The Anatomy of Cultural Proximity in Credit Markets[•]

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Abstract

In this paper, we study the role of cultural proximity in credit market outcomes. We first construct a comprehensive dataset that traces all bank-firm relationships for the population of firms and banks that operate in South Tyrol – a region located in the North of Italy where two main linguistic groups (Italian and German) coexist. For each firm and bank, we use a textual algorithm to classify the predominant cultural group of the administrators. We find that firms are more likely to demand credit from culturally-close banks; the first link that firms establish with the banking system is generally within the same cultural group. We also find that cultural proximity has an impact on the *market equilibria*. Access to credit is relatively easier when firms and banks share the same cultural origin; cultural proximity also translates into larger loan quantities. Finally, we find that culture enhances *market efficiency*. Loans granted to the same group tend to be less collateralized and generally have a better performance in terms of credit quality.

JEL Classification:
Keywords: Cultural Proximity; Selection; Credit Supply

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1. Introduction

Information asymmetries in credit markets are a major source of financial frictions with relevant consequences in terms of costs of capital and credit rationing (Stiglitz and Weiss, 1981). Such frictions are exacerbated when the borrowers are more "opaque," as in the case of small businesses (Berger, 1999; Berger and Udell, 2002; Petersen and Rajan, 2002).

To mitigate the effects of such market failures, lenders use a number of screening technologies aimed at acquiring soft information that could substitute for hard data. A prominent example is relationship lending in which long-lasting and frequent relationships help the disclosure of soft information that would be otherwise difficult to acquire (Berger and Udell, 1995; DeYoung et al., 2004; Bolton and Sharfstein, 1996).[1]

Information asymmetries could also be reduced when lenders and borrowers share a common cultural or linguistic background. Cultural proximity can be defined as "*the sharing of a common identity, the feeling of belonging to the same group, and the degree of affinity between two parties*" (Felbermayr and Toubal, 2010). When lenders and borrowers share the same culture, soft-information exchanges become less costly, with a relevant decrease in transaction costs (Fisman et al., 2017). However, culturally-close relationships are typically endogenously formed. It follows that the reduction of information asymmetries might be the result of banks selecting *better* firms through culture *ex-ante*, rather than banks' ability to better monitor culturally-close firms *ex-post*.

With this paper, we investigate the role of cultural proximity in credit markets. We study the role the cultural proximity in credit markets under three main points of view. The first is *selection*: how relevant is culture in the creation of the credit market network? Does sharing the same culture matter in the establishment of a bank-firm links? The second is related to *market equilibria*: does cultural proximity matter for the extensive and intensive margins of credit? The third refers to *market efficiency*: if cultural proximity matters, does it impact the quality of credit and the collateralization of loans?

One of the main concerns in investigating the relationship between culture and economics is the difficulty in separating the effects of culture from those of formal institutions (such as contracting environment, rule of law, or legal origins). This occurs because culture and institutions deeply interact and are both endogenously determined (Accetturo et al., 2014; Accetturo et al., 2017; Fernandez, 2008; Fernandez, 2011).[2] We cope with this problem by

1 Relationship lending can also come at a cost. In fact, the long-term relationships it builds on might also induce hold-up costs (Klein et al., 1978; von Thadden, 1995), soft budget constraints (Bolton and Sharfstein, 1996), as well as evergreening or zombie-lending (Albertazzi and Marchetti, 2009).

2 As Guiso et al. (2009) point out "when we observe that Swedes evade tax less than Brazilians, we do not know to

analyzing the cultural heterogeneity within South Tyrol, a Northern Italian region at the border with Austria and Switzerland. South Tyrol represents an almost ideal setting for the analysis of the impact of cultural proximity on economic outcomes. This region is characterized by a very high degree of autonomy and self-regulation (local Governments have a relevant impact on the local economy). According to the Statute of Autonomy (a local constitution), local Governments must include both German and Italian parties; both cultural groups share the responsibility to set local rules. In every-day life, German and Italian cultural groups co-exist but conduct separate lives. In this setting we can assessment of the impact of cultural proximity holding fixed all other institutional factors.

We first construct a comprehensive dataset that traces all bank-firm relationships for the population of firms and banks that operate in South Tyrol. For each bank and firm, we link balance sheet data and all available information on the board members. Using an algorithm that is able to link names and surnames to linguistic groups (Grinblatt and Keloharju, 2001), we are able to attribute a predominant cultural group in the boards of banks and firms. The final dataset is made of roughly 140,000 bank-firm relationships recorded from 2006 to 2015 belonging to 13,000 firms and 358 banks. The dataset shows that the almost the 75% of the loans we observe are from banks and firms belonging to the same cultural group.

We find that culture plays a relevant role on *selection* in the credit market. We show that firms are more likely to demand credit from culturally-close banks; the first link that firms establish with the banking system is generally within the same cultural group.

We also find that cultural proximity has an impact on the *market equilibria*. Access to credit is relatively easier when firms and banks share the same cultural origin; cultural proximity also translates into larger loan quantities. These results holds even when we control for demand and supply factors by using the set of fixed effects recently proposed by Degryse et al. (2018). Results are practically confirmed (even in magnitude) when we use a selected sample of multi-borrowing firms for which it is possible to include firms fixed effects (Khwaja and Mian, 2008). We also analyze the link between cultural proximity and the quality of the matches between firms and banks. We find that sharing the same cultural group predicts longer-lasting relationships, a

what extent this is the effect of Sweden's higher social capital or superior tax enforcement."

feature that is usually associated with less credit restrictions in terms of both quantities and prices (Gobbi and Sette, 2015).

Finally, we find that culture enhances *market efficiency*. Loans granted to the same group tend to be less collateralized and generally have a better performance in terms of credit quality. Moreover, the standard deviation of the collateralization rate and loans granted by banks to their own cultural group is larger than the one related to the other ethnic group; this supports the idea that cultural proximity is a screening device that substitute for hard information.

All in all, our paper contributes to the literature on cultural proximity in economic, and more specifically, credit relationships by showing that endogenously-formed, culturally-based firm-bank links represent a gain in efficiency for credit markets. Cultural ties play an important role in overcoming the uncertainty that characterizes all economic exchanges: individuals or groups that share the same culture and beliefs are more likely to trade with one another due to a reduction in transaction costs (e.g. communication costs or contract enforcement, Guiso et al., 2009) and bilateral affinity (which influences consumer preferences; Disdier and Mayer, 2007). Culture plays an important role in financial markets: it affects stock market participation (Guiso et al. 2008), cross-border mergers (Ahern et al., 2015), and lending decisions (Giannetti and Yafeh, 2012; Fisman et al., 2017; Haselmann et al., 2018).[3] Our paper contributes to the recent works on cultural proximity and loan outcomes by studying the extent to which selection affects market efficiency. The closest papers to our focus (Fisman et al., 2017; Haselmann et al., 2018) have exploited quasi-experimental variations to establish a causal link between culture and lending decisions. We depart from these papers by precisely analyzing the role of selection and how this translates into loan outcomes, and by showing – for the first time in the literature – that selection in culturally-close loans leads to an improvement in market efficiency. Moreover, compared with these papers, we do not rely on case studies (which have strong internal validity but generally lack of external validity) but we analyze population data for an area in which cultural groups are easily identifiable.

From a methodological perspective, our paper adds to the literature on cultural proximity by exploiting a within-country cultural variation to keep other institutional factors fixed. Traditionally, papers have taken a cross-country approach and compared how cultural traits

[3] The literature on the impact of linguistic proximity on international trade is also particularly large. See, among others, Rose (2000), Helpman et al. (2008), and Disdier and Mayer (2007). Accetturo et al. (2018) analyze the impact of common culture on international tourism (the most relevant trade in services) in South Tyrol.

affect social and economic outcomes based on different institutional settings (see Alesina et al., 2013). By focusing on a bilingual region such as South Tyrol, and in a similar spirit as Egger and Lassmann (2015); Maggioni and Lo Turco (2018); Accetturo et al. (2018); Bedendo et al. (2018) among others, we can limit any confounding factors and non-cultural related differences that can bias our results.

The paper proceeds as follows: in Section 2 we present the context and discuss the institutional background of South Tyrol. Data and descriptive statistics are presented in Section 3. Results on selection are presented in Section 4. Evidences on market equilibrium are in Section 5. Estimations on market efficiency are presented in Section 6. Section 7 concludes.

2. Cultural heterogeneity in South Tyrol

South Tyrol ("Provincia di Bolzano" in Italian) is a region in the North of Italy at the border with Austria and Switzerland. Its history as an Italian administrative unit began after the First World War (WWI). Before WWI the region was predominately German-speaking: according to the 1910 census, 90% of population was German speaking, while just 7% was Italian speaking;[4] following Italian annexation, the region was heavily Italianized by favoring both the immigration of Italian speakers from other regions and the outmigration of German speakers to Germany and Austria.[5] This process permanently changed the balance across linguistic groups: according to the 2011 Census, the share of German-speaking population was 69% while Italian speakers account for roughly more than one-quarter of total population.

The current institutional framework of South Tyrol dates back to 1972 when a "Statute of Autonomy" to the region was granted.

According to the "Statute of Autonomy," the regional Government is provided with very large legislative and economic resources. 90% of all taxes collected in South Tyrol must be spent locally by the regional Government;[6] local administrations have a very large number of competencies on taxation, subsidies, education, and transportation. Both linguistic groups are

[4] Half of these non-German speakers were actually Ladins which, in that period, were included in the Italian-speaking group.

[5] This was part of the so-called Agreement on the Options of Citizenships between Fascist Italy and Nazi Germany (that already annexed Austria) in 1939. See Accetturo et al. (2018) for more historical details on the Italianization process.

[6] This is an important feature for one of the richest region in Europe that, as a consequence for these rules, does not participate to the regional redistribution in Italy.

involved in the creation of regional laws; according to the "Statute of Autonomy," all local governments must be composed by at least a German-speaking party (so far, the SüdTiroler Volkspartei) and an Italian-speaking party (typically, the most-voted one). This basically implies that both cultural groups share the responsibility to set all formal rules and institutions (regional laws, regulations, etc.); the very large number of competencies held by local administrations makes these rules extremely relevant the local economy.

The 1972 rule also established the right for citizens to use their own mother tongue in all occasions.[7] The application of this right in the every-day life has created a permanent separation between the two linguistic groups. In South Tyrol childcare, eldercare, and schools are separated for each language group;[8] several non-Governmental associations generally display separate sections for Italian and German speakers.[9] Segmentation in every-day life is a feature that characterizes the South Tyrolean society (Forer et al., 2008) despite the fact that almost 80% of South Tyrolean students are proficient in the both languages (Eurac, 2017).

The fact that German and Italian speakers face the same formal institutional setting but live in an extremely segmented society makes South Tyrol an ideal setting for studying the impact of cultural proximity on economic outcomes.

3. Data and descriptive statistics

3.1 Datasets

To investigate how cultural proximity has an impact on the credit markets, we combine several data sources.

Central Credit Register (CCR). – CCR is an information system on the debt of the customers of banks and financial companies supervised by the Bank of Italy. Banks and financial companies supervised by the Bank of Italy are required to report the performing loans in excess of a given amount (75,000 euros until December 2008, 30,000 euros afterwards) plus all their nonperforming loans. CCR also contains information on loan applications. A loan application is identified whenever an intermediary lodges an enquiry to the CCR to obtain information on the current credit position of a potential borrower (*Servizio di prima informazione*, SPI; preliminary

[7] In order to reach a fair allocation of jobs in public service a system called ethnic proportion has been established. Every ten years, when the general census of population takes place, each citizen has to declare to which linguistic group they belong or want to be aggregated to. According to the results they decide how many people of which group are going to be hired for public service.

[8] The regional Government has also an extra-budget for keeping two Ministries of Education.

[9] Like, for example, the Alpine Club and Caritas.

information request; Albertazzi et al., 2017). Enquiries can be placed only when the intermediary formally receives a request for credit but lodging a request is a chargeable service. This implies that banks may decide not to use this service if they already know the applicant.

Segnalazione sugli organi societari (OR.SO.). – OR.SO. provides information on all banking boards for financial institutions that lend South Tyrolean firms. OR.SO. is kept by the Supervision Department of the Bank of Italy and records all the members of the governing bodies and the top executives of each bank.[10] We use these data to attribute a cultural origin to all bank administrators based on the procedure that we describe in the next section.

Infocamere. – Firms' cultural origin is detected by analyzing the composition of firms' boards. This information is included in the Infocamere database that is a dataset kept by the Italian Chambers of Commerce, using information on all firms headquartered in South Tyrol. Infocamere data have information on names, gender, place of birth, and age for all individuals that have a managerial or an auditing role in the firm.[11]

Firm and bank level data. – Infocamere data on boards are merged with firm level data on the number of employees (INPS) and balance sheet information (CERVED). INPS is the Italian Social Security Service; its dataset provides information on the number of employees for all active Italian firms with at least one employee (this basically implies that it excludes micro-firms where workers and owners coincide). CERVED database contains balance sheets information of the universe of Italian limited liability companies; it draws information from official data recorded at the Italian Registry of Companies and from financial statements filed annually at the Italian Chambers of Commerce on a compulsory basis. OR.SO. and CCR data are instead merged with *Matrice dei conti*, an information system kept by the Supervision Department of the Bank of Italy that includes all balance sheet information on Banks operating in Italy.

3.2 Classification of the manager's cultural origin

A crucial aspect in our analysis is to classify firms and banks into their cultural group, namely German and Italian. To establish whether firms and banks are of Germanic or Italian cultural origin we analyze their boards using a method akin to Bedendo et al. (2018).

Our focus on boards is due to data availability. Infocamere and OR.SO. data only include information on boards and there are no available datasets on names and gender for all other employees (see Infante and Piazza, 2014, for a similar approach). This is a relevant limitation

[10] We consider the following roles: Administrator, General Director (and her deputies), CEO (and her deputies), President (and her deputies), and single auditor.

[11] We consider the following roles: Administrator, CEO (and her deputies), President (and her deputies), and shareholder.

especially for banks since loan officers may have a relevant impact on the lending decision. However, it is important to point out that the South Tyrol credit market is dominated by local banks (half of the banks in the dataset are credit cooperatives) for which the "distance" between the firm and the bank board is quite limited.

For each board member of each firm and bank, we utilized search algorithms that identify the most common: Germanic surnames; Germanic male given names; Germanic female given names; Italian surnames; Italian male given names; Italian female given names.[12] Subsequently, a firm- or bank-board member is classified as having a Germanic cultural origin if all his/her given names and surname can be found in the Germanic listings, while he/she is classified as having an Italian cultural origin if given names and surname are in the Italian lists. We require that both the given name and the surname are Germanic (Italian) for a board member to be associated with a Germanic (Italian) origin.[13] We then manually double-checked the allocation of each to the two categories to ensure that such requirement is satisfied.

Bedendo et al. (2018)'s approach basically classifies individuals into five categories: Italian, German, Mixed (e.g., a Germanic first name and an Italian surname or vice versa), Foreign, and Unclassified. Infocamere data provide us with the names of 31,525 firms' administrators and 19,401 banks' administrators. We concentrate only on unambiguously Italian and German names that account for more than 90% of the sample, thus discarding all firms and banks that contain mixed, foreign, or unclassified managers.[14]

A firm or a bank are defined German (Italian) if the majority of its administrators are German (Italian).

3.3 Descriptive statistics

Table 1 presents some basic descriptive statistics. For each year, our dataset has information on roughly 13,000 firms and 350 banks. These are relatively large numbers for the South Tyrolean

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[12] We retrieve Italian surnames from http://www.cognomix.it/origine-cognomi-italiani, which lists the most common Italian surnames explaining their origin. We obtain German and Austrian surnames, respectively, from https://de.wiktionary.org/wiki/Verzeichnis:Deutsch/Liste_der_h%C3%A4ufigsten_Nachnamen_Deutschlands and https://de.wiktionary.org/wiki/Verzeichnis:Deutsch/Liste_der_h%C3%A4ufigsten_Nachnamen_%C3%96sterreichs, which are based on telephone directories of the countries and were manually cleaned to eliminate foreign last names. Finally, first names come from http://www.vornamen-weltweit.de/maennlich-deutsch.php, http://www.vornamen-weltweit.de/weiblich-deutsch.php, and http://www.vornamen-weltweit.de/geographisch.php?land=4.

[13] The only exception to this rule is for individuals born during the Fascist regime, when German-speaking individuals were frequently given Italian first names in an effort to Italianize the area.

[14] German individuals are 65% and 55%, respectively, of firms' and banks' administrators. The share for firms basically reflects the share of German-speaking population in South Tyrol. The percentage for banks is lower because we consider all banks that *operate* in South Tyrol (even without an headquarter or a branch).

economy; according to the 2011 census, firms headquartered in South Tyrol are 43,000 including artisans, independent contractors, freelance workers, and cooperatives. Moreover, it should be noted that in our dataset we only consider firms with a relationship with the banking system. The percentage of Italian firms (23%-25%) is relatively low and reflects population shares; this basically implies that entrepreneurship rates are quite similar in the German and Italian groups. The percentage of Italian banks is much larger (around 70%). The difference between the two percentages is due to the fact that all Italian banks are allowed to operate in South Tyrol even without a branch.

Firms' and Bank-Firm characteristics are reported in table 2. Firms in our sample are relatively big; the average number of employees is 13, a figure that is slightly larger than the one that we obtain when we use census data (above 4). Median size is instead much lower (3), thus suggesting that our dataset is characterized by the presence of very large firms which are more likely to have a credit relationship with a bank; not surprisingly, the standard deviation of the number of employees (127.5) is almost ten times the average. Table 2 also reports some information on bank-firm relationships. On average, each company has links with 1.6 banks. Even in this case, heterogeneity is huge; the standard deviation in the number of banking relationship (1.4) is large than the average and almost 75% of the firms in our dataset have just one banking relationship. Bank links within the same cultural groups are 1.2 thus suggesting almost three-fourth of all bank-firm relationships in South Tyrol are established within the same group.[15]

The average granted loan size is half a million euros; one-third of all loans are collateralized while the share of NPL (which include bad loans and other minor anomalies like unlikely to pay and overdues) is comparatively low (10%). Loans with minor anomalies are instead 8.7% of the total.

The distribution of bank-firm relationships is portrayed in figure 1. Half of the firms in our sample have a relationship with only one bank and this bank belongs to the same cultural group; this share is definitely larger for German firms while it is lower for Italian companies. As we said, less than one-third of the firms have multiple banking relationships; roughly half of this group has relationship only with banks belonging to the same cultural group while only 3% borrow from financial institutions from both groups.

The distribution of firms in their links with the banking system is highly heterogeneous according to age (figure 2) and size (measured by the number of employees; figure 3). On average, younger and smaller firms have generally only one relationship with a bank belonging to the same cultural group. As long as age and size grow, firms are more likely to be multi-

[15] The share of same-group bank links ranges between 58% for the Italian-speaking group and 73% for the German-speaking group.

borrowing and tend to establish relationships with banks belonging to different groups. This preliminary evidence tend to support the idea that sharing the same culture substitutes for the lack of hard information and the more firms are able to provide this information the less likely the use this channel to apply for loans.

4. The role of Selection

As already mentioned, in the first part of our analysis we study the role of *selection* in order to understand how relevant culture in the creation of credit market networks is. We use different specifications and datasets that could potentially capture different aspects of the creation of the credit market networks.

We first analyze the demand for new credit by exploiting the information available in the SPI on loan applications. We estimate the following equation by OLS:

$$SPI_{\mathrm{ibt}} = \beta_0 + \beta_1 SameGroup_{\mathrm{ib}} + \beta_2 X_{it}^F + \beta_3 X_{bt}^B + \varepsilon_{ibt} \qquad (1)$$

Where i, b, and t denote, respectively, firms, banks, and time (years). SPI_{ibt} is a dummy equal to one if bank b (with at least a branch in the Local Labor Market – LLM – where firm i is located[16]) lodged an enquiry to the CCR to obtain information on the current credit position of firm i.

The variable of interest is $SameGroup_{\mathrm{ib}}$ that is a dummy equal to one if the firm and the bank share the same cultural origin; as we said, this measure is time invariant since we basically do not observe cultural switches in our dataset. X_{it}^F and X_{bt}^B are set of variables aimed at capturing, respectively, firm economic conditions and credit supply factors that might have an impact on loan applications and are possibly be correlated with the $SameGroup_{\mathrm{ib}}$ variable. To control for these factors we adopt the approach recently proposed by Degryse et al. (2018). Firm economic conditions are proxied by a very granular set of fixed effects at Industry-Size-Age-Location-Year level.[17] Supply factors are instead captured by Bank-Year fixed effects. Standard errors are clustered at the firm-bank level, as it is standard in this type of specifications.

The coefficient β_1 captures the difference in probabilities (measured in percentage points) that firms' loan demands are addressed to banks belonging to the same cultural group rather than to a financial institution belonging to a different cultural group.

[16] LLMs are self-contained commuting zones that are computed – for each population census – by the Italian Statistical Office. LLMs are based on commuting patterns of population; a LLM is a self-contained area in which at least 75% of population works and lives. Using the 2011 census, South Tyrol was partitioned in 14 LLMs.

[17] Industry is defined at 3-digit Nace classification level. We consider 20 equally-sized size bins; age groups are based on the actual age (in years) of the firm. As for location we use the LLMs.

The information contained in the SPI is particularly useful to proxy for loan demand; however, as we described in the previous section, it also has some drawbacks. The most important one is that lodging an inquiry to the SPI is neither compulsory nor costless for a bank. This means that – if the bank already has some information on the applicant – the financial institution will not use SPI to gather information on the applicant; from an econometric point of view, this might imply that the dependent variable is plagued by a non-classical measurement error (i.e. there is a correlation with the variable of interest $SameGroup_{\mathrm{ib}}$). The second drawback is that the information on loan applications does not necessarily reflect the actual formation of a credit network. Stated in a different way, the creation of new credit relationships may also depend on supply factors, which could be as relevant as demand factors.

To solve these problems we complement SPI information with the entire CCR that has data on all credit relationships in South Tyrol. In particular, we concentrate on the actual creation of *new* credit relationships in South Tyrol; a credit relationship is considered new if bank b and firm i did not have a credit relationship in the past (this means that we do not consider as new a re-activated credit relationship). We estimate the following equation by OLS:

$$Y^S_{\mathrm{ibt}} = \beta_0 + \beta_1 SameGroup_{\mathrm{ib}} + \beta_2 X^F_{it} + \beta_3 X^B_{bt} + \varepsilon_{ibt} \qquad (2)$$

Where Y^S_{ibt} is a dummy equal to one if firm i and bank b have created a new credit relationship at time t; b is a bank with an active branch at time t in the LLM where i is located.

As before, credit demand and supply factors are controlled by using the same set of fixed effects (X^F_{it} and X^B_{bt}) that we included in equation (1).[18]

The coefficient β_1 is now the difference in probabilities (measured in percentage points) that a new credit relationship is established within the same cultural group rather than outside.

In a robustness check, equation (2) is estimated on the subsample of start-ups (defined as firms with less than two years of activity), which are generally less able to provide hard information and – therefore – should rely more on cultural proximity to obtain credit.

4.1 Results

[18] Standard errors are clustered at bank-firm level.

Table 3 presents the first set of the results on selection in which we consider the impact of culture on credit demand using SPI (equation (1)). The first column presents the conditional correlation between our proxy for loan demands and $SameGroup_{\mathrm{ib}}$ by controlling for Year fixed effects only. Loan demands more frequently target banks belonging to the same cultural group; the difference in the probability is 0.6 percentage points which compares with an average dependent variable of 1.4%. The coefficient of interest remains quite constant across specifications when we include Industry-Size-Age-Location-Year (col. 2), Bank (col. 3), or Bank-Year fixed effects (col. 4).

The result is practically confirmed in table 4, Panel (A) in which a dummy for the creation of new credit relationships is used as a dependent variable (equation (2)). We first present the results when only Year dummies are included in the regression. The estimated effect is positive and highly significant; in each year, the probability for a firm to establish a new relationship with a bank belonging to the same group is almost 2 percentage points higher than the likelihood to establish it with a bank of a different cultural group. This impact is quantitatively large if we consider that the mean of the dependent variable is 2.0%.
The impact becomes quantitatively smaller but still sizable if we consider both demand and supply factors (columns 2 to 4). In our preferred specification (in which supply factors are controlled with Bank-Year fixed effects; column 4), the estimated coefficient is equal to 0.7 percentage points.

The quantitative impact is more relevant when we consider start-ups only (table 4, panel (B)); in our preferred specification (col. 4) the probability for a newly-created firm to establish a new relationship with a bank belonging to the same cultural group (controlling for demand a supply effects) is 0.6 percentage points larger than the likelihood to establish it with a bank belonging to a different group; this compares with a mean dependent variable of 1.6%.

5. Market equilibrium

So far, we have shown that cultural proximity plays a relevant role in the creation of the credit network (selection). Firms' loan demands generally target banks belonging to the same cultural group; new credit relationships (both for incumbent firms and start-ups) are more likely to be created within the same group. In this section we now analyze the in impact of the cultural proximity on the credit market equilibrium by analyzing all credit relationships in South Tyrol. In particular, we study three aspects: the extensive margin (i.e. credit access); the intensive margin (i.e. loan quantities); and the quality of bank-firm match (i.e. proxied by the length of the relationship).

As before, identification will be based on the estimation (by OLS) of the following equation:[19]

$$Y_{\mathrm{ibt}}^{E} = \beta_0 + \beta_1 SameGroup_{\mathrm{ib}} + \beta_2 X_{it}^{F} + \beta_3 X_{bt}^{B} + \varepsilon_{ibt} \qquad (3)$$

Y_{ibt}^{E} is the dependent variable that will capture various aspects of market equilibrium. In particular, when we analyze the extensive margin of credit, Y_{ibt}^{E} is a dummy equal to one if firm i and bank b have a credit relationship at time t; as in the previous section, b is a bank with an active branch at time t in the LLM where i is located. For the analysis of the intensive margin of credit, we use the log of granted loans; in this case, the analysis will be made on the subsample of active bank-firm relationships (i.e. when granted loans are non-zeros). As for the quality of bank-firm matches, we employ the (log) length (in years) of bank-firm relationship that,[20] as shown by Gobbi and Sette (2015), is associated with a higher growth of credit and lower interest rates.[21]

5.1 Results

Table 5, panel (A) presents the results on the extensive margin. As in the previous regressions, the first column displays the coefficient of interest when only Year dummies are included; it shows that the probability to observe a credit relationship within the same cultural group is one percentage point larger that observing one with a different group. This value compares with an average dependent variable equal to 1%. Once we control for demand and supply factors, the coefficient of interest reduces to 0.5 percentage points but remains highly significant. In relative terms, the impact of cultural proximity on the extensive margin is similar to the one we have estimated in the previous section for selection. This can be interpreted as evidence that the estimated impact on the creation of credit links is highly persistent and fully translates on the characteristics of the entire credit network.

Table 5, panel (B) provides evidence that not only cultural proximity has an impact on the extensive margin but also on the size of the loans. In our most preferred specification, granted loans to a firm belonging to the same cultural group is – coeteris paribus – 7% larger that those

[19] Standard errors are clustered at bank-firm level.

[20] More precisely, we use log(1+year) to use information on newly created relationships.

[21] Unfortunately, in this paper, we are not able to exploit the information on the cost of credit due to the fact that the survey on the cost of credit in CCR does not include minor financial institutions, which are overrepresented as Raiffeisenbanken in South Tyrol.

granted to firms of a different cultural group. Cultural proximity explains 6% of the entire standard deviation of the dependent variable and 7% of the residual standard deviation, once we control for demand and supply factors.

Results on the intensive and the extensive margin are further confirmed in table 6 in which we adopt an alternative identification strategy based upon Khwaja and Mian (2008). In this case, we substitute Industry-Size-Age-Location-Year with Firm-Year fixed effects to control, in a more precise way, for the impact of demand factors.[22] In our most preferred specifications (with Firm-Year and Bank-Year fixed effects), the impact of cultural proximity on the extensive margin is (even quantitatively) similar to those estimated in table 5. The impact on granted loans are lower and slightly less precisely estimated; this is due to the fact that the estimation sample is now both smaller and more biased toward larger firms (for which cultural proximity is likely to be less relevant for credit access).

Finally, we analyze the impact of cultural proximity on the quality of the bank-firm link. As we said, our proxy for the quality is the ability for the bank and firm to create a stable relationship that – as shown by the literature on relationship banking on Italian data – has a positive impact on both quantities and prices even during negative macroeconomic shocks. The (log) of length of the relationship (in years) is used as a dependent variable. Table 7 confirms the hypothesis that cultural proximity has an impact on the creation of longer-lasting connections; our preferred specification shows that belonging to the same cultural group raises the length of the relationship by 3.8% (roughly one year). This corresponds to 5% of the entire standard deviation of the dependent variable and 7% of the residual standard deviation (controlling for demand and supply factors).

6. Efficiency

Results so far have shown that selection plays an important role in explaining how firms establish bank links – they are significantly more likely to request a loan to banks from the same cultural group. We also find that access to credit is relatively easier when firms and banks share

[22] Note that the introduction of Firm-Year fixed effects does not change the estimation sample of the regression on extensive margin; this is due to the fact that – in the construction of the dependent variable – we already have multiple observations of each firm in each year. The estimation sample for the intensive margin is now, instead, radically different since it is now made of multi-borrowing firms that borrow from at leas one bank belonging to the same group and one bank belonging to a different group.

the same cultural origin and that their credit relationships last longer; cultural proximity also translates into larger loan quantities.

As a next step in our analysis, we study increased loan quantities or better access to credit as a result of cultural proximity represents an *efficient* outcome for the economy. As already mentioned, an increase in lending could be driven by both a better screening ability of the bank deriving from an improved signal on the borrower's quality through cultural proximity, or by banks' tendency to favor firms belonging to the same cultural group.

To study which hypothesis is dominant, we analyze the issue from both the lender and the borrower point of view. Market equilibrium is efficient if (i) cultural proximity positively correlates with the quality of credit and (ii) the degree of collateralization is lower. Higher quality of credit is good for the bank since it lowers the probability of default by the borrower; lower collateralization is good for the firm since it increases the resources available at firm level for alternative investments.

To test this issue we estimate the following equation:

$$Y_{\mathrm{ibt}}^{Q} = \beta_0 + \beta_1 SameGroup_{\mathrm{ib}} + \beta_2 X_{it}^{F} + \beta_3 X_{bt}^{B} + \varepsilon_{ibt} \qquad (4)$$

where Y_{ibt}^{Q} is a proxy for market efficiency.

As for the quality of credit, Y_{ibt}^{Q} is a dummy equal to one if bank b signaled firm i as non-performing in the years between t and t+3.[23] Non-Performing Loans (NPL) are a very broad definition that includes bad loans and loans with minor anomalies (like unlikely to pay, overdues, etc.); according to the Italian rules, the decision to signal a bad loan is based on the banks' assessment of the borrower's economic situation which, in principle, could be influenced by the fact that banks and firms may belong to the same cultural group. To cope with this problem, as an alternative definition for Y_{ibt}^{Q}, we drop bad loans and we only use minor anomalies (which are less subject to the bank's assessment) as a dependent variable.

As for the collateralization, Y_{ibt}^{Q} is a dummy equal to one if the loan between bank b and firm i is warranted by collateral.

An alternative way to test for market efficiency is to consider loan and collateral dispersion. If banks use cultural proximity as a screening device (as opposed to crony lending), then loan sizes and collateralization rates (i.e. the ratio between the value of the collateral and the size of the granted loan) should display more variability within the same cultural group. This is due to the

[23] We use three-years moving windows because banks usually employ three years to actually report in their balance sheet a loan as non-performing.

fact that banks can target each same-cultural firms with a more precise credit supply and credit conditions.

To study whether this is the case, we estimate the following regression equation:

$$dispersion_{bgt} = \beta_0 + \beta_1 \mathrm{D_g} + \beta_2 D_b + \beta_3 D_t + \beta_4 mean_{bgt} + \varepsilon_{bt} \qquad (5)$$

where $dispersion_{bgt}$ is the standard deviation of either the log of the granted loans or the collateral ratio for all loans made by bank b at time t to cultural group g. We include Bank and Year fixed effects and we cluster at Bank-Year level; $mean_{bgt}$ is the mean of either the log of the granted loans or the collateral ratio at bank-group-time level. The variable of interest is $\mathrm{D_g}$ which is a dummy equal to one for all loans granted to the same cultural group. If $\beta_1 > 0$, the dispersion in both loan size and collateral ratio is larger for the credit granted to the same cultural group thus suggesting that banks are more able to screen loan applicants when they both belong to the same cultural group.

6.1 Results

Table 8 presents the estimation results of equation (4). Results suggest that cultural proximity has a positive impact on market efficiency. When firms and banks belong to the same cultural group both the share of collateralized loans and the percentage of NPL are both lower by roughly 3 percentage points (average dependent variables are, respectively, equal to 0.32 and 0.10). Stated in a different way, loans to firms belonging to the same cultural group generally entail a lower probability of default and a lower need to present collateral. This is good news for the economy since it firms are able to employ more resources in alternative investments without increasing the riskiness of the banks' portfolio. The result on credit quality is confirmed when we exclude bad loans and we concentrate on minor anomalies; in this case the point estimate is equal to -1.9 percentage points, with a mean dependent variable equal to 8.7%.

Further evidence on the fact that cultural proximity is positively correlated with the screening abilities by banks is reported in Table 9; the standard deviation of both loan sizes and collateral ratios are larger for loans granted to the same cultural group.

All in all, results strengthen our hypothesis that cultural proximity leads to credit market efficiency. In the context of South Tyrol, better credit market driven by cultural proximity is due to the fact that culture is a good screening device for banks; there is no evidence that belonging to the same culture leads to crony lending.

7. Conclusions

In this paper, we study the role of selection in culturally-close bank-firm relationships and its impact on demand and credit-supply, as well as on credit market efficiency. We first construct a comprehensive dataset that traces all bank-firm relationships for the population of firms and banks that operate in South Tyrol. For each bank and firm, we link all available information on the board members. Using an algorithm that is able to link names and surnames to linguistic groups (Grinblatt and Keloharju, 2001), we are able to attribute a predominant cultural group in the boards of banks and firms.

We find that culture plays a relevant role on *selection* in the credit market. We show that firms are more likely to demand credit from culturally-close banks; the first link that firms establish with the banking system is generally within the same cultural group. Using a proxy for loan demand (*Servizio di Prima Informazione*; Albertazzi et al., 2017), we also show that firms generally tend to target same-group banks for their loan requests.

We also find that cultural proximity has an impact on the *market equilibria*. Access to credit is relatively easier when firms and banks share the same cultural origin; cultural proximity also translates into larger loan quantities. These results holds even when we control for demand and supply factors by using the set of fixed effects recently proposed by Degryse et al. (2018). Results are practically confirmed (even in magnitude) when we use a selected sample of multi-borrowing firms for which it is possible to include firms fixed effects (Khwaja and Mian, 2008).

Finally, we find that culture enhances *market efficiency*. Loans granted to the same group tend to be less collateralized and generally have a better performance in terms of credit quality. Moreover, the standard deviation of loans granted by banks to their own cultural group is larger than the one related to the other ethnic group; this supports the idea that cultural proximity is a screening device that substitute for hard information.

All in all, our paper contributes to the literature on cultural proximity in economic, and more specifically, credit relationships by showing that endogenously-formed, culturally-based firm-bank links represent a gain in efficiency for credit markets.

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Appendix – Figures and Tables

Table 1. Descriptive statistics I

	# unique firms	#unique banks	%Italian firms	%Italian banks
2005	8213	174	25.0%	67.2%
2006	8503	189	24.8%	69.3%
2007	8693	197	24.9%	69.5%
2008	8728	208	24.4%	71.2%
2009	8413	217	24.3%	73.7%
2010	8409	225	24.1%	75.1%
2011	8258	223	23.6%	74.9%
2012	8019	226	23.1%	75.7%
2013	8046	222	23.2%	73.9%
2014	8134	219	23.3%	74.4%
2015	8150	224	23.3%	75.4%
Total	13469	361	23.3%	75.4%

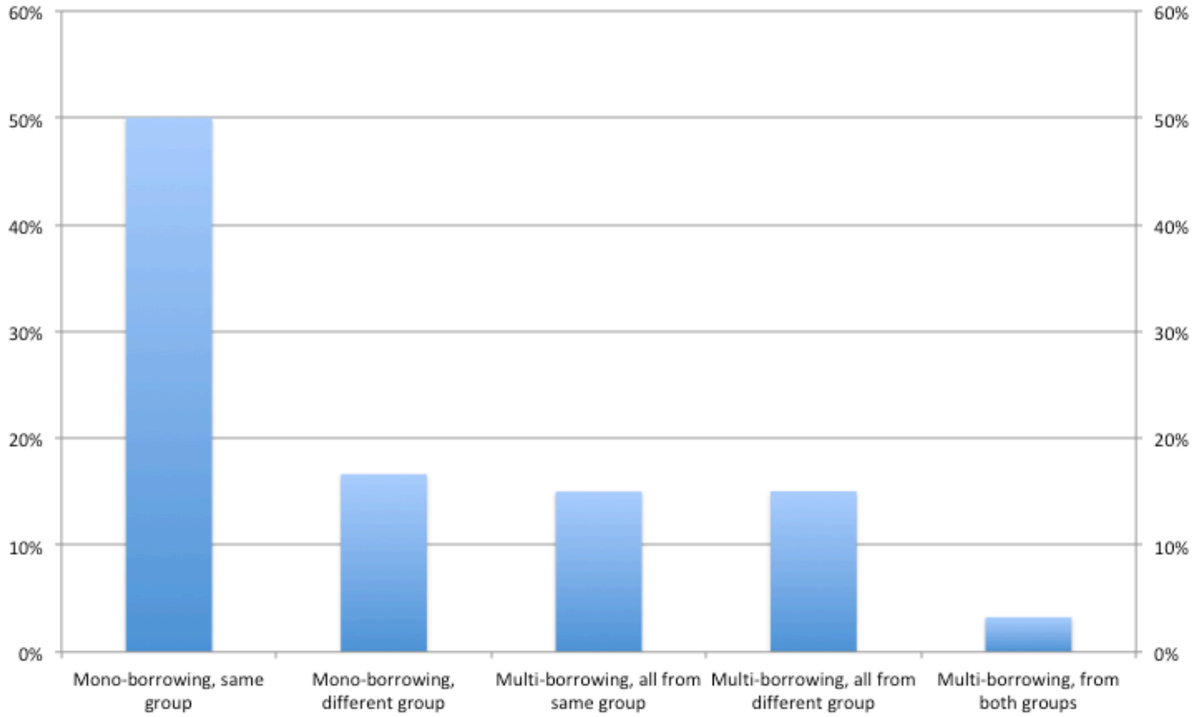
Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.

Table 2. Descriptive statistics II

	Mean	Standard deviation	p25	p50	p75
Age	15.93	13.30	6	14	23
Number of employees	12.96	127.5	0	3	8.75
Average bank links per firm	1.632	1.408	1	1	2
Average bank links within the same group	1.182	1.136	1	1	1
Log(1+Length of the bank-firm relationship)	1.861	0.837	1.386	2.079	2.485
Log(granted loans)	13.06	1.237	12.04	12.90	13.89
Collateral	0.324	0.468	0	0	1
NPL	0.100	0.300	0	0	0
Minor anomalies	0.087	0.281	0	0	0

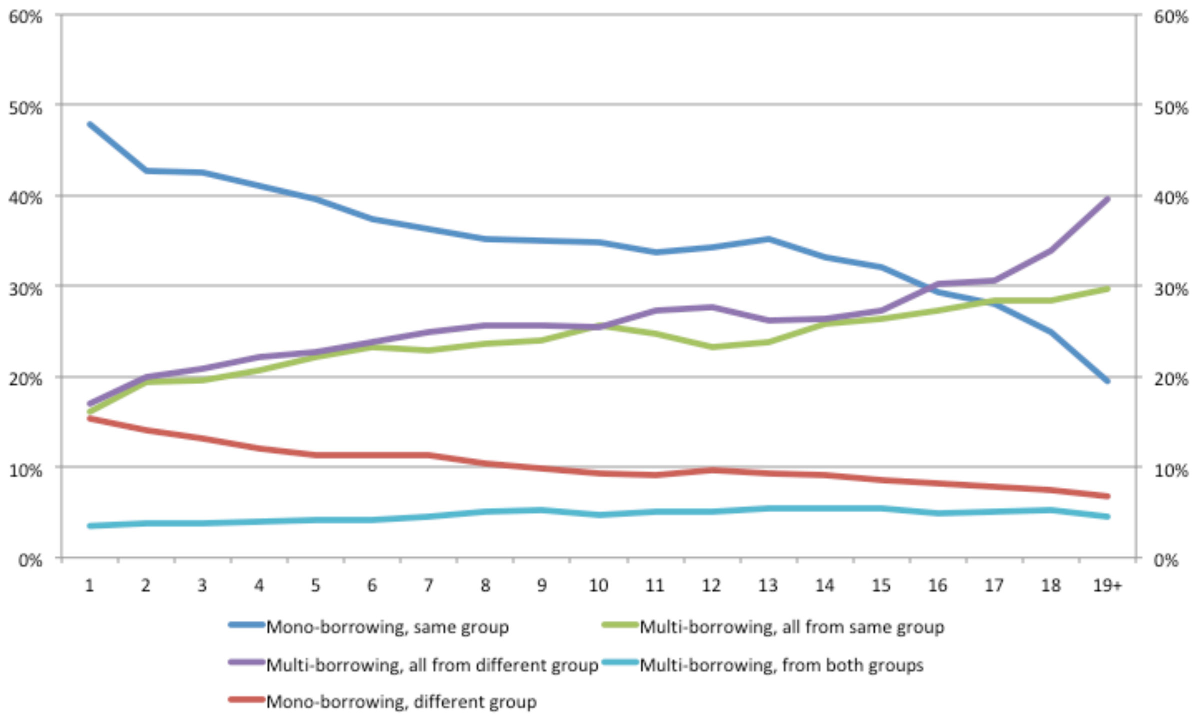
Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.

Figure 1. Distribution of firms according to their banking relationships



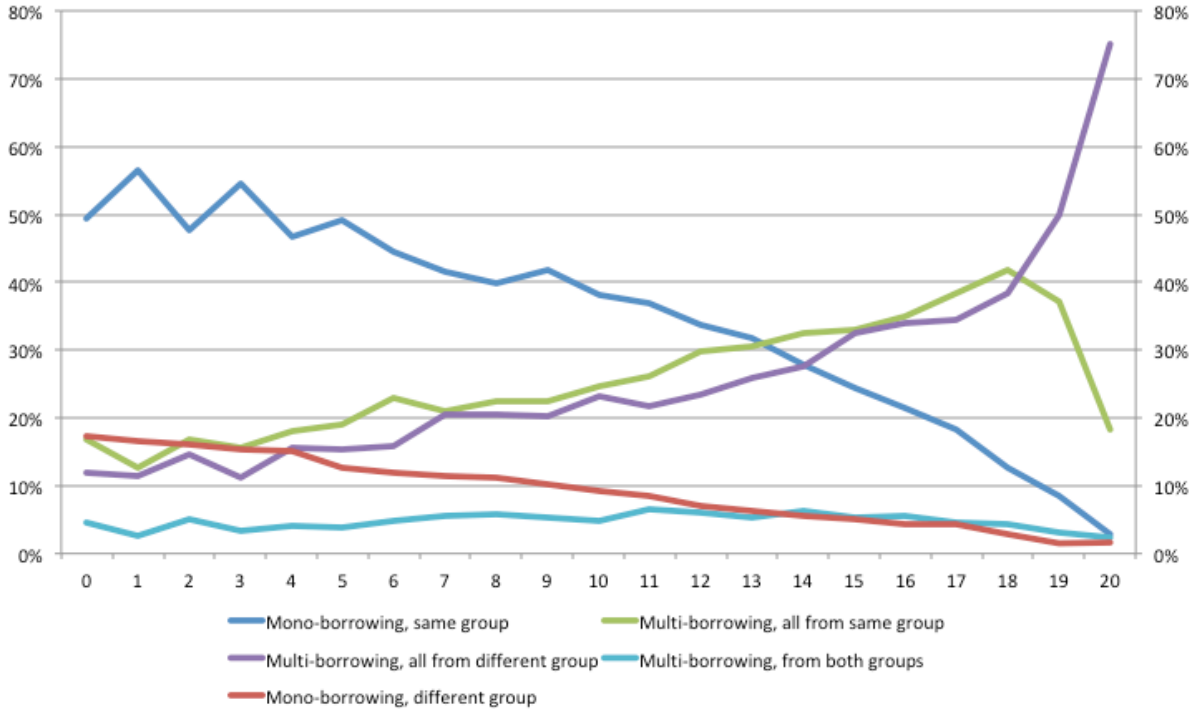
Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.

Figure 2. Distribution of bank-firm relationships according to firm age



Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.

Figure 3. Distribution of bank-firm relationships according to firm size



Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.

Table 3. Selection: Loan demands

	(1)	(2)	(3)	(4)
Same group	0.00562***	0.00818***	0.00608***	0.00601***
	(27.56)	(35.48)	(29.56)	(29.04)
Fixed effects:				
Year	YES	NO	NO	NO
Industry-Size-Age-Location-Year	NO	YES	YES	YES
Bank	NO	NO	YES	NO
Bank-Year	NO	NO	NO	YES
R^2	0.001	0.009	0.087	0.095
No. Obs.	2710594	2710594	2710594	2710594

Notes: Authors' calculation on CCR(SPI)-ORSO-Infocamere-INPS dataset.
OLS regressions, see equation (1). T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-firm level. Dependent variable: dummy equal to one if bank b lodged an inquiry on firm i that applied for a loan. Average dependent variable: 0.014. Industry is defined at 3-digit Nace classification level. We consider 20 equally-sized size bins; age groups are based on the actual age (in years) of the firm. As for location we use the LLMs.

Table 4. Selection: The impact of culture on network formation

	(1)	(2)	(3)	(4)
Panel (A)				
Same group	0.0189***	0.0194***	0.00696***	0.00682***
	(54.00)	(54.05)	(21.35)	(20.92)
R^2	0.005	0.024	0.149	0.150
No. Obs.	662581	662576	662541	662355
Panel (B). Subsample: start-ups				
Same group	0.0127***	0.0133***	0.00598***	0.00584***
	(18.80)	(18.86)	(9.253)	(8.999)
R^2	0.003	0.016	0.115	0.116
No. Obs.	135289	135289	135256	134685
Fixed effects:				
Year	YES	NO	NO	NO
Industry-Size-Age-Location-Year	NO	YES	YES	YES
Bank	NO	NO	YES	NO
Bank-Year	NO	NO	NO	YES

Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.
OLS regressions, see equation (2). T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-firm level. Dependent variable: dummy equal to one if bank b created a new credit relationship with firm i. Average dependent variable Panel (A): 0.020; Average dependent variable Panel (B): 0.016. Industry is defined at 3-digit Nace classification level. We consider 20 equally-sized size bins; age groups are based on the actual age (in years) of the firm. As for location we use the LLMs.

Table 5. Market equilibrium: The extensive and intensive margin of cultural bias

	(1)	(2)	(3)	(4)
Panel (A): Extensive margin				
Same group	0.0100***	0.0109***	0.00525***	0.00526***
	(66.82)	(68.72)	(37.62)	(37.64)
R^2	0.003	0.023	0.083	0.085
No. Obs.	1,444,040	1,444,040	144040	1,444,040
Panel (B): Log(loan)				
Same group	-0.0129	0.0876***	0.0661***	0.0716***
	(-0.688)	(4.769)	(3.450)	(3.716)
R^2	0.002	0.210	0.246	0.242
No. Obs.	143422	135071	135032	134325
Fixed effects:				
Year	YES	NO	NO	NO
Industry-Size-Age-Location-Year	NO	YES	YES	YES
Bank	NO	NO	YES	NO
Bank-Year	NO	NO	NO	YES

Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.
OLS regressions, see equation (3). T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-firm level. Panel (A). Dependent variable: dummy equal to one if bank b and firm i have a credit relationship. Average dependent variable: 0.010. Panel (B). Dependent variable: log of granted loan. Average dependent variable: 13.04. Industry is defined at 3-digit Nace classification level. We consider 20 equally-sized size bins; age groups are based on the actual age (in years) of the firm. As for location we use the LLMs.

Table 6. Robustness on market equilibrium: evidence from multi-borrowing firms

	(1)	(2)	(3)	(4)
	Extensive margin	Extensive margin	Intensive margin	Intensive margin
Same group	0.0124***	0.00604***	0.160***	0.0419*
	(63.03)	(33.97)	(6.619)	(1.701)
R^2	1,444,039	1,444,039	81137	80299
No. Obs.	0.027	0.089	0.443	0.474
Fixed effects:				
Firm-Year	YES	YES	YES	YES
Bank	YES	NO	YES	NO
Bank-Year	NO	YES	NO	YES

Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.
OLS regressions. T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-firm level. Columns (1) and (2). Dependent variable: dummy equal to one if bank b and firm i have a credit relationship. Average dependent variable: 0.010. Columns (3) and (4). Dependent variable: log of granted loan. Average dependent variable: 13.23.

Table 7. Culture and length of relationship

	(1)	(2)	(3)	(4)
Same group	0.148***	0.154***	0.0410***	0.0381***
	(13.65)	(15.45)	(4.332)	(4.054)
R^2	0.039	0.369	0.461	0.470
No. Obs.	143422	135071	135032	134325
Fixed effects:				
Year	YES	NO	NO	NO
Industry-Size-Age-Location-Year	NO	YES	YES	YES
Bank	NO	NO	YES	NO
Bank-Year	NO	NO	NO	YES

Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.
OLS regressions, see equation (3). T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-firm level. Dependent variable: log of 1+length of the relationship between the firm and the ban (in years). Average dependent variable: 1.862. Industry is defined at 3-digit Nace classification level. We consider 20 equally-sized size bins; age groups are based on the actual age (in years) of the firm. As for location we use the LLMs.

Table 8. Efficiency: Collateralization and Credit Quality

	(1)	(2)	(3)	(4)
Panel (A). Dep. Var.: Collateral				
Same group	0.0198***	-0.00518	-0.0259***	-0.0263***
	(2.867)	(-0.714)	(-3.419)	(-3.448)
R^2	0.007	0.106	0.144	0.141
No. Obs.	143422	135071	135032	134325
Panel (B). Dep. Var.: NPL				
Same group	-0.0155***	-0.0211***	-0.0247***	-0.0250***
	(-3.766)	(-4.708)	(-5.141)	(-5.155)
R^2	0.004	0.082	0.096	0.090
No. Obs.	133669	125308	125265	124623
Panel (C). Dep. Var.: Minor anomalies				
Same group	-0.00881**	-0.0144***	-0.0193***	-0.0194***
	(-2.304)	(-3.446)	(-4.308)	(-4.305)
R^2	0.003	0.053	0.067	0.062
No. Obs.	133669	125308	125265	124623
Fixed effects:				
Year	YES	NO	NO	NO
Industry-Size-Age-Location-Year	NO	YES	YES	YES
Bank	NO	NO	YES	NO
Bank-Year	NO	NO	NO	YES

Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.
OLS regressions, see equation (4). T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-firm level. Panel (A). Dependent variable: dummy equal to one if the loan between bank b and firm i is guaranteed by collateral. Average dependent variable: 0.319. Panel (B). Dependent variable: dummy equal to one if the loan was signaled as Non Performing. Average dependent variable: 0.101. Panel (C). Dependent variable: dummy equal to one if the loan was signaled as a Minor Anomaly (overdue, unlikely to pay, etc.). Average dependent variable: 0.087. Industry is defined at 3-digit Nace classification level. We consider 20 equally-sized size bins; age groups are based on the actual age (in years) of the firm. As for location we use the LLMs.

Table 9. Efficiency: Loan size and collateral ratio dispersion

	(1)	(2)	(3)	(4)
	Sd(Loan size)	Sd(Loan size)	Sd(Collateral ratio)	Sd(Collateral ratio)
Same group	0.112***	0.0782***	0.0276***	0.0211***
	(6.093)	(3.275)	(3.768)	(2.616)
Average		0.110***		0.0215
		(2.995)		(1.527)
R^2	0.473	0.476	0.549	0.549
No. Obs.	2243	2243	2243	2243
Fixed effects:				
Year	YES	YES	YES	YES
Bank	YES	YES	YES	YES

Notes: Authors' calculation on CCR-ORSO-Infocamere-INPS dataset.
OLS regressions, see equation (5). T-stat are in parenthesis. * (**) [***] denotes significance at the 10% (5%) [1%] level. Standard errors clustered at bank-year level. Columns (1) and (2). Dependent variable: standard deviation of the log of granted loan by bank b to group g. Average dependent variable: 1.066. Columns (3) and (4). Dependent variable: standard deviation of the collateral ratio of the granted loans by bank b to group g. Average dependent variable: 0.277.