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DOES CORRUPTION AFFECT ACCESS TO BANK CREDIT FOR MICRO AND SMALL BUSINESSES? EVIDENCE FROM EUROPEAN MSMES

Emma Galli, Danilo V. Mascia,
and Stefania P.S. Rossi

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Emma Galli is at the Department of Social and Economic Sciences, Sapienza University of Rome. Danilo V. Mascia is at the Department of Economics and Business, University of Cagliari. Stefania P.S. Rossi (corresponding author) is at the Department of Economics, Business, Mathematics and Statistics (DEAMS), University of Trieste.

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Please contact the authors for information about this paper.

Email: emma.galli@uniroma1.it, danilo.mascia@gmail.com, stefania.rossi@deams.units.it

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Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

In this paper, we aim to assess how a specific socio-institutional environment, identified according to the level of corruption, may affect the access to credit for micro, small, and medium-sized enterprises (MSMEs). Using a sample of 68,115 observations – drawn from the ECB-SAFE survey – related to MSMEs chartered in 11 euro area countries during the period 2009–2014, we investigate whether the level of corruption affects their demand for bank loans.

Overall, we find that the degree of corruption seems to play a role in the applications for bank loans when small firms are under investigation. Interestingly, results highlight that small businesses chartered in highly corrupt countries face a greater probability of self-restraint regarding their loan applications (about 7.4%) than small firms located in low-corruption economies (around 6%). The results are robust to various model specifications and econometric methodologies. Our findings suggest that anti-corruption policies and measures enhancing transparency in the economy may be crucial in reducing the negative *spillovers* generated by a low-quality institutional environment on the access to credit by small firms.

Keywords: credit access, bank loans, MSMEs, corruption

JEL Classification: G20, G21, G30, G32, D73

Contents

1. INTRODUCTION AND RELATED LITERATURE

Bank credit is a crucial financing tool for the development of micro, small, and medium-sized enterprises (MSMEs), given their difficulties in easily entering the equity markets (Ayadi and Gadi 2013; Kremp and Sevestre 2013; Vermoesen, Deloof, and Laveren 2013). However, the access to bank credit is not as easy as one might think. Specifically, MSMEs often come into trouble when they have to provide good collateral for the loan officers (Cowan, Drexler, and Yañez 2015; Öztürk and Mrkaic 2014; Vos et al. 2007). Additionally, in times of crisis – like the one that recently occurred in Europe – liquidity shortages and credit restrictions further weaken the access to bank loans for MSMEs (Popov and Van Horen 2015; Popov and Udell 2012). This is not inconsequential, given that MSMEs are important drivers of the European economy. Indeed, they represent 99% of nonfinancial firms in the European Union (EU), provide jobs for more than 91 million people (67% of employment in the EU), and generate about 60% of the total added value of the entire Union (EIF, 2016).

Apart from the economic and financial features, the quality of the institutional environment may play an important role in affecting the credit market in many regards. A vast branch of the empirical literature has shown that some factors such as the efficiency in the enforcement of legal rights – i.e., creditor rights protection and judicial enforcement (La Porta et al. 1997; Qian and Strahan 2007; Djankov et al. 2008; Moro, Maresch, and Ferrando 2016; Galli, Mascia, and Rossi 2017) – and the competitiveness of the bank market (Cavalluzzo, Cavalluzzo, and Wolken 2002) play a role in the credit market, thereby affecting MSMEs' loan applications. Little literature exists, however, about the effects of corruption on MSMEs' access to bank credit. This is particularly unfortunate given that corruption is considered a major obstacle to economic growth (see, among others, Myrdal 1989; Andvig and Moene 1990; Shleifer and Vishny 1993; Mauro 1995; Keefer and Knack 1997; Hall and Jones 1999; La Porta et al. 1999; Li, Xu, and Zou 2000; Gyimah-Brempong 2002; Tanzi and Davoodi 2002; Kaufmann 2005; Blackburn and Sarmah 2008; World Bank 2007; World Bank various years). More specifically, corruption mainly acts as a barrier to competition, reduces both domestic and foreign private investments, misallocates public resources – negatively affecting the efficiency of public investments – and reduces the level of trust in the institutions (Hunt 2005; Hunt and Laszlo 2005). In particular, some papers (e.g., Bhagwati 1982; Campos, Estrin, and Proto 2010; Svensson 2003) emphasize that in a highly corrupt environment, bribes represent a barrier to entry, especially for the micro, small, and medium firms, because the scarcity of their financial resources, the lower bargaining power, and the difficulty in accessing bank credit make it very difficult for them to refuse the payment of bribes. In other words, the burden per output is obviously greater for MSMEs than for the large companies and multinationals (Gbetnkom 2012; Seker and Yang 2012). In contrast, social capital supposedly stimulates the opposite mechanisms in the credit market. By increasing the level of trust and reducing the asymmetric information characterizing credit contracts, social capital improves the credit conditions for firms – thereby easing their access to bank loans (Uzzi 1999; Guiso, Sapienza, and Zingales 2004; Moro and Fink 2013; Mistrulli and Vacca 2014) – and facilitates the collection of soft information, which in turn reduces adverse selection and moral hazard phenomena.

Therefore, while social capital allows a more efficient allocation of the resources in the credit market by reducing transaction costs, corruption negatively affects the business environment, diminishing the level of horizontal and vertical trust and producing uncertainty. However, to the best of our knowledge, the literature still lacks empirical contributions regarding the effect that corruption has on the access to bank credit of MSMEs.

Our paper aims to include corruption among the determinants of the MSMEs' access to bank credit on the demand side, using a sample of 68,115 observations – drawn from the ECB-SAFE[1] – related to MSMEs chartered in 11 euro area countries during the period 2009–2014 (i.e., from the first to the twelfth wave of the survey). We add to the literature by empirically analyzing whether and to what extent corruption affects the access to bank credit for small firms. Interestingly, we perform our tests on a sample whose initial years are characterized by financial turbulence and heavy credit restrictions.

The paper is organized as follows. In Section 2, we illustrate the data and the methodology. In Section 3, we discuss the steps of our empirical strategy and comment on the results. Section 4 draws some conclusions.

2. DATA AND METHODOLOGY

2.1 Data Description

Most of the data that we use in the paper comes from the SAFE, which is jointly run by the European Central Bank (ECB) and the European Commission (EC) and has been conducted every six months since 2009 with the aim of collecting economic and financial information about European MSMEs. Each wave of the survey is addressed to a randomly selected sample of nonfinancial enterprises from the Dun & Bradstreet business register; firms in agriculture, public administration, and financial services, however, are deliberately excluded.

We conduct our tests on a subsample of enterprises chartered in the 11 largest euro area economies (i.e., Austria, Belgium, France, Finland, Germany, Greece, Italy, Ireland, the Netherlands, Portugal, and Spain), where the differences in the micro and macroeconomic features, as well as in the socio-institutional environment, are relevant.

All the macrodata that we employ as control variables in our regressions are retrieved from different sources (i.e., Heritage Foundation, Worldwide Governance Indicators, OECD, ECB Data Warehouse, World Bank).

Therefore, our sample consists of 68,115 firm observations and is stratified by country, firm size, and activity. Table 1.a shows the distribution of our observations by country, with France, Germany, Spain, and Italy exhibiting the highest sample representativeness. Table 1.b, on the other hand, displays the distribution of our sample observations by firm size.

[1] Survey on the Access to Finance of Enterprises (SAFE): https://www.ecb.europa.eu/stats/money/surveys/sme/html/index.en.html

Table 1.a: Observations by Country

Country Name	Observations	
	Freq.	%
Austria	4,101	6.02
Belgium	4,075	5.98
Finland	3,787	5.56
France	9,991	14.67
Germany	9,950	14.61
Greece	4,088	6.00
Ireland	3,708	5.44
Italy	9,930	14.58
Netherlands	4,239	6.22
Portugal	4,288	6.30
Spain	9,958	14.62
Total	68,115	100.00

Table 1.b: Observations by Firm Size

Firm Size	Observations	
	Freq.	%
Micro (up to 9 employees)	22,921	33.65
Small (between 10 and 49 employees)	22,730	33.37
Medium (between 50 and 249 employees)	17,287	25.38
Large (more than 250 employees)	5,177	7.60
Total	68,115	100.00

2.2 Dependent and Key Variables

In order to assess whether corruption affects the access to bank credit of small firms, we employ question "*q7a_a*" of the survey as a dependent variable (especially in the first and third stage of our analysis). In particular, the question is aimed at detecting whether a firm applied for bank loans, and if not, the reasons why it did not. More specifically, the question is:

> *"[With regards to bank loans], could you please indicate whether you: (1) applied for any over the past 6 months; (2) did not apply because you thought you would be rejected; (3) did not apply because you had sufficient internal funds; or (4) did not apply for other reasons"*

The values from 1 to 4, outlined in parentheses, represent the way each respondent's answers were coded.

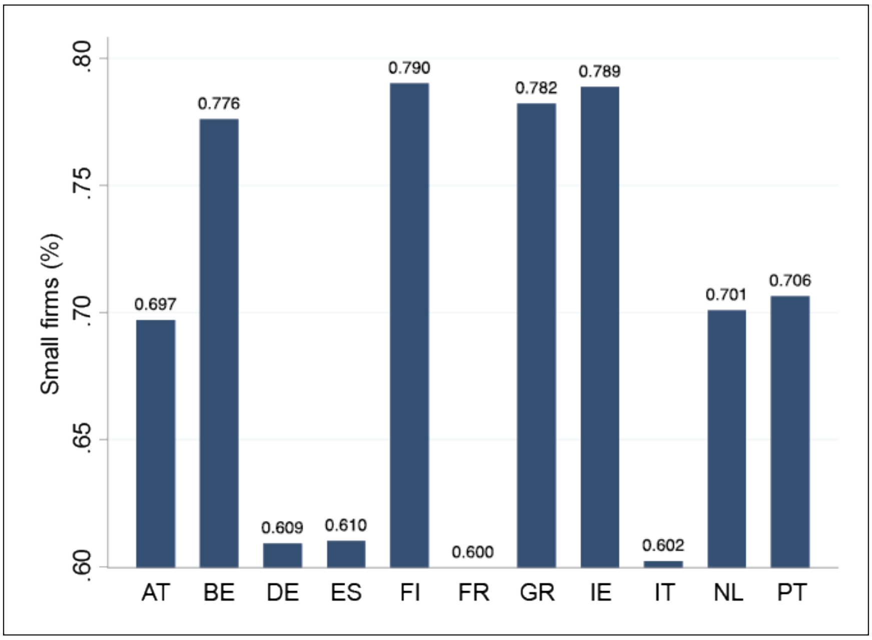
In the second stage of our investigation, we employ a dummy called ***Fear*** as a dependent variable. This dummy is generated by utilizing information from answer (2) of the above-mentioned question *q7a_a* – hence taking a value of 1 when an enterprise did not apply for fear of rejection, and 0 when a firm did not apply for other reasons.

Then we identify two key variables for our analyses, namely the size of the firm and the country's level of corruption. The former is measured with a dummy (***Small)*** that is equal to 1 when a firm has fewer than 50 employees, and 0 otherwise. As regards the latter, it is worth noting that the literature recognizes a variety of measures that proxy for corruption: perception-based indicators, experience-based indicators, and objective measures such as the number of corruption-related trials or cases (Gutmann, Padovano, and Voigt 2014). In this paper, we decide to employ two alternatively comparable survey measures, namely ***Freedom from corruption*** (drawn from the Heritage Foundation) – whose score is primarily derived from Transparency International's Corruption Perception Index (CPI) – and ***Control of corruption*** (Worldwide Governance Indicators), which are both available for all countries and on a yearly basis.

With regards to firm size, Figure 1 reports the percentage of small firms in our sample, by country. Interestingly, we note that in Belgium, Finland, Greece, and Ireland small firms cover more than 75% of all firm observations.

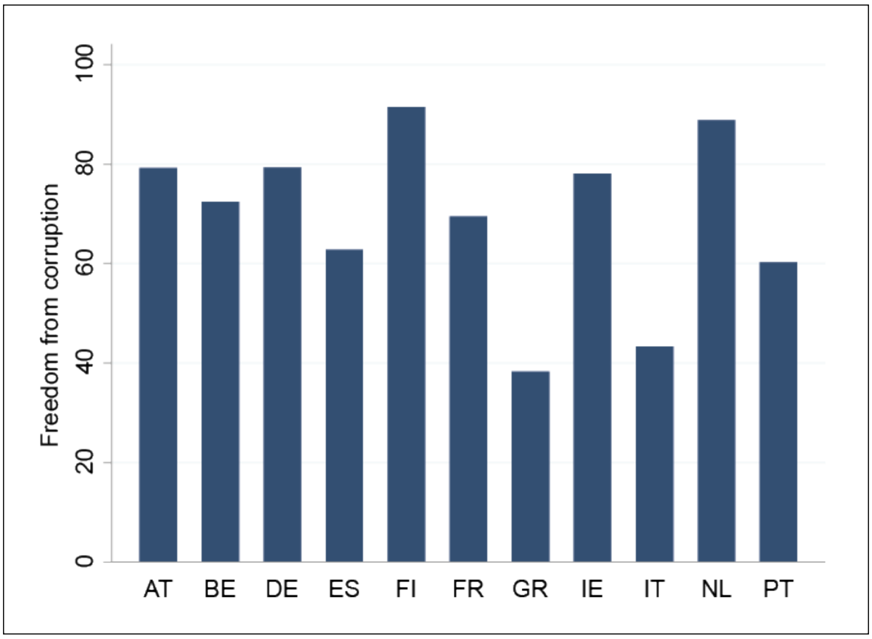
Figure 2 and Figure 3, on the other hand, show the average value of the two corruption indicators employed in our analyses, by country. For the sake of clarity, please note that the higher (lower) the value shown for each indicator, the lower (higher) the level of corruption in that country.

Figure 1: Percentage of Small Firms by Country



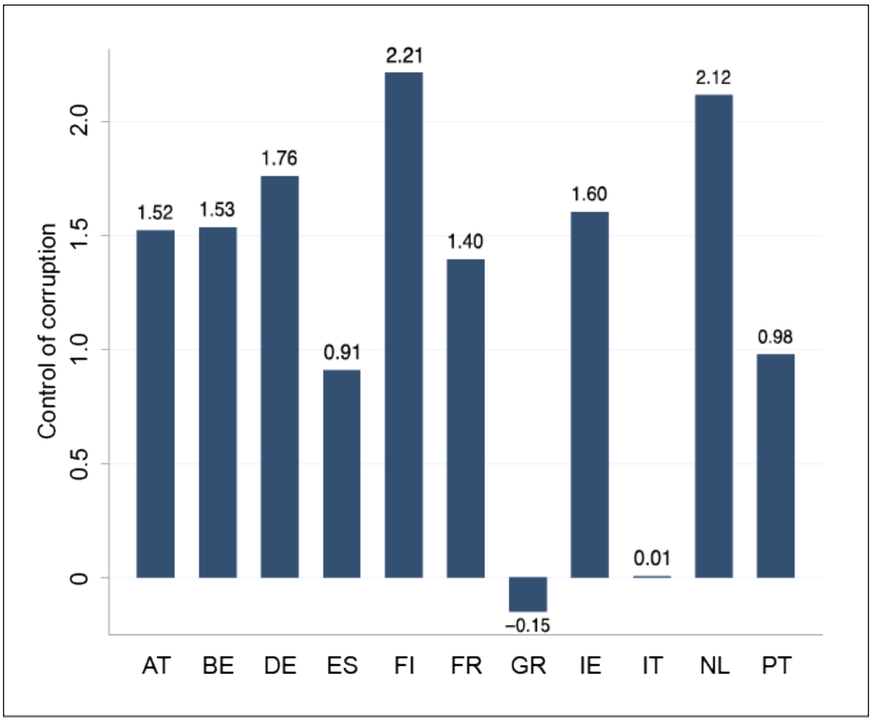
AT = Austria, BE = Belgium, DE = Germany, ES = Spain, FI = Finland, FR = France, GR = Greece, IE = Ireland, IT = Italy, NL = The Netherlands, PT = Portugal.

Figure 2: Freedom from Corruption by Country



AT = Austria, BE = Belgium, DE = Germany, ES = Spain, FI = Finland, FR = France, GR = Greece, IE = Ireland, IT = Italy, NL = The Netherlands, PT = Portugal.

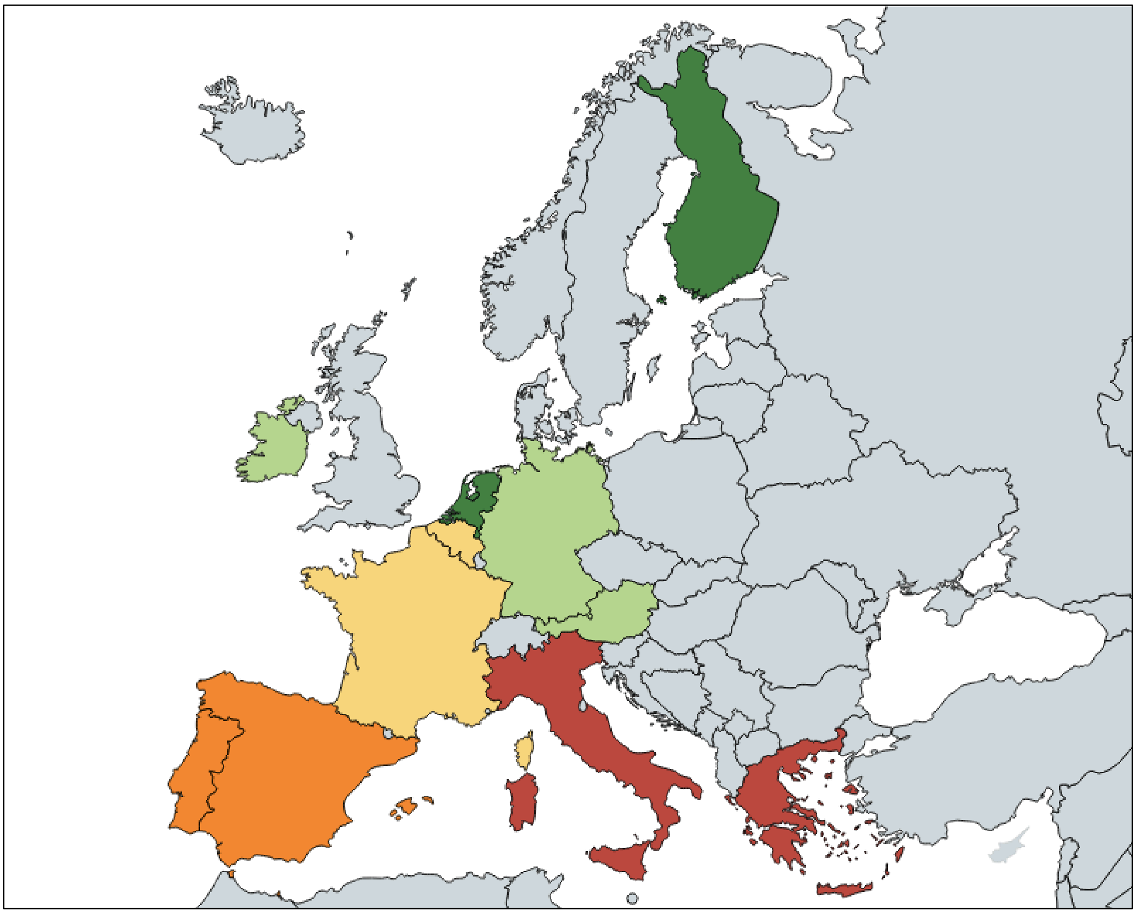
Figure 3: Control of Corruption by Country



AT = Austria, BE = Belgium, DE = Germany, ES = Spain, FI = Finland, FR = France, GR = Greece, IE = Ireland, IT = Italy, NL = The Netherlands, PT = Portugal.

Finally, Figure 4 depicts a picture of the level of corruption in the euro area through the use of a map. More specifically, based on the “Freedom from corruption” indicator, we assign different colors to the countries in our sample according to their perceived degree of corruption. In particular, we employ the following scale of colors to highlight the territories from the most to the least corrupt ones: red, orange, yellow, light green, and dark green. For instance, countries in red (i.e., Greece and Italy) represent the most corrupt economies. In contrast, areas in dark green (i.e., Finland and the Netherlands) are the least corrupt ones.

Figure 4: Map Depicting the Degree of Corruption in our Sample



Source = Map customized by the authors, according to the degree of corruption provided by the Heritage Foundation.

2.3 Econometric Strategy and Control Variables

The hypothesis under investigation is the following:

H1: *Where corruption is higher, small firms are more likely to refrain from applying for bank loans than larger firms.*

We test our hypothesis with the following model [1]:

P_i (applying for loans) = f (small firms, corruption, firm controls, macro, country, wave) [1]

The specification includes standard firm controls such as age; sector (construction, manufacturing, mining, wholesale); financial firm controls, such as change in leverage, capital, profitability, and credit history; and macro controls such as GDP growth, the Herfindahl Index (HI) of bank concentration, nonperforming loans over gross loans (NPL ratio), and a dummy that captures the expansionary monetary policy phase that followed the Outright Monetary Transaction (OMT) announcement by the ECB. Finally, we use country and time dummies as additional controls.

We perform our analysis in three steps. First we estimate equation [1] by employing a multinomial logit model as in Demirguc-Kunt, Klapper, and Singer (2013) and Badoer and James (2016), because: *i*) our dependent variable is a discrete one, given that it takes more than two outcomes and the outcomes have no natural ordering (see description in Section 2.2); *ii*) it is suitable for the use of continuous variables and multiple categorical variables as regressors.

Secondly, we test model [1] by employing our ***Fear*** dummy as a dependent variable through the use of logit models, and further corroborate our findings with a series of robustness checks that we carry out via Heckman selection models.

Table 2: Summary Statistics

	Observations	Mean	Median	St. Dev.	p1	p99
Dependent variables						
q7a_a	68,115	2.626	3.000	1.094	1.000	4.000
Fear	50,096	0.083	0.000	0.276	0.000	1.000
Key variable						
Small	68,115	0.670	1.000	0.470	0.000	1.000
Country-level controls						
Freedom from corruption	68,115	67.588	69.000	15.489	34.000	94.000
Control of corruption	68,115	1.187	1.420	0.712	–0.250	2.220
GDP Growth	68,115	–0.620	0.050	2.934	–8.200	5.050
Concentration	68,115	0.088	0.060	0.077	0.021	0.370
NPL	68,115	7.101	4.295	6.254	0.500	31.899
OMT	68,115	0.437	0.000	0.496	0.000	1.000
Firm-level controls						
Profit up	68,115	0.238	0.000	0.426	0.000	1.000
Profit down	68,115	0.472	0.000	0.499	0.000	1.000
Credit up	68,115	0.204	0.000	0.403	0.000	1.000
Credit down	68,115	0.142	0.000	0.349	0.000	1.000
Capital up	68,115	0.243	0.000	0.429	0.000	1.000
Capital down	68,115	0.204	0.000	0.403	0.000	1.000
Leverage up	68,115	0.207	0.000	0.405	0.000	1.000
Leverage down	68,115	0.276	0.000	0.447	0.000	1.000
Demand up	68,031	0.191	0.000	0.393	0.000	1.000
Demand down	68,031	0.131	0.000	0.337	0.000	1.000
Very recent	68,115	0.020	0.000	0.139	0.000	1.000
Recent	68,115	0.069	0.000	0.253	0.000	1.000
Old	68,115	0.128	0.000	0.334	0.000	1.000
Construction	68,115	0.100	0.000	0.300	0.000	1.000
Manufacturing	68,115	0.255	0.000	0.436	0.000	1.000
Wholesale/Retail	68,115	0.337	0.000	0.473	0.000	1.000

Finally, we repeat our multinomial logit estimations by splitting the sample into low- and high-corruption areas in order to check whether the behavior of small firms changes according to the level of a country's corruption.

All regressions include time and country dummies. Calibrated weights are employed to adjust the sample to be representative of the population (as in Ferrando, Popov, and Udell 2017). Standard errors are corrected for heteroskedasticity, and clustered at the country-level, to remove possible bias in the estimations.

Table 2 shows the summary statistics of the variables employed in our analysis. Table A1 in the Appendix, meanwhile, provides descriptions of variables and sources.

3. EMPIRICAL RESULTS

3.1 Multinomial Logit Models – Full Sample

The empirical results of our estimations regarding the likelihood that small firms will apply for bank loans are presented in Table 3. Following the assumptions of the multinomial logit methodology, here we set the first answer to question *q7a_a* (i.e., "applied") as our base outcome. Panel A (B) reports the estimate of model [1] when we control for corruption as proxied by ***Freedom from corruption*** (***Control of corruption***). Estimated marginal effects are reported in brackets.

Table 3: Bank Loan Applications: Multinomial Logit Model

	(1) Applied	(2) Did_not_apply_fear	(3) Did_not_apply_suff	(4) Did_not_apply_other
Panel A				
Small	(base)	1.034***	0.363***	0.528***
		(0.08)	(0.08)	(0.07)
		[0.064]		
Freedom from Corruption		–0.079**	–0.025***	–0.009
		(0.03)	(0.01)	(0.01)
SAFE Controls	YES	YES	YES	YES
Observations	68,115	68,115	68,115	68,115
Pseudo R-squared	0.0752	0.0752	0.0752	0.0752
Panel B				
Small	(base)	1.031***	0.361***	0.527***
		(0.08)	(0.08)	(0.07)
		[0.065]		
Control of Corruption		–1.764*	–0.746***	–0.893**
		(0.96)	(0.22)	(0.35)
SAFE Controls	YES	YES	YES	YES
Observations	68,115	68,115	68,115	68,115
Pseudo R-squared	0.0749	0.0749	0.0749	0.0749

Note: This table shows regression results of the multinomial logit model regarding the likelihood that small firms do not apply for bank loans. The dependent variable – which is also described in Section 2.2 – equals 1/2/3/4 if a firm applied/did not apply because of possible rejection/did not apply because of sufficient internal funds/did not apply for other reasons during the past six months, respectively. ***Small*** is a dummy that equals 1 if the firm has fewer than 50 employees, and 0 otherwise. Regressions control for "Freedom from corruption" ("Control of corruption") in Panel A (B). Though not showing, both specifications include a wide set of firm-level characteristics. See Table A1 in the Appendix for all variable definitions and sources. All regressions use sampling weights that adjust the sample to be representative of the population. Additionally, all regressions include time and country dummies. Heteroskedasticity-robust standard errors, clustered at the country level, appear in parentheses. Estimated marginal effects are reported in brackets. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Overall, we see that – after having controlled for a wide set of firm characteristics – small firms are about 6.5% more likely than their larger counterparts to refrain from applying for bank loans due to fear of rejection (Column 2). Interestingly, we also note that the two proxies for corruption show a negative and significant coefficient – thereby signaling that a lower level of corruption in a country translates into a lower probability of refraining from applying for fear of rejection. In other words, our result anticipates that the share of discouraged borrowers should be lower when the quality of the economic environment is higher (i.e., when the degree of corruption is low).

3.2 Logit Models – Fear of Rejection

As a second step of our investigation, we test our hypothesis by employing logit models and we further corroborate our findings through a series of robustness checks carried out via Heckman selection models. More specifically, to estimate equation [1] we now employ the dummy ***Fear*** (already described in Section 2.2) as a dependent variable.

Results are reported in Table 4 and Table 5, where we employ ***Freedom from corruption*** and ***Control of corruption*** as proxies for corruption, respectively. Moreover, the regressions displayed in both Table 4 and Table 5 vary, among the different columns, because of the progressive inclusion of the country-level controls (Column 2), and the interaction term with the proxy of corruption (Column 3).

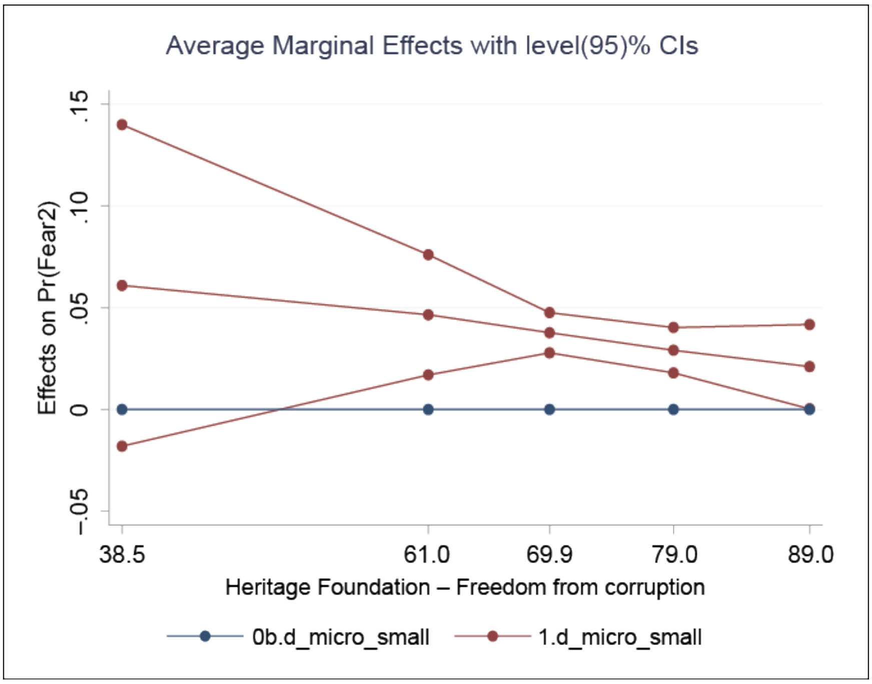
Table 4: Logit Model – with Freedom from Corruption

	(1) **Fear**	**(2)** **Fear**	**(3)** **Fear**
Small	0.632***	0.634***	0.081
	(0.09)	(0.09)	(0.30)
Freedom from Corruption	–0.067**	–0.049	–0.055
	(0.03)	(0.04)	(0.04)
Small x Freedom from Corruption			0.008**
			(0.00)
GDP Growth		0.081	0.081
		(0.06)	(0.06)
Concentration		–13.519*	–13.551*
		(7.98)	(7.98)
NPL		0.081***	0.081***
		(0.03)	(0.03)
OMT		–0.507***	–0.505***
		(0.16)	(0.16)
SAFE Controls	YES	YES	YES
Observations	50,096	50,096	50,096
Pseudo R-squared	0.0984	0.101	0.102

Note: This table shows regression results of the logit model regarding the likelihood that small firms do not apply for bank loans for fear of rejection. The dependent variable (***Fear***) – which is also described in Section 2.2 – is a dummy that equals 1 if a firm did not apply because of possible rejection, and 0 otherwise. ***Small*** is a dummy that equals 1 if the firm has fewer than 50 employees, and 0 otherwise. Though not showing, all the models include a wide set of firm-level characteristics. See Table A1 in the Appendix for all variable definitions and sources. All regressions use sampling weights that adjust the sample to be representative of the population. Additionally, all regressions include time and country dummies. Heteroskedasticity-robust standard errors, clustered at the country level, appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

The results from Table 4 highlight that – in line with the findings previously obtained with the multilogit analysis – small firms refrain from applying for bank loans for fear of rejection, as they anticipate a negative response from the lender. The variable ***Freedom from corruption*** presents a negative and significant sign suggesting that, when the level of corruption is lower, firms may experience a lower probability of self-restraint. Interestingly, the interaction between size and corruption shows a positive and significant sign. For this reason, we decide to plot the probability that a small firm does not apply for fear of rejection, for different levels of corruption (see Figure 5). Figure 5 shows that the higher the freedom from corruption (i.e., the lower the corruption), the lower the probability that small firms will not apply for a bank loan for fear of seeing their application rejected. Put another way, the lower the corruption, lower the share of discouraged borrowers.

Figure 5: Marginal Effect of Small Firms Not Applying for Fear of Rejection for Different Levels of Corruption (As Proxied by Freedom from Corruption)



We now try to corroborate our findings by employing a different proxy of corruption, namely ***Control of corruption***. The results, reported in Table 5, are consistent with those presented in Table 4. Namely, we find that small firms refrain from applying for bank loans, and we also see that corruption influences their financing strategy.

Table 5: Logit Model – with Control of Corruption

Variables	(1) Fear	(2) Fear	(3) Fear
Small	0.627***	0.633***	0.409***
	(0.09)	(0.09)	(0.13)
Control of Corruption	–0.998	–0.664	–0.798
	(1.04)	(0.70)	(0.69)
Small x Control of Corruption			0.176**
			(0.08)
GDP Growth		0.057	0.056
		(0.04)	(0.04)
Concentration		–12.582	–12.622
		(8.67)	(8.68)
NPL		0.106***	0.106***
		(0.04)	(0.04)
OMT		–0.591***	–0.589***
		(0.15)	(0.15)
SAFE Controls	YES	YES	YES
Observations	50,096	50,096	50,096
Pseudo R-squared	0.0964	0.101	0.101

Note: This table shows regression results of the logit model regarding the likelihood that small firms do not apply for bank loans for fear of rejection. The dependent variable (***Fear***) – which is also described in Section 2.2 – is a dummy that equals 1 if a firm did not apply because of possible rejection, and 0 otherwise. ***Small*** is a dummy that equals 1 if the firm has fewer than 50 employees, and 0 otherwise. Though not showing, all the models include a wide set of firm-level characteristics. See Table A1 in the Appendix for all variable definitions and sources. All regressions use sampling weights that adjust the sample to be representative of the population. Additionally, all regressions include time and country dummies. Heteroskedasticity-robust standard errors, clustered at the country level, appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

As for the marginal effects, Figure 6 plots the probability that a small firm does not apply for fear of rejection, for different levels of corruption (as proxied by ***Control of corruption***). The results – in this case too – show that the lower the degree of corruption, the lower the fear of rejection experienced by small firms.

3.3 Robustness Checks: Heckman Selection Models

In this section we present further robustness checks. Because the tests in Section 3.2 (i.e., logit models) have been conducted on a sample of firms that did not apply for bank loans (thereby excluding those who applied), one might raise concerns that our results are affected by a sample selection bias. To overcome this potential criticism, we re-estimate our models following the Heckman (1979) approach, which requires us to specify a selection equation that includes a set of variables affecting the possibility of observing the phenomenon but not the outcome itself. The results are displayed in Table 6 and Table 7 and corroborate our previous findings.

Figure 6: Marginal Effect of Small Firms Not Applying for Fear of Rejection for Different Levels of Corruption (As Proxied by Control of Corruption)

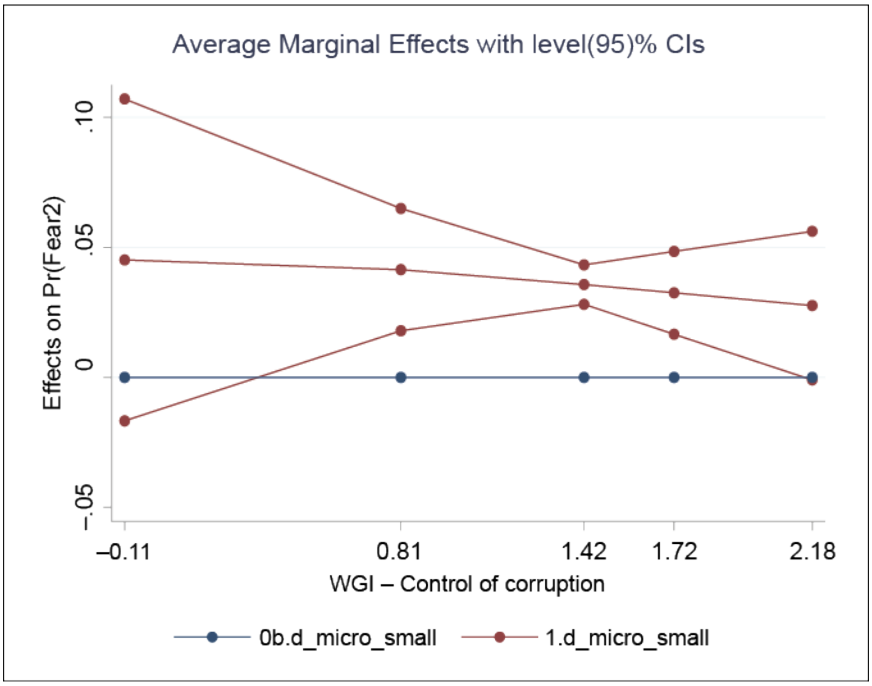


Table 6: Heckman Selection Model – with Freedom from Corruption

	(1) Fear	(2) Fear	(3) Fear
Regression equation			
Small	0.027***	0.027***	0.003
	(0.00)	(0.00)	(0.01)
Freedom from Corruption	–0.003***	–0.001*	–0.001**
	(0.00)	(0.00)	(0.00)
Small x Freedom from Corruption			0.000**
			(0.00)
GDP Growth		0.001	0.001
		(0.00)	(0.00)
Concentration		–0.437***	–0.433***
		(0.13)	(0.13)
NPL		0.005***	0.005***
		(0.00)	(0.00)
OMT		–0.029***	–0.029***
		(0.01)	(0.01)
SAFE Controls	YES	YES	YES

continued on next page

Table 6 *continued*

	(1) Fear	(2) Fear	(3) Fear
Selection equation			
Demand up	–1.364***	–1.364***	–1.364***
	(0.01)	(0.01)	(0.01)
Lambda (Mills ratio)	0.216***	0.214***	0.214***
	(0.01)	(0.01)	(0.01)
Observations	72,372	72,372	72,372
Prob > chi2	0	0	0

Note: This table shows regression results of the Heckman selection model regarding the likelihood that small firms do not apply for bank loans for fear of rejection. The dependent variable (***Fear***) – which is also described in Section 2.2 – is a dummy that equals 1 if a firm did not apply because of possible rejection, and 0 otherwise. ***Small*** is a dummy that equals 1 if the firm has fewer than 50 employees, and 0 otherwise. Though not showing, all the models include a wide set of firm-level characteristics. See Table A1 in the Appendix for all variable definitions and sources. All regressions use sampling weights that adjust the sample to be representative of the population. Additionally, all regressions include time and country dummies. Heteroskedasticity-robust standard errors, clustered at the country level, appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: Heckman Selection Model – with Control of Corruption

	(1) Fear	(2) Fear	(3) Fear
Regression equation			
Small	0.027***	0.027***	0.017***
	(0.00)	(0.00)	(0.01)
Control of Corruption	–0.042**	–0.019	–0.025
	(0.02)	(0.02)	(0.02)
Small x Control of Corruption			0.008**
			(0.00)
GDP Growth		0.001	0.001
		(0.00)	(0.00)
Concentration		–0.363***	–0.362***
		(0.12)	(0.12)
NPL		0.005***	0.005***
		(0.00)	(0.00)
OMT		–0.030***	–0.030***
		(0.01)	(0.01)
SAFE Controls	YES	YES	YES
Selection equation			
Demand up	–1.364***	–1.364***	–1.364***
	(0.01)	(0.01)	(0.01)
Lambda (Mills ratio)	0.216***	0.214***	0.214***
	(0.01)	(0.01)	(0.01)
Observations	72,372	72,372	72,372
Prob > chi2	0	0	0

Note: This table shows regression results of the Heckman selection model regarding the likelihood that small firms do not apply for bank loans for fear of rejection. The dependent variable (***Fear***) – which is also described in Section 2.2 – is a dummy that equals 1 if a firm did not apply because of possible rejection, and 0 otherwise. ***Small*** is a dummy that equals 1 if the firm has fewer than 50 employees, and 0 otherwise. Though not showing, all the models include a wide set of firm-level characteristics. See Table A1 in the Appendix for all variable definitions and sources. All regressions use sampling weights that adjust the sample to be representative of the population. Additionally, all regressions include time and country dummies. Heteroskedasticity-robust standard errors, clustered at the country level, appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

3.4 Further Analysis: Multinomial Logit Models – Sample Split by Corruption

In this section we discuss the results obtained when estimating our equation [1] for two subsamples that we get by splitting the initial data set into low- and high-corruption areas. Indeed, after having calculated the mean level of ***Freedom from corruption*** across the full sample, we are able to build two distinct clusters that distinguish the low-corruption countries (observations above the mean) from the high-corruption ones (observations below the mean).[2] The results of our estimations are tabulated in Table 8.

Table 8: Bank Loan Applications – Multinomial Logit Model – Sample Split by Corruption

	(1) Applied	(2) Did_not_apply_fear	(3) Did_not_apply_suff	(4) Did_not_apply_other
Panel A: Low corruption				
Small	(base)	1.061***	0.333**	0.543***
		(0.09)	(0.13)	(0.12)
		[0.062]		
SAFE Controls	YES	YES	YES	YES
Observations	36,907	36,907	36,907	36,907
Pseudo R-squared	0.0677	0.0677	0.0677	0.0677
Panel B: High corruption				
Small	(base)	0.947***	0.461***	0.574***
		(0.17)	(0.03)	(0.06)
		[0.074]		
SAFE Controls	YES	YES	YES	YES
Observations	25,739	25,739	25,739	25,739
Pseudo R-squared	0.0713	0.0713	0.0713	0.0713

Note: This table shows regression results of the multinomial logit model regarding the likelihood that small firms do not apply for bank loans. The dependent variable – which is also described in Section 2.2 – equals 1/2/3/4 if a firm applied/did not apply because of possible rejection/did not apply because of sufficient internal funds/did not apply for other reasons during the past six months, respectively. ***Small*** is a dummy that equals 1 if the firm has fewer than 50 employees, and 0 otherwise. Table A (B) reports regressions on a subsample of firms chartered in low- (high-) corruption countries. Though not showing, both specifications include a wide set of firm-level characteristics. See Table A1 in the Appendix for all variable definitions and sources. All regressions use sampling weights that adjust the sample to be representative of the population. Additionally, all regressions include time and country dummies. Heteroskedasticity-robust standard errors, clustered at the country level, appear in parentheses. Estimated marginal effects are reported in brackets. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

More specifically, Table 8 presents the coefficients and the marginal effects of our key variable (***Small firms***) in the economies characterized by lower (Panel A) and higher (Panel B) levels of corruption. In both cases, the results in Column 2 confirm the evidence previously found in the overall sample – namely, small firms (in both *regional* clusters) are more likely not to apply for fear of rejection than larger enterprises. In particular, small firms are 7.4% (6.2%) more likely than their larger peers to refrain from applying for a bank loan for fear of rejection in high- (low-) corruption economies.

[2] For the sake of clarity, the high-corruption countries are Greece, Italy, Portugal, and Spain. The low-corruption nations are Austria, Belgium, Finland, France, Germany, Ireland, and the Netherlands. In this regard, see Figure 4 that shows the degree of freedom from corruption by country.

4. CONCLUSIONS

The global financial crisis worsened the conditions of access to the credit market for enterprises in Europe. Therefore, improving access to bank credit, especially for MSMEs, becomes important to safeguard the survival and development of their businesses. In this paper, we have attempted to assess how the level of corruption – combined with several economic and financial features – affected the access to credit for MSMEs during our observed period.

To this end, we employed a sample of 68,115 observations – drawn from the ECB-SAFE survey – related to MSMEs chartered in 11 euro area countries during the period 2009–2014. The level of corruption seems to play a role in the behavior of small firms in the credit market since they are more likely to refrain – especially in high-corruption areas – from applying for bank loans than their larger peers.

Interestingly, results indicate that small firms chartered in high-corruption countries are more likely to refrain from applying for loans (more than 7.4%) than small firms located in low-corruption economies (about 6.2%).

Results are robust to different specifications and econometric methodologies.

Overall, our findings advise that policymakers should intervene in most corrupt areas in order to limit the aforementioned negative *spillovers* and to support the access to bank credit for small firms.

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APPENDIX

Table A1: Variable Descriptions and Sources

Variables	Description	Source
Dependent variables		
Bank loan – application	Variable that equals one/two/three/four if (considering bank loans) a firm applied/did not apply because of possible rejection/did not apply because of sufficient internal funds/did not apply for other reasons during the past six months, respectively.	ECB: SAFE
Fear	Variable that equals one if a firm did not apply for a bank loan because of possible rejection during the past six months.	ECB: SAFE
Key variables		
Small firms	Dummy variable that equals one if the firm has fewer than 50 employees.	ECB: SAFE
Country-level controls		
Freedom from corruption	The higher the level of corruption, the lower the level of overall economic freedom and the lower a country's score.	Heritage Foundation
Control of corruption	The higher the level of corruption, the lower a country's score.	World Bank: WGI
GDP Growth	The annual growth rate of real GDP based on averages of quarterly data for each survey round.	OECD
Concentration	The Herfindahl index (HI) of total assets concentration (for the banking sector).	ECB: Data Warehouse
NPL	The ratio of bank nonperforming loans to total gross loans.	World Bank
OMT	Dummy variable that equals one from the year of announcement (2012) of the Outright Monetary Transactions (OMT) program.	*Our calculation*
Firm-level controls		
Profit up	Dummy variable that equals one if a firm experienced an increase of the net income after taxes in the past six months.	ECB: SAFE
Profit down	Dummy variable that equals one if a firm experienced a decrease of the net income after taxes in the past six months.	ECB: SAFE
Creditworthiness up	Dummy variable that equals one if the firm's credit history improved in the past six months.	ECB: SAFE
Creditworthiness down	Dummy variable that equals one if the firm's credit history worsened in the past six months.	ECB: SAFE
Capital up	Dummy variable that equals one if a firm's own capital has improved in the past six months.	ECB: SAFE
Capital down	Dummy variable that equals one if a firm's own capital has deteriorated in the past six months.	ECB: SAFE
Leverage up	Dummy variable that equals one if a firm experienced an increase in the debt-to-assets ratio in the past six months.	ECB: SAFE
Leverage down	Dummy variable that equals one if a firm experienced a decrease in the debt-to-assets ratio in the past six months.	ECB: SAFE
Demand up	Dummy variable that equals one if a firm's needs for a bank loan increased in the past six months.	ECB: SAFE
Demand down	Dummy variable that equals one if a firm's needs for a bank loan decreased in the past six months.	ECB: SAFE
Very recent	Dummy variable that equals one if the firm is less than 2 years old.	ECB: SAFE
Recent	Dummy variable that equals one if the firm is between 2 and 5 years old.	ECB: SAFE
Old	Dummy variable that equals one if the firm is between 5 and 10 years old.	ECB: SAFE
Construction	Dummy variable that equals one if the firm's main activity is construction.	ECB: SAFE
Manufacturing	Dummy variable that equals one if the firm's main activity is manufacturing.	ECB: SAFE
Wholesale/Retail	Dummy variable that equals one if the firm's main activity is wholesale or retail trade.	ECB: SAFE