firms' indebtedness. Using firm-level information on a large sample of European SMEs, observed in the period 2001-2008, and adopting both parametric and non-parametric measures of efficiency, we find that the positive impact of longer lending relationships decreases as indebtedness increases, suggesting that the interplay of moral hazard problems may endanger firms' technical efficiency.

JEL code: G20, G21, D24, L6.

Keywords: enduring lending relationships, SMEs, technical efficiency, DEA, SFA, EFIGE data.

* Corresponding author. Department of Economics, Statistics and Finance "*Giovanni Anania*", Cubo 1C, Ponte Pietro Bucci, University of Calabria, 87036 Rende (Cosenza), Italy. e-mail:Sabrina.Ruberto.2013@live.rhul.ac.uk

1. INTRODUCTION

A large strand of the banking literature has shown that lending relationships' characteristics, such as concentration and duration, may have favourable as well as detrimental effects on the financing and performance of firms. On one hand, by allowing banks to collect proprietary (*soft*) information on firms, close lending relationships might alleviate asymmetric information problems (e.g.: Diamond, 1984,1991; Boot and Thakor, 1994; see Gorton and Winton, 2003, for a review), encourage greater borrowers' discipline (Foglia et al., 1998), and enable firms to signal their willingness to abstain from strategic default (Bannier, 2007). Such benefits might increase credit availability (e.g.: Petersen and Rajan, 1994,1995; Berger and Udell, 1995; Cole, 1998; Harhoff and Korting, 1998; Hernandez-Canovas and Martinez-Solano, 2010; Kano et al., 2011), reduce loan interest rates (e.g.: Harhoff and Korting, 1998; D'Auria et al., 1999; Brick and Palia, 2007; Bharath et al., 2011), lower collateral requirements (e.g.: Berger and Udell, 1995; Harhoff and Korting, 1998; Voordeckers and Steijvers, 2006; Chakraborty and Hu, 2006; Jimenez et al., 2006; Brick and Palia, 2007; Steijvers et al., 2010; Bharath et al., 2011; Agostino and Trivieri, 2017), provide stronger protection against the interest rate cycle (Ferri and Messori, 2000), promote firms' product and process innovations (Herrera and Minetti, 2007; Benfratello et al., 2008; Giannetti, 2012), reduce firms' dependence on trade debt (Petersen and Rajan, 1994 and 1995), and foster firms' foreign direct investment (De Bonis et al., 2015).

On the other hand, strong bank-firm ties may have some "dark sides" (for reviews, see Boot, 2000; Elyasiani and Goldberg, 2004; Udell, 2008). By easing debt renegotiation, that is *softening* budget constraints, close lending relationships could induce a risk-taking behaviour (e.g.: Dewatripont and Maskin 1995; Bolton and Scharfstein 1996). Moreover, a high degree of relationship commitment could lead banks to monopolise the information they acquire to *hold-up* borrowers and exploit rents (e.g.: Sharpe, 1990; Rajan, 1992). These drawbacks might entail an increase in loan rates charged (Petersen and Rajan, 1994; Blackwell and Winters, 1997; D'Auria et al., 1999; Degryse and Van Cayseele, 2000; Hernandez-Canovas and Martinez-Solano, 2010; Stein, 2011; Kano et al., 2011), and to a higher probability of pledging collateral (Hernandez-Canovas and Martinez-Solano 2006 and 2010; Ono and Uesugi, 2009; Kano et al., 2011). Moreover, they might induce banks to avoid financing risky long-term investment projects even though profitable (Weinstein and Yafeh, 1998), lower firms' profitability (Montoriol Garriga, 2006), and hamper small businesses' growth (Gambini and Zazzaro, 2013).

With this paper, we intend to contribute to the above literature by empirically investigating to what extent the closeness of bank-firm ties affects firms' technical efficiency. This issue has been largely neglected so far, to the best of our knowledge the only paper dealing with this topic being Yildirim (2017). We focus on the duration of a lending relationship, which is commonly used as the main indicator of its closeness/strength, and build our research hypotheses by linking the theoretical predictions of the research on costs and benefits of banking relationships with those of the literature on agency costs (e.g.: Jensen and Meckling, 1976; Jensen, 1986; Nickell et al., 1997; Schmidt, 1997; Nickell and Nicolitsas, 1999).

The literature on managerial incentives has shown that a higher indebtedness might either reinforce managers' motivations to perform, in order to offset the adverse effects of greater financial pressure, or – due to the asymmetry of gains and losses from hazardous investments – lead managers to behave opportunistically at the expenses of debtholders, by investing in riskier projects (e.g. Jensen and Meckling, 1976). Bearing these conclusions in mind, we hypothesise that the benefits and costs of lasting lending relationships might have heterogeneous effects on managers' incentives – and, consequently, on firm's technical efficiency – depending on the firm's debt level. For low indebtedness, enduring credit relationships should have a positive impact on a firm's technical efficiency: easier access to funding should help managers to smooth the production process, while *soft budget constraint* and *hold-up* problems should be irrelevant. The latter may, however, become relevant as the firm's debt increases and as a result, one of two scenarios may emerge. If managers are interested in preserving the benefits of a credit relationship, higher *hold-up* costs should reinforce disciplined behaviour, prevailing on moral hazard temptations related to higher indebtedness and softer budget constraints. In this case, as managers might seek higher efficiency in the production process, the impact of longer banking relations on firm's efficiency could be positive. On the other hand, if greater *hold-up* costs – as well opportunistic incentives related to easier debt renegotiation – exacerbate moral hazard behaviour due to higher indebtedness, managers' interests to achieve the best technical practice might be compromised, and the positive impact of enduring credit relationship on firm's efficiency could decline or even vanish.

We focus on small and medium-sized enterprises (henceforth SMEs), for which lending relationships are of crucial relevance, and conduct the empirical investigation using microdata (provided by the EU-EFIGE dataset) on manufacturing firms operating in three European countries, France, Italy and Spain. In these countries, as in other bank-based economies of continental Europe, lending relationships are a common practice – despite some differences in their features, the most notable one likely being the diffusion of the multi-bank lending phenomenon in Italy (e.g.: Ongena and Smith, 2000; Agostino et al. 2011).[1]

To measure efficiency and model the relationship between efficiency and its determinants, we adopt both a parametric and a non-parametric frontier approach. Indeed, we first employ a (2-step bootstrapped) DEA procedure, proposed by Simar and Wilson (2007), and then a (one-step) SFA model, suggested by Battese and Coelli (1995).

Our main results show that, as firm's indebtedness increases, the positive impact of enduring credit relationships on firms' technical efficiency tends to decline in absolute value. We inter-

[1] Nonetheless, the multiple borrowing practice does not preclude Italian firms from having strong ties with an individual bank, especially in the case of SMEs (e.g.: D'Auria et al., 1999; Carmignani and Omiccioli, 2007).

pret this finding as evidence that as firm's debt increases, the costs of longer lending relationships might overcome their benefits, aggravating moral hazard problems related to indebtedness and, thus, spurring managers towards opportunistic behaviours. Indeed, higher firm's debt might exacerbate managers' moral hazard behaviour, thus endangering firms' technical efficiency.

This interpretation is corroborated by the finding that long-term debt, plausibly associated with higher risk of opportunistic behaviour, seems to affect more heavily the link between lending relationships and efficiency.

The remainder of the paper is organised as follows. The next section illustrates the empirical methodology. Section 3 summarises the data employed, while section 4 discusses the results obtained and robustness checks performed. Finally, section 5 provides some concluding remarks.

2. METHODOLOGY AND EMPIRICAL MODEL

The response variable of our analysis is pure technical efficiency (EFF), defined as the ability of firms to maximise their output given their productive resources and technology.[2] The main approaches that have being applied to retrieve firms' efficiency measures are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). While DEA is a linear programming-based methodology (introduced by Charnes et al., 1978) providing non-parametric measures of efficiency relative to the sample employed, SFA is an econometric method based on the assumption of a specific production function, typically a Cobb-Douglas or a Translog function

[2] Vice versa, efficiency may be also defined as the ability to minimize the amount of inputs required to produce a given output level.

(Aigner et al., 1977; Meeusen and Broeck, 1977).[3] In this paper, we adopt a 2-step DEA estimator as our main method, and a SFA one-stage procedure as a robustness check. More in detail, to account for the uncertainty in the data, ensure valid inference, and improve statistical efficiency, we adopt a double (smoothed) bootstrap procedure, proposed by Simar and Wilson (2007). Thus, we first bootstrap DEA scores in the first stage to obtain bias corrected efficiency scores, and then we regress them on covariates with the use of a bootstrapped truncated regression. In the latter equation, the explanatory variables of interest are the duration of the lending relationship with the main bank, and leverage. When retrieving firms' efficiency scores, we allow for different technologies in different sectors (i.e. we carry out separate computations at the NACE-CLIO classification level). To further corroborate our findings, we also adopt the one-step method proposed by Battese and Coelli (1995), which allows to estimate a stochastic frontier and a model relating inefficiency to its determinants simultaneously. In particular, we choose a Translog production function specified as follows:[4]

$$lnY_{it} = \beta_0 + \beta_k lnK_{it} + \beta_L lnL_{it} + \beta_R lnR_{it} + 0.5\beta_{KK} lnK_{it}^2 + 0.5\beta_{LL} lnL_{it}^2 + 0.5\beta_{RR} lnR_{it}^2 + \beta_{KL} lnK_{it} \cdot lnL_{it} + \beta_{KR} lnK_{it} \cdot lnR_{it} + \beta_{LR} lnL_{it} \cdot lnR_{it} + \sum_{s=1}^{m-1} \lambda_s S_s + \theta trend + (V_{it} - U_{it}) \quad (1)$$

where Y is sales of the firm *i-th* at time t ($i = 1, \dots, N$; $t = 1, \dots, T$) and the three production inputs are capital (K), workers (L) and raw materials (R). To account for different technologies, we include sectorial dummies (S). The key assumption is that the inefficiency terms (Us) have a truncated distribution, being independently but not identically distributed. The inefficiency model

[3] For a detailed description of these two methodologies we refer to Coelli et al. (2005). Further, Simar and Wilson (2007) offer an extensive bibliography of the literature investigating the impact of "contextual variables" on DEA efficiency estimates, contextual variables being defined as external operational environment and internal firms characteristics that are expected to influence the firm's ability to operate efficiently (Johnson and Kuosmanen, 2012).

[4] The Translog function is supported by the result of a likelihood ratio (LR) test, suggested by Coelli (1996) and reported in Table 3.

is specified as in equation (2), described below. A more technical description of both methods so far outlined is provided in the Appendix.

2.1 Specifying a model of technical (in)efficiency

The benchmark (in)efficiency model is the following:

$$EFF_{it} = \alpha + \beta_1 DURAT_{i(t-1)} + \beta_2 LEV_{i(t-1)} + \beta_3 DURAT \cdot LEV_{i(t-1)} + \phi X_{i(t-1)} + \vartheta TREND + \sum_s \delta_s S_s + \sum_c \varphi_c C_c + \epsilon_{it} \qquad (2)$$

where the dependent variable is either the measure of technical efficiency based on DEA or the estimated inefficiency retrieved from the stochastic frontier (equation 1), described above and in the Appendix. On the right hand side: DURAT is the duration of the relationship with the main bank; LEV is our measure of a firm's indebtedness, computed as total debt to total assets; DURAT*LEV is the interaction term included to test our conditional hypothesis; the vector X includes control variables summarized in Tables 1 and 2 and described below – while S and C are sets of sector and country dummies, respectively.[5]

[TABLES 1 and 2]

In what follows, we briefly illustrate the determinants of firms' efficiency which enter our estimating equation as controls, along with the duration of lending relationships. Our specification is rooted in a large body of research, investigating the determinants of firms' efficiency, and suggesting the interplay of firms' characteristics and external factors (e.g.: Caves and Barton, 1990; Caves, 1992; Frydman et al., 1999; Aw et al., 2000; Djankov and Murrell, 2002; Alvarez and Crespi, 2003; Sinani et al., 2007). However, it is worth highlighting that the data availability has conditioned our choices.

[5] To preserve the anonymity of the firms surveyed, the EFIGE dataset provides information on industrial sectors in the form of a randomized identifier ranking from 1 to 11, these values not mapping "any particular ordering of the original data" (Altomonte and Aquilante 2012, p. 18).

The conditioning variable, LEV, is employed as a proxy of indebtedness towards banks (which is available for one year only, as described in the data section). Indeed, in our sample, the median value of the percentage of bank debt on total liabilities is 100%, the 75% of firms displaying a percentage higher than 90%. Hence we employ leverage in our main estimations to avoid imputation, while we use the imputed bank debt ratio in a sensitivity check. As already discussed, the literature provides conflicting predictions on the relationship between leverage and firms' performance (for a detailed discussion, we refer to Weill, 2008). Summarising, on the one hand, firms may better exploit their productive capacity by using greater liquidity that may help to smooth the production process. On the other, as debt increases managers might act opportunistically at the expenses of debtholders, making choices that do not increase firm efficiency and value, and generating agency costs.

Furthermore, firm's age and size – measured by the logarithm of the firm's age and total assets respectively – are taken into account, together with their squares to control for potential non-linear effects. Given that our dependent variable is technical efficiency purged from scale efficiency, the SIZE control (logarithm of total assets) is not much intended to capture economies of specialisation resulting from larger dimensions, rather other potential effects of size on the ability of firms to successfully manage their input combinations. For instance, larger firms may have better access to finance, attract employees with higher skills, and be more export-oriented hence more exposed to international competition and "learning by exporting" effects. Yet, in larger firms, inefficient hierarchical structures may cause negative effects on firm's efficiency (see Williamson, 1967; Margaritis and Psillaki, 2007). As far as AGE is concerned, older firms might exploit "learning by doing" effects and be more able to access credit, given their longer records. On the other hand, younger enterprises may be more motivated to build reputation, more inclined to internationalisation and more capable to absorb new technological knowledge. Moreover, we control for the inventory requirement of each firm (INV), since higher rates of inventories (to sales) might be a sign of inefficient inventory management, and vice versa (Fisman, 2001). Finally, we take into account the degree of industry concentration by the Herfindahl-Hirschman index based on sales (HHIs). The expected sign of this regressor is ambiguous. Indeed, according to the *Structure-Conduct-Performance* paradigm, higher concentration may foster collusive behaviour among firms, thus reducing the degree of competition, and negatively affecting firms' efficiency. On the other hand, considering the *Efficient-Structure Hypothesis*, higher concentration does not necessarily indicate lower competition, but it may reflect market selection and consolidation through survival of more efficient companies, hence having a positive effect on efficiency (Margaritis and Psillaki, 2007). To limit potential simultaneity bias, we assume lagged values of all regressors defined at the firm-level (i.e. all explanatory variables except HHIs).

Using equation (2) estimates, the marginal effect of DURAT, and the relative standard error, are computed conditional on the level of LEV.[6] Hence, the marginal effect of DURAT may change sign and gain or lose significance according to the values of the conditioning variable. Therefore, in the results' section, we resort to a graphical representation, illustrating magnitude, sign and significance of the DURAT marginal effect for all values of the modifying variable.

3. DATA

Our data are drawn from the EFIGE-Bruegel-Unicredit dataset, containing survey information on 14,759 firms with more than 10 employees operating in seven European countries: Austria, France, Germany, Hungary, Italy, Spain and the United Kingdom.[7] The qualitative and quantitative data from the EFIGE survey, conducted in 2010, refer mostly to the span 2007-2009 or ~~to~~

[6] When estimating the bootstrapped truncated regression, we account for the non-linear nature of the model (as highlighted by Karaca-Mandic et al., 2012) .

[7] For more information on the EU-EFIGE dataset, see: bruegel.org/2012/10/the-eu-efigebruegel-unicredit-dataset/.

one year only (either 2008 or 2009). Firms' accounting data are sourced from BvD Amadeus databank and are available from 2001 to 2009. Hence, to exploit the panel structure of the data, an imputation process should be undertaken for several survey variables, with undesirable consequences in terms of errors in variables bias. In particular, this is the case for graduate employees (a measure of human capital), group membership, and bank debt, all theoretically relevant for the present analysis. To avoid jeopardising our estimates, we do not include imputed regressor in our benchmark model, adding them in robustness check regressions (Table 3, columns 2-3). It is worth noting that, despite our key variable DURAT is reported for 2009, we can easily retrieve its values for the previous years (2001-2008), by subtracting from the 2009 entry a number from 8 to 1.[8]

Focusing on France, Italy and Spain – as several variables employed in the econometric analysis display several missing values for the other nations – and considering the 2001-2008 period to rule out the consequences of the great financial crisis in Europe, we end up with an unbalanced panel of 54,693 observations on 7,924 firms.[9]

[8] When this subtraction results in negative numbers (or when the 2009 record is missing), we treat the observations as missing, as in these cases we don't know whether firms had not established any kind of relationships or they had a relationship with another main bank. Incidentally, the EFIGE survey does not provide the identity of a firm's main bank, and information concerning other lending relationships' characteristics – such as the percentage of the firm's total bank debt held by the main bank, and the number of lending banks (e.g.: Petersen and Rajan, 1994; Ferri and Messori, 2000; Ongena and Smith, 2000; Agostino et al., 2012) – is available only for the last year of the EFIGE survey.

[9] It should be also recalled that the EFIGE dataset neglects firms with less than 10 employees, thus implying that our results may not be generalized to the smallest of firms. Furthermore, accounting information refers to firms that are surveyed in 2010, thus defaulted entities are excluded. Hence, our findings are conditional on survival (as in other works based on the same source of data, such as Barba Navaretti et al., 2014; Agostino and Trivieri, 2017; and Agostino and Trivieri, 2017).

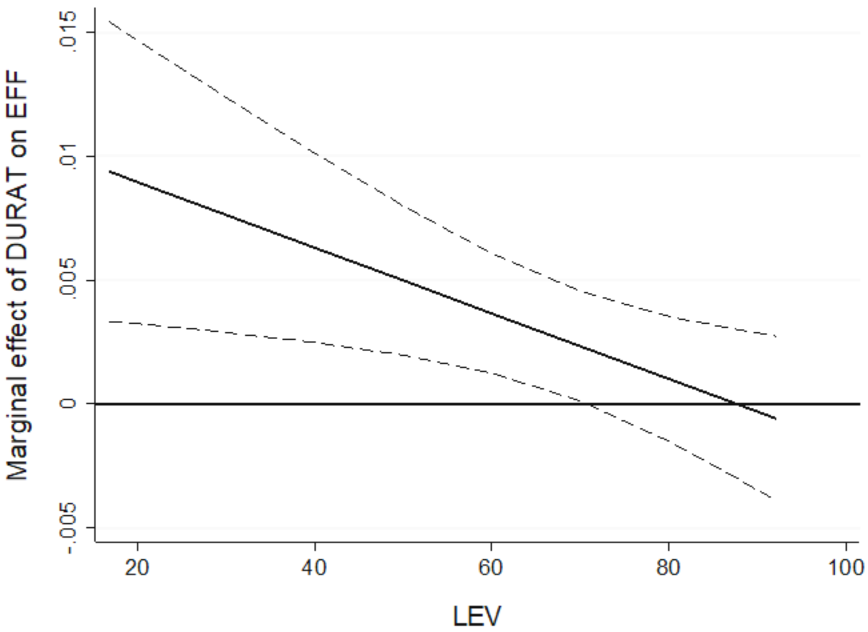
4. EMPIRICAL RESULTS

Table 3, column 1, reports the results concerning the benchmark model (equation 2), obtained by adopting a bootstrapped truncated estimator.

[TABLE 3]

Focusing on our key variables, whilst the DURAT coefficient is positive and statistically significant, the interaction term parameter is negative and significant. Hence these estimates seem to support the hypothesis that longer lending relationships may enhance technical efficiency, and that their positive effects are dependent on the amount of financing. However, the individual coefficients of our main regressors do not allow us to easily discern whether there exists a level of LEV beyond which the influence of DURAT changes sign and, what is more, whether the impact of DURAT is always statistically significant in our sample. To condense the information on sign, magnitude and significance of the effect of DURAT on firms' efficiency, we depict the marginal effects of DURAT, and the relative confidence intervals, in an appropriate graph.

FIGURE 1 – Marginal effect of DURAT on EFF as LEV changes
(--- 95% confidence interval)



The continuous line in Figure 1 shows the DURAT marginal impact for all the values of the modifying variable reported on the x-axis, while the dashed lines delimit 95% confidence intervals. At low levels of firms' indebtedness, the DURAT estimated marginal effect is positive and statistically significant (the confidence band does not include the zero line). When indebtedness increases, the impact of DURAT decreases, becoming not statistically significant beyond a leverage value of about 72%. Our interpretation of this finding is that, for low firm's indebtedness, the benefits of longer lending relationships might prevail on their costs, thus increasing manager's incentive to achieve efficient technical practices. However, as indebtedness increases, the costs of credit relationships may overcome the benefits, exacerbating moral hazard problems related to a firm's debt and, eventually, reducing managers' incentives to pursue higher production efficiency.

Briefly considering the explanatory variables, the coefficients of both INV and HHIs are negative and statistically significant, suggesting that higher inventories and higher concentration in the operating sector may plague firms' efficiency. As concerns AGE and SIZE, their effects on EFF are different in magnitude and significance according to their level. Looking at graphs analogous to Figure 1 (and available upon request), the AGE estimated marginal effect is positive and statistically significant for younger firms, and turns negative and statistically significant for firms older than 27 years. Moreover, the marginal effect of SIZE on EFF is negative and statistically significant only for smaller firms, while it becomes positive and statistically significant for the majority of our sample observations (about 90%).

4.1 Robustness Checks

In this subsection, we verify the sensitivity of our findings to the efficiency model specification, the methodology adopted and the potential endogeneity issue concerning our key regressors.

In column 2 of Table 3, we substitute the variable LEV with BDEBT, computed as total bank debt to total assets. As described in the Data section, since BDEBT is available only for

2009, we impute the latter value to all other years. In column 3, we add the (imputed) variable GROUP (coded 1 if firms belong to a group, and zero otherwise); we compute HHI on assets (HHIa) rather than on sales; and INV is replaced with INVR, the ratio of firm's inventories to the annual mean inventory requirement computed at the sector level.[10] In column 4, year fixed effect are included instead of the trend regressor. In column 5, sectorial dummies (individuating 11 NACE-CLIO manufacturing sectors) are substituted with sector fixed effects defined at a higher disaggregation level (NACE-CLIO classification, 2-digit level). Finally, since Yildirim (2017) finds evidence that banking relationships improve the efficiency of firms that have high default probabilities, in column 6 we add the variable ZSCORE, an indicator of financial health employed by several authors (e.g.: Laeven and Levine, 2009; Houston et al. 2010; Kanagaretnam et al. 2012; Mihet, 2012; Jin et al., 2013). Since it gauges the distance from insolvency, higher ZSCORE values indicate more stable and financially healthy firms.[11] Our results seem robust to all the specification's amendments mentioned above.

Furthermore, we adopt the parametric approach proposed by Battese and Coelli (1995) to simultaneously estimate the degree of firm inefficiency and the relationship between inefficiency and its determinants, specified in the benchmark equation 2. The results of this robustness check are presented in column 7 of Table 3. It is worth underlining that a negative coefficient in this model entails a reduction of firms' inefficiency and, hence, an increase in firms' efficiency.

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[10] We do not add the percentage of graduate employees, proxy of human capital, as defined on a limited number of observations (even after imputing).

[11] The Z-score is the sum of return on assets plus the capital asset ratio divided by the standard deviation of return on assets, the latter being computed over 3-year rolling time windows (Schaeck et al., 2012; Panetta and Pozzolo, 2010; Agostino and Trivieri, 2017). In the literature, this Z-score is employed as a measure of distance from insolvency, as it can be shown that – if profits follow a normal distribution – its value is negatively associated with the probability of insolvency.

Thus, the estimates concerning our main variables are consistent with the pattern so far illustrated.

To further corroborate our main conclusion, we also allow for different maturity of indebtedness. In Table 4, columns 1-2, we distinguish short from long-term debt (LEV_{ST} and LEV_{LT}).

[TABLE 4]

Consistently with the evidence so far presented, the DURAT parameter is positive and significant, while the interaction term coefficients are negative and significant. Yet, the interaction term parameter is smaller in absolute value when considering short-term debt (0.0001) than when conditioning on long-term debt (0.0004). Therefore, long-term debt seems exerting a higher (conditional) influence. Indeed, a longer duration of debt is expected to put less constraints on firms, likely entailing higher moral hazard problems, reinforcing the negative effects associated with higher debt.[12]

These findings are confirmed when adopting the Battese and Coelli's (1995) model (see columns 3 and 4 of Table 4): the influence of DURAT tends to decrease in absolute value as the conditioning variable (either LEV_{ST} or LEV_{LT}) increases, yet the detrimental impact of long-term debt is higher.

As a final point, we further address concerns of endogeneity relating to our explanatory variable of interest. Indeed, DURAT could be simultaneously determined with firms' technical efficiency, if banks select the best performer firms when developing relationships (Binks and Ennew, 1996). So far, in our regressions, we have limited potential endogeneity problems by

[12] It worth mentioning that the LEV_{ST} parameter is positive, while the LEV_{LT} coefficient is negative. Thus, the different debt structure seems to have an opposite influence on efficiency. Results are confirmed also when we consider all possible interactions among the constitutive terms (LEV_{ST}, LEV_{LT}, and DURAT), simultaneously.

lagging all explanatory variables defined at the firm level. [13] Here, we first adopt a test recently proposed by Karakaplan and Kutlu (2017), to assess the endogeneity of DURAT. [14] To perform this test, we instrument DURAT and the interaction term with the mean value of DURAT computed over the other firms operating in the same region, along with its square and cube terms. The rationale is that the average duration within a region should be correlated to the single firm's duration, but exogenous with respect to the single firm's efficiency. Since the test (reported at the bottom of Table 3, column 7) is not significant at conventional levels, the traditional frontier models seem appropriate.

To support this finding using external instruments, we replicate this test on the subsample of Italian firms, by employing as instrumental variables some indicators of the geographical distribution of banks and branches in 1936 in Italy, as suggested by Guiso et al. (2004, 2007), and several other studies, such as Alessandrini et al. (2009), De Bonis et al. (2015), Herrera and Minetti (2007), Agostino et al. (2011). Indeed, Guiso et al. (2004) show that the territorial structure of the Italian banking system in 1936 – the year in which, in response to the crisis of 1930–36, strict banking regulations were introduced (that remained substantially unchanged until the second half of the 1980s) – 'was the result of historical accidents and forced

[13] We have also tried to exploit the internal instruments that the panel structure of our data makes available, by adopting a SYS-GMM estimator (Blundell and Bond, 1998). Despite the results so far described are confirmed (i.e. the DURAT parameter is positive and significant, while the interaction term coefficient is negative and significant), we cannot emphasize this piece of evidence as some diagnostic tests are not passed, even using different subsets of the available lags as instruments.

[14] Karakaplan and Kutlu (2017) suggest a one-step maximum likelihood based methodology that allows to estimate the parameters of a stochastic frontier, where the error term is composed by a strictly nonnegative measure of inefficiency and a two-sided error term from a symmetric distribution. This methodology can account for endogenous variables both in the frontier and the inefficiency model. Further, it provides a test of endogeneity, relying "on ideas similar to the standard Durbin-Wu-Hausman test for endogeneity" (Karakaplan and Kutlu, 2017, page 6) .

consolidation, with no connection to the level of economic development at that time' (p. 946). Moreover, the 1936 regulation, were not driven by different regional needs, 'but it was random' (p. 943). Therefore, the geographical distribution of banks and branches in 1936 can be considered exogenous with respect to firm performance in subsequent years, while – as found by Guiso et al. (2004, 2007) – the geographical distribution of banking is significantly correlated with local banking development in the 1990s.

Looking at the Karakaplan and Kutlu (2017) test result reported in column 8, Table 3, again we cannot reject the null hypothesis of exogeneity.[15] Finally, column 8 of Table 3 shows the estimates obtained adopting a 2SLS estimator, applying the logit transformation to the dependent variable EFF, and using the same set of IVs just mentioned (which satisfies the Sargan test of overidentifying restrictions). These results appear to be in line with the main findings discussed above, although they are obtained by using the Italian subsample and a different estimator.[16]

5. CONCLUSION

In this paper, we have considered to what extent lasting lending relationships impact on firms' technical efficiency, an issue on which there is scant empirical evidence. The hypothesis underlying our research is twofold. First, the balance between benefits and costs of longer banking relationships depends on firm's indebtedness. Indeed, the drawbacks of lending relationships are expected to be more relevant at higher levels of debt. Second, these drawbacks may alter managers' incentives associated with debt, spurring them toward either virtuous or

[15] This result is based on instrumental variables defined in 1936 at regional level: the number of branches per million inhabitants (p.m.i); the number of saving banks (p.m.i).; the number of mutual cooperative banks (p.m.i).; the share of branches owned by cooperative Popolari banks, and the share of branches owned by large banks.

[16] Since our IVs are time invariant, a fixed effect estimator cannot be employed. Furthermore, as the endogenous variable DURAT is discrete, we cannot apply an IV Tobit.

opportunistic behaviour, and so the *net* effect of enduring credit relationships on firms' technical efficiency is an open empirical question.

To carry out our empirical investigation we employed microdata on manufacturing SMEs operating in three European countries (France, Italy and Spain). Rather than more usual productivity indicators, we adopt non-parametric measures of efficiency – correcting for the potential bias implied by the uncertainty in the data, and assuming that not all firms are operating at their optimal scale, as it is plausible when focusing on SMEs. Furthermore, our findings are fairly robust when adopting parametric measures of inefficiencies, based on a SFA procedure.

Overall, regardless of the methodology adopted, we find that the impact of lending relationships duration on SMEs' efficiency is positive for low levels of firms' debt, and declines as indebtedness increases. This pattern seems more pronounced when we take into account debt maturity, and carry out separate estimations considering short-run and long-run debt. In line with our hypothesis, we interpret these results as evidence that – for firms with higher debt levels – the costs of lasting banking relationships tend to prevail over their benefits, thus exacerbating managers' moral hazard behaviour related to debt and, eventually, compromising firm's technical efficiency.

Two features of our work may inspire promising future research. Indeed, the source of data we employ excludes firms with fewer than ten employees, and doesn't provide information for the years after 2009. Hence, future investigation could be carried out to assess whether our findings may be generalised to the smallest of businesses and whether the link between lending relationships duration and firms' efficiency has been influenced by the evolution of the last financial crisis.

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TABLE 1 - Description and summary statistics of the variables in the benchmark model

VARIABLE	DESCRIPTION	Mean	Std. Dev.	Min	Max	Obs
Entering the production function						
TOTREV [(a)]	Total sales	53.90	69.36	3.14	671.03	54,693
KAP [(a)]	Tangible plus intangible assets plus depreciation	13.73	22.40	0.15	253.35	54,693
RAWM [(a)]	Expenditure for raw materials	27.13	43.48	0.17	416.52	54,693
EMPLO [(b)]	Number of employees	35	33	10	248	54,693
Entering the efficiency model						
EFF	Pure technical efficiency based on bootstrapped DEA (Simar and Wilson 2007)	0.45	0.18	0.02	0.97	44,135
DURAT [(c)]	Duration of the relationships with the main bank	12.37	9.77	0	45	26,584
AGE [(c)]	Current year minus firm's year of establishment	26.09	20.90	1	111	53,093
SIZE [(a)]	Total assets	3943	4951	245	28072	53,525
LEV	Total debt to total assets	65.77	20.05	16.80	92.16	44,135
LEV_{ST}	Short-run debt to total assets	51.30	18.26	0.00	78.47	44,135
LEV_{LT}	Long-run debt to total assets	13.03	10.73	0.00	32.88	44,135
INV	Raw materials inventories to total assets	42.63	18.64	4.24	85.63	44,135
HHIs	Herfindahl-Hirschman index on firms' sales	0.02	0.05	0.00	0.34	44,135

(a) in thousands of Euro; (b) in units; (c) in years.

TABLE 2 - Correlation matrix

	DURAT	LEV	LEV_{ST}	LEV_{LT}	AGE	SIZE	HHIs	INV
DURAT	1							
LEV	-0.133	1						
LEV_{ST}	-0.110	0.748	1					
LEV_{LT}	-0.025	0.391	-0.270	1				
AGE	0.365	-0.221	-0.175	-0.044	1			
SIZE	0.025	0.011	-0.008	0.052	0.197	1		
HHIs	-0.019	-0.021	-0.008	-0.019	0.007	0.044	1	
INV	-0.090	0.153	0.179	-0.036	-0.067	0.318	0.064	1

For the description of the variables see Table 1.

TABLE 3 - Estimation results and robustness checks (bootstrapped truncated regressions, and Battese and Coelli 1995).

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	Benchmark	BDEBT instead of LEV	Changing specification	Year fixed effects	Nace 2-digit dummies	Adding ZSCORE	BC 1995 Benchmark	2SLS ITALY
DURAT	0.0112***	0.0081***	0.0112***	0.0114***	0.0131***	0.0106**	-0.0586***	6.9577***
	0.004	*0.001*	*0.008*	*0.006*	*0.001*	*0.015*	*0.000*	*0.000*
LEV	0.0001		0.0001	0.0001	0.0001	0.0001	-0.0013***	0.1934***
	0.466		*0.55*	*0.472*	*0.34*	*0.478*	*0.000*	0.003
BDEBT		0.00004						
		0.646						
DURAT*LEV	-0.0001**		-0.0001**	-0.0001**	-0.0002**	-0.0001**	0.0006***	-0.0752***
	0.019		*0.035*	*0.029*	*0.011*	*0.038*	*0.000*	0.005
DURAT*BDEBT		-0.0001**						
		0.01						
AGE	0.0153***	0.0157***	0.0158***	0.0153***	0.0186***	0.0149**	0.0589***	-0.3912
	0.008	*0.006*	*0.004*	*0.006*	*0.001*	*0.013*	*0.000*	0.32
AGE^2	-0.2658***	-0.0028***	-0.2647***	-0.2657***	-0.0033***	-0.0029***	-0.0084***	0.0049
	0.000	*0.000*	*0.000*	*0.000*	*0.001*	*0.005*	*0.000*	0.914
SIZE	-0.0028***	-0.2601***	-0.0028***	-0.0028***	-0.2580***	-0.2602***	-0.5273***	-1.4476***
	0.004	*0.000*	*0.003*	*0.004*	*0.000*	*0.000*	*0.000*	*0.000*
$SIZE^2$	0.0209***	0.0205***	0.0207***	0.0209***	0.0203***	0.0205***	0.0256***	0.1128***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
INV	-0.0006***	-0.0006***		-0.0006***	-0.0006***	-0.0006***	0.0229***	-0.0034***
	0.000	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	0.002
INVR			-0.0216***					
			0.000					
HHIs	-0.0720***	-0.0705***		-0.0572**	-0.0671***	-0.0001	0.1998***	-0.6599
	0.002	*0.002*		*0.024*	*0.003*	*0.998*	*0.000*	0.152
HHIa			-0.4049***					
			0.000					
GROUP			0.0088***					
			0.002					
ZSCORE						-0.00001		
						0.162		
TREND	-0.0009*	-0.0009*	-0.0016***		-0.0010**	-0.0017***	-0.0061***	-0.0032
	0.064	*0.077*	*0.000*		*0.02*	*0.005*	*0.000*	0.775
N.obs	21 519	21 944	21 519	21 519	21 047	18980	21 519	8652

(continued)

TABLE 3 (continued) - Estimation results and robustness checks (bootstrapped truncated regressions, and Battese and Coelli, 1995).

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	Benchmark	BDEBT instead of LEV	Changing specifica-tion	Year fixed effects	Nace 2-digit dummies	Adding ZSCORE	BC 1995 Benchmark	2SLS ITALY
Model test	15772	15266	14394	15954	14062	12574		53.1
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		*0.000*
LRT(a)							8176	
							0.000	
LRT(b)							30155	
							0.000	
Eta test							3.180	1.03
							0.075	0.309
Sargan test								4.359
								0.2252

For the description of the variables see Table 1. In Italics are reported the p-values of the tests. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Constant, country and sectorial dummies always included but not reported. In columns from 1 to 6 and in column 8 the dependent variable is efficiency, whilst in column 7 is inefficiency. Columns 1-6 report marginal effects of bootstrapped truncated regressions (Simar and Wilson, 2007). In all the columns, DURAT, AGE and SIZE are in logarithmic form. In column 2, BDEBT is total bank debt to total assets. In column 3, INV is replaced by INVR, HHIs is replaced by HHIa, and the dummy GROUP (equal to 1 if the firm belongs to a group, 0 otherwise) is added. In column 4, TREND is subtituted with annual fixed effects, and in column 5 sectorial dummies (individuating 11 NACE-CLIO manufacturing sectors) are subtituted with sector fixed effects defined at a higher disaggregation level, NACE-CLIO classification (2-digit) level. In column 6, ZSCORE is the sum of return on assets plus the capital asset ratio divided by the standard deviation of return on assets, the latter being computed over three-year rolling time windows. In column 7, BC1995 stands for Battese and Coelli (1995) Stochastic Frontier Analysis. In column 8, the 2SLS estimator is applied on the sub-sample of Italian firms, using the following instruments, defined in 1936 at regional level: the number of branches per million inhabitants (p.m.i); the number of saving banks (p.m.i.); the number of mutual cooperative banks (p.m.i.); the share of branches owned by cooperative Popolari banks, and the share of branches owned by large banks. Model test is the test of joint significance of all explanatory variables (Wald chi2 test). LRT stands for Likelihood ratio test. LRT(a) compares the Translog (H1) with the Cobb-Douglas production function (H0); LRT(b) compares the fitted model (H1) with a corresponding model without inefficiency, estimated by OLS (H0); Eta Test is the Karakaplan and Kuntlu's (2017) endogenity test on DURAT and DURAT*LEV. The null hypothesis of the Sargan test is the validity of the over-identifying restrictions.

TABLE 4 - Long and short term leverage. Boostrapped truncated regressions, and Battese and Coelli (1995)

	1	*2*	*3*	*4*
	DURAT*LEV_{ST}	DURAT*LEV_{LT}	BC 1995 (DU-RAT*LEV_{ST})	BC 1995 (DU-RAT*LEV_{LT})
DURAT	0.0089***	0.0078***	-0.0602***	-0.0036**
	0.006	*0.000*	*0.000*	*0.034*
LEV_{ST}	0.0008***	0.0005***	-0.0027***	-0.0009***
	0.000	*0.000*	*0.000*	*0.000*
LEV_{LT}	-0.0025***	-0.0017***	0.0028***	0.0005**
	0.000	*0.000*	*0.000*	*0.044*
DURAT*LEV_{ST}	-0.0001*		0.0007***	
	0.06		*0.000*	
DURAT*LEV_{LT}		-0.0004***		0.0001
		0.000		*0.573*
AGE	0.0119**	0.0106**	-0.0839***	0.0215***
	0.032	*0.038*	*0.000*	*0.000*
AGE^2	-0.2444***	-0.2437***	0.0171***	-0.0032***
	0.000	*0.000*	*0.000*	*0.000*
SIZE	-0.0021**	-0.0019**	-0.2038***	-0.6878***
	0.031	*0.035*	*0.000*	*0.000*
$SIZE^2$	0.0197***	0.0196***	-0.0018	0.0386***
	0.000	*0.000*	*0.573*	*0.000*
INV	-0.0010***	-0.0010***	0.0119***	0.0224***
	0.000	*0.000*	*0.000*	*0.000*
HHIs	-0.0776***	-0.0770***	-0.1718	-0.0394
	0.001	*0.001*	*0.288*	*0.428*
TREND	-0.0006	-0.0006	-0.0128***	0.0139**
	0.159	*0.159*	*0.000*	*0.008*
N.obs	21 519	21 519	21 519	21 519
Model test	18496	17631		
	0.000	*0.000*		
LRT			12445	32902
			0.000	*0.000*

For the description of the variables see Table 1. In Italics are reported the p-values of the tests. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. Constant, countries and sectorial dummies always included but not reported. In columns 1 and 2 the dependent variable is efficiency, whilst in columns 3 and 4 is inefficiency. In all the columns, DURAT, AGE and SIZE are in logarithmic form. Columns 1 and 2 report the marginal effects of bootstrapped truncated regressions (Simar and Wilson, 2007). BC1995 stands for Battese and Coelli (1995) Stochastic Frontier Analysis. Model test is the test of joint significance of all explanatory variables (Wald chi2 test). LRT, likelihood ratio test, compares the fitted model (H1) with a corresponding model without inefficiency, estimated by OLS (H0).

APPENDIX. MEASURING TECHNICAL EFFICIENCY

The DEA approach has been extensively employed to obtain non-parametric measures of (firm, sector, institution or country) efficiency, which are based on distance functions from a benchmark production frontier. The basic idea underlying such distances is that, at any point in time, we can draw a piece-wise production frontier, locus of technically efficient input-output combinations, given the existing technology. Hence, the distance between the best practice frontier and a combination not belonging to the frontier can be regarded as a measure of technical inefficiency, and interpreted as "a summary measure of incomplete contracts, different principal-agent objectives and inadequate motivation" (Margaritis and Psillaki, 2007, p. 1448).

Distance functions may be either output or input orientated, and allow to measure firms' efficiency without imposing assumptions on firms' behaviour, such as profit maximization or cost minimization. Formally, an *output* distance function gauges the largest proportional expansion of the output vector, conditional on given input levels.[17] In other words, "we could think of deflating the output vector so that the resulting deflated output vector is just producible by the input vector x" (Diewert and Fox, 2010, p. 76). Hence, an output distance function, in period t, may be defined as follows:

$$D^t(q_t, x_t) = min\{\delta: (q/\delta) \in P(x)\} \tag{A1}$$

[17] An *input* distance function provides the largest proportional contraction of the inputs, given an output vector. Both concepts allow to completely characterize the technology and, when constant returns to scale prevail, the input distance function is the reciprocal of the output distance function. An output orientation is commonly adopted when it is fair to assume that firms seek to maximize output for given input combinations (as in the manufacturing case, see for instance Milana et al., 2013). By contrast, when producers have a statutory obligation to meet demand, and they also have to guarantee certain quality levels, it is proper to assume that firms attempt to minimize input for given output levels (see Saal et al., 2007 for water and sewerage services, and Giuffrida, 1999 for primary care provision by Family Health Service Authorities).

where $P(x)$ is the production possibilities set for the technology available in period t. The minimum value of the parameter δ is equal to unity for all combinations on the frontier (when production is technically efficient, in Farrell's 1957 terminology), while is lower than one for all other combinations belonging to the production set $P(x)$. Adopting the conventional notation, we indicate with N the number of firms (or decision making units, DMUs) belonging to each sector (defined at the 2-digit ATECO level). If the *ith* firm employs K inputs to produce M outputs (represented by the vectors x_i and q_i, respectively) the (K×N) input matrix X, and the (M×N) output matrix, Q, represent the data of all N firms in each sector. Assuming variable returns-to-scale (VRS), the general linear programming problem that has to be solved for each firm is:

$$max_{\lambda,\phi}\ \phi \quad s.t: \ Q\lambda\text{-}\phi q_i \geq 0;\ x_i\text{-}X\lambda \geq 0;\ I1'\lambda = 1;\ \lambda \geq 0 \qquad \text{(A2)}$$

where ϕ is a scalar, while λ is a N*1 vector of constants. Recalling that the output-based Farrell (1957) measure of technical efficiency is reciprocal to the output distance function (Färe et al., 1994), it is possible to retrieve $[D^t(q_t, x_t)] = \phi^{*-1}$, which defines the efficiency score for the *ith* firm, lower or equal to unity, with a value of 1 corresponding to a point on the frontier.

It is worth emphasizing that, by allowing for VRS we assume that not all firms are operating at their optimal scale, as it is plausible when focusing on SMEs. Thus, as Alvarez and Crespi (2003), "we measure inefficiency that is caused only by an excessive use of inputs and not by inadequate plant size" (p. 238). Furthermore, our DEA efficiency measure is based on contemporaneous frontiers, i.e. we consider as benchmark for each observation in a given year all other observations in the same year. Finally, to rule out potential outliers, we eliminate the observations lying in the first and last percentile of the distribution of each variable (output and inputs) entering the production function.

Battese and Coelli (1995) propose to estimate simultaneously a stochastic frontier production function for panel data with a regression model for the predicted technical inefficiency effects.[18] In particular, they consider the following stochastic frontier production function:

$$y_{it} = \exp\,(x_{it}\beta + V_{it} + U_{it}) \tag{A3}$$

where y_{it} is the production at time t (t=1,2,…,T) for the i-th firm (i=1,2,…N); x_{it} is a (1xk) vector of known functions of inputs of production and other explanatory variables; β is a (kx1) vector of unknown parameters to be estimated; V_{it}s are assumed to be iid N(0, σ_V^2) random errors, independently distributed of the U_{it}s; which are non-negative random variables, associated with technical inefficiency of production. They are obtained by truncation (at zero) of the normal distribution with mean, $z_{it}\delta$, and variance, σ^2, where z_{it} is a vector (1xm) of explanatory variables, and δ a vector (mx1) of parameters to be estimated. Thus, the inefficiency terms are independently but not identically distributed, and may be specified as follows:

$$U_{it} = z_{it}\delta + W_{it} \tag{A4}$$

where W_{it}, is defined by the truncation of the normal distribution with zero mean and variance, σ^2. To simultaneously estimate the parameters of (A3) and (A4), the maximum likelihood method is adopted, expressing the likelihood function in terms of the variance parameters, $\sigma_S^2 = \sigma_V^2 + \sigma^2$ and $\gamma \equiv \frac{\sigma^2}{\sigma_S^2}$. The technical efficiency of production, assuming values between zero and one is defined as:

$$TE_{it} = \exp(-U_{it}) = \exp\,(-z_{it}\delta - W_{it}) \tag{A5}$$

In this work, estimations are performed using the R-software (package FRONTIER).

[18] There are several advantages of this approach: simultaneous estimation of the frontier and the technical inefficiencies; distinction between a firm specific inefficiency and the statistical noise; relationships between inputs and outputs follow known functional forms, and hypotheses can be tested with statistical rigour.