CREATING ASSOCIATIONS AS A SUBSTITUTE FOR DIRECT BANK CREDIT. EVIDENCE FROM BELGIUM

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Abstract

Firms' incentives to join up with other firms to apply collectively for a single loan are studied empirically in this paper. When several firms make a joint application for a single loan an association of firms is created. We identify the associations that had access to credit in Belgium over the period 2001-2011 and the firms that made up each association, observing the amount of credit that both the firms and the associations obtained from each financial institution they used. We analyse the amount of credit obtained by firms according to whether or not they belonged to an association, the likelihood of firms forming associations, the impact of belonging to an association on the amount of credit firms receive from banks and the effect of firms not obtaining any direct credit on the amount obtained by the associations formed by such firms. We also analyse whether associations formed by common-ownership firms are able to access more credit than other associations. We find that large and long-established firms are more likely to join up with other firms to make joint loan applications and that associations obtain more credit if all their members use the same bank as the association does to obtain credit. Furthermore, the lower a firm's credit over the previous year, the more likely it is to form an association to obtain credit, and we show that associations comprising small firms with no credit history are especially credit constrained.

Keywords: associations, finance, access to credit, relationship banking, Belgium.

JEL classification: G21, G30.

Resumen

El artículo analiza empíricamente los incentivos de distintas empresas a unirse para pedir un préstamo de manera conjunta. Cuando distintas empresas se unen para pedir un único préstamo, estas constituyen una asociación. Identificamos las asociaciones que tuvieron acceso al crédito en Bélgica durante 2001-2011 y las empresas que crearon cada asociación, observando el montante del crédito que obtuvieron tanto las empresas como las asociaciones por parte de cada institución financiera que utilizaron. Analizamos la cuantía del crédito obtenido por las empresas cuando pertenecen o no a una asociación, la probabilidad de que las empresas creen una asociación, el impacto de pertenecer a una asociación sobre la suma del crédito que obtienen las empresas, así como la consecuencia de no obtener crédito directamente sobre la cantidad de crédito que obtienen las asociaciones creadas por estas empresas. Asimismo, analizamos si las asociaciones creadas por empresas que tienen vínculos de propiedad entre ellas tienen acceso a mayores volúmenes de crédito que el resto de asociaciones. El artículo muestra que las empresas más antiguas y grandes tienen una mayor probabilidad de crear asociaciones para pedir préstamos, y que las asociaciones obtienen más crédito si todos sus miembros constituyentes usan el mismo banco que usa la asociación. Además, la probabilidad de una empresa de crear una asociación aumenta cuanto menor sea el volumen de crédito que obtuvo el año pasado, y las asociaciones creadas por empresas pequeñas sin ninguna historia de crédito tienen un acceso a este especialmente restringido.

Palabras clave: asociaciones, financiación, acceso al crédito, relaciones bancarias, Bélgica.

Códigos JEL: G21, G30.

1 Introduction

The most common methods firms use to finance themselves are through their owners' own capital contribution, debt financing or equity financing. However, when firms choose to finance through acquiring debt they can still decide whether to engage in a direct individual loan with a financial institution or join some other firm(s) to collectively apply for credit which later may be divided among the participants. Several firms may join and collectively apply for a loan to any financial institution, where all the associations' members will be liable for repayment, creating thus an association of firms. An association of firms is defined as a union of firms which are jointly liable as co-debtors of a same loan. Thus, members of any association share a united and undivided responsibility towards third parties they have dealt with. However, these associations do not constitute any legal entity. In this research we focus on associations which have obtained credit from any financial institution.

If several firms apply together for a common loan to be shared ex-post among them, they might obtain better financing conditions than aggregating the requirements each firm individually would have to fulfill had they applied separately for several loans. Besides, it may well be the case that several firms apply for a common loan to jointly finance a common project, such as large building sites or highways. The better conditions they might obtain applying as one unit may possibly be due to a lower aggregate risk it represents for the financial institution conceding the loan, since all firms guaranteeing the loan are responsible to repay the loan as well as its interests implying that the risk of default is widespread among several debtors, i.e. there are coinsurance gains. Thus, given the lower default risk and consequently the higher the loan's repayment probability, the financial institution might concede better credit conditions to the unique loan all firms secure compared to the conditions it would demand if loans were applied (and thus secured) individually. Therefore, these positive financial synergies might encourage firms to apply together for a loan, creating associations of firms. However, there exist some drawbacks to constituting associations to jointly apply for credit, mainly related to firms' mistrust and moral hazard, or to the risk that the benefits of a good project might be outweighed by the loses of a poorly performing project.

Firms might not be able to distinguish between firms that represent a positive opportunity to apply for credit with, and firms that would like to found an association, which due to their negative outlook or poor performance, they are not individually eligible for credit and have no other option to obtain credit but to joining other better-performing firms to jointly apply. Thus, firms looking for partners to set up an association might face adverse selection and not be able to separate "good" from "bad" firms to engage with because of asymmetric information, which might discourage firms to establish associations forgoing the potential benefits it may bring.

The literature on bank credit has extensively focused on firms' credit access and on its conditions such as its price in terms of interest rate (see e.g. the seminal paper of Petersen and Rajan (1994), Cole (1998) and more recently Berger et al. (2014)) and non-price terms such as existence and nature of collateral or maturity (see e.g. Berger and Udell (1995), Degryse and Van Cayseele (2000)), but few has been studied about associations of firms demanding for credit, specially empirically due to the limited access to data covering this subject. For instance, Leland (2007) provides a theoretical comparison between firms' expected profits under separate and joint financing of different activities depending on these activities' default costs, tax rates, relative sizes, correlation, and riskiness of their expected cash flows. Similarly, Banal-Estanol et al. (2013) theoretically study the conditions on expected returns, riskiness and default costs of potential projects several firms would like to finance, to determine whether it is preferable for a firm to individually apply for a loan to finance its own project or jointly applying with other firms to finance all projects with a unique loan. They establish that when an individually financed project does not yield a return sufficiently high to pay back the financial obligations it engaged to respect, the project automatically fails, while if a project is jointly financed with other projects, an individual project will fail if the average yield of all projects is lower than the financial obligation. Thus, they show that a well performing project might fail due to risk contamination and a poorly performing project might prevail thanks to coinsurance gains. Besides, they state that under some circumstances separate financing is more profitable even if the interest rate of the jointly financing option is lower. Similarly, Inderst and Muller (2003) theoretically examine firms' costs and benefits to raise funds, either separately to finance each project individually or merging contracts through a headquarter to finance multiple projects, concluding that grouping financially constrained firms' projects might lead to an increased access to credit.

Subramanian and Tung (2016) conduct a cross-country comparative analysis about the number of project finance loans granted in different countries with different corporate and bankruptcy laws, concluding that borrowers make more use of project finance loans than "regular corporate loans" in countries where laws concerning creditor rights are loose, where project finance loans are defined as financing evaluated upon the expected cash flows derived from the project it is intended to finance and not upon the participating agents' solvency. Kleimeier and Megginson (2000) reach similar conclusions stating that project finance loans are more common than other loans in countries with a high level of economical and political risk, such as non-OECD countries. Ambrus-Lakatos and Hege (2012) focus on internal capital markets to theoretically show that the contagion effect prevails over the coinsurance gains in volatile firms while the contrary holds in stable firms, since whenever a several illiquidity shock hits one department it might drag down money from profitable projects in other departments. They show that in the case of a strong negative illiquidity shock conglomerates usually perform worse than individual and independent firms. However, conglomerates or centralization might bring other advantages such as a higher access to credit since the risk of non-repayment of an individual project is lower (Faure-Grimaud and Inderst (2005) and Inderst and Muller (2003)).

Hann et al. (2013) study the benefits of coinsurance –defined as imperfectly correlated cash flows– to obtain cheaper credit. They show that if a given firm's business units have imperfectly correlated cash flows, the firm can benefit from a lower systemic risk (emergence of coinsurance gains) and therefore obtain cheaper credit than otherwise. They empirically show that firms operating in diversified areas benefit from a lower credit price than firms concentrated in a single market.

Dimitrov and Tice (2006) also focus on the differences between diversified and non-diversified firms, concluding that non-diversified firms' sales and inventory rate growth fall significantly more than the ones of diversified firms during economic recessions, basing their study on three recessions that arose between 1978 and 1996. Similarly, Kuppuswamy and Villalonga (2010) focus on the financial crisis of 2008 to show that conglomerated firms had more access to credit than comparable individual firms due to the debt coinsurance provided by the conglomerate. The paper acknowledges that coinsurance gains become specially more valuable during crisis periods. In line with these findings, Yan et al. (2010) covering the period 1985-1997 show that diversified firms profit from a higher access to credit in external markets compared to single-segmented firms, and that when the cost of external financing increases, diversified firms are less affected than non-diversified firms in terms of amounts borrowed, since they have the possibility to substitute external financing with access to internal financing.

In the present paper light is shed on Belgian established firms' access to credit as a determinant of their likelihood to create associations, and the paper is organized as follows: section 1 has provided the introduction and the literature review, section 2 explains the hypotheses and the empirical strategy used throughout the paper, section 3 presents the data description, section 4 shows the results and section 5 concludes.

2 Hypotheses and empirical strategy

The main goal of this study is to pin down the causes and the conditions under which some firms join other firms to apply collectively for credit through the creation of associations. In order to do so, we hereafter expose several hypothesis and the empirical methodology we use to test them.

First, we argue whether firms in need of credit create more associations, since it might be that firms which have not had much access to credit over the last year look for alternative ways to have credit. Indeed, one of this alternatives is to create associations, so we claim that firms which have had few credit over the last year are more likely to create associations. Similarly, it is accustomed (and in Section 4 in Table 5 it is shown that it is indeed the case) that big firms have higher credit needs than smaller firms, so we also discuss whether firms' size positively influences the likelihood to create associations to satisfy bigger firms' higher credit demands. Apart from that, we are interested to discover whether the amount of direct credit a firm obtains from a bank is influenced by the fact that the firm belongs to an association which gets credit from the same bank, since if that was the case it could imply that the lending relation a firm keeps with a bank gets affected if the firm uses the bank for different services.

A key fact when firms create associations is their decision to increase or decrease the credit amount they individually demand to their lenders. If during the time a firm belongs to an association the credit it gets directly from a bank increases, we could conclude that the firm receives credit through the association as a way to complement the credit it gets directly since it might not get enough directly, so it creates an association to compensate the credit it needs but does not receive directly. However, if the total direct credit a firm acquires during the period it belongs to an association decreases, we could argue that the firm uses the credit it receives through an association as a substitute to the credit it would have obtained if it did not create an association.

Besides, it seems reasonable to argue that a bank is more prone to awarding credit to an association composed of firms which are already the bank's customers than to an association composed of firms which the bank has never done business with. The fact that the bank knows the firms behind the association and has access to their private or soft information due to its previous interaction with them (Cole (1998)) might imply that the bank does not have to monitor those firms as much as otherwise, or that during the process of applying for credit less documentation and references are requested since it might be that the bank had already asked for those requirements before in time, simplifying the process and thus organizational costs. Moreover, Cole (1998) concludes that a lender is more likely to provide credit to a firm with which it has already an existing relationship (in terms of number of financial services the firm uses from the lender) than to a potentially new borrower. Besides, the higher the amount of information the higher the ability of the bank to better assess the association's members' creditworthiness and as a consequence the association's financial strength as a whole. Then, the fact that every member of an association uses for credit purposes the bank the association to which they belong gets credit from, allows the bank to obtain more information about the firms forming the association. The supplementary information the bank has access to due to the personal interaction it keeps with the firms lowers the existing information asymmetry between the association and the bank, and thus the risk of the loan granted to the association. Besides, a lender's access to a debtor's soft information reduces the debtor's financial constrains (Berger et al. (2005)). Therefore, we expect the association to be less financially constrained if all its members use the same bank the association uses, consequently expecting a higher access to credit by that association, ceteris paribus.

The credit an association gets might also be motivated by the fact that none of the firms that built it up has access to credit individually and thus by the fact that these firms can just get credit through forming associations. In that case we would expect the association to receive less credit than otherwise mainly for two reasons. First, firms which do not get any credit directly might indeed not need much credit; and second, firms which do not get any credit directly might not be creditworthy enough to get it. Therefore and in any case, we would expect that associations formed by these firms get less credit than associations formed by firms which have access to direct credit. This negative effect might be exacerbated by the amount of private information firms have, since the less the information available about a firm the higher the risk it represents to grant it a loan. Given that small firms have on average a higher amount of private information than big firms (Berger et al. (2005)), we expect that associations made up of small firms which do not have access to direct credit during the time they belong to an association suffer from a more severe restriction of credit than associations made up of big firms without access to direct credit.

In order to estimate firms' likelihood to create associations and the amount of total credit firms and associations obtain during a year from each bank they use, we propose and test three equations.

We estimate a logistic model by maximum likelihood (Eq. 1) where we regress the indicator variable $BTA_{i,t}$ (Belong To Association) –which takes value equal 1 if firm i belongs to at least one association in year t, and 0 otherwise– on the log of the total amount of direct credit the firm obtained during the previous year, and a vector of control variables z_i:

$$P(BTA_{i,t} = 1) = \frac{1}{1 + exp(-(\alpha + \beta \cdot log(credit_{i,t-1}) + \delta \cdot z_{i,t-1}))} \tag{1}$$

We estimate a model (Eq. 2) where we regress the size of firm i's credit from bank b in year t –the natural logarithm of the credit obtained by a firm during a year from a given bank– on a firm's predicted probabilities to belongs to an association in year t, and a vector of control variables z_i:

$$log(credit_{i,b,t}) = \alpha + \beta \cdot \widehat{BTA}_{i,t} + \delta \cdot z_{i,t-1} + \epsilon_{it} \tag{2}$$

Given the simultaneity concern that would arise if the variable BTA was included as an explanatory variable in Eq. 2 as well as dependent variable in Eq. 1, we predict firms' probabilities to create and belong to an association and use these fitted values as regressors in Eq. 2. In Section 2.1 this procedure is further explained in detail.

We estimate a model (Eq. 3) where we regress the credit an association a obtains from bank b in year t –the natural logarithm of the credit obtained by an association during a year from a given bank– on a binary variable denoting whether every association's member received no direct credit in year t, and a vector of control variables z_a. Moreover, in order to consider the fact that the lack of credit might affect in a different manner associations made up by firms of different sizes, we interact the dummy accounting for whether an association's members got direct credit in year t with the log of the association's members' average assets measured in year $t-1$:

$$log(credit_{a,b,t}) = \alpha + \beta \cdot (members\_no\_credit_{a,t} * log(members\_avg\_assets_{a,t-1})) + \delta \cdot z_{a,t-1} + \epsilon_{at} \tag{3}$$

The vector z_i includes a set of firm-specific variables, industry, region and time fixed effects to account for cross-industry, cross-regional heterogeneity and the economic fluctuations occurred during the time period under consideration. The vector z_a includes the average of associations' members' some firm-specific variables such as the average of members' assets or age and also industry, region and time fixed effects. In Eq. 2 and Eq. 3 the vector of control variables z_i and z_a, respectively, also include bank fixed effects to control for heterogeneity across banks used to get credit from.

Firm-specific variables encompass firms' age, value of assets, number of different banks used, return on assets, a firm's profits' variability measured by the standard deviation of its returns on assets over the entire period we consider and the ratio between a firm's fixed assets over its total assets to account for the "collaterialisable assets" a firm has at its disposal (as defined by Michaelas et al. (1999)). Besides, we control for the number of firms that are in each firm's industry, region, and both in their industry and region together. The vector z_a includes some association-specific variables regarding characteristics of its members and information about the association. Some of these variables are indicators to assess whether its members operate in the same activity or are located in the same region, the number of firms constituting the association, the number of different banks the association uses, and its members' average amount of assets, assets structure, age and return on assets, measured at a yearly level. Besides, the model used to estimate the credit obtained by associations (Eq. 3) includes variables to account for whether some member of an association has created another association before having created the one to which it currently belongs to, and whether all members of an association get credit from the same bank the association to which they belong gets credit from.

The number of banks a firm or an association uses might proxy a high level of leverage or a positive quality signal they want to show to other banks (Ogawa et al. (2007)). We include this variable into the aforementioned three equations to control for the credit and diversification needs firms or associations might have, since when using several sources they might obtain on average more or less credit from each of them compared to other firms or associations using less sources. On the one hand, if they obtain less credit from each of the several sources they use a possible conclusion could be that they use many sources to diversify their credit income and not to depend solely on few sources, so they divide their credit requirements into several banks. On the contrary, it could be that they receive less credit from each of the sources they use because the value of the debtor's private or soft information for each creditor is inversely proportional to the number of creditors a debtor uses (Cole (1998) and Jimenez and Saurina (2004)), so each source decides to provide less credit given that the information it has about the firm/association is worth less, implying that the debtor needs to use more sources to compensate it. On the other hand, if a firm or association receives more credit from each source when using several sources, one possible conclusion could be that either the firm or the association is very creditworthy and it can diversify its credit needs using several banks without having its credit flow reduced from each of the banks. Alternatively, it could be that the firm/association needs high amounts of credit which no individual bank wholly provides and it therefore uses many lenders from which it gets on average more credit than debtors using fewer banks do.

Some firms create associations several times as an alternative way of obtaining credit. Then, we consider whether having created an association before in time helps to explain the amount of credit the association receives, since the fact of having created an association by the time the firm creates another association might reduce the uncertainty other firms might face when creating an association for the first time. Then, we contemplate that an association which one of its member has created at least another association before in time might benefit from a favourable treatment due to at least one of the association's firms' experience at creating associations.[1]

[1] Experience at creating association might help to comply faster or more efficiently all the paperwork required by the bank or being more productive at creating the association, which reduces the time span between the time in which the application for credit is done until the date in which the loan is granted.

Khanna and Palepu (2000), in some way similar to the present article, study the effect of business groups on firms' performance in India.[2] They analyze whether the performance of affiliated Indian firms significantly differs from the performance of non-affiliated Indian firms. They regress through ordinary least squares firms' performance (continuous variable) on a dummy indicating whether the firm is a member of a group. Other covariates include firm-specific variables (such as age and size) and industry dummies. This econometric specification is similar to the one used in the present paper where group membership is similar to belonging to an association, and while Khanna and Palepu (2000) study firm performance depending on belonging to a business group, we study a firm's amount of accessed credit depending on belonging to an association. We also analyze this relationship using ordinary least squares. Nevertheless, Khanna and Palepu (2000) do not study the probability of an Indian firm to belong to a group. Thus, they do not face the possibility to face endogeneity due to simultaneity as in the present paper.[3]

Nevertheless, similar to Khanna and Palepu (2000), we study whether associations created by firms which hold shares of each other obtain higher amounts of credit than associations set-up by independently owned firms. This is motivated by the fact that firms under the same ownership structure might face less moral hazard, and have access to both hard and soft financial information about the other firms. Independent firms might find it more difficult to avoid moral hazard and to have full information about the other firms' financial situation. Thus, associations created by co-owned firms might be more creditworthy than associations created by independent firms and consequently, banks might be willing to provide more credit to associations created by firms sharing the same ownership structure. Besides, when formalizing the credit, it may also be easier to negotiate with the bank if there is one same owner for every firm constituting the association, reducing bureaucratic costs, which may translate into higher credit granting.

Given that we have a panel data at our disposal we use fixed- and between-effects linear model to study the determinants of the amount of credit obtained by firms and associations over time. Even if random-effects linear model is more efficient than fixed-effects because it generally creates estimates with lower standard errors and it therefore provides more precise measurements, if the assumption of random-effects (it assumes that the model is well-specified and if there are omitted time-invariant variables that those are uncorrelated with the regressors included in the model) are not satisfied, the parameter estimates may be biased. After running the Hausman specification (Hausman (1978)) where the fixed-

[2]From Khanna and Palepu (2000): "Indian business groups are collections of publicly traded firms in a wide variety of industries, with a significant amount of common ownership and control, usually by a family."

[3]Moreover, due to the confidentiality of the data used throughout the present paper, to the best of our knowledge, a similar research question has not been tackled in the literature and thus the methodology nor the results obtained cannot be directly compared to similar studies.

effects and random-effects estimators are compared when estimating Eq. 2, we obtain that both models' estimators significantly differ (see Appendix C). Then, it is better to use a consistent and unbiased model (fixed-effects) which is not efficient than using random-effects model which is efficient but not unbiased.[4] However, in order to quantify the effect of time-invariant variables that fixed-effects models do not estimate but only control for, we use between-effects. Then, we use a fixed-effects model to account for possible time-invariant omitted variables in the model focusing on the within-individual variation, and between-effects to estimate the effects of observed time-invariant variables exploiting the differences between individuals. We use cluster-robust covariance estimators when using fixed-effects so each individual is treated as a cluster and we control for potential heteroscedasticity and/or serial correlation. Further, given that endogeneity due to simultaneity might also arise in our framework we cover this issue in the next section.

2.1 Endogeneity due to simultaneity

We do have an endogeneity problem due to simultaneity since we consider that the decision to create and belong to an association is an explanatory variable to determine the amount of credit a firm receives from a given bank. At the same time, a key determinant of firms' likelihood to belong to an association is the amount of outstanding credit the firm has along the previous year with every bank it used. Therefore, when firms decide the amount of credit they want to use they take into consideration whether they belong or not to an association, since depending on whether they have other sources of credit income they might request more or less credit directly. Then, as firms decide both the amount of credit they would like to use and the decision to create an association, the latter is an endogenous decision when we estimate the former decision. The effect of existence of endogeneity when using Ordinary Least Squares (OLS) is that the coefficients' estimates are biased, hence not allowing the researcher to identify the effect of interest.

In order to reduce the presence of endogeneity an Instrumental Variable approach is an option which allows to correct the estimates removing their bias if the identifying assumption of the IV approach are correct. An instrument is a variable that explains or predicts the endogeneous variable and which is exogenous to the main equation. In the present case, we would need an instrument that explains a firm's decision to create and to belong to an association which is at the same time not related to the firm's decision of how much credit it applies for. Unfortunately, we have not found such a valid instrument. Another alternative is to predict firms' probabilities of creating an association and using these predicted probabilities instead of the endogenous variable as a regressor on firms' decisions to apply for credit. If we were to predict firms' probabilities of creating an association by means of non-linear models (such as probit or logit) due to firms' dichotomous decision of creating an association (either they create it or not), and plug these predicted values into the main equation to estimate the determinants of firms' decisions to apply for given amounts of credit, we would be incurring in the so-called "forbidden regression" as first termed by Jerry Hausman

[4] See Allison (2009) and Cameron and Trivedi (2010) for further description and differences between fixed-effects and other comparable models.

in 1975 (Angrist and Pischke (2009) p.190). This approach of predicting probabilities in the first stage using non-linear methods and plugging them into a second stage equation which is estimated by linear methods (OLS) produces inconsistent estimates (Angrist and Pischke (2009) p.190 and Wooldridge (2002a) section 15.7.3 on p. 477). The source for the inconsistency is that a non-linear regression does not generate fitted values that are uncorrelated with the residuals, so a linear regression might be used in the first stage in order to correct for this inconsistency, even in presence of a dummy endogenous variable, since only in the case where the non-linear model is perfectly specified (not realistic in practice) it generates consistent estimates (Angrist and Krueger (2001)). Angrist (2001) also states that even if the endogenous variable is binary, a non-linear first stage creates inconsistent estimates and that therefore it is "safer" to use a linear model first-stage.

Therefore, there exists a trade-off between using linear and non-linear models in the first stage. Using a linear regression model, the estimates behind the variables will be consistent but also less efficient than what they would be if a non-linear model were used to take into account the binary dimension of the dependent variable. In order to keep consistency and in line with the suggestions of the literature, a linear first and second stage model is carried out in this study.

The first stage consists of estimating firms' predicted probabilities of creating associations, and these probabilities are estimated through the Linear Probability Model (LPM). Given that the decision to create an association is modelled as a binary response variable, the expected value of this dependent variable is interpreted as a probability, and the probability of creating an association is a linear function of the explanatory variables, so a linear regression model such as OLS can be used to estimate the parameters.

However, the use of LPM to predict the probabilities of creating an association in a first stage presents some drawbacks too. The literature recognizes mainly four weaknesses (see Long (1997) p. 38-40). First, as its name states, the LPM estimates linear probabilities, that is, the probability of creating an association is linearly related to the explanatory variables which might be continuous, so increasing the value of the independent variables might possibly lead the probability of a positive outcome to be higher than one, which is not possible in practice. By the same reasoning, it is plausible that the value of a predicted probability falls below zero. Second and related to the previous reasoning, the linearity form of the LPM implies that an increase of an explanatory variable entails a constant change in the probability of the event independently of the explanatory variable's level. It does not account for the fact that the predictors might have diminishing partial effects as the probability of a positive event approaches the unity. In the present case, the linearity of the function implies that say, an increase of one million in the value of a firm's assets has the same effect on the probability that firm to create an association if the firm has zero assets or assets worth a hundred million euros. This is a strong limitation of the LPM for situations in which diminishing marginal returns do exist. Third, as the dependent variable is binary, whether to create an association or not, the conditional variance of the binary variable is not constant, implying that the errors are heteroskedastic.[5] As a consequence, the estimator is inefficient and the standard errors are biased, which affects the test statistics and may lead to incorrect conclusions arguing that a coefficient before a variable is statistically significant when it is not (Type I error), or vice versa (Type II error). Fourth and last, the residuals arising after a regression run by LPM are not normally distributed, since the residual is the distance between the observed value and the expected value of the dependent variable. As the dependent variable can just take two values, the residual can also only take two values, breaking the residuals' normality assumption. As a consequence, when dealing with small samples the distributions based on residuals' normality assumption such as the t-test are not reliable.

Nevertheless, some of the drawbacks of the LPM can be controlled for when using it for estimation purposes. According to the first critique that the predicted values might fall outside the unit interval, Wooldridge (2002b) states on p. 236 that "predicted probabilities outside the unit interval are a little troubling when we want to make predictions, but this is rarely central to an analysis". Indeed and as it is the case in the present study, firms' predicted probabilities of creating associations are not used to state any result directly nor to make any prediction, they are used to get rid of the endogeneity problem when estimating firms' decisions to apply for a given amount of credit. Regarding to the second critique about the constant marginal partial effects, even if this feature eases the coefficients' interpretations since they do not depend on the predictors' values and Angrist and Pischke (2009) state on p. 107 that in practice marginal effects computed with linear and non-linear models are "similar", we do not interpret these values since once again, it is not the aim of the analysis and the values are only used as predictors in another second stage equation. With regards to the third and fourth critique related to residuals' heteroskedasticity and the violation of their normality assumption, we correct it by running the LPM implementing the Huber-White sandwich estimator to estimate robust standard errors, which deals with heteroskedasticity and non-normality concerns. Besides, we are not constrained to deal with a small sample. Anyway, realize that estimates obtained through OLS remain BLUE (best linear unbiased estimator) even when the errors are not normally distributed (nor they need to be independent and identically distributed), since they only need to be uncorrelated with mean zero and have constant variance (homoscedasticity), as indicated by the Gauss-Markov theorem.

Hence, we apply the LPM considering and controlling for the critiques it is subject to, in order to deal with the endogeneity issue that arises in Eq. 2. Furthermore, Wooldridge (2002b) states on p. 236 about the LPM that "even with these (aforementioned) problems, the linear probability model is useful and often applied in economics". Moreover, Wooldridge (2002a) on p. 468 in Table 15.1 provides an example where labor force participation (binary variable since either a person works or does not work) is estimated through linear and non-linear models (LPM, Logit and Probit) and it is stated that coefficients' signs and statistical validity are the same across models. Angrist and Pischke (2009) on p. 106 in Table 3.4.2 provide another example where they show the marginal effects of several explanatory

[5]For a binary variable y with mean μ, the variance of y is $\mu(1-\mu)$. Hence, the conditional variance $Var(y|x) = x\beta(1-x\beta)$ depends on the regressors implying that the variance of the errors is not constant.

variables on the effect of childbearing on mothers' labor supply, stating that marginal effects obtained through linear and non-linear methods are similar. In the literature, Basinger and Ensley (2010) study the effect of the US President's public appearances on the success of his proposals, where presidents' decisions about which public appearances to be involved at is related to success since they make the decisions strategically, so public appearances are endogenous to success. They control for the endogeneity using the LPM as a first stage to estimate predicted probabilities of public appearances (dichotomous variable) which are then used in a second stage equation to estimate its level of success (continuous variable). Other four models are used to deal with the existing endogeneity problem and the paper provides a comparison between these models' results. Lundberg et al. (1999) study assistance policies to African families which experience an adult's death. They argue that there exists endogeneity between these variables since a household's adult's death is related to the household's socio-economic conditions, which affects the assistance the household would receive in case of an adult's death, in terms of timing and amount of private transfers and public assistance. Their econometric analysis includes a first stage LPM of a household's adult death and a second stage estimation where the fitted values from the first stage are used. In the present paper we follow a similar approach where in the first stage we estimate a LPM of firms' probabilities of creating an association and in a second stage we use these predicted probabilities to estimate the amount of credit they apply for.

When we obtain the predicted probabilities in the first stage when estimating firms' probabilities to create an association using a LPM, around 4% of the predicted probabilities fall below zero, that is, they have a negative predicted probability to create an association. This is one of the potential problems that might arise when a LPM is used to estimate predicted probabilities, namely that some predictions fall outside the unit interval. However, the aim of these predictions is not related to their interpretation but to use them as regressors in a second stage equation where firms' decision to apply for given amounts of credit is analyzed.[6] Besides, as Horrace and Oaxaca (2006) state, the LPM remains unbiased and consistent if the number of predicted probabilities falling outside the unit interval is very few or none, while the bias increases with the relative proportion of predicted probabilities taking values lower than zero and higher than one. As in our case the values outside the unit interval represent only around 4% of all predicted probabilities, it does not create a significant problem.

3 Data description

We use several databases to cover all the information we exploit in the empirical analysis. The most determinant for our study is the Belgian Central Corporate Credit Register (CCCR) which registers relevant information about credit awarded by every financial insti-

[6]We have also run the second stage equation without considering the observations for which the predicted probabilities are negative in the first stage, and results are qualitatively identical, mainly due to the few number of observations dropped.

tutions established in Belgium for business purposes.[7] Every credit institution located in Belgium has to report to the CCCR information on a monthly basis on the amount of credit extended, amount of ongoing debt, the identities of the borrowers, initial duration of the credit extended and its remaining length for each ongoing or new loan. These information are collected, managed and used by the National Bank of Belgium for mainly financial regulatory and stability purposes.

From the Belgian Central Corporate Credit Register we obtain information about all private loans awarded by every credit institution established in Belgium since 2001 until 2011 to any firm or groups of firms, established in Belgium or abroad, which credit exposure with respect to the bank is at least 25,000 €. We have access both to the maximum authorized monthly credit the firm might have access to and to the actual monthly credit the firm uses from each loan it gets. For our analyses we use the maximum authorized credit since it represents the amount of credit the bank is willing to grant to the firm. Besides, the duration of each loan and the identity of the firm and the financial institution which grants it are known, which allows us to follow the credit relation a firm keeps with all the different banks it might use over time. Therefore, we identify the number of banks firms use at each time and the total credit the firm has access to from all its credit sources. Moreover, there is the same information available for associations made up of firms, so we exploit the authorized credit they obtain, the sources they use and the time frame over which they obtain credit. Last, we concentrate on legal persons established in Belgium[8] and disregard firms and associations which even if they receive credit from a financial institution established in Belgium, they are located abroad and thus they do not have a Belgian postal code. Moreover, a second database we have access to, the Belgian Central Balance Sheet Office, provides no information regarding these firms, so we would not be able to control for these firms' characteristics in any case.

The CCCR also allows us to identify the firms that joined associations between 2001 and 2011, so we can observe the direct credit those firms obtained during the time they belonged to associations and the credit associations got. Furthermore, we can note whether firms creating an association use the same bank the association uses to get credit from and the number of associations firms create over time. A limitation of our data is that we cannot disentangle the distribution of credit within associations, i.e. we cannot single out the credit each firm within an association receives from the credit the association gets as a whole.

Apart from that, we have access to the Belgian Central Balance Sheet Office which collects the balance sheets of every firm established and operating in Belgium between 2001 and 2011 so we can use several variables such as their size, profitability, industry or activity they

[7] Loans to individuals for exclusively private purposes are registered in another database, namely the Central Individual Credit Register.

[8] Even if the focus of the present paper is on associations of firms and not on associations of natural persons nor on associations of natural and legal persons, it should be noted for completeness that around four fifth of associations in the plain data are constituted by both natural and legal persons, and that half of these associations are composed of uniquely one natural and one legal person. This probably connotes that business owners create an association with the firm they own, probably to pledge a higher collateral to the credit the firm is willing to obtain. We leave the analysis of this fact for further research.

are focused at and their geographical location. In order to control for firms' industries and location we use the first two digits of the NACE code and the first two out of the four digits of the postal code they report in their balance sheets, respectively, not to focus on industry niches or too small geographical areas. However, not every firm is obliged to file their annual accounts with the National Bank of Belgium, so we disregard firms included in the database which are sufficiently small not to be legally forced to prepare financial statements and file them with the National Bank of Belgium, given that these firms do not report some financial information necessary to our analysis, such as their level of assets.

In Table 1 the number of associations which members belong to the same industry (measured with the two digit NACE code) and/or to the same area (measured with the two digit postcode) are shown. We observe that 65.59% of associations are made up by firms all located in the same region and around 2/3 of associations (5,000/7,484) are made up by firms which do not all operate in the same industry. The number of observations used in Table 1 is 7,484, which corresponds to the number of different associations in the sample which all its members have non-missing industry and postal code information. In this study we consider 81 different Belgian two digit postcodes and 87 different two digit NACE codes. We observe 372,992 different firms over the period 2001-2011, out of which 73,434 different firms create 69,527 different associations. Only 7,484 associations have non-missing information and are used for the analysis. These 7,484 associations account for 16,249 observations, i.e. each association is observed on average for 2.17 years, and each of the 372,992 different firms we analyze is observed for 3.94 years on average, which sum up to 1,470,557 observations.

We also have at our disposal data about Belgian firms' holdings on other Belgian firms, so we can observe Belgian firms' ownership of other Belgian firms. This information allows us to detect whether an association is formed by firms which are co-owned among them. We observe the identity of the firm who owns shares of other firms, the identity of the firm whose shares are held, the number of shares the holder owns of the held company, and the proportion of the held company's equity these shares represent, for each year between 2001 and 2011. This information is provided by the Belgian firms themselves in their annual accounts.

Nevertheless, the data presents some limitations, given that it does not allow to identify whether firms which do not have direct ownership links belong to a same conglomerate of firms. Thus, we can only note whether one firm is partially or completely owned by another firm in certain years and then identify whether they have created an association during that period. Equally, we are able to identify whether any two firms within an association have ownership links between themselves. Unfortunately, we are not able to discern whether firms which have no direct ownership link between themselves belong to a same conglomerate.

Given that firms' balance sheet information is measured at a yearly level we annualize our monthly credit data in such a way that we have the total authorized credit a firm has obtained from each bank it uses over a year (from January to December). In Table 2 and Table 3 a descriptive statistics of the main variables used in the analysis are provided, regarding firms and associations, respectively. Definitions of these variables are provided in Appendix

Table 1: Number of associations which members are in the same activity and/or region.

same activity	same region No	same region Yes	Total
No	1,730	3,270	5,000
	34.60%	65.40%	100.00
Yes	845	1,639	2,484
	34.02%	65.98%	100.00
Total	2,575	4,909	7,484
	34.41%	65.59%	100.00

A in Table 8. As we lag some of our variables for one period (year) to avoid reverse causality in our estimations and the year 2001 is the first year available in our data, descriptive statistics for that year are omitted. Besides and as a explanatory note, the variables starting with "lag" regard to the values that variable took the year before, i.e. lag_log_avg_assets in 2011 regard to the value of log_avg_assets in 2010. Then, for every lagged variable we consider, we show the values used in the regression at time *t*, which correspond to the variables' values at time *t-1*.

Table 2: Descriptive statistics of firms' variables used in the regression of probability to create associations, by year

YEAR	2002		2003		2004		2005		2006	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
belong_to_association	0.09	0.28	0.08	0.27	0.08	0.27	0.08	0.28	0.09	0.28
lag_log_total_assets	13.10	1.41	13.09	1.39	13.09	1.38	13.11	1.37	13.15	1.37
log_total_credit_last_year	7.34	1.58	7.35	1.56	7.34	1.58	7.35	1.59	7.38	1.58
lag_log_number_region_industry	4.71	1.35	4.70	1.34	4.72	1.33	4.75	1.33	4.76	1.32
lag_log_number_industry	8.72	1.17	8.73	1.16	8.75	1.15	8.78	1.15	8.80	1.14
lag_log_number_region	7.96	0.73	7.95	0.72	7.97	0.72	7.99	0.71	8.01	0.71
lag_number_banks_used	1.30	0.66	1.30	0.66	1.26	0.58	1.26	0.57	1.26	0.57
lag_asset_structure	0.49	0.31	0.49	0.31	0.50	0.31	0.50	0.31	0.50	0.31
lag_leverage	8.10	1,062.23	9.28	1,292.79	3.83	1,165.47	3.64	595.86	7.67	875.29
lag_log_age	2.31	0.79	2.33	0.79	2.35	0.79	2.37	0.79	2.39	0.79
lag_roa	-0.06	11.29	-0.44	153.01	-0.00	1.54	-0.37	148.29	-0.00	2.82
lag_roa_std_dev	3.91	768.50	3.98	757.41	3.78	744.04	2.36	520.67	2.01	503.21
Number obs.	126,312		130,684		135,177		139,260		143,089	

YEAR	2007		2008		2009		2010		2011	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
belong_to_association	0.09	0.29	0.09	0.29	0.09	0.28	0.08	0.27	0.08	0.27
lag_log_total_assets	13.18	1.37	13.20	1.38	13.22	1.39	13.21	1.38	13.23	1.40
log_total_credit_last_year	7.41	1.59	7.44	1.61	7.44	1.61	7.45	1.60	7.46	1.61
lag_log_number_region_industry	4.79	1.32	4.83	1.31	4.86	1.30	4.88	1.29	4.90	1.29
lag_log_number_industry	8.83	1.13	8.87	1.12	8.91	1.12	8.93	1.11	8.95	1.11
lag_log_number_region	8.04	0.71	8.07	0.71	8.11	0.70	8.13	0.70	8.15	0.70
lag_number_banks_used	1.25	0.56	1.25	0.56	1.26	0.56	1.27	0.58	1.25	0.56
lag_asset_structure	0.50	0.31	0.50	0.31	0.50	0.31	0.51	0.31	0.51	0.31
lag_leverage	1.15	1,189.05	6.44	615.68	13.89	3,563.15	9.32	882.38	9.13	1,320.74
lag_log_age	2.39	0.80	2.39	0.82	2.40	0.82	2.41	0.82	2.43	0.81
lag_roa	0.02	9.48	0.00	5.78	-0.07	16.97	-0.07	11.21	0.16	76.63
lag_roa_std_dev	3.13	706.88	1.79	498.13	0.51	53.24	0.60	75.61	0.44	57.11
Number obs.	148,777		155,691		160,267		164,044		167,256	

Total number of observations: 1,470,557.

Table 3: Descriptive statistics of the variables used in the regression of credit obtained by associations, by year

YEAR	2002		2003		2004		2005		2006	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
log_credit_year_bank	8.57	2.22	8.65	2.03	8.61	2.03	8.69	1.96	8.64	2.04
number_firms_in_association	2.19	0.57	2.20	0.60	2.20	0.58	2.20	0.57	2.18	0.51
d_members_same_postal	0.71	0.45	0.71	0.45	0.72	0.45	0.74	0.44	0.74	0.44
d_members_same_activity	0.36	0.48	0.36	0.48	0.35	0.48	0.36	0.48	0.35	0.48
number_banks_used	1.65	1.37	1.46	1.01	1.44	0.99	1.43	0.96	1.43	0.98
d_no_direct_credit	0.00	0.02	0.00	0.05	0.00	0.05	0.00	0.03	0.00	0.00
d_created_association_before	0.00	0.00	0.05	0.22	0.10	0.30	0.15	0.36	0.20	0.40
lag_log_avg_assets	15.52	2.07	15.41	1.95	15.40	1.90	15.44	1.85	15.40	1.84
lag_assoc_asset_structure	0.47	0.21	0.47	0.21	0.47	0.21	0.46	0.22	0.47	0.21
lag_d_members_use_same_bank	0.63	0.48	0.60	0.49	0.60	0.49	0.59	0.49	0.59	0.49
lag_log_avg_age	2.83	0.57	2.84	0.55	2.86	0.52	2.90	0.50	2.90	0.51
lag_avg_roa	0.01	0.24	0.01	0.07	0.03	0.20	-0.15	6.53	0.02	0.16
Number of obs.	1841		1679		1605		1559		1632	

YEAR	2007		2008		2009		2010		2011	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
log_credit_year_bank	8.59	2.13	8.56	2.14	8.51	2.23	8.60	2.04	8.61	2.00
number_firms_in_association	2.17	0.48	2.19	0.59	2.18	0.56	2.18	0.61	2.19	0.62
d_members_same_postal	0.72	0.45	0.72	0.45	0.71	0.45	0.72	0.45	0.72	0.45
d_members_same_activity	0.34	0.47	0.34	0.47	0.34	0.47	0.32	0.47	0.31	0.46
number_banks_used	1.38	0.89	1.38	0.92	1.38	0.93	1.34	0.90	1.32	0.79
d_no_direct_credit	0.00	0.04	0.00	0.03	0.00	0.04	0.00	0.04	0.00	0.03
d_created_association_before	0.24	0.43	0.29	0.45	0.32	0.47	0.34	0.47	0.35	0.48
lag_log_avg_assets	15.41	1.84	15.37	1.75	15.37	1.73	15.34	1.71	15.38	1.75
lag_assoc_asset_struc	0.46	0.22	0.46	0.22	0.46	0.23	0.48	0.23	0.48	0.23
lag_d_members_use_same_bank	0.58	0.49	0.59	0.49	0.58	0.49	0.57	0.49	0.56	0.50
lag_log_avg_age	2.92	0.52	2.92	0.53	2.93	0.52	2.96	0.52	2.97	0.52
lag_avg_roa	0.02	0.31	0.00	1.04	0.02	0.11	-0.00	0.66	0.03	0.12
Number of obs.	1628		1649		1620		1535		1501	

Total number of observations: 16,249.

4 Results

We start our analysis by estimating Eq. 1 which results are shown in Table 4. We observe that the size of the firm and its past credit are key elements to determine the likelihood of a firm to create an association, in terms of both economic and statistical significance. The higher the credit a firm has obtained the previous year the less its likelihood to create an association next year, i.e. the higher the past credit a firm obtains the less its probability to create an association next year, ceteris paribus. This leads to the fact that firms are more likely to create associations when they have not had access to much credit, implying that firms might create associations as a mean to substitute the credit they did not obtain individually.

More explicitly, given that we transform the credit a firm obtained the previous year to logarithmic in order to account for a decreasing marginal effect of obtaining credit, one unit increase of the log of a firm's past year's credit leads to a decrease of around 31% of the odds ratio of creating an association the following year, ceteris paribus.[9] This is equivalent to

[9] The odds ratio of creating an association expresses the ratio between the probability that a firm creates or belongs to an association to the probability it does not, i.e. it equals $P(BTA_{i,t} = 1)/(1 - P(BTA_{i,t} = 1))$.

state that one percentage increase of a firm's past year's credit (of its absolute value and not of its log) decreases the odds ratio of creating an association the following year by around 0.38%. In other words, one percentage increase of the credit obtained the previous year decreases the relative probability ratio of creating an association the following year by more than a third of that percentage, and this holds independently of the value the credit is held at.[10]

Odd ratios, even if they may not be interpreted as straightforwardly as probabilities, present some advantages over marginal effects. Marginal effects of any variable of interest are estimated using specified values of the covariates used in a previously fitted model. Therefore, modifying the set of covariates (adding or removing a covariate) affects the predictions of the model which are used to estimate marginal effects, so the estimates obtained through the marginal effects are dependent on the model specification. This is not the case when using odds ratios. Besides, marginal effects estimate the effect of a regressor on the probability of positive outcome of the dependent variable depending on the value the regressor takes, while odd ratios express the constant effect of the variable/predictor of interest on the outcome of the dependent variable. Therefore, in our case, given that the amount of credit a firm obtained the previous year is a continuous variable, the odds ratio is constant across values of the amount of credit, while the probabilities obtained thanks to the marginal effects would not be constant. Thus, if a firm experienced a 1% increase in the credit it obtained in a given year, its odds ratio of creating an association the following year are 0.38% lower, independently of the firm's initial level of credit.

The higher the value of a firm's assets the higher its likelihood to create an association, and the absolute amount of a firm's assets seems to explain better the odds of creating an association than the proportion of its fixed assets over its total assets. Moreover, in Table 5 where the regression results of estimating Eq. 2 are shown, we observe that bigger firms have access to higher amounts of credit, and in Table 6 where the regression results of estimating Eq. 3 are displayed, that the bigger the firms making up the associations the higher the amount of credit associations get. Thus, bigger firms not only obtain more credit directly but are also likelier to create associations and the associations they create get on average more credit allowance than associations made up of smaller firms. Besides, in Appendix B in Table 10 we provide several estimation results of Eq. 2 considering different sub-samples of firms according to their SME level, where we show that firms' size remains a statistically significant determinant to explain the amount of credit firms get when the sample is only formed by more similar and comparable firms.

Another insight of the substitution effect between obtaining credit directly or through an association are the results concerning firms' age. In Table 4 we observe that older firms have higher odds of creating an association and in Table 5 that older firms receive less direct

[10]As credit obtained the previous year is expressed as logarithm, the higher the increase of the credit the lower it is proportionally its effect on the decrease of the probability to create an association the following year. Numerically, a 100% increase of the credit obtained last year involves a reduction of 31% on the odds ratio of creating an association (a net effect of 31% of the credit increase), while a 1% increase implies a proportionally higher negative effect, namely, a reduction of 0.38% (a net effect of 38% of the credit increase).

credit. However, in Table 6 the average age of an association's members is not statistically significant to explain the credit the association obtains, so we can just conclude that old firms receive less credit than younger firms and that old firms have higher odds of creating associations. Old firms, as it is for big firms, are more likely to create associations likely because they are more established or better known than younger or smaller firms –both by their commercial partners, by the banks they use and by the market in general, so they make use of their notoriety to create associations since they benefit from a low adverse selection.

Firms getting credit from many banks are more likely to create associations than firms using fewer banks for credit purposes (see Table 4). Besides, the higher the number of banks used by firms the higher the credit they get from each of them on average (see Table 5). Associations can also obtain credit from more than one source, and as it is shown in Table 6, the higher the number of banks used by an association the higher the amount of credit it obtains on average from each of them, as it is the case for firms. The positive relation between the number of lenders and the amount of credit borrowed from each of them might be due to a signal of firms' and associations' high solvency to secure the repayment of every loan (Ogawa et al. (2007)), which might increase the amount each bank grants it.

Highly leveraged firms are not statistically more likely to create associations than firms with different debt ratios (see Table 4). Then, the level of debt does not seem to affect a firm's likelihood to look for alternative credit incomes such as the creation of an association.

Regarding the credit associations get (see Table 6), we observe that associations using a bank which all its members use get on average more credit than when not all its members use the bank (16.6% more). Thus, the supplementary information banks obtain by dealing directly with every firm making up the association reduces the information asymmetry between both parties and, as we see, banks provide on average higher amount of credit to the association when it is also a direct lender of each of its members.

If none of the members of an association has obtained any direct credit during the year in which they belong to the association, that association gets on average less credit than otherwise, even if the negative effect decreases with the average size of the association's members, i.e. the negative effect of not having access to credit on its own is more severe for smaller firms. Not having any direct credit implies that every firm creating the association has faced difficulties obtaining credit signaling lack of creditworthiness or that they do not need much credit, so in either case we would expect the association they create to obtain less credit than otherwise.

We do not find any statistically significant effect of the variable accounting for whether at least one member of an association has created another association by the time they form an association.

As expected, the higher the number of members in an association the higher the credit awarded to that association since the amount has to be divided among more members. Besides, if every member of an association is located in the same region (defined as the first two digits of the postal code) the association receives on average more credit (around 20% more) than otherwise. This positive effect might arise because it results easier to the bank to monitor the members of the association given that they all are located physically close to each other. Besides, the geographical proximity between firms might reduce adverse selection to form an association, since firms' owners might know each other better if their firms are located within a low distance to each other.[11] If the bank's loan officer is aware of the fact that an association's members might know each other better than the members of another association, the bank's loan officer might assign a lower probability of default to the loan and thus concede more credit to the former. This idea is reinforced by the fact that the majority of associations are formed by firms within the same region (see Table 1), implying that the physical proximity between firms is a key factor to form associations.

In order to conduct some robustness checks of the results presented so far, we estimate the aforementioned equations using different samples where we group firms in terms of their characteristics. For instance, Eq. 2 is estimated considering only micro firms, small firms, medium firms and big firms separately (see Appendix B Table 10). The difference between the different levels is done considering firms' number of employees and turnover or balance sheet total amount, as defined by the European Commission's factors to determine the eligibility of a firm into different levels of SME.[12] Besides, Eq. 1 is estimated distinguishing firms depending on to which group of SME they belong to and also depending on their level of assets, i.e. we group firms belonging to the same assets quartiles and estimate Eq. 1 considering uniquely these groups of firms. We use firms' assets quartiles in addition to their SME level in this case because this way we can use many more observations for each group (see Table 12 and Table 13 in Appendix D.) However, we do not provide any estimation result of Eq. 3 using different sub-samples composed of associations which members belong to a given SME level or to a given assets quartile because the low number of observations by group and year that results from this decomposition is too low to provide significant and reliable results.

4.1 Creation of associations over time

Both the number of new loans awarded to firms and associations follow a similar trend. The number of new loans awarded to firms monotonically increases from the year 2003 until 2008 to later decrease from 2008 until 2011. Similarly, the number of new loans awarded to associations soars from 2002 until 2006 where it reaches its peak and then it decreases from 2006 until 2010. Nevertheless, the average amount of credit of the newly conceded loans to firms during the first year the loans are granted, is negatively related to the number of associations created during that year. On the one hand, we observe in Fig. 1 and Fig. 2 that from 2003 to 2006 the average loan's amount to firms decreases while the number of new associations

[11] For instance, Petersen and Rajan (2002) show that firms with opaque information have lenders geographically closer to them than otherwise, and Berger et al. (2005) state that the less the distance between the lender and the firm the less the bank's cost of obtaining soft information. Thus, firms located geographically close to each other might also have an easier access to each other's soft information than otherwise.

[12] The eligibility criteria is shown in Appendix B in Table 9.

Table 4: Estimation results of Eq. 1. Firms' likelihood to create associations.

VARIABLES	(1) belong_to_association
log_total_credit_last_year	-0.378***
	(0.01)
L.log_total_assets	1.107***
	(0.01)
L.log_number_region_industry	0.042
	(0.03)
L.log_number_region	-0.667***
	(0.20)
L.log_number_industry	1.043***
	(0.07)
L.number_banks_used	0.157***
	(0.01)
L.asset_structure	0.790***
	(0.03)
L.leverage	0.000
	(0.00)
L.log_age	0.338***
	(0.01)
L.roa	-0.000
	(0.00)
L.roa_std_dev	0.000
	(0.00)
Constant	-24.072***
	(1.96)
lnsig2u	3.288***
	(0.01)
Observations	1,470,557
Number of firms	265,395

Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Standard errors in parentheses. "L." means that the variable is lagged by one year. The term "lnsig2u" is the log of the variance due to time level variation (panel variation). Time, industry and region fixed effects are included.

Table 5: Firms' obtained direct credit. Estimation results of Eq. 2. In columns (1) and (2) estimation results using Fixed-Effect (FE) and Between-Effects (BE) are shown, respectively.

	(1)	(2)
	credit_firms_fe	credit_firms_be
VARIABLES	log_credit_year_bank	log_credit_year_bank
BTA_hat	-18.08***	-36.81***
	(0.127)	(0.061)
L.log_number_region_industry	0.06***	0.08***
	(0.012)	(0.004)
L.log_number_region	-0.11***	-0.94***
	(0.041)	(0.060)
L.log_number_industry	0.36***	0.91***
	(0.018)	(0.020)
L.number_banks_used	0.44***	0.62***
	(0.005)	(0.003)
L.asset_structure	0.90***	1.44***
	(0.009)	(0.006)
L.leverage	0.00***	0.00***
	(0.000)	(0.000)
L.log_total_assets	1.21***	1.96***
	(0.006)	(0.003)
L.log_age	-0.40***	-0.12***
	(0.007)	(0.002)
L.roa	-0.00***	-0.00***
	(0.000)	(0.000)
L.roa_std_dev	-	0.00***
		(0.000)
Constant	-9.53***	-17.41***
	(0.362)	(0.582)
Observations	1,719,310	1,719,310
R-squared	0.195	0.687
Number of firm-bank pairs	360,490	360,490

Significance level: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. "L." means that the variable is lagged by one year. Time, industry and region fixed effects are included.

Table 6: Credit associations obtain. Estimation results of Eq. 3. In columns (1) and (2) estimation results using Fixed-Effect (FE) and Between-Effects (BE) are shown, respectively.

VARIABLES	(1) credit_assoc_fe log_credit_year_bank	(2) credit_assoc_be log_credit_year_bank
d_no_direct_credit	-6.528***	-15.551***
	(2.40)	(3.98)
L.log_avg_assets	0.472***	0.513***
	(0.09)	(0.02)
d_no_direct_credit#L.log_avg_assets	0.303**	0.830***
	(0.12)	(0.23)
d_created_association_before	-	-0.077
		(0.06)
L.assoc_asset_structure	0.170	0.397***
	(0.20)	(0.12)
L.d_members_use_same_bank	-0.025	0.166***
	(0.05)	(0.05)
L.number_banks_used	0.116**	0.249***
	(0.05)	(0.03)
number_firms_in_association	-	0.320***
		(0.04)
d_members_same_activity	-	0.046
		(0.05)
d_members_same_postal	-	0.206***
		(0.05)
L.log_avg_age	-0.262	-0.060
	(0.25)	(0.05)
L.avg_roa	0.006***	0.067*
	(0.00)	(0.04)
Constant	2.577	-1.008**
	(1.59)	(0.44)
Observations	16,249	16,249
R-squared	0.088	0.399
Number of association-bank pairs	5,311	5,311

Significance level: *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses. "L." means that the variable is lagged by one year; "d_" means that the variable is a dummy. Time, industry and region fixed effects are included.

rises.[13] On the other hand, from 2006 to 2009 the average loan's amount to firms increases while the number of associations created decreases over that period. Therefore, we observe that firms substitute the credit they obtain from banks with the alternative of creating associations with other firms; the periods during which the average loan to a firm gets reduced (increased) coincides with the period where firms create more (less) associations. In Fig. 2 we can observe the evolution of the number of associations created over time, with a clear trend of an increasing number from the year 2002 until 2006 and a decrease from 2006 on.

Regarding the financial crisis originated in 2008, even if the number of new loans to both firms and associations decreased after the negative credit supply shock of 2008 (see Fig. 1 and Fig. 2), we observe in Fig. 3 that the average credit awarded to firms considering all the ongoing loans and not only the newly granted ones decreased from 2008 until 2011, while the average credit awarded to every association over that period increased. This result holds considering the average yearly credit received by firms and associations by every bank and not only by each single bank. This fact might denote that after the crisis only associations made up by solvent or creditworthiness firms could have access to credit through associations, obtaining higher average credit at the expense of associations created by less attractive firms which credit applications were rejected. Then, banks granted fewer number of new loans to associations but with a higher average credit. The reason why the average credit awarded to associations increases is not due to an average increase of the number of participants in each association, since the average number of firms constituting an association remains more or less constant over time (around 2.65 members).

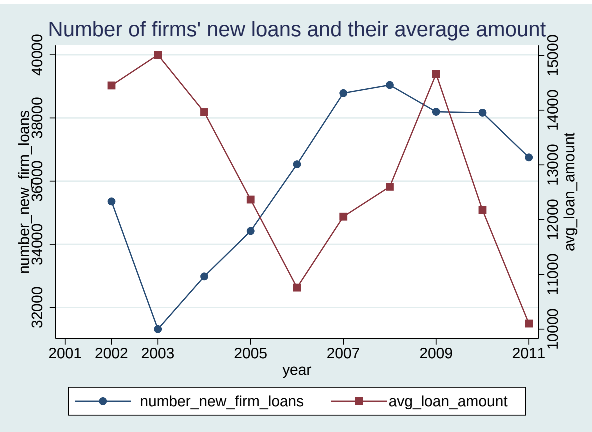

Figure 1: Number of new loans to firms and their average amount. Credit is shown in thousands of euros.

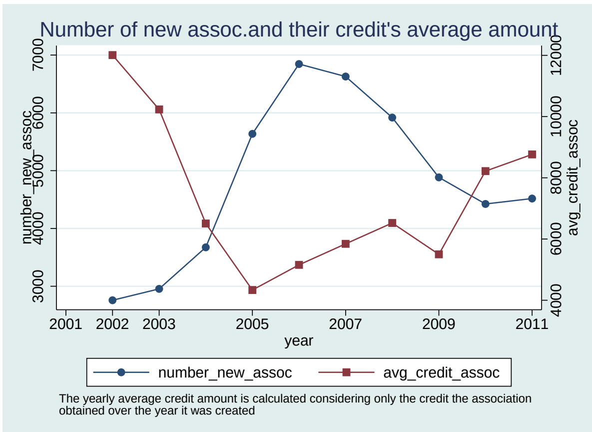

Figure 2: Number of new associations created and the average credit they received. Credit is shown in thousands of euros.

[13]Both in Fig. 1 and Fig. 2 there is no observation for the year 2001 because even if we observe the number of active associations in year 2001 we cannot disentangle whether there are associations created in 2001 or if they were created before and they were still active in 2001. Then, the first year in which we can assure that new associations were created during that year and did not exist before is year 2002.

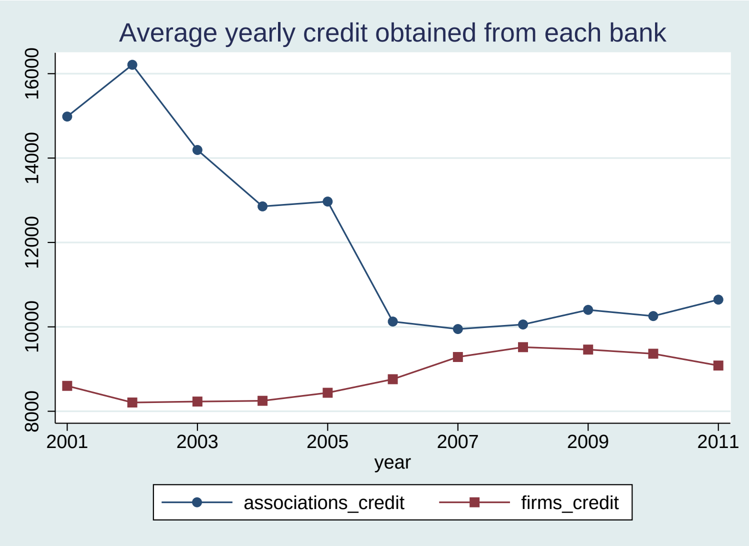

Figure 3: Average yearly credit obtained by firms and associations from each bank. Credit is shown in thousands of euros.

4.2 Focus on firms creating associations

Firms creating associations obtain on average less direct credit during the time in which they belong to some association compared to firms that do not belong to any association during that period. We compare in Fig. 4 the average direct credit obtained by firms creating associations at some time between 2001 and 2011 when they belong and when they do not belong to an association, so we now focus on the sub-sample of firms creating at least one association over time. We observe that the yearly average credit obtained by firms belonging to an association and the yearly average credit received by firms not belonging to an association that year behave in opposite ways over time. Furthermore, the average credit obtained by firms when they do not belong to an association outweighs firms' average credit when they do belong to an association. Therefore, once a firm belongs to an association we observe that its average direct credit gets reduced compared to the average direct credit of firms not belonging to an association, implying that firms cut down the amount of credit they get directly from banks when they get credit through the association they belong to. Moreover, the lower the direct credit firms obtain when they belong to an association the higher the credit the firms not belonging to associations get, so we observe that banks shift the supply of credit from firms which lower their demand for credit when they create associations, to other firms which do not belong to any association at that time. The only period of time during which the credit obtained by firms is reduced independently of whether they belong to an association is over 2008-2010, where after the negative shock of the crisis the average credit obtained by every firm is reduced for two years in a row.

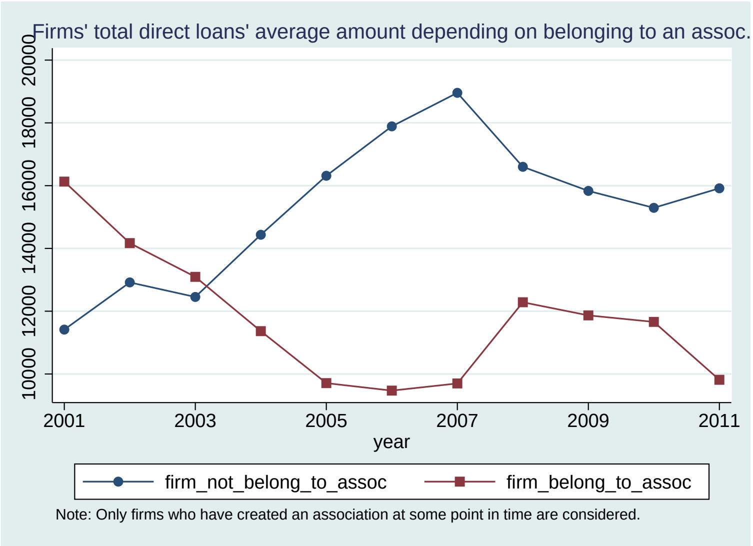

Figure 4: Average direct credit obtained by firms when they belong to an association and when they do not belong to any. Credit is shown in thousands of euros.

We now study the determinants of firms' access to credit but allowing the fact that firms may get credit from the same bank the association to which the firm belongs gets credit from. Then, we further restrict the sample to consider only those firms belonging to an association for each year under consideration. We estimate a similar equation to Eq. 2 with the particularity of focusing only on firms which have created associations and considering the possibility that firms receive direct credit from the same bank as the association to which they belong does. The new equation we estimate is Eq. 4 and its results are shown in Table 7.

$$log(credit_{i,b,t}|BTA_{i,t} = 1) = \alpha + \beta \cdot same\_bank_{i,t} + \delta \cdot z_{i,t-1} + \epsilon_{it} \tag{4}$$

We note from Table 7 that when a firm belongs to an association and it also gets credit directly from the same bank that supplies credit to the association it belongs to, the firm receives less direct credit (around 26% less) compared to other years in which it belongs to an association but it does not use the same bank as the association does. This is due tot he fact that as the bank knows better the firm behind the association, it grants more credit to the association and therefore the firm demands less direct credit, since the firm substitutes the credit it needs directly with the credit it obtains through the association. This last fact is supported by the result in Table 6 where we observe that associations composed of firms which all use the same bank as the association does receive on average higher amount of credit (16.6% more) compared to other associations which not all its members get credit from the same bank as their association does. However, we also note in Table 7 that firms using the same bank as the association to which they belong uses, receive on average slightly more credit (around 4% more) than other firms which belong to an association but do not use its same bank. Thus, firms receive more direct credit than other firms if they use the same bank as the association to which they belong does, but receive less direct credit during the years in which they use these banks compared to the credit they get during the years they do not use these banks.

Besides, we observe in Table 7 that the number of different banks used by firms positively affects the amount of credit firms obtain from each bank they use, as it was the case when we considered every firm in the sample independently of whether they had created an association (see Table 5). Remind that associations using many banks had also access to higher amounts of credit than associations using fewer banks (see Table 6, where we noted that for each extra bank an association used it received on average around 25% more of credit in each loan than other associations.).

Table 7: Credit firms with FE and BE considering only firms belonging to associations. Estimation results of Eq. 4. In columns (1) and (2) estimation results using Fixed-Effect (FE) and Between-Effects (BE) are shown, respectively.

VARIABLES	(1) same_bank_firm_assoc_fe log_credit_year_bank	(2) same_bank_firm_assoc_be log_credit_year_bank
L.same_bank_firm_assoc	-0.26***	0.04**
	(0.043)	(0.018)
L.log_number_region_industry	0.10	0.03
	(0.074)	(0.021)
L.log_number_region	0.65***	0.33
	(0.250)	(0.282)
L.log_number_industry	-0.17	0.17*
	(0.111)	(0.096)
L.number_banks_used	0.02*	0.06***
	(0.013)	(0.009)
L.asset_structure	0.28***	0.67***
	(0.052)	(0.031)
L.leverage	0.00	0.00**
	(0.000)	(0.000)
L.log_total_assets	0.51***	0.52***
	(0.022)	(0.006)
L.log_age	-0.17***	-0.07***
	(0.057)	(0.013)
L.roa	-0.00**	-0.02
	(0.002)	(0.016)
L.roa_std_dev	-	0.00
		(0.000)
Constant	-3.26	-5.26*
	(2.215)	(2.759)
Observations	140,421	140,421
R-squared	0.034	0.294
Number of firm-bank pairs	44,059	44,059

Significance level: *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses. Time, industry and region fixed effects are included.

Further, we study the fact that associations made up by co-owned firms may obtain higher amounts of credit. According to the data, only a minority of associations are formed by firms sharing a common ownership, but within this sample and in the majority of associations made up by two firms, one firm fully controls the other.

In fact, only around 5% of associations have at least one member which holds shares of at least another member, and in 60% of the cases within this subset of associations of common ownership, half the members of an association hold shares of the other half of the members. Besides, focusing on associations created by just two firms where one holds shares of the other, in 75% of the cases one of the firms holds more than 50% of the shares of the other, that is, it fully controls the other firm.[14]

In order to analyze whether associations formed by common-ownership firms receive higher amounts of credit due to the lower adverse selection these associations may represent, we estimate the following equation 5:

$$log(credit_{a,b,t}) = \alpha + \beta \cdot same\_ownership_{a,t} + \delta \cdot z_{a,t-1} + \epsilon_{at}, \tag{5}$$

where *same_ownership* is the variable accounting for whether there is common ownership within an association.

Given that we have access to Belgian firms' ownership structure, we create two different ownership variables that assess whether a firm holds shares of another firm. We first use an indicator variable that states whether at least one firm within an association has equity of at least another firm it creates an association with. Second, we create a continuous variable which states the proportion of firms which hold shares of other firms within an association. That is, if an association is formed by just 2 firms and both firms have shares of the other firm, the proportion of firms with shares of other firms within the association equals a 100%, and if there are three firms and two of them have shares of the other two, the proportion equals 66%. Thus, we estimate two equations where different ownership variables are used.

As the two variables of interest are not statistically significant in the regressions' results, the two estimations' outputs are shown in Appendix E in Table 15.

Thus, it seems that forming an association together with co-owned firms does not statistically affect the amount of credit these associations get compared to associations formed by independently owned firms.

[14] In 55% of the cases where an association is created by two firms where one hold shares of the other, one of the firms keeps more than 90% of the shares of the other firm; in 35% of the cases one of the firms keeps more than 99% of the shares of the other firm; and in 10% of the cases one of the firms keeps exactly 100% of the shares of the other firm.

5 Conclusions

We have studied firms' incentives to create associations as an alternative way of obtaining credit. We show that firms are more likely to create associations when they have not obtained much direct credit over the past year and that they reduce the amount of direct credit they obtain during the time they belong to an association. Therefore, firms try to obtain credit through alternative ways when they do not obtain credit directly and they reduce the amount of direct credit they get when they find other sources of credit, implying that firms substitute the credit they directly get from banks for the credit they obtain when they create associations. Besides, we show that associations which members do not have access to any direct credit receive less credit than otherwise, the effect being more severe for associations made up by small firms, either because they do not need much credit or because they face financial constrains which make the risk contamination outweigh any financial coinsurance that could emerge when they pool together to create an association. We also find that big firms create more associations and get higher amounts of credit than associations made up by smaller firms. Old firms are also more likely to create associations compared to younger firms and we observe that old firms receive on average less direct credit than younger firms. Associations get more credit if all its members use the same bank the association uses to get credit from, implying that if banks know better their debtors and have access to extra information about them they lend on average higher amounts of credit. Furthermore, if firms creating an association are geographically close to each other the association receives higher amounts of credit than otherwise due to the lower adverse selection the members of the association represent. Besides, we find no evidence that associations created by firms which hold equity of each other have access to higher amounts of credit than associations made up by independently owned firms.

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Appendix

A Definition of variables

Definitions of variables mentioned in Table 2 and Table 3 are provided in the following Table 8:

Table 8: Definition of variables described in Table 2 and Table 3

Firms' variables	Definition
belong_to_association	dummy=1 if a firm belongs to an association (=0 otherwise)
lag_log_total_assets	lag of a firm's total assets (in logarithm)
log_total_credit_last_year	total credit a firm obtained the previous year (in log)
lag_log_number_region_industry	lag of the number of firms within a firm's region and industry (in log)
lag_log_number_industry	lag of the number of firms within a firm's industry (in log)
lag_log_number_region	lag of the number of firms within a firm's region (in log)
lag_number_banks_used	lag of the number of banks a firm uses
lag_asset_structure	lag of a firm's asset structure (fixed assets / total assets)
lag_leverage	lag of a firm's leverage (total liabilities / equity)
lag_log_age	lag of a firm's age (in log)
lag_roa	lag of a firm's return on assets
lag_roa_std_dev	lag of the standard deviation of a firm's return on assets over the period 2001-2011

Associations' variables	Definition
log_credit_year_bank	credit obtained by an association in a given year from a given bank (in log)
number_firms_in_association	number of firms (members) which create an association
d_members_same_postal	dummy=1 if every member has the same postal code (=0 otherwise)
d_members_same_activity	dummy=1 if every member has the same activity code (=0 otherwise)
number_banks_used	number of banks used by an association
d_no_direct_credit	dummy=1 if no member obtained credit directly (=0 otherwise)
d_created_association_before	dummy=1 if at least one member has created an association in any previous year (=0 otherwise)
lag_log_avg_assets	lag of members' average assets (in log)
lag_assoc_asset_structure	lag of members' average asset structure (fixed assets / total assets)
lag_d_members_use_same_bank	lag of dummy=1 if every member uses the same bank (=0 otherwise)
lag_log_avg_age	lag of members' average age (in log)
lag_avg_roa	lag of members' average return on assets

B Firm characteristics to determine their SME level

In Table 9 firms' necessary characteristics to belong to each of the SME category levels are shown.

In the following Table 10 we show different regression results focusing on different samples to estimate Eq. 2 under two different estimation strategies. We consider a reduced sample of firms for each regression to study the determinants of credit when only similar firms in terms of belonging to the same level of SME classification are considered. The level of SME is established considering firms' number of employees and turnover or balance sheet total (see Table 9). Results obtained are qualitatively the same to the results obtained in Table 5 where no distinction in the pooled sample was made. A fact to mention, however, is that

Table 9: Firm characteristics to define their SME category level.

Firm category	**Employees**	**Turnover**	or	**Balance sheet total**
Large	≥ 250	$>$ €50 m	or	$>$ €43 m
Medium	< 250	$\leq$ €50 m	or	$\leq$ €43 m
Small	< 50	$\leq$ €10 m	or	$\leq$ €10 m
Micro	< 10	$\leq$ €2 m	or	$\leq$ €2 m

Source: European Commission. `http://ec.europa.eu/enterprise/policies/sme/facts-figures-analysis/sme-definition/index_en.htm`.

the number of different banks used plays a role of different magnitude depending on the sample of firms used. The effect is economically more relevant the larger the firms considered in the set. This difference might be due to the fact that small firms rely on soft information in their relation with their lenders due to their lack of hard information (Berger et al. (2005)), so the higher the number of sources a micro or small firm uses the lower the value of the private information the creditor might have (Cole (1998)) and the lower the bank's monopoly power gained through its informational advantage (Degryse and Ongena (2001)). Therefore, the positive effect is lower than the one observed for large firms. Besides, the literature recognizes that smaller firms use less sources than bigger firms. Petersen and Rajan (1994) for the US market, Harhoff and Korting (1998) for the German one and Farinha and Santos (2002) for the Portuguese one state that small firms generally have a single relationship with their lenders, and that the number of sources used increases with firms' size.

Table 10: Firms' obtained direct credit estimating Eq. 2 considering micro, small, medium and large firms separately. Estimates in columns (1)-(4) are obtained using OLS with fixed-effects while in columns (5)-(8) OLS with between-effects is used. In columns (1) and (4) only micro firms are considered; in columns (2) and (5) only small firms are considered; in columns (3) and (7) only medium firms are considered and in columns (4) and (8) only large firms are considered.

VARIABLES	(1) sme1_fe log_credit	(2) sme2_fe log_credit	(3) sme3_fe log_credit	(4) sme4_fe log_credit	(5) sme1_be log_credit	(6) sme2_be log_credit	(7) sme3_be log_credit	(8) sme4_be log_credit
BTA_hat	-14.85***	-21.60***	-20.57***	-20.99***	-35.12***	-38.26***	-39.06***	-35.26***
	(0.180)	(0.598)	(1.188)	(1.483)	(0.092)	(0.303)	(0.583)	(1.162)
L.log_number_region_industry	0.06***	0.13***	0.12	-0.11	0.07***	0.05**	0.12**	-0.01
	(0.017)	(0.041)	(0.090)	(0.202)	(0.005)	(0.020)	(0.049)	(0.154)
L.log_number_region	-0.31***	-0.20	-0.32	-0.16	-1.14***	-0.97***	0.45	5.32**
	(0.057)	(0.173)	(0.462)	(1.198)	(0.074)	(0.340)	(0.882)	(2.363)
L.log_number_industry	0.31***	0.33***	0.59***	0.89***	0.87***	0.95***	0.77**	1.17*
	(0.028)	(0.077)	(0.185)	(0.295)	(0.028)	(0.127)	(0.324)	(0.652)
L.number_banks_used	0.27***	0.58***	0.65***	0.76***	0.43***	0.76***	0.98***	1.09***
	(0.007)	(0.020)	(0.040)	(0.058)	(0.004)	(0.011)	(0.021)	(0.039)
L.asset_structure	0.98***	0.89***	0.71***	0.47	1.43***	1.35***	1.28***	1.64***
	(0.013)	(0.052)	(0.153)	(0.341)	(0.008)	(0.045)	(0.127)	(0.329)
L.leverage	0.00***	0.00***	-0.00	0.00	0.00***	0.00**	-0.00**	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.log_total_assets	1.10***	1.27***	1.19***	1.30***	1.93***	2.02***	2.00***	1.66***
	(0.008)	(0.031)	(0.075)	(0.132)	(0.004)	(0.017)	(0.039)	(0.084)
L.log_age	-0.32***	-0.46***	-0.34*	-0.99**	-0.17***	-0.19***	-0.23***	-0.07
	(0.011)	(0.049)	(0.192)	(0.434)	(0.003)	(0.014)	(0.036)	(0.082)
L.roa	-0.00***	-0.00***	-0.09	-0.09	-0.00***	0.02	-0.03	-0.52**
	(0.000)	(0.000)	(0.118)	(0.347)	(0.000)	(0.021)	(0.252)	(0.225)
L.roa_std_dev	-	-	-	-	0.00***	0.00	-0.01	-0.43
					(0.000)	(0.006)	(0.046)	(0.313)
Constant	-6.47***	-9.10***	-9.06**	-11.37	-14.01***	-17.78***	-29.42***	-71.45***
	(0.512)	(1.571)	(3.847)	(11.132)	(0.738)	(3.410)	(9.152)	(23.540)
Observations	635,396	101,471	24,843	9,117	635,396	101,471	24,843	9,117
R-squared	0.185	0.151	0.152	0.160	0.655	0.512	0.577	0.583
Number of firm-bank pairs	158,197	22,247	5,275	1,986	158,197	22,247	5,275	1,986

Significance level: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. Time, industry and region fixed effects are included.

C Hausman

In this section we show the Hausman test's result to see whether there are significant differences between the coefficients estimated using fixed-effects and random-effects when estimating Eq. 2. We observe that we can reject the null hypotheses that both regressions' coefficients are not different at 1% significance level.

Table 11: Hausman test comparing fixed-effects and random-effects when estimating Eq. 2. Time, industry and region fixed effects are included.

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixed	random	Difference	S.E.
BTA_hat	-18,0764	-24,008	5,931626	0,022698
L.log_number_region_industry	0,05841	0,059924	-0,00151	0,007713
L.log_number_region	-0,11107	-0,43113	0,320062	0,010477
L.log_number_industry	0,357987	0,560863	-0,20288	0,008093
L.number_banks_used	0,436805	0,514325	-0,07752	0,001283
L.asset_structure	0,904715	1,157038	-0,25232	0,003721
L.leverage	9,08E-06	1,22E-05	-3,15E-06	4,36E-08
L.log_total_assets	1,212115	1,464979	-0,25286	0,001745
L.log_age	-0,4022	-0,33296	-0,06925	0,004821
L.roa	-0,00022	-0,00023	1,42E-05	7,72E-06

b = consistent under Ho and Ha; obtained from xtreg.
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic

$$\begin{aligned} chi2(18) &= (b-B)'[(V\_b - V\_B)^{-1}](b-B) \\ &= 112504.43 \\ Prob > chi2 &= 0.0000 \end{aligned}$$

D Estimations of Eq. 1 using different samples

In this section we provide results derived from estimating Eq. 1 considering different samples according to firms' assets quartiles (see table 12) and firms' SME levels (see Table 13). The results obtained for each sub-sample are qualitatively the same to the results obtained when we considered the entire sample (see Table 4) except for the sub-sample made up of firms which are classified as SME=4 (Table 13, column (4)), mainly due to the low number of observations considered in that sub-sample. Furthermore, when we divide the firms in terms of their assets so we can have a higher number of observations, we see that the results corresponding to large firms (Table 12, column (4)) are more in line with the other results -in terms of coefficients' sign and their statistical significance.

Table 12: Probability to create associations grouping firms into different assets quartiles

VARIABLES	(1) logit_q1 belong_to_assoc	(2) logit_q2 belong_to_assoc	(3) logit_q3 belong_to_assoc	(4) logit_q4 belong_to_assoc
log_total_credit_last_year	-0.250***	-0.353***	-0.336***	-0.150***
	(0.01)	(0.01)	(0.00)	(0.00)
L.log_total_assets	0.903***	0.897***	0.564***	0.388***
	(0.02)	(0.03)	(0.02)	(0.00)
L.log_number_region_industry	0.078***	0.005	0.020	0.047***
	(0.03)	(0.02)	(0.02)	(0.01)
L.log_number_region	-0.546	-0.402	-0.844***	-0.730***
	(0.35)	(0.25)	(0.22)	(0.17)
L.log_number_industry	-0.214*	0.239***	0.107	0.215***
	(0.13)	(0.09)	(0.08)	(0.06)
L.number_banks_used	0.333***	0.288***	0.296***	0.285***
	(0.03)	(0.02)	(0.01)	(0.01)
L.asset_structure	0.590***	0.734***	0.726***	0.230***
	(0.04)	(0.03)	(0.02)	(0.02)
L.leverage	0.000	0.000	0.000*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
L.log_age	0.018	-0.021**	-0.050***	-0.008
	(0.01)	(0.01)	(0.01)	(0.01)
L.roa	-0.000	-0.024***	-0.384***	-0.311***
	(0.00)	(0.01)	(0.05)	(0.04)
L.roa_std_dev	-0.000	0.000*	-0.001	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-7.191**	-10.683***	-1.373	-2.266
	(3.41)	(2.44)	(2.17)	(1.64)
Observations	367,210	367,470	367,481	367,250

Total number of observations: 1,469,411. Significance level: *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses. Time, industry and region fixed effects are included.

Table 13: Probability to create associations grouping firms into SME levels

VARIABLES	(1) logit_sme1 belong_to_assoc	(2) logit_sme2 belong_to_assoc	(3) logit_sme3 belong_to_assoc	(4) logit_sme4 belong_to_assoc
log_total_credit_last_year	-0.357***	-0.209***	-0.099***	0.030*
	(0.00)	(0.01)	(0.01)	(0.02)
L.log_total_assets	0.673***	0.467***	0.373***	0.368***
	(0.01)	(0.02)	(0.03)	(0.05)
L.log_number_region_industry	0.007	0.031	0.166***	0.765***
	(0.02)	(0.03)	(0.05)	(0.13)
L.log_number_region	-0.442**	0.232	-2.174***	1.106
	(0.20)	(0.42)	(0.79)	(1.54)
L.log_number_industry	0.289***	0.267	-0.933***	-1.478***
	(0.07)	(0.17)	(0.30)	(0.51)
L.number_banks_used	0.318***	0.259***	0.087***	0.037
	(0.01)	(0.01)	(0.02)	(0.03)
L.asset_structure	1.044***	0.543***	0.742***	1.213***
	(0.02)	(0.06)	(0.12)	(0.22)
L.leverage	0.000	-0.000	-0.000	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
L.log_age	-0.046***	-0.090***	-0.158***	0.154**
	(0.01)	(0.02)	(0.04)	(0.06)
L.roa	-0.000	-0.837***	-0.182	-0.397
	(0.00)	(0.13)	(0.24)	(0.32)
L.roa_std_dev	-0.000	0.007	-1.647***	-0.041
	(0.00)	(0.01)	(0.35)	(0.23)
Constant	-8.188***	-11.893***	21.294***	-14.291
	(1.95)	(4.19)	(8.05)	(15.36)
Observations	548,019	59,622	12,256	3,583

Total number of observations: 623,480. Significance level: *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses. Time, industry and region fixed effects are included.

E Same ownership

In Table 14 we provide descriptive statistics of the two associations' common ownership variables used in Eq. 5. Descriptive statistics of the rest of the variables used in Eq. 5 are provided in the main text in Table 3. The categorical variable "form_association" indicates whether at least one firm within an association has shares of at least another firm within the same association, and the variable "proportion_owners" shows the proportion of firms within an association which hold shares of other firms within the same association.

In the following Table 15 estimation results of Eq. 5 using uniquely the Between Effect (BE) approach are shown (comparison across associations). The Fixed Effects approach (comparison within associations) is not used since the two variables' of interest values, "form_association" and "proportion_owners", do not vary within each association, and therefore their estimated coefficients' values would be omitted.

Table 14: Descriptive statistics of the two associations' common ownership variables used in Eq. 5 and estimated in Table 15, by year

Year	2002		2003		2004		2005		2006	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
form_association	0.60	0.49	0.58	0.49	0.58	0.49	0.58	0.49	0.56	0.50
proportion_owners	31.91	28.36	31.03	28.71	30.98	29.10	31.22	29.36	29.97	29.36
Number of obs.	1841		1679		1605		1559		1632	

Year	2007		2008		2009		2010		2011	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
form_association	0.53	0.50	0.52	0.50	0.50	0.50	0.50	0.50	0.50	0.50
proportion_owners	28.93	29.91	28.23	29.89	26.82	29.22	26.96	29.29	26.52	28.95
Number of obs.	1628		1649		1620		1535		1501	

Total number of observations: 16,249.

We observe in Table 15 that our variables of interest regarding firms' common ownership are not statistically significant.

Table 15: Credit associations obtain. Estimation results of Eq. 5. In columns (1) and (2) estimation results using Between-Effects (BE) are shown.

VARIABLES	(1) credit_assoc_be log_credit_year_bank	(2) credit_assoc_be log_credit_year_bank
form_association	0.066	-
	(0.05)	
proportion_owners	-	0.001
		(0.00)
d_no_direct_credit	-15.580***	-15.585***
	(3.98)	(3.98)
L.log_avg_assets	0.509***	0.509***
	(0.02)	(0.02)
d_no_direct_credit#L.log_avg_assets	0.831***	0.832***
	(0.23)	(0.23)
d_created_association_before	-0.078	-0.078
	(0.06)	(0.06)
L.assoc_asset_structure	0.378***	0.377***
	(0.12)	(0.12)
L.d_members_use_same_bank	0.167***	0.166***
	(0.05)	(0.05)
L.number_banks_used	0.248***	0.248***
	(0.03)	(0.03)
number_firms_in_association	0.312***	0.316***
	(0.04)	(0.04)
d_members_same_activity	0.045	0.046
	(0.05)	(0.05)
d_members_same_postal	0.203***	0.204***
	(0.05)	(0.05)
L.log_avg_age	-0.067	-0.067
	(0.05)	(0.05)
L.avg_roa	0.067*	0.069*
	(0.04)	(0.04)
Constant	-0.915**	-0.920**
	(0.44)	(0.44)
Observations	16,249	16,249
R-squared	0.399	0.399
Number of association-bank pairs	5,311	5,311

Significance level: *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses. Time, industry and region fixed effects are included.

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