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ABSTRACT

Since bank credit lines are a major source of corporate funding and liquidity, we examine the determinants of credit line usage with a database of Spanish corporate credit lines. A line's default status is the primary factor driving its usage, which increases as a firm approaches default. Several lender characteristics suggest an important role for bank monitoring in firms' usage decisions. Credit line usage is found to be inversely related to macroeconomic conditions. Overall, while several factors influence corporate credit line usage, our analysis suggests that default and supply-side variables are the most important.

Keywords: credit lines, firm default, bank lending, exposure at default

JEL codes: E32, G18, M21

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ABSTRACT

Since bank credit lines are a major source of corporate funding and liquidity, we examine the determinants of credit line usage with a database of Spanish corporate credit lines. A line's default status is the primary factor driving its usage, which increases as a firm approaches default. Several lender characteristics suggest an important role for bank monitoring in firms' usage decisions. Credit line usage is found to be inversely related to macroeconomic conditions. Overall, while several factors influence corporate credit line usage, our analysis suggests that default and supply-side variables are the most important.

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I. Introduction

Bank credit lines are a major source of funding and liquidity for corporations as well as an important business line for commercial banks. Sufi (2007) found that credit lines account for over 80% of the bank financing provided to U.S. public firms, while Kashyap et al. (2002) found that 70% of bank lending by U.S. small firms is through credit lines. For Spanish firms, the subject of our study, credit lines account for 42% of firms' bank financing and 32% of banks' total new lending commitments, on average. Given this pervasive use of credit lines in practice and the importance assigned to them in theory, such as in Holstrom and Tirole (1998), our goal is to examine empirically the primary factors influencing firms' decisions to use their credit lines.

A clearer understanding of corporate credit line usage should provide meaningful insights into several inter-related questions regarding corporate finance and credit risk management. Sufi (2007) finds that credit lines are an important component of firms' liquidity management decisions and that credit line use is determined by an interaction between the firm and its lender primarily through covenants based on performance measures, such as profitability. Our empirical results support this finding, as well as the finding by Gatev and Strahan (2006) that banks are key liquidity providers for firms.

Our results also highlight the importance of firms' default risk in determining credit line use. In particular, our results indicate that firms heading into default draw on their credit lines quite heavily. Hence, understanding the determinants of a lender's exposure at default (commonly know as EAD) through credit lines is an important, but scarcely researched, topic in credit risk management.

For our analysis, the variable of interest is the percentage of a firm's committed credit line that was actually drawn down in a given year. Our datasource is the credit register maintained by the Banco de España, the Spanish central bank and primary banking supervisory agency. Known as the *Central de Información de Riesgos* (CIR), the dataset contains information on any loan commitment above €6,000 granted by any bank operating in Spain since 1984. The dataset has three unique features that permit us to examine corporate credit line use. First, the dataset contains information on the amounts drawn and available for all corporate credit lines. To our knowledge, this set of corporate credit lines is the most comprehensive examined to date. Second, the dataset contains default information specific to individual credit lines and across all of the borrowers' credit commitments. Hence, we have a complete history of firm default behavior. Third, since our sample period spans a complete business cycle, we can analyze credit line utilization during expansions and contractions, contributing to the literature regarding the role played by economic fluctuations on credit constraints and credit risk measures, such as EAD.

One of our main findings is that credit line usage is very different for firms that eventually default and those that do not, even several years in advance of the default year. "Default" is defined here to mean that the firm has not met or is judged by its creditors to be unable to meet its scheduled payments. Credit lines to non-defaulting firms in our sample have a median usage ratio of about 43%. Credit lines to defaulting firms have a median ratio of 50% five years prior to default, and it rises to 71% in the default year. We examine this difference further within a reduced form model using line-specific, borrower-specific, and lender-specific factors as well as general economic conditions.

This finding is an important contribution to the credit risk management literature because EAD is a key element of credit loss calculations. While EAD is a random variable that represents the sum of a lender's current exposure to a borrower plus the expected value of any additional drawdown on existing credit lines up to the date of possible default, most credit risk models currently treat EAD as known. Even more surprisingly, EAD is assumed to be independent of a firm's default probability (commonly known as PD). Our analysis indicates that PD and EAD are closely related and that this correlation must be accounted for to generate accurate credit risk measures, such as value-at-risk. Similarly, the pricing of the options embedded within credit lines to draw down funds is an important risk management tool for lenders (i.e. a credit line can be divided into a funded loan and an option to borrow). While we do not have access to such prices in our dataset, our empirical results, advancing understanding of cross-sectional and systematic determinants of EAD, provide some of the necessary foundations for future work on that subject by producing a set of stylized facts about what drives drawdown rates.

As suggested by the raw data, firms that default on their credit lines during the sample period have significantly higher usage rates, and these rates increase as the default year approaches. The quantification of this "default effect" on how firms that eventually default use their credit lines is a new finding in this literature. In addition, the age of the credit line is found to contribute to the usage rate. This "aging effect" seems to decrease the usage rate by 10% per year, although this effect is smaller for defaulted firms. The combination of these two effects accounts for much of the differences between usage ratios of defaulted and non-defaulted firms.

The CIR database has limited information on the borrowing firms beyond their default histories. Using this information, we find that borrowers identified ex-ante as riskier due to prior defaults use less of their new credit lines. This result is roughly analogous to the finding by Sufi (2007) that banks use financial covenants based on profitability to limit credit line use when performance declines. To increase the number of the firm-level explanatory variables in our study, we merge the CIR database with the Informa database of accounting variables for a representative sample of Spanish firms. While the merged sample is smaller than the CIR sample, we can examine the impact of more informative firm-specific variables on credit line usage. For example, we find that firm asset size and age are negatively correlated with credit line usage, which is consistent with our earlier default variable; that is, younger and smaller firms have higher default rates in the CIR database. Firm profitability, as measured by return on assets (ROA), is also negatively correlated with credit line usage, a result consistent with Sufi (2007). However, for our study, firm-specific variables have a relatively small economic impact; for example, a one percentage point increase in ROA leads only to a 0.4 percentage point decline in the usage ratio. Our results suggest that firm performance is not a primary driver of credit line use by Spanish firms.

Since the CIR database contains detailed information on the bank lenders, we examine several questions relating to funding supply issues using lender-specific variables. We find that a firm's banking relationships affect their credit line usage in several ways. As the length of a banking relationship increases, usage rates decrease, which suggests that older firms draw down less on their credit lines. The findings that firms actually draw less on the credit lines managed by their main banks (i.e., the banks with which a firm does the bulk of its borrowing) and that the duration of the bank-borrower relationship affects negatively the usage rate are both consistent with the classic "hold up" argument that banks limit funding to their most dependent borrowers. We find that credit line usage decreases with a firm's number of banking relationships, suggesting, as in Farinha and Santos (2002), that less creditworthy firms and those with bad past performance are more likely to establish multiple banking relationships in order to obtain more funds when their main banks deny their requests.

As noted in both, banking and macroeconomic literatures, the state of the business cycle has a definite effect on firm balance sheets, default probabilities and credit line usage (see, for example, Morgan, 1998). In our analysis, we find that Spanish GDP growth is inversely correlated with credit line usage; increases in GDP growth are associated with a modest, but statistical significant, decline in credit line usage. Additionally, there is an asymmetric nature to this relationship such that a decline in GDP growth leads to a larger increase in credit line usage. This result suggests that credit lines could be a liquidity insurance mechanism for firms, as discussed by Gatev and Strahan (2006) as well as Sufi (2007). However, we do not have information on the interest rate and fees charged on these credit line needed to examine this finding further.

In summary, our study uses the Spanish credit register to examine the determining factors driving corporate credit line usage. Our empirical results suggest that a wide variety of loan-level, firm-level, lender-level and macroeconomic factors impact these activities. However, the most important factors seem to be a firm's default experience, the lifespan of the credit facility, and certain lender characteristics, such as the length of the banking relationship. While firm-level performance variables are significant in our regressions, their marginal impact is much smaller than these other variables. Our results suggest that short of firm default, credit line usage by Spanish firms is primarily driven by banking relationships and less by firm performance. Finally, the finding that the exposure at default in a credit line is closely related to the probability of default of that line has important implications for credit risk management and modeling techniques, such as value-at-risk measures and the option pricing of credit lines.

The paper is structured as follows. Section II provides a short literature review, highlighting empirical studies that informed our choice of explanatory variables. Section III describes the CIR database and our sample of credit line usage observations. We present some descriptive statistics and analysis that highlight the importance of firm default on these usage rates. We also discuss the properties of the smaller sample based on merging the CIR database with the Informa database of borrowers' balance sheet variables. Section IV presents our regression models and our empirical results, and Section V concludes.

II. Literature review

The extant academic literature related to corporate credit lines examines a variety of issues, ranging from credit line origination, which measures loan supply, to utilization, which measures loan demand.[i] Melnik and Plaut (1986) found for a surveyed group of U.S. corporations that credit line commitment size was an increasing function of maturity, fees, collateral, firm size, firm liquidity and risk premium. Ham and Melnik (1987) found for a sample of 90 U.S. nonfinancial firms that credit line size was related positively to total sales, borrowed reserves and collateral, while related negatively to interest rate costs. Berger and Udell (1995) found for a sample of small U.S. firms that credit line terms, such as interest rates and collateral requirements, are negatively related with the length of the banking relationship. Shockley and Thakor (1997) examined credit line pricing using data for one large bank. Dennis et al. (2000) examined jointly several credit line terms, such as maturity, interest rate spread, fees and collateralization, at origination and found an important degree of interdependence between these variables.

A few papers have used corporate credit lines to analyze the role of banks within the financial system. Morgan (1998) uses credit line data from bank surveys collected from the mid-1970s through the mid-1980s to examine the monetary transmission mechanism in the U.S. He shows that loans based on existing credit lines accelerate or remain unchanged after a policy tightening, but that origination of new term loans slows. This distinction reflects a decrease in loan supply and not loan demand. Saidenberg and Strahan (1999) find that firms drew upon their bank lines when access to the commercial paper market was limited in 1998. Gatev and Strahan (2005) further examine banks' role in providing liquidity to the financial system using data on credit lines established to support commercial paper issuance. They find that banks are able to supply credit via these lines when liquidity is low because banks are the natural recipients of funds when this occurs.

Our paper focuses directly on the determinants of corporate credit line use, as in Sufi (2007) and Agarwal et al. (2004). Sufi (2007) takes a corporate finance angle looking at the role of credit lines as an alternative liquidity management tool. Using a sample of public U.S. firms from 1996 to 2003, he finds that credit line access and use was influenced by firm profitability, industry, age and size. He finds the supply of credit lines to be particularly sensitive to firm profitability; a one standard deviation move EBITDA raises line commitments by 20% to 25%. He finds that technical defaults (i.e., the violation of line covenants) the year before lead to increased restrictions on the undrawn portions of credit lines, although the reduction seems to be temporary. The amount available from the credit line appears to return to its prior level two years after the violation. Agarwal et al. (2004) examine a proprietary dataset of loan commitments extended by a single bank to 712 privately-held U.S. firms. They find that firms with higher growth commit to larger lines of credit and have a higher rate of line utilization. Furthermore, firms facing higher rates and fees as well as firms facing more uncertainty in their funding needs commit to smaller credit lines.

As mentioned in the introduction, the Spanish CIR data allows us to examine a larger set of credit lines across a wide cross-section of firms and a longer time period than these prior studies. In addition, the structure of the CIR database allows us to examine a wider variety of line-specific, firm-specific and borrower-specific factors, as well as general macroeconomic factors, influencing corporate credit line usage. As in Sufi (2007), we examine how defaulting on a credit line (or any related credit) affects credit line usage. In addition, we examine several other line-specific variables, such as the line's lifespan (i.e., the number of years active) as well as the use of collateral (see Boot and Thakor, 1994, for a theoretical discussion and Jiménez et al., 2006, for empirical evidence).

Regarding firm-specific variables, the CIR database only permits a limited study due to a dearth of accounting variables; in contrast, banking relationship variables, such as prior default status and the nature of firms' banking relationships, as per Petersen and Rajan (1994), are available. However, we merge the CIR database with the Informa database of Spanish firms, which includes a much richer set of accounting variables. This combined dataset is smaller, but it allows the analysis of such key variables as borrower size, age, leverage and profitability.

For lender-specific variables, the CIR database allows us to examine several features. For example, Coleman et al. (2002) found that lender characteristics impact loan contract terms. Specifically, they found that riskier banks and banks with greater bargaining power lend for longer maturities and charge higher spreads; see also Hao (2004). For our study, we examine the impact that measures of bank risk and main bank status have on corporate credit line use. In addition, Salas and Saurina (2002) found that the type of lending institution has an important effect on corporate lending within the Spanish banking system.

III. Database and descriptive statistics

III.A. The CIR database

Our datasource is the credit register maintained by the Banco de España, the Spanish central bank and primary banking supervisory agency. Known as the *Central de Información de Riesgos* (CIR), the dataset contains information on any loan commitment above €6,000 granted by any bank operating in Spain. The database is essentially a census of all corporate bank lending within Spain from 1984 to 2005, a period that includes the deep recession of 1992 to 1994 and two expansionary periods from the late 1980s through early 1990s and from 1997 onwards. The database is updated at a monthly frequency, but our analysis is conducted at an annual frequency using data as of the last month of each sample year.

The CIR database contains detailed information about loan characteristics such as instrument type (i.e., commercial loan, lease financing, etc.), currency, maturity, collateralization, default status as well as the amount drawn and the total commitment available for credit lines.[ii] The definition of default within the CIR database is that the borrower has loan payments overdue by more than 90 days, which is the legal definition of default in Spain, or it has been classified as a doubtful borrower by the bank (i.e., the lender itself believes there is a high probability of non-payment). Here we differ from Sufi (2007) for whom default means a breach of the existing covenants on the credit line. In addition, information on the borrower's industry and province of headquarters are available.

Given the nature of the CIR database, we can also obtain information on the bank-borrower relationship via simple data transformations; for example, the length of a banking relationship, the number of loans outstanding, and the percentage of a firm's credit line commitments provided by a specific bank (i.e., we can determine whether a bank is a firm's sole bank lender or holds just a small share of its bank debt).

To construct our dataset, we first identify *new* bank credit lines to non-financial firms in the CIR database. Despite the fact that most credit lines have a maturity of a year or less, it is quite common to find them again the following year with exactly the same characteristics (in particular, the commitment size), changing only the amount drawn. For those cases, following Moral (2006), we assume it is the same credit line, although we classify the observations as having a short maturity. Then, we track those lines through time using all their available characteristics (i.e., borrower, total amount, collateral, etc.).

If we find that the commitment amount for a firm's credit line has increased, we treat this as a new credit line in our dataset. However, if the commitment amount declines, we assume that it is the same credit line. The rationale behind this choice is that an increase in commitment amount reflects a renewed lending relationship, whereas a reduction is simply a risk management technique available to the bank under the existing relationship. Empirical support for this filtering choice is provided by Sufi (2007), who found that credit line commitments were reduced immediately after a technical default only to be returned to their previous levels the year after.

After applying our filtering procedures, we have a sample of 2,078,434 credit line-year observations corresponding to 770,371 credit lines granted to 368,977 firms by 407 banks over a twenty year period. This dataset is a clear improvement over previous studies since it is not limited to a single bank, a specific set of firms, or a narrow time period. Roughly 55% of the observations correspond to credit lines held by a firm with a single bank, 20% correspond to firms that hold two banking relationships, 10% with three banks, and the remaining 15% with more than three. In terms of defaults, 1.80% of the firms in our sample default on 0.59% of their credit lines, which make up 0.22% of our credit-line year observations.

For our analysis, we compute the credit line usage rate as the ratio between the drawn amount at each time and the total commitment size of the line at the time it was granted. In terms of notation, the usage rate of credit line i by firm j as issued by bank k in year t is calculated as

$$RDRAWN_{ijkt} = \frac{DRAWN_{ijkt}}{COMMIT_{ijk\tau}}, \tag{1}$$

where $DRAWN_{ijkt}$ is the amount drawn on the credit line at the end of year t and $COMMIT_{ijk\tau}$

is the original commitment provided in year τ (i.e., the year of the line's origination). The histogram of $RDRAWN_{ijkt}$ for the whole sample is presented in Figure 1. Just over 15% of all credit line-year observations are zero, corresponding to 306,274 unique credit lines. Conversely, almost 6% of these observations are at 100% usage. For the remaining 79% of the observations, the distribution is relatively symmetrical around the 50% value.

III. B. Univariate event study

Figure 2 presents one of our most important empirical results. Since the CIR database has information on when firms default on their credit lines, we can transform our credit line usage data from calendar time to event time, where the default year is designated as time zero. For each of the 17 years for which we have event-time data (i.e., 21 sample years - 5 years of prior event time), $\mathrm{RDRAWN}_{\mathrm{ijkt}}$ for defaulted credit lines are placed into event time with that year as time zero. These ratios are then tracked for five years prior to (i.e., back to event time -5). The figure presents the median values of the usage rates for defaulted credit lines. We also plot the median value for non-defaulting firms, which is 47%, for reference. Table I presents the underlying numbers.

Firms that default on a credit line draw down more than firms that do not default up to three years before the default year. At that point, the median usage rate for defaulting firms is at 58%. By the default year, the median $\mathrm{RDRAWN}_{\mathrm{ijkt}}$ ratio for defaulting firms reaches its maximum of about 70%. This univariate analysis shows that the default status of a firm on a credit line is a major driver of its credit line usage. Our subsequent regression analysis, presented in Section IV, confirms that this factor remains the most important one, even after controlling for line-specific, firm-specific and lender-specific factors as well as for general macroeconomic conditions. This empirical result also highlights the importance of modeling credit line usage within a risk management context and, in particular, the need to pay attention to the interaction between PD and EAD (see Jiménez et al.(2007) for a detailed analysis of EAD measures using the CIR database).

III.C. Subsample based on merging with firm balance sheet data

As mentioned, the CIR database does not contain firm-level accounting data, which several other studies have used to investigate corporate credit lines. To address this shortcoming, we merge our credit line dataset with the annual balance sheet reports collected by the Spanish government's Commercial Register and made available electronically by Informa from 1992, the Spanish subsidiary of Bureau van Dyck. The Informa dataset should contain the financial statements that the banks had at the time the credit lines were granted and allow us to use a richer set of firm-specific variables in our analysis.

After this merging of datasets, the Informa subsample contains 425,939 credit line observations corresponding to 183,723 credit lines to 85,949 firms by 301 banks. The merged sample of credit lines is different from the full sample in several important ways. First, the sample period of Informa data is shorter and only spans from 1992 to 2004 with lower coverage in the first two years. Second, the size distribution of the firms within this sample is larger; that is, typically larger firms are recorded in the Informa database relative to all the CIR firms. Third, the default rates are lower in the merged dataset, being only 0.1% of credit line observations for the merged sample relative to 0.4% for the whole sample in the same range of years. However, the histogram and event study corresponding to the Informa subsample are similar to those of the full sample.

IV. Econometric modeling

IV.A. Baseline model

The baseline model we propose for analyzing the determinants of credit line usage is:

$$RDRAWN_{ijkt} = \beta_0 + \beta_1 Credit\ \ Line_{it} + \beta_2 Firm_{jt} + \beta_3 Bank_{kt} + \beta_4 Economic\ \ Cycle_t + \eta_{ijk} + \varepsilon_{it}\ , (2)$$

where $Credit\ Line_{it}$ is a vector of credit line characteristics, both time-varying and constant; $Firm_{jt}$ is a vector of firm-specific characteristics; $Bank_{kt}$ is a vector of variables that control for bank characteristics; $Economic\ \ Cycle_t$ is a measure of expected macroeconomic conditions in t+1; η_{ijk} is an unobservable credit line effect that is fixed over time and thus also encompasses unobservable firm and bank effects; and ε_{it} is an error term. Note that we cluster the standard errors in our calculations on the basis of the firms in the sample.

We structure the *Credit Line*$_{it}$ vector of explanatory variables to reflect relevant features of the credit lines and to highlight the impact of firm defaults using interaction terms. Specifically,

$$\begin{aligned}\beta_1\text{Credit Line}_{it} = \; & (\beta_{11} + \beta_{12}\#\text{ years from default}_{it} + \beta_{13}\#\text{ years from default}_{it}^2)\cdot\text{Defaulted}_i \\ & + (\beta_{14} + \beta_{15}\text{Defaulted}_i)\cdot\text{Line age}_{it} \\ & + \beta_{16}\text{Long term}_i + \beta_{16}\text{Collateralized}_i.\end{aligned} \tag{3}$$

With this specification, we highlight the impact of the credit line's default status over the sample period and its age effects. The "*default effect"* captured in the first term measures both the impact of credit line default through the *Defaulted* indicator variable, which equals one for credit lines that are defaulted on during our sample period, and through its prior-to-default effect.[iii] We set this latter variable equal to the actual number of years prior to default for defaulting credit lines, such that it is an ordinal variable less or equal than zero (i.e. it takes the values -11, -10, …, 0). We also introduce a quadratic effect to allow for a greater flexibility of response. As mentioned before, the proportion of observations corresponding to defaulted credit lines is only 0.57%. From the descriptive analysis presented earlier, we expect a positive sign for the β_{12} coefficient since usage rates rise as the default year approaches. Moreover, if credit lines to riskier borrowers have higher usage rates, we expect a positive β_{11} coefficient, which would capture the difference in levels of usage rates between defaulted and non-defaulted credit lines.

We also model the "*age effect"* of the credit line; that is, we examine how credit line utilization evolves over the life of the contract. We capture this effect in the second term with the *Line age*$_{it}$ variable, which is simply a linear trend. We also permit a different slope for defaulted credit lines by using an interaction term with the *Defaulted*$_i$ indicator. The effect of *Line age*$_{it}$ on the usage rate is unknown. A positive coefficient would indicate that firms increase line use as the credit line ages. However, a negative value would suggest that credit lines are used more intensively during the first year and decline afterwards. If this is the case, we expect a smaller effect for defaulted credit lines, since their usage rates are higher. Thus, if β_{14} is estimated to be negative, the estimated β_{15} is expected to be positive, such that $\beta_{14} + \beta_{15} < 0$.

We also introduce two time-invariant, credit line characteristics. The *Long term*$_i$ variable is equal to one if the reported maturity of the credit line is greater than one year. While these cases account for only 24% of the observations, longer maturities could be indicative of differences in drawdown patterns. The *Collaterlized*$_i$ variable is equal to one if the credit line is collateralized, which was found to be significant in Jiménez and Saurina (2004) as well as Jiménez et al. (2006). Eleven percent of the observations correspond to collateralized lines.

Turning to the firm-specific variables based on the CIR database, our baseline model specifies the firm-specific variable as:

$$\begin{aligned}\beta_2\text{Firm}_{\text{jt}} = {} & \beta_{21}\text{Ln(Total commitments}_{\text{jt-1}}) + \beta_{22}\text{Firm risk}_{\text{jt-1}} \\ & + \beta_{23}\text{Ln}(1 + \#\text{ years with the bank}_{\text{jt-1}}) \\ & + \beta_{24}\text{Ln}(\#\text{ bank relationships}_{\text{jt-1}}).\end{aligned} \quad (4)$$

Note that these variables are lagged to better capture the firms' decision process regarding its credit line usage, following Sufi (2007) and Jiménez et al. (2006). The *Ln(Total commitments*$_{jt-1}$*)* variable is the only proxy for firm size available within the CIR database and is constructed as the logged sum of all of a firm's debt commitments. The expected sign on β_{21} is ambiguous; that is, larger firms could be more creditworthy and capable of handling a higher debt load $(\text{i.e.}, \beta_{21} > 0)$, but they may also have access to lower cost funding sources $(\text{i.e.}, \beta_{21} < 0)$.

A firm's degree of solvency or financial risk is a key element of its overall funding decisions and its credit line use. However, the only CIR variable that may be used as a proxy for firm risk is a binary default variable equal to one if the firm had defaulted on any other loan prior to time *t*. Note that just 2% of the observations correspond to such firms. Since this *Firm risk*$_{jt-1}$ proxy is available to all its lenders, we should expect closer monitoring of firms with prior defaults, which could result in their having lower credit line usage rates $(\text{i.e.}, \beta_{22} < 0)$.[iv] In addition, the credit line effect η_{ijk} should also capture firm-level fixed effects related to firm risk.

The last two firm-specific variables are related to the nature of corporate banking relationships, which are proxies for the firm's bargaining power and solvency. The $\text{Ln}(1+\#\text{ years with the bank}_{\text{jt-1}})$ variable measures the length of the relationship with the bank underwriting the credit line, which has been used to examine the possibility of the so-called "hold-up" problem faced by borrowers with their main banks. In contrast, the $\text{Ln}(\#\text{ bank relationships}_{\text{jt-1}})$ variable acts in the opposite direction since multiple bank relationships suggest greater bargaining power by the borrower and hence probably less information exchange with individual lenders. To measure appropriately the impact of these two variables is necessary to control by the age of the firm. Although this information is not available is the CIR it can be obtained from the Spanish Commercial Register.

In a related sense, several studies have shown that bank characteristics impact loan access and pricing, and we examine here whether these variables impact credit line usage. The third term of our baseline model is constructed as[v]:

$$\begin{aligned}\beta_3\text{Bank}_{\text{kt}} = \quad & \beta_{31}\text{ Main bank}_{\text{ijk}} + \beta_{32}\text{ Bank share}_{\text{kt}} + \beta_{33}\text{ Bank NPL ratio}_{\text{kt}} \\ & + \beta_{34}\text{Savings bank}_{\text{k}} + \beta_{35}\text{Credit cooperative}_{\text{k}}.\end{aligned} \tag{5}$$

The $\text{Main bank}_{\text{ijk}}$ variable equals one if the credit line is handled by the firm's largest lender; just over 41% of the observations fall into this category. Sharpe (1990) argues that the monitoring process provides the main lending bank better information on borrower credit quality and gives it the monopoly of this information, which could lead to a "hold-up" situation. If this is the case, the main bank could constrain the liquidity of the firm since it is tied, suggesting the β_{31} coefficient should be negative. Alternatively to the "hold-up" theory we know from different empirical and theoretical papers (see, for instance, Farinha and Santos, 2002) that firms with past poor performance and those that more often had loans that were past due are more likely to initiate multiple relationships. The reason is the main bank's unwillingness to provide more funds to the firm due to its poor past history and the incentives of banks to share risks of lower credit quality firms. This would imply a positive coefficient on the number of banking relationships ($\beta_{24}>0$) and a negative one on the main bank variable ($\beta_{31}<0$) if less creditworthy firms decide to enter into new relationships keeping their main bank unchanged. Thus, loans with the main bank will collect those more screened, and hence, less used credit lines of high-risk firms and those loans of low-risk firms.

The *Bank share*$_{kt}$ variable is constructed as a bank's share of the corporate loan market and is a proxy for bank size. The *Bank NPL ratio*$_{kt}$ variable, constructed as the ratio of a bank's nonperforming loans within the CIR database to its total loans minus the average bank NPL in that year, is a proxy for bank riskiness. The signs on the coefficients for these two variables are unclear a priori, and we view them more as control variables. We also include as control variables the type of the bank, which was shown by Salas and Saurina (2002) to be important within the Spanish economy. Our sample consists of corporate credit lines originated by commercial banks, savings banks and credit cooperatives, which account for 99% of lending in the economy.

Finally, general macroeconomic conditions should play an important role in credit line usage from a theoretical point of view. The literature on the lending channel of monetary policy transmission has established that firms are more constrained in their access to external financing during recessions and hence more likely to draw on their credit lines (see Saidenberg and Strahan, 1999, for analysis of a recent such episode). This outcome would imply that firms will use their existing credit lines more in anticipation of economic downturns. As we do not have firm-level data on sales and orders, we use as a proxy real, annual Spanish GDP growth in aggregate from period t+1 as our measure of expected conditions. Our specification is

$$\beta_4 \text{ Economic} \quad \text{cycle}_t = \beta_{41}\text{GDPG}_{t+1}. \tag{6}$$

We would expect a positive GDP growth rate to lead to a decline in credit line use and thus β_{41} to be negative. However, we would expect a negative GDP growth rate to increase credit line use, suggesting that β_{42} is positive and that $\beta_{41}+\beta_{42}$ is positive.

Table II presents the summary statistics for the dependent and explanatory variables for the full sample from 1986 to 2005. The distribution of the utilization ratio *RDRAWN*$_{ijkt}$ for is symmetric with mean and median values of 47.5% and 50.0% respectively. As mentioned, the proportion of observations corresponding to defaulted credit lines is only 0.57%. The year-to-default variable ranges from -11 to 0, but has average and median values of -1. The average line age for our sample is 1.2 years. With respect to firm characteristics, the total commitment amount shows a high degree of dispersion with an interquartile size of between €115,000 and €1.6 million with a median value of €408,000. The average length of the bank relationship is 4 years, while firms have, on average, 2.8 lenders. Note that these latter two variables are winsorized at the 1% and 99% percentiles and at the 99% percentile, respectively, to reduce estimation bias due to outliers.

Regarding bank level variables, 41% of the credit line usage observations are linked to banks that are the main lender for the firm. The average loan market share of each bank is relatively low at 0.03%, although the maximum is 14.7%. The deviation of the non-performing loan ratio with respect to the yearly average has a zero mean, with considerable dispersion. As determined by Salas and Saurina (2002), it is important to mention of the types of Spanish banks. Both commercial and savings banks play a significant role in credit and deposit markets, holding similar shares of each market. Yet, their organizational structures are quite different. Commercial banks are for-profit firms under shareholder control, while savings banks (or *cajas de ahorros*) are effectively commercial entities operated by not-for-profit organizations controlled by depositors, employees and other public and private groups. These two bank types exhibit important differences in non-performing loan ratios, a result that might be relevant for their underwriting of credit lines. For our sample, commercial and savings banks have a 47% and 48% share, respectively, of the credit line-year observations, while credit cooperatives make up the remaining 5% of the observations. At the beginning of the sample period in 1986, commercial banks dominated the market with a market share of 80%. The progressive entrance of savings banks into corporate lending, mainly after the regulatory changes introduced in the late 1980s, caused a steady decline in the market share of commercial banks in favor of savings banks.[vi]

IV.B. Model estimation

In this paper, we estimate our model using three econometric techniques. First, we use OLS regression with random effects, which assumes strict exogeneity between the unobserved, credit line effects (i.e., η_{ijk}) and the explanatory variables. Note that the common fixed effects also control for firm and bank effects, but we cannot separate them out. To examine the robustness of the OLS results, the second estimation technique we use is a Tobit model with a double censure, since the $RDRAWN_{ijkt}$ variable is bounded by the unit interval.

We motivate our use of the Tobit model by thinking of y^* as a firm's desired level of credit line utilization as opposed to the observed value y. In such cases, OLS techniques could generate downward biased coefficients. By taking account of the censoring, the Tobit model should avoid these biases and provide a form of robustness analysis.

Our third estimation technique is Within-Groups estimation that treats η_{ijk} as a fixed effect. This estimation technique controls for possible correlation of the unobserved fixed effects with the regressors; that is, this technique helps account for the possibility that banks may have more information about the risk profile of the firm than is captured and observable in the CIR dataset. Therefore, our preferred approach is the Within-Groups estimation, as it controls for those possible correlations. Thus, a comparison of the OLS and Within-Groups estimation techniques allows us to investigate whether any of the OLS parameter estimates are biased due to the potential correlation between the unobserved error components and the corresponding explanatory variables.

Finally, it is worth noting that given the large number of observations, denoted as N, in our sample, the estimated standard errors will be very low since they are proportional to 1/N. Thus, almost all our explanatory variables will be statistically significant, despite their relatively small marginal effects on the dependent variable. For this reason, we show both the p-values of the coefficients and the semi-elasticities of the variables. The semi-elasticities measure the percentage change in the dependent variable to unit increases in the explanatory variables expressed in levels or 100% increases in the explanatory variables expressed in logged form, while the other explanatory variables are kept at their means.

IV.C. Empirical results

Table III presents the estimation results for our baseline model. The first set of results is based on a OLS regression with random effects. The coefficient on the default indicator variable is positive and significant with a semi-elasticity of 38%, which implies that defaulted credit lines have an usage rate 38% higher than non-defaulted ones. Since the average usage rates for the defaulted and non-defaulted firms in the sample are 63 percentage points and 47 percentage points, the model's 38% increase (47 percentage points * 1.38 = 65 percentage points) seems reasonable. The two interacted years-to-default variables show a positive and very significant relationship, suggesting an increasing use of credit lines as a firm's time to default approaches. The semi-elasticity of these two terms is about 14%, which means that one year closer to default raises the usage rate 14% relative to the average usage rate.

We also find that our line age variable is quite important. The age effect is captured through a trend, which has a negative and significant coefficient, and implies that the usage rate decreases almost 10% per year with respect to the average usage rate. The effect is weaker for defaulted credit lines at a 7.7% decrease (=-9.7% + 2.0%). The countervailing positive default effect and negative age effect suggest an interesting U-shaped pattern in credit line, as illustrated in Figure 3. Using the average values for all the other explanatory variables, Figure 3 shows the impact of the age effect for non-defaulting firms and the joint impact for defaulting firms. Starting at 7 years prior to default and with a new line, usage rates are at 52.9% and 56.3%, respectively. As we approach default, the age effect linearly lowers the usage rate for non-defaulting firms to 20.4% by the default year. For defaulting firms, this linear decline is more gradual and is outweighed by the default effect starting at four years prior to default.

While these two effects are the main drivers of credit line usage, the line-specific maturity indicator has an important impact, where higher maturity lines have a usage rate that is 5.4% higher than one-year lines. This result suggests that firms treat longer-term credit lines as a more stable funding source and hence use them more. Interestingly, collateralized credit lines are found to have slightly lower usage rates than uncollateralized lines. Since collateral is an ex-ante proxy of credit risk, as found by Jiménez and Saurina (2004), the negative β_{16} coefficient is in line with the assumption that banks restrict credit line use by less creditworthy firms.

Turning to the firm-specific effects in the CIR dataset, firm size, measured as the total commitment amount of firm lines, does not have a material impact on the usage rate, most probably due to the limited effectiveness of this size proxy. The $\text{Firm risk}_{jt\text{-}1}$ measure based on prior defaults is negatively correlated with credit line use, suggesting that lower-quality borrowers use their lines more carefully or are closely monitored by their lenders. Finally, the length of the banking relationship is negatively related with usage, suggesting that older firms do not draw down as much, which also might be the result of hold-up problem. The OLS results also suggest that firms have higher usage rates with their main banks and once they establish more banking relationships.

In terms of the lender characteristics, if the lender is the firm's main bank, line usage increased by just over 7%, implying that borrowers may be dependent of their main banking relationship for financing. Bank size, defined as the total share of lending within our CIR data sample, has a negative correlation with credit line usage, decreasing the usage rate by 8.3% when the banks' share increases by a percentage point. Credit lines granted by savings banks and cooperatives have lower usage rates at 8.5% and 3.8%, respectively, than commercial banks. This result may be due to savings banks' entrance to the corporate market through lending to high-quality firms, or perhaps to their more conservative policies than commercial banks, as per Salas and Saurina (2002). Note, however, that credit lines granted by high-risk banks (i.e., higher *NPL* with respect to the yearly average) do not show a different pattern.

Our results also imply a significant relationship between macroeconomic conditions and credit line use. As suggested in the theoretical literature, such as Thakor (2005), firms use their credit lines to secure liquidity during worsening economic conditions, but instead rely more on their own cash flows or other cheaper sources of liquidity during periods of improved conditions. Unfortunately, we do not have further information, such as on the interest rates paid on these credit lines, to examine whether credit lines are used as a liquidity insurance mechanism with a corresponding premium over other funding sources. We also test for possible asymmetries in response to positive and negative GDP growth rates[vii] and found that positive GDP growth leads to a reduction in credit line use by about 1%, whereas negative GDP growth leads to nearly 3% increase in credit line use.

The second column of Table III presents the baseline model's parameter estimates using the Tobit model with random effects. Overall, the results are in line with the OLS estimation results. Notably, the default and age effects are more pronounced here, leading to a stronger U-shaped pattern in their combination (Figure 4).

The test statistics for first- and second-order autocorrelation in the residuals of OLS estimation indicate a significant autocorrelation, consistent with the presence of credit line fixed effects that could bias the estimated coefficients. Furthermore, the autocorrelation coefficients for the residuals show a slow decline from 0.65, corresponding to the first-order autocorrelation, to 0.42, corresponding to the fifth. This pattern also supports the existence of persistent differences among credit lines that remain in the data over at least a 5-year period. To take account of these characteristics, we use panel data techniques to estimate the baseline model; i.e., we estimate the model using the Within-Groups estimator and considering η_{ijk} as a fixed effect. The estimation results are presented in the third column of Table III.[viii]

Most of the OLS results remain robust to this change in estimation technique. In particular, the line default, line age, prior default and macroecononic effects remain the same. That is, the usage ratio increases with the probability of default of the borrower and the worsening of the business cycle, while it decreases with the age of the credit line and the observed risk of the firm. Yet, certain of the variables seem to exhibit some bias. For example, the β_{21} coefficient on firms' logged total commitments becomes positive and has a larger marginal effect on credit line usage. However, the reasonableness of this variable as a proxy for firm size is an open question that we address in the next section.

Regarding the estimation results related to some of the relationship banking variables, the β_{24} and β_{31} estimates (corresponding to the number of banking relationships and the main bank indicator variable, respectively) change signs. The Within-Group estimates indicate that firms with multiple bank relationships exhibit lower levels of credit line use, as they are potentially less well known by their lenders. This result is consistent with Farinha and Santos (2002), who found that less creditworthy firms and those with bad past performance are more likely to establish multiple banking relationships to obtain more funds when their lead banks deny their funding requests. Credit lines granted by the firm's main bank have a lower level of use, due to a possible "hold-up" as per Sharpe (1990). Our overall conclusion is that the Within-Group estimates for these relationship variables are more statistically reliable, but further analysis is necessary to understand their economic interpretation.

IV.D. Analysis of the Informa subsample

As discussed, to complement the scant firm-specific information available in the CIR database, we merged it with the Informa database of accounting variables that firms report to the Spanish Commercial Register. Table IV presents the summary statistics for this Informa subsample. This data is only available from 1992 to 2004, and since coverage is limited in the first few years that correspond to the Spanish recession, useful observations regarding defaulted credit lines are unfortunately lost. We observe that the average number of defaulted observations is 0.11%, much lower than the 0.55% in the whole sample, again partly due to the loss of observations in the early 1990s. This fact suggests a bias of this sub-sample towards higher-quality firms, which must be taken into account when analyzing the results. In addition, the firms have longer and more banking relationships in this subsample.

We again use the baseline model described before, but the firm-specific vector of variables is redefined as:

$$\begin{aligned}\beta_2\text{Firm}_{jt} = \; & \beta_{21}\text{Ln(Total assets}_{jt-1}) + \beta_{22}\text{Firm risk}_{jt-1} \\ & + \beta_{23}\text{Ln}(1 + \text{\# years with the bank}_{jt-1}) \\ & + \beta_{24}\text{Ln(\# bank relationships}_{jt-1}). \\ & + \beta_{25}\text{ln(1+Age of the firm}_{jt-1}) \\ & + \beta_{26}\text{ROA}_{jt-1} \\ & + \beta_{27}\text{Equity/Total assets}_{jt-1} + \beta_{28}\text{Liquidity ratio}_{jt-1}.\end{aligned} \tag{7}$$

The $\mathit{Ln(Total\ assets}_{jt-1})$ variable is the logged book value of the firm. Profitability is measured here by ROA_{jt-1}, which is the ratio of earnings (before interest and taxes) to total assets. As proxies for firm solvency and liquidity, we use the $\text{Equity} / \text{Total assets}_{jt-1}$ and $\text{Liquidity ratio}_{jt-1}$ variables, defined as the ratio of firm cash to total assets. Since more profitable, larger and more liquid firms are likely to have a higher credit quality, we expect a negative relationship between all these variables and credit line usage. As before, the Firm risk_{jt-1} measure of the firm default history, the number of bank relationships, and the length of the main bank relationship are included.

Table V reports the three sets of regression results for the merged dataset. The results show that the *default effect* remains the primary factor regarding credit line use. Defaulting credit lines have a usage level just over 40% greater than non-defaulting ones. Interestingly, the time-to-default effect is not present in this subsample, most probably due to the presence of the firm-level accounting variables that better track defaulting firms' declining performance. As with the full sample, the age effect decreases line use. Non-defaulting credit lines decrease at a pace of between 10% and 12% per year, while defaulting credit lines decrease between 12% and 15% per year. Regarding other credit line's characteristics, longer maturities are correlated with greater line use. The results of the lender-specific and general economic variables are similar to those for the full sample.

With regard firm-specific variables, the rough CIR proxy for firm risk and the richer proxies available from the merged dataset both provide similar results; that is, increased firm risk leads to increased credit line usage. Specifically, the coefficients on the firm size, age, ROA, solvency ratio, and liquidity ratio variables are all negative and significant, although their economic impact is limited. This empirical evidence is in line with the results obtained by Sufi (2007), who finds that profitability and liquidity are the measures banks take into account when deciding to grant a corporate credit line. This overall result is in line with the assumption that less creditworthy firms (i.e., smaller, younger, less profitable and less solvent firms) use their credit lines more intensively than high-quality ones. Furthermore, these results suggest that banks' monitoring of firms within the Spanish banking system seems to be based more on prior default indicators than on the near-term financial performance of the firm as the coefficient on the default history of the firm is still negative and significant and, based on its high economic impact, seems to be one of the main factors driving the behaviour of credit lines.

V. Conclusions

In this paper, we examine corporate credit line usage based on the Spanish Credit Register, a huge transaction-based database known as the *Central de Información de Riesgos* (CIR), which covers all Spanish banks lending over the last twenty years. The extensive nature of the CIR dataset allows us to examine the determinants of corporate credit line usage as a function of loan-specific, firm-specific, and lender-specific factors as well as general macroeconomic conditions.

One of our main findings is that credit lines are drawn down more by firms that eventually default on these lines than firms that do not. This usage rate is higher in a statistically significant way from at least three years prior to default and increases monotonically as default approaches. As far as we know, this empirical finding is new to the literature and has important implications for credit risk modeling and management in that exposure at default (EAD) in corporate credit lines cannot be considered independent of firm default probability. Moreover, given the option characteristics of credit lines, our results provide stylized facts that any pricing model must account for.

From a multivariate perspective, we find that credit line default is the largest explanatory factor for credit line usage, with the age of the line being the second largest factor. We find that borrowers identified ex-ante as riskier (i.e., those that defaulted before) access their credit lines less, a result that is analogous to the firm profitability result found by Sufi (2007). For a subsample of credit lines for which firm-level accounting data is available, we find that smaller, younger, less profitable and less solvent firms use their credit lines more intensively. However, the economic significance of these variables is muted relative to funding supply variables, such as the length and number of a firm's banking relationships. We also find that credit line use has asymmetric cyclical characteristics, with usage declines during expansions being a third as large as increases in downturns. Thus, credit lines seem to work as a liquidity insurance mechanism for firms, as discussed by Gatev and Strahan (2005) and Sufi (2007). However, we do not have information on the interest rate charged on each line to examine this finding further. With regard to the impact of borrower-lender relationship variables, the results suggest that firms face some hold-up cost when dealing with banks, together with the restrictive policies of the main bank to increase it exposure to a firm due to its default history.

In summary, our analysis suggests that a wide variety of loan-level, firm-level, lender-level and macroeconomic factors drive corporate credit line usage. While firm-level performance variables are significant in our regressions, their marginal impact is much smaller than these other variables. We believe that our results suggest that short of firm default, credit line usage by Spanish firms is primarily driven by banking relationships and less by firm performance.

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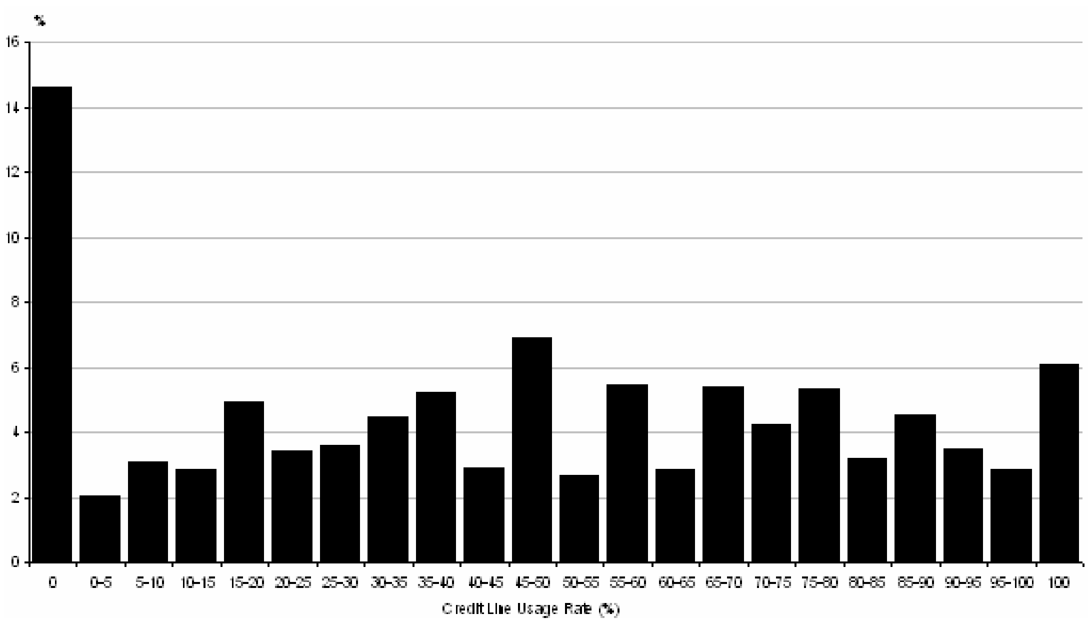
Figure 1.

Histogram for the Full Sample of Credit Line Usage Rates ($RDRAWN_{ijkt}$)



The histogram presents the 2,078,434 credit line observations in our full sample.

Figure 2.

Usage ratio of credit lines that default

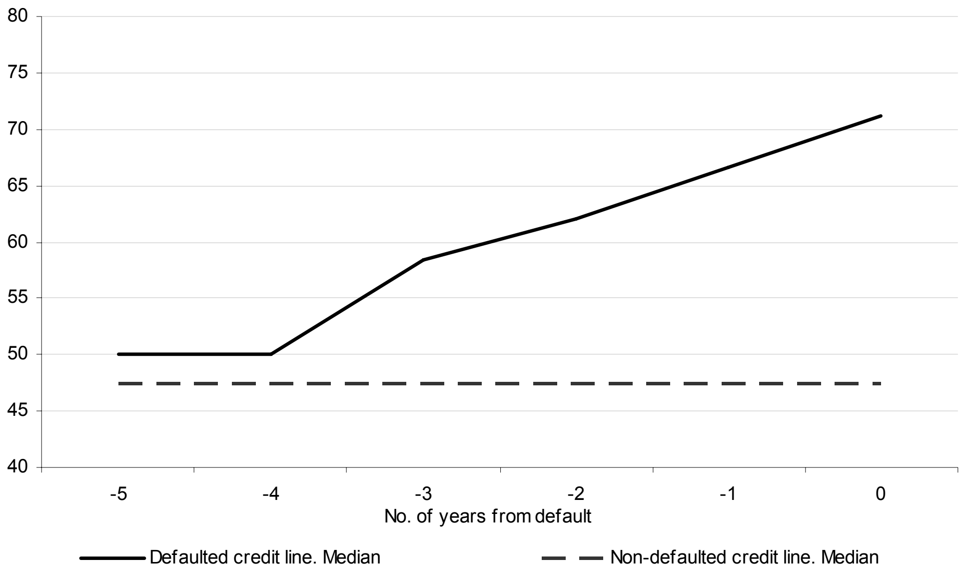


Table I.

Mean and median values of usage rate for defaulted credit lines

Years from default	# obs.	Median	Mean
-5	85	50.0	52.1
-4	228	50.0	50.3
-3	717	58.3	56.2
-2	1,939	62.1	60.4
-1	4,512	66.7	64.2
0	4,512	71.1	64.7

Table II.

Descriptive statistics for the baseline model

No. of observatios: 2,078,434
No.of credit lines: 770,371
No.of firms: 368,977
Sample period: 1986-2005

	Mean	*S.D.*	*Min*	*Q25*	*Median*	*Q75*	*Max*
Credit Line Characteristics							
$RDRAWN_{ijkt}$ (%)	47.53	32.97	0.00	19.05	50.00	76.11	100.00
Defaulted credit $line_i$ (0/1)	0.01	0.08	0.00	0.00	0.00	0.00	1.00
No. years from $default_{it}$ (for defaulted credit lines)	-1.01	1.09	-11.00	-2.00	-1.00	0.00	0.00
Life of the $loan_{it}$	1.17	1.40	0.00	0.00	1.00	2.00	20.00
Long $term_i$ (0/1)	0.24	0.43	0.00	0.00	0.00	0.00	1.00
$Collateralized_i$ (0/1)	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Firm Characteristics							
Total $commitments_{jt-1}$ (thousand of euros)	1,694.86	2,884.92	0.00	115.48	408.20	1,558.40	10,346.99
Firm $risk_{jt-1}$ (0/1)	0.02	0.14	0.00	0.00	0.00	0.00	1.00
No. of years with the $bank_{jt-1}$	3.87	3.82	0.00	1.00	3.00	6.00	21.00
No. of bank $relationships_{jt-1}$	2.82	2.90	0.00	0.00	2.00	4.00	9.00
Bank Characteristics							
Main $bank_{ikt}$ (0/1)	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Bank $share_{kt}$ (%)	0.03	0.07	0.00	0.01	0.02	0.05	14.72
Bank NPL $ratio_{kt}$ (%)	0.00	0.81	-11.97	0.00	0.00	0.00	99.58
Savings $bank_k$ (0/1)	0.48	0.50	0.00	0.00	0.00	1.00	1.00
Credit $cooperative_k$ (0/1)	0.05	0.21	0.00	0.00	0.00	0.00	1.00
Cycle Characteristics							
$GDPG_{t+1}$ (%)	3.36	1.22	-1.03	2.76	3.33	3.86	5.55

$RDRAWN_{ijkt}$ is the ratio of the amount drawn at t to the amount available (drawn plus undrawn) when the credit lines was granted of a credit line *i* to firm *j* by bank *k*. The variable $Defaulted\ credit\ line_i$ takes one if the credit line defaults anytime during its life and zero otherwise; $No.\ years\ from\ default_{it}$ measures the time to default in years for those credit lines that do default during its life; $Life\ of\ the\ loan_{it}$ measures the number of years since the credit line was grated; $Long\ term_i$ is a dummy variable worth 1 if the maturity of the credit lines is longer that 1 year and 0 otherwise $Collateralized_i$ is a dummy variable worth 1 if the credit line is collateralized and 0 otherwise ; $Total\ commitments_{it}$ is the sum of all loans and credit lines that the firm has; $Firm\ risk_{jt_i}$ controls for the observed risk of the firm *j* and takes the value of 1 if the borrower defaulted any time until *t;* ; $No.of\ years\ with\ the\ bank_{jt-1}$ measures the number of years since the firm got the first loan with the bank; $No.of\ bank\ relationships_{jt-1}$ is the number of banks with which the firm has loans; $Main\ bank_{ikt}$ is a dummy variable that takes one if the bank that granted the loan is the main bank for the firm and 0 otherwise; $Bank\ share_{kt}$ proxies the size of the bank through its market share in loans to firms; $Bank\ NPL\ ratio_{kt}$ is the non-performing loan ratio of bank *k* at time *t* with respect to the NPL ratio of the year; $Savings\ bank_k$ is a dummy variable worth 1 if the bank is a savings bank, 0 otherwise; $Credit\ cooperative_k$ is a dummy variable worth 1 if the bank is a credit cooperative, 0 otherwise.; and $GDPG_{t+1}$ is the GDP rate of growth of the Spanish economy at t+1.

Table III.

Estimation of the baseline model and robustness analysis

Estimation Method No. of observatios: 2,078,434 No.of credit lines: 770,371 No.of firms: 368,977 Sample period: 1986-2005 Dependant variable $RDRAWN_{ijkt}$	OLS levels		Tobit with Random effects		Within-Groups	
	Model 1		Model 2		Model 3	
	Coefficient	*Semi-elasticity*	*Coefficient*	*Semi-elasticity*	*Coefficient*	*Semi-elasticity*
Credit Line Characteristics						
Default effect						
Defaulted credit line$_i$ (0/1)	18.061 ***	38.0	23.693 ***	40.7	--	--
No. years from default$_{it}$	6.705 ***	14.1	10.365 ***	17.8	6.166 ***	13.0
No. years from default$^2_{it}$	0.661 ***		1.071 ***		0.288 **	
Age effect						
Life of the loan$_{it}$	-4.631 ***	-9.7	-6.052 ***	-10.4	-4.678 ***	-9.8
Life of the loan$_{it}$*Defaulted credit line$_i$	0.961 *	2.0	3.425 ***	5.9	--	--
Other effects						
Long term$_i$ (0/1)	2.585 ***	5.4	2.906 ***	5.0	--	--
Collateralized$_i$ (0/1)	-0.529 ***	-1.1	0.243 **	0.4	--	--
Firm Characteristics						
Ln(Total commitments$_{jt-1}$)	-0.041 **	-0.1	0.369 ***	0.6	1.238 ***	2.6
Firm risk$_{jt-1}$	-3.708 ***	-7.8	-4.599 ***	-7.9	-5.551 ***	-11.7
Ln(1+# years with the bank$_{jt-1}$)	-3.691 ***	-7.8	-3.974 ***	-6.8	-1.125 ***	-2.4
Ln(# bank relationships$_{jt-1}$)	3.089 ***	6.5	2.355 ***	4.0	-0.694 ***	-1.5
Bank Characteristics						
Main bank$_{ikt}$	3.363 ***	7.1	2.522 ***	4.3	-2.063 ***	-4.3
Bank share$_{kt}$	-3.945 ***	-8.3	-4.233 ***	-7.3	-0.654	-1.4
Bank NPL ratio$_{kt}$	0.018	0.0	0.027	0.0	0.025	0.1
Savings bank$_k$ (0/1)	-4.047 ***	-8.5	-4.450 ***	-7.7	--	--
Credit cooperative$_k$ (0/1)	-1.824 ***	-3.8	-1.751 ***	-3.0	--	--
Cycle Characteristics						
GDPG$_{t+1}$	-0.937 ***	-2.0	-0.992 ***	-1.7	-0.569 ***	-1.2
Constant	57.909 ***	--	57.077 ***	--	50.615 ***	--
Credit Line/Firm/Bank fixed effect (η_{ijk})	No		No		Yes	
F-test (p-value)	0.00		0.00		0.00	
1^{rst} order serial correlatoin	0.65		0.65		-0.43	
2nd order serial correlatoin	0.58		0.59		0.06	

Linear model:

$$RDRAWN_{ijkt} = \beta_0 + \beta_1 Credit\ \ Line_{it} + \beta_2 Firm_{jt} + \beta_3 Bank_{kt} + \beta_4 Economic\ \ Cycle_t + \eta_{ijk} + \varepsilon_{it}\ .$$

Tobit model:

$$RDRAWN_{ijkt} = Max(Min(\beta_0 + \beta_1 Credit\ \ Line_{it} + \beta_2 Firm_{jt-1} + \beta_3 Bank_{kt} + \beta_4 Economic\ \ Cycle_t + \eta_{ijk} + \varepsilon_{it}, 100), 0)\ .$$

The dependant variable is the ratio of the amount drawn at t to the amount available (drawn plus undrawn) when the credit lines was granted of a credit line *i* to firm *j* by bank *k*. The variable $Defaulted\ credit\ line_i$ takes one if the credit line defaults anytime during its life and zero otherwise; $No.\ years\ from\ default_{it}$ measures the time to default in years for those credit lines that do default during its life; $Life\ of\ the\ loan_{it}$ measures the number of years since the credit line was grated; $Long\ term_i$ is a dummy variable worth 1 if the maturity of the credit lines is longer that 1 year and 0 otherwise $Collateralized_i$ is a dummy variable worth 1 if the credit line is collateralized and 0 otherwise ; $Total\ commitments_{jt-1}$ is the sum of all loans and credit lines that the firm has; $Firm\ risk_{jt-1}$ controls for the observed risk of the firm *j* and takes the value of 1 if the borrower defaulted any time until *t;* $No. of\ \ years\ with\ the\ bank_{jt-1}$ measures the number of years since the firm got the first loan with the bank; $No. of\ bank\ relationships_{jt-1}$ is the number of banks with which the firm has loans;*;* $Main\ bank_{ikt}$ is a dummy variable that takes one if the bank that granted the loan is the main bank for the firm and 0 otherwise; $Bank\ share_{kt}$ proxies the size of the bank through its market share in loans to firms; $Bank\ NPL\ ratio_{kt}$ is the non-performing loan ratio of bank *k* at time *t* with respect to the NPL ratio of the year; $Savings\ \ bank_k$ is a dummy variable worth 1 if the bank is a savings bank, 0 otherwise; $Credit\ cooperative_k$ is a dummy variable worth 1 if the bank is a credit cooperative, 0 otherwise; $GDPG_{t+1}$ is the GDP rate of growth of the Spanish economy at t+1. η_{ijk} is an unobservable credit line effect fixed over time; and ε_{it} is an error term. T-ratios are robust to heteroskedasticity and serial correlation. Test for serial correlation are based on estimates of the residuals in first differences except where the model has been estimated in levels. ***, **, *: statistically significant at the 1%, 5% and 10% level, respectively. The Semi-elasticity is computed as the marginal effect divided by the sample mean of the usage rate.

Figure 3

The behavior of the usage ratio of credit lines distinguishing between defaulting and non-defaulting ones using the results of Model 1 Table III

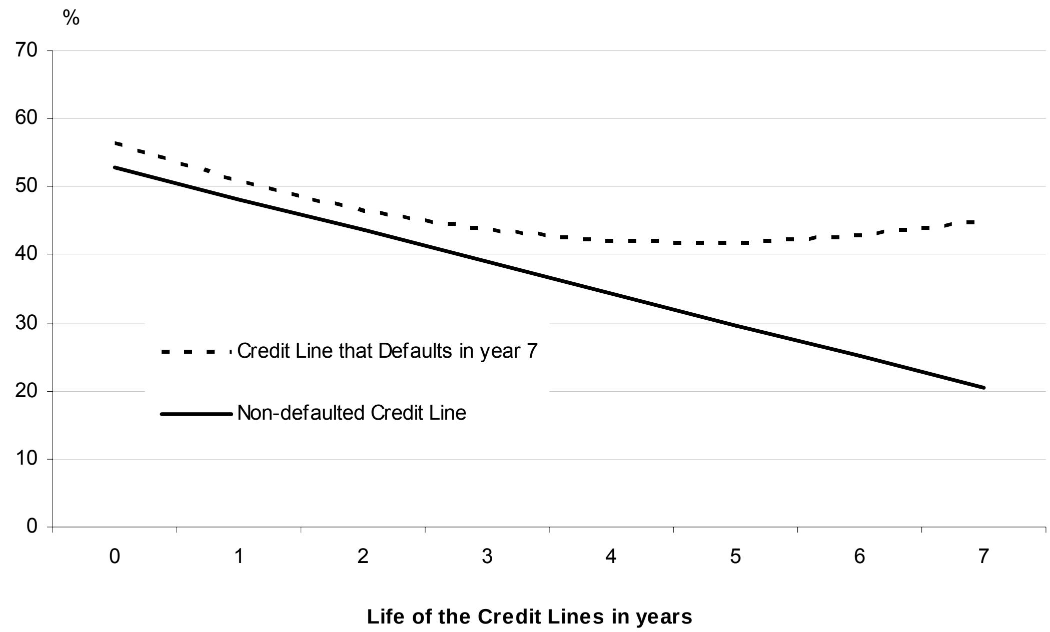


Figure 4

The behavior of the usage ratio of credit lines distinguishing between defaulting and non-defaulting ones using the results of Model 2 Table III

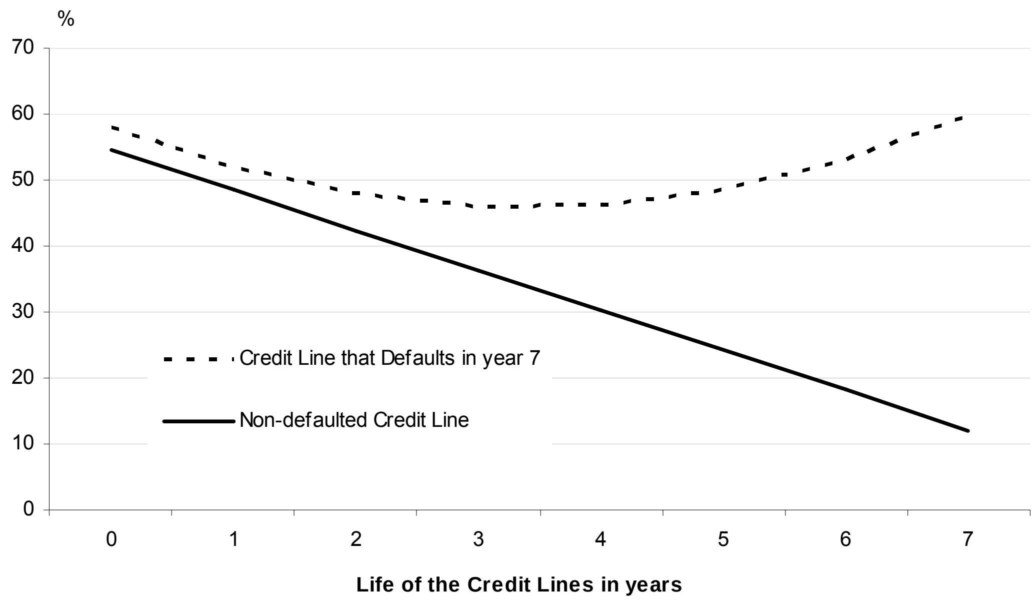


Table IV.

Descriptive statistics for the model including firm characteristics

No. of observatios: 425,939 No.of credit lines: 183,723 No.of firms: 85,949 Sample period: 1993-2004	*Mean*	*S.D.*	*Min*	*Q25*	*Median*	*Q75*	*Max*
Credit Line Characteristics							
$RDRAWN_{ijkt}$ (%)	44.91	33.34	0.00	13.33	44.44	74.49	100.00
Defaulted credit $line_i$ (0/1)	0.00	0.04	0.00	0.00	0.00	0.00	1.00
No. years from $default_{it}$ (for defaulted credit lines)	-0.91	0.90	-6.00	-1.00	-1.00	0.00	0.00
Life of the $loan_{it}$	1.36	1.56	0.00	0.00	1.00	2.00	18.00
Long $term_i$ (0/1)	0.22	0.41	0.00	0.00	0.00	0.00	1.00
$Collateralized_i$ (0/1)	0.08	0.28	0.00	0.00	0.00	0.00	1.00
Firm Characteristics							
Total $assets_{jt-1}$ (thousand of euros)	2,723.78	2,851.08	43.68	498.15	1,345.20	4,446.00	7,900.09
Age of the $firm_{jt-1}$	3.48	7.47	1.00	1.00	1.00	1.00	26.00
ROA_{jt-1} (%)	7.23	7.95	-37.68	3.08	6.10	10.31	60.55
Equity/Total $assets_{it-1}$ (%)	27.03	19.12	0.01	12.14	23.09	37.95	100.00
Liquidity $ratio_{jt-1}$ (%)	6.09	9.48	0.00	0.54	2.59	7.51	100.00
Firm $risk_{jt-1}$ (0/1)	0.01	0.12	0.00	0.00	0.00	0.00	1.00
No. of years with the $bank_{jt-1}$	5.09	4.29	0.00	2.00	4.00	7.00	21.00
No. of bank $relationships_{jt-1}$	3.48	2.93	0.00	1.00	3.00	5.00	9.00
Bank Characteristics							
Main $bank_{ikt}$ (0/1)	0.39	0.49	0.00	0.00	0.00	1.00	1.00
Bank $share_{kt}$ (%)	0.04	0.06	0.00	0.01	0.02	0.09	14.72
Bank NPL $ratio_{kt}$ (%)	0.00	0.57	-9.05	0.00	0.00	0.00	98.70
Savings $bank_k$ (0/1)	0.52	0.50	0.00	0.00	1.00	1.00	1.00
Credit $cooperative_k$ (0/1)	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Cycle Characteristics							
$GDPG_{t+1}$ (%)	3.53	0.72	2.38	3.00	3.43	3.86	5.04

$RDRAWN_{ijkt}$ is the ratio of the amount drawn at t to the amount available (drawn plus undrawn) when the credit lines was granted of a credit line *i* to firm *j* by bank *k*. The variable *Defaulted credit line*$_i$ takes one if the credit line defaults anytime during its life and zero otherwise; *No. years from default*$_{it}$ measures the time to default in years for those credit lines that do default during its life; *Life of the loan*$_{it}$ measures the number of years since the credit line was grated; *Long term*$_i$ is a dummy variable worth 1 if the maturity of the credit lines is longer that 1 year and 0 otherwise *Collateralized*$_i$ is a dummy variable worth 1 if the credit line is collateralized and 0 otherwise; *Ln(Total assets*$_{jt-1}$*)* proxies for the size of the firm; *Ageofthefirm*$_{jt-1}$ is the number of years since the firm was set up; profitability is measured by ROA_{jt-1}, the ratio between EBIT and total assets; *Equity/Total assets*$_{jt-1}$ measures the solvency of the firm; *Liquidity ratio*$_{jt-1}$, is the quotient between cash and total assets of the firm; *Firm risk*$_{jt-1}$ controls for the observed risk of the firm *j* and takes the value of 1 if the borrower defaulted any time until *t*; *No. of years with the bank*$_{jt-1}$ measures the number of years since the firm got the first loan with the bank; *No. of bank relationships*$_{jt-1}$ is the number of banks with which the firm has loans; *Main bank*$_{ikt}$ is a dummy variable that takes one if the bank that granted the loan is the main bank for the firm and 0 otherwise; *Bank share*$_{kt}$ proxies the size of the bank through its market share in loans to firms; *Bank NPL ratio*$_{kt}$ is the non-performing loan ratio of bank *k* at time *t* with respect to the NPL ratio of the year; *Savings bank*$_k$ is a dummy variable worth 1 if the bank is a savings bank, 0 otherwise; *Credit cooperative*$_k$ is a dummy variable worth 1 if the bank is a credit cooperative, 0 otherwise; and $GDPG_{t+1}$ is the GDP rate of growth of the Spanish economy at t+1.

Table V.

Baseline model including firm characteristics

Estimation Method	OLS		Tobit with Random effects		Within-Groups	
No. of observatios: 425,939						
No.of credit lines: 183,723						
No.of firms: 85,949						
Sample period: 1993-2004						
Dependant variable RDRAWN$_{ijkt}$						
	Model 1		Model 2		Model 3	
	Coefficient	*Semi-elasticity*	*Coefficient*	*Semi-elasticity*	*Coefficient*	*Semi-elasticity*
Credit Line Characteristics						
Default effect						
Defaulted credit line$_i$ (0/1)	18.275 ***	40.7	23.493 ***	42.4	--	--
# years from default$_{it}$	4.973	11.1	9.595 **	21.4	0.556	1.2
No. years from default$^2_{it}$	0.583		1.311		0.610	
Ageeffect						
Life of the loan$_{it}$	-4.524 ***	-10.1	-6.437 ***	-11.6	-4.705 ***	-10.5
Life of the loan$_{it}$*Defaulted credit line$_i$	-2.387	-5.3	-0.200	-0.4	--	--
Other effects						
Long term$_i$ (0/1)	3.067 ***	6.8	3.560 ***	6.4	--	--
Collateralized$_i$ (0/1)	0.031	0.1	2.066 ***	3.7	--	--
Firm Characteristics						
Ln(Total assets$_{jt-1}$)	-1.225 ***	-2.7	-1.372 ***	-2.5	-0.826 **	-1.8
Ln(1+Age of the firm$_{jt-1}$)	-0.475 ***	-1.1	-0.444 ***	-0.8	-0.556 *	-1.2
ROA$_{jt-1}$	-0.165 ***	-0.4	-0.159 ***	-0.3	-0.053 ***	-0.1
Equity/Total assets$_{jt-1}$	-0.130 ***	-0.3	-0.153 ***	-0.3	-0.021 *	0.0
Liquidity ratio$_{jt-1}$	-0.229 ***	-0.5	-0.213 ***	-0.4	0.027 **	0.1
Firm risk$_{jt-1}$	-1.582 ***	-3.5	-1.645 ***	-3.0	-4.128 ***	-9.2
Ln(1+# years with the bank$_{jt-1}$)	-2.595 ***	-5.8	-2.737 ***	-4.9	-1.418 ***	-3.2
Ln(No. of bank relationships$_{jt-1}$)	4.645 ***	10.3	4.833 ***	8.7	0.734 **	1.6
Bank Characteristics						
Main bank$_{ikt}$	2.376 ***	5.3	1.229 ***	2.2	-2.493 ***	-5.6
Bank share$_{kt}$	-1.291	-2.9	-3.043 ***	-5.5	-0.822	-1.8
Bank NPL ratio$_{kt}$	0.164 **	0.4	0.163 *	0.3	0.147	0.3
Savings bank$_k$ (0/1)	-3.260 ***	-7.3	-3.720 ***	-6.7	--	--
Credit cooperative$_k$ (0/1)	-1.770 ***	-3.9	-1.995 ***	-3.6	--	--
Cycle Characteristics						
GDPG$_{t+1}$	0.352 ***	0.8	0.252 ***	0.5	-0.639 ***	-1.4
Constant	63.132 ***	--	65.351 ***	--	62.730 ***	--
Credit Line/Firm/Bank fixed effect (η_{ijk})	No		No		Yes	
F-test (p-value)	0.00		0.00		0.00	
1^{rst} order serial correlation	0.60		0.62		-0.43	
2nd order serial correlation	0.52		0.55		0.03	

The dependant variable ($RDRAWN_{ijkt}$) is the ratio of the amount drawn at t to the amount available (drawn plus undrawn) when the credit lines was granted of a credit line *i* to firm *j* by bank *k*. The variable $\textit{Defaulted credit line}_i$ takes one if the credit line defaults anytime during its life and zero otherwise; $\textit{No. years from default}_{it}$ measures the time to default in years for those credit lines that do default during its life; $\textit{Life of the loan}_{it}$ measures the number of years since the credit line was grated; $\textit{Long term}_i$ is a dummy variable worth 1 if the maturity of the credit lines is longer that 1 year and 0 otherwise $\textit{Collateralized}_i$ is a dummy variable worth 1 if the credit line is collateralized and 0 otherwise; $\textit{Ln(Total assets}_{jt-1})$ proxies for the size of the firm; $\textit{Ageofthefirm}_{jt-1}$ is the number of years since the firm was set up; profitability is measured by ROA_{jt-1}, the ratio between EBIT and total assets; $\textit{Equity/Total assets}_{jt-1}$ measures the solvency of the firm; $\textit{Liquidity ratio}_{jt-1}$, is the quotient between cash and total assets of the firm; $\textit{Firm risk}_{jt-1}$ controls for the observed risk of the firm *j* and takes the value of 1 if the borrower defaulted any time until *t*; $\textit{No. of years with the bank}_{jt-1}$ measures the number of years since the firm got the first loan with the bank; $\textit{No. of bank relationships}_{jt-1}$ is the number of banks with which the firm has loans; $\textit{Main bank}_{ikt}$ is a dummy variable that takes one if the bank that granted the loan is the main bank for the firm and 0 otherwise; $\textit{Bank share}_{kt}$ proxies the size of the bank through its market share in loans to firms; $\textit{Bank NPL ratio}_{kt}$ is the non-performing loan ratio of bank *k* at time *t* with respect to the NPL ratio of the year; $\textit{Savings bank}_k$ is a dummy variable worth 1 if the bank is a savings bank, 0 otherwise; $\textit{Credit cooperative}_k$ is a dummy variable worth 1 if the bank is a credit cooperative, 0 otherwise; and $GDPG_{t+1}$ is the GDP rate of growth of the Spanish economy at t+1; η_{ijk} is an unobservable credit line effect fixed over time; and ε_{it} is an error term. T-ratios are robust to heteroskedasticity and serial correlation. Test for serial correlation are based on estimates of the residuals in first differences except where the model has been estimated in levels. ***, **, *: statistically significant at the 1%, 5% and 10% level, respectively. The Semi-elasticity is computed as the marginal effect divided by the sample mean of the usage rate.

Footnotes

i There is a reasonably large literature on consumer credit lines, such as credit card financing; see Gross and Souleles (2002), Calem et al. (2006), and the references therein. Agarwal et al. (2006) examined home equity lines of credit.

ii Note that the CIR dataset does not contain information on credit line pricing, such as fees and interest rates. For a more detailed explanation of the CIR dataset, see Jiménez and Saurina (2004).

iii Please note that differences in the usage ratios of defaulted credit lines are captured by the $Defaulted_i$ indicator and/or by the η_{ijk} fixed effect term. The #years from defaultit variable thus measures the pure impact of firm behavior prior-to-default.

iv Note that our Firm $risk_{jt-1}$ variable is similar in spirit to the modeling strategy used by Sufi (2007) regarding his technical default indicator. The key difference is that he includes his indicator variable in a regression with other measures of firm risk. In fact, his Table 8 shows that credit line availability depends crucially on that variable and not on other firm specific variables. Hence, a default indicator might possibly be a sufficient statistic for other financial characteristics of a firm.

v Note that these explanatory variables are not lagged since they are exogenous to the firm's drawdown decision and are not expected to change much over time.

vi The banking liberalization process in Spain and its impact can be seen in Salas and Saurina (2003).

vii This result is available upon request.

viii The behaviour of the residual's autocorrelation for OLS estimates plus the possible correlation between unobserved fixed effects and some of the explanatory variables explain why we favour the Within-Group estimates.