

The role of culture in firm-bank matching

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Abstract

We assemble a unique dataset containing population-level information on loan applications in a region hosting two cultural groups to study the role of culture in firm borrowing decisions. We find that firms are more likely to apply for loans to culturally-close banks. This effect is stronger for opaque firms, but not for less performing firms, indicating that firms do not expect a preferential treatment from same-culture banks. Loan applications to culturally distant banks increase sharply with firms' size and age. Our results suggest that culture is an important determinant of firm-bank matching which facilitates the transmission of soft information.

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1 Introduction

In recent years, several empirical studies have documented the benefits of borrowing from lenders that share a cultural identity (Giannetti and Yafeh, 2012; Fisman, Paravisini, and Vig, 2017; Beck, Ioannidou, and Schäfer, 2018). Altogether, this literature documents that borrowing from culturally close banks benefits both firms, which receive better loan terms, and banks, which face lower default rates. Yet, firms also heavily rely on culturally-distant credit (Claessens and Van Horen, 2014; Bruno and Hauswald, 2014; Giannetti and Ongena, 2012). These results raise the following questions: Why do we observe that some firms borrow from culturally distant banks? Which firms and banks are more likely to engage with culturally proximate vs. culturally distant counterparties?

In this paper, we address these questions by focusing on the role of culture in the formation of credit relationships. The empirical identification of the effect of culture on the formation of lending relationships is challenging, because firms and banks belonging to different cultural groups are usually located in different countries. Thus, culturally distant lending relationships tend to occur in a selected sample of firms that participate in international markets (for example, importers or exporters) and are geographically distant from their lenders. In addition, cross-country differences in economic conditions (such as interest rates, inflation, or expectations about the business cycle), as well as the rules and incentives provided by foreign institutions and regulations, can affect financing choices. As such, comparisons of culturally proximate vs. culturally distant loans may for example capture differences in loan terms or credit availability across jurisdictions rather than the effect of culture, even if the comparisons are within the same borrower (Fernández, 2011). We overcome these empirical challenges by analyzing population data on loan applications within a contained geographical area that features a single regulatory, institutional, and macroeconomic setting: The autonomous province of South Tyrol in Northern Italy.

The Italian province of South Tyrol represents an excellent natural laboratory to assess the role of culture in the formation of lending relationships. One of the richest areas in Italy and in the European Union, the economically active region of South Tyrol is home to individuals belonging to two different cultural groups: Italian and Germanic. Both Italian and German are official languages and the two cultural groups share a common Catholic religious background and live next to each other within municipalities. However, they lead relatively segregated social lives: Children attend separate schools and individuals of Germanic (Italian) origin interact and socialize mostly with Germanic (Italian) peers. Importantly for our study, the region hosts a large number of firms from a representative range of industry sectors, as well as several types of banks. Moreover, all firms in the province are privately held and most of them are small and owner-managed, which obviates agency problems. Due to its uniqueness, the South Tyrol setting has been used in previous studies to investigate the influence of culture on other economic and financial outcomes ([Angerer, Glätzle-Rützler, Lergetporer, and Sutter, 2016](#); [Sutter, Angerer, Glätzle-Rützler, and Lergetporer, 2018](#); [Bellido, Garcia-Appendini, and Siming, 2020](#)).

Leveraging this unique setting and detailed credit register data on loan applications, we are able to quantify the effect of culture on firms' new loan applications (i.e., credit requests made by firms to banks with which they had no previous relationship), and to exploit the heterogeneity in borrowers' financial characteristics to analyze the determinants of the formation of culturally-close lending relationships. The large degree of detail and granularity in our data allows us to identify the effect of culture on lending relationships from the demand-side of credit by controlling for all observed and unobserved, time-varying lender characteristics (using bank-time fixed effects). In addition, in all our specifications we account for a large set of observable firm-level and bank-firm pair characteristics. Our most stringent specifications

identify the effects of interest by accounting for time-varying observable and unobservable firm characteristics, as we compare for the same firm, in the same time period, loan applications with banks of the same- vs. different-culture banks (Khwaja and Mian, 2008; Degryse et al., 2019). Our results show that demand-side factors play a key role in the formation of culturally close credit relationships.

More precisely, we find that firms are up to 52% more likely to apply for a loan with a bank of their same culture (+0.76 percentage points of a mean value of 1.4%, which represents the unconditional probability of applying for a loan with any random bank in their locality). This result cannot be explained by time-varying or time-invariant firm or bank characteristics, as it is robust to controlling for firm-time and bank-time fixed effects. It also cannot be explained by the plausibly higher likelihood of finding culturally proximate banks in the close vicinity, as we control for the presence of nearby bank branches in our specifications (Degryse and Ongena, 2005; Alessandrini, Presbitero, and Zazzaro, 2009). Moreover, estimating the same coefficient on a simulated placebo sample where we use the true distribution of cultural groups within a locality to randomly assign the culture to firms and banks leads to a tightly estimated zero effect of culture on loan applications, which is several standard deviations away from our estimate. Overall, these findings indicate that culture is a first-order determinant of the choice of banking relationships when firms apply for loans.

There are two prominent explanations for why firms are more likely to demand loans to same-culture banks. On the one hand, cultural proximity may reduce information asymmetry and search frictions by facilitating firms' communication and contracting with the lender (Rogers and Bhowmik, 1970; Giannetti and Yafeh, 2012). On the other hand, borrowers may apply more often to a same-group lender for preference-based reasons, or because they expect some degree of in-group favoritism (Hewstone, Rubin, and Willis, 2002; Haselmann, Schoenherr,

and Vig, 2018; D’Acunto, Ghosh, Jain, and Rossi, 2020). Both explanations are consistent with our findings, but they have divergent implications for the composition of applicants of same- versus different-group loans.

We analyze firm heterogeneity in loan applications and find that information asymmetries and search frictions are the main driver of same-group loan applications. In fact, the larger propensity to apply for loans of the same cultural group is highest for relatively opaque borrowers: Young startups, small firms, and high growth firms – which are typically associated with high information asymmetries (Berger and Udell, 1998)– are more likely to seek same-culture lending relationships than older and more established firms. Loan applications to culturally distant banks increase sharply as firms become older and larger – arguably, as they establish a reputation or a credit record and their opaqueness is reduced. In line with this interpretation, we also find that banks lending to different-culture firms are larger, non-cooperative banks whose lending technology is better suited for processing hard information (Stein, 2002; Berger et al., 2005).

From our heterogeneity analysis we find no evidence that firms with lower profitability or higher risk are more likely to apply for loans with a same- vs. a different-culture lender. This suggests that expectations of receiving a preferential treatment are not driving the high prevalence of same-group credit applications, further reinforcing our interpretation that search frictions and information asymmetries are the main driver of loan applications.

We extend our main analysis by examining loan approvals *conditional* on loan applications, and find that lenders are not more likely to approve loans from same-group borrowers relative to different-group borrowers. We also do not find evidence of heterogeneity in the loan approval of same-group firms based on firm opaqueness or observable measures of profitability

and risk. These results show that banks do not discriminate based on culture, and provide support to our interpretation that firms do not apply for loans to same-culture banks expecting a preferential treatment. As a further confirmation of our interpretation, we find that conditional on loan application and approval, same-culture loans perform better than loans to different-group firms, consistently with previous findings. Overall, these results show that the reduction in asymmetric information that leads to good loan outcomes can be also facilitated by an endogenous selection of firms into same-culture relationships, and highlight the need for a quasi-random setup to further investigate the effects of culture on loan terms. Although our estimates warrant a causal interpretation only under rather strict assumptions, they reveal a central role of cultural proximity in the formation of lending relationships and in facilitating the credit screening process.

This paper contributes to several strands of literature. First and foremost, it is related to the literature on the formation of firm-bank matches. [Stein \(2002\)](#) argues and [Berger et al. \(2005\)](#) show evidence that the less hierarchical structure of small banks is more adequate for processing soft information, and thus for lending to smaller, more opaque firms. [Schwert \(2018\)](#) finds that bank-dependent firms borrow from well-capitalized banks, a result that is in line with theoretical predictions of [Sharpe \(1990\)](#) and [Holmstrom and Tirole \(1997\)](#), among others. [Farinha, Kokas, Tsoukas, and Sette \(2021\)](#) find that firm-bank matching can affect access to credit and real outcomes. We add to this literature in several ways. First, we identify an additional factor, cultural proximity, as a first-order determinant of the formation of firm-bank matches. Our results show that firm-bank matching based on culture facilitates the transfer of information that can lead to better outcomes. This might help explain the relevance and success of similar culture banks across borders (e.g. Spanish banks in Latin America), and might play an especially relevant role in the context of multi-cultural jurisdictions such as Belgium, Canada, Switzerland or the European Union. Second, we observe

loan application data for the whole population of borrowers and lenders in one region, which allows us to explicitly study the role of culture in the formation of matches, while at the same time circumventing the need to perform comparisons across countries. Our findings show that small, opaque firms endogenously select into culturally proximate banks and by thus doing they facilitate the processing of soft information. In addition, we find that this matching generates a degree of bank specialization into lending to culturally similar firms.

Our paper also adds to the literature on the role of soft information when firms are informationally opaque (Berger and Udell, 1995, 2002; Petersen and Rajan, 1994, 1995; Farinha and Santos, 2002). Our results show that cultural proximity facilitates the formation of lending relationships, enabling a lending technology that produces soft information and reduces information asymmetries. The richness of our data allows us to account for other sources of soft information available to the bank in the analysis, such as the one collected through personal interactions (i.e., whether the bank is situated in close geographical proximity to the firm; Petersen and Rajan, 2002; Degryse and Ongena, 2005; Alessandrini et al., 2009) or through long-time interactions (i.e., the length of pre-existing relationships, Petersen and Rajan, 1995). The effects of cultural proximity on loan applications and loan performance are robust to the inclusion of these controls, indicating that cultural identity represents an additional source of soft information beyond the information that can be collected through geographical proximity or lengthy relationships.

Finally, our paper contributes to the literature that studies the role of cultural origin in economic exchanges (see, for example, Guiso, Sapienza, and Zingales, 2009; Helpman, Melitz, and Rubinstein, 2008; Alesina and Giuliano, 2015; Accetturo, Cascarano, Degasperi, and Modena, 2019) and financial contracts (Giannetti and Yafeh, 2012; Fisman et al., 2017; Beck et al., 2018; Bofondi et al., 2018). Our contribution to this literature is twofold. First,

by observing loan applications we are able to explicitly analyze the selection of firms into culturally proximate lending relationships. In this respect, our results complement previous findings by showing that the reduction in asymmetric information that leads to good loan outcomes is facilitated by an endogenous selection of the most opaque firms into same-culture relationships. Second, we rely on population-level data of a single economic area with two coexisting cultural groups, which allows us to distinguish the effect of cultural proximity from other confounding factors inherent in cross-country comparisons.

2 Institutional setup: Cultural heterogeneity in South Tyrol

South Tyrol is a North-Italian region located at the border with Austria and Switzerland. The region was part of the German and Austro-Hungarian Empire until the First World War, when it was annexed to Italy following the defeat of the Dual Alliance. At the time of the annexation, 89% of the population spoke German, 3% spoke Italian, and the remainder of the population spoke either Ladin or other languages of the Austro-Hungarian Empire (Istituto Provinciale di Statistica, 2015). However, this situation changed shortly after, as the fascist government initiated a process of “Italianization” of the region which favored both the immigration of Italian speakers from other regions and the outmigration of German speakers to Germany and Austria.¹ Among other changes, this process permanently altered the distribution of the population across both linguistic groups. As of the last available census, in 2011 the share of German-speaking population was 69%, while Italian speakers accounted for slightly more than one-quarter of the total population.

¹This was part of the so-called Agreement on the Options of Citizenships between Fascist Italy and Nazi Germany (that had already annexed Austria) in 1939. See [Accetturo et al. \(2019\)](#) for more historical details on the Italianization process.

The current institutional framework of South Tyrol dates back to 1972, when a “Statute of Autonomy” was granted to the region. Among other issues, the 1972 agreement established the right for citizens to use their own mother tongue in all occasions. The application of this right has enabled the two linguistic groups to preserve their culture, as everyday life activities – such as childcare, eldercare, and schooling – are separated for each language group. In fact, segmentation in everyday 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 both languages (Vettori and Abel, 2017).

Importantly for our study, South Tyroleans face the same institutional and economic setup in spite of the strong segmentation of their everyday lives. For example, the regulations for all banks that operate in the region are defined at the national level. Similarly, all firms headquartered in South Tyrol are subject to autonomous regulations that are set at the province level (and agreed upon by both cultural groups, to avoid the empowerment of one over the other),² and the chamber of commerce of the province is in charge of their enforcement. Thus, banks and firms in our study share a common legal and regulatory framework which is independent of the cultural origin of their owners or managers. Overall, the fact that German and Italian speakers face the same formal institutional framework but live in an extremely segmented society makes South Tyrol an ideal setting for studying the role of cultural proximity on economic outcomes without confounding factors such as institutions, norms, geographical distance, among others (Fernández, 2011). In addition, there is a wide geographic variation in the composition of the linguistic groups across the region.³

²According to the “Statute of Autonomy”, all local governments must be composed at least by one German- and one Italian-speaking party.

³Figure 1 illustrates the distribution of Italian speakers in South Tyrol.

3 Data and stylised facts

3.1 Data sources

Our main source of data in this analysis is the Italian Central Credit Registry, owned and administered by the Bank of Italy. This registry contains information about all performing and non-performing loans extended by all banks and financial companies that operate in Italy. From this database, we obtain information on all the lending relationships held by firms headquartered in the South Tyrol region over the period 2005-2015 (13,469 unique firms, for a total of 142,594 firm-bank lending relationships over the study period).⁴

We also obtain information on new loan applications. We identify a new loan application whenever an intermediary lodges a preliminary information request (Servizio di Prima Informazione, SPI) about the borrower. An SPI can be thought of as a credit check: it is an enquiry made by a bank about the current credit position of a potential borrower. Since these enquiries can be placed only when the intermediary receives a formal request for credit from an individual or a firm, and at a small cost for the financial intermediary, we assume that SPI checks represent all new loan applications to non-incumbent banks ([Albertazzi, Bottero, and Sene, 2017](#); [Branzoli and Fringuellotti, 2020](#)).

For the firms in our sample, we collect information on their number of employees (an indicator of firm size) from the Italian Social Security Service (INPS). We also obtain the names, gender, place of birth, and age for all members of the firms' management and executive boards from Infocamere. This database is maintained by the Italian Chamber of Commerce and contains management information for all the firms that are headquartered in Italy. Following

⁴For a loan observation to appear in the credit registry, the legal reporting threshold is a total borrower exposure of 30,000 euros towards a given financial intermediary; however, this threshold was 75,000 until December 2008. Following the related literature, to ease comparability throughout all years in our sample period we only consider firm-bank pairs for which the total granted amount is greater than 75,000 euros ([Cingano, Manaresi, and Sette, 2016](#)).

the procedure described in [Grinblatt and Keloharju \(2001\)](#) and [Bedendo, Garcia-Appendini, and Siming \(2020\)](#), we use these data to manually classify the cultural origin of all administrators, which is then used to identify the firms' overall cultural origin. We classify a firm as belonging to an Italian or Germanic cultural group if the majority of the members of the board and top executives are, respectively, of Italian or Germanic cultural origin (see [Online Appendix A](#) for more details). Finally, for a subset of firms in our sample, we are able to obtain additional accounting variables from the CERVED Group dataset.

Additionally, for all banks in our sample (361 unique banks over the study period), we obtain balance sheet information from Bank of Italy's supervisory reports, and information about the management board from the Segnalazione sugli Organi Societari (Or.So.) database. Or.So. is maintained by the Bank of Italy and records information on the names, gender, place and date of birth of all the members of the governing bodies and the top executives of each bank. Using these data, and adopting the same procedure as for firms, we classify a financial intermediary either of Italian or German origin.

Mostly due to data availability, we focus on the management board to classify the cultural origin of banks and firms ([Infante and Piazza, 2014](#)). To the best of our knowledge, there are no available data sets with the names and gender for other employees, such as the loan officers. However, this is not likely to represent a large limitation for our study, as (i) the credit market in the South Tyrol region is dominated by local banks, where the distance between the firm and the bank board is quite limited ([Benvenuti, Casolaro, Del Prete, and Mistrulli, 2017](#)) and (ii) the vast majority of firms in the region are small, privately held establishments where owners and managers are likely to be the same person, or linked by family (and hence, cultural) ties ([Bedendo, Garcia-Appendini, and Siming, 2020](#)).

3.2 The anatomy of credit relationships

Table 1 provides a description of the base credit registry sample, which contains loan equilibrium outcomes. On a given year in our sample period (2005-2015), this dataset contains loan-level information on more than 8,000 unique firms and roughly 200 unique banks, for a total of 13,469 unique firms and 361 unique banks over our sample period. According to the 2011 census, firms headquartered in South Tyrol were 43,000 including artisans, independent contractors, freelance workers, and cooperatives. Thus, our base sample — which only considers firms that have a borrowing relationship with the banking system over the reporting threshold and with a precise cultural classification — covers a large fraction of the universe of the South Tyrolean firms.

Table 1 also shows that the percentage of Italian firms is relatively low (23%-25%) and reflects population shares, suggesting that entrepreneurship rates are quite similar in the Germanic and Italian cultural groups. The larger percentage of Italian banks reflects the fact that all Italian banks may operate in the South Tyrolean credit market.

Table 2 contains summary statistics on firms, banks, and bank-firm relationships. Panel A summarizes firms, banks, and loans in the credit registry. Firms in the credit registry are 16 years old on average. They are relatively large compared to the population: the average number of employees in our sample is 17, whereas it is 4 when calculated using census data. The median size is much lower than the average (5.5 employees), and the standard deviation is several times the average (144), suggesting that our data contains some large firms which are more likely to have a credit relationship with a bank. Each firm has outstanding links with an average of 1.6 banks. However, the variation is very large: the standard deviation in the number of banking relationships is 1.4, and almost 70% of the firms in our data have only one banking relationship. The average number of bank links within the same cultural

groups is 1.1, implying that the majority (72.7%) of all bank-firm relationships in the region are established within the same group.

Around half of the banks in the credit registry are credit cooperative banks (48%). The average bank size is 1.2 billion euros in total assets; the average capital to assets ratio is 18%. Finally, the ratio of non-performing loans over total loans is 11%.

Panel A of Table 2 also shows that the average log length of the relationship between a firm and a bank in the credit registry is 1.9, corresponding to 5.4 years, and the average (median) of the log of granted loan size is 13.04 (12), corresponding to around half a million (400,000) euros. One-third of all loans are collateralized, while the share of Non-Performing Loans (NPL, which include bad loans and other minor anomalies such as loans that are unlikely to be paid back and overdue loans) is 10%, 8.7% of the total corresponding to minor anomalies.⁵

Panel B contains information on loan applications drawn from the SPI dataset. Firms in this sample are statistically very similar to firms in the credit registry. The median firm in the SPI dataset is in fact very similar to the median firm in the credit register in terms of size, age, profitability and risk. Banks are very similar, as well: 43% of the banks in the SPI dataset are credit cooperative banks; the capital to assets ratio is 18%; and the NPL ratio is 11%. Panel B also shows that on average, each firm in the sample applies for credit with 1.7 non-incumbent banks, 59.4% of which correspond to same-culture banks.

⁵According to the Bank of Italy classification, minor anomalies comprise two specific categories of NPLs, aside from bad loans: i) exposures unlikely to be repaid (loans which banks believe the debtors are unlikely to meet their contractual obligations in full unless action such as the enforcement of guarantees is taken), and ii) overdrawn and/or past-due exposures (loans that are overdrawn above a predefined amount and/or are past-due by more than 90 days).

3.3 Stylised facts on culture and firm-bank matching

The summary statistics presented in Section 3.2 indicate that the choice of culture of lenders and borrowers is not a random choice. In fact, from Table 1, we observe that 77% of the firms and 25% of the banks are of Germanic origin. If the choice of culture of lenders and borrowers were randomly assigned, then roughly 36% ($= 0.77 \times 0.25 + 0.23 \times 0.75$) of all lending relationships would belong to firm-bank pairs sharing the same cultural origin. However, the fraction of same-group relationships, which we observe in Table 2, is twice as large (72.7%). This finding represents our first stylized fact regarding the role of cultural proximity in the lending process:

Stylized fact 1. *The observed fraction of firms borrowing from a bank of its same cultural group is twice as large as the one implied by random matching between firms and banks.*

Stylized fact 1 suggests that culture is an important determinant of the existence of a transaction. We analyze which characteristics of firms correlate more strongly with same-group borrowing by collapsing our data to the firm-year level and comparing the characteristics of firms that borrow exclusively from banks of their same cultural group with those of firms that borrow from at least one bank of a different culture. Results from the univariate analysis are shown in Table 3; they also hold in a multivariate setting, and are robust to controlling – in a smaller sample for which these observations are available – for other measures of firm and bank risk and performance (see Table A1 in Online Appendix B).

Firms that borrow exclusively from banks of the same cultural origin are slightly younger, and significantly smaller, on average, than firms that form relationships with banks of a different cultural origin. The former firms have also fewer lending relationships than firms

that form relationships with banks of a different cultural origin, and their sales growth is slightly higher. All these characteristics are typical of startups or of firms in their early life cycle, and are usually associated with high informational opaqueness (Berger and Udell, 1998, 2002). However, these characteristics are not associated with worse quality: firms that borrow exclusively from banks of the same culture are on average more profitable, and less risky, than firms with relationships with banks of a different cultural origin. These results suggest that same-group lending may be preferred in the early stages of a firm’s life cycle, when the levels of information asymmetries between borrowers and lenders are particularly acute. From these findings, we derive the second stylized fact:

Stylized fact 2. *Firms borrowing exclusively from same-culture banks are younger, smaller, and have larger sales growth than firms borrowing from different-culture banks.*

In Table 4, we study the role of cultural proximity in loan approvals by comparing the characteristics of banks lending to a high fraction of firms of the same cultural group, relative to banks lending to a lower fraction of firms of the same cultural group. We collapse our firm-bank-year level database to the bank-year level, and calculate the fraction of firms in each bank’s portfolio that belong to the same cultural group. We then split the resulting observations at the median of the fraction of borrowers of the same cultural group in each year.⁶ Results show stark differences between these groups: for banks with high fractions of same-group lending, the average fraction of firms of a different culture is only 2.4%, while the other banks lend on average to 63.3% firms of a different culture. We find similar results in a multivariate setting (Table A2 in Online Appendix B). This result suggests that the former banks specialize on same-group lending, while the latter diversify their lending pool across the two cultures. We also find that banks lending to a large fraction of firms from the same

⁶The average across all years of the median yearly fraction of borrowers of a different group is 15.4%.

cultural group are significantly smaller, and are more often local credit cooperative banks (BCC), than those lending to a smaller fraction of same culture firms. This finding constitutes our third stylized fact:

Stylized fact 3. *Banks lending to large fractions of same-culture firms are smaller, and much more likely to be cooperative banks, than those lending to different-culture firms.*

Overall, stylized facts 2 and 3 indicate that firms relying on same-culture loans to a higher extent are more opaque, and that banks that lend more to same-culture firms rely on soft information to a larger extent. These findings suggest that information asymmetries are of first-order importance to determine the prevalence of same-culture relationships. However, we note that results in this section consist of equilibrium credit outcomes, and are therefore not informative about whether the observed effects are driven by firms' selection into same-versus different culture loans, or by lenders' lending decisions. In addition, these univariate analysis at most show correlations between the variables. In the next sections, we analyze the formation of lending relationships in order to explore the effects of information asymmetries on the emergence of same-culture lending relationships in greater detail.

4 The role of culture in the formation of lending relationships

4.1 Loan applications

We examine the role of culture on the formation of lending relationships by looking at firms' selection of a lender bank. For this analysis, we emulate the loan application process by creating a database with all the possible pairs of firms and banks that operate in the same local labor market in each period. This database represents all the potential banks where a

firm could submit an application for a loan. The underlying assumption of relating banks and firms in the same local labor market is that, when deciding to apply for a loan, a firm could potentially apply to any branch of banks operating locally. This assumption builds on prior findings that suggest that most lending is done at a local level (Petersen and Rajan, 2002; Degryse and Ongena, 2005), hence when deciding to apply for a loan firms typically consider the pool of banks that operate locally.

Based on this expanded database, we use the SPI database on loan applications to create a binary variable, $LoanApplication_{ijt}$, which equals one if firm i requested a loan from bank j during year t , and zero otherwise. As mentioned before, only banks without prior information about the borrower will submit a request for information to the SPI; thus, this variable is a good proxy for new credit applications.⁷

To analyze whether cultural proximity plays a role in the loan application process, we regress $LoanApplication_{ijt}$ on $SameGroup_{ij}$, an indicator of whether the bank and the firm belong to the same cultural group or not, and a set of firm-, bank, and relationship-specific controls (respectively X_{it} , X_{jt} , and X_{ijt}), which are likely to affect the formation of new banking relationships and be correlated with $SameGroup_{ij}$. More formally, we estimate a regression of the following type:

$$LoanApplication_{ijt} = \beta_0 + \beta_1 SameGroup_{ij} + \beta_2 X_{it} + \beta_3 X_{jt} + \beta_4 X_{ijt} + \epsilon_{ijt}. \quad (1)$$

Table 5 contains the results from estimating different specifications of Equation 1.⁸ In col-

⁷Lodging an inquiry to the SPI is neither compulsory nor costless for the bank, albeit the cost is low, amounting to a few cents on the euro (Branzoli and Fringuellotti, 2020). Similarly, a bank might lodge a request of information for a borrower that did not necessarily apply for a loan at the bank. Thus, analyses using this data could result in a non-classical measurement error, potentially biasing the coefficient towards zero.

⁸The average value in this expanded database of variable $SameGroup$ is 0.491, with a standard deviation of 0.500.

umn 1, we present a benchmark specification in which we only control for the macroeconomic conditions in the region by adding year fixed effects. We find a very strong and positive effect of *SameGroup* on the creation of a new lending relationship: The coefficient is 0.006, and it is statistically significant at the 1% level. Economically, the coefficient is very relevant, as it corresponds to 36% of the average value of the dependent variable (0.014).

In columns 2 to 5, we include bank \times year fixed effects in vector X_{jt} . This allows us to control for all time-invariant and time-varying bank characteristics which may affect the supply of credit – including the banks’ lending technology and financial conditions, which were shown in the previous section to be correlated with cultural proximity. With these controls, the coefficient of *SameGroup* is only slightly changed relative to the one in column 1. In columns 3 to 5 of Table 5, we additionally include variables that affect the demand for new credit, X_{it} . Following Degryse et al. (2019), we control for credit demand using very granular sets of fixed effects which result from interacting several discrete variables. More precisely, in columns 3 and 5 we include industry \times location \times firm size \times firm age \times year fixed effects.⁹ In column 4, we control for all time-invariant and time-varying firm characteristics which may affect the demand for credit by adding firm \times year fixed effects (Khwaja and Mian, 2008). The coefficient for variable *SameGroup* increases relative to the ones in columns 1 to 3 with the inclusion of these demand-side controls.

One concern of the estimations in columns 1-4 is that firms might be more likely to demand credit from banks that are located in the closest vicinity within the local labor market

⁹Industry fixed effects are dummy variables corresponding to each of the 201 3-digit NACE industrial groups; location fixed effects are the 14 different local labor markets in the South Tyrol region; and we consider 4 equally-sized bins to control respectively for firm size and firm age. To preserve our sample size throughout specifications, we include one bin for missing firm size; results do not change if we exclude this category from the bins. In unreported specifications, we substitute the interacted fixed effects with controls for industry fixed effects, location fixed effects, year fixed effects, firm size, age, growth, and all measurable financial conditions. Results are also qualitatively unchanged.

(Petersen and Rajan, 2002; Degryse and Ongena, 2005; Alessandrini et al., 2009). To the extent that the banks closest to the firm belong to its same cultural group, the coefficient for *SameGroup* could be capturing this effect. To address this issue, we repeat the estimations of regressions 1-4 with the addition of a dummy variable *NearbyBranch_{ij}* which equals 1 if there is a branch of bank *j* operating in the close vicinity (i.e., in the same municipality) as firm *i*, and 0 otherwise.¹⁰ For the benefit of space, we only report the estimated coefficient corresponding to the regression in column 3 augmented with this variable; however, results are very similar (qualitatively and quantitatively) for all other specifications. As illustrated in column 5, the inclusion of this dummy has virtually no effect on the coefficient of variable *SameGroup*, implying that its importance cannot be explained away by the physical proximity to the lender bank.

Results from Table 5 show that firms are disproportionately more likely to apply for credit with same-culture banks and indicate that cultural proximity is an important determinant in lender selection. The high statistical and economic significance of the *SameGroup* variable coefficient survives to controlling for all possible time-invariant and time-varying factors that affect the supply and the demand for credit, and to the geographical distance between lenders and borrowers. The estimated coefficients are also economically significant, corresponding to 36 to 54% of the average value of the dependent variable.

To rule out that the significantly higher rate of loan applications to culturally-close banks observed in Table 5 is mechanically driven by the distribution of culture of banks and firms within the local labor market, we perform the following placebo simulation: We first randomly assign the cultural origin to firms and banks in our dataset, following their true population

¹⁰There are 116 municipalities in the South Tyrol region; thus, this geographical subdivision by municipalities achieves a much more granular subdivision of the region than the local labor market. The mean and standard deviation of variable *NearbyBank_{ijt}* in the estimation sample is 0.114 and 0.318, respectively.

distribution within the loan labor market area. Then, we estimate the specification in column 5 of Table 5 using the simulated culture of banks and firms in place of the true one. We repeat this exercise 200 times, and obtain the distribution of the estimated coefficients. Results are graphically shown in Figure 2. The distribution of the coefficient of $SameGroup_{ij}$ with random pair allocations is centered around zero, and several standard deviations away from the coefficient estimated in column 5 of Table 5. This finding leads us to reject the hypothesis that the analysis shown in Table 5 is mechanically biased, and confirms the central and unique role of cultural proximity in the demand for loans.

Another concern about the above results might be that the effects we identify are not driven by firms actively seeking loans from same-culture banks, but rather by banks being less likely to request credit checks on same-culture firms (for example, if the bank knows the firm better and hence does not require such information). This scenario could potentially lead to biases in our dependent variable. To test the idea that requests of information might be unbalanced for same- vs. different culture pairs, we compare, using a simple test of difference in means, whether the share of new credit relationships in the credit registry that are also observed in the SPI database is similar for bank-firm pairs of same vs. different cultural groups. We find that this is indeed the case: the p-value of the null hypothesis that the share is different is 0.795. In line with the almost negligible cost of requiring information about firms in the SPI, this result suggests that banks do not make distinctions when requiring information for firms of same and different cultures and provides further validation to our estimates.

4.2 Heterogeneity analysis of credit applications

By showing strong and significant effects of cultural proximity on loan applications, Table 5 highlights the existence of frictions that could potentially make credit markets transactions

deviate from the profit-maximization objective predicted by the neoclassical model.

In this section, we analyse these frictions in detail, regressing *LoanApplication* on interactions of *SameGroup* with standard measures of the firm’s opaqueness (size, age, and sales growth) and creditworthiness (profitability and risk). If speaking the same language and sharing a common set of behavioral rules and social conventions facilitates communication and thus reduces information asymmetries and search frictions, we should expect informationally opaque firms (younger, smaller, and growing firms, as discussed by Berger and Udell, 1998, 2002) to resort to same-group borrowing more often. On the other hand, if firms expect a favorable treatment from same-culture lenders due to taste-based preferences or in-group favoritism (Akerlof and Kranton, 2000), then we should observe that less profitable, or riskier, firms are more likely to apply for loans from an in-group bank.

We present the heterogeneous effects of cultural proximity on loan applications in Table 6. In all specifications of Table 6, we include all variables involved in the interaction term separately. We also account for macroeconomic conditions and supply of credit in the local area by adding industry \times location \times year fixed effects, and for the supply of credit by adding bank \times year fixed effects. Finally, we control for the geographical proximity between borrowers and lenders using variable *NearbyBranch*.

We first consider the effect of firm age and firm size on loan applications in columns 1 and 2 of Table 6, respectively. In column 1, we find that the uninteracted coefficient for age is positive and statistically significant. This result indicates that the demand for loans from banks of a different cultural group increases as the firms grow older. In addition, the negative and statistically significant coefficient for the interaction term shows that the difference between the demand for loans from banks of same vs. different cultural groups is reduced as the

firms mature. A similar picture emerges when we analyze, in column 2, the effect of size on requests for loans from new banks. In column 3, we consider size and age simultaneously and continue to find negative interaction terms of both variables with *SameGroup*. These results continue to hold when we control for firm growth and its interaction with *SameGroup*, in column 4. Moreover, the interaction of firm growth with *SameGroup* is positive and statistically significant.

The coefficients of the interaction terms with age, size, and firm growth all indicate that asymmetric information plays an important role in the selection of an in-group lender, and are in line with stylized facts 2 and 3. These results are consistent with an information asymmetries story whereby informationally opaque firms (young, small firms, or those with large sales growth) have the greatest benefits of applying for loans to same-group lenders, as cost of communication and search frictions are likely highest for these firms.

Columns 5 and 6 of Table 6 expand the heterogeneity analysis to test for possible favoritism by adding interactions of *SameGroup* with firm profitability and risk.¹¹ While the results discussed above for size and age continue to hold, we do not find that firm risk or lower profitability correlates significantly with selection to same-group banks. If anything, in column 5 we find that the interaction of firm profitability with *SameGroup* is positive and significant, indicating that better-quality firms are more likely to apply for loans to banks of the same culture.¹²

¹¹Information on firm profitability and quality is only available for approximately half of the firms in our sample. This explains the sharp drop in the number of observations for the analysis reported in column 5 and 6.

¹²Another way to see this is to use the sample of firms in the SPI database and compare the unconditional distribution of the profitability and the riskiness of those applying to same- versus different-culture banks. Figure 5 shows that the distribution of profitability is virtually identical, while the unconditional distribution of risk – a variable that correlates with size and age – is remarkably similar across the two groups.

Taken together, results from 6 indicate that information asymmetries and search costs represent the major market friction explaining the disproportionately higher share of firm’s loan applications to same-culture banks. In contrast, firms’ choices of lenders that share the same cultural identity does not seem to be motivated by the expectation of a preferential treatment.

To illustrate the effect of asymmetric information on loan applications, in Figures 3 and 4 we plot the marginal effects of firm age and firm size on the likelihood of applying for a loan from a bank of the same or of a different cultural group, using the estimates in columns 1 and 2 of Table 6, respectively. Essentially, these specifications capture changes in the preference for financing from different-culture banks during their life-cycle – i.e., as they grow older and larger, and hence, less opaque. The horizontal axis in Figure 3 corresponds to firm age (in years) and in Figure 4 to firm size (measured in number of employees).

Figure 3 shows a decreasing effect of age on demand for loans from new banks of the same culture (red line). The youngest firms in the sample are about 0.5 percentage points more likely to require a loan from a bank of their same cultural group than the oldest firms in the sample. As firms become more mature, the probability of requesting a new credit from a bank of a different group increases (blue dotted line). In fact, the youngest firms (i.e., the startups) virtually never seek a new relationship with a bank of a different cultural group, while the oldest firms are 0.4 percentage points more likely than startups to request a loan from a bank of a different group. As a consequence of these two results, the difference between asking for a new loan from a bank of the same versus a different cultural group is strongly reduced as firms mature (black dotted line).

Similar results emerge for firm size. Figure 4 shows a very steep upward-sloping relation between firm size and the probability of requesting a new loan from banks of a different group,

and a more gradual decrease in the likelihood of requesting a loan from a same-group bank as the firm grows larger. Similarly to what we observed for firm age, the smallest firms in the sample are also virtually unlikely to request a loan from a bank of a different group, and become increasingly more likely to do so as they grow larger. As it was the case with firm age, the difference between both lines is also decreasing with firm size, as seen by the dotted black line. Results in Figures 3 and 4 are consistent with information asymmetries playing an important role in firms' selection into same-culture lending relationships.

5 Cultural proximity and loan approvals

Our analysis of cultural proximity and loan applications shows that more informationally-opaque firms demand same-culture loans to a larger extent. Lack of evidence that less profitable and riskier firms seek same-culture loans indicates that firms do not expect a more favorable treatment by lenders that share their cultural background. Yet, banks may still exert favoritism in the loan approval process, in the form of granting preferential access to credit to same-culture firms. This may result into costly discrimination (Berkovec, Canner, Gabriel, and Hannan, 1998; Lu, Zhu, and Zhang, 2012) and less performing loans (D'Acunto, Ghosh, Jain, and Rossi, 2020).

In this section we extend our main results to assess the role of cultural proximity on banks' lending decisions, by restricting the credit registry dataset to all the firm-bank matches for which we have information on loan applications. This is used to study whether, conditional on receiving a loan request, banks are more likely to grant credit to firms from the same culture. We estimate the following equation through Ordinary Least Squares:

$$LoanApproval_{ijt} = \beta_0 + \beta_1 SameGroup_{ij} + \beta_2 X_{it} + \beta_3 X_{jt} + \beta_4 X_{ijt} + \epsilon_{ijt}, \quad (2)$$

where $LoanApproval_{ijt}$ is a dummy variable that equals one if bank j approves a credit re-

quest from firm i at time t , and zero otherwise. To construct this variable, we assign the value of one to all observations in the SPI database that eventually ended up in the credit registry, and a zero otherwise. Loan requests reported in the credit registry are informative of the formation of a credit relationship between a bank and a firm that most likely did not have a previous relationship, and hence are a good measure for the approval of a new loan application. X_{it} , X_{jt} , and X_{ijt} are firm-, bank-, and relationship-specific controls, respectively.

Results from estimating equation 2 are shown in Table 7. In column 1 of Table 7, the only controls added are year fixed effects. The coefficient in this simple specification suggests that the probability banks accept a loan request from a firm of the same cultural group is 3.9 percentage points significantly larger than from a firm of a different group. However, once we control for bank-year fixed effects (column 2), the coefficient of interest loses its statistical and economic significance. From the results in column 2, we cannot reject the hypothesis that cultural proximity does not matter for loan applications to turn successful. This result continues to hold after controlling for demand-side controls: industry-size-age-location-year fixed effects (columns 3 and 5) and firm-year fixed effects (column 4).¹³ The coefficient of $SameGroup_{ij}$ remains statistically and economically insignificant also after controlling for the availability of soft information potentially obtained through personal interactions, through the presence of a nearby branch (column 5).

The results in columns 2-5, which contain bank \times year fixed effects, indicate that, *within* the pool of loan applications a given bank receives, same-culture firms are not more likely to receive loan than different-culture firms. Thus, banks do not seem to favor firms belonging to the same cultural group when screening loan requests. Taken together, results from

¹³These estimations with firm fixed effects account for sample selection in loan applications.

Table 5 and 6 show that the cultural proximity is an important determinant of the choice of banking relationships when firms *apply* for loans. However, Table 7 shows that conditional on advancing a loan request (which, as we have seen, depends on culture), firms belonging to the same culture access credit with the same average probability as firms from a different culture.¹⁴

5.1 Heterogeneity analysis for loan approvals

The study of cultural proximity and loan approvals has shown that banks are not more likely, *on average*, to grant loans to same-culture firms. However, it is still possible that banks exert favoritism towards specific segments of borrowers, for example by approving loan requests from riskier firms. In this section, we test for heterogeneity in cultural proximity on loan approvals along the same firm characteristics studied for heterogeneity on loan applications.

Results are shown in Table 8. Mirroring the analysis reported in Table 6, we control for macroeconomic conditions and supply of credit in the local area by adding in all the specifications industry×location×year fixed effects, and by the supply of credit by adding bank×year fixed effects. We also include *NearbyBranch* as a proxy for the geographical distance between borrowers and lenders.

Results show that most of the characteristics we consider for heterogeneity analysis (firm size, sales growth, profitability and risk) do not affect the likelihood of approval for loans to same-culture firms. In fact, only the interaction of SameGroup and *Age* is statistically significant in columns 1 and 3, suggesting that same group banks are less likely to approve

¹⁴This is a relevant qualification to interpret our results. As we have seen in the previous section, culture is extremely relevant in the demand for loans. This implies that the loan approval process occurs in a selected sample. Stated in a different way, our coefficients in this section must be interpreted as a “treatment effect on the treated” rather than a (more general) “treatment effect” (Heckman, Urzua, and Vytlačil, 2006).

loans of older firms. However, this effect is not robust to inclusion of other firm controls such as growth, profitability or risk.

Taken together, results from Tables 6, 7 and 8 provide robust evidence that cultural proximity is an important determinant of the choice of banking relationships when firms apply for loans. Heterogeneity analysis on both loan applications and loan approvals indicate that informationally opaque firms are more likely to seek loans from culturally-close banks, but they do not expect more favorable treatment from culturally-close banks. Nor do banks favor culturally-close firms in accessing credit. These findings strengthen the hypothesis that the formation of culturally-close lending relationship is mostly driven by the demand side of credit.

5.2 Loan performance

An alternative interpretation of our results is that informationally opaque firms – whose underlying credit quality is more difficult to observe by the econometrician – are more likely to apply to same-culture banks because they expect to receive a preferential treatment. An implication of this favoritism story would be resource misallocation (Berkovec et al., 1998; D’Acunto et al., 2020), so these loans should perform worse.

We estimate the impact of cultural proximity on loan performance through Ordinary Least Squares using a similar equation as before:

$$Y_{ijt} = \beta_0 + \beta_1 \text{SameGroup}_{ij} + \beta_2 X_{it} + \beta_3 X_{jt} + \beta_4 X_{ijt} + \epsilon_{ijt}. \quad (3)$$

Here, Y_{ijt} is measured as a dummy equal to one if the loan is non-performing anytime in the

three-year period after it was granted.¹⁵ X_{it} , X_{jt} , and X_{ijt} are firm-, bank-, and relationship-specific controls, respectively.

We regress equation 3 on the original credit registry data, which contains all active bank-firm relationships during our sample period.¹⁶ Results are shown in Table 9. For consistency, each column in this table contains the same set of fixed effects as those in Tables 5 and 7. Here we would like to acknowledge – especially in light of the results from the previous sections – that this analysis is not free from sample selection issues. The inclusion of fixed effects allows us to mitigate these issues by comparing loan terms for groups of very similar firms, or – in our most stringent specifications – for the same firm applying to two banks in the same year, one of which is in the same culture and another in a different culture.

In Panel A of Table 9, we measure loan quality using non-performing loans (NPL), a dummy equal to one if bank j registered its loan with firm i in year t as a non-performing loan anytime between years t and $t + 3$.¹⁷ NPLs are a very broad definition that includes bad loans and loans with minor anomalies (such as unlikely to be repaid, overdues, etc.). According to Italian rules, the decision to register a bad loan is based on the banks' assessment of the borrower's economic situation. Thus, in principle, this variable could be influenced by the fact that banks and firms may belong to the same cultural group. To deal with this problem, in Panel B we exclude bad loans and we only use minor anomalies (a subset of NPLs which are less subject to the bank's assessment) as an alternative dependent variable.

¹⁵In case a firm has more than one loan outstanding with the same bank in a given year, we aggregate to the firm-bank-year level by adding the total granted amounts over all loans outstanding on that year, calculating the fraction of the approved amount that corresponds to term loans (long-term debt), assigning a value of one to the collateral dummy if the bank requires collateral on at least one of the firm's loans, or assigning the value one if at least one loan is non performing.

¹⁶Our analysis of loan terms contains all approved loans in the credit registry, and as such, the number of observations is larger than the sample in Table 7, which only considers applications for loans with banks that had no previous relationship with the firm.

¹⁷We use a three-year moving window because banks usually employ three years to actually report in their balance sheet a loan as non-performing.

Column 1 in Panel A shows that loans to same-culture firms are 1.6 percentage points less likely to be registered as non-performing than loans to different-culture firms. Economically, this corresponds to 15% of the average value of the dependent variable (0.101), and it is statistically significant at the 1% level. With the exception of column 4 – which, as mentioned before, consists of larger firms for which information asymmetries are likely to be less of a concern –, this result does not change qualitatively in the rest of specifications of Panel A. Panel B shows similar findings: when we concentrate on minor anomalies, the point estimate ranges between -8 and -18 percentage points, with a mean dependent variable equal to 8.7%.

Overall, results from Table 9 provide evidence of same-culture loans being on average significantly better performing than different-culture loans. These findings once more indicate that the self-selection of firms into same-group lending relationships helps banks gather additional information upon their perspective borrowers. This translates into a better screening of firms rather than fostering lending favoritism.

6 Robustness checks

In this final section, we discuss additional robustness checks that validate our findings.

6.1 Italian versus Germanic cultures

The sign and coefficient of $SameGroup_{ij}$ is positive and significant across all specifications of Table 5. Since we are considering two cultural groups in our paper (German and Italian), one may wonder whether our findings are culture-specific: if this were the case, we would not be capturing the effects of culture on loan applications and approvals, but rather the effect

of being German versus being Italian.

To rule out this hypothesis, we split the *SameGroup_{ij}* dummy into two indicators: *Italian Bank and Firm_{ij}* and *German Bank and Firm_{ij}*. We then regress Equation 1 on the two dummies, separately. Results from this analysis are shown in Table A3.¹⁸ The coefficients of both dummies are positive and significant, indicating that firms' selection into same-culture loans is not driven by one of the cultures.

6.2 Endogenous allocation of culture in South Tyrol

Another potential threat to the validity of our analysis is that our results are driven by specific local labour markets where the German versus Italian culture distributions are particularly skewed hence they might not be representative of South Tyrol as a whole. In fact, the Germanic population is overrepresented in many of the less populated cities in the mountain regions.

To rule out this hypothesis, we perform our analysis only in the local labour market areas of the two largest cities in South Tyrol (Bolzano and Merano). In addition to being large, the distribution of Italian and German populations is very homogeneous in these two cities. Results, reported in table A4, are economically and statistically similar to those shown in the paper.

A similar concern is that the set of industry \times location \times firm size \times firm age \times year fixed effects we use in our main specifications (Degryse et al., 2019) may underlie an uneven cultural distribution that could in turn bias our results. To account for this, we run our estimates

¹⁸For this particular regression we cannot estimate the coefficients with firm \times time fixed effects because this fixed effect perfectly determines the culture of the firm, and hence, whether the firm and bank pair is Italian or German.

excluding size, age, or industry groups with disproportionate shares of Italian versus German firms. Results from this robustness analysis are also reported in the appendix (table A5) and do not significantly differ from our main findings.

7 Conclusions

In this paper, we study the effect of culture in firms' borrowing decisions. For this purpose, we use a comprehensive dataset that contains all bank-firm relationships for the population of firms and banks that operate in a bi-cultural region in Italy. Most importantly, our database allows us to observe loan applications, the culture of the board members of banks and firms, and a large number of accounting variables about firms and loan outcomes.

Our analysis uncovers several novel facts. First, we find that firms are up to 52% more likely to apply for a loan with a bank of their same culture, than to apply with a different-culture bank. Second, we find that the larger propensity to apply for loans of the same cultural group is highest for relatively opaque borrowers, but loan applications to culturally proximate banks decrease sharply as firms become more transparent (as measured by size and age). In contrast, we find no evidence that firms with lower profitability or higher risk are more likely to apply for a loan with a same-culture lender. Third, conditional on loan applications, lenders are not more likely to approve loans from same-group borrowers relative to different-group borrowers. Fourth, loans to same-culture firms perform better.

Our findings suggests that firms endogenously self-select into same-culture relationships when they apply for credit, especially when information asymmetry and search frictions are high. Importantly, this endogenous selection into same-culture relationships is efficient, as it allows lenders to perform a better screening of the credit application and improve overall loan

performance. Our findings are not consistent with same-group lending leading to favoritism and resource misallocation.

To the best of our knowledge, ours is the first study to analyze the the selection of firms into culturally proximate lending relationships. Our paper allows us to qualify previous results in the literature, by showing that culture plays an active role in borrowers' selection of lenders, and that information asymmetries and search frictions are fundamental drivers of this selection. In turn, this leads to a more efficient screening process and allocation of resources, and ultimately, to better loan performance.

From a policy perspective, our findings highlight the importance of local banks in lending to small businesses (e.g., [Angelini, Di Salvo, and Ferri \(1998\)](#); [Alessandrini, Presbitero, and Zazzaro \(2009\)](#); [Barboni and Rossi \(2019\)](#)). By sharing the same culture as the firms in the markets where they operate, these financial intermediaries may play a key role in promoting access to credit, particularly for more informationally-opaque firms.

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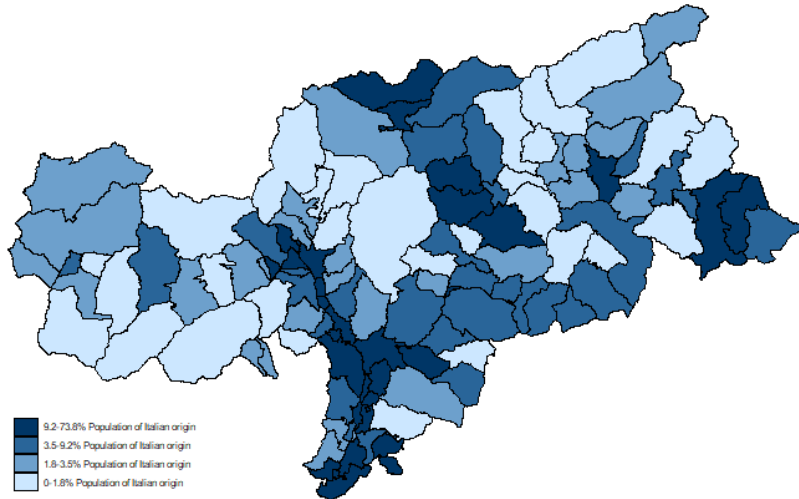
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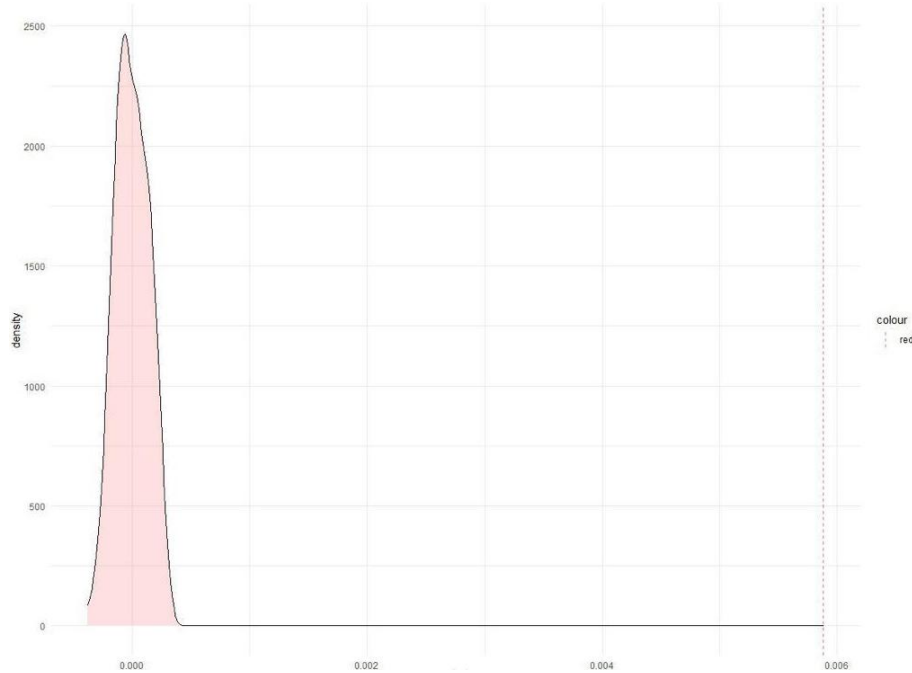
8 Figures and Tables

Figure 1: Geographic distribution of linguistic groups in South Tyrol.



Note: This figure shows the distribution (quartiles) of the Italian-speaking population by municipality in the South Tyrol, as reported by the 2011 Census (Istituto Provinciale di Statistica, 2015).

Figure 2: Placebo test with random assignment of culture



Note: The figure shows the results of the following placebo experiment: We randomly assign the culture of banks and firms in our sample, using the population distribution of the culture of banks and firms in each local labor market, and estimate Equation 1 using the resulting sample. We repeat this experiment 200 times. The figure shows the distribution of the estimated coefficients for variable *SameGroup* using the simulated samples. The vertical line at the right of the graph is the actual estimated coefficient using the true culture of the banks and firms in the sample.

Table 1: Descriptive statistics: Sample distribution

	No. of unique firms	No. of unique banks	Share of Italian firms	Share of Italian banks
2005	8213	174	0.25	0.672
2006	8503	189	0.248	0.693
2007	8693	197	0.249	0.695
2008	8728	208	0.244	0.712
2009	8413	217	0.243	0.737
2010	8409	225	0.241	0.751
2011	8258	223	0.236	0.749
2012	8019	226	0.231	0.757
2013	8046	222	0.232	0.739
2014	8134	219	0.233	0.744
2015	8150	224	0.233	0.754
Total	13469	361	0.233	0.754

Notes: This table contains a description of the number of firms and banks in our sample across the years, and their distribution across cultural groups. Authors' calculation on CR-Or.So.-Infocamere-INPS dataset.

Table 2: Descriptive statistics: Firm, bank & loan characteristics

	No. Obs.	Mean	St. dev.	p25	p50	p75	
A: CR data	<i>Firm characteristics</i>						
	Age (years)	91,190	15.584	13.386	6.000	13.000	23.000
	No. of employees	64,851	17.456	143.986	2.333	5.500	12.167
	Risk score	24,870	1.859	0.826	1.000	2.000	3.000
	Profitability	26,624	0.039	0.224	0.001	0.044	0.099
	Multi-borrowing	91,182	0.317	0.465	0	0	1.000
	Bank links	91,182	1.573	1.353	1.000	1.000	2.000
	Bank links in same group	91,182	1.143	1.096	1.000	1.000	1.000
	<i>Bank characteristics</i>						
	BCC	2,336	0.480	0.500	0	0	1.000
	$\log(\text{Total assets})$	1,913	20.939	2.027	19.354	20.708	22.450
	Capital to assets ratio	1,913	0.176	0.277	0.101	0.140	0.198
	NPL ratio	1,902	0.112	0.074	0.058	0.094	0.147
	<i>Loan characteristics</i>						
	Same group	143,422	0.727	0.446	0	1.000	1.000
	Nearby branch	143,594	0.732	0.443	0	1.000	1.000
	$\log(1 + \text{Length of relationship})$	143,594	1.861	0.837	1.386	2.079	2.485
	$\log(\text{granted loans})$	143,594	13.041	1.251	12.005	12.862	13.856
	Collateral	143,594	0.320	0.467	0	0	1.000
NPL	133,807	0.101	0.301	0	0	0	
Minor anomalies	133,807	0.087	0.282	0	0	0	
B: SPI data	<i>Firm characteristics</i>						
	Age (years)	24,058	13.845	13.842	4.000	10.000	21.000
	No. of employees	14,524	33.797	241.897	2.750	7.000	18.333
	Risk score	8,575	1.894	0.824	1.000	2.000	3.000
	Profitability	8,593	0.034	0.193	0.000	0.041	0.092
	No. of applications	24,058	1.684	1.335	1.000	1.000	2.000
	<i>Bank characteristics</i>						
	BCC	1,380	0.433	0.496	0	0	1.000
	$\log(\text{Total assets})$	1,191	21.184	2.191	19.261	20.953	22.972
	Capital to assets ratio	1,189	0.177	0.205	0.100	0.141	0.208
	NPL ratio	1,180	0.106	0.069	0.057	0.091	0.140
	<i>SPI inquiry characteristics</i>						
	Same group	31,190	0.594	0.491	0	1.000	1.000

Notes: This table contains summary statistics for the main variables used in our analysis. Panel A contains information taken from the credit registry (CR). The CR sample consists of all firm-bank-year observations for firms in the South Tyrol Region appearing in the credit registry between years 2005 and 2015 (i.e. having a loan). Panel B describes the SPI sample, consisting of all firm-bank-year observations for firms in the South Tyrol Region such that the bank has lodged an SPI inquiry for the firm in the credit registry between years 2005 and 2015. To calculate firm characteristics, we use a single observation per firm and year. *Profitability* is Earnings before interest and taxes (EBIT) divided by total assets. *Risk score* measures the risk of the firm in a scale of 1 (low risk) to 3 (high risk). *Multi-borrowing* is a dummy variable equal to one if the firm has multiple banking relationships. *Bank links* is the total number of bank relationships established by the firm during the year. *Bank links in the same group* is the total number of relationships with banks of the same cultural group established by the firm during the year. To calculate bank characteristics, we use a single observation per bank and year. *BCC* is a dummy variable taking a one if the bank is a credit cooperative, *Banca di Credito Cooperativo* (BCC). $\log(\text{Total assets})$ is the natural logarithm of total bank assets. *Capital to assets ratio* is the ratio between total capital and total bank assets. *NPL ratio* is the ratio of non performing loans (NPLs) to total loans. *Same group* is a dummy variable taking a one if the bank and the firm belong to the same cultural group, and zero otherwise. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. $\log(1 + \text{length of relationship})$ corresponds to the natural logarithm of one plus the length of the bank-firm relationship, measured in years since 1997. $\log(\text{granted loans})$ corresponds to the natural logarithm of the total amount of loans granted by the bank to the firm in each year. *Collateral* is a dummy taking the value of one if the loans were collateralized, zero otherwise. *NPL* is a dummy taking a value one if the loan is classified as non-performing, zero otherwise. *Minor anomalies* is a dummy taking value one if the loan is classified as unlikely to pay. Authors' calculation on CR-Or.So.-Infocamere-INPS dataset.

Table 3: Firm characteristics: Borrowing from banks of same versus different culture

Variable	All loans from a bank of same culture			At least one loan with a bank of different culture			p-value
	Mean (1)	St. dev. (2)	N (3)	Mean (4)	St. dev. (5)	N (6)	
Age	15.395	13.563	62,749	16.004	12.976	28,433	0.000
Size	9.696	15.658	44,295	18.028	31.124	20,555	0.000
Growth	0.135	0.795	42,741	0.123	0.774	19,823	0.085
Risk score	1.837	0.825	14,969	1.891	0.827	9,896	0.000
Profitability	0.046	0.143	14,995	0.037	0.130	9,905	0.000
# bank links	1.327	0.967	62,749	2.114	1.838	28,433	0.000
Rel. length	7.557	4.906	62,749	6.954	4.515	28433	0.000

Notes: The sample corresponds to firm-year observations of firms headquartered in the South Tyrol region and included in the Italian credit registry between years 2005 and 2015. Firms are classified into those that establish relationships only with banks of their same group (columns 1-3) and those that establish relationships at least with one bank of a different cultural group (columns 4-6). The p-value for the univariate test of difference in means is contained in the last column. *Age* is measured in years. *Size* is the natural logarithm of the number of employees. *Growth* corresponds to the yearly sales growth rate. *# bank links* corresponds to the total number of banks lending to the firm in each year. *Rel. length* corresponds to the average, across all banks lending to the firm in a given year, of the length of the relationship between the firm and the bank (number of years since 1997). Source: Authors' calculation on CR-Or.So.-Infocamere-INPS dataset.

Table 4: Bank characteristics: Lending to firms of same vs. different culture

Variable	Share of firms of same group above the median			Share of firms of same group below the median			p-value
	Mean (1)	St. dev. (2)	N (3)	Mean (4)	St. dev. (5)	N (6)	
Different group	0.024	0.048	1,155	0.633	0.283	1,146	0.000
BCC	0.652	0.477	1,155	0.312	0.464	1,181	0.000
Total assets	20.072	1.579	990	21.868	2.044	923	0.000
Total capital	17.857	1.364	990	19.394	1.819	923	0.000
Capital ratio	0.119	0.052	990	0.095	0.048	923	0.000
NPL ratio	0.109	0.070	981	0.115	0.079	921	0.096

Notes: The sample corresponds to bank-year observations of banks lending to firms located in the South Tyrol region and included in the Italian credit registry between years 2005 and 2015. Banks are classified into those that lend to a share of firms of the same cultural group that is above (columns 1-3) or below the yearly median (columns 4-6). The p-value for the univariate test of difference in means of each variable is contained in the last column. *Different group* is the share of firms from a different cultural group borrowing from the bank. *BCC* is a dummy variable equal to one for cooperative banks *Banca di Credito Cooperativo* (BCC). *Total assets* is the natural logarithm of total bank assets. *Total capital* is the natural logarithm of total bank capital. *Capital ratio* is the ratio of total capital to total assets. *NPL ratio* is the ratio of non-performing loans (NPL) to total loans. Source: Authors' calculation on CR-Or.So.-Infocamere-INPS dataset.

Table 5: Cultural proximity and new loan applications

	(1)	(2)	(3)	(4)	(5)
Same group	0.00562*** (27.56)	0.00515*** (27.70)	0.00620*** (28.22)	0.00755*** (27.41)	0.00588*** (26.97)
Nearby branch					0.0323*** (39.43)
Adj. R^2	0.001	0.095	0.094	0.092	0.098
No. Obs.	2710594	2710594	2710594	2710594	2710594
Dep. Var. Mean	0.0145	0.0145	0.0145	0.0145	0.0145
Fixed effects:					
Year	✓				
Bank-Year		✓	✓	✓	✓
Ind-Size-Age-Loc-Yr			✓		✓
Firm-Year				✓	

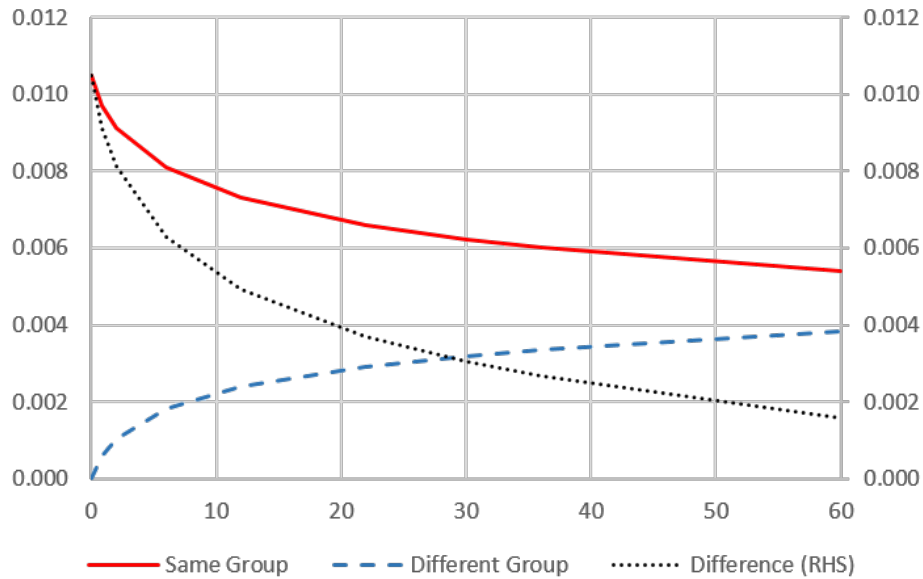
Notes: The sample consists of all firm-bank-pairs where the firm is located in the South Tyrol and the bank has a branch operating in the same local labor market as the firm between years 2005 and 2015. The dependent variable is *LoanApplication*, a dummy variable taking the value one if the bank lodged a request of information from the firm (as recorded in the SPI database), and zero otherwise. *Same group* is a dummy that equals one if the firm and the bank share the same cultural origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Ind* are 201 firm sector groups; *Size (Age)* are 4 equally-sized size (age) bins; *Loc* are indicators for 14 local labor markets. T-stats are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at bank-firm level.

Table 6: Cultural proximity and new loan applications: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Same group (SG)	0.0105*** (17.39)	0.0112*** (25.02)	0.0141*** (14.66)	0.0131*** (11.56)	0.0148*** (10.80)	0.0152*** (9.627)
SG × Age	-0.00217*** (-8.811)		-0.00124*** (-3.286)	-0.000479 (-1.142)	-0.00177*** (-3.279)	-0.00186*** (-3.396)
SG × Size		-0.00308*** (-15.71)	-0.00296*** (-14.65)	-0.00336*** (-15.17)	-0.00290*** (-9.625)	-0.00287*** (-9.430)
SG × Growth				0.000599*** (2.676)		
SG × Profitability					0.00640*** (2.677)	
SG × Medium Risk						-0.000434 (-0.487)
SG × High Risk						0.0000641 (0.0678)
Nearby branch	0.0317*** (38.95)	0.0318*** (28.47)	0.0318*** (28.46)	0.0302*** (25.86)	0.0214*** (14.39)	0.0214*** (14.38)
Uninteracted vars.	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.099	0.090	0.090	0.088	0.088	0.088
No. Obs.	2710594	1389694	1389694	1270239	647188	646221
Dep. Var. Mean	0.0145	0.0160	0.0160	0.0159	0.0157	0.0157
Fixed effects:						
Industry-Location-Year	✓	✓	✓	✓	✓	✓
Bank-Year	✓	✓	✓	✓	✓	✓

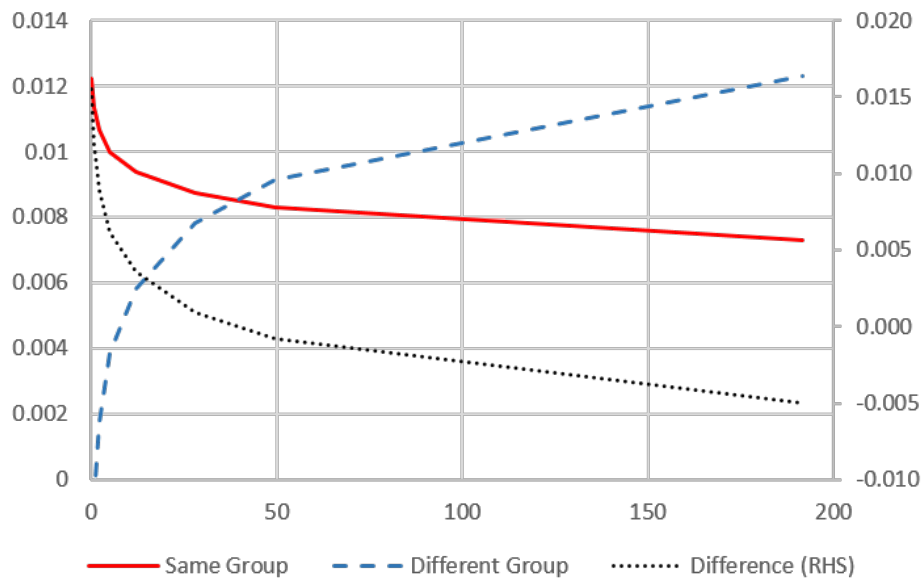
Notes: The sample consists of all firm-bank-pairs where the firm is located in the South Tyrol and the bank has a branch operating in the same local labor market as the firm between years 2005 and 2015. The dependent variable is *LoanApplication*, a dummy variable equal to one if the bank lodged a request of new information from the firm, and zero otherwise. *Age* is natural logarithm of the years of activity. *Size* is the natural logarithm of the number of employees. *Growth* corresponds to the yearly sales growth rate. *Same group* is a dummy that equals one if the firm and the bank share the same cultural origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Industry* are 201 firm sector groups and *Location* are indicators for 14 local labor markets. All other independent variables are defined in Table 3. Apart from the included variables, the regressions include the un-interacted variables which appear in the interaction term. T-stats are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at the bank-firm level.

Figure 3: Firm age and demand for loans from a new bank



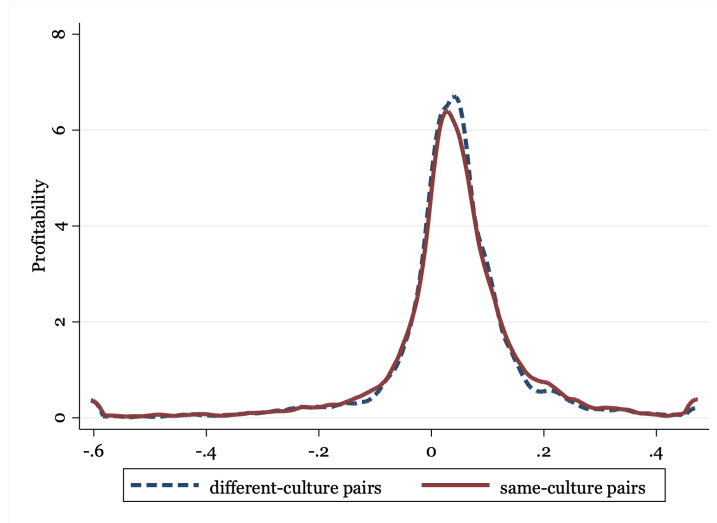
This figure shows the marginal effect of firm age (log of years of activity) on the demand for new loans from a bank of the same cultural group (solid red line) or from a bank from a different cultural group (broken blue line). The difference is represented by the dotted line. Estimated coefficients correspond to column 1 of Table 6.

Figure 4: Firm size and demand for loans from a new bank



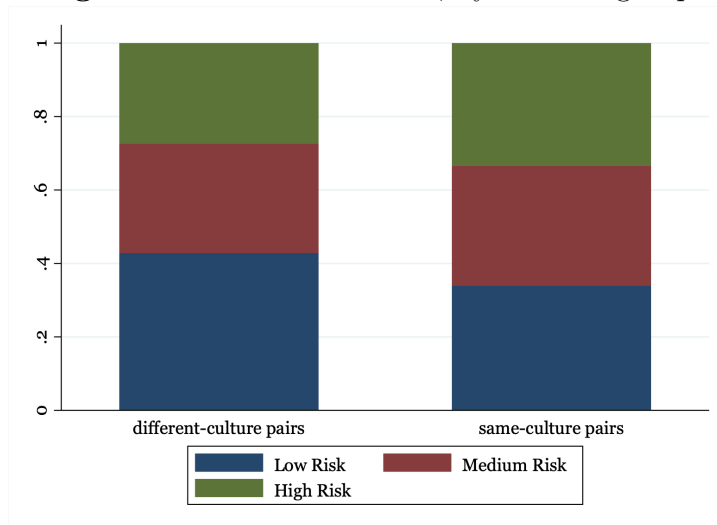
This figure shows the marginal effect of firm size (number of employees) on the demand for new loans from a bank of the same cultural group (solid red line) or from a bank from a different cultural group (broken blue line). The difference is represented by the dotted line. Estimated coefficients correspond to column 2 of Table 6.

Figure 5: Profitability of firms, by cultural group



Note: The figure shows the distribution of firm's profitability for firms applying to a loan to banks from a different cultural group (blue solid line), and banks from the same cultural group (red dotted line). The database corresponds to the SPI.

Figure 6: Riskiness of firms, by cultural group



Note: The figure shows the distribution of firm's risk (we identify three categories of risk: high, medium and low) for firms applying to a loan to banks from a different cultural group (blue solid line), and banks from the same cultural group (red dotted line). The database corresponds to the SPI.

Table 7: Cultural proximity and loan approvals

	(1)	(2)	(3)	(4)	(5)
Same group	0.0390*** (7.507)	-0.00337 (0.613)	-0.0114* (1.710)	0.000702 (0.0540)	-0.0110 (1.645)
Nearby branch					-0.0107 (1.332)
Adj. R^2	0.005	0.100	0.162	0.192	0.162
No. Obs.	31,190	30,830	25,613	11,662	25,613
Dep. Var. Mean	0.229	0.226	0.226	0.229	0.226
Fixed effects:					
Year	✓				
Bank-Year		✓	✓	✓	✓
Ind-Size-Age-Loc-Yr			✓		✓
Firm-Year				✓	

Notes: This table shows OLS estimates for Equation 2. The sample consists of firms-bank-year observations in the SPI dataset, indicating loan applications by firms to banks with which they had no prior relationship. The dependent variable is $LoanApproval_{ijt}$, a dummy that equals one if firm i has an outstanding credit relationship appearing in the credit registry with the bank in year t . *Same group* is a dummy that equals one if the firm and the bank share the same cultural origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Ind* are 201 firm sector groups; *Size* (*Age*) are 20 equally-sized size (age) bins; *Loc* are indicators for 14 local labor markets. T-stat are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at bank-firm level

Table 8: Cultural proximity and loan approvals: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Same group (SG)	0.0462*** (3.063)	0.000915 (0.0609)	0.0382 (1.612)	-0.0105 (-0.364)	0.00247 (0.0662)	0.0203 (0.442)
SG × Age	-0.0258*** (-4.402)		-0.0188** (-2.172)	0.00336 (0.330)	-0.00977 (-0.703)	-0.0101 (-0.717)
SG × Size		-0.00656 (-1.162)	-0.00461 (-0.804)	-0.00745 (-1.250)	0.00509 (0.560)	0.00214 (0.230)
SG × Growth				0.00624 (0.748)		
SG × Profitability					0.0359 (0.362)	
SG × Medium Risk						0.0254 (0.821)
SG × High Risk						-0.0449 (-1.403)
Nearby branch	-0.00151 (-0.198)	0.00205 (0.196)	0.00254 (0.246)	0.0000 (-0.00898)	0.0133 (0.795)	0.0127 (0.754)
Uninteracted vars.	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.152	0.125	0.143	0.130	0.175	0.175
No. Obs.	27789	16438	16431	14885	6813	6796
Dep. Var. Mean	0.228	0.252	0.252	0.227	0.238	0.237
Fixed effects:						
Industry-Location-Year	✓	✓	✓	✓	✓	✓
Bank-Year	✓	✓	✓	✓	✓	✓

Notes: The sample consists of all firm-bank-pairs where the firm is located in the South Tyrol and the bank has a branch operating in the same local labor market as the firm between years 2005 and 2015. The dependent variable is *LoanApprovals*, a dummy variable equal to one if the bank lodged a request of new information from the firm, and zero otherwise. *Age* is natural logarithm of the years of activity. *Size* is the natural logarithm of the number of employees. *Growth* corresponds to the yearly sales growth rate. *Same group* is a dummy that equals one if the firm and the bank share the same cultural origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Industry* are 201 firm sector groups and *Location* are indicators for 14 local labor markets. All other independent variables are defined in Table 3. Apart from the included variables, the regressions include the un-interacted variable in the interaction term. T-stats are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at the bank-firm level.

Table 9: Loan performance

	(1)	(2)	(3)	(4)	(5)
Panel A: Non Performing Loans (NPL)					
Same group	-0.0155*** (3.766)	-0.0225*** (4.923)	-0.0135*** (2.837)	0.00159 (0.357)	-0.0141*** (2.954)
Nearby branch					-0.0181*** (3.528)
Length relationship					0.0156*** (6.544)
Adj. R^2	0.004	0.016	0.157	0.565	0.158
No. Obs	133,669	132,991	117,048	72,367	117,048
Dep. Var. Mean	0.101	0.101	0.0992	0.0932	0.0992
Panel B: Minor Anomalies					
Same group	-0.00881** (2.304)	-0.0183*** (4.318)	-0.00992** (2.219)	0.00311 (0.663)	-0.00104* (2.330)
Nearby branch					-0.0132*** (2.716)
Length relationship					0.0134*** (5.936)
Adj. R^2	0.003	0.015	0.118	0.446	0.119
No. Obs	133,669	132,991	117,048	72,367	117,048
Dep. Var. Mean	0.0873	0.0872	0.0857	0.0781	0.0857
Fixed effects:					
Year	✓				
Bank-Year		✓	✓	✓	✓
Ind-Size-Age-Loc-Yr			✓		✓
Firm-Year				✓	

Notes: This table shows OLS estimates for Equation 2. The dependent variable in Panel A is a dummy that equals one if the loan granted by bank b to firm i is guaranteed by collateral. Mean dependent variable Panel A: 0.319. The dependent variable in Panel B is a dummy that equals one if the loan was signaled as Non Performing in the period $(t, t + 3)$. Mean dependent variable Panel B: 0.101. The dependent variable in Panel C is a dummy that equals one if the loan was signaled as a Minor Anomaly (overdue, unlikely to pay, etc.) in the period $(t, t + 3)$; minor anomalies are a subset of NPLs. Mean dependent variable in Panel C: 0.087. For Industry-Size-Age-Location-Year FE: 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 where the firm is located. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at bank-firm level

Online Appendix

A Classification of the manager’s cultural origin

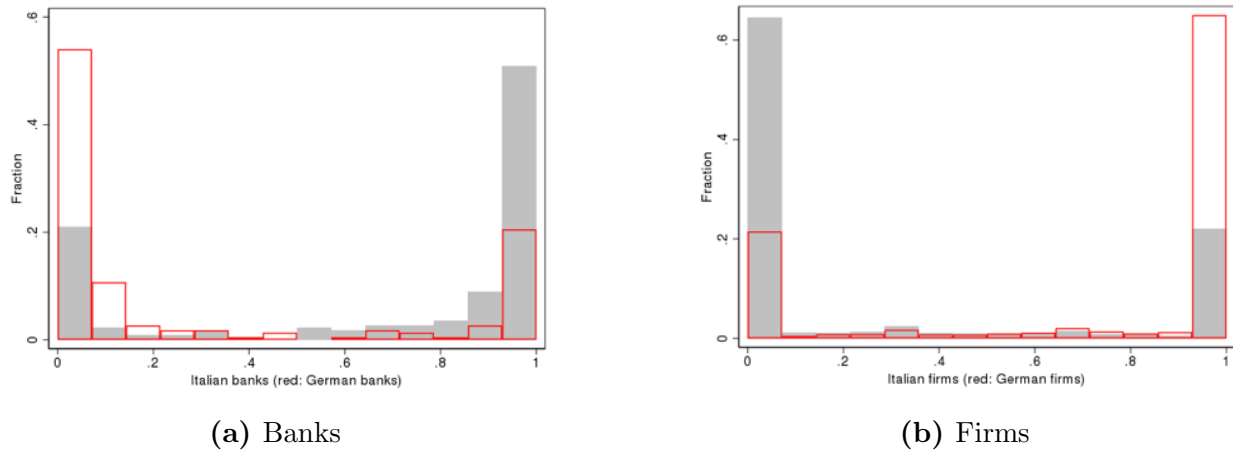
A crucial aspect in our analysis is to classify firms and banks into their cultural group, namely German and Italian. To establish whether firms and banks are of Germanic or Italian cultural origin we analyze their boards using a method akin to [Bedendo et al. \(2020\)](#).

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. 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. We then manually double-checked the allocation of each to the two categories to ensure that such requirement is satisfied.

[Bedendo et al. \(2020\)](#)’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 (both managers and shareholders). We use OR.SO. to retrieve names of 7,995 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. 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 a headquarter or a branch).

A firm or a bank are defined German (Italian) if the majority (50%+1) of its administrators are German (Italian). The choice of this threshold is basically inconsequential with respect to the robustness of the results. Figure A1 plots the share of Italian and German administrators for banks (Panel (A)) and firms (Panel (B)); both graphs show that the distribution of the share of Italian (or German) administrators is predominately bimodal. Both banks and firms have either 100% or 0% share of Italian (or German) administrators. This result suggests that the choice of different thresholds would leave the attribution of cultural origin at bank and firm level basically unchanged.

Figure A1: Share of German administrators in banks and firms



Notes: Authors' calculation on CR-OR.SO.-Infocamere-INPS dataset.

B Characteristics of same-culture relationships

Table A1: Firm characteristics and same-culture relationships

	(1)	(2)
Age (log)	-0.00369 (0.624)	-0.0412*** (4.167)
Size (log)	-0.0550*** (13.72)	-0.0779*** (11.98)
Growth	0.00476** (2.039)	0.00209 (0.528)
Tangibility		0.189*** (6.120)
Profitability		-0.225*** (3.777)
Leverage		-0.190*** (7.142)
Cash		0.165** (2.086)
Cash Flow		0.374*** (4.549)
Medium Risk		-0.0174 (1.142)
High Risk		-0.0228 (1.113)
Year FE	✓	✓
Industry FE	✓	✓
LLM FE	✓	✓
Observations	62,283	19,346
Adjusted R^2	0.128	0.151

Notes: The sample corresponds to firm-year observations of firms headquartered in the South Tyrol region and included in the Italian credit registry between years 2005 and 2015. Coefficients correspond to OLS estimates for a regression equation in which the dependent variable is a dummy that equals one if all of the firm's banking relationships correspond to banks of the same cultural group, 0 if the firm has at least one relationship with a bank of a different group. *Age* is the natural logarithm of one plus firm age (measured in years). *Size* is the natural logarithm of the number of employees of the firm. *Leverage* is the ratio of total debt to total assets. *Profitability* is the ratio of earnings before interest and taxes (EBIT) to total assets. *Tangibility* is the ratio of total fixed assets to total assets. *Cash* is the ratio of cash to total assets. *Cash flow* is the ratio of cash flows to total assets. Sector fixed effects (FE) are dummy variables indicating the industrial sector of the firm. LLM FE are 14 indicator variables for the local labor market where the firm is located. All other variables are defined in Table 3. T-statistics are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at firm level

Table A2: Bank characteristics and same-group relationships

	(1)	(2)
BCC	0.110*** (6.450)	0.113*** (6.797)
Total assets (log)	-0.0564*** (14.40)	-0.0466*** (12.06)
Capital ratio	1.515*** (10.50)	1.588*** (11.24)
ROA	1.216 (0.722)	2.042 (1.242)
ROE	0.0707 (0.494)	0.0115 (0.0822)
NPL ratio	-0.276*** (2.932)	-0.309*** (3.359)
Coverage ratio	0.144*** (3.462)	0.101** (2.477)
Year FE	✓	✓
LLM FE		✓
Observations	5,322	5,322
Adjusted R^2	0.296	0.331

Notes: The sample corresponds to bank-year observations for banks lending to firms headquartered in the South Tyrol and included in the Italian credit registry between years 2005 and 2015. Coefficients correspond to OLS estimates for a regression in which the dependent variable is the fraction of firms borrowing from the bank which belong to the same cultural group. *BCC* is a dummy variable taking a one if the bank is a credit cooperative (*Banca di Credito Cooperativo (BCC)*). *NPL ratio* is the ratio between non performing loans (NPL) and total loans. *Coverage ratio* is the ratio between credit risk adjustments and NPL. *ROA* is the ratio between bank net income and total assets. *ROE* is the ratio between net income and total equity. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at firm level

C Robustness checks and additional analysis

Table A3: Cultural proximity and new loan applications, Italian and German

	(1)	(2)	(3)	(4)
Italian bank and firm	0.00315*** (17.02)	0.00357*** (15.55)	0.00160*** (8.66)	0.00272*** (11.93)
German bank and firm	0.0118*** (22.87)	0.0114*** (21.48)	0.0136*** (26.02)	0.0121*** (22.84)
Nearby branch			0.0267*** (35.04)	0.0326*** (39.67)
Adj. R^2	0.095	0.095	0.098	0.098
No. Obs.	2710594	2710594	2710594	2710594
Dep. Var. Mean	0.0145	0.0145	0.0145	0.0145
Fixed effects:				
Bank-Year	✓	✓	✓	✓
Ind-Size-Age-Loc-Yr		✓		✓

Notes: The sample consists of all firm-bank-pairs where the firm is located in the South Tyrol and the bank has a branch operating in the same local labor market as the firm between years 2005 and 2015. The dependent variable is *LoanApplication*, a dummy variable taking the value one if the bank lodged a request of information from the firm (as recorded in the SPI database), and zero otherwise. *Italian bank and firm* is a dummy that equals one if both the firm and the bank are of Italian origin. *German bank and firm* is a dummy that equals one if both the firm and the bank are of German origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Ind* are 201 firm sector groups; *Size (Age)* are 4 equally-sized size (age) bins; *Loc* are indicators for 14 local labor markets. T-stats are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at bank-firm level.

Table A4: Cultural proximity and new loan applications, Bolzen and Merano

	(1)	(2)	(3)	(4)	(5)
Same group	0.00299*** (15.94)	0.00347*** (20.07)	0.00391*** (19.34)	0.00488*** (18.54)	0.00378*** (18.73)
Nearby branch					0.0200*** (23.89)
Adj. R^2	0.000	0.082	0.082	0.080	0.083
No. Obs.	2270346	2270346	2270346	2270346	2270346
Dep. Var. Mean	0.0104	0.0104	0.0104	0.0104	0.0104
Fixed effects:					
Year	✓				
Bank-Year		✓	✓	✓	✓
Ind-Size-Age-Loc-Yr			✓		✓
Firm-Year				✓	

Notes: The sample consists of all firm-bank-pairs where the firm is located in the South Tyrol and the bank has a branch operating in the same local labor market as the firm between years 2005 and 2015. The dependent variable is *LoanApplication*, a dummy variable taking the value one if the bank lodged a request of information from the firm (as recorded in the SPI database), and zero otherwise. *Same group* is a dummy that equals one if the firm and the bank share the same cultural origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Ind* are 201 firm sector groups; *Size (Age)* are 4 equally-sized size (age) bins; *Loc* are indicators for 14 local labor markets. T-stats are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at bank-firm level.

Table A5: Cultural proximity and new loan applications, accounting for cultural distribution

	(1)	(2)	(3)	(4)	(5)
Same group	0.00434*** (21.50)	0.00453*** (24.39)	0.00530*** (24.29)	0.00654*** (23.41)	0.00505*** (23.31)
Nearby branch					0.0303*** (35.65)
Adj. R^2	0.000	0.090	0.090	0.088	0.093
No. Obs.	2448420	2448420	2448420	2448420	2448420
Dep. Var. Mean	0.0129	0.0129	0.0129	0.0129	0.0129
Fixed effects:					
Year	✓				
Bank-Year		✓	✓	✓	✓
Ind-Size-Age-Loc-Yr			✓		✓
Firm-Year				✓	

Notes: The sample consists of all firm-bank-pairs where the firm is located in the South Tyrol and the bank has a branch operating in the same local labor market as the firm between years 2005 and 2015. The dependent variable is *LoanApplication*, a dummy variable taking the value one if the bank lodged a request of information from the firm (as recorded in the SPI database), and zero otherwise. *Same group* is a dummy that equals one if the firm and the bank share the same cultural origin. *Nearby branch* is an indicator variable for the existence of a bank branch in the same municipality as the firm. For the fixed effects: *Ind* are 201 firm sector groups; *Size (Age)* are 4 equally-sized size (age) bins; *Loc* are indicators for 14 local labor markets. T-stats are in parenthesis. *, **, *** denotes significance at the 10%; 5%; 1% level, respectively. Standard errors clustered at bank-firm level.