A known unknown? Networks of firms and access to credit in Italy

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Abstract

We test whether joining a network of firms has a positive impact - by providing valuable information about the joining firm and disciplining its behavior - on the access of a firm to bank credit. We use data on bank-firm relationship in Italy to evaluate this effect, identifying networks through interlocking directorates and avoiding possible confounding effects due to internal capital markets by controlling for business groups within the network. Using several specifications to control for selection issues, we conclude that there is a tangible effect linked to the entry into a network in terms of available credit.

Keywords: Network of firms, Bank lending, Asymmetric Information

1 Introduction

The role of business and social networks in reducing asymmetric information and incentives to strategic default in credit markets has been growingly investigated in recent years. While direct interaction between borrowers and lenders within a network is clearly the main route through which they get to know each others[1], there is a significant amount of evidence that also indirect relationships contribute in reducing asymmetric information or incentives to strategic default.

In this vein, we investigate here whether a lender collects useful information about a firm by looking at the fact that this firm is joining a network of firms. The underlying idea is that this entry: (i) may help perspective lenders to better evaluate the firm by signaling to them that it has a relationship with other established firms; and/or(ii) it may provide some assurance that the firm will

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[1]For Italy, for example, Cau and Stacchini (2010) find that boardroom interlockings between banks and firms facilitate credit relationships by reducing asymmetric information.

not strategically default. Membership of a network may, therefore, contribute to change lenders' attitude toward a firm, especially if these lenders are already financing this network of firm or if they have some knowledge of the network and some sort of leverage toward it. The observed outcome of this different attitude could be better credit conditions, for example in terms of greater volumes of funds, lower interest rates, less collateralization or longer maturities.

This idea is not new. Several contributions, especially with reference to less developed credit markets, found that network membership may convey information and/or provide a disciplinary effect (e.g. McMillan-Woodruff, 1999). More generally, the idea that lenders may extract information from the association of a (unknown) borrower with a (known) group has been at the root of several contribution on ethnic and race discrimination in credit markets, as noted in a recent survey about inter-firm networks and access to finance by Scalera and Zazzaro (2009). They also mentioned the role of "explicit or implicit forms of cross-debt guarantees which the network can provide its members so as to reduce asymmetric information problems and gain easier access to bank debt". In this vein, Hainz (2007) shows that lending relationships of other firms in a network may prevent the strategic default of a firm member of the network.

Informational and disciplinary effects of networks have been shown to be valuable also in social networks in two recent contributions on on-line peer-to-peer lending. Freedman and Jin (2008) and Lin *et al.* (2009) find that endorsement by friends and, more generally, relational characteristics help reduce the adverse selection problems in this type of lending. More generally, the effect of social networks on borrowing has been repeatedly supported by evidence, the idea being that 'the possibility of losing valuable friendships secures informal transactions the same way that the possibility of losing physical collateral can secure formal lending' (Leider *et al.* (2009)).

A third area where a mechanism similar to that studied in this paper has been found at work is trade credit. Burkart *et al.* (2008) find that firms using trade credit tend to borrow from a larger number of banks, utilize more distant banks, and have shorter relationships with their banks. "It appears that firms that are being offered trade credit can secure funding from less-informed financial intermediaries. The positive relationship between uninformed bank credit and trade credit is consistent with Biais and Gollier (1997) theoretical result that the extension of trade credit reveals favorable information to other lenders, thereby increasing their willingness to lend.". In other words, banks may be more willing to lend if they observe that suppliers extend trade credit.

The contribution closer to our own, however, is Khwaja *et al.* (2011) which focuses on firm networks and bank lending in Pakistan. The authors define a network as firms linked through interlocking directorates (i.e. members of the board in common[2]) and they find that entering into a network of firms

[2] Although this link does not necessarily imply some skin in the game, this may often be the case (e.g. trade credit and supply relationships). When there are no pecuniary stakes, reputation concerns may still make unlikely that a good entrepreneur joins the board of a bad (or unknown) firm. Even when interlocking is aimed to strengthen collusion with a competitor, there is probably an underlying evaluation that the other firm is a viable concern

sizeably increases external financing and reduces probability to enter financial distress. They also find that improved financial access is mainly due to new lenders, especially those already lending to firms that are neighbours in the joined network.

To deal with selection issues and to support a causal interpretation of their findings, Khwaja *et al.* (2011) introduced the distinction between direct and incidental entrants, the latter being those firms that join a network as an indirect effect of a board connection established by two other firms, one linked to the incidental entrant and the other to the network. In their view, the incidental entrants can be considered as casual joiners because their entry is not the outcome of an intentional choice and looking at them should avoid most issues related to the existence of possible common drivers of entry and lending terms, as, for example, a better outlook for a given firm due to an idiosyncratic shock in the sample period.

In this paper, we adopt a similar approach, identifying networks in basically the same way[3] and using the distinction between direct and incidental entrants in several specifications. We add, however, a further test of the causality link between entry in a network of firms and lending terms in the spirit of the highly influential paper by Rajan and Zingales (1998). We argue, in fact, that if network benefits are supposed to come from the reduction of strategic defaults and asymmetric information, these benefits should be stronger in areas where characteristics such as trust, law enforcement and firm size - linked to asymmetric information and strategic defaults and known to widely differ among Italian regions (e.g. Bianco *et al.* (2005)) - are less developed. This hypothesis can be tested, taking advantage of a regional breakdown of our data, to provide additional evidence in support of the idea that network of firms may have an impact on lending terms.

In a similar vein, we test whether the benefits of joining a network are higher for younger firms which lack a credit history and are therefore more likely to be affected by the problems mentioned before with respect to more mature firms for which more information may be available. A final element of our empirical analysis looks at the creditor side. We check, in fact, whether banks which are already lending to firms that are immediately adjacent in the network to the entrant firm are more likely to grant credit to it, as it could be the case if joining a network is indeed conveying information to the perspective lenders as it is hypothesized here.

In our work, we also control for the difference between business groups and other types of networks, an issue not addressed by Khwaja *et al.* (2011). This seems, however, a rather important check as intra-group transfers of funds may

(otherwise one would simply tend to push it out of the market). A support for the importance of interlocking comes, for example, from the findings in Gopalan *et al.* (2007) where it is shown that intra-group loans among Indian firms are mainly directed to avoid default by a group firm and consequent negative spillovers to the rest of the group and that spillover costs are much stronger for group firms that have board connections.

[3]We include top executives in addition to board members (e.g. we consider two firms as linked if a top executive of the first firm is a member of the second firm's board)

make very difficult to single out the effect of joining a network on external finance availability. In fact, the parent company may either centralize most of the borrowing and then redistribute resources among subsidiaries (Bianco and Nicodano (2006) on Italian data) or, vice versa, it may raise the leverage of subsidiaries to take advantage of the presence of minority shareholder (Faccio and Lang (2002)). From the point of view of the supply of credit by a bank, group membership may increase the opacity of a firm, compensating the possible informational and disciplinary effect of this membership. Not surprisingly, the impressive body of literature on business groups, internal capital markets and intra-group transfers of funds does not provide an unambiguous answer on the issue of whether group membership triggers a greater availability of external finance with respect to stand-alone firms or not and on whether controlling entities in a business group are generally more or less indebted than subsidiaries. In Italy, available empirical evidence shows that controlling entities tend to be more indebted than subsidiaries (Bianco and Nicodano (2006), Fratianni and Marchionne (2008)), consistent (i) with the idea that they want to signal that subsidiaries will not be expropriated and with the possibility that controlling entities are able to get better conditions on external finance and (ii) with the possibility that lenders penalize subsidiaries of groups (Fratianni and Marchionne (2008)), presumably out of concerns about the opaqueness of internal transactions. In principle, this suggests that not including business group affiliation in our regressions could imply a bias, if any, against finding any impact of network membership. This notwithstanding, we include available data on group affiliation to avoid any confounding effect of internal capital markets on our findings.

Our results support the idea that being part of a network has a significant effect on the volume of credit available to the firm. A firm joining a network may get a significant greater bank credit than standing alone and a notable positive effect on credit volumes is consistently found across different specifications. Results are robust to the distinction between direct and incidental entrants (albeit the latter coefficient is smaller).

We also find that networks effects are indeed larger in geographical areas where information asymmetries are stronger and law enforcement is weaker and for younger firms, in line with the expectation that the network effects are stronger when informational asymmetries and incentives for strategic default are presumably more relevant.

2 Data

We define a network of firms as a set of firms linked by interlocking directorates, meaning that two firms are in the same network if they share at least one member of either the managing board or the top management. A network is therefore composed by all the firms with at least one link through a member of the board or a top executive. We identified networks for each year from 2005 to 2009, obtaining five snapshots of the structure of networks of firms in Italy. Data on top executives and members of the boards, for the entire universe of the Italian firms different from individual firms, were collected from the Infocamere database[4].

We have, on average, about two and a half millions of firms per year in our initial database. Using our definition of network, we show that, on average, two thirds of the firms are never linked to other firms in each of the five periods under examination while the remaining third belongs to a network in at least one period. The size distribution of networks shows a rather stable structure: network size varies in each period from 2 to 500 firms, with the overwhelming majority of networks belonging to the smaller size class (2-50 firms). We also find a single Giant Network (identified as such from now on) of more than 60,000 firms on average during the sample period (see table 1). This structure resembles quite strikingly the outcome of the similar analysis carried out for Pakistan, also characterized by the presence of a giant network, by Khwaja *et al.* (2011). The authors also show that giant networks are present in advanced countries such as United States and United Kingdom as well as in large emerging ones as India, although in all these cases the analysis is carried out on much smaller samples of large/public firms.

	Year				
Network size	2005	2006	2007	2008	2009
2-50	341,834	351,349	358,178	361,948	362,729
51-100	84	88	91	106	114
101-200	12	16	21	25	21
201-500	1	1	1	3	4
Giant Network	1	1	1	1	1

Table 1: Distribution of Network Sizes.

From now on, our analysis focuses on this Giant Network: this choice is in line with the approach chosen by Khwaja *et al.* (2011), in addition of being computationally easier in light of the structure summarised in table 1. Moreover, potential drawbacks of networks, such as a smaller set of opportunities outside the network, as highlighted by part of the literature (e.g., Portes and Landolt (1996)), are presumably less relevant in a large, complex and diversified network such as the Giant Network considered here[5] (Granovetter (2005), Woolcock (2001)). The size of the Giant Network grows up from about 57,000 firms in

[4]Infocamere is the IT consortium of the Italian Chambers of Commerce and it keeps an electronic Companies Register, which is the most complete source of demographic information about firms. Its records include 9 million individuals on the Register (entrepreneurs, shareholders, directors, auditors and managers) and more than 6 million registered businesses. For further information, one may see the Infocamere website, http://www.infocamere.it.

[5]A network like our Giant Network could be categorized, using the taxonomy of social capital used in the literature, as an expression of bridging social capital, i.e. relations that reach out to unlike people in dissimilar situations, such as those who are entirely outside of the community, thus enabling members to leverage a far wider range of resources than are available in the community (Woolcock (2001)). In fact, regional distribution of the percentage

2005 to about 82,000 firms in 2009. In table 2 we report the transitional matrix for the first couple of subsequent years in our dataset[6]. On average, about 18,000 firms join the Giant Network every year while about 10,000 firms leave it; only 33,169 firms are always part of it in all the sample period. This leaves us in principle[7] with plenty of observations to work with, even focusing only on joiners and leavers in order to obtain a clean estimate of the impact of network membership on credit conditions.

	2006		
2005	Giant Net.	Network	No Net.
Giant Net.	47,837	8,708	619
Network	13,152	574,805	13,283
New firms (born in 2006)	4,674	50,663	10,124
No Net.	793	28.192	>2 mill

Table 2: Transition Matrix, 2005 to 2006.

In fact, considering the entire universe of Italian firms (apart from individual ones) allows us both a correct representation of networks and to include in the analysis small enterprises for which informational asymmetries (and accordingly network benefits) are potentially more relevant. It implies, however, that less data are available for several firms and that fixed effects need to be included in the empirical exercise in order to control for all the (time-invariant) individual characteristics of the firms that could drive their borrowing conditions.

This amounts, in turn, to focus the analysis only on joiners and leavers as including in the sample firms which never change their status in the time span analyzed would add no information to the estimate of our parameter of interest[8]. Focusing only on joiners and leavers has, however, the drawback of a possible underestimation of the overall impact of network membership.

We extract, therefore, from the whole population of firms a subset C constituted uniquely by the firms which change their Giant Network membership status E_{it} at least once in the sample period 2005-2009 where E_{it} is a dummy variable equal to 1 at time t if the i firm is in the Giant Network. While this measure fully takes into account that the beneficial effect, if any, of joining a network (i) may take some time to fully show up and (ii) it is likely to last at least as long as the firm is in the network, it does not fully reflect (as the variable E_{it} goes immediately to 0 when a firm leaves the network) that the effect of the network membership may fade away only slowly after the exit of a firm, at

of firms participation to the Giant Network is strictly and positively correlated (0.73 per cent) to a measure of bridging social capital at territorial level provided by Sabatini (2009).

[6]Matrices for the other years are analogous.

[7]Part of these firms could borrow less than the threshold for the reporting to the Central Credit Register and therefore they would not be included in our exercise, as explained later on.

[8]We use a within estimator to get a measure of the network effect.

least for the informational part of it (while the disciplinary effect should stop working immediately).

For this reason, we will carry out, first, a preliminary exercise on both joiners and leavers which shows that the aggregate result is basically driven by the observations on joiners while the coefficient on leavers alone is not significant. Then, the rest of our exercise will focus on joiners and in this context we will take advantage of the distinction introduced by Khwaja *et al.* (2011) between incidental and direct entrants. We already referred to incidental entrants as casual joiners, as they enter the network not intentionally but uniquely as a consequence of the choice of a different entity. In order to better explain this concept, we show in figure 1 two types of incidental entries.

In table 3 a summary statistics of the different types of entrants into the Giant Network is shown. New firms immediately joining the Giant Network at their birth are automatically defined as direct entrants but are not included in the table.

	Direct Entries	Incidental Entries	Total
2006	7104	6841	13945
2007	6910	6540	13450
2008	6729	6866	13595
2009	6386	6731	13117

Table 3: Type of entries of existent firms.

From the Infocamere database we also collect data, where available, on the annual sales of firms. As data were available for about the 80 per cent of our sample, we estimated the missing data, using information on sector, province and year.

As we already mentioned, a distinctive characteristic of this paper is that we use data about business group affiliation to control for possible confounding effects of internal capital markets. Our data, from 2005 to 2007, include two different definition of business group: the first one (drawn from the Central Balance Sheet data on groups[9]) identifies groups on the basis of a share above 50 per cent, the second definition is drawn from the Infocamere archives and it is based on a broader concept of control. We can therefore define whether a firm is belonging to a group (according to each one of the two definitions) or not for each year from 2005 to 2007. To avoid losing all the observations for the two subsequent years, we extended the time span of these dummies until 2009 using an algorithm jointly based on the group status in 2007 (last available observation) and the presence of links with other firms in 2008 [10]. If a firm

[9]Details on this database can be found, in Italian, at http://www.centraledeibilanci.it

[10]through either a common shareholder or cross-shareholdings. In fact, we have this latter information for all our sample period but it is clearly too broad a concept of group to be used as our unique proxy. We use it, therefore, only as a part of our algorithm to update data on groups.

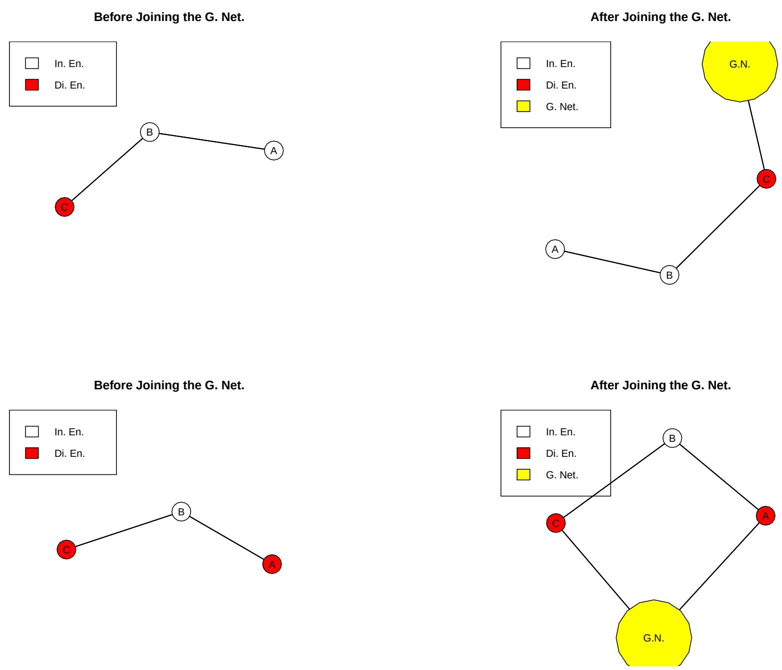

Figure 1: This figure provides two examples of incidental entry into the giant network. The three firms in the top left panel are connected to each other because they each have a director in common, but there is no director common to all three. The director who sits on the board of firms C (red color) enters the giant network (top right panel). Firm C is thus defined as direct entrant while firms A and B as incidental ones. The second case is showed in the two bottom panels. The three firms in the bottom left panel are again connected as the three above. This time two different director of firms A and C (red color) enter the board of a giant network firms. Thus, firm B (colored white) becomes a incidental entrant, while firms A and C become direct entrants into the giant network.

was belonging to a group in 2007 *and* it has a link (as defined above) with other firms in 2008, then it is assumed that it is still part of the group. The same algorithm is then applied recursively for 2009. On average, 3.5 per cent and 14 per cent, according respectively to the Central Balance Sheet definition and to the Infocamere definition, of the incidental entrants belong to a group. As an alternative, in the robustness section we excluded from our exercise all observations related to firms belonging to a group, even if they belong to it for just one period.

Finally, we collect for all the joiners and leavers the credit granted (and other information) from the Central Credit Register, an information system on the debt of the customers of the banks and financial companies supervised by the Bank of Italy. Banks and financial companies supervised by the Bank of Italy are required to report all their non performing loans and the performing loans in excess of a given threshold (75,000 euros until December 2008, 30,000 euros afterwards). We exclude all the data below 75,000 euros in order to keep the different years comparable. Therefore, firms borrowing less than this threshold with each bank are not included in our regressions.

3 Methodology and Results

We take fully advantage of the longitudinal data available in the Central Credit Register for each firm (as long as it is borrowing more than the threshold mentioned above) by estimating a panel model with firm fixed effects. In the baseline regressions we have individual data on firms but not on banks but we extend the same framework to individual firm-bank in the robustness section.

The relevant shock intervened in our sample period with the onset of the worldwide financial crisis is a good reason, in our view, to avoid collapsing all our observations in a single pre- and post-entry period for each of the firm. We include, instead, annual time dummies in our specification to take into account common shocks to available credit. With the inclusion of firm fixed effects[11] firm-specific factors are fully accounted for as long as they are time-invariant in our five-years sample period. To control for time-varying firm characteristics, we include in our specifications the annual sales and the growth rate of granted credit until the period in which the firm joins the network, to control for possible growth opportunities - leading to a higher demand for credit - not yet reflected in sales data (e.g. a patent).

[11] The inclusion of firm fixed effects implies that the parameters estimation is influenced only by firms changing their status with respect to the network sometime during our sample period. As we lack observations on firms that change status in other covariates but not on E_{it}, the estimated coefficients associated to these other covariates are biased unless they are considered only in interaction with E_{it}. At the same time, this would mean that the coefficient associated to the interaction term between E_{it} and the covariate of interest would absorb also the individual effect of the covariate: for example, the coefficient associated to E_{it}*Group would include the individual effect of Group membership. As we are basically interested to the overall effect of E_{it}, alone and in interaction with other covariates, we include in the estimation also individual covariates different from E_{it}.

We measure the benefits accruing from network participation with the log of the total outstanding amount of credit *granted* by banks and financial intermediaries (i.e. the amount of credit that the customer can use directly insofar as it derives from a fully effective contract that has been concluded) even if not yet utilized by the firm[12]. We first run a preliminary regression focusing on the entire set of joiners and leavers (the subset C constituted by those firms which change their Giant Network membership status E_{it} at least once in the sample period 2005-2009):

$$\log(Y_{it}) = \alpha_i + \gamma_t + \beta_1 E_{it} + \epsilon_{it}, \tag{1}$$

where Y_{it} is the total amount of loan facilities (used and unused) obtained by firm i at time t from the banking system, α_i and γ_t are respectively firm and time fixed effects, E_{it} is a dummy variable equal to 1 when the i firm in the subset C is in the Giant Network at time t.

We have almost 115,000 observations related to more than 30,000 firms changing their status in the network in the period. Belonging to a network would imply, in this very rough specification, an additional 10,5 per cent of credit (column (i) in table 4)[13]. We then split the sample between joiners (almost 84,000 observations) and leavers (almost 31,000 obs.): in fact, there are good reasons to expect a more muted effect when leavers are considered as, in this case, it is only the disciplinary benefit of the network membership to immediately disappear while the information accumulated may still be valid in the immediate post-exit periods.

This is supported by the results of our sample split as the coefficient associated to the exit is not significant while the coefficient associated to the entrants is again strongly significant with a positive sign (results are shown in table 4, respectively in column (ii) for leavers and column (iii) for joiners).

In what follows, therefore, we focus exclusively on entrants and we add further covariates in addition to firm fixed effects and time dummies:

$$\begin{aligned} \log(Y_{it}) = &\alpha_i + \gamma_t + \beta_1 E_{it} + \beta_2 E_{it} * G_{it} + \theta_1 G_{it} + \delta_1 LSALES_{it} + \\ &\delta_2 LGROWTHY_{it} + \delta_3 NUMBOARD_{it} + \epsilon_{it}, \end{aligned} \tag{2}$$

where G_{it} is a categorical variable indicating whether the i-th firm belongs or not to a business group, LSALES is the log of the annual turnover, LGROWTHY

[12] To control that results are not biased by the nominal growth of credit (that was, however, quite subdued in the second half of the sample period), we also use, as an alternative dependent variable, the ratio between the log of total credit granted to a firm and the log of the same aggregate for all the firms in the same region and sector of that firm (in order to further control for any trend in the volumes of credit) without difference in results (not reported).

[13] In order to find the direct effect of the covariates on the mean of the total amount of lending we should operate the following simple transformation:

$$E(Y_{it}) = e^{\widehat{\beta}_1 E_{it} + \widehat{\beta}_2 E_{it} * G_{it}}$$

where $\widehat{\beta}_j$ is the j coefficient estimated in model (1) with Ordinary Least Squares and E_{it} is the dummy on entry whatever incidental or direct. Hence we get a multiplicative models where the effect of the single covariate is given by the expression $e^{\widehat{\beta}_j} - 1$.

	(i)	(ii)	(iii)
Entry+exit	0.088***		
	(0.008)		
Exit		-.004	
		(0.012)	
Entry			0.051***
			(0.007)
Const.	15.298***	14.001***	15.292***
	(0.007)	(0.008)	(0.004)
Obs.	114528	30787	83762
F statistic	71.938	40.496	60.766

Table 4: Preliminary regressions on entry and exit.

is the lagged rate of growth in the loan facilities before joining the network and NUMBOARD is the log of the number of board members and top executives in each firm. Results are shown in table 5, column (i).

We then further refine our model, by adopting the distinction between incidental and direct entrants introduced by Khwaja et al.:

$$\begin{aligned}\log(Y_{it}) = & \alpha_i + \gamma_t + \beta_1 IE_{it} + \beta_2 DE_{it} + \beta_3 IE_{it} * G_{it} + \beta_4 DE_{it} * G_{it} + \\ & \theta_1 G_{it} + \delta_1 TURN_{it} + \delta_2 LGROWTHY_{it} + \\ & \delta_3 NUMBOARD_{it} + \epsilon_{it},\end{aligned} \tag{3}$$

where IE_{it} is a dummy variable equal to 1 when the $i-th$ firm is an incidental entrant, as defined in the previous section, and 0 otherwise and DE_{it} is dummy variable which is equal to 1 when the $i-th$ firm is a direct entrant. As incidental entrants did not join the network as a result of an explicit choice but as an indirect effect of another firm's choice, as we already recalled, one may assume that selection issues are less of a concern and that the associated coefficient provides a better estimates of the true effect of network membership.

In table 5, column (ii) we show the results of our estimations when separating incidental and direct entry dummy variables. When a firm joins the network incidentally the effect is still positive but lower than the direct entrant case. The incidental entry would imply an additional amount of credit facilities slightly above 3 per cent of the total[14]. It is important to underline that this lower coefficient may well be due to the selection issues stressed by Khwaja and his

[14] It is important to note that this increase in credit can in principle be determined by both supply and demand effect. The distinction between direct and incidental entrants should, however, provide a rough way to get a glimpse of the relative importance of the two effects, although one might still argue that also joining the network incidentally may increase business opportunities and consequently increase the demand for credit. At least in the short-run, however, it seems reasonable to approximate supply effects with the impact of incidental entry. Khwaja *et al.* (2011) take a slightly different perspective noting that "'this impact of network membership could reflect an increase both in the demand for credit by a firm and in the supply of credit from a bank. [..] While some of our subsequent results hint at the

coauthors but it could also be the consequence of the fact that stand-alone firms, i.e. firms that are not connected to any network of any size before joining the giant network, are - by definition of incidental entrants - necessarily direct entrants and these stand-alone firms are likely those for which the benefits of entering the network are greater. To check for this possibility, we will carry out in the robustness section of the paper an exercise where we look at the impact of the entry depending on the size of its connections the period before the entry, i.e. if the entrant was a stand alone firm or if it was member of a network (and of which size). The expectation here is that the magnitude of the coefficient associated to the entry (the benefit of entry) is decreasing on this size, the underlying idea being that the greater the (non giant) network in which the firm was embedded the smaller the additional benefits of joining the giant network.

4 Network effects across Italian regions

Results in the previous section show that joining a network of firm is associated to an increase in credit availability and evidence on incidental entrants suggests that there is a causal relationship between the two facts. In this section, we assess causality in a different way, that is by focusing on the mechanisms underlying the influence of network membership on credit conditions. The review of the literature in the Introduction suggests that the channels through which joining a network may affect credit availability (and more generally terms of lending) are the reduction in asymmetric information and the disciplinary effect on strategic defaults. We take advantage, therefore, of well-known differences across Italian regions in trust, law enforcement and firm size - three aspects that are clearly linked to asymmetric information and incentives to strategic default - to provide further evidence in support of the causality link running from network membership to credit access.

The basic idea here is that we should observe a stronger effect of joining a network in geographical areas where law enforcement and trust are weaker and firm size is smaller, because in these areas the value of joining a network should be more tangible due to informational asymmetries and greater incentives to strategic default. With respect to law enforcement, if a lender knows that it will take much longer to recover its funds in case of a default in a certain area, it could rely more on other disciplinary mechanisms while these other mechanisms may be irrelevant in areas where the judicial enforcement is quick and efficient. Existing empirical studies show that judicial enforcement is very different among Italian provinces and that credit is less widely available in provinces with longer trials or more pending trials (Bianco *et al.* (2005)). Moreover, a

relative importance of these two channels, we want to emphasize that separating the supply and demand channels is beyond the scope of this paper. The focus instead is on trying to obtain a causal estimate of the net effect of entering the giant network, whether driven by changes in the demand for or supply of credit."'

	(i)	(ii)
Entry	0.043***	
	(0.007)	
Entry*group	0.001	
	(0.014)	
Incidentalentry		0.032***
		(0.009)
Directentry		0.055***
		(0.009)
Incidentalentry*group		0.015
		(0.02)
Directentry*group		-.011
		(0.018)
Group	0.078***	0.08***
	(0.018)	(0.018)
LogSales	0.08***	0.08***
	(0.003)	(0.003)
logNumboard	0.09***	0.088***
	(0.011)	(0.011)
logLgrowthY	0.078***	0.078***
	(0.005)	(0.005)
Const.	14.833***	14.832***
	(0.022)	(0.022)
Obs.	69521	69521
F statistic	157.832	129.589
R^2	0.206	0.238

Table 5: Regressions distinguishing between incidental and direct entries

longer period for a bank to recover its funds in case of a default in a certain area may affect its propensity to lend and the pricing of funds (Guiso (2006)). Ceteris paribus, we expect that the disciplining effect of network may matter more in these provinces. Evidence on the same vein was found by Carmignani (2004) showing that the use of trade credit is correlated to the effectiveness of the judiciary. Similarly, being financial contracts "the ultimate trust intensive contracts" (Guiso *et al.* (2004)), local differences in the level of trust could affect lenders decisions. These effect could be further magnified if firms in some areas are more dependent from banks (due to a slower development of financial markets) or if financial intermediaries are less sophisticated and therefore less able to process information (for an historical example, see Faini et al., 1993). Finally, with reference to firm size, some literature highlights how information acquisition for a bank becomes more and more difficult the smaller the size of the borrowing firm (Stein (2002), Beck *et al.* (2008)).

Before carrying out this analysis, we show some descriptive statistics, starting with the percentage of firms participating to the giant network in every Italian region in relation to the entire firm population in that region; this ratio is higher in Northern Italy rather than in the South (respectively 3.2 and 1.3 in average over the period 2005-2009). Northeastern regions, specifically Trentino Alto Adige, Emilia Romagna and Friuli-Venezia-Giulia, are those with the higher participation to the giant network. In Northwest, Lombardy has the highest presence of firms linked to the giant Network while Umbria has the higher percentage in the Centre. In the South, Sicily, Calabria and Campania have the lower participation to the giant network. These regional differences in participation to the Giant network (Table 6) could, in principle, be mainly driven by regional differences in the average number of board members for local firms (as the number of board members mechanically increases the possibility of interlocking): this effect seems, however, rather modest as the correlation coefficient is less than 0.2.

Table 7 summarizes regional data on the regional characteristics relevant for our analysis: efficiency of law enforcement, firm size and levels of trust.

Judicial efficiency is measured by two indicators: the average length of trials in civic courts and number of pending civic trials scaled by population between 2005 and 2007[15]. The measure of trust in a territory is taken from the results of a survey carried by the National Statistical Institute (ISTAT) using a question on the level of trust toward unknown people in the same area (Istat 2006). The measure of firm size has been drawn by REGIO (a database maintained by Eurostat with regional data), using, as an approximation, the ratio between the number of employees and the number of units in each region for all the non-financial sectors on average over the years 2005-2007. Taking into account the significant correlation between these measures and the potential conceptual interactions between firm size, judicial efficiency and trust (see Cingano *et al.* (2011), Giacomelli and Menon (2011)), we carried out a principal component analysis whose results are reported in table 8: the first component explains the

[15]The source are the statistics collected by ISTAT, the Italian National Statistics Institute.

	Percentage of firms in the giant network	Percentage of firms in any network	Average n.of firms in any network
Piedmont	3.0	28.8	6758
Aosta Valley	3.5	28.0	7954
Lombardy	3.7	33.5	6606
Liguria	2.8	25.6	7164
North-West	3.4	31.6	6688
Veneto	2.6	28.7	5823
Trentino Alto Adige	4.7	31.2	10019
Friuli Venezia Giulia	3.5	31.4	7158
Emilia Romagna	4.4	29.6	9735
North-East	3.6	29.5	7894
Marche	2.2	25.8	4697
Tuscany	2.4	27.4	5534
Umbria	3.5	28.5	8000
Lazio	2.6	32.8	5228
Centre	2.6	30.0	5424
Abruzzo	1.5	29.5	3304
Molise	2.4	36.4	5913
Campania	1.1	32.5	2955
Apulia	1.7	29.6	5153
Basilicata	2.0	30.1	4211
Calabria	1.3	25.9	3235
Sicily	1.0	23.8	2654
Sardinia	1.6	26.0	3988
South and Isles	1.3	26.5	3128
Italy	2.7	29.5	6629

Table 6: Geographical distribution of network participation (average 2005-2009).

	Average length of civic trials (days)	Number of pending civic trials	Average firm size (employees)	Level of trust (index)
Northwest	635	1059	4.97	21.5
Northeast	877	1339	4.65	20.5
Center	886	1952	4.03	20.9
South, Isles	1111	2098	3.16	16.4

Table 7: Judicial efficiency, firm size, trust: macro-area distribution.

	Eigenvalue	Proportion	Cumulative	
Comp1	2.93	0.73	0.73	
Comp2	0.53	0.13	0.86	
Comp3	0.35	0.09	0.95	
	Average length of civic trials	Number of pending civic trials	Average firm size	Level of trust
eigenvectors of Comp1	0.5355	0.5285	-0.4866	-0.4440

Table 8: Principal component analysis results.

73 per cent of the variability. This component is positively correlated with the average length and the pending number of trials and negatively with trust and firm size and represents a synthetic measure of territorial factors reducing credit availability (TFRCA).

This first component has been split in quartiles where regions were ranked according to their endowment of this measure (i.e. the fourth quartile indicates the worst performers, regions with the lowest combined measure of firm size, trust and judicial efficiency). Our empirical strategy to verify the role of territorial aspects is to interact the categorical dummy TFRCA with the dummies on entry after having merged data using information on the headquarters of the firm. We add therefore to our specification, reported in (3), a time-invariant covariate which reflects the quartile of the composite territorial factor (TFRCA) for the region i where the borrowing firm is headquartered. It has to be noted that in this case a causality link between volumes and credit and network participation is suggested by the underlying theoretical mechanism rather than by the distinction between incidental entrants and direct entrants, although in table 9, column (ii) we also report the results of a regression distinguishing between the two types of entries.

Results from this specification (table 9, column i) show that the effect of joining a network is higher in areas where territorial factors tend to depress, ceteris paribus, credit availability. The coefficients of the interactions $\beta_2 E_{it} * TFRCA_i$ is almost trebled and highly significant for the quartile of regions where judicial efficiency, firm size and trust are at their lowest level (in their summary index TRFCA)[16].

[16]Taking each territorial variable individually may provide some insights on the relative importance of each territorial factor, and accordingly of the underlying issue. Apart from the trust variable, the hypothesis that the size of the coefficient of the interaction factor (entry and firm's location) grows with each quartile is fully confirmed and the coefficients are generally significant for the number of pending trials and for firm size (especially when the fourth quartile is considered). In particular, in areas with the lowest firm size (highest quartile) the interaction term has a much higher coefficient than other quartiles. This analysis by individual factor may also prove useful in getting a very preliminary idea on whether information and disciplinary effects are both playing a role: this seems to be the case as judicial enforcement

	(i)	(ii)
Entry	0.029^{***}	
	(0.009)	
Incidental entry		0.03^{***}
		(0.011)
Direct entry		0.027^{**}
		(0.011)
Entry*TFRCA$_q$2	0.026^{**}	
	(0.011)	
Entry*TFRCA$_q$3	0.022	
	(0.015)	
Entry*TFRCA$_q$4	0.068^{***}	
	(0.021)	
Inc. Entry*TFRCA$_q$2		-.010
		(0.016)
Inc. Entry*TFRCA$_q$3		0.037^{*}
		(0.021)
Inc. Entry*TFRCA$_q$4		0.033
		(0.031)
dir. entry*TFRCA$_q$2		0.06^{***}
		(0.016)
dir. entry*TFRCA$_q$3		0.008
		(0.02)
dir. entry*TFRCA$_q$4		0.098^{***}
		(0.028)
Group	0.079^{***}	0.08^{***}
	(0.017)	(0.017)
LogSales	0.08^{***}	0.08^{***}
	(0.003)	(0.003)
LogNumboard	0.091^{***}	0.089^{***}
	(0.011)	(0.011)
logLgrowthY	0.077^{***}	0.077^{***}
	(0.005)	(0.005)
Const.	14.835^{***}	14.836^{***}
	(0.021)	(0.021)
Obs.	69373	69373
F statistic	128.554	95.56
R^2	0.232	0.234

Table 9: Regression on regional data

5 Robustness

In this section, we carry out a few additional exercises to support the previous findings. Part of these exercises are indeed additional tests of the impact of network membership (subsections 1, 2 and 3) while a few others (summarized together in subsection 4) are more directly aimed to check that results are not driven by specific assumptions or settings.

5.1 Network benefits and credit history

A trivial implication of the assumption that network membership matters because it conveys information to perspective lenders is that benefits should be larger for lesser known firms. We test this implication by dividing the firms in our sample according to the number of years a firms has been recorded in the Central Credit Register (variable AGE). We divided the firms in three classes, young (from 0 to 5 years of credit history), middle age (5 to 10 years) and mature (more than ten years) and we interacted our dummy on entry with the categorical variables corresponding to the three different AGE classes. From the results reported in table 10, it is clear that this is indeed the case as the coefficient of the interaction term is strongly different between age classes. Benefits notably decrease in the two older classes (while remaining significant) with respect to the baseline case of young firms confirming that firms that have yet to establish a credit history which allows a potential lender to evaluate their credit worthiness have more to benefit from joining a network.

5.2 Do network benefits depend on your previous links?

A similar exercise looks at the differences, if any, in the impact of entry depending on the links a firm had before joining the giant network. The underlying idea is that the benefits accruing to a firm should be smaller if this firm was already part of a large network of firms (although not of the giant one) while they should be tangible if the firm was part of small networks. We divided the firms according to their situation before joining the giant network: the baseline case is when the firm was stand alone, while the three subsequent classes of NETSIZE refer to firms belonging, at time $t-1$, respectively to networks of size $2-50$ (firms), $51-100$, >100. Results are supportive of the idea that benefits are greater for firms that were previously disconnected from any network. The difference in terms of available credit between stand alone firms and firms already belonging to network of over 100 firms is above 10% (table 10).

5.3 A lender of a friend is my lender

An interesting result arises by looking at specific aspects of the impact of networks on credit. We investigate whether newly extended credit to the joining

hint to a problem of discipline while firms size seems more related to an issue of asymmetric information and both are significant individually taken.

firm is granted by banks that were already lending to firms that are adjacent to the entrants in the network and are therefore those banks more likely to benefit from the information accruing with the entry. We use the following specification

$$(Y_{ijt}) = \beta_0 + \beta_1 A_{ijt} + \beta_2 Reg + \beta_3 T + \beta_4 J + \epsilon_{ijt}, \quad (4)$$

where Y_{ijt} is the ratio between the total amount of loan facilities (used and unused) obtained by firm i at time t from bank j (I_{ijt}) and the total amount of loan facilities (used and unused) obtained by firm i at time t from the entire banking system (I_{it}), and A_{ijt} a dummy variables indicating whether the bank j is a bank lending at time $t-1$ at the neighboring firm in the network of firm i. Other variables are the usual time (T), regional (Reg) and bank fixed-effects (J). Results are reported in Table 11 and support the idea that an important channel of the greater availability of credit are the existing links between lenders and adjacent firms in the network.

5.4 A few final robustness checks

We carried out three final robustness checks related respectively (i) to the validity of our algorithm to extend the group affiliation to 2008 and 2009 by excluding from our analysis all the firms that were affiliated to a group (between 2005 and 2007 when we have this information), (ii) to the inclusion of the level of collateralization to check if this affect the results and (iii) to an extension of our analysis to bank-firm data using firm-bank fixed effects. In all cases, the results (not reported for the first two exercise, in tab. 12 for the last exercise) are fully in line with the previous ones.

	(i)	(ii)
Entry	0.105***	
	(0.023)	
Incidental entry		0.073***
		(0.017)
Direct entry		0.087***
		(0.015)
age class medium	-0.003 **	-0.003 **
	(0.013)	(0.013)
age class high	-0.016 **	-0.016 **
	(0.018)	(0.018)
entry*age class medium	-.045***	
	(0.014)	
entry*age class high	-.047***	
	(0.014)	
incentry*age class medium		-.064***
		(0.019)
incentry*age class high		-.041**
		(0.019)
directentry*age class medium		-.030*
		(0.017)
directentry*age class high		-.052***
		(0.017)
entry * network size before entry class low	-0.021	
	(0.021)	
entry * network size before entry class medium	-0.037	
	(0.025)	
entry * network size before entry class high	-0.077 ***	
	(0.029)	
Group	0.078***	0.079***
	(0.017)	(0.017)
Logsales	0.08***	0.08***
	(0.003)	(0.003)
LogNumboard	0.089***	0.088***
	(0.011)	(0.011)
LogLgrowthY	0.082***	0.082***
	(0.005)	(0.005)
Const.	14.827***	14.832***
	(0.024)	(0.024)
Obs.	69104	69521
F statistic	96.588	96.813
R^2	0.03	0.029

Table 10: Robustness regressions on age and network size before entry

	(i)	(ii)	(iii)
adjacent bank	0.086***	0.088 ***	0.046 ***
	(0.012)	(0.012)	(0.012)
DUMMYREG	NO	YES	YES
DUMMYBANK	NO	NO	YES
Const.	0.173***	0.174***	0.165***
	(0.003)	(0.009)	(0.022)
Obs.	10498	10498	10498
F statistic	51.613	5.029	2.764
R^2	0.005	0.01	0.149

Table 11: Robustness regressions on the role of banks granting adjacent firms

6 Conclusions

It is well known that serious informational asymmetries and strategic defaults may seriously hamper the functioning of credit markets. It should come therefore as no surprise that mechanisms which attenuate these asymmetries and put some discipline on borrowers' behaviors may raise the volume of credit available to the economy. In this paper, we argue that joining a network of firm may play this role as it may provide information about the joining firm and it may discipline a firm behavior through several channels. We test this hypothesis in several ways, all targeted to control as much as possible that the association between network participation and available credit is not driven by a common factor (e.g. the improvement of a firm outlook). We distinguish, for example, between direct and incidental entrants where only the former are joining the network as a result of an intentional choice. We also test whether the link between network and credit is stronger where our priors (derived from both economic theory and available evidence) suggest it should be. Results are supportive of the idea that joining a network may help firms in getting more credit: the effect is not negligible ranging from three per cent in the more conservative estimates up to ten per cent of the total credit.

	(i)	(ii)	(iii)
Entry	0.02***		
	(0.004)		
Incidentalentry		0.018***	-.003
		(0.006)	(0.008)
Directentry		0.022***	-.002
		(0.005)	(0.007)
Incidentalentry*TFRCA$_q$2			0.035***
			(0.011)
Incidentalentry*TFRCA$_q$3			0.040***
			(0.015)
Incidentalentry*TFRCA$_q$4			0.074***
			(0.023)
Directentry*TFRCA$_q$2			0.050***
			(0.01)
Directentry*TFRCA$_q$3			0.044***
			(0.014)
Directentry*TFRCA$_q$4			0.046**
			(0.02)
Group	0.052***	0.052***	0.051***
	(0.01)	(0.01)	(0.01)
logSales	0.062***	0.062***	0.063***
	(0.002)	(0.002)	(0.002)
LogNumboard	0.038***	0.038***	0.041***
	(0.007)	(0.007)	(0.007)
Const.	13.969***	13.970***	13.966***
	(0.016)	(0.016)	(0.016)
Obs.	306748	306748	306064
F statistic	215.399	188.509	111.595
R^2	0.084	0.084	0.081

Table 12: Regression on bank-firm data

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