What Do One Million Credit Line Observations Tell Us about Exposure at Default? A Study of Credit Line Usage by Spanish Firms

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ABSTRACT

Bank credit lines are a major source of funding and liquidity for firms and a key source of credit risk for the underwriting banks. In fact, credit line usage is addressed directly in the current Basel II capital framework through the exposure at default (EAD) calculation, one of the three key components of regulatory capital calculations. Using a large database of Spanish credit lines across banks and years, we model the determinants of credit line usage by firms. We find that the risk profile of the borrowing firm, the risk profile of the lender, and the business cycle have a significant impact on credit line use. During recessions, credit line usage increases, particularly among the more fragile borrowers. More importantly, we provide robust evidence of more intensive use of credit lines by borrowers that later default on those lines. Our data set allows us to enter the policy debate on the EAD components of the Basel II capital requirements through the calculation of credit conversion factors (CCF) and loan equivalent exposures (LEQ). We find that EAD exhibits procyclical characteristics and is affected by credit line characteristics, such as commitment size, maturity, and collateral requirements.

KEY WORDS: credit lines, exposure at default (EAD), loan equivalent exposure (LEQ), credit conversion factors (CCF), Basel II

JEL codes: E32, G18, M21

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1. Introduction

Credit lines are a major source of funding and liquidity for firms. In this paper, we examine the use of bank credit lines by Spanish firms, where these debt instruments account for 19% of banks' total new lending commitments, on average. Our datasource is the Spanish Credit Register known as the *Central de Información de Riesgos* (CIR), which contains information on any loan commitment above €6,000 euros granted by any bank operating in Spain since 1984.

This dataset has a number of unique features that permit us to examine firms' credit line usage ratios. First, information on the amounts drawn and available for individual credit lines is recorded. Thus, we can contribute to the literature that tries to understand the use of credit lines by non-financial firms. Second, since our sample period spans a business cycle, we can analyze credit line utilization during expansions and contractions, contributing to the literature regarding the role played by credit constraints on economic fluctuations. Finally, the dataset allows us to calculate exposures at default (EAD) for a variety of default horizons and credit line characteristics. EAD is the third component, in addition to the probability of default (PD) and the loss given default (LGD), of the expected loss calculations used in credit risk measurement and in the new regulatory capital requirements set out by the Basel Committee on Banking Supervision. To our knowledge, this is the first paper to provide such extensive analysis of EAD calculations.[1]

The extant literature on corporate credit line usage has been framed mainly within a corporate finance perspective, either as studies of liquidity for expanding firms (Ham and Melnik, 1987; Agarwal, Chomsisengphet, and Driscoll, 2004; and Sufi, 2006) or as an alternative to commercial paper financing (Gatev and Strahan, 2005).[2] Our paper more closely follows the methodological path developed by Sufi (2006), who analyzed the role played by bank credit lines in the overall corporate liquidity management of public firms. He found that the supply of credit lines is sensitive to firm profitability. However, our paper has some key differences.

[1] For prior studies providing EAD calculations, see Asarnow and Market (1995), Araten and Jacobs (2001), and Moral (2006).

[2] Berger and Udell (1995) analyze the impact of bank-firm relationships on credit lines while Shockley and

First, in our analysis to date, we have not yet incorporated firm balance sheet data, but have focused on the data available from the CIR. We find significantly different behavior in credit line utilization by defaulted and non-defaulted firms well in advance of the date of default. By default, we mean not just that the firm violates some of the credit line covenants (i.e., exceeds a certain debt threshold), but that the firm is unable to meet the scheduled payments. That leads us to shift the focus of the paper from liquidity management to the financial condition of firms and bank behavior. Second, we have a much larger data set that covers the whole population of loans and credit lines granted to Spanish firms by Spanish banks. Third, the dataset spans more than 20 years, which allows us to analyze the cyclical behavior of the utilization rate. Finally, our paper focuses more on the banks' perspective by considering possible and actual exposures at default.

One of the main findings of the paper is that credit line usage is very different for firms that eventually default and those that do not default. Credit lines to non-defaulting firms have an average usage ratio of about 50%, while credit lines to defaulting firms have a ratio of around 60% five years prior to default. Moreover, the usage rates increase monotonically as default approaches and reach an average of almost 90% at the time default occurs. Therefore, we find robust empirical evidence of more intensive use of credit lines by firms that are approaching financial difficulties. After default, the credit line utilization does not show any significant change.

We model the credit line usage as a function of a firm's number of years to default, measures of its risk profile, the risk profile of its lender, and the business cycle. We find that borrowers identified ex-ante as riskier get less access to credit lines; this result is analogous to the firm profitability result found by Sufi (2006). We also find that credit line use has cyclical characteristics; usage declines during expansions and increases in recessions. As far as we know, this is the first empirical evidence of this type. Thus, credit lines seem to work as a liquidity insurance mechanism for firms, as discussed by Sufi (2006). However, we do not have information on the interest rate charged on each line to examine this finding further.

We extend the analysis of our baseline empirical model to encompass additional variables by using interaction terms with the years-to-default variable. We find that ex-ante

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Thakor (1997) and Kashyap, Rajan, and Stein (2002) focus on the impact of the type of lender.

riskier borrowers that have defaulted on prior loans access their credit lines less than other firms, suggesting a greater degree of bank monitoring. In agreement with this result, we find that larger credit commitments with longer maturities and collateral requirements have lower usage ratios for firms that eventually default.

Our analysis points towards other two areas of research.[3] First , we may be able to contribute to the study of the financial fragility of firms and, in particular, to early warning signals of strain at firms.[4] The quantification of how firms that eventually default have higher rates of credit line usage is a new finding in this literature and might be used to augment models of default probabilities.

Second, we provide empirical evidence on EAD, one of the three components of expected loss and of economic and regulatory capital requirements for credit risk. Spurred on by the development of the Basel II capital framework, a huge literature on default probabilities (PD) and, to a lesser extent, on losses given default (LGD) has developed. However, there is practically no analysis of EAD or, alternatively, on the credit conversion factors (CCF) or loan equivalent exposures (LEQ) used to calculate EAD. Despite the lack of emphasis it has received to date, EAD is a key driver of capital calculations since it enters the capital calculations linearly.

Our empirical results suggest that EAD exhibits procyclical behavior, a result that has not previously been documented. Our analysis of loan equivalent exposures (LEQ) and credit conversion factors (CCF) show that various factors, such as commitment size, maturity and collateral requirements, appear to impact EAD values. Our findings show that the EAD parameterization in the standardized approach of the Basel II framework may be too low, while the parameterization for the foundation approach seems to be in relatively agreement. Overall, the procyclical behavior of EAD would seem to augment the expected higher procyclicality in the default probabilities used for the Basel II capital requirements.

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[3] The third line of research were the paper fits in is in the literature on credit card financing; see Gross and Souleles (2002), Calem, Gordy and Mester (2006), and the references in them. However, in Spain, credit cards are mostly confined to its use by individuals and, more importantly, the use by them is rather limited; credit card exposures are less than 1% of total loan exposures of Spanish banks. Therefore, although the issues involved are interesting, we focus on credit lines to firms, which are much more relevant in quantitative terms.

[4] There is a vast literature on this issue starting with the seminal paper by Altman (1968). See Altman (1993) and Altman and Saunders (1998) for detailed surveys of this literature.

The remaining of the paper is organized as follows. Section 2 describes the CIR database and how we constructed the credit line data that we examine. We provide a preliminary statistical analysis of the data as well as a quick review of the relatively scarce literature related to credit line. Section 3 presents the results of our econometric analysis of the determinants of corporate credit line utilization. Section 4 explores the policy issues that stem from the credit line analysis of defaulted creditors and its usefulness for the Basel II framework, and Section 5 concludes.

2. Database, descriptive statistics and a quick review of the related literature

2.1. Database

This paper uses data from the Spanish Credit Register maintained by the Bank of Spain. This dataset contains information about all loans granted by Spanish credit institutions within Spain above a threshold of €6,000.[5] The database is essentially a census of all corporate bank lending within Spain from 1984 to 2005.[6] The CIR database contains detailed information about loan characteristics such as instrument type (i.e., commercial loan, lease financing, etc.), currency, maturity, use of collateral, its default status as well as the amount drawn and the total available for credit lines.[7] 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).[8]

In addition, information on the borrower's industry and province of headquarters are available. Given the nature of the 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). Note we do not have

[5] Reporting institutions include commercial banks, not-for-profit savings banks, credit cooperatives and credit finance establishments.
[6] While consumer loans may be below this threshold, loans to firms below that threshold are scarce.
[7] For a more detailed explanation of the CIR, see Jiménez and Saurina (2004).
[8] Here we depart significantly from Sufi (2006) for whom default means a breach of the existing covenants on

information on the interest rate charged on individual loans.

We identify *new* bank credit lines (i.e. those lines that appear for the first time in a given year) to non-financial firms in the CIR database by filtering out loans where the amount lent (or drawn) is equal to the total commitment amount, and then we track them through time. In order to track credit lines through time, we use all their available characteristics (borrower, total amount, collateral, etc.). Despite the fact that most credit lines nominally are short term (i.e., maturity less than one year), 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.

For this study, we focus on those credit lines granted to firms by only one bank. That is, we combine several credit lines obtained by a firm from a single bank into observations in our data, but we exclude credit lines obtained by a firm with multiple banking relationships. We apply this filter to remove possible instances of strategic behavior by firms trying to take advantage of their relationships with several banks.[9] After applying our filtering procedures, we have a sample of 915,563 credit line-year observations corresponding to 352,328 credit lines granted to 258,532 firms by 444 banks. Roughly 85% of the observations are individual credit lines held by a firm with a single bank, and the remaining 15% of the observations correspond to firms that hold more than one credit line with a bank. We examine the period from 1985 to 2005, which includes a deep recession around 1993, and two expansionary periods around the late 1980s and early 1990s and from 1997 onwards.

2.2. Descriptive statistics

Figure 1 presents the histogram of our credit line usage rates across firms and time. Just over 14.3% of all credit line-year observations are zero; these observations correspond to 90,051 unique credit lines. Conversely, almost 11% of these observations are at 100% usage. For the remaining 75% of the observations, the distribution is relatively symmetrical around the 50% value. Note that the results presented below do not change when we exclude both

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the credit line.

[9] In any case, the results of the descriptive analysis would not change too much if we included those firms holding credit lines from several banks.

sets of extreme observations. In Section 3, we model the determinants of the utilization ratio.

Figure 2 contains one of the most important empirical results of the paper. Since the CIR database has information on when firms default on their loan payments, we are able to transform our credit line usage data from calendar time to event time, where the default year is designated as time zero. The figure shows the average value of the credit line usage ratios for firms that do and do not default during the sample period. For every year in our sample, the credit line usage rates for both nondefaulted and newly 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) and two years after (i.e., event year +2) time zero.

The figure presents the average values of the usage rates for defaulted and nondefaulted firms across the 17 years for which we have event-time data (i.e., 21 sample years - 5 years of prior event time). Firms that default on a credit line draw down more than firms that do not default, even up to five years before the default year. At five years prior, the average usage rate for defaulting firms is close to 60%, as compared to 50% for nondefaulting firms. As default approaches, these firms draw down their credit lines at a monotonically increasing rate, while nondefaulting firms do not change their behavior. At the default year, the average usage rate for defaulting firms reaches its maximum of about 90%. The Wilcoxon rank sum test and the mean test presented in Table 1 suggest that these two sets of usage ratios are significantly different at the 1% level for event years -5 through 0.[10]

To better understand these results, Figure 3 and Table 2 show a more detailed analysis of the distributions of the defaulted firms' utilization ratios across the event window. Clearly, the dispersion in year -5 is quite large with an interquartile rate from 33% to 80%. This dispersion remains roughly constant as firms headed into default, although the level increases as they increasingly draw down their credit lines. For example, in the year prior to default, the usage ratio's interquartile range is from 51% to 97%. However, the level increases and the dispersion shrinks sharply in the default year; the interquartile range is from 92% to 100% with a median value of 100%. Note that in Section 4 we use these time characteristics of the usage rates in our analysis of the EAD measures used for economic and regulatory capital requirements.

[10] The former results have policy implications for bank managers, analysts and regulators, which will be pursued

Figure 4 presents our event-time analysis for the individual years of our sample.[11] Across these sample years, the median values of the usage rates follow a similar upward-sloping pattern. The pattern is more pronounced in 1993, the year of the worst Spanish recession in the past forty years, when the median utilization ratio goes from around 30% in event year -5 to more than 90% in event year zero. In Section 3, we provide a more detailed analysis of utilization rates across the business cycle.

Event study analysis based on credit line size, maturity and collateral requirements were conducted, but no clear cut difference between defaulted and nondefaulted firms were found. We also examined whether bank characteristics, such as bank type, size or degree of riskiness, impact the usage rates of defaulted firms, but the results did not indicate a clear significant relationship.

2.3. A short review of the literature

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. Melnik and Plaut (1986) study the determinants of credit line commitment size for a surveyed group of U.S. corporations. They found that commitment size was an increasing function of maturity, fees, collateral, firm size, firm liquidity and risk premium. Ham and Melnik (1987) examine commitment usage for a sample of 90 U.S., nonfinancial firms. They found that line utilization was related positively to total sales, borrowed reserves and collateral, while related negatively to interest rate costs. Berger and Udell (1995) found using a sample of small U.S. firms that credit line terms, such a s interest rates and collateral requirements, are negatively related with the length of the banking relationship.

Using a sample of public U.S. firms from 1996 to 2003, Sufi (2006) found that credit line access and use was influenced by firm profitability, industry, age and size. He takes a corporate finance angle looking at the role of credit lines as an alternative liquidity

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in Section 4, but also contribute to the literature on early warning systems of firm default.

[11] Obviously, we exclude 1985 through 1988, whereas 1989 lacks the *t-5* observation and 2004 and 2005 lack the *t+1* and *t+2* observations.

management tool. He found the supply of credit lines to be particularly sensitive to firm profits: in particular, a one standard deviation move in profits (measured by the EBITDA) raises commitments by 20% to 25%. His preferred liquidity measure is the ratio of bank liquidity, measured as the undrawn credit amount, to total liquidity, defined as the undrawn commitments plus cash on the balance sheet. He found that technical default (i.e. commitments violated) the year prior leads to reduced undrawn capacity of more than 30%, evaluated at the mean.

Agarwal, Chomsisengphet, and Driscoll (2004) examine a proprietary dataset from a large financial institution of loan commitments made to 712 privately-held U.S. firms. They test the Martin and Santomero (1997) model where credit lines give firms the speed and flexibility to pursue investment opportunities. Firms facing higher rates and fees have smaller credit lines. Firms with higher growth commit to larger lines of credit and have a higher rate of line utilization. Firms facing more uncertainty in their funding needs commit to smaller credit lines.

As far as we know, there is no academic, empirical work on exposure at default (EAD), which is a transformation of the credit line usage ratio if the firm where to default. As mentioned earlier, EAD is one of the key risk components of expected loss for credit risk exposures and has become a key parameter in regulatory capital requirements. To date, the most commonly cited papers regarding EAD are Asarnow and Marker (1995) as well as Araten and Jacobs (2001), both of which examine selected credit portfolios from individual banks over narrow time periods. Recently, Moral (2006) presented some further evidence.

3. Econometric modeling

In this section, we use a variety of regression models to examine the determinants of credit line utilization.

3.1. Model and sample variables

Following the literature on corporate finance, we model the usage ratio, defined as the ratio of a line's drawn amount to its total commitment amount. We denote the usage rate of credit line *i* granted to firm *j* by bank *k* at time *t* as $RDRAWN_{ijkt}$. Since the ratio can only take values on the [0,100] interval, we transform it using a logistic function to increase its variability; i.e.,[12]

$$\mathrm{Ln\_RDRAWN}_{\mathrm{ijkt}} = \ln\left(\frac{\mathrm{RDRAWN}_{\mathrm{ijkt}}}{100-\mathrm{RDRAWN}_{\mathrm{ijkt}}}\right).$$

The baseline model used to examine the determinants of the credit line usage ratios is:

$$Ln\_RDRAWN_{ijkt} = \beta_1\delta_{it} + \beta_2 Firm_{jt} + \beta_3 Bank_{kt} + \alpha_1 GDPG_t + \alpha_2 RIR_t + \eta_i + \varepsilon_{it},$$

where η_i is an unobservable credit line effect that is fixed over time; δ_{it} measures the time to default for those credit lines that default at time t+τ, τ>0; $Firm_{jt}$ is a set of variables that controls for firm characteristics; $Bank_{kt}$ is a set of variables that control for bank characteristics; $GDPG_t$ is the real, annual growth rate in Spanish GDP and a measure of macroeconomic conditions at time t; RIR_t is the three-month real interbank interest rate and a measure of funding costs at time t; and ε_{it} is an error term.[13]

Our variable of interest is δ_{it}, which measures the impact of the time to default on the credit line usage rate. We specify this variable in two ways. The less restrictive specification uses a set of dummy variables for the number of years to default; for example, five years prior to default, $\delta_{\mathrm{it}}(-5)=1$ and $\delta_{\mathrm{it}}(\tau)=0$ for τ = [-10,-6] $\cup$ [-4,0]. The second specification sets δ_{it} equal to the actual number of years prior to default, such that $\delta_{it} \in [-10,0]$ and imposes a strict linear relationship on the variable. From the descriptive analysis presented earlier, we expect a positive sign for the δ_{it} coefficient; that is, as the default time approaches (i.e., δ_{it} increases), the usage rate increases.[14]

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[12] Ln_RDRAWN_{ijkt} is not defined for extreme values, but we resolve this by setting its value to Ln[0.001/(100-0.001)] when $RDRAWN_{ijt}$ is equal to 0 and to Ln[99.999/(100-99.999)] when $RDRAWN_{ijt}$ is 100.

[13] In fact, the credit line effect is η_{ijk} and the time to default effect is δ_{ijkt}, but we use the notation η_i and δ_{it} for simplicity.

[14] It is worth noting that the level of the usage ratio of defaulted credit lines is captured by the fixed effect η_i; thus, the δ_{it} variable measures the pure prior-to-default effect.

The information contained in the CIR database about firms' characteristics is very limited and lacks variability over time. For this reason, it is important to control for firm fixed effects, which are absorbed into the credit line effect η_i. Moreover, all credit line time-invariant characteristics, such as its maturity or collateral requirements, are also included in η_i. However, the CIR database does provide a measure of firm risk since information on prior firm defaults on any bank loan are recorded. We construct a dummy variable, denoted as Firm risk_{jt}, that equals one if the firm had defaulted on any loan prior to time t. This prior default indicator is used as proxy for a firm's reputation with its lenders. We expect closer monitoring by banks of these riskier firms, which could result in their having lower credit line usage rates and hence a negative coefficient.[15]

As per the empirical work of Berger and Udell (1995), we include bank characteristics derived from the CIR database into our analysis. Specifically, a bank's non-performing loan ratios for corporate lending, denoted as *Bank NPL ratio*$_{kt}$, is a proxy for bank riskiness, and a bank's share of the corporate loan market, denoted *Bank share*$_{kt}$, is a proxy for bank size. The signs on the coefficients for these two variables are unclear a priori, and we view them as control variables.

Macroeconomic conditions should play an important role from a theoretical point of view. The literature on the lending channel of monetary policy transmission has established that during recessions, firms are more constrained in their access to external financing. This outcome would imply that firms will use their existing credit lines more in bad times, provided that banks do not impose further restrictions on their use. Thus, we expect a higher usage rate during recessions and a negative coefficient on real annual GDP growth, denoted as $GDPG_t$. We include the real, short-term interest rate variable RIR_t to control for the general cost of credit lines. While correlated with GDP growth, interest rates may have independent fluctuations that would impact the cost and usage of credit lines. As noted earlier, we do not have the interest rate for each credit line, but by including the real interest rate, we hope to control for funding costs in general. We expect a positive coefficient on RIR_t since the use of

[15] Note that the use of the variable is close to the modeling strategy used by Sufi (2006) with the key difference that we use only one variable to summarize the financial position of the firm. In fact, his Table 9 shows that when his technical default variable is included in the model, credit line availability depended crucially on that variable and not on other firm specific variables. So, it seems that a default indicator may be a sufficient statistic for other financial characteristics of the firm.

prearranged credit lines should be cheaper than raising new funds.

To examine further the impact that upcoming default may have on credit line utilization, we extend the baseline model using interaction terms. Specifically,

$$Ln\_RDRAWN_{ijkt} = (\beta_1 + \gamma X_{it})\delta_{it} + \beta_2 Firm_{jt} + \beta_3 Bank_{kt} + \alpha_1 GDPG_t + \alpha_2 RIR_t + \eta_i + \varepsilon_{it},$$

where X_{it} corresponds to individual variables of interest. This specification allows us to examine whether, say, commitment size or macroeconomic conditions have a differential impact on the credit line usage of firms that eventually default.

Note that for the empirical analysis in this section, we introduce some additional filters. As in the previous section, we only use credit lines of firms that work with only one bank, but we now drop credit lines granted by financial credit establishments in order to allow for a clearer comparison of the remaining bank types. These observations accounted for only 0.4% of the sample. We also drop credit line-year observations for the years after the default event. These adjustments slightly reduce our estimation sample size to 904,542 credit line-year observations.

Table 3 presents the summary statistics for the dependent and explanatory variables. The distribution of the utilization ratio $RDRAWN_{ijkt}$ for our regression sample remains symmetric with mean and median values of 49.6% and 50.0% respectively. The proportion of observations corresponding to actual defaults is only 0.76%. The year-to-default variable δ_{it} ranges from -9 to 0, while the proportion of observed risky firms, as indicated by having $\text{Firm risk}_{jt} = 1$ is 1.9%. Regarding bank level variables, the average non-performing loan ratio is 0.53% with considerable dispersion. The average loan market share of each bank is 0.03%, with a maximum of 14.7%. For the macroeconomic variables, the time period analyzed includes a deep recession in 1993 with a -1.03% annual real growth rate and two expansions with a maximum growth rate of 5.55%. Real interest rates, although positive on average, did achieve negative values in certain years as the Spanish economy experienced high inflation at the beginning of the period.

For our interaction analysis, we also examine some variables not used in the baseline regression. In terms of credit line characteristics, only 20.8% have a maturity greater than one year, denoted as the indicator variable *Long term*$_i$. The percentage of observations corresponding to collateralized credit lines is quite low at 8.6%. The commitment amount varies considerably with the maximum being 100 times more than the minimum, even after winsorizing the upper 5% tail.

The last interaction variable we examine is bank type. In Spain, 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 not-for-profit organizations controlled by depositors, employees and other public and private groups. As determined by Salas and Saurina (2002), 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 40.6% and 54.2% share, respectively, of the number of credit line-year observations, while credit cooperatives make up the remaining 5.2% of the observations. At the beginning of the sample period, commercial banks dominated the market with a market share of 80% in 1986. 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.[16]

3.2. Regression results

Table 4 presents the estimation results for our baseline model. The first set of results are based on an OLS regression. To avoid the potential biases due to the possible correlation between η_i and δ_{it}, we also present results using the within-group estimation technique. In both cases, we account for possible autocorrelation in the error term when calculating the standard errors and assume the explanatory variables are uncorrelated with the error term.

If δ_{it} and η_i are correlated, we would expect the OLS parameter estimates to be biased. For Model 1 in Table 4, the coefficient on δ_{it} is negative and significant, suggesting

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

that as a firm approaches default (i.e., δ_{it} increases towards zero), it credit line usage decreases. This result clearly goes against the descriptive analysis in Figure 2. Furthermore, the test statistics for first- and second-order autocorrelation in the residuals indicate significant autocorrelation, consistent with the presence of credit line fixed effects.[17]

Focusing on the results for the within-group estimates, Model 2 based on the linear specification of years-to-default variable shows a positive and very significant relationship. This result implies an increasing use of credit lines as a firm's time to default approaches. As far as we know, this empirical result is new in the literature. The *Firm risk*$_{jt}$ measure based on prior defaults is negatively correlated with credit line usage, which probably indicates that lower-quality borrowers are closely monitored by banks and may even have access to credit lines curtailed somehow. This result is fully in line with Sufi (2006). In terms of the lender characteristics, credit lines granted by higher-risk banks (i.e., higher *NPL*$_{kt}$) have a higher level of use, perhaps suggesting that these banks are more lenient in their credit line management. Finally, bank share, as defined within our CIR data sample, has a positive correlation with credit line usage, perhaps pointing to more confidence and experience by larger institutions.

Our results also imply a significant relationship between macroeconomic conditions and credit line use. The coefficient on real GDP growth is negative. During expansions, firms thus tend to reduce their usage ratios, but during recessions, firms increase their use of credit lines. As suggested in the theoretical literature, 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 information on the interest rates paid on these credit lines, and thus we cannot determine if credit lines are used more as a liquidity insurance mechanism with the corresponding premium over other sources of funds.[18] Regarding the prevailing short term real interest rate in the economy, our results support a positive relationship. When funding costs increase, firms draw more from their credit lines, probably because the interest rate for a new loan or other funding is higher than that agreed upon in an existing credit line.[19]

[17] Moreover, the autocorrelation coefficients for the residuals show a slow decline from 0.69, corresponding to the first serial correlation, to 0.44, corresponding to the 8th serial correlation, which also supports the existence of credit line fixed effects.

[18] Thakor (2005) rationalizes bank loan commitments as partial insurance against credit rationing.

[19] Table 4 also shows the first- and second-order autocorrelations tests for the differenced residuals. If ε_{it} is

As mentioned, we also examine an alternative form of the years-to-default variable that permits a more flexible, piecewise-linear relationship with credit line usage rates. Model 3 in Table 4 introduces a time dummy for defaulted credit lines such that δ_{-r} equals one if the time to default is r years and zero otherwise. The coefficient estimates form a clear quadratic pattern, although only the coefficients for the last two years prior to default and for the year of default are significant. This result suggests that as a firm enters into financial difficulties, it draws increasingly from its credit line. Given that Model 2 introduces the linear dependence as an approximation to that observed in Model 3 and that empirical results are similar, we use the linear specification in our analysis of the interacted variables.

3.3. Differential impacts on credit line use by defaulted firms

In this section, we present the empirical results for our interacted models. Specifically, we deepen the analysis of credit line usage by interacting the years-to-default variable with firm, credit line, bank, and business cycle characteristics.

Firm characteristics

Table 5 presents the empirical results for Model 4, which interacts the δ_{it} and *Firm risk*$_{jt}$ variables. The coefficient on the interaction is negative and significant. Thus, for a given value of δ_{it}, lower-quality borrowers in our sample (i.e, those for *Firm risk*$_{jt}$ =1) are seen to use their credit lines less, suggesting that banks work to constrain their exposure to these firms more strictly. A related result was found by Jiménez, Salas and Saurina (2006), who show that firms with prior defaults as noted in the CIR database are required to pledge more collateral.

Credit line characteristics

serially independent, the first-order autocorrelation test of its first-differences should not be rejected, because $\Delta\varepsilon_{it}$ and $\Delta\varepsilon_{it-1}$ shares the term ε_{it-1}, while the second-order should be rejected. Model 2 shows that ε_{it} is serially correlated, as expected from the diagnostic of Model 1, but this correlation is quite low as shown by the fourth-order test, which can be rejected at 10%, and all the subsequent ones, and is taken into account to perform the tests.

As discussed in Section 2, credit line usage seems to depend on the characteristics of the credit lines themselves, although not always in clear cut ways. Table 6 presents the empirical results for the three different credit lines characteristics we examined using our interaction model. These characteristics are fixed over time and hence take the form X_i and are embedded within the baseline model in η_i term. We examine the impact of commitment size, denoted as *Ln(COMMIT$_i$)* and winsorized at the upper 5% tail; maturity, denoted as *Long term$_i$* and taking a value of one if it is longer than one year; and collateral, denoted as *Collateralised$_i$* and taking a value of one if the credit line is collateralized.

The results for these three regressions suggest that the larger the commitment, the longer the maturity or whether collateral is used decreases credit line usage for firms that eventually default. These results suggest that bank monitoring of larger credit lines or those of longer duration is more thorough. Both of these variables are directly related to the amount of credit risk a bank is willing to bear. As to the role of collateral, the result is consistent with the perspective that riskier borrowers are required to provide more guarantees and hence less likely to miss loan payments.

Bank characteristics

A priori, it is reasonable to assume that bank characteristics might impact credit line usage. For example, different ownership concerns could lead to different credit risk management techniques. In this section, we examine the impact of bank riskiness, size and type (i.e., commercial bank, savings bank or credit cooperative) on credit line usage. Table 7 shows the empirical results.

Model 8 introduces the interaction term between *Bank NPL ratio$_k$* and δ_{it}. The coefficient is positive and significant at the 1% level, which implies that the higher the risk of the bank, the larger the draw down of credit lines prior to default. Moreover, it is important to note that although this rate is higher, the utilization ratio of credit lines in general is also higher for risky banks, as shown by the positive coefficient on *Bank NPL ratio$_k$* variable itself. Putting together both results, it seems that riskier banks monitor their credit lines less well than less risky banks.

With respect to bank size, Model 9 shows that this interaction term is positive and significant. Therefore, larger banks allow firms to use their credit lines more as the default event approaches.

For bank type, Model 10's interacted terms for savings banks and cooperatives are insignificant, meaning that the utilization rate for defaulted credit lines is the same as for commercial banks. The F-test for equal coefficients between the savings bank and credit cooperatives dummies cannot be rejected at the 1% value. This result is somewhat surprising given the historical experience of savings banks in the corporate lending market. In the early 1990s, they started to lend to firms due to market deregulation and suffered a very significant increase in non-performing loans shortly thereafter. They were paying the price of inexperienced players in the credit market to firms. However, regarding credit lines, savings banks may have been more careful over the entire period.

Business cycle characteristics

The impact of macroeconomic conditions on credit line usage seems to be clearly laid out in various theoretical models, but the empirical results are scarce to nonexistent. The results in Table 8 show that the coefficient on the interacted variable for δ_{it} and real GDP growth is negative and significant at the 5% level. This result implies that credit line usage by firms that eventually default increases during recessions and decreases during expansions. This is, to our knowledge, the first empirical evidence on the procyclical behavior of credit line usage and hence of exposure at default. Therefore, not only do the PD and LGD parameters in capital calculations fluctuate over the business cycle, but the EAD parameter does as well.

Robustness of the results

First, it is important to note that the coefficients on the non-interacted variables do not change in sign or significance across our model specifications. This result suggests the robustness of the original baseline specification. Second, we have repeated the baseline estimation replacing δ_{it} with the age of the credit line relationship. Model 12 in Table 9 shows that the coefficient on this age variable is negative for non-defaulted credit lines and positive for defaulted credit lines. This result suggests that as time passes, corporate credit lines are used less, except for those firms that are headed toward default. The latter drawn down their lines more so as time goes by. This result is fully consistent with those obtained in the previous regressions and shows, again, the robustness of the baseline model.

4. Policy analysis

4.1. Background discussion

A key component of the credit risk management issues surrounding corporate credit lines is the drawdown behavior of firms that eventually default. In simple terms, a bank needs to set aside capital not only against the amount that a firm has borrowed through a credit line, but must also against funds that might be borrowed in the future. A bank's exposure through credit line *i* at time *t* for a default horizon τ, which is denoted as $EAD_{it}(\tau)$, is the sum of the drawn amount at time t and a fraction of the undrawn amount, where that fraction takes into account at least the default horizon. This fraction is commonly known the loan equivalent amount (LEQ).[20] Using notation, EAD is expressed as:

$$EAD_{it}(\tau) = DRAWN_{it} + LEQ_{it}(\tau) * UNDRAWN_{it}.$$

The method for calculating $LEQ_{it}(\tau)$ is algebraically straightforward. For credit lines with some undrawn amount,

$$LEQ_{it}(\tau) = \frac{DRAWN_{it+\tau} - DRAWN_{it}}{UNDRAWN_{it}}.$$

Obviously, the variable $DRAWN_{it+\tau}$ is not observable at time t and must be replaced with a forecast for operational purposes.

The only published empirical analysis of LEQ to our knowledge is Araten and Jacobs

[20] See, for instance, Engelmann and Rauhmeier (2006).

(2001).[21] Based on 408 facilities to 399 defaulted borrowers within a single financial institution over the period 1994 to 2000, the authors find an unconditional LEQ of 43.4%.[22] The authors found $LEQ_{it}(\tau)$ to be a decreasing function of τ; i.e., as the time to default approaches, borrowers that eventually default are more likely to drawn down their credit lines. The authors also found that LEQs declined with facility risk ratings, however that relationship was not considered to be robust. The authors further concluded that a number of variables did not impact LEQ values; in particular, type of lender, commitment size, or borrower industry.

EAD is clearly a key component of economic capital calculations with respect to credit risk, and it has been formalized as a key ingredient of regulatory capital requirements under the Basel II Capital framework. Within Basel II, EAD is expressed slightly differently than the LEQ form presented above; that is, EAD is expressed as:

$$\mathrm{EAD}_{it}(\tau) = \mathrm{CCF}_{it}(\tau) * \left(\mathrm{DRAWN}_{it} + \mathrm{UNDRAWN}_{it}\right),$$

where CCF stands for credit conversion factor. While LEQ is the percentage of the undrawn amount at time *t* that the borrower will have used at default time τ, CCF is the fraction of the total commitment at time t that will have been drawn when the borrower reaches default time τ. CCF and LEQ are related as follows:

$$\mathrm{CCF}_{it}(\tau) = \frac{\mathrm{EAD}_{it}(\tau)}{\mathrm{DRAWN}_{it} + \mathrm{UNDRAWN}_{it}} = \frac{\mathrm{DRAWN}_{it} + \mathrm{LEQ}_{it}(\tau) * \mathrm{UNDRAWN}_{it}}{\mathrm{DRAWN}_{it} + \mathrm{UNDRAWN}_{it}}.$$

Within the Basel II framework, CCF parameterizations appear in various capital calculations. Under the standardized approach, commitments with an original maturity up to one year will receive a CCF of 20%, and commitments with an original maturity over one year will receive a CCF of 50%. However, any commitments that are unconditionally cancelable at any time by the bank without prior notice, or that effectively provide for

[21] Asarnow and Marker (1995) report LEQ estimates based on public ratings, but do not conduct any analysis.

[22] Note that multiple credit lines to a single borrower were combined by the authors. The default event for this study was when a credit line's risk rating first reached the bank's substandard category, which is the point at which borrowers were unable to draw down further amounts.

automatic cancellation due to deterioration in a borrower's creditworthiness, will receive a CCF of 0%.[23] Under the foundation approach, a CCF of 75% will be applied to standard commitments that do not have effective cancellation clauses.[24] Under the advanced approach, banks that meet the minimum requirements for use of their own estimates of EAD will be allowed to use their own internal CCF estimates for credit lines.[25] The additional minimum requirements for internal EAD estimation specify that the EAD estimates must be made for each facility. Moreover, they should reflect the possibility of future draw downs up to and after a default event.[26]

4.2. Empirical estimates of LEQ

Our analysis here is focused on LEQ since this is the more common form used by practitioners, but we also generate CCF estimates to compare with the values in the Basel II framework. The sample analyzed here contains all defaulted credit lines in our database. We have 8,384 defaulted credit line-year observations, corresponding to 2,883 different credit lines, out of our original close-to-one million observations.

Figure 5 shows that our $LEQ_{it}(\tau)$ estimates decrease monotonically from 73.2% at five years prior to default to 36% at one year prior to default. That is, a credit line that will default the following year increases its exposure at the time of default by 36% of the undrawn amount. This result is consistent with an increasing use of the credit lines as the time to default approaches. The unconditional mean value for $\tau \in [1,5]$ is 48.12%, which is similar to the 43.4% reported by Araten and Jacobs (2001).

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[23] See paragraph 83 of the Basel II document (BCBS (2004)).

[24] See paragraph 312 of the Basel II document. Nevertheless, paragraph 311 states that for instruments different of commitments, note issuance facilities and revolving underwriting facilities, the CCF of the standardized approach apply.

[25] See paragraph 316 of the Basel II document.

[26] "Advanced approach banks must assign an estimate of EAD for each facility. It must be an estimate of the long-run default-weighted average EAD for similar facilities and borrowers over a sufficiently long period of time, but with a margin of conservatism appropriate to the likely range of errors in the estimate. If a positive correlation can reasonably be expected between the default frequency and the EAD magnitude, the EAD estimate must incorporate a larger margin of conservatism. Moreover, for exposures for which EAD estimates are volatile over the economic cycle, the bank must use EAD estimates that are appropriate for an economic downturn, if these are more conservative than the long-run average. For banks that have been able to develop their own EAD models, this could be achieved by considering the cyclical nature, if any, of the drivers of such models. Other banks may have sufficient internal data to examine the impact of previous recessions. However,

The observed pattern for LEQ varies when we consider different characteristics of the credit lines. As before, the size of the commitment, the maturity of the credit line or whether the line is collateralized are used as explanatory variables. We categorize our sample into four size quantiles, two maturity groups based on a one-year threshold, and into collateralized and non-collateralized groups.

Figure 6 presents the average LEQ for the eight different categories considered. For almost all categories, the LEQ curve decreases as the default year approaches. Only very large credit lines do not show this pattern clearly, as we also noted in the regression analysis. In line with the results obtained in Section 3.3, large credit lines have lower LEQ averages, and the smallest credit lines have the highest values, providing a monotonically decreasing relationship between LEQ and commitment size. Credit lines with shorter maturity have higher LEQ values consistently along time to default, and collateralized credit lines also have lower LEQ values.

We now turn to a discussion of the CCF values used within the Basel II framework. Our goal is to examine the current parameterizations in light of our empirical results. First, the average usage rate our sample is 51.5% with a value of 50.1% for credit lines with a maturity below one year and 56.5% for those above one year. Thus, maturity does not seem to play a large role in the average amount drawn from credit lines, which contrasts with the different treatment of commitments in the standardized approach depending on its maturity. Second, the estimated one-year horizon CCF is 86.8%, which is above the 75% value specified for the foundation approach. Third, if the credit line is collateralized, we obtain an average CCF of 78.5%, whereas it is larger at 88.8% for non-collateralized ones. Fourth, the CCF depends on the total commitment size in a negative way; that is, as commitment size increases, the CCF decreases. The largest credit lines have an average CCF of 76.9%, while the smallest ones average at 95.6%. This result contrasts with the conclusions presented in Araten and Jacobs (2001).

some banks may only have the option of making conservative use of external data".

5. Conclusions

In this paper, we make use of the Spanish Credit Register, a huge database known as the *Central de Información de Riesgos* (CIR), that covers most loans granted by banks operating in Spain over the last twenty years, to analyze credit line usage by corporate borrowers. The paper fits into the corporate finance literature as it studies the determinants of credit line use. However, the findings also fit into the literature on early warning systems for corporate default. More importantly, the paper is one of the few, if any, that provides empirical evidence on exposure at default (EAD), one of the key risk factors used in economic and regulatory capital calculations, such as laid out in the Basel II framework.

Using almost one million credit line-year observations, we find that credit lines are drawn down more by firms that eventually default than firms that do not. This usage rate is higher in a statistically significant way from at least five years prior to default and increases monotonically as default approaches. As far as we know, this empirical finding is new to the literature. We find that this usage pattern holds for each year in our sample, but does fluctuate with macroeconomic conditions.

We model the credit line utilization ratio as a function of a firms' years to default, measures of its risk profile, the risk profile of the lender, and the business cycle. We find that borrowers identified ex-ante as riskier access their credit lines less; this result is analogous to the firm profitability result found by Sufi (2006). We also find that credit line use has cyclical characteristics; usage declines during expansions and increases in recessions. As far as we know, this is the first empirical evidence of this type. Thus, credit lines seem to work as a liquidity insurance mechanism for firms, as discussed by Sufi (2006). However, we do not have information on the interest rate charged on each line to examine this finding further.

We extend the analysis of our baseline empirical model to encompass additional variables by using interaction terms with the years-to-default variable. We find that ex-ante riskier borrowers that have defaulted on prior loans access their credit lines less than other firms, suggesting a greater degree of monitoring. In agreement with this result, we find that larger credit commitments with longer maturities and collateral requirements have lower usage ratios for firms that eventually default.

Finally, the paper contributes to the almost non-existent literature on exposure at default (EAD), a key parameter used for economic and regulatory capital calculations. Our empirical results suggest that EAD exhibits procyclical behavior, a result that has not previously been documented. Our analysis of loan equivalent exposures (LEQ) and credit conversion factors (CCF) show that various factors, such as commitment size, maturity and collateral requirements, may impact EAD values. Our findings show that the EAD parameterization in the standardized approach of the Basel II Capital framework may be too low, while the parameterization for the foundation approach seems to be in relatively agreement. Overall, the procyclical behavior of EAD would seem to augment the expected higher procyclicality in the default probabilities used for the Basel II capital requirements.

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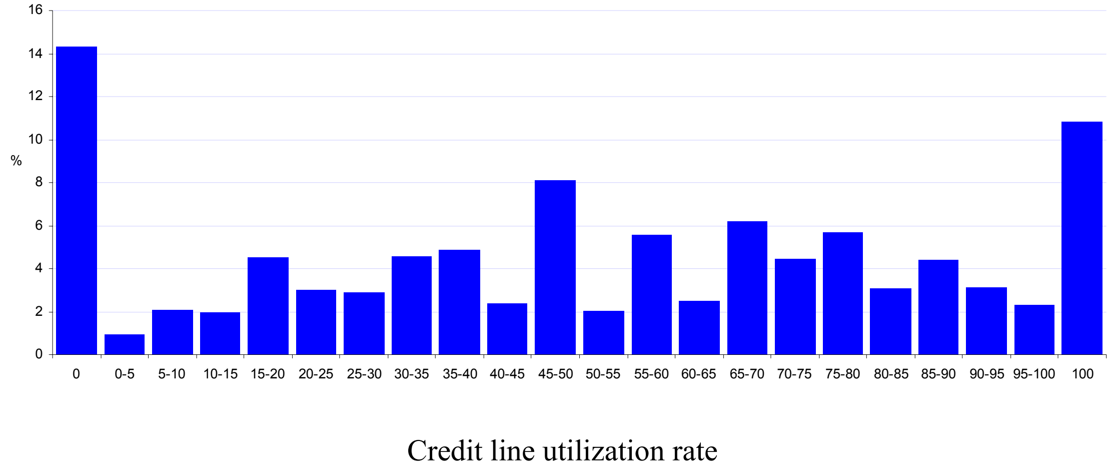
Figure 1. Histogram of the usage ratio of all credit lines



Note: The histogram is based on the 915,563 credit line-year observations in our sample.

Figure 2. *The behavior of the usage ratio of credit lines distinguishing between defaulted and non-defaulted ones*

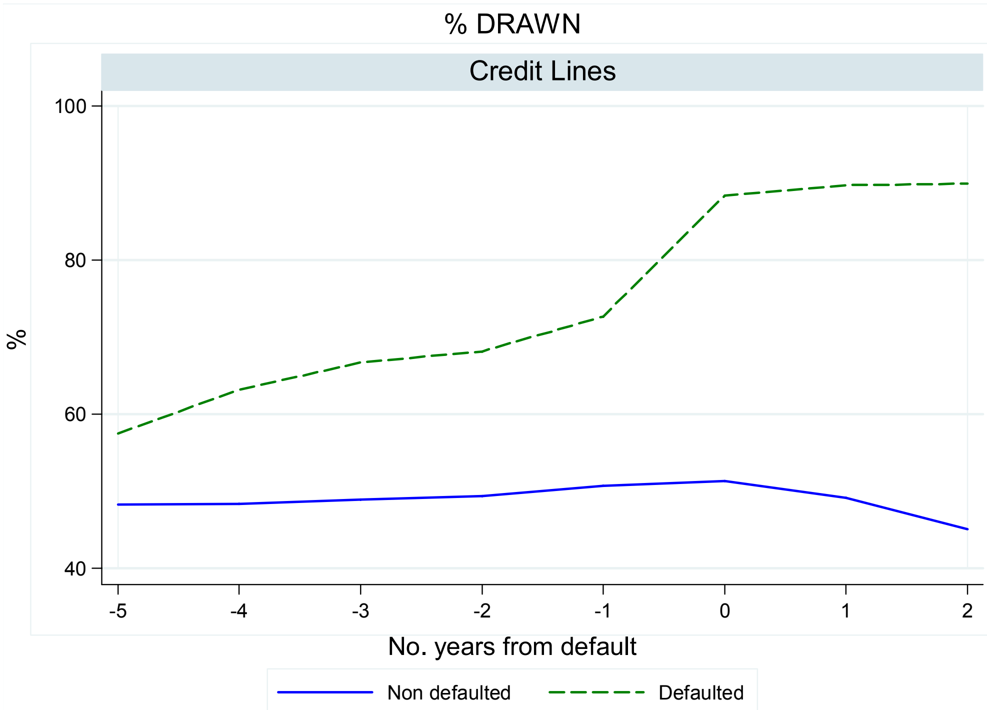


Table 1. *Mean and Wilconxon rank sum tests*

The Wilconxon test examines whether it is likely that the two groups came from populations with the same median

	Non-defaulted			Defaulted			Mean test	Wilconxon test
Years from default	No. Observs.	Mean	Median	No. Observs.	Mean	Median	p-value	p-value
-5	39,200	48.3	50.0	115	57.5	60.0	0.00	0.00
-4	63,202	48.4	50.0	226	63.2	66.7	0.00	0.00
-3	106,867	48.9	50.0	525	66.7	66.7	0.00	0.00
-2	197,341	49.4	50.0	1,101	68.2	72.0	0.00	0.00
-1	450,867	50.8	50.0	2,021	72.7	80.0	0.00	0.00
0	852,947	51.3	50.5	2,883	88.4	100.0	0.00	0.00
1	440,958	49.2	50.0	871	89.7	100.0	0.00	0.00
2	188,816	45.1	44.4	327	89.9	100.0	0.00	0.00

Figure 3. *Quartiles of the usage ratio of defaulted credit lines*

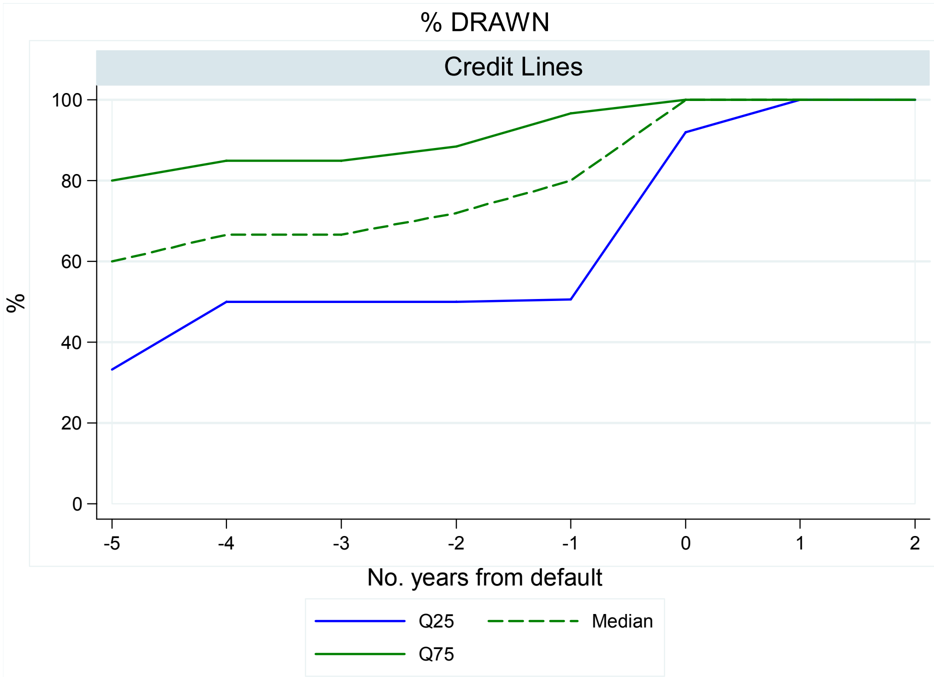


Table 2. *Distribution of the usage ratio of defaulted credit lines by years from default*

Years from default	p5	p10	p25	p50	p75	p90	p95
-5	11	20	33	60	80	93	100
-4	20	30	50	67	85	100	100
-3	20	33	50	67	85	100	100
-2	21	33	50	72	89	100	100
-1	24	34	51	80	97	100	100
0	27	50	92	100	100	100	100
1	20	50	100	100	100	100	100
2	20	50	100	100	100	100	100

Figure 4. *Evolution along time of the median of the usage ratio of defaulted credit lines*

Each year collects the credit lines becoming defaulted on that year and the behavior the five previous years and the two following ones

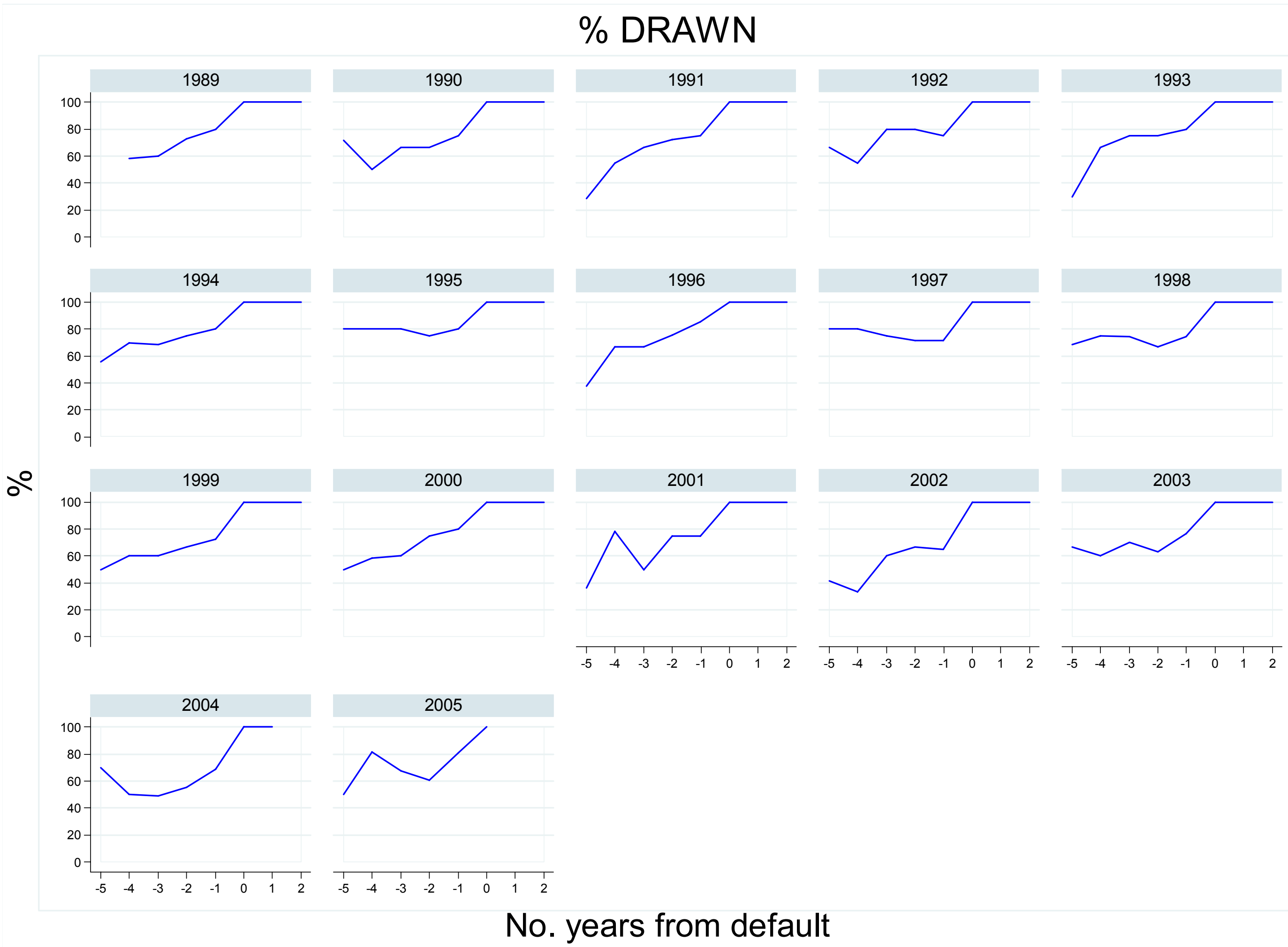


Table 3. *Descriptive statistics*

$RDRAWN_{ijkt}$ is the ratio of the amount drawn to the amount available (drawn plus undrawn) of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable *No. years form default$_{it}$* measures the time to default in years for those credit lines that do default during its life; $Firm\ \ risk_{jt}$ controls for the observed risk of the firm *j* and takes the value of 1 if the borrower defaulted any time until *t*; *NPL ratio$_{kt}$* is the non-performing loan ratio of bank *k* at time *t; Share$_{kt}$* proxies the size of the bank through its market share in loans to firms; $GDPG_t$ is the rate of growth in Gross Domestic Product in real terms; *RIR_t* is the three-month real interbank interest rate; *$COMMIT_i$* is the amount of total credit commitment in thousands of euros; *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; *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.

No. observatios 904,542 Sample period 1987-2005	*Mean*	*S.D.*	*Min*	*Max*
$RDRAWN_{ijkt}$ (%)	49.61	37.52	0.00	100.00
Firm $risk_{jt}$ (0/1)	0.02	0.14	0.00	1.00
Bank NPL $ratio_{kt}$ (%)	0.53	1.79	0.00	100.00
Bank $Share_{kt}$ (%)	0.03	0.06	0.00	14.72
$GDPG_t$ (%)	3.40	1.20	-1.03	5.55
RIR_t (%)	1.74	3.21	-1.47	10.73
$COMMIT_i$ (thousand of euros)	104.06	147.66	6.00	601.00
Long $term_i$ (0/1)	0.21	0.41	0.00	1.00
$Collateralised_i$ (0/1)	0.09	0.28	0.00	1.00
Savings $bank_k$ (0/1)	0.05	0.23	0.00	1.00
Credit $cooperative_k$ (0/1)	0.53	0.50	0.00	1.00

Table 4. *Baseline model*

Estimation of the equation:. $Ln\_RDRAWN_{ijkt} = \beta_1\delta_{it} + \beta_2 Firm_{jt} + \beta_3 Bank_{kt} + \alpha_1 GDPG_t + \alpha_2 RIR_t + \eta_i + \varepsilon_{it}$. The dependant variable is the logistic transformation of the ratio of amount drawn to the amount available (drawn plus undrawn) of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable δ_{it} measures the time to default for those credit lines that do default during its life; $Firm\ risk_{jt}$ controls for the observed risk of the firm and takes the value of 1 if the borrower defaulted any time until *t*; *NPL ratio*$_{kt}$ is the non-performing loan ratio of bank *k* at time *t,* while *Share*$_{kt}$ proxies the size of the bank through its market share in loans to firms; $GDPG_t$ is the rate of growth in Gross Domestic Product in real terms; RIR_t is the three-month real interbank interest rate; η_i 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% level.

	OLS levels		Within-Groups		Within-Groups	
No. observatios 904,542						
Sample period 1987-2005						
Dependant variable Ln_RDRAWN_{ijkt}						
	Model 1		Model 2		Model 3	
	Coefficient	*t-ratio*	*Coefficient*	*t-ratio*	*Coefficient*	*t-ratio*
δ_{-9}	--	--	--	--	3.535	1.51
δ_{-8}	--	--	--	--	-1.004	-0.53
δ_{-7}	--	--	--	--	2.264	1.23
δ_{-6}	--	--	--	--	0.690	0.42
δ_{-5}	--	--	--	--	0.607	0.38
δ_{-4}	--	--	--	--	2.065	1.30
δ_{-3}	--	--	--	--	2.353	1.50
δ_{-2}	--	--	--	--	4.097	2.62 ***
δ_{-1}	--	--	--	--	7.349	4.73 ***
δ_{0}	--	--	--	--	12.320	7.95 ***
No. years from default$_{it}$	-2.204	-13.08 ***	2.761	41.48 ***	--	--
Firm risk$_{jt}$	-0.426	-4.01 ***	-0.685	-8.13 ***	-0.800	-9.53 ***
Bank NPL ratio$_{kt}$	-0.039	-5.68 ***	0.015	3.24 ***	0.015	3.24 ***
Bank Share$_{kt}$	-1.410	-3.75 ***	0.598	4.79 ***	0.591	4.75 ***
$GDPG_t$	-0.049	-4.21 ***	-0.043	-5.23 ***	-0.044	-5.37 ***
RIR_t	0.239	59.52 ***	0.231	43.07 ***	0.231	43.09 ***
Constant	-0.792	-16.16 ***	-0.524	-16.41 ***	-12.831	-8.28 ***
F-test (p-value)	0.00		0.00		0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	128.24	0.00	-168.96	0.00	-169.21	0.00
Test 2nd order serial correlatoin (m2) /p-value	76.15	0.00	-7.80	0.00	-7.96	0.00

Table 5. *Firm characteristics*

The dependant variable is the logistic transformation of the ratio of amount drawn to available of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable *No. years form default*$_{it}$ measures the time to default for those loans that do default during its life; $Firm\ \ risk_{jt}$ controls for the observed risk of the firm and takes the value of 1 if the borrower defaulted any time until *t*; *NPL ratio*$_{kt}$ is the non-performing loan ratio of bank *k* at time *t,* while *Share*$_{kt}$ proxies the size of the bank through its market share in loans to firms; $GDPG_t$ is the rate of growth in Gross Domestic Product in real terms; RIR_t is the three-month real inter-bank interest rate; η_i 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. ***, **, statistically significant at the 1% and 5% levels, respectively.

Within-Groups			
No. observatios 904,542			
Sample period 1987-2005			
Dependant variable Ln_RDRAWN$_{ijkt}$			
	Model 4		
	Coefficient	*t-ratio*	
No. years from default$_{it}$	2.762	41.48	***
No. years from default$_{it}$*Firm risk$_{jt-1}$	-0.900	-2.49	**
Firm risk$_{jt}$	-0.698	-8.26	***
Bank NPL ratio$_{kt}$	0.015	3.24	***
Bank Share$_{kt}$	0.597	4.79	***
GDPG$_t$	-0.043	-5.23	***
RIR$_t$	0.231	43.07	***
Constant	-0.524	-16.41	***
F-test (p-value)	0.00		
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.96	0.00	
Test 2nd order serial correlatoin (m2) /p-value	-7.79	0.00	

Table 6. *Loan characteristics*

The dependant variable is the logistic transformation of the ratio of amount drawn to available of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable *No. years form default$_{it}$* measures the time to default for those loans that do default during its life; *COMMIT$_i$* is the amount of total credit commitment in thousand of euros; *Long term$_i$* is a dummy variable that takes 1 if the maturity of the credit lines is longer that 1 year; *Collateralized$_i$* is a dummy variable that takes 1 if the credit line is collateralized; $Firm \;\; risk_{jt}$ controls for the observed risk of the firm and takes the value of 1 if the borrower defaulted any time until *t*; *NPL ratio$_{kt}$* is the non-performing loan ratio of bank *k* at time *t,* while *Share$_{kt}$* proxies the size of the bank through its market share in loans to firms; GDPG$_t$ is the rate of growth in Gross Domestic Product in real terms; *RIR$_t$* is the three-month real inter-bank interest rate; η_i 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. ***, **, statistically significant at the 1% and 5% levels, respectively.

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 5	
	Coefficient	*t-ratio*
No. years from default$_{it}$	4.209	14.53 ***
No. years from default$_{it}$*Ln(COMMIT$_i$)	-0.391	-5.46 ***
Firm risk$_{jt}$	-0.665	-7.88 ***
Bank NPL ratio$_{kt}$	0.015	3.22 ***
Bank Share$_{kt}$	0.596	4.78 ***
GDPG$_t$	-0.043	-5.28 ***
RIR$_t$	0.231	43.10 ***
Constant	-0.523	-16.39 ***
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.99	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.81	0.00

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 6	
	Coefficient	*t-ratio*
No. years from default$_{it}$	2.832	35.31 ***
No. years from default$_{it}$*Long term$_i$	-0.327	-2.40 **
Firm risk$_{jt}$	-0.679	-8.05 ***
Bank NPL ratio$_{kt}$	0.015	3.24 ***
Bank Share$_{kt}$	0.597	4.79 ***
GDPG$_t$	-0.043	-5.24 ***
RIR$_t$	0.231	43.08 ***
Constant	-0.524	-16.41
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.97	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.80	0.00

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 7	
	Coefficient	*t-ratio*
No. years from default$_{it}$	2.822	38.32 ***
No. years from default$_{it}$*Collateralised$_i$	-0.572	-3.62 ***
Firm risk$_{jt}$	-0.677	-8.02 ***
Bank NPL ratio$_{kt}$	0.015	3.24 ***
Bank Share$_{kt}$	0.597	4.79 ***
GDPG$_t$	-0.043	-5.25 ***
RIR$_t$	0.231	43.09 ***
Constant	-0.523	-16.40 ***
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.97	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.80	0.00

Table 7. *Bank characteristics*

The dependant variable is the logistic transformation of the ratio of amount drawn to available of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable *No. years form default*$_{it}$ measures the time to default for those loans that do default during its life; *Saving bank*$_k$ is a dummy variable that takes 1 if the bank is a saving bank; *Credit cooperative*$_k$ is a dummy variable that takes 1 if the bank is a credit cooperative; $Firm\ risk_{jt}$ controls for the observed risk of the firm and takes the value of 1 if the borrower defaulted any time until *t*; *NPL ratio*$_{kt}$ is the non-performing loan ratio of bank *k* at time *t,* while *Share*$_{kt}$ proxies the size of the bank through its market share in loans to firms; GDPG$_t$ is the rate of growth in Gross Domestic Product in real terms; *RIR*$_t$ is the three-month real inter-bank interest rate; η_i 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. ***, **, statistically significant at the 1% and 5% levels, respectively.

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 8	
	Coefficient	*t-ratio*
No. years from default$_{it}$	2.699	39.71 ***
No. years from default$_{it}$*NPL ratio$_{kt}$	0.122	4.64 ***
Firm risk$_{jt}$	-0.683	-8.09 ***
Bank NPL ratio$_{kt}$	0.016	3.44 ***
Bank Share$_{kt}$	0.598	4.79 ***
GDPG$_t$	-0.044	-5.29 ***
RIR$_t$	0.231	43.07 ***
Constant	-0.522	-16.37 ***
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.68	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.80	0.00

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 9	
	Coefficient	*t-ratio*
No. years from default$_{it}$	2.685	36.32 ***
No. years from default$_{it}$*Bank share$_{kt}$	3.201	2.13 **
Firm risk$_{jt}$	-0.688	-8.15 ***
Bank NPL ratio$_{kt}$	0.015	3.16 ***
Bank Share$_{kt}$	0.581	4.63 ***
GDPG$_t$	-0.045	-5.39 ***
RIR$_t$	0.231	43.07 ***
Constant	-0.518	-16.16 ***
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.97	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.80	0.00

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 10	
	Coefficient	*t-ratio*
No. years from default$_{it}$	2.801	30.43 ***
No. years from default$_{it}$*Savings bank$_k$	-0.059	-0.42
No. years from default$_{it}$*Credit cooperative$_k$	-0.241	-0.97
Firm risk$_{jt}$	-0.685	-8.12 ***
Bank NPL ratio$_{kt}$	0.015	3.24 ***
Bank Share$_{kt}$	0.597	4.79 ***
GDPG$_t$	-0.043	-5.22 ***
RIR$_t$	0.231	43.07 ***
Constant	-0.524	-16.41 ***
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.96	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.80	0.00

Table 8. *Business cycle*

The dependant variable is the logistic transformation of the ratio of amount drawn to available of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable *No. years form default*$_{it}$ measures the time to default for those loans that do default during its life; $Firm\ risk_{jt}$ controls for the observed risk of the firm and takes the value of 1 if the borrower defaulted any time until *t*; *NPL ratio*$_{kt}$ is the nonperforming loan ratio of bank *k* at time *t,* while *Share*$_{kt}$ proxies the size of the bank through its share in terms of the amount of loans to firms; $GDPG_t$ is the rate of growth in Gross Domestic Product in real terms; RIR_t is the three-month real inter-bank interest rate; η_i 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. ***, **, statistically significant at the 1% and 5% levels, respectively.

Within-Groups		
No. observatios 904,542		
Sample period 1987-2005		
Dependant variable Ln_RDRAWN$_{ijkt}$		
	Model 11	
	Coefficient	*t-ratio*
No. years from default$_{it}$	2.988	24.13 ***
No. years from default$_{it}$*GDPG$_t$	-0.073	-2.40 **
Firm risk$_{jt}$	-0.690	-8.18 ***
Bank NPL ratio$_{kt}$	0.015	3.17 ***
Bank Share$_{kt}$	0.594	4.77 ***
GDPG$_t$	-0.045	-5.42 ***
RIR$_t$	0.231	43.10 ***
Constant	-0.517	-16.15 ***
F-test (p-value)	0.00	
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.97	0.00
Test 2nd order serial correlatoin (m2) /p-value	-7.81	0.00

Table 9. *Robustness check*

The dependant variable is the logistic transformation of the ratio of amount drawn to available of a credit line *i* at time *t* granted to firm *j* by bank *k*. The variable *No. years since the credit was granted$_{it}$* measures the number of years since the credit was granted; *Defaulted credit line$_i$* is a dummy variable that takes one if the credit line default during its life; *NPL ratio$_{kt}$* is the non-performing loan ratio of bank *k* at time *t,* while *Share$_{kt}$* proxies the size of the bank through its market share in loans to firms; *RIR$_t$* is the three-month real inter-bank interest rate; η_i 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. ***, statistically significant at the 1%.

Within-Groups
No. observatios 904,542
Sample period 1987-2005
Dependant variable Ln_RDRAWN$_{ijkt}$

	Model 12		
	Coefficient	*t-ratio*	
No. years since the credit was granted$_{it}$	-0.199	-33.03	***
No. years since the credit was granted$_{it}$*Defaulted credit line$_i$	2.876	43.42	***
Bank NPL ratio$_{kt}$	0.012	2.68	***
Bank Share$_{kt}$	0.318	2.73	***
GDPG$_t$	-0.062	-7.56	***
RIR$_t$	0.094	15.41	***
Constant	0.032	0.91	
F-test (p-value)	0.00		
Test 1^{rst} order serial correlatoin (m1) /p-value	-168.98	0.00	
Test 2nd order serial correlatoin (m2) /p-value	-7.79	0.00	

Figure 5. *Average LEQ for defaulted credit lines*

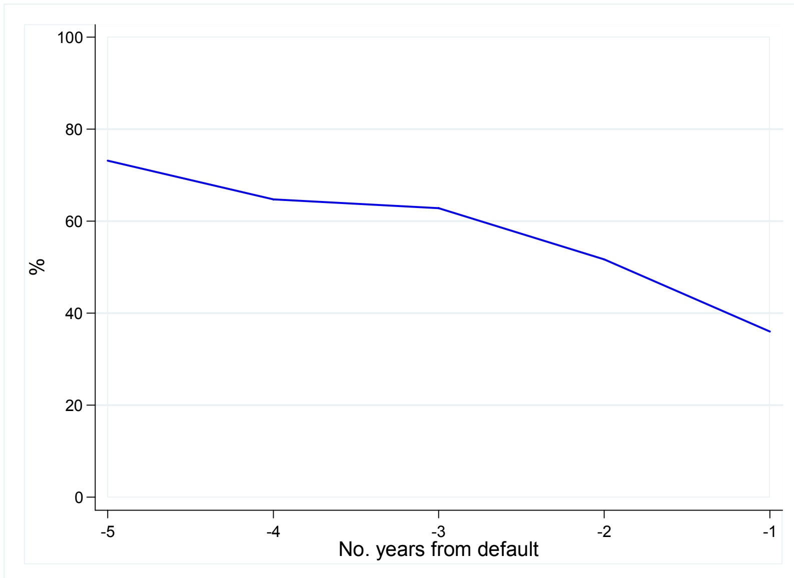


Figure 6. *Average LEQ for defaulted credit lines depending on loan characteristics*