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Working Paper

2024-06

Once Upon a Loan: How Folk Tales Shape Access to Credit

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October 2024

Once Upon a Loan: How Folk Tales Shape Access to Credit⁺

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Abstract

We investigate the effect of folklore on firms' access to credit. Using firm-level data on a large sample of 38,000 firms covering 124 countries and 274 cultural societies over the 2005-2022 period, we test the hypothesis that oral traditions linking risk-taking to success or failure influence access to credit. We find that folklore affects access to credit. Oral traditions associated with successful challenges increase access to credit, while those associated with unsuccessful challenges decrease access to credit. We further show that folklore influences access to credit through borrower discouragement and loan approval.

JEL Codes: G21, O16, Z10, Z13

Keywords: culture, folklore, access to credit, borrower discouragement.

⁺ We thank Aurore Burietz-Barakat, Michael Troege, and participants in the 40th Symposium on Money Banking and Finance (Orléans, July 2024) for their helpful comments and suggestions.

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1. Introduction

Access to credit is a key driver of economic growth. By easing financing constraints, the availability of credit allows firms to make productive investments in physical capital, technology, and human resources that drive innovation and expansion. Empirical evidence shows that better access to credit enables firm creation, favors firm growth, and increases firm productivity (Gorodnichenko and Schnitzer, 2013; Popov, 2014; Rodriguez-Pose et al., 2021). Policy reforms that reduce credit constraints thus hold the promise of fueling broader economic growth.

A large strand of literature has therefore examined what shapes access to credit. It has extensively analyzed the impact of firm-level characteristics such as the gender of the owner (Asiedu et al., 2013), size (Angori et al., 2019) or firm ownership (Mertzanis, 2017). It has also identified the influence of national or regional characteristics like institutions and culture. Many works have already studied a large number of institutional features (such as corruption with Qi and Ongena, 2019, or regional favoritism with Osei-Tutu and Weill, 2024). However, only a few works have considered the potential impact of culture by focusing on two cultural aspects: trust (Guiso et al., 2004), and Hofstede's cultural dimensions with a particular focus on individualism versus collectivism (Osei-Tutu and Weill, 2023). In this paper, we aim to investigate the influence of folklore on access to credit.

We build on the recent work from Michalopoulos and Xue (2021), who examine how folklore influences economic outcomes and attitudes in contemporary societies. They define folklore as the “collection of traditional beliefs, customs, and stories of a community passed through the generations by word of mouth” (Michalopoulos and Xue, 2021, p. 1994). Building on the work of anthropologist Yuri Berezkin, they use a catalogue of oral traditions covering 958 societies for which 2,564 motifs (“a combination of images, episodes, or structural elements found in two or more texts, including sacred and profane ones”) have been identified. After showing that this catalogue reflects geographic and social attributes, they use a semantic network as well as human classification to infer cultural traits of the societies. They provide country-level evidence that oral traditions explain contemporary differences in terms of trust, gender bias, and risk-taking between societies. For example, with respect to risk-taking, they find that individuals are more risk-averse if they were raised on stories that portrayed competitions and challenges as more likely to be detrimental than advantageous.

Following the results of this article, we aim to provide an innovative perspective to the literature on access to credit by testing the hypothesis that folklore affects access to credit by influencing risk-taking behavior. Access to credit is conditional on loan approval of banks (loan supply) and on borrower discouragement (loan demand). On the one hand, access to credit depends on the willingness of banks to lend. Banks may be reluctant to lend to firms requesting loans, leading to reduced access to credit. On the other hand, access to credit also depends on the behavior of borrowers. Firms may refrain from applying for credit if they expect their loan application to be rejected. Thus, risk attitudes influence both dimensions of access to credit (loan approval and borrower discouragement). Increased risk aversion may reduce banks' willingness to grant loans and firms' willingness to apply for credit, while increased risk tolerance should produce the opposite effect.

Thus, we expect that oral traditions linking risk-taking to success will be associated with greater access to credit by promoting bank loan approval and reducing borrower discouragement. Conversely, oral traditions that associate risk-taking with failure should reduce access to credit.

To conduct our research, we use the dataset from Michalopoulos and Xue (2021), which provides information on folklore. Data are available for cultural groups for a set of 199 countries. The authors use motifs, which they define as “an episode or an image found in a set of narratives recorded in an ethnolinguistic community” (2021, p.1995), based on earlier work published by anthropologist Yuri Berezkin. Then, they break down risk-taking related motifs into groups, based on their outcome. For example, the main character(s) of a motif can either succeed or fail in taking up a challenge or competition. This leads the authors to describe a motif as either *successful* or *unsuccessful*. We use data on the share of motifs in a country that belong to the different occurrences of risk-taking behavior (such as rewarded with success, or not) to create variables that measure how folklore views risk-taking behavior.

We use firm-level data of the World Bank Enterprise Survey (WBES) to measure access to credit. Adopting the approach from Popov and Udell (2012) and Léon (2015), we define firms without access to credit as those that have applied for credit and been rejected, or that did not apply for credit because they were discouraged. This allows us to disentangle the effect of folklore on access to credit through loan approval by banks as well as borrower discouragement, and therefore to identify the mechanisms through which this effect occurs. By combining information on access to credit with data on oral traditions, we construct a final sample of 38,263 firms from 274 cultural groups in 124 countries over the period 2005-2022.

By way of preview, we find that folklore affects access to credit. Oral traditions related to challenge and competition have an impact on firms' credit constraints. The prevalence of successful challenges in a folklore increases access to credit, while more unsuccessful challenges decrease access to credit. We further find that the effect of folklore takes place through both borrower discouragement and loan approval, although the former is influenced by a wider range of oral traditions than the latter. We also document that folklore plays a greater role in access to credit for domestic firms than for foreign firms, consistent with the view that oral traditions exert a stronger influence on the local population. We thus conclude that traditional oral stories associated with challenge and competition do influence present-day attitudes to risk-taking.

Our paper contributes to the literature on the impact of culture on economic outcomes. By showing that folklore affects access to credit, we bring evidence that folklore can influence modern economic activities and attitudes in a society through the transmission of cultural values. This transmission can then lead to differences in economic development, given the key role of access to credit in economic development.

We also contribute to the nascent literature on folklore in economics by adding to the seminal work of Michalopoulos and Xue (2021) in two ways. First, we show that oral traditions associated with risk-taking influence access to credit. In doing so, we confirm their conclusion that folklore can affect economic outcomes. Second, we conduct a firm-level investigation with measures of folklore at the subnational level. We do not measure folklore at the country level, but examine folklore for each cultural group, taking into account the location of the firm. In comparison, Michalopoulos and Xue (2021) perform a country-level investigation. Thus, our estimations at a more disaggregated level allow us to test the relevance of their findings.

Finally, we contribute to the literature on the determinants of access to credit. This strand of the literature has identified a large number of determinants at the firm and country levels that help to understand credit constraints and design policies to improve access to credit. We add to this body of analysis by showing the long-lasting impact of folklore, bolstering the view that cultural factors can exert an impact on access to credit.

The rest of the paper is organized as follows. In Section 2, we present the background of the research question. Section 3 explains the data and methodology. Section 4 presents the main estimations. Section 5 contains the additional estimations. Section 6 presents the robustness checks. Section 7 concludes.

2. Background

2.1 A folklore and mythology catalog

To create a dataset on folklore suitable for a quantitative approach, Michalopoulos and Xue (2021) use the work of anthropologist and folklorist Yuri Berezkin who has conducted comprehensive studies on mythology and oral traditions around the world. He defines folklore as “all kinds of traditional stories and tales, long and short, sacred and profane” (Berezkin, 2015, p.58) that can be found in more than one cultural group. These stories are transmitted orally either vertically, from one generation to another, or horizontally, through communication and exchange between different groups. Research conducted by Spolaore and Wacziarg (2013) supports the existence of such a mechanism. For example, they explain that the vertical transmission of cultural traits through direct parents’ education or through complex symbolic systems (such as through religious institutions and education) may explain the direct effects of deep-rooted values and beliefs on contemporary economic outcomes. On the other hand, they also describe the horizontal transmission of traits as across populations and individuals that are not directly related.

To enable comparisons across cultures, Berezkin defines a set of “motifs” based on the content of multiple oral traditions. A motif is a text element, episode, or image “retold or described in narratives that are registered in at least two [...] different traditions” (Berezkin, 2015, p.61). For example, a widespread motif titled “Tasks of the in-laws” in Berezkin’s catalog is associated with the following description: “Father or other kinsmen of hero’s wife or bride try to kill or test him and/or suggest to him difficult tasks”. In total, Berezkin identifies 958 cultural societies across 199 countries from all continents, categorizing 2,564 motifs, with the median motif spanning 18 oral traditions and the median group comprising 62 motifs. Based on this information, it is therefore possible to store data on how many stories in a cultural group contain a particular motif, and therefore on the shares of motifs depicting any specific outcome of interest.

There are reasons to think that the motifs depicted in oral traditions still carry deep-rooted values and beliefs nowadays, although most of the materials used for Berezkin’s work comes from the early twentieth century. Indeed, a strand of the anthropology literature supports the idea that contemporary tales find their origin thousands of years ago. This means that their influence on a group’s set of values and beliefs should hold over long periods. For example, Silva and Jamshid (2016, p.8) use phylogenetic methods and autologistic modelling to show

that the Beauty and the Beast fairy tale “can be securely tracked back to [...] between 2500 and 6000 years ago”.

Furthermore, Michalopoulos and Xue (2021) show that the effect of folklore on contemporary economic outcomes is persistent over second-generation immigrants. Thus, the vertical transmission of cultural traits through oral traditions is resilient to the migration of individuals. Such a result further supports the idea that the sets of values and beliefs depicted in a folklore produce long-lasting effects on a population.

Thus, because the motifs depicted in oral traditions persist over millennia and migrations, they are most likely to carry representations of values and beliefs that are still characteristic of a cultural group nowadays. Furthermore, the tales present in folklore should also produce a direct effect on shaping groups’ cultural characteristics as they are still transmitted nowadays. This leads Michalopoulos and Xue to conclude that “images and episodes in folklore appear to endure and possibly still shape how individuals perceive the world today” (2021, p.2041).

Interestingly, Akerlof and Snower (2016) write on the role of narratives in shaping a society’s economic behaviours, through the historical case of the Bolshevik and Soviet telling of the revolution. They show that such narratives carry “categories”, mental images that are imperfect reflections of reality, but that allow individuals to perceive the world and make decisions through simplified processes. These categories are reminiscent of the motifs mentioned earlier in Berezkin’s catalogue of folklore, as Akerlof and Snower also show that they shape individuals’ mental representations.

2.2 Classifying motifs

In order to estimate the relationship between a country’s folklore and the contemporary values of its population, Michalopoulos and Xue (2021) first categorize the different motifs based on the attributes of interest they study. They focus on three cultural aspects: risk-taking, trust, and gender norms. Since they analyze the relationship between folklore and cultural variables at the country-level, they have to aggregate folklore measures on Berezkin’s societies to follow country borders.

First, they use *ConceptNet*, a semantic network able to find many different ideas related to any specific word. This tool establishes a list of the top-50 terms related to any seed concept. By doing so, it is possible to get how many motifs of Berezkin’s catalog are associated with a defined concept. For risk-taking, which we care about in our work, they use two seed words by choosing motifs whose description depicts a situation of *challenge* or *competition* as an indicator of the perception of risk in different cultures. For example, *Beauty and the Beast*

corresponds to the group in folkloristics referred to as *The Animal as Bridegroom* (Thompson, 1977), and in which a woman marries an animal that later turns out to be a human prince. In the folklore dataset, similar stories include the motif k56ab, which describes the tale of a snake who wants to marry a girl. However, she gets the animal to shed one of its skins each time she takes off one of her shirts. In the end, the snake runs out of skins before she runs out of clothes, and it turns it into a “handsome young man”. This motif matches one of the terms highlighted by *ConceptNet* as related to *challenge* or *competition*. In our example, therefore, the semantic network used in step one associated motif k56ab with risk-taking.

Then, the authors used human intelligence as well, by asking on average nine workers from Amazon Mechanical Turk (MTurks) to further categorize each motif designated by *ConceptNet* as being related to challenges and competitions. To ensure the quality of the data, the authors use modal answers allowing for multiple categorizations for a single motif, based on the four following possibilities. The workers can classify the outcome for the character(s) as *successful*, *unsuccessful*, or *unclear*. Otherwise, they also have the choice to contradict *ConceptNet* results by stating that the motif in question does not depict a situation related to challenges or competitions. In these cases, we further refer to such data as *N/A*. Still with our example, most of the MTurks classified motif k56ab as *successful*, in the sense that the main character of the tale succeeds in taking up a challenge or competition. Furthermore, they do not contradict the artificial intelligence, which confirms that this motif is indeed related to risk-taking.

This method applies to all motifs of the folklore dataset, which eventually provides us with the number of motifs in each cultural group that depict a situation of risk-taking, and characterized by its outcome. It is therefore possible to compute a share of *successful* or *unsuccessful* motifs for each culture, which we use as an indicator of risk-taking perceptions in a cultural society.

2.3 Folklore, risk-taking, and access to credit

By measuring the share of motifs on challenges and competitions depicting every type of outcome, Michalopoulos and Xue (2021) are able to build six variables. First, they compute the percentage of motifs in a country related to this theme (*All*). Then, they compute a share for each of the three outcomes (*Successful*, *Unsuccessful*, and *Unclear*). Furthermore, the proportion of motifs considered by the workers not to describe challenges or competitions is also available (*N/A*). Finally, they construct a relative variable that is equal to the proportion of

unsuccessful motifs from which they subtract the percentage of those where the outcome is successful or unclear, which they name the *Relatively unsuccessful* variable.

The authors then run regressions of three country-level risk-taking measures on these six variables. They consider the Global Preference Survey (GPS) risk-taking score, which is a survey-based measure of risk preference provided by Falk et al. (2018), the number of new business registration per capita, and the number of patents per capita.

They consider all folklore variables to explain the GPS risk-taking score. They find that a higher share of motifs that depict a situation of challenge or competition where the character is successful is associated with a higher GPS risk-taking score. However, a more important percentage of motifs characterized by an unsuccessful outcome is not significantly associated with a lower Global Preference Survey score. Thus, their results already suggest that the effects of the successful and unsuccessful representations of the outcomes for these motifs may not be symmetrical.

They concentrate on the single relative folklore measure, the *Relatively unsuccessful* variable, to explain the two other risk-taking measures, the number of new business registrations per capita, and the number of patents per capita. For both variables, they find that a more important percentage of motifs characterized by an unsuccessful outcome relative to motifs characterized by a successful outcome exerts a significant and negative impact. In other words, country-level cultural groups characterized by the prevalence of relatively more unsuccessful motifs are more risk-averse nowadays.

Thus, Michalopoulos and Xue (2021) provide support that oral traditions associated with risk-taking do influence entrepreneurship and innovation at the country-level. It is therefore possible to measure the cultural level of risk-taking using folklore data. To this extent, a comparison of different groups at the country-level allows for their relative categorisation as more or less risk-loving or risk-averse. We extend their work in our research by examining the impact of folklore on access to credit, using economic data at the firm-level and folklore data at the cultural society level.

Thus, groups whose folklore displays a lower degree of risk-aversion through narrating tales of success should have a higher propensity to ask for credit, and therefore lower borrower discouragement. We also expect folklore to influence banks by increasing their tendency to grant loans. Still, we first expected the supply side to be less sensitive to this effect compared to borrowers. Conversely, groups whose folklore reports a higher degree of risk aversion with the narration of tales of failure should have higher borrower discouragement and lower bank loan approval.

3. Data and methodology

3.1 Data

To examine how folklore affects access to credit, we combine firm-level data on access to credit from the World Bank Enterprises Survey (WBES) with data on folklore from Michalopoulos and Xue (2021). Using a firm's location, we can match it with the closest cultural society using Berzkin's coordinates of the *centroids* of each folklore group to compute a geographical distance. Doing so, we take advantage of the granularity of the cultural data at the subnational level without aggregating it at the country-level.

Our final sample consists of a maximum of 38,263 firms from 124 countries over the period 2005-2022. The size of the initial WBES sample of 195,824 observations diminishes for several reasons. First, the survey screeners record how they rate the answers of the respondent as either trustful, somewhat truthful, or untruthful. Thus, we keep only those observations for which the level of reliability is the highest, which reduces the sample size to 121,753. Second, we drop observations for which the information on the dependent variable is not available. There are many cases where a respondent provides information for only one or two of the dependent variables, which explains why the samples for each dependent variable are of different sizes. We further decide not to include observations for which data are available for the loan application variable but not for the credit constraints one. Third, we keep only those observations for which control variables are available. Overall, we end up with 38,263 observations for these two dependent variables, and a sample size of 19,715 for the loan approval variable for which the number of available observations is much smaller.

3.2 Measuring access to credit

To measure access to credit, we follow the approach developed by Popov and Udell (2012) and extended by Léon (2015). We refer to a series of questions about the credit experience of firms in WBES.

We exclude firms without a need for loans because it is impossible to know whether these firms are constrained or not. A firm is defined as credit-constrained if it applied for a loan and was denied or did not apply for credit because it felt discouraged. Firms with approved credit applications are classified as credit-unconstrained. We then create the variable *Constrained* as a dummy equal to one if the firm is credit-constrained, and zero otherwise.

We construct two additional variables to examine whether credit constraints are influenced by loan approval, borrower discouragement, or both. We construct the variable *Apply* as a dummy equal to one if the firm needed a loan and made a formal loan application, and zero if the firm needed a loan but did not apply because it was discouraged. This variable takes borrower discouragement into account. We capture loan approval by constructing the variable *Approved* as a dummy equal to one if the firm applied for loan and was approved, and zero if the firm's loan application was turned down.

3.3 Measuring folklore

We measure folklore variables, using data on folklore gathered by Berezkin (2015). We define them following the work of Michalopoulos and Xue (2021) with the aim of capturing the culture-specific characteristics that reflect the degree of risk-loving or risk-aversion.

As explained in the previous section, oral traditions are categorized based on the motifs depicted in each oral tradition. We therefore define six independent variables based on the classification used by Michalopoulos and Xue (2021).

First, they construct the *Success* and *Not success* variables, which correspond to the share of motifs in a cultural group in which a character faces a situation of challenge or competition, and whose outcome is successful or unsuccessful, respectively.

Second, they define the *Unclear* variable as the share of motifs for which it is not possible to categorize the outcome for a character as successful or unsuccessful. In addition, they construct a *N/A* predictor that corresponds to the share of motifs that semantic network methods classified as related to risk-taking, while human categorization contradicts this classification. Furthermore, we follow their approach and create an *All* variable, which is the share of motifs that belong to the first four predictors we mentioned just above. In other words, the *All* predictor tells us about the overall focus of a folklore on risk-taking, without any insight on the outcome of the motifs. To express all variables as shares, we divide the number of motifs for each of these categories by the total number of motifs identified in a culture. In this way, each variable is less sensitive to the differences in the total number of motifs collected for each group. For example, the *Udin* society, located in Azerbaijan, is one of the most risk-loving cultural groups in our final sample, with 14.29% of motifs that depict a successful challenge. Oppositely, the most risk-averse one is the *Kariri* group, located in Brazil, and for which 11.11% of its total motifs tell stories of failures in a context of challenge and competition.

Finally, we follow the authors and provide an alternative and unique measure by constructing a relative variable that we call *Relatively unsuccessful*. It corresponds to the share

of challenge-related motifs with an unsuccessful outcome, from which we subtract both those with a successful outcome and those with an unclear outcome. In other words, *Relatively unsuccessful* is equal to *Not successful* from which we subtract *Successful* and *Unclear*.

Although the median number of motifs is between 100 and 117 depending on the dependent variable, the lowest percentiles include companies belonging to cultures where the total number of registered motifs is less than or equal to six. However, this does not introduce much skewness anyway in the distribution of the data for the main predictors, since there are no motifs about challenge and competition in these cultures. Nevertheless, this motivates us to perform a robustness test using a sample where we remove the observations associated with folklores from the lowest decile of observations based on their total number of motifs.

3.4 Methodology

To test the hypothesis that folklore affects access to credit, we estimate probit regressions with the following model specification:

$$P(Y_{ik} = 1) = \phi(\alpha + \beta.Folklore_{ik} + \delta.Controls_{ik} + \varepsilon_{ik})$$

Where i is the firm, k the society, Y_{ik} the dependent variable (*Constrained*, *Apply*, or *Approved*), $Controls_{ik}$ the set of control variables, ϕ the cumulative distribution function of the standard normal distribution, and ε_{ik} the error term. For each country, we can have from one to seven surveys in WBES. We therefore include year fixed effects to capture any exogenous shock on one specific year.

A potential source of concern is that our results could be subject to endogeneity. Our research question avoids the concern of reverse causality since folklore pre-dates access to credit. Data on access to credit are for the two last decades, while Berezkin (2015) used sources from the early twentieth century to encode all motifs from oral traditions. Regarding omitted variables bias, the inclusion of a large set of variables at the firm, centroid¹, and country levels should capture the effect of several unobserved characteristics. Still, we perform a robustness test to remedy any potential endogeneity bias, notably due to a potential omitted variable effect.

The independent set of variables of interest is $Folklore_{ik}$. We consider the specifications of Michalopoulos and Xue (2021) for this set of variables. As explained earlier, they construct different variables based on the outcome of the risk-related motifs, and express them in terms

¹ Centroid means subnational in the sense that it takes place at the cultural society level.

of share with respect to the total number of motifs recorded in a cultural group. Doing so, they consider three specifications.

In the first specification, we use only the *All* variable, as a way to estimate the effect of the overall focus on folklore. In the second specification, we use the variables *Success*, *Not success*, *Unclear*, and *N/A* for folklore, in order to identify the specific effect of the outcome on access to credit. Including the shares of motifs for which the outcome (*Unclear*) or topic (*N/A*) is uncertain allows us to separate these effects from the two first variables to get more accurate estimates. In the third specification, we also use a single measure of a cultural group's relative risk-aversion using *Relatively unsuccessful*. Although this specification should not yield very different results with respect to the second one, we follow the authors' methodology to make our final estimates comparable. This is also a more synthetic measure of folklore, as it comprises a single predictor that tells us directly about both risk-loving and risk-averse characteristics of a culture. Furthermore, this allows us to verify our estimates by comparing the results for the second and third specifications.

Following previous works on the determinants of access to credit (Popov and Udell, 2012; Léon, 2015; Osei-Tutu and Weill, 2023, 2024), we include three types of control variables at the firm, subnational, and country levels.

For firm controls, we calculate the *Sales growth* of a company using its reported sales on the most recent three-year period. Since some of the recorded data are well above a 100% growth rate², while the minimum possible negative rate is 100%, we winsorize the 2% most extreme value in the right tail of the distribution. Thus, we rule out the bias introduced by these outliers, without eliminating the reported data that the survey screeners deemed reliable, and that indicate high sales growth dynamics for these firms. We also compute the *Age* of the company, by subtracting the year of incorporation from the last complete fiscal year, which is often approximated using the year preceding the survey date. We consider *Size* with the natural logarithm of the number of full-time permanent employees. We take into account the *Experience* of the manager with the number of years the manager has been in the industry. To control for firm ownership, we include dummies equal to one if the firm is *Sole proprietorship*, *Private or non-traded*, *Publicly traded*, and *Foreign-owned*, and zero otherwise. We also include dummies equal to one if the firm's financial statements are audited (*Audited*), whether the firm is an exporter (*Exporter*), and if the firm belongs to a larger group (*Subsidiary*). We also include the degree of perceived competition with *Competition*, which indicates on a range

² Some reported sales growth data over this three-year period reach an abnormal $3 * 10^{11}$ percent rate.

from 0 to 4 how much the firm perceives competition as an obstacle. We control for the industry with dummies equal to one if the firm is in *Manufacturing* or *Retail*. Finally, we use the perceived corruption to construct the *Corruption* dummy, equal to one if the firm considers corruption as either a major or severe obstacle to its operations. All variables are defined in the Appendix.

We create three subnational controls at the centroid-level to take into account cross-regional differences within countries that may affect access to credit as in Osei-Tutu and Weill (2024). We assign the location of each firm to a cultural group by computing the shortest distance between the coordinates of the city where the firm is located and the coordinates of all cultural “centres”. This is possible because Berezkin (2015) defined centroids for each culture, all of which are associated with a latitude and longitude. For each firm, we use the coordinates of the largest administrative and population centres of a region if the exact name of the city where the firm is located is not available. Thus, we assign each observation to a cultural group, which means that our predictors use folklore data at the subnational level, which in this case we call the “centroid level”, using Berezkin (2015)’s terminology. In fact, oral traditions do not necessarily follow national borders. Importantly, the distribution of the different centroid locations in the world is sufficiently diverse to ensure the relevance of our matching method³. Therefore, our approach should improve the quality of our results compared to an aggregated country-level analysis, which helps to extend the work of Michalopoulos and Xue (2021). However, this means that we also need a set of centroid-level controls to avoid any bias when estimating the coefficients of our folklore variables.

We choose to compute them based on the available WBES data by computing a group mean for each culture. Thus, we use the winsorized three-year sales growth data at the firm-level to construct an *Growth centroid* variable by computing a mean rate by cultural group. Similarly, we create the variable *Informal credit centroid*, defined as the percentage of firms in a centroid whose share of working capital or fixed assets funded by moneylenders, friends, or relatives is greater than zero. Again, we need to winsorize 1% of the observations in the right tail of the distribution to remove the unwanted skewness effect of outliers, since some cultures have only a small number of firms for which such information is available. This allows us to retain the insight they bring to their cultural group, here that their informal credit level is high, without keeping extreme positive values that introduce a bias into our estimates. Finally, we construct an *Electricity centroid* variable to account for the level of development of the

³ See Figure 1 of groups in Berezkin’s catalogue (Michalopoulos and Xue, 2021, p.1997).

electricity grid and infrastructures in the region of the respondent. To do this, we use WBES data on the perceived degree of difficulty related to access to electricity for firms, ranging from 0 (“no obstacle”) to 4 (“very severe obstacle”). Thus, we calculate the median by group and round it down to the nearest unit, following a conservative approach.

Finally, we include country-level controls to capture country-specific characteristics. We consider two macroeconomic variables that reflect the short-term economic situation (*GDP growth*, *Inflation*). We take into account economic development with the natural logarithm of income per capita (*GDP per capita*) and financial development with the ratio of domestic credit to the private sector to GDP (*Credit to GDP*). All of these country-level variables come from the World Development Indicators. Finally, we include *Rule of law*, extracted from the World Governance Indicators, to capture the quality of institutions. We rescale this indicator from an initial range of -2.5 to 2.5 to a range of 0 to 10, to allow for a better reading of the results. Descriptive statistics for all variables are reported in Table 1.

4. Results

4.1 Main estimations

We display the main estimations for the effect of folklore on access to credit in Table 2. To examine whether folklore affects access to credit, we consider the three specifications adopted by Michalopoulos and Xue (2021) for the set of folklore variables. In column (1), we include *All* to take into account all motifs related to challenge and competition. In column (2), we consider *Success*, *Not success*, *Unclear*, and *N/A* to distinguish between the different outcomes of tales. We include *Unclear* and *N/A* to be consistent with Michalopoulos and Xue (2021) and to better isolate the effects of *Success* and *Not success*. Although these predictors are less straightforward to understand, they represent information on folklore that we can use to disentangle the effects between our different main cultural variables. Still, we do not develop the interpretation of *Unclear* and *N/A* because they are not easily interpretable with respect to our key hypothesis. In column (3), we use the single measure of the outcome of challenges and competitions *Relatively unsuccessful*, which assesses relative risk aversion.

We start the analysis of the results by considering the first specification. We find that *All* is significantly negative, meaning that firms belonging to cultural groups characterized by a higher focus on challenge and competition are less likely to be credit constrained. Thus, the mere mention of tales associated with challenge and competition affects access to credit.

We can then question whether the effect of oral traditions on access to credit is conditional on the outcome of tales. The results of the second and third specifications answer this question. In the second specification, we observe that *Success* is significantly negative while *Not success* is significantly positive. These results mean that a higher share of motifs in which the outcome for the character is successful promotes access to credit, while reversely a higher share of motifs in which the outcome for the character is unsuccessful hinders access to credit. The results of the third specification confirm these findings. We observe that the single measure *Relatively unsuccessful* is significantly positive. This means that increasing the relative share of motifs with failures compared to motifs with success leads to lower access to credit. These results are also economically significant, since a 1% increase in the share of successful motifs in a folklore is associated with a 1.02 percentage points decrease in the probability for a firm to be credit constrained. On the other hand, the effect of a more risk-averse folklore is less important, as a 1% increase in the share of unsuccessful motifs translates into a rise of 0.45 percentage point in the probability of suffering from credit constraints.

Therefore, our main finding is that folklore affects access to credit. The outcome of oral traditions in tales related to challenge and competition affects credit constraints of firms. More successful challenges lead to wider access to credit, consistent with the view that they lead to higher risk tolerance. Conversely, more unsuccessful challenges lead to lower access to credit by increasing risk aversion for symmetric reasons.

Overall, our results validate the hypotheses with respect to the role played by folklore in explaining access to credit. They are consistent with the conclusion of Michalopoulos and Xue (2021) that the deep-rooted values and beliefs carried by folklore are associated with contemporary economic outcomes and attitudes.

4.2 Exploring the channels of folklore

Our main estimations have shown that folklore affects access to credit. We explore this evidence in more detail by examining the channels through which this effect works. We aim to know whether the transmission goes through the loan approval channel, by increasing the number of loan applications approved by banks, and/or through the borrower discouragement channel, by encouraging firms to apply for loans. Greater access to credit can result from differences in loan approval by banks but also from differences in expectations of loan approval for firms.

The literature has shown that borrower discouragement plays an equally if not more important role in limiting access to credit (Brown et al., 2011; Chakravarty and Xiang, 2013).

In our sample, borrower discouragement was pervasive, with 52.4% of firms in need of loan refusing loan applications. This discouragement effect suppressed lending, as the rejection rate was much lower in practice, with 83.7% of actual applicants successfully obtaining loans.

We first examine whether folklore influences firms' decision to apply for a loan. A firm associated with a folklore whose stories depict heroes who successfully overcome challenging situations can feel less discouraged from applying for credit. Conversely, the firm manager can feel more discouraged if he brought up with stories in which challenges cause more harm than good.

To test these hypotheses, we rerun our estimations by using *Apply* as the dependent variable. We consider the same specifications of the set of folklore variables than above. We report the results in Table 3.

We observe that *All* is significantly positive. Thus, oral traditions that describe competitions without specifying an outcome increase the willingness of firms to apply for a loan. We find significant coefficients for *Success* as positive and for *Not success* as negative in the second specification, and a significantly negative coefficient for *Relatively unsuccessful* in the third specification. These results imply that firms located in societies with more stories associated with success are more likely to apply for a loan, while firms located in societies with more stories associated with failure are more discouraged from applying for a loan.

Thus, we find clear support for the view that folklore affects access to credit by discouraging borrowers. The presence of oral traditions associated with challenge and competition in a cultural society affects the perceptions of borrowing firms by influencing their decision to apply for a loan.

We now examine whether folklore exerts an impact on the banks' decision to approve loans. We test whether bankers are influenced by oral traditions in the same way as firm managers in their lending behavior. Higher risk tolerance should lead to more loan approvals, while higher risk aversion should lead to more loan rejections.

We investigate these hypotheses by redoing our estimations with *Approved* as the dependent variable. We again consider the three specifications of the set of folklore variables. We display the estimations in Table 4.

As a first result, *All* is significantly positive, supporting the view that a greater presence of oral traditions associated with challenge and competition increases the likelihood that banks will approve a loan. Looking at the outcome of the tales, *Success* is significantly positive while *Not success* is not significant. This result is particularly interesting: it means that oral traditions associated with success affect bank behavior by increasing loan approval, but oral traditions

associated with failure do not influence bank behavior. In other words, folklore affects bank behavior but only through stories of success. Bankers are insensitive to stories in which the challenge is harmful. Moreover, we find that *Relatively unsuccessful* is significantly negative. Given the construction of *Relatively unsuccessful*, we can explain this result by the findings obtained for *Success* and *Not success*.

We show that folklore affects access to credit through its impact on bank loan approval. Oral traditions in which heroes successfully tackle challenging situations increase the likelihood that banks will grant loans.

Taken together, these patterns offer important conclusions. They reveal that folklore affects access to credit through borrower discouragement and loan approval. Both channels are important in the relation between folklore and access to credit. However, borrower discouragement is affected by oral traditions that emphasize success and failure, while only tales in which challenge is rewarded with success influence loan approval. Firm managers appear to be more influenced by tales of challenge when applying for a loan than bankers are when deciding on a loan approval.

4.3 Additional estimations

The results reported so far show the influence of folklore on access to credit. However, we have conducted our analysis for all types of firms without taking into account the fact that this effect can differ across firms. Therefore, we now investigate the influence of three firm-level characteristics: having audited financial statements, being foreign-owned, and firm size.

For these estimations, we consider only the second specification of the set of folklore variables, meaning the one that includes four variables (*Success*, *Not success*, *Unclear*, and *N/A*). As explained earlier, we focus our comments on *Success* and *Not success*. *Unclear* and *N/A* are less straightforward to interpret, but their inclusion in the estimations allows us to better isolate the effects of the other two key variables.

First, we examine the effect of providing audited financial statements. We have found evidence that tales associated with challenge affect access to credit by influencing borrower discouragement and bank loan approval. We ask whether providing audited financial statements can help rule out the effects of culture on access to credit. The idea is that the influence of folklore could be stronger for non-audited firms. Greater information availability through audited financial statements should reduce risk-taking behavior of the borrower in applying for a loan and of the bank in approving a loan. Therefore, the cultural influence of folklore on the risk-taking behavior of firms and banks could be weaker.

We conduct a subsample analysis to examine whether the effect of folklore on access to credit is affected by the fact that the firm provides financial statements. We split the sample into audited and non-audited firms. The results are reported in Table 5.

On the one hand, the coefficients for *Success* have the same sign and significance for audited and non-audited firms when explaining *Constrained* and *Apply*. We however observe that *Success* is only significantly positive for non-audited firms when explaining *Approved*. This result is in line with our expectation that folklore has a stronger influence for non-audited firms. On the other hand, the coefficients for *Not success* are not significant for audited and non-audited firms when explaining *Approved*, but they differ for the two other dependent variables. The coefficient is significantly positive for audited firms but not significant for non-audited firms when explaining *Constrained*, while it is significantly negative for audited firms but not significant for non-audited firms when explaining *Approved*. In other words, these results suggest that oral traditions play a stronger role for audited firms than for non-audited firms, which is contrary to our expectation. Thus, we find some differences for the impact of folklore conditional on the effect of providing audited financial statements but we do not observe a clear pattern.

Second, we examine whether foreign ownership affects the impact of folklore on access to credit. Oral traditions from the location of the firm should have less influence on owners of foreign-owned firms because, by definition, they come from another country. Therefore, foreign firms could be partially immune to oral traditions. We do not expect the absence of influence of folklore for foreign firms: the firm's staff can come from the region and as such can be influenced by local folk tales. Furthermore, there exists a horizontal transmission of folklore, as explained earlier. This lower impact of folklore for foreign firms should be more pronounced for borrower discouragement, since this is the channel that takes place on the firm side. However, we could also observe an effect of foreign ownership on bank loan approval since foreign firms are more likely than domestic firms to seek loans from foreign banks (Harrison and McMillan, 2003, Giannetti and Ongena, 2012). Thus, banks of foreign firms could also be less influenced by folklore, and thus their loan approval decisions should be less influenced by oral traditions. To test these hypotheses, we conduct the analysis by considering foreign and domestic firms separately. We display the results in Table 6.

We find evidence supporting the view that folklore has a greater effect on access to credit for domestic firms than for foreign firms. When explaining *Constrained*, we observe that *Success* is significantly positive only for domestic-owned firms while *Not success* is significantly negative for all firms.

When considering the channels through which folklore affects access to credit, we observe similar results for foreign firms and domestic firms for *Not success* (significantly negative when explaining *Apply*, not significant when explaining *Approved*). However, we point out different results for *Success*: it is significantly positive for domestic firms when explaining *Apply* and *Approved*, while it is not significant for foreign firms.

These results support the view that folklore affects more domestic firms than foreign firms. Oral traditions affect both types of firms in their access to credit. However, they are all affected by stories in which challenges are more harmful than beneficial, while only domestic firms respond to stories in which challenges are rewarding. These effects take place through borrower discouragement and loan approval. This finding is consistent with the hypothesis that folklore affects domestic firms more than foreign firms, in line with the expectation that oral traditions have a greater influence on the local population.

Third, we examine whether the impact of folklore on access to credit varies with firm size. This question is particularly important given the lower access to credit for small firms, as these firms are more opaque to banks (Beck and Demirgüç-Kunt, 2006; Devos et al., 2012, Cole, 2013).

We could explain a lower influence of folklore for large firms for several reasons. First, large firms might have a higher degree of rationalization in their financial decision-making process, which reduces the potential influence of culture. Second, they might have a less local presence than small firms with more subsidiaries and more recruitment outside the location region. To sum up, small firms could be more influenced by the local environment including folklore.

We divide the sample into three firm sizes: small, medium, and large, using the number of full-time employees. Following the WBES classification, we consider a firm to be small when it has 19 or less employees, medium when it has between 20 and 99 employees, and large when its labor force is greater than 99 employees. We run separate estimations for the three subsamples. The results are reported in Table 7.

We do not find that the effect of folklore varies with firm size. When explaining *Constrained*, we get the same results for *Success* and *Not success* for the three types of firms. When considering the channels through which folklore affects access to credit, we point out limited differences. For *Apply*, we observe that *Success* is significantly positive for all types of firms while *Not success* is significantly negative only for medium firms. For *Approved*, while the result is the same for *Not success* for all types of firms, *Success* is significantly positive only for small and large firms. In other words, no clear pattern emerges from these differences.

In sum, we find limited evidence that heterogeneity across firms influences the effect of folklore on access to credit. We find that the effect of folklore on access to credit varies with foreign ownership. It is stronger for domestic firms, which supports the view that oral traditions have a greater influence on the local population. For the rest, we do not observe clear evidence of differences across firms based on firm size and the provision of audited financial statements.

4.4 Robustness checks

We now turn to evaluating the robustness of our results. We have already built several robustness tests into our estimations. We ran all estimations with three different sets of controls to test the sensitivity of our results. Furthermore, we used three different specifications of the set of folklore variables. We add two robustness tests to the analysis.

First, we perform an additional robustness check by removing the observations that belong to folklores for which the number of collected motifs is the lowest. By doing so, we hope to overcome a weakness of our sample, which is that the limited number of available motifs available in a culture might be so small that its corresponding observations are unrepresentative of the population.

Before we skipped observations for which data were not available for the main estimations, the initial dataset had 78,234 observations. Using this initial dataset, we compute ten deciles following the total number of motifs collected in a culture. We then choose to remove all observations that belong to any folklore that is part of the first decile, i.e., whose corresponding number of total motifs is less than or equal to 27. Table 8 below shows the results for each probit regression without the observations from the first decile, with each of our three new sample sizes, once again following the explained variables.

We obtain very similar findings to those in the main estimations. Thus, our main results are robust to the use of a reduced sample size after removing potential outliers from the regressions.

Second, we tackle the possibility that our estimates suffer from endogeneity that would stem from an omitted variables bias. To do so, we create an instrumental variable of folklore using the neighboring cultures for each cultural group in our sample. As the *Relatively unsuccessful* predictor is the one that best summarizes the degree of risk-loving and risk-aversion of a group, we focus on this particular measure.

We use a radius in kilometers, as our threshold to define which group is a valid neighbor. We test different distances, and keep the one that best maximizes three criteria for the instrumental variable: correlation, exogeneity, and data conservation. Using an 875 km radius,

we create an instrument with the best correlation with the instrumented variable, the lowest correlation with the residuals of the initial model, and the lowest number of cultural groups for which the number of neighbors' motifs is null. Here, we even keep all groups in our sample.

Once we have identified all neighboring groups, we use them to build an “average” culture composed of all of their folklore motifs. Then, we compute the *Relatively successful* variable following the same approach as for the initial predictor in the main regressions, as if we consider that all neighbors formed a single macro folklore.

We use a two-step instrumental variable probit using this newly formed variable as the instrument, which are reported in Table 9. We reject the null hypothesis for each Wald test, and conclude that there was indeed endogeneity in our initial model. Our second step estimates are consistent with the results of our main regressions for all three dependent variables. Both the signs and statistical significance of the estimates hold. Therefore, we conclude that our results are robust, which supports the existence of a relationship between folklore and access to credit.

5. Conclusion

This paper examines the effect of folklore on access to credit. We build on the work of Michalopoulos and Xue (2021), which provides evidence that oral traditions can influence contemporary economic outcomes and attitudes. This question is of major importance for economic development given the key role of access to credit in firm growth.

We test the hypothesis that oral traditions linking risk-taking to success or failure affect access to credit by influencing bank loan approval and borrower discouragement. To this end, we match firm-level data including information on access to credit with subnational data on folklore to construct samples up to 38,263 firms from 124 countries and 274 cultural societies.

Our key finding is that folklore affects access to credit. We show that oral traditions related to challenge and competition have an impact on firms' credit constraints. More successful challenges increase access to credit, while more unsuccessful challenges decrease access to credit. The effect of folklore occurs through borrower discouragement and loan approval, implying that oral traditions affect the behavior of both firms and banks.

Growing up with stories in which heroes successfully overcome challenging situations increases risk tolerance, which eases credit constraints. Symmetrically, growing up with stories in which challenges cause more harm than good increases risk aversion, and thus diminishes access to credit.

Interestingly, the behavior of firms is influenced by oral traditions that emphasize success and failure, while the behavior of banks is only influenced by stories in which challenges are rewarded with success. Moreover, the impact of folklore is more important for firms than for banks, even through the risk-loving effect. Thus, we find that stories with challenging situations affect access to credit more through borrower discouragement than through loan approval.

We further document that the effect of folklore on access to credit is stronger for domestic firms than for foreign firms, which is consistent with the view that oral traditions have a greater influence on local agents. We find that the effect of folklore on access to credit is not conditional on firm size nor on the fact that the firm reports audited financial statements.

These findings are consistent with Michalopoulos and Xue (2021)'s view that traditional oral stories have a significant impact on present-day economic outcomes and attitudes. We bring support to their view by showing that the content of ancestral folklore predicts economic attitudes in access to credit. Thus, we show that the transmission of cultural values through oral traditions can influence economic development due to the role of access to credit in economic growth.

Our findings provide a better understanding of the obstacles to access to credit. They suggest that one policy to address credit constraints cannot fit all societies, as its effectiveness can depend on the culture of the target population. Therefore, our results advocate for the use of targeted programs that follow cultural societies rather than administrative boundaries.

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Table 1.
Summary statistics

This table reports the descriptive statistics for the variables employed in the analysis. All variables are defined in Table A.1 in the Appendix.

	Obs	Mean	Std. Dev.	Min	Max
Constrained	38,263	0.575	0.494	0	1
Apply	38,263	0.476	0.499	0	1
Approved	19,715	0.837	0.369	0	1
All	38,263	5.284	3.946	0	27.273
Success	38,263	2.33	2.109	0	20
Not success	38,263	0.936	1.439	0	11.111
Unclear	38,263	2.018	1.85	0	10
N/A	38,263	0.183	0.471	0	4.762
Relatively unsuccessful	38,263	-3.411	2.774	-20	11.111
Age	38,263	19.664	17.324	1	220
Size (ln)	38,263	3.345	1.373	0	11.067
Sole proprietorship	38,263	0.315	0.464	0	1
Private or non-traded	38,263	0.433	0.496	0	1
Publicly traded	38,263	0.053	0.223	0	1
Exporter	38,263	0.177	0.382	0	1
Foreign-owned	38,263	0.059	0.235	0	1
Subsidiary	38,263	0.166	0.372	0	1
Audited	38,263	0.544	0.498	0	1
Sales growth	38,263	64.987	201.516	-100	1,219.973
Competition	38,263	1.515	1.383	0	4
Manufacturing	38,263	0.569	0.495	0	1
Retail	38,263	0.167	0.373	0	1
Corruption	38,263	0.327	0.469	0	1
Experience	38,263	19.02	11.184	0	72
Growth centroid	38,263	67.647	49.777	-40.987	512.08
Electricity centroid	38,263	1.363	1.008	0	4
Informal credit centroid	38,263	9.83	7.36	0	43.056
GDP per capita (ln)	38,263	9.131	0.95	6.626	11.649
GDP growth	38,263	4.865	3.837	-12.037	31.914
Credit to GDP	38,263	45.229	30.084	.005	191.69
Inflation	38,263	6.483	5.24	-2.431	59.22
Rule of law	38,263	4.555	1.431	1.325	9.069

Table 2.
Explaining credit constraints

This table reports the results of probit regressions. The dependent variable is *Constrained*. All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)
All	-0.0017*** (0.0006)		
Success (risk-loving)		-0.0102*** (0.0012)	
Not success (risk-averse)		0.0045** (0.0019)	
Unclear (risk-taking)		0.0034** (0.0014)	
N/A		-0.0353*** (0.0047)	
Relatively unsuccessful			0.0048*** (0.0009)
Age	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
Size (ln)	-0.0587*** (0.0019)	-0.0583*** (0.0019)	-0.0586*** (0.0019)
Sole proprietorship	0.0357*** (0.0066)	0.0375*** (0.0066)	0.0365*** (0.0066)
Private or non-traded	-0.0460*** (0.0063)	-0.0426*** (0.0063)	-0.0456*** (0.0063)
Publicly traded	-0.0209* (0.0110)	-0.0164 (0.0109)	-0.0187* (0.0110)
Exporter	-0.0517*** (0.0061)	-0.0524*** (0.0061)	-0.0520*** (0.0061)
Foreign-owned	0.0244*** (0.0093)	0.0267*** (0.0093)	0.0252*** (0.0093)
Subsidiary	-0.0058 (0.0062)	-0.0077 (0.0062)	-0.0064 (0.0062)
Audited	-0.0729*** (0.0048)	-0.0739*** (0.0048)	-0.0732*** (0.0048)
Sales growth	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Competition	0.0057*** (0.0017)	0.0059*** (0.0017)	0.0056*** (0.0017)
Manufacturing	0.0355*** (0.0053)	0.0345*** (0.0053)	0.0353*** (0.0053)
Retail	-0.0262*** (0.0069)	-0.0265*** (0.0069)	-0.0260*** (0.0069)
Corruption	0.0265*** (0.0050)	0.0239*** (0.0050)	0.0262*** (0.0050)
Experience	-0.0020*** (0.0002)	-0.0019*** (0.0002)	-0.0020*** (0.0002)
Growth centroid	-0.0002*** (0.0001)	-0.0002*** (0.0001)	-0.0002*** (0.0001)
Electricity centroid	-0.0095*** (0.0028)	-0.0075*** (0.0028)	-0.0094*** (0.0027)
Informal credit centroid	0.0036***	0.0034***	0.0035***

	(0.0004)	(0.0004)	(0.0004)
GDP per capita (ln)	-0.1015***	-0.0978***	-0.0988***
	(0.0041)	(0.0042)	(0.0041)
GDP growth	0.0053***	0.0049***	0.0052***
	(0.0008)	(0.0008)	(0.0008)
Credit to GDP	0.0006***	0.0007***	0.0006***
	(0.0001)	(0.0001)	(0.0001)
Inflation	0.0063***	0.0063***	0.0064***
	(0.0005)	(0.0005)	(0.0005)
Rule of law	-0.0155***	-0.0147***	-0.0154***
	(0.0027)	(0.0027)	(0.0026)
Observations	38,263	38,263	38,263
Pseudo R ²	0.1845	0.1908	0.1863
Log likelihood	-21,279.073	-21,115.330	-21,231.249
Year FE	Yes	Yes	Yes

Table 3.
Explaining loan application

This table reports the results of probit regressions. The dependent variable is *Apply*. All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)
All	0.0021*** (0.0006)		
Success (risk-loving)		0.0129*** (0.0012)	
Not success (risk-averse)		-0.0056*** (0.0019)	
Unclear (risk-taking)		-0.0041*** (0.0014)	
N/A		0.0261*** (0.0047)	
Relatively unsuccessful			-0.0059*** (0.0009)
Age	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Size (ln)	0.0553*** (0.0019)	0.0549*** (0.0019)	0.0551*** (0.0019)
Sole proprietorship	-0.0297*** (0.0065)	-0.0324*** (0.0066)	-0.0306*** (0.0066)
Private or non-traded	0.0518*** (0.0064)	0.0475*** (0.0064)	0.0514*** (0.0063)
Publicly traded	0.0329*** (0.0112)	0.0267** (0.0112)	0.0304*** (0.0112)
Exporter	0.0671*** (0.0063)	0.0678*** (0.0062)	0.0673*** (0.0063)
Foreign-owned	-0.0291*** (0.0095)	-0.0310*** (0.0095)	-0.0299*** (0.0095)
Subsidiary	0.0002 (0.0062)	0.0017 (0.0062)	0.0010 (0.0062)
Audited	0.0772*** (0.0048)	0.0782*** (0.0048)	0.0776*** (0.0048)
Sales growth	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
Competition	-0.0008 (0.0017)	-0.0010 (0.0017)	-0.0007 (0.0017)
Manufacturing	-0.0397*** (0.0053)	-0.0387*** (0.0053)	-0.0393*** (0.0053)
Retail	0.0164** (0.0069)	0.0168** (0.0069)	0.0162** (0.0069)
Corruption	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Experience	0.0553*** (0.0019)	0.0549*** (0.0019)	0.0551*** (0.0019)
Growth centroid	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0003*** (0.0001)
Electricity centroid	0.0076*** (0.0028)	0.0056** (0.0028)	0.0074*** (0.0028)
Informal credit centroid	-0.0042***	-0.0039***	-0.0040***

	(0.0004)	(0.0004)	(0.0004)
GDP per capita (ln)	0.1004***	0.0955***	0.0970***
	(0.0041)	(0.0041)	(0.0041)
GDP growth	-0.0072***	-0.0066***	-0.0071***
	(0.0008)	(0.0008)	(0.0008)
Credit to GDP	-0.0007***	-0.0008***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)
Inflation	-0.0060***	-0.0061***	-0.0061***
	(0.0005)	(0.0005)	(0.0005)
Rule of law	0.0199***	0.0184***	0.0199***
	(0.0027)	(0.0027)	(0.0027)
Observations	38,263	38,263	38,263
Pseudo R ²	0.1841	0.1913	0.1863
Log likelihood	-21,602.039	-21,411.654	-21,544.698
Year FE	Yes	Yes	Yes

Table 4.
Explaining loan approval

This table reports the results of probit regressions. The dependent variable is *Approved*. All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)
All	0.0010 (0.0006)		
Success (risk-loving)		0.0022** (0.0011)	
Not success (risk-averse)		-0.0007 (0.0017)	
Unclear (risk-taking)		-0.0003 (0.0014)	
N/A		0.0283*** (0.0053)	
Relatively unsuccessful			-0.0016** (0.0008)
Age	0.0003* (0.0001)	0.0003** (0.0001)	0.0003* (0.0001)
Size (ln)	0.0285*** (0.0019)	0.0282*** (0.0019)	0.0285*** (0.0019)
Sole proprietorship	-0.0146** (0.0070)	-0.0141** (0.0070)	-0.0148** (0.0070)
Private or non-traded	0.0031 (0.0064)	0.0026 (0.0064)	0.0030 (0.0064)
Publicly traded	-0.0023 (0.0109)	-0.0014 (0.0109)	-0.0029 (0.0109)
Exporter	0.0002 (0.0058)	0.0002 (0.0058)	0.0003 (0.0058)
Foreign-owned	-0.0141* (0.0082)	-0.0150* (0.0082)	-0.0144* (0.0082)
Subsidiary	-0.0086 (0.0060)	-0.0070 (0.0060)	-0.0084 (0.0060)
Audited	0.0086* (0.0046)	0.0091** (0.0046)	0.0085* (0.0046)
Sales growth	0.0000* (0.0000)	0.0000* (0.0000)	0.0000* (0.0000)
Competition	-0.0010 (0.0015)	-0.0011 (0.0015)	-0.0009 (0.0015)
Manufacturing	-0.0038 (0.0051)	-0.0028 (0.0051)	-0.0036 (0.0051)
Retail	0.0214*** (0.0065)	0.0219*** (0.0065)	0.0213*** (0.0065)
Corruption	-0.0253*** (0.0048)	-0.0243*** (0.0048)	-0.0252*** (0.0048)
Experience	0.0005** (0.0002)	0.0005** (0.0002)	0.0005** (0.0002)
Growth centroid	-0.0002*** (0.0001)	-0.0002*** (0.0001)	-0.0002*** (0.0001)
Electricity centroid	-0.0040 (0.0026)	-0.0052** (0.0026)	-0.0039 (0.0026)
Informal credit centroid	-0.0016***	-0.0016***	-0.0016***

	(0.0005)	(0.0005)	(0.0005)
GDP per capita (ln)	0.0342***	0.0337***	0.0330***
	(0.0039)	(0.0040)	(0.0040)
GDP growth	0.0016*	0.0016*	0.0017*
	(0.0009)	(0.0009)	(0.0009)
Credit to GDP	-0.0002*	-0.0003*	-0.0002
	(0.0001)	(0.0001)	(0.0001)
Inflation	-0.0021***	-0.0020***	-0.0021***
	(0.0004)	(0.0004)	(0.0004)
Rule of law	-0.0031	-0.0026	-0.0027
	(0.0026)	(0.0026)	(0.0025)
Observations	19,715	19,715	19,715
Pseudo R ²	0.3321	0.3345	0.3325
Log likelihood	-5,852.1131	-5,830.8814	-5,847.8005
Year FE	Yes	Yes	Yes

Table 5.
Influence of providing audited financial statements

This table reports results of probit regressions. The dependent variable is at the top of the column. All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Constrained		Apply		Approved	
	Audited	Not audited	Audited	Not audited	Audited	Not audited
Success (risk-loving)	-0.0077*** (0.0018)	-0.0100*** (0.0017)	0.0091*** (0.0018)	0.0131*** (0.0017)	0.0021 (0.0015)	0.0035* (0.0018)
Not success (risk-averse)	0.0057* (0.0030)	0.0032 (0.0025)	-0.0082*** (0.0029)	-0.0029 (0.0026)	0.0007 (0.0024)	-0.0025 (0.0026)
Unclear (risk-taking)	-0.0009 (0.0020)	0.0068*** (0.0020)	0.0003 (0.0019)	-0.0078*** (0.0020)	-0.0001 (0.0018)	-0.0013 (0.0022)
N/A	-0.0278*** (0.0068)	-0.0354*** (0.0064)	0.0168** (0.0067)	0.0255*** (0.0067)	0.0275*** (0.0068)	0.0341*** (0.0087)
Observations	20,807	17,456	20,807	17,456	11,893	7,822
Pseudo R ²	0.2216	0.2028	0.2369	0.1932	0.3445	0.3443
Log likelihood	-11,219.671	-9,034.3899	-10,972.498	-9,523.4794	-3,130.4965	-2,569.6459
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Centroid-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 6.
Influence of foreign ownership

This table reports results of probit regressions. The dependent variable is at the top of the column. All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Constrained		Apply		Approved	
	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic
Success (risk-loving)	-0.0044 (0.0053)	-0.0103*** (0.0013)	0.0083 (0.0052)	0.0129*** (0.0013)	0.0038 (0.0046)	0.0020* (0.0012)
Not success (risk-averse)	0.0181** (0.0084)	0.0033* (0.0020)	-0.0145* (0.0081)	-0.0047** (0.0020)	-0.0070 (0.0071)	-0.0002 (0.0018)
Unclear (risk-taking)	0.0011 (0.0060)	0.0037** (0.0014)	-0.0039 (0.0059)	-0.0041*** (0.0014)	-0.0020 (0.0057)	-0.0003 (0.0014)
N/A	0.0020 (0.0210)	-0.0381*** (0.0048)	-0.0255 (0.0206)	0.0302*** (0.0049)	0.0380* (0.0221)	0.0269*** (0.0055)
Observations	2,242	36,014	2,242	36,014	1,330	18,243
Pseudo R ²	0.1629	0.2221	0.1619	0.2233	0.4374	0.3336
Log likelihood	-1,298.6470	-19,050.9550	-1,279.2514	-19,335.5350	-386.59062	-5,356.5916
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Centroid-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7.
Influence of firm size

This table reports results of probit regressions. The dependent variable is at the top of the column. All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Constrained			Apply			Approved		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Success (risk-loving)	-0.0121*** (0.0017)	-0.0069*** (0.0022)	-0.0078*** (0.0029)	0.0151*** (0.0018)	0.0095*** (0.0022)	0.0086*** (0.0028)	0.0039* (0.0021)	0.0002 (0.0017)	0.0046** (0.0020)
Not success (risk-averse)	0.0036 (0.0027)	0.0052 (0.0034)	0.0061 (0.0048)	-0.0041 (0.0028)	-0.0083** (0.0033)	-0.0042 (0.0045)	-0.0025 (0.0031)	0.0006 (0.0026)	-0.0004 (0.0034)
Unclear (risk-taking)	0.0034* (0.0020)	0.0023 (0.0024)	0.0081** (0.0032)	-0.0053*** (0.0020)	-0.0022 (0.0024)	-0.0065** (0.0031)	0.0012 (0.0025)	0.0004 (0.0021)	-0.0046* (0.0025)
N/A	-0.0261*** (0.0071)	-0.0492*** (0.0080)	-0.0335*** (0.0102)	0.0177** (0.0075)	0.0363*** (0.0079)	0.0259*** (0.0097)	0.0286*** (0.0098)	0.0439*** (0.0095)	0.0129 (0.0085)
Observations	17,359	13,135	7,769	17,359	13,135	7,769	7,295	7,370	4,918
Pseudo R ²	0.1827	0.1926	0.2193	0.1714	0.2074	0.2574	0.3523	0.3076	0.2776
Log likelihood	-8,757.5140	-7,345.2143	-4,104.4082	-9,456.8477	-7,199.9139	-3,806.7906	-2,671.2157	-1,935.7337	-1,063.7796
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centroid-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8.
Robustness check: estimations without the first decile of folklores (total number of motifs)

This table reports the results of probit regressions. The dependent variable is at the top of the column. We perform estimations without the first decile of folklores (total number of motifs). All variables are defined in the Appendix. Estimated marginal effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) Constrained	(2) Constrained	(3) Constrained	(4) Apply	(5) Apply	(6) Apply	(7) Approved	(8) Approved	(9) Approved
All (risk-taking)	-0.0030*** (0.0008)			0.0043*** (0.0008)			0.0002 (0.0007)		
Success (risk-loving)		-0.0138*** (0.0016)			0.0183*** (0.0016)			0.0027* (0.0015)	
Not success (risk-averse)		0.0051** (0.0024)			-0.0065*** (0.0023)			-0.0022 (0.0022)	
Unclear (risk-taking)		0.0015 (0.0015)			-0.0008 (0.0015)			-0.0013 (0.0016)	
N/A		-0.0231*** (0.0051)			0.0140*** (0.0052)			0.0249*** (0.0056)	
Relatively unsuccessful			0.0064*** (0.0011)			-0.0086*** (0.0011)			-0.0011 (0.0010)
Observations	33,796	33,796	33,796	33,796	33,796	33,796	17,527	17,527	17,527
Pseudo R ²	0.2168	0.2186	0.2172	0.2166	0.2190	0.2174	0.3524	0.3540	0.3524
Log likelihood	-18,070.6740	-18,027.7490	-18,060.7490	-18,321.4390	-18,265.7130	-18,304.6340	-5,054.3339	-5,041.6408	-5,053.7901
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centroid-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9.
Robustness check: testing for endogeneity

This table reports the results of probit regressions with instrumental variables (IV) following a two-step approach. The dependent variable is at the top of the column. The instrument is the *Relatively unsuccessful* variable constructed using data from the neighbouring folklores in a radius of 875 km. The Wald Test compares the instrumented model and non-instrumented model. Under the null hypothesis, both models provide similar results. Estimated effects are reported and standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Constrained		Apply		Approved	
	1 st step	2 nd step	1 st step	2 nd step	1 st step	2 nd step
Relatively unsuccessful (neighbour - instrument)	0.3402*** (0.0129)		0.3402*** (0.0129)		0.1800*** (0.0182)	
Relatively unsuccessful		0.1594*** (0.0219)		-0.2208*** (0.0224)		-0.1325* (0.0693)
Constant	3.7551*** (0.2335)	4.1163*** (0.1661)	3.7551*** (0.2335)	-3.6524*** (0.1685)	5.6276*** (0.3812)	-0.1361 (0.4994)
Observations	38,263	38,263	38,263	38,263	19,715	19,715
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Centroid-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	47.00***		94.19***		3.24*	

Appendix

Definitions and sources of variables

Variable	Definition and source
<i>Dependent variables</i>	
Constrained	Dummy=1 if no request for a loan/line of credit was accepted, or if was discouraged, =0 otherwise. Source: WBES.
Apply	Dummy=1 if the firm applied for a loan/line of credit, =0 otherwise. Source: WBES.
Approved	Dummy=1 if at least one request for a loan/line of credit was accepted, =0 otherwise. Source: WBES.
<i>Folklore variables</i>	
All	Share (%) of motifs that depict a challenge/competition. Source: Berezkin (2015).
Success	Share (%) of motifs that depict a successful outcome for a challenge/competition. Source: Berezkin (2015).
Not success	Share (%) of motifs that depict an unsuccessful outcome for a challenge/competition. Source: Berezkin (2015).
Unclear	Share (%) of motifs for which the outcome is unclear. Source: Berezkin (2015).
N/A	Share (%) of motifs for which it is uncertain whether they depict a challenge/competition. Source: Berezkin (2015).
Relatively unsuccessful	Relative unsuccessfulness (%) in a culture, computed as $Relative = Not\ success - Success - Unclear$. Source: Berezkin (2015).
<i>Firm variables</i>	
Age	Age of the firm (number of years since incorporation). Source: WBES
Size (ln)	Natural logarithm of the number of full-time permanent employees. Source: WBES.
Sole proprietorship	Dummy=1 if the firm is a sole proprietorship, =0 otherwise. Source: WBES.
Private or non-traded	Dummy=1 if is private or non-traded, =0 otherwise. Source: WBES.
Publicly traded	Dummy=1 if is publicly traded, =0 otherwise. Source: WBES.
Audited	Dummy=1 if the firm's financial statements were checked and certified by an external auditor, =0 zero otherwise. Source: WBES.
Experience	Top manager's number of years of experience in the sector. Source: WBES.
Foreign-owned	Dummy=1 if at least 50% of the firm's ownership is held by foreigners, =0 otherwise. Source: WBES.
Exporter	Dummy =1 if at least 10% of the firm's annual sales is derived from direct exports, =0 otherwise. Source: WBES.
Subsidiary	Dummy=1 if a firm is part of a large group, =0 otherwise. Source: WBES.
Sales growth	Sales growth rate of the firm over a three-year period (winsorized). Source: WBES.
Competition	Categorical variable between 0 and 4 on how much the firm perceives competition as an obstacle (from "no obstacle" to "very severe obstacle"). Source: WBES.
Corruption	Dummy=1 if the firm reported perceiving corruption as an obstacle to be 3 ("major") or 4 ("very severe") on scale ranging from 0 ("no obstacle") to 4. Source: WBES.
Manufacturing	Dummy=1 if the firm's sector is manufacturing. Source: WBES.
Retail	Dummy=1 if the firm's sector is retail. Source: WBES.

Centroid variables

Growth centroid Mean of the sales growth rates of firms over a three-year period (winsorized). Source: WBES.

Electricity centroid Median of the categorical variable of the degree to which firms perceive access to electricity as an obstacle, ranging from 0 (“no obstacle”) to 4 (“very severe obstacle”). Source: WBES.

Informal credit centroid Mean share (%) of firms whose share of working capital or fixed assets funded by moneylenders, friends, or relatives is greater than 0 (winsorized). Source: WBES.

Country variables

GDP per capita (ln) Natural logarithm of GDP per capita, PPP (constant 2017 international dollar). Source: World Bank.

GDP growth GDP growth rate (annual %). Source: World Bank.

Credit to GDP Domestic credit to private sector (% of GDP). Source: World Bank.

Inflation Inflation rate, consumer prices (annual %). Source: World Bank.

Rule of law Score on the degree to which agents have confidence in and abide by the rules of society, rescaled to a 0 to 10 range, from the worst to the best state of rule of law Source: World Governance Indicators.
