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Credit bureaus and financial constraints do corruption matter?

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ABSTRACT

This study aims to assess whether or not the presence of credit bureaus is associated with more or fewer financing constraints while considering the interfering effect of corruption in a sample of 18 countries in Eastern Europe and the Middle East and North Africa (MENA) region during the period 2011–2014. We consider various financial constraint measures and corruption indices, and assess the stability of the relationship for different levels of economic development and corruption. The estimation outcomes suggest that countries with higher levels of corruption might produce less transparent and falsified information that would make access to sources of financing more difficult for firms. Our findings suggest that curbing corruption creates more efficient credit bureaus that, in turn, decrease financial constraints for firms. The subsample estimations confirm these findings and show that the higher and longer-term corruption in MENA countries than in Eastern European countries make credit bureaus' less effective, imposing more financial constraints. Our findings remain robust with different corruption indices and with the addition of new control variables such as firms' sales and size, government and exporting firms, and per-capita GDP, inflation, trade, population and human capital.

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1. Introduction

Credit is a significant and important source of financing for firms in developing and emerging economies. Limited access to finance has serious repercussions on firm's growth and productivity (Beck et al. 2006; Dinh et al. 2010) and on the development of the private sector. It has a first-order effect on economic development (Levine, 2005) and on growth (Love and Mylenko, 2003).

Access to finance is a major challenge for most of the small and medium enterprises (SME) that constitute the major part of the developing and emerging countries' industries. A determinant factor that contributes to this challenge is the presence of an information asymmetry in the lenders–borrowers relationships. Information plays a central role in credit decisions because its asymmetric availability could induce inefficient allocation of resources and distort them away from their best use.

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The information asymmetry theory has received considerable attention in economic and finance literature since the seminal papers of Akerlof (1970), Jaffee and Russel (1976), Spence (1973), Stiglitz (1974), Stiglitz and Weiss (1981) among others. One strand of the literature advocates for collateralization when dealing with information asymmetry in credit decisions. However, this is not a likely solution for developing countries where small business lack assets that can be collateralized. Another strand of the literature argues that in order to reduce information asymmetry, credit decisions should be made based on the cash flow history of borrowers. Overall, information asymmetry can delay the financing process for many firms.

Studies in the literature showed that information asymmetry can be reduced through information sharing on non-performing loans (Brown et al., 2009; Brown and Zehnder, 2007; Djankov et al., 2007). Information sharing on non-performing loans can provide two main benefits: a screening effect and a motivation effect (Brown et al., 2009; Djankov et al., 2007). First, sharing information provide a screening effect. That is, information sharing provides a reliable information on borrowers' history increasing by the way the predictive power of banks on borrower's ability to repay their loans. Information sharing makes banks more able to distinguish good borrowers from the bad ones and insures therefore a screening effect (Brown et al., 2009; Djankov et al., 2007). Second, as information on delinquent borrowers is shared between all lenders, borrowers are inclined to repay their loans in due time to avoid loans denial in the future. That is, information sharing induces an incentive effect (Brown et al., 2009; Djankov et al., 2007).

Although much literature has been devoted to different aspects of information, less attention has been given to the institutional side to overcome the asymmetry information problem between borrowers and lenders. Numerous economists, policy makers and international institutions called however to institute formal bodies and regulations that can improve information sharing to reduce information asymmetry and the non-performing loans problem. 'Credit registries' or 'credit bureaus', are seen as a solution to this problem (Brown and Zehnder, 2010; Jappelli and Pagano, 1999; Padilla and Pagano, 2000; Pagano and Japelli, 1993).

Credit bureaus date back to more than two centuries ago. They were first established in Latin America by the Chamber of Commerce with the main objective of collecting information on defaulting customers. In many countries, 'credit registries' were established to record information on delinquent borrowers. Moreover, most of the central bankers worldwide created data registries to provide information to national financial institutions on defaulting borrowers. As a result of the advances in technology and changes in the banking industry, credit registries have expanded worldwide and their use has increased during recent years, where collected and recorded information about delinquent customers has largely expanded in both developed and developing countries.

Pagano and Jappelli (1993) show how information sharing by credit registries can affect the problem of adverse selection. Indeed, banks are able to collect information about applicants' first-hand or can acquire it from other creditors who have already conducted business with the applicant (Brown et al., 2009). Scoring the credit quality of borrowers is now a fundamental element of any credit decision in small business loans or mortgage markets, where information asymmetry is the most noticeable. The information accumulated by creditors on borrowers' historical behavior can be exchanged among different lenders through these credit registries. This can help assess the creditworthiness of borrowers by reducing the information asymmetry and allocating credit more efficiently.

Information sharing can occur spontaneously and voluntarily between lenders via private credit bureaus or else through public credit bureaus when information sharing is enforced by law. Actually, two main kinds of institutions can be distinguished: public credit registries and private credit bureaus. The former are public institutions aiming to supervise the banking sector and where laws about sharing information on borrowers are enforced on national banks. However, the latter may be a private initiative by lenders to collect and share information in the credit market. By collecting and analyzing information on borrowers' behavior, financial institutions improve credit market performance and credit allocation, and can deal with the moral hazard problem, especially when borrowers patronize several banks (Bennardo et al., 2007). According to Padilla and Pagano (1997), sharing information can impose more discipline on credit users, which, in turn, can reduce the problems of moral hazard and adverse selection.

As far as credit constraints are concerned, the question now is if the presence of credit bureaus can potentially ease the access to credit or make it more difficult. Early studies assessing the impact of credit bureaus on financing showed that the correlation between the performance of credit bureaus and firms' access to debt was positive (Galingo and Miller, 2001). Information sharing through credit bureaus decreases information asymmetry in the relationship between borrowers and lenders and may simulate the credit market to expand (Djankov et al, 2007). Overall, information sharing is associated with more abundant and cheaper credit (Brown et al., 2009). At the firm level, studies argued that private bureaus are associated with lower perceived financial constraints (Love and Mylenko, 2003). In the same context, Pagano and Jappelli (1993) showed that information sharing reduces adverse selection by improving the pool of borrowers. It can also address the moral hazard problem and curtail imprudent or risky borrowers (Padilla and Pagano, 1997). Some recent studies, however, show that information sharing by credit registries imposes stricter financial constraints on borrowers (Bennardo et al., 2010; Doblas-Madrid and Minetti, 2013). However, in countries with higher levels of corruption, credit bureaus might not operate efficiently, since potential borrowers and firms could manipulate the information contained in their files by bribing credit bureau agencies.

Institutions in general and corruption in particular are now regarded by numerous researchers, academicians and policy makers as a major hinder for almost all aspects of economic development such as banking stability (Ben Ali et al. 2018, 2020), on public spending (Swaleheen et al., 2019), on international trade (Ben Ali and Mdhillat, 2015), and inflation (Ben Ali and Sassi, 2016) among others.

In developing countries, access to credit for firms is the main channel through which economies develop and expand. Developing countries usually with relatively high level of corruption might be an interfering factor that could make access to credit with more or less constraints. By collecting and analyzing information on borrowers' behavior, credit bureaus impact the credit market performance and credit allocation. Indeed, corrupted agents may decide to interfere with the quality of information that these institutions can deliver which might undermine their effectiveness and therefore ease financial constraints or make credit more difficult for firms. The impact of corruption is therefore suspected to be an interfering channel in the credit bureau–financial constraint relationship.

Our study therefore tackles this issue and investigates the extent to which corruption could derail credit bureaus' decisions when it comes to lending and whether corruption eases financial constraints for borrowers or if it makes corporate access to finance more difficult.

We use a firm-level dataset in 18 countries from the Eastern Europe (EE) and the Middle East and North Africa region (MENA). Our investigation contributes to the literature in several ways. Firstly, we shed the light on the relationship between financial constraints and the presence of credit bureaus by including the potential effect of corruption. In this regard, we consider firm-level data, which allow us to focus on the internal details of firms such as their sizes, whether they are private or government-owned, and whether they are exporters or locally oriented. Second, we use a nonlinear ordered probit model by setting cutoff points for the links between financial constraints, credit bureau and corruption. Third, we use two different measures of corruption to test the robustness and the validity of our results. Finally, we check for the stability of the relationship across regions based on their levels of economic development to investigate if the relationship is similar or different when countries are on different development paths and levels of corruption. To the best of our knowledge, there is no discussion in the current literature about the role of corruption in credit registries on financial constraints in general and for MENA countries in particular. This is the first study to provide cross-country firm-level empirical evidence about the interfering effect of corruption on this relationship. The remainder of the paper is structured as follows: Section 2 presents the model, variables, the data and the methodology we use for econometric estimation. Section 3 presents and discusses the results. Section 4 presents the robustness tests and Section 5 concludes.

2. Methodology, variables and data

To explore the relationship among financial constraints, credit bureaus and corruption, we estimate an ordered probit model since our dependent variable is an ordinal variable. The idea is to estimate the financial constraints as a nonlinear function of the independent variables, namely credit bureaus and corruption, by adding their interaction term. By using the ordered probit model, we are able to set cutoff points. Specifically, the probability of observing outcome *i* is the probability that both the random error term and the estimated function are within the range of the cutoff points estimated for the outcome as follows:

$$\Pr(\text{Financial\_Constraints}_j = i) = \Pr(\mu_{i-1} < \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 * X_2 + \ldots + \beta_k X_{kj} + \varepsilon_j \le \mu_i)$$

where ε_j is normally distributed; the coefficients β_1, β_2 and β_3 correspond to the coefficients of credit bureaus, corruption and the interaction term between credit bureaus and corruption; $\mu_1, \mu_2, \ldots \mu_{i-1}$ are the number of possible outcomes. X_1 measures the level of credit bureau registration and X_2 measures the level of corruption.

In this study, we use both microdata on firms across industries and countries on credit bureaus and macroeconomic data on corruption. We use the European Bank for Reconstruction and Development's combined BEEPS V and MENA ES data. These data provide information on financial constraints, firm size, types of industry, ownership and exports for more than 22,449 firms in 39 countries in the EE, Central Asia and the MENA region (the list of countries is displayed in Table A3 in the Appendix). The data cover the period from 2011 to 2014. This database allows us to use the financial constraints variable of firms, which were obtained by answers to the question on: 'How problematic is financing for the operation and growth of your business?' The responses to this question varied from 0 to 4, where 0 indicates that there is no obstacle and 4 indicates significant obstacles to obtaining finance (*Financial Constraint*). We also use different variables to consider the firm size (*Size*), whether the firm is owned by the government or not (*Gov. owned*) and whether it is an exporting firm or not (*Exporting*). The variable S*ize* is proxied by the natural logarithm of the number of firms' employees. *Gov. owned* and *Exporting* are dummy variables that take a value of 1 if the firm is owned by government (or, correspondingly, an exporting company) and 0 otherwise. These variables also come from the BEEPS V and MENA ES dataset. Our dataset has two main benefits. First, the use of firm-level data allows us to identify the firms for which information sharing was beneficial. This also allows us to overcome any limitations in the aggregated data. Second, the BEEPS data allow us to control for any changes in the macroeconomic variables and unobserved firm-level heterogeneity.

At the country level, we use a credit bureau variable (*CB*), corruption indices and other controls. We use the Private credit bureau coverage taken from the World Bank. Specifically, *CB* provides the number of adult individuals or firms listed by a private credit bureau who hold current information on the borrowers' credit outstanding, repayment history and/or unpaid debts. Two of the most commonly used measures of corruption are used in this study. The first is *Transparency International*'s corruption perception index (CPI), which provides scored ranging from 0 to 10, where a 0 indicates a very corrupt country and 10 indicates a 'clean' or corruption-free country. The second index is the World Bank' control of corruption (COC) index. This index ranges from – 2.5 to 2.5, where the lowest value of the index indicates a high level of corruption and the highest value indicates a clean country. Data related to corruption are collected from *Transparency International* and the World Bank for the CPI and the COC, respectively. As highlighted above, we introduce interaction variables between credit bureaus (*CB*) and corruption as proxied by the CPI (CB × CPI), and between credit bureaus and the COC index (CB × COC). We also consider per-capita GDP (*per capita GDP*) and the ratio of exports and imports to GDP as an indicator of openness (*Trade*). We also include a measure of inflation as proxied by the one-year lagged consumer price index. A measure of population is also considered in our specification. Macroeconomic annual data related to inflation, GDP and the credit bureau variable were extracted from the World Bank's WDI database. Our strategy is to estimate the model for the full sample over the study period. We then test the stability of our results for two subsamples: the EE and the MENA subsamples.

The descriptive statistics for our variables are reported in Table A1. As noted earlier, we use two main dependent variables in our estimations, namely the ordered financial constraints ranging between 0 and 4, where 0 indicates the absence of any financial constraints and 4 indicates a high level of constraints. The second dependent variable is a dummy showing the absence or the existence of constraints when dealing with financing. Our sample countries show a low level of disparity regarding access to credit for both dependent variables. The first measure of financial constraint has a mean of

1.11, a minimum of 0 and a maximum of 4. We also report certain discrepancies in the value of the credit bureau variable among countries, with a maximum of 91% and minimum of 0% (standard deviation = 26%).

The correlation matrix reported in Table A2 shows a positive correlation between the two indices of financial constraint. The credit bureau indicator is negatively correlated with the two financial constraint indices. In addition, corruption measures display negative correlations, showing that curbing corruption and increasing the level of transparency is correlated with a lower level of financial constraints for firms. In addition, when firms are government-owned, they have fewer financial constraints and can easily access to finance. The correlation coefficients show that wealthier countries are correlated with few financial constraints. In countries with an educated population, firms are also less financially constrained. From a microeconomic perspective, exporting firms and those involved in international trade face more financial constraints, probably because of a risk component compared with firms operating in domestic markets. However, the correlation matrix shows that large firms, in terms of size and sales, have less difficulty accessing finance.

3. Results and discussion

Table 1 displays the estimation outcomes for the ordered probit model. Columns (1)–(4) report the estimation results with the CPI and Columns (5)–(8) display the results with the COC index. We introduce our variables a set by set to have the best estimation possible. The interaction terms between the credit bureau variable and measures of corruption are our coefficients of interest. The credit bureau coefficient became positively and significantly different from 0 in Columns (1)–(4) ($P < .01$), suggesting that the presence of credit bureaus increases financial constraints for firms. This result is in line with previous findings that have reported that credit bureaus increase financial constraints, even though earlier studies showed a negative but non-robust relationship between credit bureaus and financial constraints (Love and Mylenko, 2003). For example, the theoretical model of Bennardo et al. (2010) showed that after joining a credit bureau, lenders become more aware of the credit applicants' debt exposure and apply tighter criteria for granting credit. More recently, Doblas-Madrid and Minetti (2013) confirmed these results and argued that information sharing does not induce lenders to relax their lending criteria. However, the results may also depend on the nature of credit bureaus (private or public). Private and public credit agencies collect different types of information (Jappelli and Pagano, 2002). However, public credit registries tend to have wider coverage than their private equivalents (Jappelli and Pagano, 2002). Furthermore, historical data are not provided by public credit registries to financial institutions (Miller, 2003). Therefore, the presence of private and public credit bureaus might have different impacts on lending decisions and therefore on financial constraints.

The estimation outcomes show that the corruption indices are significantly and positively correlated with financial constraint measures. This finding suggests that a lower level of corruption means that decision makers will probably be less influenced by briberies and other corrupt practices influencing credit bureaus' managers. This would therefore impose more financial constraints on firms for accessing credit.

Table 1. The ordered Probit model for financial constraints, corruption and credit bureaus.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB	0.0178***	0.017***	0.022***	0.024***	0.001**	0.001*	0.004***	0.004***
	(0.0019)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
CPI	0.056***	0.051***	0.159***	0.178***				
	(0.017)	(0.019)	(0.039)	(0.042)				
CB × CPI	−0.004***	−0.004***	−0.004***	−0.004***				
	(0.000)	(0.000)	(0.000)	(0.000)				
ln(sales)		−0.008		−0.007		−0.008		−0.005
		(0.005)		(0.006)		(0.005)		(0.006)
ln(size)		−0.022*		−0.023*		−0.024**		−0.024*
		(0.012)		(0.012)		(0.012)		(0.012)
Gov. owned		−0.003*		−0.002		−0.003		−0.002
		(0.001)		(0.002)		(0.001)		(0.002)
Exporter		0.000		−0.000		−0.000		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)
per-capita GDP			−0.298***	−0.297***			−0.260***	−0.252***
			(0.049)	(0.055)			(0.061)	(0.068)
Inflation			−0.007***	−0.002			−0.009***	−0.004
			(0.002)	(0.002)			(0.00)	(0.003)
Trade			−0.000	−0.000			0.000	0.001
			(0.000)	(0.001)			(0.000)	(0.001)
Population			−0.014	0.003			0.000	0.020
			(0.013)	(0.016)			(0.013)	(0.016)
School			0.004***	0.004***			0.003***	0.003**
			(0.001)	(0.001)			(0.001)	(0.001)
COC					0.133***	0.130***	0.340***	0.382***
					(0.039)	(0.045)	(0.099)	(0.108)
CB × COC					−0.010***	−0.010***	−0.011***	−0.012***
					(0.001)	(0.001)	(0.001)	(0.001)
Pseudo-*R2*	0.010	0.011	0.016	0.015	0.010	0.012	0.016	0.015
chi2	200.577	197.373	416.037	301.162	216.827	209.427	417.586	302.923
N. of observations	8316	6812	8316	6812	8316	6812	8316	6812

Note that *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Each regression contains the constant coefficient. Standard errors are in parentheses.

The most informative and innovative result is the negative coefficient of the interaction variables between the credit bureau variable and the two measures of corruption. In Columns (1)–(8) in Table 1, the interaction terms between *CB* and the measures of corruption are negative and significant at $P < .01$, suggesting that reducing corruption makes credit bureaus more efficient by decreasing the frequency of bribes to tamper or falsify information about firms, which decreases financial constraints for firms. This finding confirms and validates our conjecture.

All the remaining variables show conventional results. Government-owned firms seem to be less financially constrained, as they might carry an implicit debt guarantee, making it easier to obtain finance. GDP per capita is negatively associated with financial constraints, suggesting that wealthier countries have more access to different sources of financing. Though it is significant, the inflation level is not a determinant variable when it comes to financing. Furthermore, trade, population and level of education within a country do not seem to have any significant effect on access to finance (Table 1).

The second set of estimations is conducted with the dummy variable for financial constraints. This variable took a value of 1 if a firm was financially constrained and 0 otherwise. The estimations outcomes reported in Table 2 show the same result as those obtained with the ordered variable. The interaction variable still produces a negative and significant sign, suggesting that credit bureaus in countries with lower levels of corruption are more likely to share true information on borrowers to lenders, thus making access to credit easier for firms. However, credit bureaus in countries with higher levels of corruption are more likely to make access to credit more difficult. We will conduct further investigation to confirm or infirm these results.

More results reported in Table 2 also show a positive and significant relationship between CB and financial constraints, showing that the presence of credit bureaus helps to reduce information asymmetry, avoid delinquent borrowers and therefore increases financial constraints for firms as above. This finding is in line with the studies of Bennardo et al. (2010) and Doblas-Madrid and Minetti (2013). The remaining variables using the CPI and the COC index display the same signs as seen in Table 1 for the dummy variable. For example, per-capita GDP and population are negatively associated with financial constraints suggesting that firms in wealthier countries with larger populations face fewer financing constraints.

4. Robustness checks

Numerous studies report the existence of a nonlinear relationship between corruption and countries' level of development (Saha and Ben Ali, 2017; Saha and Gounder, 2013). To check the stability of the relationships among financial constraints, credit bureaus and corruption, we split our sample into two subsamples depending on their level of development and on their levels of corruption namely the EE and the MENA subsamples. The estimation outcomes are reported in Table 3. The first two columns display the estimation outcomes for the MENA countries using the ordered probit model with the CPI and the COC index, respectively. The third and the fourth columns report the estimation results for the dummy variable model for these two corruption measures, respectively. Columns 5–8 report the estimation outcomes for the EE countries using the two

Table 2. The Probit model for financial constraints (dummy variable), corruption and credit bureaus.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB	0.027***	0.026***	0.031***	0.035***	0.001	0.002*	0.004***	0.008***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
CPI	0.180***	0.145***	0.266***	0.263***				
	(0.033)	(0.036)	(0.065)	(0.070)				
CB × CPI	−0.006***	−0.006***	−0.006***	−0.006***				
	(0.001)	(0.001)	(0.001)	(0.001)				
ln(sales)		−0.023**		−0.038***		−0.022**		−0.035***
		(0.010)		(0.011)		(0.010)		(0.011)
ln(size)		−0.055**		−0.038*		−0.056**		−0.041*
		(0.022)		(0.023)		(0.022)		(0.0234)
Gov. owned		−0.000		−0.001		−0.000		−0.000
		(0.004)		(0.004)		(0.004)		(0.004)
Exporter		−0.000		−0.000		−0.000		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)
per-capita GDP			−0.217**	−0.304***			−0.251**	−0.313***
			(0.085)	(0.0971)			(0.104)	(0.113)
Inflation			0.002	0.009*			0.002	0.007
			(0.004)	(0.004)			(0.004)	(0.005)
Trade			−0.000	0.000			0.000	0.001
			(0.001)	(0.001)			(0.001)	(0.001)
Population			−0.035	−0.053*			−0.016	−0.030
			(0.024)	(0.028)			(0.024)	(0.028)
School			0.002	0.001			0.002	0.000
			(0.002)	(0.002)			(0.002)	(0.002)
COC					0.422***	0.345***	0.687***	0.658***
					(0.076)	(0.084)	(0.170)	(0.179)
								(0.0012)
CB × COC					−0.015***	−0.014***	−0.016	−0.016***
					(0.002)	(0.002)	(0.002)	(0.002)
Pseudo-$R2$	0.018	0.025	0.021	0.032	0.017	0.024	0.021	0.031
chi2	42.399	55.199	66.753	81.480	48.141	58.325	68.346	81.256
N. of observations	8316	6812	8316	6812	8316	6812	8316	6812

Note that *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Each regression contains the constant coefficient. Standard errors are in parentheses.

Table 3. Financial constraints, corruption and credit bureaus: subsample estimations.

	MENA countries				Eastern European countries			
	Ordered Probit model		Dummy variable model		Ordered Probit model		Dummy variable model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB	0.195***	0.024***	0.082*	0.003	0.016	0.001	−0.008	0.008***
	(0.028)	(0.004)	(0.046)	(0.008)	(0.012)	(0.001)	(0.021)	(0.002)
CPI	1.473***		0.742**		−0.095		−0.027	
	(0.191)		(0.306)		(0.106)		(0.172)	
CB × CPI	−0.029***		−0.012*		−0.004		0.003	
	(0.004)		(0.007)		(0.003)		(0.005)	
ln(sales)	−0.057***	−0.057***	−0.077***	−0.077***	0.022**	0.022**	−0.026	−0.025
	(0.014)	(0.014)	(0.025)	(0.025)	(0.009)	(0.008)	(0.016)	(0.015)
ln(size)	0.001	0.001	−0.058	−0.058	−0.038**	−0.040**	−0.007	−0.009
	(0.022)	(0.022)	(0.042)	(0.042)	(0.017)	(0.017)	(0.031)	(0.031)
Gov. owned	−0.013**	−0.013**	−0.006	−0.006	−0.003*	−0.002	−0.003	−0.002
	(0.006)	(0.006)	(0.012)	(0.012)	(0.002)	(0.002)	(0.004)	(0.004)
Exporter	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.001	−0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Per-capita GDP	−1.877***	−0.972***	−0.914***	−0.456**	0.083	0.111	−0.143	−0.171
	(0.201)	(0.113)	(0.315)	(0.190)	(0.069)	(0.080)	(0.124)	(0.133)
Inflation					0.002	0.004	0.027***	0.033***
					(0.004)	(0.005)	(0.008)	(0.008)
Trade					−0.007***	−0.006***	−0.014***	−0.008***
					(0.001)	(0.001)	(0.003)	(0.002)
Population					−0.040*	0.011	−0.109**	−0.057
					(0.024)	(0.023)	(0.050)	(0.046)
School					0.008***	0.006***	0.002	0.004
					(0.001)	(0.002)	(0.003)	(0.003)
COC		2.451***		1.237**		−0.011		0.644**
		(0.318)		(0.507)		(0.190)		(0.294)
CB × COC		0.035***		−0.013		−0.014***		−0.018***
		(0.006)		(0.010)		(0.003)		(0.006)
Pseudo-R^2	0.052	0.052	0.095	0.095	0.020	0.022	0.035	0.038
chi^2	404.797	404.797	95.205	95.205	224.926	249.303	62.538	69.880
N. of observations	2716	2716	2716	2716	4096	4096	4096	4096

Note that *, ** and *** * indicate significance at the 10%, 5% and 1% levels, respectively. Each regression contains the constant coefficient. Standard errors are in parentheses.

financial constraint variables (ordered and dummy variables) and the two measures of corruption.

The estimation results show that the credit bureau variable still produces the same positive impact on the financial constraint variable for both corruption measures, suggesting that the information delivered by these institutions helps distinguish between good and bad borrowers, which make access to credit more difficult. This effect is seen for both MENA and the EE countries. However, the impact is more pronounced for MENA countries than for the EE countries. This result suggests that firms in MENA countries are less mature than their EE counterparts that have mixed and non-audited financial states that might be rejected for financing when information is disseminated by credit bureaus.

Another interesting result supports the idea that increased corruption is linked to fewer financial constraints. This impact is particularly important and significant for MENA countries, which have higher levels of corruption, than for the EE countries. The CB × CPI interaction variable still has a negative impact for MENA countries, which have more corruption than their EE counterparts, where the impact is insignificant. In the MENA countries, when a firm is a state-owned, it displays less risk and has more access to sources of finance. In addition, in the EE counties, being a government-owned firm does not influence access to financing.

5. Conclusion and policy recommendations

Credit bureaus are private or public institutions that deliver information on potential borrowers to lenders. Access to different sources of financing can be impacted by the presence of these institutions, making financial constraints more or less difficult for firms. Corruption can interfere, making the delivery of information less transparent or increasing the likelihood of artificially falsified information, reducing financial constraints. This paper investigated this issue in a sample of 18 countries over 2011–2014 period with two financial constraint measures and two corruption indices.

The estimation outcomes support the idea that the interaction between credit bureaus and corruption decreases financial constraints for firms. Specifically, in less corrupt countries, credit bureaus are more efficient and this decreases financial constraints for firms. We checked the robustness of our relationship by running an estimation on subsamples with different levels of economic development and corruption. The subsample estimation confirmed this result and showed that the higher and sometimes longer-term corruption in MENA countries than in EE countries made these institutions less effective.

Our findings presented in this paper have important policy implications for governments in EE and MENA countries and other international organizations that are helping these countries to establish credit bureaus in order to promote access to credit and increase economic development, as they show that credit bureaus will be more efficient if countries decrease their levels of corruption. Beyond that, credit bureaus can reduce information asymmetry, avoid delinquent borrowers and therefore increase help promoting effective allocation of credit.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Summary statistics.

Variables	Obs	Mean	Std. Dev.	Min.	Max.
Financial constraints	8316	1.108	1.296	0	4
Dummy financial constraints	8316	0.064	0.245	0	1
Credit bureau (CB)	8316	28.400	25.986	0	90.963
Control of corruption (COC)	8316	−0.064	0.518	−0.889	0.927
Corruption perception index (CPI)	8316	4.017	1.151	2.336	6.490
Per-capita GDP	8316	8.489	0.795	6.847	10.048
Inflation	8316	9.891	8.610	1.815	34.555
Trade	8316	90.685	27.926	48.612	138.525
Population	8316	16.361	1.211	14.121	18.031
ln(sales)	6830	15.280	2.799	0	29.710
ln(size)	8271	3.159	1.347	0	9.392
Gov. owned	8316	0.745	7.386	0	99
Exporter	8316	83.379	31.083	0	100

Table A2. Correlation matrix.

	Finconst	Dfinconst	CB	COC	CPI	GDP	School	Inflation	Trade	Pop	ln(sales)	ln(size)	Gov. owned	Exporting
Finconst	1.000													
Dfinconst	0.584	1.000												
CB	−0.093	−0.026	1.000											
COC	−0.099	−0.023	0.524	1.000										
CPI	−0.098	−0.025	0.399	0.964	1.000									
GDP	−0.136	−0.045	0.738	0.811	0.721	1.000								
School	−0.039	−0.024	0.285	0.101	0.076	0.367	1.000							
Inflation	−0.042	−0.026	−0.262	−0.515	−0.495	−0.161	0.090	1.000						
Trade	0.044	0.014	−0.404	0.013	0.122	−0.261	0.351	−0.130	1.000					
Pop	0.001	−0.022	−0.039	−0.429	−0.493	−0.187	−0.201	0.484	0.567	1.000				
ln(sales)	−0.063	−0.060	0.149	−0.066	−0.060	0.022	0.005	0.224	0.050	0.021	1.000			
ln(size)	−0.041	−0.051	−0.045	0.007	0.028	−0.021	−0.141	0.038	0.069	0.083	0.477	1.000		
Gov. owned	−0.029	−0.0147	0.051	−0.061	−0.046	−0.029	0.053	0.142	0.087	0.008	0.182	0.105	1.000	
Exporting	0.002	0.0058	0.067	−0.075	−0.091	−0.054	0.107	−0.032	0.067	0.024	−0.040	−0.315	−0.001	1.000

Table A3. List of countries.

Country	Fin. constr.	Dummy Fin. constr.	Credit bureau	CPI	COC
Armenia	1.720	0.115	43.972	2.844	−0.622
Belarus	1.011	0.040	0	3.01	−0.698
Bulgaria	0.965	0.048	2.190	3.863	−0.148
Croatia	1.298	0.084	72.945	3.823	0.030
Estonia	0.400	0.011	25.736	6.154	0.831
Hungary	0.793	0.020	36.054	5.036	0.537
Israel	0.528	0.012	90.963	6.490	0.927
Jordan	1.972	0.150	0	4.9	0.202
Latvia	1.109	0.040	5.745	4.163	0.078
Lithuania	0.940	0.075	42.954	4.718	0.161
Moldova	0.651	0.026	1.836	2.772	−0.685
Morocco	1.299	0.051	13.127	3.5	−0.218
Poland	1.077	0.058	64.627	4.136	0.331
Romania	1.503	0.140	30.554	3.190	−0.280
Slovenia	1.197	0.085	54.445	6.127	0.893
Tunisia	1.138	0.074	0	4.736	0.032
Turkey	0.739	0.043	29.163	3.790	−0.136
Ukraine	1.319	0.052	16.463	2.336	−0.889