AN ESTIMATION OF THE DEFAULT PROBABILITIES OF SPANISH NON-FINANCIAL CORPORATIONS AND THEIR APPLICATION TO EVALUATE PUBLIC POLICIES

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Roberto Blanco, Elena Fernández,
Miguel García-Posada and Sergio Mayordomo

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Roberto Blanco

BANCO DE ESPAÑA

Elena Fernández

BANCO MUNDIAL

Miguel García-Posada

BANCO DE ESPAÑA

Sergio Mayordomo

BANCO DE ESPAÑA

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Abstract

We model the one-year ahead probability for default of Spanish non-financial corporations using data for the period 1996-2019. While most previous literature considers that a firm is in default if it files for bankruptcy, we define default as having non-performing loans during at least three months of a given year. This broader definition allows us to predict firms' financial distress at an earlier stage that cannot generally be observed by researchers, before their financial conditions become too severe and they have to file for bankruptcy or engage in private workouts with their creditors. We estimate, by means of logistic regressions, both a general model that uses all the firms in the sample and six models for different size-sector combinations. The selected explanatory variables are five accounting ratios, which summarise firms' creditworthiness, and the growth rate of aggregate credit to non-financial corporations, to take into account the role of credit availability in mitigating the risk of default. Finally, we carry out two applications of our prediction models: we construct credit rating transition matrices and evaluate a programme implemented by the Spanish government to provide direct aid to firms severely affected by the COVID-19 crisis.

Keywords: default, financial distress, non-performing loans, logistic regression.

JEL classification: G30, G33, G21.

Resumen

Este documento modeliza la probabilidad de impago a un año de las sociedades no financieras españolas utilizando información del período 1996-2019. Mientras que, en general, la literatura previa considera que una empresa está en situación de impago si solicita concurso de acreedores, aquí se define dicha situación como tener préstamos dudosos durante al menos tres meses en un mismo año. Esta definición más amplia permite predecir problemas financieros en una fase más temprana, antes de que estos sean demasiado graves y las empresas tengan que recurrir a procedimientos formales de insolvencia o a reestructuraciones privadas de deuda, lo que generalmente no puede ser observado por el investigador. En concreto, se estiman mediante regresiones logísticas tanto un modelo general que hace uso de todas las empresas de la muestra como seis modelos para diferentes combinaciones de tamaño y sector productivo. Las variables explicativas seleccionadas son cinco ratios financieras, que resumen la calidad crediticia de las empresas, y el crecimiento agregado del crédito a las sociedades no financieras para capturar el papel de la disponibilidad de crédito en mitigar el riesgo de impago. Finalmente, se llevan a cabo dos aplicaciones prácticas de estos modelos de predicción: se construyen matrices de transición de calificaciones crediticias y se evalúa el programa de ayudas directas del Gobierno español durante la crisis del COVID-19.

Palabras clave: impago, problemas financieros, préstamos dudosos, regresión logística.

Códigos JEL: G30, G33, G21.

Índice

1 Introduction

The prediction of financial distress, a subject of study since the 1930's, has clear practical applications, as assessing firms' creditworthiness is essential for the lending decisions of banks and other financial intermediaries and for evaluating the health of a country's productive sectors, with obvious implications for financial stability. Against this backdrop, the aim of this paper is to estimate the one-year ahead probability of default (PD) of Spanish non-financial corporations (NFCs).

While most of the literature considers that a firm is in default if it files for bankruptcy (e.g. Chapters 7 and 11 in the U.S.), we define a default event as having non-performing loans (NPLs) during at least three months of a given year. This broader definition of default allows us to predict firms' financial distress at an early stage, before their financial conditions are too severe and they must file for bankruptcy or engage in private out-of-court workouts with their creditors, which cannot be generally observed by the researcher. This is especially important in the case of small distressed firms, which rarely file for bankruptcy (Morrison 2008, 2009; García-Posada and Mora-Sanguinetti, 2014) because out-of-court restructuring agreements are generally cheaper and less subject to holdout problems for small firms with few creditors.

For our empirical analyses, we combine two large proprietary datasets of Banco de España, the Central Balance Sheet Data Office (CBSDO) and the Credit Register of (CIR). The CBSDO contains the balance sheets and profit & loss accounts, as well as other non-financial characteristics, of a large sample of NFCs. The CIR contains monthly information on virtually all bank-firm relationships over a reporting threshold of €6,000 for credit institutions operating in Spain.[1] As loans to companies are normally much larger than the reporting threshold, the CIR comprises almost the whole population of bank loans to firms. Our final sample comprises nearly one million privately-owned NFCs with bank debt for the period 1996-2019, which amounts to more than 5.6 million observations. A firm is observed, on average, 5.6 years.

We estimate, by means of logistic regressions, both a general model that uses all the firms in the sample and six models for different size-sector combinations. These six models allow us to use different explanatory variables for the prediction of default by different firms (for instance, micro-firms vs. larger firms) and estimate different coefficients of the predictors, thereby improving forecasting accuracy. The explanatory variables are accounting ratios that summarize firms' financial conditions in five dimensions: activity, current assets and liabilities, leverage, profitability, and liquidity. To select the best predictors for each model, we first estimate linear probability models and apply the Shorrocks-Shapley decomposition of the R-squared of each regression to measure the relative contribution of each accounting ratio, so that we choose the covariates with the highest explanatory power. In addition to

1 As a matter of fact, since 2016 there is no reporting threshold in the CIR.

those accounting ratios, we also include a macroeconomic variable in all models, the growth rate of the aggregate credit to NFCs, so that we can adjust the estimated probabilities of default to different stages of the credit cycle and analyze the role of credit availability in reducing the risk of corporate default. We then assess the goodness of fit of our models by comparing the predicted and observed probabilities of default by means of the Receiver Operating Characteristic (ROC) curve.

Finally, we provide two applications of our prediction models. First, we construct transition matrices, for the whole sample period and for expansions and recessions, to study the share of firms that migrate from one risk class to another in the following year, conditional on no default and no exit. To do so, we define risk classes following the Eurosystem's harmonized credit quality assessment framework, which maps values of estimated probabilities of default onto credit ratings (Credit Quality Step, CQS). The main finding is that, during the long recession period 2008-2014, the share of companies moving to higher risk classes was substantially greater than the share of companies moving to lower risk classes, arguably because the adverse economic conditions had a detrimental effect on firms' creditworthiness. This intuitive result supports the validity of our estimated probabilities of default.

Second, we evaluate a policy implemented by the Spanish government during the COVID-19 crisis to improve the financial condition of the firms most affected by such crisis by providing direct aid to repay debts incurred during the pandemic. We find that granting direct aid reduced firms' PD marginally.

2 Related literature

The literature on bankruptcy prediction is vast and dates back to the 1930's (Bellovary *et al.*, 2007).[2] The variety of models considered in this literature is ample, and empirical specifications often differ on the definition of default, the explanatory variables used to predict default and the statistical methods exploited for estimation. One of the classic works in the field was Beaver (1967), who developed a univariate predictive test that classified firms into failed and non-failed. The classification was made considering an arbitrary cutoff point; if the financial ratio of a firm was below (above) the specific cutoff, the firm was classified as failed (non-failed). Beaver found that a number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure, concluding that the cash flow to debt ratio was the best single ratio predictor.

The first multivariate method was implemented in the seminal paper of Altman (1968), who relied on multivariate discriminant analysis (MDA)[3] and a matched sample that comprised 66 publicly held manufacturing firms during the period 1946-1965. Those firms were classified into two groups of 33 firms each. The first group comprised firms that filed for bankruptcy. The second group consisted of firms from the same industry and similar size that were not under bankruptcy proceedings. He first started with a list of 22 accounting ratios that were potentially good predictors of financial distress, on the basis of their popularity in the literature and their potential relevance to the study, which were classified into five categories: liquidity, profitability, leverage, solvency, and activity. Second, from the original list of 22 variables, five were selected on the basis of their joint prediction capacity of corporate bankruptcy. Finally, he computed a discriminant score (Z-score), i.e., a linear combination of five accounting ratios, to classify firms into bankrupt or non-bankrupt. After Altman's seminal work, MDA prevailed as the most used statistical technique in default prediction models during the 1970's [see, inter alia, Deakin (1972), Blum (1974), Altman *et al.* (1977), and Sinkey (1975)].

Since the 1980's several studies made use of regression techniques such as logit models [e.g. Ohlson (1980), Gentry *et al.* (1985), Zavgren (1985), Lau (1987), Hopwood *et al.* (1989).][4] Ohlson (1980) was the first one in using a conditional logit model[5] to predict default. As Ohlson noted, logit models, unlike MDA, do not require to make assumptions regarding the prior probabilities of default and/or the distribution of predictors. Using data for 1970-1976, Ohlson constructed an unmatched sample of more than 2,000 firms and found that firm size, financial structure, performance and liquidity were the key variables that explained the probability of filing for bankruptcy. And, from the 1990's, several studies applied neural

2 Early works are, inter alia, those of FitzPatrick (1932), Smith and Winakor (1935), Merwin (1942), and Jackendoff (1962).

3 MDA is a statistical technique used to classify an observation into one of several a priori groups dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, such as male or female, bankrupt or non-bankrupt, etc. MDA attempts to derive a linear combination of these characteristics which "best" discriminates between the groups.

4 See also Altman and Sabato (2007) for a later application of logistic regression for the prediction of default by SMEs.

5 The conditional logit model is also called the fixed effects logit model because it controls for time-invariant unobserved heterogeneity. See Wooldridge (2010), pages 621-624.

networks [Bell (1997), Tam and Kiang (1992), Altman *et al.* (1994), Wilson and Sharda (1994), Fletcher and Goss (1993), Lee *et al.* (1996), and Pan (2012)].

A more recent strand of the literature makes use of hazard models (Shumway, 2001; Chava and Jarrow, 2004; Campbell *et al.*, 2008)[6] to overcome the limitations of single-period classification models (static models) with multiple-period bankruptcy data. As highlighted by Shumway (2001), static models estimate biased and inconsistent bankruptcy probabilities because they ignore the fact that firms change over time. This problem is particularly acute because, since bankruptcy is a rare event, researchers generally use samples that span several years to estimate their models, but the characteristics of most firms change from year to year.[7] As forecasters who apply static models to bankruptcy prediction have to select when to observe each firm's characteristics (for instance, in the year before bankruptcy), they ignore data on healthy firms that eventually go bankrupt. Hence, by choosing when to observe each firm's characteristics arbitrarily, they introduce a selection bias into their estimates. Hazard models solve the problems of static models by explicitly accounting for time, as they use all the available information to determine each firm's bankruptcy risk at each point in time.[8] In particular, they specify that a firm's risk of bankruptcy changes through time, and its health is a function of its latest financial data, its age and time-invariant characteristics, while the probability of bankruptcy that a static model assigns to a firm does not vary with time. This feature is particularly relevant when sampling periods are long, because it is important to control for the fact that some firms file for bankruptcy after many years of being at financial distress while other firms do it in their first year. In addition, hazard models incorporate time-varying covariates. If a firm deteriorates progressively before bankruptcy, then allowing its financial data to reveal its changing health may lead to more accurate forecasts.

One problem of the previous literature is that the uncertainty surrounding the model selection step is ignored. To address this problem González-Aguado and Moral-Benito (2012) propose to use Bayesian model averaging (BMA) techniques. By estimating all candidate models resulting from different combinations of regressors, BMA avoids the model selection step.

Finally, during the last decades many studies have applied machine learning[9] and artificial intelligence techniques [Beynon and Peel (2001), Mckee (2003), Li and Sun (2009, 2011, 2012), Lin *et al.* (2011), Xiao *et al.* (2012), Yu *et al.* (2013), Wang and Wu (2017)].[10]

6 Note that those indicators use market-based information. However, as most Spanish companies are not publicly traded, we must rely on accounting information. Whether accounting or market-based information should be employed to predict corporate default is a long-standing debate. For a thorough analysis see Li and Faff (2019).

7 For instance, as noted before, the sample period of Altman (1968) was 1946-1965. As acknowledged by Altman (2000, page 7): "A 20-years period is not the best choice since average ratios do shift over time. Ideally, we would prefer to examine a list of ratios in time period *t* in order to make predictions about other firms in the following period *(t+1)*. Unfortunately, it was not possible to do this because of data limitations."

8 The dependent variable in a hazard model that estimates the probability of bankruptcy is the time spent by a firm in the healthy group. When firms leave the healthy group for some reason other than bankruptcy (e.g., merger), they are considered censored. Static models simply consider such firms healthy.

9 For a thorough analysis of machine learning models see Alonso and Carbó (2022).

10 Kim (2011) compares the performance of multivariate discriminant analysis, logistic regression, artificial neural networks (ANN), and support vector machine (SVM) models in bankruptcy prediction, and finds that ANN is the best early warning technique.

3 Data sources, sample selection and descriptive statistics

3.1 Data

Our main data sources are the Banco de España's Central Balance Sheet Data Office (CBSDO) and the Credit Register of Banco de España (CIR). The CBSDO contains the balance sheets and profit & loss accounts, as well as other non-financial characteristics such as industry, year of incorporation, location of the company's headquarters and whether the firm is listed on a stock exchange, for a large sample of non-financial corporations per year between 1996 and 2019. The CBSDO does not include information on sole proprietorships. The CIR contains monthly information on virtually all bank-firm relationships over a reporting threshold of €6,000 for credit institutions operating in Spain. As loans to companies are normally much larger than the reporting threshold, the CIR comprises almost the whole population of bank loans to firms.

3.2 Sample

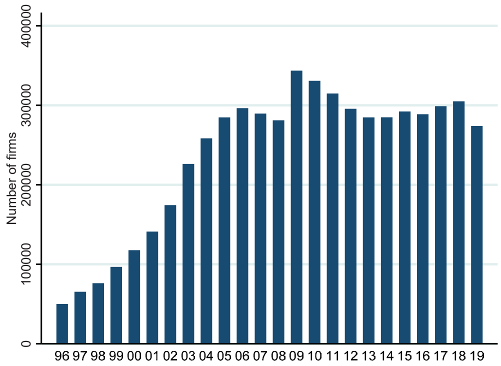
We apply several filters to clean the data of the CBSDO and CIR. We exclude firms with financial ratios that may not be comparable with those of the rest of firms, as their goal is not profit maximization: state-owned companies, local corporations, non-profit organizations, membership organizations, associations, foundations and religious congregations. We also exclude holding companies and publicly held companies (which account for a very small proportion of all the Spanish firms) because their financials may not be comparable with those of the rest of firms. We only keep Spanish companies because foreign firms are not available in the CBSDO. Financial firms and companies that do not belong to the market economy are also removed according to the NACE industry classification.[11] We also apply two filters provided by the CBSDO: (i) balance sheets with non-reliable monetary units; (ii) firms with inadequate information in their financial statements (with blatant accounting errors, such as large mismatches in balance sheet amounts, negative values in items that should be positive by definition, missing headings, or figures of disproportionate magnitude). Finally, we eliminate firms that entered the CIR already in default because this type of firms can have different characteristics that are highly correlated with their probabilities of default. After applying all these filters, we merge the CBSDO with the CIR to construct an unbalanced panel with annual information on nearly one million privately-owned non-financial firms with bank debt for the period 1996-2019, which amounts to more than 5.5 million observations.

Chart 1 shows the distribution of the number of observations during the sample period, while Table 1 presents the size distribution of firms in our sample. Notably, micro-firms account for 76.7% of the observations of the sample while the rest (large, medium, and small firms) account for the remaining 23.3% of the sample.

11 Financial service activities, except insurance and pension funding (64). Insurance, reinsurance and pension funding, except compulsory social security (65). Activities auxiliary to financial services and insurance activities (66). Public administration and defence; compulsory social security (84). Activities of membership organisations (94). Activities of households as employers of domestic personnel (97). Undifferentiated goods- and services-producing activities of private households for own use (98). Activities of extraterritorial organisations and bodies (99).

Chart 1
ANNUAL SAMPLE DISTRIBUTION

Distribution of the number of observations during the sample period



SOURCE: Authors' own elaboration.

Table 1
SIZE DISTRIBUTION

Size	Freq.	Percent
Large	87,989	1.55
Medium	118,328	2.09
Small	1,114,721	19.69
Micro	4,338,947	76.66
Total	**5,659,985**	**100**

SOURCE: Authors' own elaboration.

Table 2
SECTOR BREAK-DOWN

Size	Freq.	Percent
Manufacturing	861,531	15.22
Construction	863,518	15.26
Other sectors	3,934,936	69.52
Total	**5,659,985**	**100**

SOURCE: Authors' own elaboration.
NOTE: The category “Other sectors” comprises: Primary sector; Energy; Retail and wholesale trade; Hospitality, restoration and leisure; Transport and storage; Other market services; Motor vehicles.

Table 2 displays the sectoral breakdown we will use in our analyses, which considers manufacturing (15.2%), construction (15.3%) and the rest of sectors of activity, labeled as “other sectors” (69.5%).

4 Methodology

4.1 Definition of default

We consider that a firm has defaulted on its debt if it has NPLs (i.e., 90 days or more in arrears), during at least three months in a given year.[12] We impose that NPLs must be observed for at least three months in a year to distinguish between firms that are experiencing limited or incipient periods of financial difficulties within a given year from those that exhibit a stronger signal of financial distress.[13] Since it is possible for a firm to default more than once during the period of analysis, we exclude all the observations of a firm after its first default event to ensure that results are not biased towards firms that have recurrent defaults (Antunes *et al.*, 2016). As shown in Table 3, the proportion of firms that have NPLs during at least three months in a given year accounts for 1.5% of the observations.[14] By comparison, the use of the traditional measure of default (bankruptcy filings) would reduce this proportion to only 0.3%.

Table 3
DISTRIBUTION OF DEFAULT

Default	Freq.	Percent
NPLs, 1	82,807	1.46
Otherwise, 0	5,577,178	98.54
Total	**5,659,985**	**100**

SOURCE: Authors' own elaboration.
NOTE: we consider that a firm has defaulted on its debt if it has non-performing loans (NPLs) during at least three months in a given year.

4.2 Models

We develop a general model that uses all the firms in our sample and six models for different size-sector combinations. We consider three sectors, construction, manufacturing and other sectors, as displayed in Table 2. The size breakdown is implemented by considering small, medium and large firms in one group, and micro-firms in another one.[15] We use this breakdown because of the large proportion of micro-firms in the sample, as they account

12 Note that we do not require the firm to have NPL during three *consecutive* months in a given year to consider that it has defaulted on its debt.

13 A loan that is 90 days or more in arrears will be in default and classified as NPL according to bank accounting rules in Spain (see Annex 9 of Circular 4/2017 https://www.boe.es/boe/dias/2017/12/06/pdfs/BOE-A-2017-14334.pdf). For the purposes of this article, the definition of bank distress applied requires at least a 3-month persistence of this situation, being hence stricter than the accounting requirement to present a default within the year. In this way, we ensure that we have a more significant signal of bank debt distress for that given year.

14 Note that this number does not necessarily compare with the average NPL ratio in Spain given that (i) firms in CBSDO are more creditworthy than those in the population, (ii) we apply several filters to companies in the CBSDO to select only those that exhibit an adequate accounting quality, which are also more creditworthy than those with inadequate quality, and (iii) we remove firms after the first year they are classified as failed.

15 We use the “European Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises” for the size classification. For more details, see https://ec.europa.eu/growth/smes/sme-definition_es

for 76% of the observations, while the sum of small, medium and large firms account for the remaining 23%.

Given that our dependent variable is dichotomous and we want to estimate the probability of default, we use a logit model:

$$P(D = 1|X) = \Lambda(X\beta) \tag{1}$$

where D is the dummy variable that denotes default, X is the matrix of explanatory variables, $\Lambda(\cdot)$ is the cumulative function of the logistic distribution and is the vector of regression coefficients.

In order to estimate the one-year ahead probability of default of Spanish non-financial firms, we run two different specifications. The short specification only includes the accounting ratios as explanatory variables:

$$D_{i,t} = \beta_0 + \beta_1^{'} AR_{i,t-1} + u_{i,t} \tag{2}$$

where $AR_{i,t-1}$ is a vector of accounting ratios at period t-1 and $u_{i,t-1}$ is the regression disturbance.

The long specification also includes the variable aggregate credit growth at period t-1 (ACG_{t-1}), which is the growth rate of aggregate credit to NFCs, in order to take into account the role of credit availability in reducing the risk of default. The aggregate credit data is available at monthly frequency. To transform this monthly information into annual data we first sum the stock of credit granted to each NFC in a given month and a given year to obtain the aggregate credit to NFCs. We then compute the year-on-year growth rate of aggregate credit to NFCs. Finally, we compute the arithmetic average of those growth rates for each year.

$$D_{i,t} = \beta_0 + \beta_1^{'} AR_{i,t-1} + \beta_2^{'} ACG_{t-1} + u_{i,t} \tag{3}$$

In addition, in order to assess the goodness of fit of our models, we compare predicted and observed probabilities of default by means of the Receiver Operating Characteristic (ROC) curve. The ROC curve is created by plotting the sensitivity (i.e., the true positive rate) against (1-specificity) (i.e., the false positive rate) at various threshold settings. It can also be regarded as a plot of the power of a test (probability of rejecting the null hypothesis given that it is false) as a function of the type I error of the test (probability of rejecting the null hypothesis given that it is true). ROC analysis is a useful tool for evaluating the performance a statistical model (e.g., logistic regression, linear discriminant analysis) that classifies subjects into 1 of 2 categories, such as diseased or non-diseased or failed or non-failed.

The area under the ROC curve, which ranges from zero to one, is a measure of how good a model is in discriminating the ones (in our application, a default event) from the zeroes. As a general rule, if the area under the ROC curve equals 0.5, the model is not better than random chance at predicting a given outcome (i.e., no discrimination). If the area under the ROC curve ranges between 0.6 and 0.7, the accuracy of the model is considered to be poor; if it ranges between 0.7 and 0.8, the model is considered to be acceptable; if it ranges between 0.8 and 0.9, it is considered to be good; if it exceeds 0.9, it is considered to be excellent (Hosmer and Lemeshow, 2000).

4.3 Selecting the regressors

In order to summarize firms' financial conditions, we create five groups of variables: turnover, capital structure, leverage, profitability and liquidity. Examples of those variables are presented in Table 4.

For the general model and the six size-sector models, we carry out the following methodology. First, we consider several accounting ratios from each group based on their popularity in the literature of prediction of corporate default. We then estimate by OLS the following regression for each group of variables:

$$D_{it} = \beta' X_{i,t-1} + \varepsilon_{it} \tag{4}$$

where i refers to a firm and t to a year, D_{it} is a dummy variable that denotes default according to the previous definition,[16] ε_i is the vector of lagged accounting ratios, β is the vector of regression coefficients, and e1 is the regression disturbance. Second, we compute the Shorrocks-Shapley decomposition of the R-squared of each regression to measure the relative contribution of each accounting ratio. Third, we select the two variables with the highest contribution to the R-squared of each regression, provided that their respective contributions are greater than or equal to 20%. Finally, we estimate (4) with all the selected variables and choose the 5 covariates with the highest explanatory power.

Table 4
TYPES OF VARIABLES

Measures of:	Examples
Activity	Sales, gross value added
Current assets & liabilities	Current assets, current liabilities, working capital
Leverage	Total liabilities, financial expenditures
Profitability	ROA, ROE, EBITDA, net income
Liquidity	Cash, short-term financial investments

SOURCE: Authors' own elaboration.

16 As a robustness check, we also use a different dependent variable to evaluate the accuracy of the model, a dummy variable that equals one if a firm has overdue debt or NPLs during at least three months in a given year and zero otherwise. Results are available upon request.

5 Results

5.1 General model

After applying the Shorrocks-Shapley decomposition of the R-squared obtained in (4) to find the accounting ratios with the highest explanatory power, the following variables are selected to estimate the probability of default of all the firms in the sample using the first specification of the general model (2).

Most of the selected ratios are in line with previous literature. According to Bellovary *et al.* (2007), ROA, the ratio of sales to total assets and the liquidity ratio have been included in more than fifty, thirty and seventeen studies, respectively.[17] Table 6 reports the summary statistics.

We then analyze the explanatory power of the accounting ratios and the growth of aggregate credit to NFCs that is included in the long specification of the global model (3). Chart 2 shows that the variables with the highest explanatory power are the ratio of own funds to total assets, the liquidity ratio, and the ratio of financial expenditures to sales, as they account for 31.9%, 23.1% and 21.8% of the variation of the R-squared, respectively.

We then run the short and long specifications (2) and (3) using logistic regression. Table 7 displays the estimated coefficients. Column (1) presents the results for the short specification, where only the accounting ratios are included as regressors, while column (2) shows the results for the long specification, which also includes the growth rate of aggregate credit to NFCs. In both columns, as expected, the ratio of own funds to total assets, ROA, the liquidity ratio and the ratio of sales to total assets are negatively associated

Table 5
SELECTED ACCOUNTING RATIOS FOR THE GENERAL MODEL

Size	Freq.	Percent
Own funds/Total Assets	Leverage	Own funds include the contributions of the firm's partners (share capital) and accumulated retained earnings
Financial Expenditures/Sales	Leverage	Financial expenditures include all the interest expenses derived from any financial liability or ownership
ROA	Profitability	Ratio of net income to total assets
Liquidity ratio	Liquidity	Ratio of liquid assets to total assets, where liquid assets are cash and cash equivalents
Sales/Total Assets	Turnover	Net amount of sales, services rendered, and other income obtained from ordinary activities
GVA /Total assets	Turnover	Ratio of gross value added to total assets

SOURCE: Authors' own elaboration.
NOTE: the variable GVA /Total assets is also displayed in this table because it is used in some of the size-sector models that are explained in Section 5.2.

17 See Bellovary *et al.* (2007), Appendix B, *Factors included in five or more studies.*

Table 6
SUMMARY STATISTICS

This table presents the summary statistics for the variables used in the prediction models.

Variable	Mean	Std. Dev.	P5	P95
Own funds/Total Assets	0.254	0.410	-0.343	0.839
Financial Exp./Sales	0.054	0.173	0.000	0.228
ROA	0.005	0.146	-0.211	0.184
Liquidity ratio	0.113	0.158	0.000	0.455
Sales/Total Assets	1.555	1.480	0.053	4.336
GVA /Total assets	0.489	0.546	0.006	1.550
Aggregate credit growth	0.066	0.113	-0.089	0.271

SOURCE: Authors' own elaboration.
NOTES: All variables are lagged one year.

Table 7
ESTIMATION OF THE PROBABILITY OF DEFAULT WITH THE GENERAL MODEL

This table presents the coefficients of (2) and (3) estimated using a logit model. The dependent variable is Default, which equals one if a firm has non-performing loans during at least three months in a year and zero otherwise. Column (1) presents the results for the short specification, where only the accounting ratios are included as regressors, while column (2) presents the results for the long specification, which also includes aggregate credit growth to NFCs. Robust standard errors, in parentheses, are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

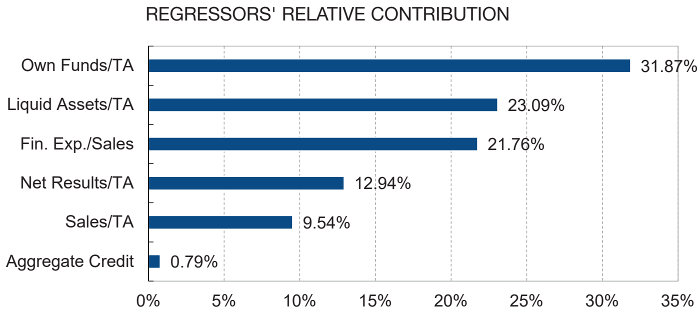
Variables	(1) *Default*	(2) *Default*
Own funds/Total Assets	-0.63271*** (0.00682)	-0.63619*** (0.00673)
Financial Exp./Sales	0.65085*** (0.01242)	0.65113*** (0.01239)
ROA	-0.51963*** (0.02268)	-0.49917*** (0.02262)
Liquidity ratio	-3.09360*** (0.04777)	-3.12500*** (0.04838)
Sales/Total Assets	-0.14448*** (0.00325)	-0.13955*** (0.00324)
Aggregate credit growth		-0.44110*** (0.03315)
Constant	-3.71243*** (0.00657)	-3.68811*** (0.00677)
Observations	5,659,985	5,659,985
Constant	Yes	Yes

SOURCE: Authors' own elaboration.

with the probability of default. By contrast, the relationship between the ratio of financial expenditures to sales and the probability of default is positive. This means that firms with a higher capital ratio, higher profitability, a higher share of liquid assets, more sales relative to their size and less financial expenditures relative to their sales have a lower probability of

Chart 2

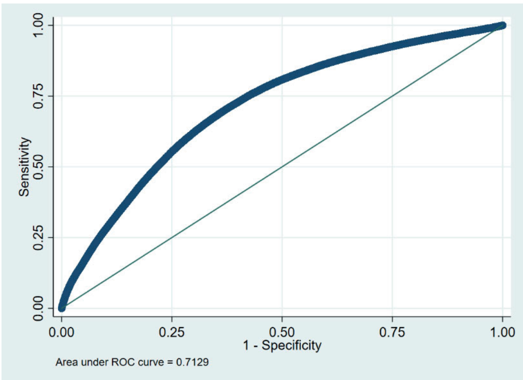
CONTRIBUTION OF EACH REGRESSOR TO THE R-SQUARED (SHORROCKS-SHAPLEY DECOMPOSITION)



SOURCE: Authors' own elaboration.

Chart 3

ROC CURVE – GENERAL MODEL



SOURCE: Authors' own elaboration.

default. According to column (2), the growth rate of aggregate credit to NFCs has a negative relationship with the probability of default, arguably because more credit availability allows some firms to avoid default by addressing their funding deficits with new loans and by refinancing their existing loans with their banks.

In order to assess the economic significance of each regressor, we multiply its marginal effect at the mean (MEM) by its standard deviation. The MEM is the partial effect of a regressor on the dependent variable while holding the values of the other covariates at their means. As Table 8 shows, the regressors with the largest effects are the liquidity ratio and the ratio of own funds to total assets. In particular, a one-standard deviation increase in the liquidity ratio reduces the probability of default by 64 pp. and a one-standard deviation increase in own funds to total assets reduces the probability of default by 32 pp.

Table 8
ECONOMIC SIGNIFICANCE OF REGRESSORS

Variables	Ec. significance
Own funds/Total Assets	-0.319***
Financial Exp./Sales	0.134***
ROA	-0.086***
Liquidity ratio	-0.635***
Sales/Total Assets	-0.248***
Aggregate credit growth	-0.059***

SOURCE: Authors' own elaboration.
NOTE: the economic significance of each regressor is computed by multiplying its marginal effect at the mean by its standard deviation.

Finally, in order to assess the goodness of fit of the long model (3), we compute the ROC curve in Chart 3. As we find that the area under the ROC curve equals 0.71, the model is considered to have an acceptable discriminating capacity (Hosmer and Lemeshow, 2000).

5.2 Size-sector models

In addition to the general model, we develop six size-sector models to adjust the regressors and their parameters to different types of firms. We consider three sectors, construction, manufacturing and other sectors (Table 2), while we distinguish between small, medium and large firms in one group and micro-firms in another one.

As before, in order to summarize firms' financial information, we create five groups of accounting ratios: turnover, capital structure, leverage, profitability, and liquidity. For each group and size-sector combination, we first estimate an OLS regression and compute the Shorrocks-Shapley decomposition of the R-squared to select the two regressors with the highest explanatory power, provided that their respective contributions are greater than or equal to 20%. Second, we estimate (4) with all the selected variables and choose the 5 covariates with the highest explanatory power. The accounting ratios that enter the final models are displayed in Table 9. They are the same as in the general model except for the ratio of gross value added to total assets, which replaces the ratio of sales to total assets in the three models for micro-firms because of its higher explanatory power.

We then estimate both the short and the long specifications (2) and (3) using logistic regression for each size group and sector-specific model. The estimation results are reported in Table 10 for micro-firms and in Table 11 for large, medium and small firms. In both tables, columns (1), (3) and (5) display the estimates of the short specification, while columns (2), (4) and (6) display the estimates of the long specification. The results for micro-firms and the three different sectors are consistent with those obtained with the general model (Table 10). In particular, the coefficients of own funds to total assets, liquidity ratio, and GVA to total assets are all negative and statistically significant, indicating that higher values of these ratios decrease the probability of default of micro-

Table 9
SELECTED ACCOUNTING RATIOS

Ratio	Measure of	Model
Financial Exp./Sales	Leverage	Micro and LMS
ROA	Profitability	Micro and LMS
Own funds/Total Assets	Leverage	Micro and LMS
Liquidity ratio	Liquidity	Micro and LMS
Gross value added/Total Assets	Turnover	Micro
Sales/Total Assets	Turnover	LMS

SOURCE: Authors' own elaboration.
NOTE: LMS stands for Large, Medium and Small firms. Micro stands for micro-firm.

Table 10
MICRO-FIRMS

This table present the coefficients of (2) and (3) using a logit model in a sample of micro-firms. The dependent variable is *Default,* which equals one if a firm has non-performing loans during at least three months in a year and zero otherwise. Columns (1), (3) and (5) presents the results for the short specification, where only the accounting ratios are included as regressors, while columns (2), (4) and (6) presents the results for the long specification, which also includes *aggregate credit growth,* i.e., the aggregate credit growth to NFCs. Robust standard errors, in parentheses, are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Variables	(1) Manufacturing	(2) Manufacturing	(3) Construction	(4) Construction	(5) Other sectors	(6) Other sectors
Financial Exp./Sales	1.16699***	1.16740***	0.76023***	0.75806***	0.60141***	0.59894***
	(0.04571)	(0.04567)	(0.02172)	(0.02166)	(0.01720)	(0.01719)
ROA	-0.24583***	-0.23764***	0.04257	0.05544	-0.36996***	-0.35444***
	(0.08659)	(0.08639)	(0.05494)	(0.05487)	(0.03249)	(0.03234)
Own funds/Total Assets	-0.53223***	-0.53543***	-0.64073***	-0.64349***	-0.58691***	-0.59350***
	(0.02466)	(0.02443)	(0.01636)	(0.01614)	(0.00983)	(0.00965)
Liquidity ratio	-3.59772***	-3.61407***	-2.56022***	-2.56503***	-2.34983***	-2.38543***
	(0.17312)	(0.17464)	(0.10136)	(0.10193)	(0.06009)	(0.06102)
Gross value added/Total Assets	-0.72002***	-0.71014***	-0.49402***	-0.48509***	-0.43251***	-0.42122***
	(0.03961)	(0.03980)	(0.02229)	(0.02221)	(0.01439)	(0.01426)
Aggregate credit growth		-0.21666**		-0.35031***		-0.70235***
		(0.10981)		(0.07862)		(0.04770)
Constant	-3.66303***	-3.65080***	-3.36825***	-3.34673***	-3.98444***	-3.94423***
	(0.02182)	(0.02254)	(0.01518)	(0.01590)	(0.00868)	(0.00902)
Observations	534,231	534,231	666,168	666,168	3,138,548	3,138,548
Constant	Yes	Yes	Yes	Yes	Yes	Yes

SOURCE: Authors' own elaboration.

firms in any sector. The coefficients of ROA are also negative and statistically significant in manufacturing and other sectors, while insignificant in construction. By contrast, the coefficients of the ratio of financial expenditures to sales are all positive and significant, implying that lower values of this ratio reduce the probability of default of micro-firms in any sector. Finally, the coefficients of aggregate credit growth in the long specifications

Table 11
LARGE, MEDIUM AND SMALL FIRMS

This table present the coefficients of (2) and (3) using a logit model in a sample of large, medium and small firms. The dependent variable is *Default,* which equals one if a firm has non-performing loans during at least three months in a year and zero otherwise. Columns (1), (3) and (5) presents the results for the short specification, where only the accounting ratios are included as regressors, while columns (2), (4) and (6) presents the results for the long specification, which also includes *aggregate credit growth,* i.e., aggregate credit growth to NFCs. Robust standard errors, in parentheses, are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Variables	(1) Manufacturing	(2) Manufacturing	(3) Construction	(4) Construction	(5) Other sectors	(6) Other sectors
Financial Exp./Sales	1.66949***	1.66664***	0.92925***	0.90281***	0.55231***	0.52061***
	(0.12319)	(0.12294)	(0.06151)	(0.06173)	(0.05350)	(0.05394)
ROA	-1.18218***	-1.07506***	-0.56750***	-0.43685***	-0.88764***	-0.81578***
	(0.14310)	(0.14414)	(0.11457)	(0.11454)	(0.07536)	(0.07504)
Own funds/Total Assets	-1.52711***	-1.55417***	-1.36467***	-1.40908***	-1.02591***	-1.03901***
	(0.04529)	(0.04501)	(0.04265)	(0.04234)	(0.02415)	(0.02371)
Liquidity ratio	-0.63616***	-0.61820***	-0.30121***	-0.29080***	-0.27483***	-0.26479***
	(0.02605)	(0.02594)	(0.01649)	(0.01634)	(0.01037)	(0.01030)
Gross value added/Total Assets	-6.66259***	-6.78683***	-3.75356***	-3.81589***	-5.74751***	-5.87294***
	(0.29471)	(0.30207)	(0.19880)	(0.20216)	(0.18608)	(0.19160)
Aggregate credit growth		-0.73177***		-0.76272***		-0.88320***
		(0.14128)		(0.14097)		(0.09612)
Constant	-2.51206***	-2.46406***	-2.47968***	-2.40746***	-3.25418***	-3.20699***
	(0.03976)	(0.04043)	(0.03345)	(0.03632)	(0.02205)	(0.02237)
Observations	327,300	327,300	197,350	197,350	796,388	796,388
Constant	Yes	Yes	Yes	Yes	Yes	Yes

SOURCE: Authors' own elaboration.

are all negative and statistically significant, suggesting that higher credit availability mitigates the risk of default. The estimation results for large, medium and small firms are very similar to those obtained for micro-firms (Table 11) in terms of the sign and significance of the coefficients.

In order to assess the economic significance of each regressor, we again multiply its marginal effect at the mean (MEM) by its standard deviation. The results are displayed in Table 12 (micro-firms) and Table 13 (large, medium and small firms). According to Table 12, the regressors with the largest effects are the liquidity ratio, the ratio of financial expenditures to sales and the ratio of GVA to total assets across all sectors. Similarly, Table 13 shows that the regressors with the largest effects are the liquidity ratio and the ratio of sales to total assets across all sectors. In addition, the area under the ROC curve is higher than 0.71 -the value obtained for the general model that includes all sectors and sizes jointly in the same estimation- for all the sector-size combinations, except for the model that uses micro-firms that operate in the industry labelled as “other sectors”. In particular, the area under the ROC curve is, in the case of the models for micro-firms, 0.72, 0.73, 0.69 for Manufacturing, Construction and Other sectors, respectively. Regarding the models for large, medium and small firms, the corresponding values are 0.78, 0.75, 0.75 for Manufacturing, Construction and Other sectors, respectively.

Table 12
ECONOMIC SIGNIFICANCE OF REGRESSORS

Micro-firms	Manufacturing	Construction	Other sectors
Variables	Ec. significance	Ec. significance	Ec. significance
Own funds/Total Assets	-0.236***	-0.191***	-0.102***
Financial Exp./Sales	0.122***	0.344***	0.281***
ROA	-0.036***	0.041	-0.073***
Liquidity ratio	-0.618***	-2.932***	-0.438***
Gross Value Added/Total Assets	-0.374***	-0.143***	-0.228***
Aggregate credit growth	-0.027**	-0.070***	-0.083***

SOURCE: Authors' own elaboration.
NOTE: the economic significance of each regressor is computed by multiplying its marginal effect at the mean by its standard deviation.

Table 13
ECONOMIC SIGNIFICANCE OF REGRESSORS

Large, medium and small	Manufacturing	Construction	Other sectors
Variables	Ec. significance	Ec. significance	Ec. significance
Own funds/Total Assets	-0.449***	-0.356***	-0.094***
Financial Exp./Sales	0.064***	0.212***	0.156***
ROA	-0.091***	-0.268***	-0.079***
Liquidity ratio	-0.921***	-1.219***	-0.871***
Gross Value Added/Total Assets	-0.605***	-0.834***	-0.345***
Aggregate credit growth	-0.078***	-0.182***	-0.085***

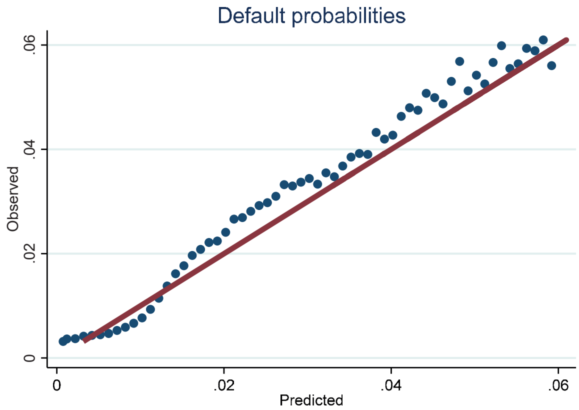
SOURCE: Authors' own elaboration.
NOTE: The economic significance of each regressor is computed by multiplying its marginal effect at the mean by its standard deviation.

Another method to evaluate the accuracy of the size-sector models is by plotting the predicted probabilities of default against the observed probabilities, as done in Chart 4. First, we sort in ascending order all the predicted probabilities we have estimated using the six sector-size models. Second, we aggregate the observations according to their predicted probabilities to create 62 groups with interval length of 0.01% each (e.g. between 0 and 0.01%, between 0.01% and 0.02%, etc.).[18] Third, for each of the 62 groups we compute the average observed probability of default. Finally, we also include the 45-degree line for reference: if the predicted and observed probabilities of default were equal, the blue dots would all lie on the red line.

Chart 4 shows that, for very low values, the predicted probabilities are slightly lower than the observed ones, implying that the six size-sector models underpredict the probability

18 Note that the number of observations within each group are not necessarily the same. For instance, in the first group, there are 374,423 observations while, in the last group, there are only 55,241.

Chart 4
ESTIMATED VS. OBSERVED PROBABILITIES OF DEFAULT



SOURCE: Authors' own elaboration.

of default somewhat at the left tail of the distribution. By contrast, for values greater than or equal to 2%, the models tend to overpredict the probability of default, as the blue dots are nearly always above the red line. In any case, as the blue dots stay relatively close to the 45-degree line for all values, we may conclude that the models estimate fairly well the probability of default across different firm sizes and sectors.

6 Applications

6.1 Transition matrices

In this section we study the share of firms that migrate from one risk class to another in the following year, conditional on no default and no exit. The main purpose of this analysis is to ascertain whether, during recessions, the share of companies moving to higher risk classes is greater than the share of companies moving to lower risk classes because adverse economic conditions are expected to have a detrimental effect on firms' financial health, as measured by their probability of default. To do so, we define risk classes following the Eurosystem's harmonized credit quality assessment framework, which maps values of estimated probabilities of default (PD) onto credit ratings. In particular, a firm with a one-year ahead PD of up to 0.1% is classified as having a Credit Quality Step (CQS) 1 or 2, a firm with a PD of up to 0.4% is classified as having a CQS 3, a firm with a PD of up to 1% is classified as having a CQS 4, a firm with a PD of up to 1.5% is classified as having a CQS 5 and a firm with a PD above 1.5% is classified as having a CQS 6.

As a preliminary analysis, we first assign each firm to its CQS rating according to its predicted probability of default and compute the proportion of firms in each risk class for the whole sample period, as shown in the first column of Table 14. We then split the sample into 3 different periods according to the state of the Spanish economy: 1997-2007 (strong expansion), 2008-2014 (strong recession due to the global financial crisis and the sovereign debt crisis) and 2015-2019 (recovery period until the COVID-19 crisis). In the case of the expansion periods (1997-2007 and 2015-2019), the category CQS 4 is the one with the highest percentage of firms. By contrast, during the whole sample period and the recession period 2008-2014 the category CQS 6 is the one with the highest percentage of firms, as the financial conditions of many companies deteriorate during economic crises, leading to higher probabilities of default.

We then analyze the share of firms that migrate from one risk class to another in the following year, conditional on no default and no exit, by means of transition matrices for the whole sample period and the three aforementioned periods. The transition matrix for the whole period (1997-2019) is displayed in Table 15. Most firms either remained in the same risk class (the highest share of firms is found in the main diagonal, highlighted in bold) or moved one category up in the subsequent year –the second highest share of firms, underlined figures.

The transition matrix for the expansionary period (1997-2007) is displayed in Table 16. As in the whole period, most firms either remained in the same risk class – the highest share of firms is found in the main diagonal, highlighted in bold- or moved one category up or down in the subsequent year –the second highest share of firms, underlined figures.

The transition matrix for the recession period (2008-2014) is displayed in Table 17. In contrast with Table 16, most firms either remained in the same risk class *or* moved one category *up* in the subsequent year. In addition, for medium-risk classes (CQS 4 and 5), the share of firms migrating to a higher risk class was substantially larger than the share of firms

Table 14
PROPORTION OF FIRMS WITHIN EACH RISK CLASS

% CQS	Probability of default (%)	1997-2019	1997-2007	2008-2014	2015-2019
1&2	[0-0.1]	1.48	1.43	0.90	2.41
3	(0.1-0.4]	9.07	9.32	5.83	13.60
4	(0.4-1]	29.17	**33.68**	19.89	**36.84**
5	(1-1.5]	27.66	31.12	24.41	27.72
6	>1.5	**32.63**	24.44	**48.96**	19.43

SOURCES: European Central Bank and authors' calculations.

Table 15
TRANSITION MATRIX. WHOLE PERIOD (1997-2019)

%	CQS in year t+1				
CQS in year t	1 & 2	3	4	5	6
1&2	**49.61**	33.14	12.18	2.82	2.25
3	5.80	**49.70**	33.49	6.63	4.38
4	0.52	10.43	**58.85**	21.57	8.63
5	0.11	1.71	23.18	**51.08**	23.92
6	0.07	1.04	7.45	20.88	**70.55**

SOURCE: Authors' own elaboration.
NOTES: All values in percentage. Rows add up to 100%.

Table 16
TRANSITION MATRIX. EXPANSIONARY PERIOD (1997-2007)

%	CQS in year t+1				
CQS in year t	1 & 2	3	4	5	6
1&2	**46.25**	35.28	13.58	2.98	1.91
3	5.42	**49.10**	36.31	6.46	2.71
4	0.42	9.57	**63.49**	21.24	5.28
5	0.08	1.32	22.82	**57.46**	18.31
6	0.07	0.78	6.36	23.83	**68.96**

SOURCE: Authors' own elaboration.
NOTES: All values in percentage. Rows add up to 100%.

migrating to a lower risk class, arguably because the negative economic conditions that characterized this period had adverse effects on firms' financial health.

Finally, the transition matrix for the recovery period until the COVID-19 crisis (2015-2019) is displayed in Table 18. As in the expansionary period 1997-2007 (Table 16), most firms either remained in the same risk class or moved one category up or down in the following year.

Table 17

TRANSITION MATRIX. RECESSION PERIOD (2008-2014)

%	CQS in year t+1				
CQS in year	1 & 2	3	4	5	6
1&2	**47.74**	33.96	12.68	2.97	2.66
3	4.50	**46.80**	36.43	7.50	4.78
4	0.34	8.44	**53.37**	26.30	11.55
5	0.06	1.08	16.15	**48.74**	33.97
6	0.02	0.36	3.73	14.46	**81.42**

SOURCE: Authors' own elaboration.
NOTES: All values in percentage. Rows add up to 100%.

Table 18

TRANSITION MATRIX. RECOVERY PERIOD (2015-2019)

%	CQS in year t+1				
CQS in year t	1 & 2	3	4	5	6
1&2	**55.28**	31.98	9.59	1.92	1.22
3	6.07	**53.68**	29.58	5.74	4.92
4	0.48	10.89	**59.79**	19.53	9.30
5	0.08	1.59	25.01	**53.29**	20.04
6	0.08	1.00	11.35	30.74	**56.83**

SOURCE: Authors' own elaboration.
NOTES: All values in percentage. Rows add up to 100%.

6.2 The impact of direct aid on the probability of default

Against the backdrop of the COVID-19 crisis, the Spanish government established the "COVID line of direct aid to sole proprietors and companies" with the chief purpose of reducing the debt incurred as from March 2020 by the firms and sole proprietors most affected by the crisis.[19] This facility, funded with a total of €7 billion, channeled direct aid to firms and sole proprietors whose activity had been most adversely affected by the economic effects of the pandemic, insofar as their income in 2020 had fallen by more than 30% of that in 2019, they had recorded profits in 2019 and they belonged to certain affected sectors.[20] In particular, it involved specific-end direct aid that allowed for the payment of debts incurred by firms since March 2020, such as payments to suppliers, supplies, wages, rentals and, in the event of any remaining amount, debts with bank creditors, giving priority to the reduction of the publicly-backed debt's face value. This aid could rise up to 40% of an over-30%

19 Royal Decree-Law 5/2021 of 12 March 2021, on extraordinary business solvency support measures in response to the COVID-19 pandemic.

20 Subsequently, in April 2021, the Royal Decree-Law was further amended to allow regional governments to apply more flexible criteria regarding the beneficiary sectors and the requirement to post earnings in 2019.

Table 19
THE IMPACT OF DIRECT AID ON FIRMS' PD OF 2022

Panel A: Firms that obtained direct aid, with increased own funds to total assets (observed scenario)

	Observations	Mean	Median	p10	p25	p75	p90
PD %	21,937	1.07	0.72	0.14	0.33	1.21	1.70

Panel B: Firms that obtained direct aid, without increased own funds to total assets (counterfactual scenario)

	Observations	Mean	Median	p10	p25	p75	p90
PD %	21,937	1.15	0.78	0.16	0.37	1.27	1.78

SOURCE: Authors' own elaboration.
NOTES: All values in percentage. Rows add up to 100%.

decline in revenue for micro-firms, SMEs and sole proprietors, and to 20% for other firms, with a fixed amount of €3,000 for sole proprietors paying tax under the objective estimate scheme and between €4,000 and €200,000 for other companies.

To assess the impact of this policy on firms' probability of default, we transform one of the explanatory variables of the six sector-size models, the ratio of own funds to total assets, to take into account the debt reduction experienced by firms that obtained direct aid under this programme. As paying off debt is, in accounting terms, equivalent to increasing a firm's capital, the ratio of own funds to total assets of the companies that received those grants increased accordingly. We then use the six sector-size models to estimate the PD in 2022[21] of the firms that received those grants under two scenarios: (i) the ratio of own funds to total assets taking into account the debt reduction (observed scenario); (ii) the ratio of own funds to total assets without taking into account the debt reduction (counterfactual scenario).

Table 19 reports the most important features of the three distributions: mean, quartiles, and the 10th and 90th percentiles. Comparing the figures of Panels A and B (observed and counterfactual scenario, respectively), we can observe that the provision of direct aid reduced firms' PD in 2022 marginally. In particular, while the median PD of the firms that obtained direct aid is 0.72, the median PD of the same firms, had they not obtained direct aid, is 0.78. The program reduced more the 90th percentile of the distribution (0.08 pp.) than its 10th percentile (only 0.02 pp.), but still the reduction was not very significant.

21 The direct aid was granted in 2021. Please recall that our explanatory variables are lagged one year.

7 Conclusions

In this paper we model the one-year ahead probability of default (PD) of Spanish non-financial corporations. We depart from most of the previous literature, which considers that a firm is in default if it files for bankruptcy, by defining a default event as having non-performing loans during at least three months of a given year. This broader definition allows us to predict firms' financial distress at an early stage, before their financial conditions are too severe and companies must file for bankruptcy or engage in private workouts with their creditors, which cannot be generally observed by the researcher. This is particularly important in the case of small distressed firms, which rarely undergo bankruptcy proceedings because out-of-court restructuring agreements are generally cheaper and less subject to holdout problems for them.

For our empirical analyses, we combine two large proprietary datasets of Banco de España, the Central Balance Sheet Data Office (CBSDO) and the Credit Register of (CIR). The CBSDO contains the balance sheets and profit & loss accounts, as well as other non-financial characteristics, of a large sample of NFCs. The CIR contains monthly information on virtually all bank-firm relationships for credit institutions operating in Spain. Our final sample comprises nearly one million privately-owned NFCs with bank debt for the period 1996-2019.

We then estimate, by means of logistic regressions, both a general model that uses all the firms in the sample and six models for different size-sector combinations. These six models allow us to use different explanatory variables for the prediction of default by different firms and estimate different coefficients of the predictors, which improves forecasting accuracy by taking into account their heterogeneity across sectors and firm sizes. The selected explanatory variables are five accounting ratios, which summarize firms' financial conditions, and the growth rate of aggregate credit to non-financial corporations, so that we take into account the role of credit availability in reducing the risk of default.

Finally, we carry out two applications of our prediction models. First, we construct transition matrices to study the share of firms that migrate from one risk class to another in the following year. With that aim, we define risk classes following the Eurosystem's harmonized credit quality assessment framework, which maps values of estimated probabilities of default onto credit ratings (Credit Quality Step). Our main finding is that, during the long recession period 2008-2014, the share of companies moving to higher risk classes was substantially greater than the share of companies moving to lower risk classes, arguably because the adverse economic conditions had a detrimental effect on firms' creditworthiness.

Second, we evaluate a policy implemented by the Spanish government to improve the financial condition of the firms most affected by the COVID-19 crisis by providing direct aid to repay debts incurred during the pandemic. We find that granting direct aid reduced firms' PD marginally.

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