Inefficiency and risk taking behavior in Spanish banking

M[a]Pilar García-Alcober
Universidad CEU-Cardenal Herrera

Manuel Illueca
Universitat Jaume I and Ivie

Diego Prior
Universitat Autònoma de Barcelona

Emili Tortosa-Ausina
Universitat Jaume I and Ivie

February 11, 2015

Abstract

After the financial crisis of 2007–2008 there are two bank performance dimensions that are partly subject to debate. One of them is bank efficiency, and the other one bank risk taking behavior. The literature on bank efficiency and productivity has expanded remarkably since almost three decades ago, and has regained momentum over the last few years in the aftermath of the financial crisis. Regarding bank risk taking behavior, whose focus has been usually on its links to monetary policy, the interest has been comparatively minor but it has also increased exponentially more recently. This paper mixes these two stems of research. Specifically, we test if more inefficient banks are riskier when selecting their borrowers, when charging interests and pledge collateral, and if these links between inefficiency and risk change depending of the type of bank. We perform this analysis on the Spanish banking system, which has been severely affected by the burst of the housing bubble and has gone through deep restructuring. In order to test our hypotheses, we build a database with information on banks and savings banks, their borrowers (non-financial firms), and the links between them. On the methodology side, we also try to contribute to the literature by considering a novel profit frontier approach. Our results suggest that more inefficient banks are riskier when selecting their borrowers, and that his high risk-taking behavior is not offset by higher interest rates.

Keywords: bank, efficiency, risk taking behavior, savings bank

JEL classification: C14, C61, G21, L50

Communications to: Emili Tortosa-Ausina, Departament d'Economia, Universitat Jaume I, Campus del Riu Sec, 12071 Castelló de la Plana, Spain. Tel.: +34 964387168, fax: +34 964728591, e-mail: `tortosa@uji.es`.

1. Introduction

Following the financial crisis of 2007, several studies on bank risk taking behavior have been gaining momentum. Most of them have put together environmental variables, interest rates and monetary policy with the increased risk assumed by banks, in order to ascertain some of the likely causes of the economic crisis. Recent related literature would include, for instance, Dell'Ariccia et al. (2014), which estimate a theoretical model to show that following a decline in interest rates there was in increase in bank risk taking—although the results varied according to leverage. Another stance is adopted by Boyd and Hakenes (2014), who model both bank risk taking behavior and regulatory policy in times of crisis, distinguishing between two types of models, namely, a model that considers only owner-managers' capital, and a second one that also includes outside equity holders. In the case of Spain, on which we focus, Jiménez et al. (2014) analyze the impact of monetary policy on the risk assumed by banks in the country in the period between 2002 and 2008.

In the field of bank efficiency and productivity the number of studies which have taken explicitly into account how controlling for risk may bias efficiency scores, despite the relevance of the issue, is remarkably lower. Within this particular group of studies, although we might consider a variety of classifications including those considered previously, it is also possible to distinguish between two additional types—depending on whether the focus is put either on the risk behavior of the lender or that of the borrower.

Therefore, on the one hand we would have those studies which control for credit risk considering variables at the <u>bank</u> level, and which use as proxy for risk loan loss provisions or, should information be available, non-performing loans. Examples of this literature abound, and some relevant ones would include Berger and DeYoung (1997), who study the relationship between non-performing loans and efficiency for US banks, or Williams (2004), who analyze the links between loan loss provisions and efficiency for European banking markets, among many others.

On the other hand, in addition to this relevant literature, we should also highlight those research initiatives that consider not only bank credit risk but also the risk attributable to the probability of bankruptcy or insolvency of their borrowing companies—i.e. we would be considering the <u>firm</u> level. In this case, although some contributions such as Foos et al. (2010) or Fiordelisi et al. (2011) have dealt with related issues (in the context of the banking industries of 16 advanced economies, and in the case of European banks, respectively) it has not been analyzed yet <u>how exactly the risk characteristics of the borrowing firms interact with banks' efficiency</u>.

However, nowadays this issue might be particularly relevant since, as indicated by Keys et al. (2010), during the booming years prior to the financial crisis, in many Western economies several factors (including the growth in securitization issuance, the degree of bank competition, external finance imbalances, corporate governance in the banking sector, the relative tightness of monetary policy, or the intensity of bank supervision and policy responses to the crisis) led to looser credit standards and laxer screening of borrowers, contributing to the expansion of credit and to the deterioration of loan quality.

In this paper we put the focus on the Spanish banking system. As noted by Foos et al. (2010), the current financial crisis is a clear example of the materialization of the risk taken by banks during the period of economic growth, including too low interest rates and excessive laxity when issuing loans. In the case of Spain this tendency has been especially serious, and the financial crisis has had devastating consequences for the entire economy, leading to the most dramatic restructuring process in the history of its banking system. Some authors refer to Spain as one of the strongest examples of the issues responsible for the crisis—a remarkable housing bubble, partly fed by financial innovation (in particular securitization) which led to looser credit standards and, ultimately, financial instability (Carbó-Valverde et al., 2012). In this scenario, our paper examines whether the most inefficient Spanish banks offered loans to financially riskier firms, among other characteristics. For this, the analysis will measure risk from three different points of view: (i) *ex ante* risk; (ii) *ex post* risk; and, finally, given some of the most intrinsic characteristics of Spanish savings banks, (iii) savings banks' risk depending on whether they carry out their main activities in either their home market or other markets.

The research conducted in this study differs from previous initiatives in the way risk is handled. First we analyze whether the most inefficient banks choose riskier customers. Second, if this risk materializes. As we shall see, results show that the most inefficient banks did actually lend to riskier customers. We also examine whether this risk is rewarded via higher interest rates. Stiglitz and Weiss (1981) argue that the riskiest customers are willing to accept higher interest rates, since they perceive the probability of repaying the loan is lower. In contrast, Foos et al. (2010) indicate that there are banks that, in order to issue a higher amount of loans, lower the interest rates and require less collateral.

The article proceeds as follows. After this introduction, Section 2 presents the key assumptions and empirical predictions. Section 4 features the different econometric models to be estimated, whereas Section 5 describes briefly the data and variables, for both banks and their borrowing firms, that will be used in the article. Finally, Section 6 explains the different results obtained while Section 7 outlines some conclusions.

2. Hypotheses on the links between banks' profit efficiency and borrowing firms

We consider three different hypotheses regarding the relationship between bank profit inefficiency and their risk taking behavior. The first of the hypotheses considers whether the most inefficient banks have sought to increase their profits by granting more loans—even to firms with the worst financial results. The second hypothesis considered is the second part to hypothesis one. I will first consider if the most inefficient banks, due to the fact they grant riskier credits, offset the extra risk by charging higher interest rates and, second, if these banks provide credit to companies with lower probability of paying back. The final hypothesis refers to savings banks only. Specifically, in light of the savings bank branch geographic expansion of the end of 1990s and 2000s, the hypothesis stipulates whether savings banks behave differently, granting new loans in their new markets compared to their home markets.

Hypothesis 1: The most inefficient banks are more risky when selecting their borrowers

This first hypothesis is in line with the "bad management" hypothesis of Berger and DeYoung (1997). As indicated in the previous chapter, these authors pointed out four hypotheses to analyze the relationship between risk and efficiency: (i) the bad management hypothesis; (ii) the skimping hypothesis; (iii) the moral hazard hypothesis; and (iv) the bad luck hypothesis.

According to the "bad managment" hypothesis, the low efficiency of banks are due to poor management skills, which might lead to taking excessive risks. Therefore, there is a <u>positive</u> relationship between the banks' inefficiency and the risk in which they incur. In addition, Williams (2004) found empirical evidence of this "bad management" hypothesis for European savings banks.

Hypothesis 1a: The most inefficient banks will lend to less profitable or more inefficient firms

This hypothesis takes into account as dependent variable the lagged Z-score. When the banks have to make a decision on whether to grant a loan to a firm or not, the information they have is related to the firm's balance sheet and profit and loss account corresponding to last year. If the lending banks grant a loan to a company with solvency problems, this can be considered as an *ex-ante* risk. Such prior information held by the bank can be considered "hard information", and it is based on objective criteria.

However, there is another type of information, called "soft information" Berger and Udell (2002) that can also affect lending decisions. This other information cannot be observed by third parties, and it is the result of the data obtained by the relationship with the company, the owner and the local community. In this sense it is necessary to include a second hypothesis to capture the effect of *ex post* risk.

Hypothesis 1b: Those firms that obtain credits from inefficient banks have more probability of going bankrupt

Berger and DeYoung (1997) find empirical evidence that inefficiency may be an important indicator of future credit problems in the US market. However, they only consider cost efficiency and bad loans, but not the profitability of the borrowing firm. Other studies also show evidence of the relationship between efficiency and loan loss provisions, which can also be considered as a proxy for *ex post* risk, (see, for instance Williams, 2004; Chortareas et al., 2011)

Hypothesis 2: The interest rates charged by the most inefficient banks are higher, due to their risk taking behavior

Regarding interest rates charged, two views are held in the literature. On the one hand, as Jiménez and Saurina (2004) explain, in a context of asymmetric information between the bank and the borrower, the loan contracts differ by type of borrowers: whereas the riskiest borrowers are charged with higher interest rates and do not provide collateral, the least risky are charged with lower interest rates and are required to provide with less collateral.

On the other hand , there are authors like Ogura (2006) who argue that, in a competitive environment, to attract new customers banks should charge lower interest rates. Foos et al. (2010) finds evidence that total lending increases when interest rates are lower. They show there is a relationship between loan growth and risk of banks' risk taking between 1997 and 2007 for 16 advanced economies.

In this chapter, I will adopt the views by Jiménez and Saurina (2004) and, therefore, our hypothesis is that the most inefficient banks charge higher interest rates. In addition, the analysis is extended to check whether riskier banks lend to companies that can provide with less collateral. Berger and Udell (1990) present empirical evidence for the U.S. market that the guarantees are more often associated with riskier borrowers and riskier banks. In the same vein, and for the Spanish case, Jiménez and Saurina (2004) show that the probability of firms' bankruptcy increases with collateral.

Hypothesis 3: The inefficiency of the savings banks will affect the type of borrowers depending on whether they are located in the savings bank's home markets or new markets

Until the end of 1988, the Spanish banking regulation did not allow savings banks to expand geographically. They could not operate in territories that were not either their region (or *comunidad autónoma*) of origin or, more properly, what may be defined as home or natural markets (Fuentelsaz et al., 2004). However, by the end of 1989, the barriers to expand to new markets, usually in other regions, were lifted for savings banks. Some savings banks began to set numerous branches outside their traditional geographic boundaries and, today, the territorial distribution of savings banks is still conditioned by the pre-1989 regulations on geographical expansions.

Originally, savings banks were specialized in lending to small businesses in their same city or province—in sum, in their *home* markets. By 1975, regulations at the state level restricted the geographic scope of savings banks' operations to their natural markets. However, the European banking harmonization process of the eighties meant the savings banks' sector was one of those going through strongest deregulation in order to increase their competitiveness, a deregulation process which included the lifting of barriers impeding territorial expansions. As a result, I will define the market of origin, or natural market of the savings in this particular context following the contributions of Illueca et al. (2009) and Illueca et al. (2014). Specifically, we may follow Illueca et al. (2014) who defined the home market of a savings bank as those provinces that met at least one of the following two criteria in 1988: (a) savings bank i has more than 5% of the total number of the branches of all of the banks located in a province or (b) savings bank I has more than 50% of its own branches in a province.[1]

Some authors argue that banks operate differently in their home markets than in new markets. For instance, Illueca et al. (2009) show that those savings banks expanding geographically outside their home markets obtain higher productivity gains. By considering this hypothesis I try to assess if savings banks behave differently depending on the markets where they are located. On the one hand, if savings banks, with the aim of issuing more loans, adopt riskier credit policies in new markets, either due to lack of information on the new markets due to the absence of "soft information", or due to more "aggressive" competitive practices. Illueca et al. (2014) found evidence for the different behavior of the Spanish savings banks. Specifically, they show that savings banks' geographic expansion is associated with increased risk. In contrast, if the savings have market power in their home markets they will be able to charge with higher interest rates. This hypothesis, in turn, can be divided into two:

[1] These definitions had initially been proposed by (Fuentelsaz et al., 2004).

Hypothesis 3a: The inefficiency of savings banks will influence on the probability of bankruptcy of their borrowers according to their location

Most savings banks, once the deregulatory initiatives of the 1980s and 1990s were over, began ambitious geographic expansion plans outside their traditional (or home) markets. Entering new markets could generate, as indicated by Shaffer (1998), adverse selection problems, which might affect the risk tanking behavior by savings banks in new markets.

Hypothesis 3b: The inefficiency of savings banks will influence the interest rate paid by corporate borrowers by location

This hypothesis is based on the idea that the savings could have market power in those regions where they have traditionally operated—i.e. in their home markets. Wong (1997) proposed a theoretical model according to which the interest margin of banks is positively related to their market power and their credit risk. Demirgüç-Kunt and Huizinga (1999) show for a database of banks from 80 countries during the years 1988–1995 that lower levels of market power lead to lower margins and higher profits. Foreign banks had higher margins and profits than their domestic peers in developing countries, while in developed countries result was the opposite.

3. Efficiency measurement

Some banks perform better than others. This is an indisputable fact, but how do we actually recognize a high performing bank? Is a very profitable bank a high performer? Before providing the answer to this question, we have to consider the degree of reliability we should accord to the variables needed to define banking industry profits. In order to do this, we first need to define the synthetic components that make up the **profits** of a banking firm:

$$\Pi = \text{Revenues} - \text{Operating costs} - \text{Loan loss provisions} = \\ = \sum_{m=1}^{M} r_m u_m - \sum_{n=1}^{N} p_n x_n - \sum_{o=1}^{O} p_o npl_o \quad (1)$$

where Π are the profits, r_m and u_m are the price and quantity for output m ($m = 1, \ldots, M$), respectively, p_n and x_n are the price and quantity for input n ($n = 1, \ldots, N$), respectively, p_o is the *estimated price* (say, the percentage of write-offs) for non-performing asset o, and npl_o refers to its monetary value (quantity).

Clearly, the degree of accuracy of Π depends on the *quality* of each of its basic elements. In this regard, in the framework of agency theory, a well developed stream in the accounting literature addresses the assessment of the quality of the variables that have an impact on periodic profits, namely, the literature on **earnings quality** (see, for instance Dechow et al., 2010, for a review of some of the variables employed by this literature). On the one hand, under some specific circumstances there are several choices to consider at the moment when transactions occur—or incentives exist to manipulate real operations (Roychowdhury, 2006)—and this can affect the amount of flow of real variables to consider (u_m, x_n, npl_o). This is what the literature on earnings quality refers to as timeliness and timely loss recognition (Dechow et al., 2010). On the other hand, when prices are determined internally (a situation that could affect both p_n and p_o), subjective and opportunistic choices could be considered in order to "embellish" (or "manipulate") the profits to be disclosed. In this respect, in the particular case of the banking industry, the manipulation of profits is commonly oriented to deal with the problems caused by credit risk—bad loans, problem loans or provisions for loans losses (see, for instance Beaver and Engel, 1996).

Dechow and Dichev (2002) define higher profit quality as existing when earnings and cash flows follow the same pace. They document that earnings quality is poorer for smaller firms, which experience losses and greater volatility in sales and cash flows. Some of these characteristics are present in the Spanish banking industry, which provides the rationale for our research objectives.

Another perspective on earnings quality is that some banks also have incentives to reduce volatility by decreasing earnings in years with unexpectedly strong performance, and increasing earnings in years with weak performance. A smoother stream of earnings might help to reduce the information asymmetry between managers and outside investors (Beatty and Harris, 1999; Beatty et al., 2002; Liu and Ryan, 2006). The majority of previous studies find evidence that managers smooth earnings via loan loss provision and recognize security gains and losses. Accordingly, these are the variables to be accounted for when the quality of the earnings is under scrutiny.

Different approaches can be considered to incorporate the risk-taking behavior of banks in estimating efficiency indicators. Following previous literature, non-performing loans can be incorporated into the production function of banks as a bad output (or, in terms of the profit function, an expense that decreases total profits). Under Spanish accounting standards, banks must classify a loan as non-performing when either interest or principal payments are more than 90 days overdue. In addition, all loans granted to borrowers in default are also considered as non-performing, irrespective of whether or not they are overdue.

Because many of these loans are finally repaid, to write off the whole amount of non-performing loans *(npl)* as an expenditure would lead us to overestimate the effects of risk on profit efficiency scores. Hence, we undertake an alternative approach which consists of including loan loss provisions (LLP, defining $LLP = \sum_{o=1}^{O} p_o npl_o$) as an expenditure in the profit function. Under Spanish banking regulations, bank managers estimate LLP following a strict set of rules devised by the Bank of Spain, which depend heavily on the time overdue. However, Bank of Spain rules determine the *minimum* losses a bank must recognize once a loan has been defined as non-performing, leaving the banks with considerable room for discretion.[2] To mitigate the effects of the *potential manipulation of LLP*, our approach consists of using *expected* loan loss provisions as an expenditure, instead of *realized* loan loss provisions. This would reveal whether banks' loan loss provision decisions to manage earnings or capital (and, therefore, circumvent strict accounting rules by over- or under-provisioning assets, or misclassifying them) are successful or not. As indicated by Pérez et al. (2008), if they were successful, having painstaking regulations on LLP might be irrelevant, and that "there is merit in having more principles-oriented accounting standards" (Pérez et al., 2008, p.424).

Expected, or "non-manipulated" loan loss provisions are estimated at the bank level, following the proposals by Nichols et al. (2009). In particular, we regress LLP on the increase in npl in npl in $t-2$, $t-1$ (backward looking component) and t. Furthermore, in order to control for accounting conservatism, the increase in npl in $t+1$ is also incorporated in our regression model as an independent variable (forward looking component):

$$LLP_t^{\text{not manipulated}} = \beta_0 + \beta_1 \triangle npl_{t-2} + \beta_2 \triangle npl_{t-1} + \beta_3 \triangle npl_t + \beta_4 \triangle npl_{t+1} + \varepsilon_t \qquad (2)$$

We run a regression for each bank for the sample period. To carry out the estimation, two different specifications are considered. We first include total loan loss provisions as the dependent variable, considering not only the specific component of loan losses, but also the *dynamic* loan loss provisions, which were introduced by the Bank of Spain in 2000. Since the dynamic provisioning system had a deep impact on the relationship between npl and LLP, we run a second set of regressions excluding the dynamic, or time series, loan loss provisions from the dependent variable.[3] This gives us two sets of "non-manipulated" loan loss provisions, i.e. static (cross-section) and dynamic (time series), for which we consider this counter-cyclical loan loss provision.[4]

[2]However, some authors such as Pérez et al. (2008) consider the Bank of Spain enforces strict regulations on the accrual of loan loss provisions which would impose, *a priori*, considerable restrictions on banks' ability to use managerial discretion.

[3]In 2000 the Bank of Spain promulgated the so-called "statistical provision", according to which banks had to use their own reserves to cover realized losses, making it easier for banks to maintain provisions for incurred losses embedded in the credit portfolios created in expansion years. This rule ultimately enforced a counter-cyclical LLP that resulted in income smoothing practices by banks (Pérez et al., 2008, p.425).

[4]Considering cross section and time series estimations is also relevant because of their economic implications

Having estimated the degree of earnings manipulation present in the Spanish banking system, we estimate a non-convex short-run profit frontier model. This model basically follows Färe et al. (1994), taking the original variables (in the case of the bad output, considering the realized loan loss provisions only) and classifying the inputs into variable (x_v) and fixed (x_f) inputs (see also Primont, 1993, for a short-run cost frontier definition). Therefore, we will be modeling **variable profit maximization**:

$$
\begin{aligned}
&\Pi^{\text{manip}}\left(r_{jm}, p_{jv}, p_{jo}\right) \\
&= \max_{(z,u_m,x_v,npl_o)} \left(\textstyle\sum_{m=1}^{M} r_{jm}u_m - \sum_{v=1}^{V} p_{jv}x_v - \sum_{o=1}^{O} p_{jo}npl_o\right) \\
&\text{s.t.} \\
&\textstyle\sum_{j=1}^{J} z_j u_{jm} \geq u_m, \qquad m = 1, \ldots, M, \\
&\textstyle\sum_{j=1}^{J} z_j x_{jv} \leq x_v, \qquad v = 1, \ldots, V, \\
&\textstyle\sum_{j=1}^{J} z_j x_{jf} \leq x_{jf}, \qquad f = 1, \ldots, F, \\
&\textstyle\sum_{j=1}^{J} z_j npl_{jo} \leq npl_o, \quad o = 1, \ldots, O, \\
&\textstyle\sum_{j=1}^{J} z_j = 1, \\
&z_j = [0,1].
\end{aligned}
\tag{3}
$$

where $r_{jm} \in \mathbb{R}_+^M$ is the vector of output prices for bank j, $r_{jm} \geq 0$, and we also have variable inputs (netputs) with prices $p_{jv} \in \mathbb{R}_+^V$, $v = 1, \ldots, V$. Analogously, $u_j \in \mathbb{R}_+^M$ is the vector of output quantities for j, $x_{jv} \in \mathbb{R}_+^V$ are the variable netputs for bank j and $x_{jf} \in \mathbb{R}_+^F$ are the fixed netputs for the same bank. However, with respect to the contributions of Färe et al. (1994) and Primont (1993) we are considering here the role of risk via loan loss provisions. Therefore, we have that $npl_j \in \mathbb{R}_+^O$ is the amount of non-performing loans for bank j, $o = 1, \ldots, O$, and $p_{jo} \in \mathbb{R}_+^O$ will be their prices.

As a second step, we will re-run the previous variable profit maximization model (3), but

since the former would be adopting an industry perspective (i.e., each bank is compared with the rest of the banks in the sample), whereas the latter implies being compared only with the bank itself and therefore would be focusing on income smoothing.

replacing the variables subject to manipulation with their estimated values:

$$
\begin{aligned}
&\Pi^{\text{not manip}}\left(r_{jm}, p_{jn}, \tilde{p}_{jo}\right)\\
&= \max_{(z,u_m,x_v,npl_o)} \left(\sum_{m=1}^{M} r_{jm}u_m - \sum_{v=1}^{V} p_{jv}x_v - \sum_{o=1}^{O} \tilde{p}_{jo}\widetilde{npl}_o\right)\\
&\text{s.t.}\\
&\sum_{j=1}^{J} z_j u_{jm} \geq u_m, \qquad m = 1, \ldots, M,\\
&\sum_{j=1}^{J} z_j x_{jv} \leq x_v, \qquad v = 1, \ldots, V,\\
&\sum_{j=1}^{J} z_j x_{jf} \leq x_{jf}, \qquad f = 1, \ldots, F,\\
&\sum_{j=1}^{J} z_j \widetilde{npl}_{j,o} \leq \widetilde{npl}_o, \qquad o = 1, \ldots, O,\\
&\sum_{j=1}^{J} z_j = 1,\\
&z_j = [0,1].
\end{aligned}
\tag{4}
$$

Obviously, $\Pi^{\text{not manip}}\left(r_j m, p_{jv}, \tilde{p}_{jo}\right)$ will provide a more objective profit target for each bank, as profits generated by **earnings manipulation** are controlled for in this second program.

The problem of programs (3) and (4) is that potential *outputs* and *inputs* are estimated in order to maximize profits for the unit under analysis, keeping constant the corresponding output and input prices. This assumption is equivalent to considering that prices are determined in competitive markets, so that firms cannot implement any strategy to influence market prices, or that local markets can absorb any level of output without any change in output prices. This assumption can be strong in the Spanish banking industry, where recent studies have been analyzing whether market power exists (see, for instance Maudos and Pérez, 2003; Maudos and Fernández de Guevara, 2007; Salas and Saurina, 2003). From the theoretical point of view, in the efficiency literature there are also contributions indicating the problems caused by setting prices in non-fully competitive settings (Camanho and Dyson, 2006; Portela and Thanassoulis, 2014; Portela, 2014; Tone, 2002; Tone and Tsutsui, 2007).

To confirm with our data the extent to which banks are oriented towards the maximization of profits in an imperfect competition setting, we followed the Monopolist Axiom of Profits Maximization (proposed by Varian, 1984) and, more specifically, the condition of downward sloping demand function:

$$(r_i - r_j).(u_i - u_j) \leq 0 \tag{5}$$

After estimating expression (5) for all possible combinations of output quantities and prices for each unit/year, the results indicated that for more than 89% of the possible comparisons, the condition was not met—i.e., the sign was negative. This might constitute evidence supporting the existence of market power, as previously found by Maudos and Pérez (2003). This would imply that we cannot artificially deal with quantities and prices separately, meaning that the two previous programs oriented towards the estimation of the profit frontier are not applicable.

One way to overcome this limitation can be to make the profit function to be dependent on the total revenues minus costs as in the following expression:

$$\begin{aligned}\Pi &= \text{Revenues} - \text{Operating costs} - \text{Loan loss provisions} \\ &= \sum_{m=1}^{M} R_m - \sum_{v=1}^{V} VC_v - \sum_{o=1}^{O} LLP_o\end{aligned} \tag{6}$$

where $R_m = r_m u_m$, $VC_v = p_v x_v$ and $LLP_o = p_o npl_o$.

This serves to define a profit frontier program depending on the revenues and the costs by combining feasible amounts of quantities and prices.

First we consider **model 0**, also referred to as the **unconstrained variable profit model**, which is defined as follows:

$$\begin{array}{ll} \Pi^0\left(FC_{jf}\right) = \max_{(z,R_m,VC_v,LLP_o)} \sum_{m=1}^{M} R_m - \sum_{v=1}^{V} VC_v - \sum_{o=1}^{O} LLP_o & \\ \text{s.t.} & \\ \sum_{j=1}^{J} z_j R_{jm} \geq R_m, & m = 1, \ldots, M, \\ \sum_{j=1}^{J} z_j VC_{jv} \leq VC_v, & v = 1, \ldots, V, \\ \sum_{j=1}^{J} z_j FC_{jf} \leq FC_{jf}, & f = 1, \ldots, F, \\ \sum_{j=1}^{J} z_j LLP_{jo} \leq LLP_o, & o = 1, \ldots, O, \\ \sum_{j=1}^{J} z_j = 1, & \\ z_j = [0,1]. & \end{array} \tag{7}$$

From the optimal solution of this program, we can obtain the optimal revenues (R_m^* and, subsequently, the optimal values of output prices $r_m^* = \sum_{j=1}^{J} z_j^* r_{jm}$ and physical outputs $u_m^* = \sum_{j=1}^{J} z_j^* u_{jm}$), the optimal values of variable costs (VC_v^* and, subsequently, the optimal values of variable input prices $p_v^* = \sum_{j=1}^{J} z_j^* p_{jv}$ and physical variable inputs $x_v^* = \sum_{j=1}^{J} z_j^* x_{jv}$), the optimal values for the loan loss provisions (LLP_o^* and, subsequently, the optimal values of loss recognition $p_o^* = \sum_{j=1}^{J} z_j^* p_{jo}$).

In the second stage, we consider the **constrained model 1**. Compared with the **unconstrained model 0**, in model 1 banking firms are price-acceptant and can influence quantities only. We will refer to this as the **price-constrained variable profit model**, according to which we will have that:

$$
\begin{array}{ll}
\Pi^1 \left(r_{jm}, p_{jv}, p_{jf}, p_{jo}, x_{jf}\right) & \\
= \max_{(z,u_m,x_v)} \left(\sum_{m=1}^{M} r_{jm}u_m - \sum_{v=1}^{V} p_{jv}x_v - \sum_{o=1}^{O} p_{jo}npl_o\right) & \\
\text{s.t.} & \\
\sum_{j=1}^{J} z_j u_{jm} \geq u_m, & m= 1, \ldots, M, \\
\sum_{j=1}^{J} z_j r_{jm} = r_{jm}, & m= 1, \ldots, M, \\
\sum_{j=1}^{J} z_j x_{jv} \leq x_v, & v= 1, \ldots, V, \\
\sum_{j=1}^{J} z_j p_{jv} = p_{jv}, & v= 1, \ldots, V, \\
\sum_{j=1}^{J} z_j x_{jf} \leq x_{jf}, & f= 1, \ldots, F, \\
\sum_{j=1}^{J} z_j npl_{jo} \leq npl_o, & o = 1, \ldots, O, \\
\sum_{j=1}^{J} z_j p_{jo} = p_{jo}, & o = 1, \ldots, O, \\
\sum_{j=1}^{J} z_j = 1, & \\
z_j = [0, 1]. &
\end{array}
\tag{8}
$$

Finally, we can also have **model 2**, which we refer to as the **quantity-constrained variable profit model**, which assumes that banks can influence output and input prices but not quantities, according to which:

$$
\begin{array}{ll}
\Pi^2 \left(u_{jm}, x_{jv}, x_{jf}, npl_{jo}\right) = & \\
= \max_{(z,r_m,p_v,p_o,)} \left(\sum_{m=1}^{M} r_m u_{jm} - \sum_{v=1}^{V} p_v x_{jv} - \sum_{o=1}^{O} p_o npl_{jo}\right) & \\
\text{s.t.} & \\
\sum_{j=1}^{J} z_j u_{jm} = u_{jm}, & m= 1, \ldots, M, \\
\sum_{j=1}^{J} z_j r_{jm} \geq r_m, & m= 1, \ldots, M, \\
\sum_{j=1}^{J} z_j x_{jv} = x_{jv}, & v= 1, \ldots, V, \\
\sum_{j=1}^{J} z_j p_{jv} \leq p_v, & v= 1, \ldots, V, \\
\sum_{j=1}^{J} z_j x_{jf} \leq x_{jf}, & f= 1, \ldots, F, \\
\sum_{j=1}^{J} z_j npl_{jo} = npl_o, & o = 1, \ldots, O, \\
\sum_{j=1}^{J} z_j p_{jo} \leq p_o, & o = 1, \ldots, O, \\
\sum_{j=1}^{J} z_j = 1, & \\
z_j = [0, 1]. &
\end{array}
\tag{9}
$$

Figure **??** illustrates the three models defined above to synthesize the characteristics of the proposed evaluation process. As can be seen, model 0 (unconstrained profit model) tries to maximize profits by estimating of the optimal level of revenues and operating costs, constrained not to have more fixed inputs than the observed values. This means that to remedy the inefficiencies found, inefficient banks should try to introduce modifications both to the outputs and operating inputs side as well as to the output and to the operating input prices. Reducing the options available, assuming that output and input prices are negotiated on competitive markets, model 1 estimates the profit inefficiency due to suboptimal levels in the outputs and the operating inputs, keeping the respective prices constant.

By definition, this will produce a smaller level of inefficiency than model 0 or, put the other way round, the differences between models 0 and 1 are due to rigidity on the prices side. One can compare model 1 (price-constrained profit model) with the standard programs of technical efficiency because, at the end of the day, both programs orient their assessment to the consideration of quantities. If this is true, model 1 will always have a better impact on profits than DEA models, as the radial increase (decrease) in outputs (inputs) does not signify that their movement should mechanically improve the level of potential profits. In contrast, our proposed model 1 allows to change the output and input mixes in order to improve profits.

From another perspective, model 2 (quantity-constrained profit model) estimates the profit frontier trying to optimize the corresponding output and operating input prices, given the observed levels of outputs and operating inputs. This is the case when, for instance, local markets restrict levels of activity once a certain limit is reached. In these circumstances, managers should orient their strategy to find the optimal levels of output and input prices (and the optimal level of financial risk) that allow the bank to improve its net profits. As a result of this, the differences between model 0 and model 2 are due to rigidity in the level of activity; in these circumstances, when the activity level is not a controlled variable, the consideration of prices and the risk assumed can drive increases in the level of profitability.

4. Econometric model

As indicated above, this chapter investigates the links between banks' inefficiency and their borrowing firms' characteristics, considering the three main hypotheses presented in the previous section.

Regarding the first of the hypotheses (**Hypothesis 1**), related to the performance of firms' lenders, two types of analyses are considered. The first one (**Hypothesis 1a**) considers bank profit efficiency and an *ex ante* risk taking behavior. The firm Z-score is the proxy for the *ex ante* risk, and it is calculated with data from the period before the bank issues the credit. For this, I estimate the following model via OLS:

$$Z_{ij} = \beta_0 + \beta_1 X_{ij}^F + \beta_2 X_{ij}^B + \beta_3 X_{ij}^I + \varepsilon_{ij} \tag{10}$$

where i and j are subscripts corresponding to firm i and bank j, respectively, Z_{ij} is the Z-score, X_{ij}^F are firm-specific variables, X_{ij}^B are bank-specific variables, X_{ij}^I are the bank profit inefficiency variables defined in Chapter **??**, and ε is the i.i.d. error term.

In the second analysis of the first hypothesis (**Hypothesis 1b**), I consider *ex post* risk. The econometric approach to test for this type of risk relies on a logit model of borrower defaults. In this case, the dependent variable is $BANKRUPT$, which equals one if a firm defaults and zero otherwise:

$$BANKRUPT_{ij} = \beta_0 + \beta_1 X_{ij}^F + \beta_2 X_{ij}^B + \beta_3 X_{ij}^I + \varepsilon_{ij} \tag{11}$$

Seven different models are tested when running the regressions corresponding to both Equation (10) and (11). For the first four models, the bank inefficiency is measured considering the variable B_INEF_ROA, which corresponds to the manipulated earnings model of Chapter **??**. This type of inefficiency includes loan loss provisions in the estimation, implying that we are controlling for risk. A univariate analysis is considered, and then we include sequentially firms' control variables (X_{ij}^F, Model (2)), banks' control variables (X_{ij}^B, Model (3)), as well as both types of variables simultaneously (X_{ij}^F and X_{ij}^B, Model (4)). The fifth and sixth models change the measurement of inefficiency. For the fifth model (Model (5)) I consider $B\_INEF\_ROA\_CS$, corresponding to the non-manipulated short-run model of Chapter **??**, and for the sixth (Model (6)) I consider $B\_INEF\_ROA\_TS$, corresponding to the non-manipulated long-run model of Chapter **??**. Finally, in Model (7) two additional variables are included in order to differentiate the effects of commercial banks from savings banks (these would be also bank-specific variables, X_{ij}^B).

Regarding the second hypothesis (**Hypothesis 2**), related to the interest rates' charges, the objective is to test both if inefficient banks charge higher interest rates and if they lend to firms with more capacity to pledge collateral. The dependent variables are, initially, interest rates paid by the firm (F_INT) and, in a second stage, an inverse measure of the ability of the firm to pledge collateral (F_INV_COLLAT). Both types of control variables (firms' and banks') are included in the different regressions. Similarly to the models featured above, I also consider different models for each type of efficiency measurement (Models (1)–(6)), as well as two additional variables to test if results are different from commercial banks or savings banks (Models (7)–(8)). The models considered are as follows:

$$F\_INT_{ij} = \beta_0 + \beta_1 X_{ij}^F + \beta_2 X_{ij}^B + \beta_3 X_{ij}^I + \varepsilon_{ij} \tag{12}$$

$$F\_INV\_COLLAT_{ij} = \beta_0 + \beta_1 X^F_{ij} + \beta_2 X^B_{ij} + \beta_3 X^I_{ij} + \varepsilon_{ij} \tag{13}$$

The third hypothesis (**Hypothesis 3**), related to savings banks' different expansion strategies, attempts to disentangle if savings banks' behavior in their home markets differs from that in the new markets. Four different models are estimated. The first two (Models (1) and (2)) consider as dependent variable the F_ZSCORE in home markets and, in a second stage, in new markets (Models (3) and (4)). Models (1) and (3) take into account firms' interest as dependent variable (F_INT), whereas Models (2) and (4) consider our inverse measure of the ability of firms to pledge collateral (F_INV_COLLAT). All the regressions include in the analysis two variables of the firm, i.e. the number of bank relationships (lagged), F_BANK_REL, and the year of firms' registration (F_REGIS). And four bank variables are also included, the bank loan to total asset ratio (B_LOANTA), bank equity to total assets ratio (B_EQTA), bank deposits to total assets ratio (B_DEPTA), and the profit inefficiency (with total loan loss provisions, B_INEF_ROA). All models include year and industry fixed effects.

$$F\_ZSCORE_{ij} = \beta_0 + \beta_1 X^F_{ij} + \beta_2 X^B_{ij} + \beta_3 X^I_{ij} + \varepsilon_{ij} \tag{14}$$

$$F\_INT_{ij} = \beta_0 + \beta_1 X^F_{ij} + \beta_2 X^B_{ij} + \beta_3 X^I_{ij} + \varepsilon_{ij} \tag{15}$$

5. Data and variables

In this chapter, the information does not entirely coincide with the information considered in previous chapters, since we have collect not only information for Spanish banking firms but also on Spanish non-financial firms, in order to create a single database at the business-bank-year level. This will enable modeling the relationship between the lending banks and their potential borrowers—i.e., new loan applicants.

Data from non-financial firms come from the SABI database (*Sistema de Análisis de Balances Ibéricos*), which is based on the commercial public registry in Spain. It contains accounting data and banking information of 42,617 non-financial firms for the 1997–2009 period. All accounting variables (balance sheet and profit and loss account) refer to the year before the start of the new banking relationship. Table 1 presents the summary statistics for the non-financial firms in the database, reporting information on firms' size, liquidity, productivity and firm-bank relationship.

Data on banking firms report financial statements, as well as information on savings banks' home markets. Information for commercial banks is provided by the Spanish association for banking (AEB, *Asociación Española de Banca*), whereas that for savings banks is provided by the Spanish confederation of savings banks (CECA, *Confederación Española de Cajas de Ahorros*). Table 2 provides accounting information on 51 financial institutions, both commercial banks and savings banks.

5.1. Data on banking firms

Apart from bank inefficiency, I consider bank control variables as well. These include the deposit to total assets ratio (B_DEPTA) as well as the loans to total assets ratio (B_LOANTA). As indicated by Keeley (1990), these two balance sheet variables reflect the notion that market power exists for both deposit and loan markets.

I also include equity to total asset ratio (B_EQTA), since a high capital ratio might suggest a highly risky loan portfolio (Casu and Girardone, 2006). Salas and Saurina (2003) found that banks with lower capital tended to operate with higher levels of credit risk in line with the moral hazard hypothesis. And, to control differences between commercial banks and savings banks I include a dummy variable which equals one if the lender is a commercial bank and zero otherwise, CB, as well as the product of CB and B_INEF_ROA, i.e. CB_INEF_ROA.

5.2. Data on non-financial firms

I also consider variables at the firm level, namely, the year of firm's registration (F_REGIS), the number of bank relationships of the non-financial firm ($F\_BANKREL$), when many banks lend to the same borrower, the "soft" information is much more diluted. I also include F_INV_COLLAT, which is the inverse measure of the ability of the firm to pledge collateral, measured as the ratio of total bank debt to non-current assets, as well as F_ZSCORE, corresponding to the lagged Altman Z-score formula for predicting bankruptcy; it is a broader concept than that of firm inefficiency or firm profitability. The last two variables on non-financial firms are F_INT, representing firms' interest rates, and $BANKRUPT$, which is a dummy variable that equals one if a firm defaults and zero otherwise. Stiglitz and Weiss (1981) show that higher interest rates induce firms to undertake projects with lower probability of success.

6. Results

This section presents evidence on the relationship of bank profit efficiency risk taken when choosing the borrowing firms (non-financial). For this purpose, three different scenarios are compared. The results are presented in Tables 3, 4, 5 and 6.

Hypothesis 1: The most inefficient banks are more risky when selecting their borrowers

Hypothesis 1a: The most inefficient banks will lend to less profitable or more inefficient firms

The first part of the first hypothesis tests if the most inefficient banks will lend to less profitable or efficient firms. The results of estimating Equation (10) are shown in Table 3 and represent the link of firms' Z-scores (F_ZSCORE), lagged, with respect to their lenders' profit efficiency levels. The F_ZSCORE variable is Altman's Z-score bankruptcy predictor, and it is used as a proxy for firms' financial distress.

In the first column of Table 3 (Model (1)) we can see the results of the regression when including as an independent variable only bank profit inefficiency. The results show a statistically significant correlation between F_ZSCORE and B_INEF_ROA (bank profit inefficiency including total loan loss provisions). The negative sign corroborates the first hypothesis, which states that the most inefficient banks will lend to less profitable firms. In other words, the most inefficient banks, despite being aware of the relative insolvency of its client, will grant the loan. Although the explanations might be multifaceted, they might possibly try to offset their lack of profit efficiency by increasing the number of customers. This increase in the number of customers would be partly achieved by relaxing the requirements when it comes to lending (Foos et al., 2010).

The second regression (second column in Table 3, Model (2)) adds two regressors related to the borrowing firms, namely, the age of the company (F_REGIS) and the number of lending banks each company has (F_BANK_REL). Results show a statistically significant effect of the three variables the firms' Z_SCORE. The signs of the relationship are negative, implying that the least profitable firms have less bank lenders, are younger, and borrow from the most inefficient banks. If a given firm has company has worse financial performance, there will be fewer banks willing to grant them loans. As indicated by Diamond (1991), companies in continuous existence for longer periods have already shown they can survive the difficulties in the early stages of their business life. Cole (1998) finds evidence that firms receiving loans are older and more profitable. However, the B_INEF_ROA variable is the one with a highest coefficient and, therefore, it is the most important variable for the least profitable companies.

The third regression (third column in Table 3, Model (3)) consider bank-related variables, instead of firm-related variables. The variables which are taken into account are B_INEF_ROA, B_LOANTA (bank loan to total assets ratio), B_EQTA (bank equity to total assets ratio) and B_DEPTA (total deposits as a share of total assets). In this case, only the B_INEF_ROA and B_LOANTA variables are statistically significant, and their effect is negative. This would indicate that banks with a higher share of loans to total assets are the one lending to the riskiest firms. This result would be in line with those of Foos et al. (2010), who found that the credit growth contributes to increasing bank risk. Again, the variable representing lender's inefficiency, with a coefficient of –1.7838, is the one with the greatest impact on the economic situation of the firm.

The fourth regression (fourth column in Table 3, Model (4)) considers both types of variables—i.e. related to both non-financial firms and banks. All variables are significant and with a negative sign, except B_DEPTA, which remains non significant. The B_LOANTA variable loses significance with respect to Model (3). However, the B_EQTA, related to banks' insolvency, is now significant—although only at the 10% significance level, i.e., banks' insolvency levels do influence on their borrowers' probability of bankruptcy.

Models (5) and (6) (fifth and sixth column in Table 3) only differ from those in Model (4) in way to measure bank inefficiency. Model (5) uses the $B\_INEF\_ROA\_CS$ variable, i.e. bank profit inefficiency with expected loan loss provisions based on year cross-section regressions. Results are similar, and the main differences are, first, that the B_EQTA variable improves the level of significance from 10% to 5% and, in addition, that the coefficient corresponding to bank inefficiency increases (in absolute terms) from –1.3365 to –1.5225. The measure of the inefficiency of banks in Model (6) is $B\_INEF\_ROA\_TS$, bank profit inefficiency with expected loan loss provisions based on bank time-series regressions, and results do not show significant differences with respect to Model (5).

For Model (7) (seventh column in Table 3) include two additional variables, CB_INEF and $COMM\_BANK$, in order to check for differences between savings banks and commercial banks. Results indicate that the B_INEF_ROA variable is not statistically significant. It can be concluded that the relationship between bank inefficiency and their borrowing firms' low profitability levels is independent from the type of bank—either commercial banks or savings banks.

All these results indicate that bank profit inefficiency reflect that they are taking an *ex ante* risk, measuring risk as the lagged Z-score of the borrowing firms. It is therefore possible to tentatively conclude that less efficient banks will grant loans to less profitable firms.

Hypothesis 1b: Those firms that obtain credits from inefficient banks have more probability of going bankrupt

The second part of the first hypothesis refers to an *ex post* risk, testing specifically whether the most inefficient banks obtain a higher number of customers in bankruptcy. Table 4 presents the results of estimating Equation (12) and, similarly to Table 3, it presents seven different models to analyze the relationship between banks' inefficiency and firms' (clients) bankruptcy.

In Model (1) (first column of Table 4) the independent variable is B_INEF_ROA. Results show that this variable is statistically significant, and has a positive sign. Therefore, Hypothesis 1.b, according to which the most inefficient banks have a higher number of borrowing firms in bankruptcy, is corroborated.

Model (2) (second column in Table 4) includes the variables specific to banks, B_LOANTA, B_EQTA and B_DEPTA. Results show that B_LOANTA, B_EQTA and B_INEF_ROA variables are statistically significant. Regarding their sign, in the case of B_EQTA it is negative, whereas in the other two cases it is positive. Therefore, we can state again that the most inefficient banks have more customers in bankruptcy. In contrast, banks with a higher proportion of loans with lower solvency levels have also more bankruptcies among their borrowers. However, the fact that banks have a higher proportion of deposits does not affect the number of bankruptcies of their borrowing firms, since the B_DEPTA variable is not significant.

Model (3) (third column in Table Table 4) includes also variables relative to borrowing firms—F_REGIS and F_BANK_REL. The three variables (not only F_REGIS and F_BANK_REL but also B_INEF_ROA) are statistically significant, with a positive sign, implying that the higher the inefficiency of the lending bank (B_INEF_ROA), the higher the age of the borrowing firm (F_REGIS), and the higher the number of banking relationships (F_BANK_REL) the borrowing firm has, the greater the probability of bankruptcy.

Model (4) (fourth column in Table 4) takes into account both types of variables—i.e. both related to banks and non-financial firms. Results show that all the variables are statistically significant, although B_EQTA is significant only at the 10% level. The signs are positive for all variables except for B_EQTA and B_DEPTA. Therefore, we can claim that the higher the number of banking relationships (F_BANK_REL), the higher the years of experience firms' have (F_REGIS), the higher the proportion of loans of the lending bank (B_LOANTA), the lower the capital ratio (B_EQTA), the lower the volume of deposits as a share of total assets (B_DEPTA), and the more inefficient the lending bank is (B_INEF_ROA), the higher the probability of bankruptcy of the borrowing firm ($BANKRUPT$).

Model (5) and (6) (fifth and sixth columns in Table 4) consider different measures of bank inefficiency. Model (5) considers the variable $B\_INEF\_ROA\_CS$, whereas Model (6) considers $B\_INEF\_ROA\_TS$. However, results are virtually identical to those corresponding to model four model, and the interpretation should be the same as well.

Model (7) (column seven of Table 4) includes two additional variables. First, a dummy (CB) indicating whether the lender is a commercial bank or not. Second, the variable CB_INEF (resulting of multiplying B_INEF_ROA and $COMM\_BANK$). These two variables are intended to determine whether there is any connection with the fact that the lender is a commercial bank or not. The main difference with model four is that B_EQTA, which represents the capital ratio corresponding to the lending bank, increases its level of significance, and the impact of the variable representing inefficiency (B_INE_ROA) lender is now lower (from 6.0942 to 4.8671). The two new variables added, CB and CB_INEF are not statistically significant.

These results of the first hypothesis are in line with the "bad management" hypothesis (Berger and DeYoung, 1997; Williams, 2004), although both studies take into account only *ex post* measure of risk, which is related to loans (not to the profitability levels of the borrowing firms). But the conclusion is that, in the case of Spanish savings banks and commercial banks, I have also found empirical evidence that the most inefficient banks are also those who take more risks.

Hypothesis 2: The interest rates charged by the most inefficient banks are higher, due to their risk taking behavior

The second hypothesis tests firstly if the most inefficient banks, because of being more risky, charge higher interest rates and, secondly, if they lend to companies with less collateral. Table 5 presents the results of estimating Equations (12) and (13).

To test this hypothesis eight different models are used. The dependent variable in the first model (Model (1), column 1 in Table 5) is F_INT (interest rate paid by firms), and the independent variables are $F\_BANKREL$, F_REGIS, B_LOANTA, B_EQTA, B_DEPTA and B_INEF_ROA. Results are statistically significant for $F\_BANKREL$, F_REGIS and B_LOANTA variables, with a negative sign for the first two. This would imply that the interest rate paid by firms is determined by fewer banking relationships, less years of existence, as well as a higher loans' ratio from the lending bank.

Regarding the number of banking relationships, it can be considered that there are firms with less access to credit and, following Stiglitz and Weiss (1981) or Petersen and Rajan (1994), it may be considered these are riskier firms which are willing to pay higher interest rates. With respect to the firms' years of existence (F_REGIS), Boot and Thakor (1994) show that, during their early years of existence, firms must pay higher interest rates. However, as time passes and they become economically viable, they are charged with lower interest rates. Furthermore, Demirgüç-Kunt and Huizinga (1999) find empirical evidence that the share of loans to total assets for banks is one of the main determinants of net margins from interest rates.

Model (2) (column 2 in Table 5) differs from Model (1) in the dependent variable, which is now F_INV_COLLAT (i.e. the ratio of total bank debt to non-current assets). As noted by Berger and Udell (1995), most of the empirical literature on collateral considers it is related to riskier borrowers and riskier loans. However, our proposal differs from others in how to estimate the variable related to the collateral. In this specific case it is an inverse measure of the ability of firms' to pledge collateral. Results are statistically significant for $F\_BANKREL$, F_REGIS and B_EQTA, with positive sign for the first two variables and negative for the third. These results would imply that the borrowing firms can pledge less collateral (and, therefore, bears more risk) has more bank relationships, is older, and the bank lender a lower capital ratio. In this case, again, the inefficiency of the lending bank is not related to the collateral of the borrowing firms.

Model (3) (column 3 in Table 5) considers as the dependent variable F_INT, and as bank inefficiency measure $B\_INEF\_ROA\_CS$. In this case, similarly to the first model, $F\_BANKREL$, F_REGIS and F_LOANTA are statistically significant, and with the same sign as in the first model. However, the measure of inefficiency, $B\_INEF\_ROA\_CS$ is also statistically significant, albeit with a significance of only 10%, and with a positive sign. Therefore, it can be argued that the interest rate paid by firms is conditioned by the inefficiency of the lending bank—the higher the banks' inefficiency, the higher interest rates they charge.

Model (4) (column 4 in Table 5) considers as the dependent variable F_INV_COLLAT, and results do not differ from those yielded by the Model (2).

Model (5) (column 5 in Table 5) uses F_INT as dependent variable, and the measure of inefficiency is $B\_INEF\_ROA\_TS$. Results are similar to those yielded by Model (3), since inefficiency is statistically significant—although only at the 10% level.

In Model (6) (column 6 in Table 5) the dependent variable is F_INV_COLLAT, and the measure of inefficiency is $B\_INEF\_ROA\_TS$. Results are similar to those corresponding to Models (4) and (2).

The last two models (Models (7) and (8), corresponding to columns 7 and 8 in Table 5) used as a measure of inefficiency the B_INEF_ROA variable, adding also the CB and CB_INEF_ROA variables. The results for Model (7) show that $F\_BANKREL$, F_REGIS, B_LOANTA and CB_INEF_ROA variables are statistically significant, although the last one with a low significance level. The sign is negative for the first two variables, and positive for the second two. Therefore, we may tentatively conclude that the interest rate paid by a firm is determined by fewer banking relationships ($F\_BANKREL$), fewer years of experience (F_REGIS), and a higher share of loans in the lending bank (B_LOANTA). These results are the same as those obtained with Model (1) but, in addition, they are conditioned by the inefficiency of commercial banks.

Model (8) differs from Model (7) on the dependent variable. In this model the dependent variable is F_INV_COLLAT. Results are similar to those corresponding to Model (2), i.e. they are statistically significant for $F\_BANKREL$, F_REGIS and B_EQTA. In addition, in this case the B_INEF_ROA variable is statistically significant and negative, whereas B_INEF_ROA is statistically significant and with positive sign. Therefore, it may be considered that the firms' ability to pledge collateral is conditioned by a higher number of bank relationships ($F\_BANKREL$), more years of experience (F_REGIS), less capital ratio (as a share of the lending bank's total assets, B_EQTA) and, especially, higher lending bank's efficiency (B_INEF_ROA)—particularly if the lender if a savings bank (CB_INEF_ROA).

A positive relationship of inefficiency with F_INV_COLLAT indicates that the most inefficient banks lend to firms with relatively less ability to pledge collateral, which contributes to increase credit risk. Jiménez and Saurina (2004) find empirical evidence for the Spanish case that loans with higher levels of collateral are more likely to default.

Hypothesis 3: The inefficiency of the savings banks will affect the type of borrowers depending on whether they are located in the savings bank's home or new markets

The third and last of the hypothesis considers if Spanish savings banks behave differently depending on whether they operate in their home markets or new markets. Table 6 reports the results corresponding to estimating Equations (14) and (15). The results corresponding to Equation (14), which considers whether banks' inefficiency influences the probability of bankruptcy of borrowing firms taking into account lenders' location. These results are presented in columns 1 and 2 (Models (1) and (2)) of Table 6.

Model (1) (column 1 in Table 6) considers as dependent variable the F_ZSCORE, and focuses on firms located in the same region of origin as the savings banks' lenders. Results are statistically significant for $F\_BANKREL$, F_REGIS and F_DEPTA, the first two with negative sign. Therefore, it could be argued that for firms located in the same region as the lending savings bank, the probability of bankruptcy depends on having more bank relationships ($F\_BANKREL$), being an older borrowing firm (F_REGIS), and that the lending savings bank has a lower ratio of deposits (B_DEPTA). However, the inefficiency of the savings banks is not significant in the home markets (B_INEF_ROA).

Model (2) (column 2 in Table 6) also considered as dependent variable F_ZSCORE, but in this case I refer to borrowing firms which savings banks classify as located in new markets—i.e. they are outside their home markets. Results indicate that the variables influencing on the probability of bankruptcy for these firms are $F\_BANKREL$, F_REGIS, B_EQTA and B_INEF_ROA; among them, only B_EQTA has a positive sign. Therefore, it may be considered that the probability of bankruptcy for these firms is determined by having more bank relationships ($F\_BANKREL$), being older (F_REGIS), and because lending savings banks have a lower capital ratio (B_EQTA) and are more inefficient (B_INEF_ROA). These results would corroborate hypothesis 3.a, since the probability of a firm to go bankrupt depends on the inefficiency of lending savings banks when they are located in new markets.

The results of estimating Equation (15) check whether savings banks' inefficiency will influence the interest rates paid by borrowing firms according to their location; these results are reported in columns 3 and 4 of Table 6.

The results for Model (3) (column 3 in Table 6) suggest that, for borrowing firms located in savings banks' home markets, the interest rates paid (as a share of total bank debt) depend on savings banks' ratio of loans on total assets (B_LOANTA), their capital ratio (on total assets, B_EQTA), and their inefficiency (B_INEF_ROA). Inefficient savings banks, therefore, might be increasing the interest rates charged because of their market power in home markets.

Regarding borrowing firms in new markets, results differ remarkably. Results for Model (4) (column 4 of Table 6) show that the interest paid by firms depends positively on their number of banking relationships ($F\_BANKREL$) and their age (F_REGIS), and negatively on the ratio of capital (on total assets, B_EQTA) of the lending savings bank as well as its inefficiency level (B_INEF_ROA). In conclusion, the efficiency of the lending savings banks will influence on the interest rates paid by their borrowers.

The results of estimating Equation (15) confirm Hypothesis 3.b, and are in line with other studies that have found empirical evidence on the differing behavior of savings banks according to the markets in which they are operating (Illueca et al., 2014).

7. Conclusions

As indicated throughout this the previous chapters, the issue of efficiency in banking has been investigated for a long time now (over twenty years) and, after the international financial crisis started, it has regained momentum, especially in those banking systems most affected by the crisis. Obviously, the issue of the risk taken by banks has been central to the crisis and, therefore, it deserves a detailed analysis. Therefore, in this chapter I extend the bank efficiency analyses of the previous ones factoring in banks' risk taking behavior, i.e. how several firms' characteristics, especially in terms of creditworthiness, are related to banks' efficiency.

Some recent research initiatives have emphasized the importance of the relationship between banks and the borrowing firms including, among others, Chong et al. (2013), who model the links between market concentration in banking and financing constrains, or Cotugno et al. (2013), who focus on the general question of firms' credit availability during the financial crisis. The research conducted in this chapter differs from previous contributions in that I attempt to model explicitly the links between the financial situation of the borrowing firms and the risk taken by banks, and how banks' efficiency affects this link.

For conducting the analysis I establish three hypotheses to be tested, namely: (i) whether the most inefficient banks are riskier when selecting their borrowers (which I further decompose in two additional hypotheses, namely, if the most inefficient banks will lend to less profitable or more inefficient firms, and if those firms that obtain credits from inefficient banks have more probability of going bankrupt); (ii) if the interest rates charged by the most inefficient banks are higher, due to their risk taking behavior; (iii) if the inefficiency of the savings banks will affect the type of borrowers depending on whether they are located in the savings bank's home markets or new markets. Testing these hypotheses requires extending the database on Spanish banks to data on their borrowing firms and some of their characteristics, including the year in which the firm was created, the number of bank relationships it has, its ability to pledge collateral, the probability of bankruptcy, the interest rates it is being charged or whether it actually went bankrupt.

The results suggest that there is actually a relationship between bank profit inefficiency and the risk taken by the banks when lending to the firms. Specifically, I find that more inefficient banks lent to the worst performance firms. Moreover, this high risk-taking behavior is not offset by higher interest rates. When considering collateral, there is not evidence about the relationship between the bank inefficiency and the firms that can pledge less collateral, but this link exists when the analysis is made to commercial banks and savings banks separately.

The last hypothesis, which applies to savings banks only, to test if their behavior is different in home markets than in new markets shows that the most efficient savings banks have and *ex-ante* risk in the new markets, and charge higher interest rates. In contrast, most inefficient savings banks charge higher interest rates in home markets. These results could constitute evidence of the savings banks' market power in their home markets, especially during the years that preceded the financial crisis.

References

Beatty, A. and Harris, D. G. (1999). The effects of taxes, agency costs and information asymmetry on earnings management: A comparison of public and private firms. *Review of Accounting Studies*, 4(3):299–326.

Beatty, A. L., Ke, B., and Petroni, K. R. (2002). Earnings management to avoid earnings declines across publicly and privately held banks. *The Accounting Review*, 77(3):547–570.

Beaver, W. H. and Engel, E. E. (1996). Discretionary behavior with respect to allowances for loan losses and the behavior of security prices. *Journal of Accounting and Economics*, 22(1):177–206.

Berger, A. and DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, 21(6):849–870.

Berger, A. N. and Udell, G. F. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, 25(1):21–42.

Berger, A. N. and Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of business*, pages 351–381.

Berger, A. N. and Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, 112(477):F32–F53.

Boot, A. W. and Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, pages 899–920.

Boyd, J. H. and Hakenes, H. (2014). Looting and risk shifting in banking crises. *Journal of Economic Theory*, 149:43–64.

Camanho, A. S. and Dyson, R. G. (2006). Data Envelopment Analysis and Malmquist indices for measuring group performance. *Journal of Productivity Analysis*, 26(1):35–49.

Carbó-Valverde, S., Marques-Ibanez, D., and Rodríguez-Fernández, F. (2012). Securitization, risk-transferring and financial instability: The case of Spain. *Journal of International Money and Finance*, 31(1):80–101.

Casu, B. and Girardone, C. (2006). Bank competition, concentration and efficiency in the Single European Market. *The Manchester School*, 74(4):441–468.

Chong, T. T. L., Lu, L., and Ongena, S. (2013). Does banking competition alleviate or worsen credit constraints faced by small- and medium-sized enterprises? Evidence from China. *Journal of Banking & Finance*, 37(9):3412–3424.

Chortareas, G., Girardone, C., and Ventouri, A. (2011). Financial frictions, bank efficiency and risk: Evidence from the eurozone. *Journal of Business Finance and Accounting*, 38:259–287.

Cole, R. A. (1998). The importance of relationships to the availability of credit. *Journal of Banking & Finance*, 22(6â8):959 – 977.

Cotugno, M., Monferrà, S., and Sampagnaro, G. (2013). Relationship lending, hierarchical distance and credit tightening: Evidence from the financial crisis. *Journal of Banking & Finance*, 37(5):1372–1385.

Dechow, P. M. and Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review*, 77:35–59.

Dechow, P. M., Ge, W., and Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics*, 50(2):344–401.

Dell'Ariccia, G., Laeven, L., and Marquez, R. (2014). Real interest rates, leverage, and bank risk-taking. *Journal of Economic Theory*, 149:65–99.

Demirgüç-Kunt, A. and Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *The World Bank Economic Review*, 13(2):379–408.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of political Economy*, 99(4):689–721.

Fiordelisi, F., Marqués-Ibáñez, D., and Molyneux, P. (2011). Efficiency and risk in European banking. *Journal of Banking & Finance*, 35(5):1315–1326.

Foos, D., Norden, L., and Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance*, 34(12):2929–2940.

Fuentelsaz, L., Gómez, J., and Polo, Y. (2004). La expansión de la red de oficinas de las cajas de ahorros. *Perspectivas del Sistema Financiero*, 80:57–71.

Färe, R., Grosskopf, S., and Lovell, C. A. K. (1994). *Production Frontiers*. Cambridge University Press, Cambridge.

Illueca, M., Norden, L., and Udell, G. F. (2014). Liberalization and risk-taking: Evidence from government-controlled banks. *Review of Finance*, forthcoming.

Illueca, M., Pastor, J. M., and Tortosa-Ausina, E. (2009). The effects of geographic expansion on the productivity of Spanish savings banks. *Journal of Productivity Analysis*, 32(2):119–143.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2):463–505.

Jiménez, G. and Saurina, J. (2004). Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of Banking & Finance*, 28(9):2191–2212.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review*, pages 1183–1200.

Keys, B. J., Mukherjee, T., Seru, A., and Vig, V. (2010). Did securitization lead to lax screening? Evidence from subprime loans. *Quarterly Journal of Economics*, 125(1):307–362.

Liu, C. C. and Ryan, S. G. (2006). Income smoothing over the business cycle: Changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. *The Accounting Review*, 81(2):421–441.

Maudos, J. and Fernández de Guevara, J. (2007). The cost of market power in banking: Social welfare loss vs. cost inefficiency. *Journal of Banking & Finance*, 31(7):2103–2125.

Maudos, J. and Pérez, F. (2003). Competencia *vs.* poder de monopolio en la banca española. *Moneda y Crédito*, 0(217):139–166.

Nichols, D. C., Wahlen, J. M., and Wieland, M. M. (2009). Publicly traded versus privately held: implications for conditional conservatism in bank accounting. *Review of Accounting Studies*, 14(1):88–122.

Ogura, Y. (2006). Learning from a rival bank and lending boom. *Journal of Financial Intermediation*, 15(4):535–555.

Pérez, D., Salas-Fumás, V., and Saurina, J. (2008). Earnings and capital management in alternative loan loss provision regulatory regimes. *European Accounting Review*, 17(3):423–445.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, 49(1):3–37.

Portela, M. C. A. S. (2014). Value and quantity data in economic and technical efficiency measurement. *Economics Letters*, 124:108–112.

Portela, M. C. A. S. and Thanassoulis, E. (2014). Economic efficiency when prices are not fixed: disentangling quantity and price efficiency. *Omega*, 47:36–44.

Primont, D. (1993). Efficiency measures and input aggregation. In Diewert, W. E., Spremann, K., and Stehling, F., editors, *Mathematical Modelling in Economics. Essays in Honor of Wolfgang Eichhorn*, pages 288–294. Springer, Berlin.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3):335–370.

Salas, V. and Saurina, J. (2003). Deregulation, market power and risk behaviour in Spanish banks. *European Economic Review*, 47:1061–1075.

Shaffer, S. (1998). The winner's curse in banking. *Journal of Financial Intermediation*, 7(4):359–392.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, 71(3):393–410.

Tone, K. (2002). A strange case of the cost and allocative efficiencies in DEA. *Journal of the Operational Research Society*, 53(11):1225–1231.

Tone, K. and Tsutsui, M. (2007). Decomposition of cost efficiency and its application to japanese-us electric utility comparisons. *Socio-Economic Planning Sciences*, 41(2):91–106.

Varian, H. R. (1984). The nonparametric approach to production analysis. *Econometrica*, 52(3):579–597.

Williams, J. (2004). Determining management behaviour in european banking. *Journal of Banking & Finance*, 28(10):2427–2460.

Wong, K. P. (1997). On the determinants of bank interest margins under credit and interest rate risks. *Journal of Banking & Finance*, 21(2):251–271.

Table 1: Descriptive statistics for firms[a]

	1st quartile	Median	Mean	3rd quartile	Std.dev.	*N*
Age and size						
F_REGIS	1979	1987	1984	1994	13.9	42,617
F_SIZE	8.49821	9.05158	9.27089	9.81809	1.20994	42,617
F_GROWTH	-0.01805	0.07575	0.14705	0.19671	0.50908	40,895
F_BANKREL	1.00	2.00	2.54	3.00	1.60	42,617
Profitabiity						
F_ROE	0.03166	0.10188	0.11367	0.20061	0.39842	42,614
F_ROA	0.00788	0.04136	0.04767	0.08483	0.09076	42,617
Capital structure						
F_CURRENT	0.99513	1.18730	1.48753	1.56776	1.26156	42,611
F_LEV	0.53992	0.70636	0.67532	0.83286	0.21499	42,617
Likelihood of default						
F_INV_COLLAT	0.12295	0.62336	1.59210	1.38118	3.70202	42,551
F_ZSCORE	1.83438	2.46602	2.65168	3.28539	1.22006	42,616

[a] The table reports accounting and banking information for 42,617 firms during the period 1997–2009. All accounting variables refer to one year before the start date of a new bank relationship. Variable definitions: *F_REGIS*, year of firm registration; *F_SIZE*, logarithm of total assets; *F_GROWTH*, annual rate of increase in total sales; *F_BANK_REL*, number of bank relationships; *F_ROE*, return on equity; *F_ROA*, return on assets; *F_CURRENT*, current ratio; *F_LEV*, ratio of total debt to total assets; *F_INV_COLLAT*, ratio of total bank debt to non-current assets; *F_ZSCORE*, Altman's *Z*-Score.

Table 2: Descriptive statistics for banks[a]

	1st quartile	Median	Mean	3rd quartile	Std.dev.	N
Balance sheet						
B_SIZE	16.9232	18.1393	18.0140	19.3800	1.6013	51
B_EQTA	0.0527	0.0634	0.0663	0.0725	0.0261	51
B_DEPTA	0.3717	0.4378	0.4491	0.5148	0.1059	51
B_LOANTA	0.5924	0.6555	0.6685	0.7608	0.1086	51
Profitability						
B_ROA	0.0060	0.0079	0.0081	0.0099	0.0043	51
B_ROE	0.0950	0.1211	0.1240	0.1555	0.0551	51
Inefficiency						
B_INEF_ROA	0.0000	0.0000	0.0057	0.0058	0.0121	51
$B\_INEF\_ROA\_CS$	0.0000	0.0000	0.0052	0.0042	0.0119	51
$B\_INEF\_ROA\_TS$	0.0000	0.0000	0.0053	0.0040	0.0119	51

[a] The table reports accounting information for 51 banks during the 1997–2009 period. Variable definitions: B_SIZE, logarithm of total assets; B_DEPTA, deposits to total assets ratio; B_EQTA, equity to total assets ratio; B_LOANTA, loans to total assets ratio; B_ROA, return on total assets; B_ROE, return on equity; B_INEF_ROA: profit inefficiency (with total loan loss provisions); $B\_INEF\_ROA\_CS$, profit inefficiency (with expected loan loss provisions based on year cross-section regressions); $B\_INEF\_ROA\_TS$, profit inefficiency (with expected loan loss provisions based on bank time-series regressions).

Table 3: Bank profit efficiency and ex-ante risk taking behavior

This table shows coefficient estimates for different regressions of firms' lagged Z-score (F_ZSCORE) on their lenders' profit efficiency and other control variables. P-values, which are reported in parentheses, are robust to heteroskedasticity and bank clustering effects. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Variable definitions: F_BANK_REL, number of bank relationships (lagged); F_REGIS, year of firm's registration; B_LOANTA, bank loan to total assets ratio; B_EQTA, bank equity to total assets ratio; B_INEF_ROA: bank profit inefficiency (with total loan loss provisions); $B\_INEF\_ROA\_CS$, bank profit inefficiency (with expected loan loss provisions based on year cross-section regressions); $B\_INEF\_ROA\_TS$, bank profit inefficiency (with expected loan loss provisions based on bank time-series regressions); $COMM\_BANK$, dummy variable which equals one if the lender is a commercial bank and zero otherwise; CB_INEF is the product of B_INEF_ROA and $COMM\_BANK$. All models include year and industry fixed effects.

	Dependent variable: F_ZSCORE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$INTERCEPT$	2.8934***	13.9390***	2.9918***	14.0277***	14.0168***	14.0153***	14.0295***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F_BANK_REL		−0.0653***		−0.0646***	−0.0645***	−0.0645***	−0.0646***
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
F_REGIS		−0.0055***		−0.0055***	−0.0055***	−0.0055***	−0.0055***
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
B_LOANTA			−0.2404**	−0.1645*	−0.1648*	−0.1636*	−0.1527*
			(0.013)	(0.066)	(0.056)	(0.059)	(0.087)
B_EQTA			−0.4677	−0.5315*	−0.5524**	−0.5491**	−0.4934**
			(0.163)	(0.055)	(0.040)	(0.041)	(0.044)
B_DEPTA			0.1357	0.127	0.1381	0.1372	0.1058
			(0.315)	(0.291)	(0.243)	(0.246)	(0.417)
B_INEF_ROA	−1.8493**	−1.3209**	−1.7838**	−1.3365**			−1.0221
	(0.011)	(0.031)	(0.012)	(0.042)			(0.268)
$B\_INEF\_ROA\_CS$					−1.5225**		
					(0.022)		
$B\_INEF\_ROA\_TS$						−1.5009**	
						(0.023)	
$COMM\_BANK$							0.0007
							(0.981)
CB_INEF							−1.3883
							(0.336)
# of observations	35,039	34,048	35,039	34,048	34,048	34,048	34,048
R^2	0.131	0.142	0.131	0.142	0.142	0.142	0.142

Table 4: Bank profit efficiency and borrower defaults

This table reports results from a logit model of borrower defaults. The dependent variable *BANKRUPT* equals one if a firm defaults (fills for bankruptcy), and zero otherwise. *P*-values, which are reported in parentheses, are robust to heteroskedasticity and bank clustering effects. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Variable definitions: *F_BANK_REL*, number of bank relationships (lagged); *F_REGIS*, year of firm's registration; *B_LOANTA*, bank loans to total assets ratio; *B_EQTA*, bank equity to total assets ratio; *B_INEF_ROA*: bank profit inefficiency (with total loan loss provisions); *B_INEF_ROA_CS*, bank profit inefficiency (with expected loan loss provisions based on year cross-section regressions); *B_INEF_ROA_TS*, bank profit inefficiency (with expected loan loss provisions based on bank time-series regressions); *COMM_BANK*, dummy variable which equals one if the lender is a commercial bank and zero otherwise; *CB_INEF* is the product of *B_INEF_ROA* and *COMM_BANK*. All models include year and industry fixed effects.

	Dependent variable: *BANKRUPT*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INTERCEPT	-4.0507^{***}	-4.2281^{***}	-32.9385^{***}	-32.8738^{***}	-32.8240^{***}	-32.8275^{***}	-32.8193^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F_BANK_REL			0.1465^{***}	0.1436^{***}	0.1434^{***}	0.1434^{***}	0.1428^{***}
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F_REGIS			0.0145^{***}	0.0144^{***}	0.0144^{***}	0.0144^{***}	0.0144^{***}
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B_LOANTA		0.8919^{***}		0.8992^{***}	0.8970^{***}	0.8933^{***}	0.8841^{***}
		(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
B_EQTA		-3.4473^{**}		-3.0617^{*}	-2.9387^{*}	-2.9492^{*}	-3.2103^{**}
		(0.033)		(0.059)	(0.068)	(0.068)	(0.039)
B_DEPTA		-0.4799		-0.7388^{**}	-0.7708^{**}	-0.7623^{**}	-0.7615^{**}
		(0.166)		(0.026)	(0.022)	(0.023)	(0.039)
B_INEF_ROA	4.9897^{***}	6.1429^{***}	4.2594^{***}	6.0942^{***}			4.8671^{***}
	(0.008)	(0.000)	(0.008)	(0.000)			(0.003)
B_INEF_ROA_CS					6.4530^{***}		
					(0.000)		
B_INEF_ROA_TS						6.2749^{***}	
						(0.000)	
CB							-0.0415
							(0.489)
CB_INEF_ROA							4.1797
							(0.137)
# of observations	45,049	45,049	41,046	41,046	41,046	41,046	41,046
R^2	0.0601	0.0614	0.0681	0.0696	0.0696	0.0696	0.0696

Table 5: Bank profit efficiency, interest rates and collateral

This table shows coefficient estimates for different regressions of firms' interest rates (F_INT) and an inverse measure of the ability of the firm to pledge collateral (F_INV_COLLAT) on their lenders' profit efficiency and other control variables. P-values, which are reported in parentheses, are robust to heteroskedasticity and bank clustering effects. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Variable definitions: F_INT, interest paid by the firm over total bank debt; F_INV_COLLAT, ratio of total bank debt to non-current assets; F_BANK_REL, number of bank relationships (lagged); F_REGIS, year of firm's registration; B_LOANTA, bank loan to total assets' ratio; B_EQTA, bank equity to total asset ratio; B_INEF_ROA: bank profit inefficiency (with total loan loss provisions); $B\_INEF\_ROA\_CS$, bank profit inefficiency (with expected loan loss provisions based on year cross-section regressions); $B\_INEF\_ROA\_TS$, bank profit inefficiency (with expected loan loss provisions based on bank time-series regressions); $COMM\_BANK$, dummy variable which equals one if the lender is a commercial bank and zero otherwise; CB_INEF is the product of B_INEF_ROA and $COMM\_BANK$. All models include year and industry fixed effects.

	Dependent variable: F_INT, F_INV_COLLAT							
	F_INT (1)	F_INV_COLLAT (2)	F_INT (3)	F_INV_COLLAT (4)	F_INT (5)	F_INV_COLLAT (6)	F_INT (7)	F_INV_COLLAT (8)
$CONSTANT$	0.2298^{***}	-34.0838^{***}	0.2302^{***}	-34.0828^{***}	0.2302^{***}	-34.0963^{***}	0.2278^{***}	-34.1249^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$F\_BANKREL$	-0.0007^{***}	0.1364^{***}	-0.0007^{***}	0.1364^{***}	-0.0007^{***}	0.1365^{***}	-0.0007^{***}	0.1355^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F_REGIS	-0.0001^{***}	0.0179^{***}	-0.0001^{***}	0.0179^{***}	-0.0001^{***}	0.0179^{***}	-0.0001^{***}	0.0179^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B_LOANTA	0.0070^{***}	0.1205	0.0070^{**}	0.1207	0.0070^{**}	0.1208	0.0061^{**}	-0.0138
	(0.010)	(0.541)	(0.010)	(0.537)	(0.011)	(0.542)	(0.018)	(0.941)
B_EQTA	-0.0129	-2.4607^{**}	-0.0126	-2.4627^{**}	-0.0125	-2.4780^{**}	-0.0147	-2.9674^{***}
	(0.267)	(0.011)	(0.278)	(0.011)	(0.281)	(0.010)	(0.199)	(0.000)
B_DEPTA	-0.0026	-0.1739	-0.0028	-0.1796	-0.0029	-0.1591	0.0002	0.0298
	(0.541)	(0.509)	(0.506)	(0.484)	(0.501)	(0.539)	(0.962)	(0.921)
B_INEF_ROA	0.0276	-0.769					0.0207	-5.0722^{**}
	(0.170)	(0.714)					(0.344)	(0.022)
$B\_INEF\_ROA\_CS$			0.0318^{*}	-0.6505				
			(0.082)	(0.790)				
$B\_INEF\_ROA\_TS$					0.0322^{*}	-1.0282		
					(0.074)	(0.677)		
CB							0.0009	-0.0391
							(0.315)	(0.596)
CB_INEF_ROA							0.0538^{*}	18.2747^{***}
							(0.097)	(0.000)
# of observations	38,142	34,007	38,142	34,007	38,142	34,007	38,142	34,007
R^2	0.379	0.067	0.379	0.067	0.379	0.067	0.379	0.067

Table 6: Profit efficiency and the lending behavior of the Spanish savings banks: home vs. new markets

This table shows coefficient estimates for different regressions of firms' lagged Altman Z-score (Z_SCORE), firms' interest rates (F_INT) and an inverse measure of the ability of the firm to pledge collateral (F_INV_COLLAT) on their lenders' profit efficiency and other control variables. P-values, which are reported in parentheses, are robust to heteroskedasticity and bank clustering effects. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Variable definitions: F_INT, interest paid by the firm over total bank debt; F_INV_COLLAT, ratio of total bank debt to non-current assets; F_BANK_REL, number of bank relationships (lagged); F_REGIS, year of firm's registration; B_LOANTA, bank loan to total asset ratio; B_EQTA, bank equity to total asset ratio; B_INEF_ROA: bank profit inefficiency (with total loan loss provisions); $B\_INEF\_ROA\_CS$, bank profit inefficiency (with expected loan loss provisions based on year cross-section regressions); $B\_INEF\_ROA\_TS$, bank profit inefficiency (with expected loan loss provisions based on bank time-series regressions); $COMM\_BANK$, dummy variable which equals one if the lender is a commercial bank and zero otherwise; CB_INEF is the product of B_INEF_ROA and $COMM\_BANK$. All models include year and industry fixed effects.

	Dependent variable: F_ZSCORE, F_INT			
	Home markets	New markets	Home markets	New markets
	F_ZSCORE	F_ZSCORE	F_INT	F_INT
	(1)	(2)	(3)	(4)
$CONSTANT$	12.6982***	12.9906***	0.1483***	−37.9152***
	(0.000)	(0.000)	(0.009)	(0.000)
$F\_BANKREL$	−0.0670***	−0.0357***	−0.0005	0.1341***
	(0.000)	(0.000)	(0.286)	(0.000)
F_REGIS	−0.0050***	−0.0053***	0	0.0199***
	(0.000)	(0.000)	(0.140)	(0.000)
B_LOANTA	−0.0714	−0.0872	0.0177**	0.3620
	(0.790)	(0.475)	(0.014)	(0.478)
B_EQTA	−0.1609	1.3337***	0.0638*	−5.6549***
	(0.826)	(0.005)	(0.061)	(0.000)
B_DEPTA	0.3708*	0.2498	−0.0038	0.1181
	(0.079)	(0.150)	(0.700)	(0.795)
B_INEF_ROA	−0.6187	−1.6645**	0.0390**	−7.5265***
	(0.650)	(0.041)	(0.045)	(0.001)
# of observations	5,920	7,321	6,787	5,701
R^2	0.141	0.157	0.325	0.082