ADBI Working Paper Series

YOUNG ENTERPRISES AND BANK CREDIT DENIALS

Danilo V. Mascia

No. 844
May 2018

Asian Development Bank Institute

Danilo V. Mascia is an assistant professor in banking at Nottingham University Business School, United Kingdom.

Suggested citation:

Mascia, D. V. 2018. Young Enterprises and Bank Credit Denials. ADBI Working Paper 844. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/young-enterprises-and-bank-credit-denials

Please contact the authors for information about this paper.

Email: Danilo.Mascia@nottingham.ac.uk

The author thanks the Asian Development Bank Institute (ADBI) for the opportunity to act as invited speaker at the "ADBI–IFABS Conference on Supply Support for SMEs" (Tokyo, 17–18 October 2017), as well as for the opportunity to publish this article within the ADBI Working Paper Series.

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

By employing a sample of 20,956 observations of non-financial SMEs headquartered in the Euro area, between 2009 and 2015, we test whether young businesses are more likely to face credit rejections from lenders than their older peers. Our findings appear to confirm our suspicions that new enterprises consistently experience higher denials from banks compared to more established businesses. Such a result is stable to different model specifications and is also confirmed once we handle the issue of sample selection bias potentially affecting our data. Additional tests also reveal that credit constraints are particularly difficult for young SMEs located in Southern and Central Europe, as well as for those operating in the "Trade" industry. Overall, our evidence suggests that actions from the policy maker could be desirable to support the viability of credit and, thus, ensure the growth of young businesses in the Euro area.

Keywords: SMEs, young enterprises, bank loans, credit rationing

JEL Classification: G20, G21, G30, L26, M13, D82

Contents

1. INTRODUCTION

It is widely accepted that Small and Medium-sized Enterprises (SMEs) represent the backbone of most economies. Not surprisingly, the story sounds pretty much the same across the globe. For instance, Yoshino and Taghizadeh-Hesary (2014) report that SMEs account for almost 98% of all enterprises in Asia, offering jobs to about 66% of the workforce. In the European Union (EU), the data offer a quite similar picture. In fact, SMEs represent 99% of all non-financial enterprises and account, on average, for 67% of the total employment (see European Commission 2017). Overall, such figures undoubtedly highlight how pivotal SMEs are for the functioning of the real economy.

Another important aspect characterizing SMEs is their high dependence on the bank-lending channel to finance their projects. As a matter of fact, SMEs are unable to access equity markets (see, inter alia, Vermoesen, Deloof, and Laveren 2013) because of the high costs involved with the issuance of equity as well as the reluctance of investors to put money in small corporations. This actually leaves SMEs heavily reliant on bank credit to satisfy their liquidity needs (Polzin, Toxopeus, and Stam 2017).

Despite this, it is worth mentioning that credit is not always easily available, as SMEs most often struggle to get financing when they turn to financial institutions. This basically occurs because of the inability to provide good collaterals; the weak credit information offered; and the informational asymmetries characterizing the bank-firm relationship (see, for instance, Andrieu, Staglianò, van der Zwan 2017; Ayadi and Gadi 2013; Beck, Klapper, and Mendoza 2010; Bonnet, Cieply, and Dejardin 2016; Shaban, Duygun, and Fry 2016; Vos et al. 2007). In addition to such a discouraging picture, conventional wisdom also claims that credit constraints may even be greater for young SMEs, which are more informationally opaque than older peers (see, inter alia, Hyytinen and Pajarinen 2008).

The Stiglitz–Weiss adverse selection model (Stiglitz and Weiss 1981) is an optimal example to illustrate how a firm's opacity may turn into credit denials. More specifically, the model claims that if a firm is classified as belonging to a group characterized by serious adverse selection (say, for instance, young firms), it will probably be unable to raise funding. Whereas, if a firm is within a group experiencing weaker adverse selection (as could be the case for firms with a stronger and longer established reputation), it would more likely get financing. Diamond's model (Diamond 1989) further elaborates on this issue, claiming that adverse selection and moral hazard jointly decrease the possibility for newcomers to get finance at fair prices. Notably, this may even be more acute for young enterprises, such as starter companies, that lack a proper credit history. Specifically, if the adverse selection is sufficiently tough – with banks offering credit at very high interest rates –, the firm might then be induced not to behave diligently (i.e., moral hazard).[1]

Overall, the consequences of the credit denials perpetrated to SMEs – and especially starter companies – are unfortunate as they may threaten and hamper the proper functioning and growth of the economy. Metaphorically, it is like failing to refuel the tank: sooner or later the car will get stuck.

Motivated by the considerations illustrated above, the aim of this paper is to empirically investigate whether young enterprises in Europe suffer significant denials from banks when they try to get access to credit. To do so, we rely on a wide sample of 20,956observations – gathered from the Survey on the Access to Finance of

[1] For a deeper review, see Hyytinen and Pajarinen (2008).

Enterprises (SAFE) across the years 2009–2015 – related to firms chartered in the major countries of the Euro area (i.e., Austria, Belgium, France, Finland, Germany, Greece, Italy, Ireland, the Netherlands, Portugal, and Spain). More specifically, we first investigate whether young SMEs are actually more likely to experience credit denials by the banks, compared to older peers. In addition, we check the robustness of our tests by employing different model specifications as well as by handling potential selection biases affecting our regressions. Finally, we exploit the country heterogeneity characterizing our sample, as well as the differences in the firms' economic activities, to see whether the likelihood for new SMEs to get credit constrained varies across the dataset.

Therefore, our main hypothesis can be summarized as follows:

H1: *Young enterprises are more likely, than older peers, to face loan denials from credit institutions.*

Overall, we find that young businesses appear to consistently face credit rejections from lenders, compared to older SMEs. This result is stable to different model specifications and is confirmed even after addressing – via the Heckman probit model – the potential selection bias that may affect our estimates. Moreover, our additional tests highlight that new enterprises located in the Southern and Central countries of the Euro area are 4% more likely to face credit denials than older enterprises; whereas young businesses in Northern Europe do not seem to suffer similar issues. Finally, the results also highlight that – among the various sectors of economic activity – new businesses operating in the "Trade" industry are the ones that, compared to older peers, face the highest probability (i.e., 8%) of being credit constrained.

The paper is organized as follows. In Section 2, we offer a description of the data and the methodology employed in our study. In Section 3, we present and discuss the results. Finally, Section 4 concludes.

2. DATA AND METHODOLOGY

2.1 Data

The main source of data in this paper is the SAFE, which is a survey that is conducted every six months, since 2009, on behalf of the European Commission (specifically, the Directorate-General Internal Market, Industry, Entrepreneurship and SMEs) and the European Central Bank (ECB).[2] The survey questions – which are administered by telephone to the firm top-level executive (owner, manager, CEO) – are mainly aimed at collecting data about the financing conditions of SMEs, along with a series of additional information such as the firm's age, financial autonomy, turnover, labor costs, etc. The surveyed firms are randomly selected from the Dun & Bradstreet register. Furthermore, the sample is stratified by firm size, economic activity, and country. Notably, with regards to the stratification by firm size, the sample is designed to provide comparable information among the various size classes created according to the total employment – namely, micro (up to 9 employees), small (10 to 49 employees), and medium (50 to 249 employees). A sample of large enterprises (more than 249 employees) is also added as a control group to allow comparability with SMEs. As regards the economic activity, the statistical stratification is based on the European NACE classification at the one-digit level. Specifically, activities are grouped into four main categories, namely "Industry" (which mostly includes firms in mining, manufacturing, electricity, gas, and

[2] The survey is available at: https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/index.en.html

water supply); “Construction”; “Trade” (which incorporates enterprises involved in wholesale and retail trade, repair of motor vehicles and motorcycles, and household goods); and “Services” (including businesses offering transport, accommodation and food service activities, communication, real estate, administrative activities, arts and entertainment). Firms belonging to agriculture, financial services, public administration, and non-profit were deliberately omitted from the survey rounds. Calibrated weights are used to restore the proportions of the economic weight (as proxied by the number of employees) of the various size classes, economic activities, and countries.[3]

Our research is carried out on a sample that includes businesses chartered in 11 of the 19 countries that have, so far, joined the Euro area. Indeed, the observations utilized in our investigation refer to firms headquartered in the following countries: Austria, Belgium, France, Finland, Germany, Greece, Italy, Ireland, the Netherlands, Portugal, and Spain. The smallest economies – namely, those representing less than 3% of the total number of employees in the common currency area – have been excluded from the survey, as their inclusion would have only marginally affected the results for the whole economic region. Furthermore, the current analysis is limited to the first 12 waves of the SAFE – that is from 2009 to 2015. In addition, we only consider firms that have submitted a bank loan application – which implies that non-applicants are omitted. This leads us to a final sample of 20,956 observations.

Table 1 displays our sample observations by wave, highlighting the presence of a roughly constant number of observations through time – ranging from 1,500 to about 2,000 per wave. Table 2, instead, provides a snapshot of the sample distribution across countries, which shows the largest Euro area economies (i.e., France, Germany, Italy, Spain) properly represented – with around 3,000 observations each – compared to the smallest ones.

Table 1: Sample Distribution by Wave

Wave	Freq.	Percent
1	1,506	7.19
2	1,573	7.51
3	1,362	6.50
4	1,862	8.89
5	1,685	8.04
6	1,854	8.85
7	1,717	8.19
8	1,804	8.61
9	1,834	8.75
10	1,839	8.78
11	1,901	9.07
12	2,019	9.63
Total	**20,956**	**100.00**

[3] Specifically, if we look at the number of enterprises in the Euro area, statistics from the EC (see European Commission 2017) highlight that 93% of firms are micro, about 6% are small, almost 1% are medium-sized enterprises, and 0.2% only are large businesses. However, if we consider the number of employees as a proxy for the economic weight, micro enterprises constitute about 30%, small firms are 20%, medium-sized enterprises are about 17%, whereas large firms are 33%.

Table 2: Sample Distribution by Country

Country Name	Freq.	Percent
Austria	1,091	5.21
Belgium	1,305	6.23
Finland	775	3.70
France	3,754	17.91
Germany	2,725	13.00
Greece	1,234	5.89
Ireland	645	3.08
Italy	3,923	18.72
Netherlands	652	3.11
Portugal	989	4.72
Spain	3,863	18.43
Total	**20,956**	**100.00**

2.2 Dependent Variable

In order to test our research hypothesis, we employ the information coming from question q7b_a of the survey, which asks the firm about the result of its bank loan application, specifically:

> *"If you applied and tried to negotiate for [bank loans] over the past 6 months, did you: (1) receive all the financing you requested; (2) receive only part of the financing you requested; (3) refuse to proceed because of unacceptable costs or terms and conditions; (4) or have you not received anything at all?"*

The numbers appearing in parentheses indicate the way the respondents' answers were coded. Hence, we utilize the information coming from answer No. 4 to generate our dichotomous dependent variable – which we label as "Rejection" – that takes the value of one when the enterprise has faced a loan denial, and zero otherwise.

2.3 Key Variable

As the SAFE collects data regarding the firm's age, we utilize such information to generate the key regressor of our analyses. More specifically, we create a dummy variable – which we label as "Young Enterprises" – that takes the value of one when the enterprise is less than two years old, and zero otherwise.

Overall, our sample contains a total of 393 observations related to young businesses. Table 3 provides a snapshot of their distribution across country and by firm size. We observe that the majority of new businesses are micro enterprises (about 60%). Additionally, among this size class, we note that France exhibits a remarkable number of observations – as they cover almost 50% of the category. Unreported data show that the majority of those observations are allocated in waves 1 and 2 – which refer to the year 2009. Such an important number of observations related to new micro enterprises in France may indeed have been the consequence of the "*Loi de modernisation de l'économie,*" which was adopted to reduce the administrative burden of businesses and favor the entrepreneurial spirit. The remaining columns of Table 3 also show that – of the young enterprises – small firms constitute 24%, whereas mediums-sized ones are about 13%, and only 3.56% are large.

Table 3: Snapshot of the Distribution of Young Enterprises across Country and by Firm Size

Country Name	Micro	Small	Medium	Large	*Total*
Austria	19	11	3	0	33
Belgium	12	7	1	0	20
Finland	5	2	0	2	9
France	115	26	4	3	148
Germany	21	17	12	2	52
Greece	2	1	1	0	4
Ireland	2	0	3	0	5
Italy	28	20	20	5	73
Netherlands	9	7	2	1	19
Portugal	7	0	1	0	8
Spain	13	4	4	1	22
Total	**233**	**95**	**51**	**14**	**393**
	59.29%	24.17%	12.98%	3.56%	100.00%

2.4 Methodology and Control Variables

We estimate the likelihood that a new business may face a loan denial – once an application is submitted – by employing probit models. In all regressions, we include calibrated weights in order to adjust the sample to be representative of the population from which it is extracted (as in Ferrando, Popov, and Udell 2017, 2018; Galli, Mascia, and Rossi 2018; Mascia and Rossi 2017). Moreover, we include country and time dummies or, alternatively, country*time dummies (as in Galli, Mascia, and Rossi 2018). Finally, to limit possible estimation bias, standard errors are clustered at the country-level or, otherwise, simply robust. Hence, our model specification is the following:

P_i *(Rejection) = f (**Young Enterprises**; firm characteristics; country-level controls)* (1)

where we expect our "Young Enterprises" dummy to display a positive sign, thus highlighting that young enterprises face a higher probability, than older peers, to see their loan requests denied by the bank. The vector "*firm characteristics*" comprises basic controls, like the firm's size and economic activity, as well as typical financial controls, such as the perceived changes in the firm's own capital and credit history. The inclusion of the basic regressors is aimed at reducing potential sources of bias, due to omitted variables. In other words, our aim is to alleviate worries that the possible observable loan denials faced by young businesses are driven by other firm characteristics rather than by the relative youth of the enterprises.[4] The firms' financial controls are included as well, in order to alleviate the effect of possible biases affecting our model. Notably, the variation in the firms' credit history is aimed at capturing changes in the firm creditworthiness. Specifically, we expect that firms that improved their credit history in the past six months are less likely to be credit constrained,

[4] More specifically, controls for the firm's size comprise the dummies "micro," "small," and "medium," which equal one when the firm has less than 10 employees, between 10 and 49 employees, and between 50 and 249 employees, respectively. Then, the controls for the economic activity include the dummies "Construction," "Trade," and "Services," which equal one when the firm belongs to the construction, trade, and services sectors, respectively.

whereas firms that worsened their creditworthiness in the past six months are more likely to face a loan rejection. Hence, we utilize this information to generate the following two dummies: "creditworthiness up" and "creditworthiness down." The former equals one if the firm perceived an increase in its credit history in the past six months, and zero otherwise; whereas the latter equals one if the firm perceived a decrease in its creditworthiness in the past six months, and zero otherwise. Furthermore, we control for the firm's own capital by including two additional dummies. We would expect that firms that increased (decreased) their capital over time might be less (more) likely to face a loan denial by the bank. Thus, we generate another two dummies: namely, "capital up" ("capital down") which equals one when the firm's own capital has increased (decreased), and zero otherwise. Note that these dummies are the outcome of the interviewees' perceptions about the variations in the firm's own capital and credit history, rather than objective and comparable levels of such items. Finally, the "*country-level controls*" include an ample set of regressors – aimed at controlling for some country characteristics – that we employ in some of our tests. More specifically, we utilize the annual GDP growth rate – retrieved from the Organization for Economic Co-operation and Development (OECD) – to account for a country's general macroeconomic conditions. We would expect that, during good times (i.e., when GDP growth rates are positive), firms are less likely to face loan denials. Furthermore, we employ the annual rate of inflation (gathered from the OECD), as well as the annual unemployment rate (retrieved from Eurostat, which is the statistical office of the European Union). Notably, the rate of unemployment should be positively correlated with our dependent variable. Indeed, a rise in the unemployment rate usually proxies for worsening economic conditions, which should then translate into a higher likelihood for firms to face credit denials. Additionally, these three macroeconomic controls (i.e., the GDP growth rate, the rate of inflation, and the unemployment rate) are all calculated as averages of quarterly data for each survey round (similarly to Ferrando, Popov, and Udell 2017; Galli Mascia, and Rossi 2018; Mascia and Rossi 2017) – provided that the SAFE is run on a bi-annual basis. The Herfindahl Index (HI) of total assets concentration in the banking industry, for each country, is also added to our models. As in more concentrated markets banks are more inclined to build durable relations with borrowers, we expect them to be less likely to deny credit (cf. Mac an Bhaird, Vidal, and Lucey 2016). Finally, we also control for the bank-credit standards, at the country-level, by retrieving the related data from the Bank Lending Survey – which is administrated quarterly by national central banks on behalf of the ECB (see, for instance, Mascia and Rossi 2017; Moro, Fink, and Maresch 2015; Moro, Maresch, and Ferrando 2016; Moro, Wisniewski, and Mantovani 2017). More specifically, we utilize the data regarding the bank lending activities towards firms, in the past three months, as a proxy for the bank propensity to provide credit. We expect higher values of this index – which proxy for poorer inclination to lend – to be positively correlated with our dependent variable – thus translating into higher loan rejections faced by the enterprises.

Summary statistics are displayed in Table 4, whereas Table A1 in the Appendix reports all variable descriptions and sources.

Table 4: Summary Statistics

	Obs.	Mean	Median	St. Dev.	p1	p99
Dependent variable						
Rejection	20,956	0.114	0.000	0.318	0.000	1.000
Key variable						
Young Enterprises	20,956	0.019	0.000	0.136	0.000	1.000
Firm-level controls						
Creditworthiness up	20,956	0.244	0.000	0.430	0.000	1.000
Creditworthiness down	20,956	0.209	0.000	0.406	0.000	1.000
Capital up	20,956	0.265	0.000	0.441	0.000	1.000
Capital down	20,956	0.217	0.000	0.412	0.000	1.000
Micro	20,956	0.246	0.000	0.431	0.000	1.000
Small	20,956	0.331	0.000	0.470	0.000	1.000
Medium	20,956	0.311	0.000	0.463	0.000	1.000
Large	20,956	0.112	0.000	0.315	0.000	1.000
Construction	20,956	0.099	0.000	0.299	0.000	1.000
Trade	20,956	0.236	0.000	0.425	0.000	1.000
Services	20,956	0.284	0.000	0.451	0.000	1.000
Country-level controls						
GDP growth	20,956	–0.516	0.150	2.755	–8.200	5.050
Inflation	20,956	1.367	1.400	1.286	–1.750	4.900
Unemployment	20,956	12.129	9.800	6.419	4.700	26.600
Concentration	20,956	0.078	0.058	0.066	0.021	0.355
Credit standards	20,956	9.279	3.500	16.052	–6.500	75.000

3. EMPIRICAL RESULTS

3.1 Probit Regressions

Table 5 presents the results of five different specifications of model (1). Specifically, we start with a basic regression in Column 1, where we only employ our key variable and all the firm-level characteristics. In addition, we control for country and time effects and use heteroscedasticity-robust standard errors. The specification in Column 2 differs from the first in the use of country-level-clustered standard errors. Column 3 adds, to the previous specification, all the country-level controls. The robustness of our results is further checked in the remaining Columns 4–5, where we drop the country-level variables and utilize, instead, country*time fixed effects. Indeed, we perform this test in order to alleviate concerns that our findings may be driven by the country controls chosen, rather than being the result of the credit denial potentially faced by young firms. Moreover, Column 4 and Column 5 only differ in the use of heteroscedasticity-robust and country-level-clustered standard errors, respectively.

Table 5: Young Enterprises and Bank Credit Denials – Probit Model

	Rejection				
	(1)	(2)	(3)	(4)	(5)
Young Enterprises	**0.307*** **	**0.307*** **	**0.311*** **	**0.338*** **	**0.338*** **
	(0.11)	**(0.07)**	**(0.08)**	**(0.11)**	**(0.08)**
Creditworthiness up	–0.119**	–0.119**	–0.116**	–0.121**	–0.121**
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Creditworthiness down	0.400***	0.400***	0.397***	0.399***	0.399***
	(0.04)	(0.02)	(0.02)	(0.04)	(0.03)
Capital up	0.062	0.062	0.066	0.068	0.068
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Capital down	0.322***	0.322***	0.322***	0.312***	0.312***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Micro	0.749***	0.749***	0.750***	0.771***	0.771***
	(0.06)	(0.11)	(0.11)	(0.06)	(0.12)
Small	0.470***	0.470***	0.472***	0.487***	0.487***
	(0.06)	(0.07)	(0.07)	(0.06)	(0.08)
Medium	0.247***	0.247***	0.249***	0.269***	0.269***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Construction	0.098*	0.098**	0.102**	0.092*	0.092**
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Trade	–0.032	–0.032	–0.032	–0.029	–0.029
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Services	0.021	0.021	0.022	0.021	0.021
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP growth			0.019		
			(0.02)		
Inflation			0.006		
			(0.04)		
Unemployment			0.050**		
			(0.02)		
Concentration			–6.042		
			(4.11)		
Credit standards			0.004*		
			(0.00)		
Observations	20,956	20,956	20,956	20,641	20,641
Pseudo R-squared	0.146	0.146	0.148	0.159	0.159
Country effects	Yes	Yes	Yes	No	No
Time effects	Yes	Yes	Yes	No	No
Country*Time effects	No	No	No	Yes	Yes
Error cluster	Robust	Country-level	Country-level	Robust	Country-level

Note: This table shows regression results for the probit model presented in Section 2.4. The estimation period is 1 January 2009 – 31 March 2015 (from the first to the twelfth of the SAFE waves). The dependent variable – which is also described in Section 2.2 – is a dummy variable that equals one if a firm applied for bank credit but was rejected during the past six months. "**Young Enterprises**" is a dummy that equals one if a firm is less than 2 years old. 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, regressions in Columns 1–3 include country and time dummies; whereas, regressions in Columns 4–5 include country*time dummies. Standard errors appear in parentheses and are either robust (Columns 1, 4) or clustered at the country level (Columns 2–3, and 5). Intercepts are included but not reported. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Overall, the results reported in the various columns of Table 5 highlight that our key variable, "Young Enterprises," enters all the specifications with a positive and highly significant (at the 1% level) coefficient. This seems to suggest that very young enterprises are more likely to face loan denials from lenders, than their older peers. Furthermore, our results remain stable across the various specifications, which leads us to think that they are not affected by the inclusion, or exclusion, of the selected country-level controls, neither are they affected by the way we cluster the errors, nor whether we employ country*time effects *in lieu of* country and time effects individually.[5] All in all, this evidence seems to point to SMEs finding it harder to get access to credit, especially in the very early stages of their businesses when external finance is rather fundamental to sustain their projects.

Moving to the "firm characteristics," we observe that the dummy "credit up" negatively and significantly enters the various specifications in Table 5, thus suggesting that credit denials are less likely to occur when firms improve their creditworthiness. On the other hand, decreases in the firm's own capital and credit history – as proxied by the dummies "capital down" and "credit down" – appear to be positively and highly significantly correlated to the loan rejections faced by SMEs. Indeed, both dummies show positive and statistically significant coefficients across all the specifications. With regards to the country-level controls included in the estimation reported in Column 3, as expected we find that the unemployment rate is positively correlated to our dependent variable, thus properly signaling that firms are more likely to see their applications rejected by the banks during the slowdowns of the economy. Finally, the proxy for the bank credit standards appears, as well, to be positively (though mildly) correlated to our dependent variable. This, ultimately, suggests that when banks increase their credit standards (i.e., when they are less willing to offer credit), SMEs are undoubtedly more likely to face loan denials by financial institutions.

Overall, our findings strongly highlight that accessing bank credit is an issue for young businesses. This is not inconsequential for new SMEs, provided that external financing might be essential – especially in the very early phases that follow the setup of an enterprise – to help firms to grow.

3.2 Robustness

As reported in the "Data" Section of this paper, our analysis is conducted on a subsample of observations gathered from the SAFE. Indeed, for the purpose of our investigation we have, so far, only relied on information coming from the enterprises that submitted an application for a bank loan – which obviously implies that firms that did not apply for credit have been excluded from our regressions. This might represent an issue that is more commonly referred to as sample selection bias. Indeed, the selection issue arises here because the firms' decision to apply for a bank loan may not be a random one. More precisely, our dependent variable is built in a way that it keeps track of the loan denials that followed a bank loan application. If firms decided to apply for credit randomly, we could ignore that not all potential denials are observed – in such a case, the use of ordinary regression techniques would be fine. However, assuming that firms randomly turn to the banker is a strong assumption. Notably, the original database is populated by firms that – although they declared to have experienced an increase in the need for external finance – might have eventually ended up not applying for fear of rejection (so-called, discouraged borrowers). Overall, such a bias needs to be properly handled, as it is common practice in a variety of strands of the

[5] Note that we face a very minor drop in observations in Column 4 and Column 5 because of technical reasons that arise when employing country*time effects.

empirical literature (see, *inter alia*, Ferrando, Popov, and Udell 2017; Moro, Wisniewski, and Mantovani 2017; Zhang 2015). In this regard, the Heckman's probit selection model (Van de Ven and Van Pragg 1981) represents an appropriate solution to deal with this problem.[6] More specifically, such methodology requires us to include a set of variables that affect the possibility of observing the phenomenon but not the outcome itself. Hence, the Heckman probit selection model assumes the existence of a *regression equation* – whose dependent variable is not always observed –, and includes the so-called *selection equation* whose regressors are supposed to determine whether the dependent variable is observed or not. Specifically, in this paper we assume that the likelihood that a firm applies for a loan is a function of the actual need for credit (in a similar fashion to Moro, Wisniewski, and Mantovani 2017) – which proxies for the demand of external finance – as declared by the surveyed firms. Additionally, as mentioned earlier, in order to carry out this exercise we rely on the whole sample of observations – which thus incorporates the data pertaining to the firms that did not apply for credit.[7] Such wider sample now contains a total of 81,258 observations, of which 60,321 are censored, and the remaining 20,937 are the uncensored ones.[8]

Table 6 displays the results of the estimates that we obtained following the Heckman procedure. Overall, we observe that even after handling the potential selection bias affecting our regressions, we find that our key variable (i.e., "Young Enterprises") consistently enters all the specifications with a positive and highly significant (at the 1% level) coefficient. This confirms that young firms really struggle in getting access to bank credit compared to their older peers. Additionally, such a result does not appear to be influenced by the way we specify the model (i.e., whether we include or not the country-level controls), neither does it appear to be influenced by the choice of error clustering, nor whether we decide to use country*time fixed effects rather than individual country and time effects. As regards the diagnostic tests, the displayed *rho*(s) highlight that the correlation coefficients between error terms (from the regression equation and the selection equation) are significant. This implies that ignoring the selection issue would lead to biased and inconsistent estimates of the probit model (Baum 2006).

3.3 Additional Analyses

In this Section of the paper, we carry out some additional analyses aimed at exploiting the cross-country as well as the firms' economic activity heterogeneity characterizing our dataset. In other words, with this exercise we aim to check whether new businesses are equally likely to face rejections from lenders – compared to their older peers – across European countries and across different sectors of the economy.

---

6 Heckman probit estimations were obtained using the "heckprobit" module in Stata.

7 Bear in mind that here, though enlarged, our sample still contains only observations related to firms chartered in the eleven (selected) EU countries across the period 2009–2015.

8 Note that we face a minor drop in the number of uncensored observations – namely from 20,956 to 20,937 – because of missing information about the credit needs for a bunch of firms.

Table 6: Young Enterprises and Bank Credit Denials – Heckman Probit Model

	Rejection				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Regression equation					
Young Enterprises	**0.302*****	**0.302*****	**0.306*****	**0.335*****	**0.335*****
	(0.11)	**(0.07)**	**(0.08)**	**(0.11)**	**(0.08)**
Creditworthiness up	–0.118**	–0.118**	–0.115**	–0.121**	–0.121**
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Creditworthiness down	0.404***	0.404***	0.402***	0.405***	0.405***
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Capital up	0.062	0.062	0.067	0.069	0.069
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Capital down	0.325***	0.325***	0.326***	0.316***	0.316***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Micro	0.745***	0.745***	0.746***	0.766***	0.766***
	(0.06)	(0.11)	(0.11)	(0.06)	(0.12)
Small	0.468***	0.468***	0.470***	0.485***	0.485***
	(0.06)	(0.07)	(0.08)	(0.06)	(0.08)
Medium	0.246***	0.246***	0.248***	0.267***	0.267***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Construction	0.097*	0.097**	0.101**	0.090*	0.090**
	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Trade	–0.031	–0.031	–0.031	–0.028	–0.028
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Services	0.022	0.022	0.022	0.021	0.021
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP growth			0.021		
			(0.02)		
Inflation			0.008		
			(0.04)		
Unemployment			0.051**		
			(0.02)		
Concentration			–6.217		
			(4.12)		
Credit standards			0.004*		
			(0.00)		
Selection equation					
Demand up	1.408***	1.408***	1.408***	1.408***	1.408***
	(0.02)	(0.08)	(0.08)	(0.02)	(0.08)
Demand down	0.225***	0.225***	0.225***	0.225***	0.225***
	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)
rho	0.038*	0.038*	0.043*	0.051*	0.051*
	(0.04)	(0.08)	(0.08)	(0.04)	(0.08)

continued on next page

Table 6 *continued*

	Rejection				
	(1)	(2)	(3)	(4)	(5)
Observations	81,258	81,258	81,258	81,258	81,258
Censored obs.	60,321	60,321	60,321	60,321	60,321
Uncensored obs.	20,937	20,937	20,937	20,937	20,937
Country effects	Yes	Yes	Yes	No	No
Time effects	Yes	Yes	Yes	No	No
Country*Time effects	No	No	No	Yes	Yes
Error cluster	Robust	Country-level	Country-level	Robust	Country-level

Note: This table shows regression results for the Heckman probit model presented in Section 2.4. The estimation period is 1 January 2009 – 31 March 2015 (from the first to the twelfth of the SAFE waves). The dependent variable – which is also described in Section 2.2 – is a dummy variable that equals one if a firm applied for bank credit but was rejected during the past six months. "**Young Enterprises**" is a dummy that equals one if a firm is less than 2 years old. The selection equation includes the dummies "Demand up" (that equals one if a firm's needs for a bank loan increased in the past six months) and "Demand down" (that equals one if a firm's needs for a bank loan decreased in the past six months). 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, regressions in Columns 1–3 include country and time dummies; whereas, regressions in Columns 4–5 include country*time dummies. Standard errors appear in parentheses and are either robust (Columns 1, 4) or clustered at the country level (Columns 2–3, and 5). Intercepts are included but not reported. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Starting with the cross-country heterogeneity, we split our sample into three main clusters. These clusters are formed in a way that they gather firms' observations from countries that ideally share some cultural affinities. Specifically, we build a "Southern Europe" cluster that brings together firms from the Mediterranean and Latin countries – namely France, Greece, Italy, Portugal, and Spain. Then a "Central Europe" group whose countries mostly share the same "Germanic" roots – namely Austria, Belgium, Germany, and The Netherlands. Finally, a "Northern Europe" group made of observations related to firms chartered in Finland and Ireland – which are the northernmost Euro area countries.[9]

Table 7 shows the results of the investigation that we carried out on these three subsamples of countries. We observe that young businesses from both Southern and Central economies seem to similarly experience credit denials from banks, compared to their older peers, whereas young firms in Northern Europe do not. More specifically, young SMEs – in Southern and Central Europe – appear to be 4% more likely than older ones to face a credit rejection from the lender. As widely emphasized earlier, this is particularly unfortunate because denying credit to young enterprises might limit their opportunities to grow as well as compromise the full success of their newly started projects.

With regards to the firms' diversity in terms of the economic activity they pursue, we decided to split our sample into four groups according to the European NACE classification at the one-digit level – which we adequately described in the Data Section of this paper. More specifically, we generated the "Industry," "Construction," "Trade," and "Services" clusters. Hence, we estimate model (1) on these four different subsamples where firms' observations are allocated according to their main activity. Table 8 reports the related regressions.[10]

[9] Our initial 20,956 observations are now allocated as follows: 13,763 to the "Southern," 5,773 to the "Central," and 1,420 to the "Northern" cluster.

[10] Note that the sum of the observations reported in the various columns of Table 8 does not reflect the initial sample size (i.e., 20,956) because some rows in the dataset were lacking information regarding the firms' economic activity.

Table 7: Young Enterprises and Bank Credit Denials – Country Heterogeneity

	Rejection		
	Southern Europe	**Central Europe**	**Northern Europe**
	(1)	**(2)**	**(3)**
Young Enterprises	**0.214****	**0.478*****	**0.604**
	(0.11)	**(0.10)**	**(0.78)**
dy/dx	[4.04%]	[3.98%]	
Creditworthiness up	–0.069*	–0.239**	–0.011
	(0.04)	(0.10)	(0.06)
Creditworthiness down	0.393***	0.457***	0.350
	(0.03)	(0.07)	(0.36)
Capital up	0.082	0.033	–0.129
	(0.07)	(0.05)	(0.08)
Capital down	0.362***	0.184***	0.454***
	(0.04)	(0.06)	(0.17)
Micro	0.652***	1.074***	0.912***
	(0.11)	(0.12)	(0.20)
Small	0.392***	0.677***	0.468***
	(0.07)	(0.08)	(0.10)
Medium	0.188***	0.373***	0.760**
	(0.05)	(0.03)	(0.34)
Construction	0.116**	0.016	0.201***
	(0.05)	(0.08)	(0.02)
Trade	–0.030	–0.036*	–0.116
	(0.05)	(0.02)	(0.12)
Services	–0.000	0.091***	0.059
	(0.05)	(0.02)	(0.13)
GDP growth	–0.027	–0.051***	0.125***
	(0.02)	(0.02)	(0.02)
Inflation	–0.074***	0.038	0.350***
	(0.02)	(0.13)	(0.03)
Unemployment	–0.004	0.169***	0.195***
	(0.01)	(0.01)	(0.04)
Concentration	1.466	–9.958**	–10.883***
	(2.55)	(4.09)	(0.01)
Credit standards	0.003*	0.004	0.070***
	(0.00)	(0.00)	(0.01)
Observations	13,763	5,773	1,420
Pseudo R-squared	0.108	0.224	0.232
Country effects	Yes	Yes	Yes
Time effects	Yes	Yes	Yes
Error cluster	Country-level	Country-level	Country-level

Note: This table shows regression results for the probit model presented in Section 2.4. The estimation period is 1 January 2009 – 31 March 2015 (from the first to the twelfth of the SAFE waves). The dependent variable – which is also described in Section 2.2 – is a dummy variable that equals one if a firm applied for bank credit but was rejected during the past six months. "**Young Enterprises**" is a dummy that equals one if a firm is less than 2 years old. 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 country and time dummies. Heteroscedasticity-robust standard errors, clustered at the country level, appear in parentheses. Marginal effects are reported in brackets. Intercepts are included but not reported. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8: Young Enterprises and Bank Credit Denials – Economic Activity Heterogeneity

	Rejection			
	Industry	**Construction**	**Trade**	**Services**
	(1)	**(2)**	**(3)**	**(4)**
Young Enterprises	**0.328**	**–0.338**	**0.376***	**0.192***
	(0.21)	**(0.24)**	**(0.22)**	**(0.10)**
dy/dx			[7.98%]	[3.84%]
Creditworthiness up	–0.184***	–0.160**	0.002	–0.015
	(0.07)	(0.07)	(0.12)	(0.04)
Creditworthiness down	0.427***	0.424***	0.342***	0.436***
	(0.05)	(0.08)	(0.09)	(0.03)
Capital up	–0.043	0.127	–0.117	–0.045
	(0.06)	(0.10)	(0.10)	(0.03)
Capital down	0.275***	0.258***	0.345***	0.297***
	(0.04)	(0.07)	(0.09)	(0.05)
Micro	0.417***	0.545***	0.659***	0.513***
	(0.05)	(0.12)	(0.11)	(0.10)
Small	0.168***	0.260***	0.401***	0.192***
	(0.03)	(0.09)	(0.05)	(0.07)
GDP growth	–0.012	–0.082	0.001	0.028
	(0.02)	(0.07)	(0.03)	(0.02)
Inflation	–0.164***	–0.140	0.009	0.081***
	(0.06)	(0.09)	(0.07)	(0.03)
Unemployment	0.027	–0.032	0.067**	0.057***
	(0.02)	(0.03)	(0.03)	(0.02)
Concentration	–9.644**	9.878	–6.801*	–6.046
	(3.83)	(6.37)	(4.12)	(3.78)
Credit standards	0.007***	0.003	0.006**	0.004
	(0.00)	(0.01)	(0.00)	(0.00)
Observations	5,622	2,085	4,955	5,945
Pseudo R-squared	0.114	0.111	0.123	0.117
Country effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Error cluster	Country-level	Country-level	Country-level	Country-level

Note: This table shows regression results for the probit model presented in Section 2.4. The estimation period is 1 January 2009 – 31 March 2015 (from the first to the twelfth of the SAFE waves). The dependent variable – which is also described in Section 2.2 – is a dummy variable that equals one if a firm applied for bank credit but was rejected during the past six months. "**Young Enterprises**" is a dummy that equals one if a firm is less than 2 years old. 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 country and time dummies. Heteroscedasticity-robust standard errors, clustered at the country level, appear in parentheses. Marginal effects are reported in brackets. Intercepts are included but not reported. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Interestingly, we observe that our "Young Enterprises" dummy appears to be statistically significant only when our model (1) is estimated for the "Trade" and "Services" subsamples. Notably, the reported marginal effects highlight that the new businesses operating in the "Trade" industry seem to be particularly unfortunate, as they face almost 8% probability of facing a loan rejection from financial institutions, compared to their older peers. Firms in the "Services" industry, instead, appear to be a bit luckier than their peers involved in "Trade" activities. Indeed, compared to older enterprises, new businesses in the “Services” field face about 4% probability (only) of experiencing a credit denial from a lender.

Overall, the evidence provided in this paper supports the view that young enterprises find it difficult to get access to external finance through the bank-lending channel. Furthermore, our additional analyses have highlighted that this issue seems to particularly affect new SMEs operating in the Southern and Central countries of the Euro area, as well as firms whose business mainly lies in trade and services activities.

4. CONCLUSIONS

SMEs represent the backbone of most economies worldwide. Because of their inability to access equity markets, SMEs strongly rely on the bank-lending channel to finance their needs. However, enterprises most often struggle to obtain credit because of their lack of ability to provide good collaterals, and also because of the information asymmetries characterizing the bank-firm relationship – indeed, the lender is less informed than the borrower about the quality of its projects.

In light of this, we believe that new SMEs may find it even harder than SMEs in general to see their loan requests satisfied. Therefore, in this paper we test whether young businesses from the major economies of the Euro area are actually more likely to face credit denials from their lenders, compared to older peers. To do so, we rely on a sample of 20,956 observations – gathered from the Survey on the Access to Finance of Enterprises – related to firms chartered in Austria, Belgium, France, Finland, Germany, Greece, Italy, Ireland, the Netherlands, Portugal, and Spain. Our analysis covers the years 2009–2015.

More specifically, we investigate whether young SMEs are actually more likely, than older peers, to face issues when they try to obtain credit from banks. In addition, we check the robustness of our tests by employing different model specifications as well as by handling potential selection biases via appropriate techniques (i.e., Heckman probit models). Finally, we exploit the country heterogeneity characterizing our sample, as well as the differences in the firms’ economic activities, to see whether the (possible) likelihood for new SMEs to experience credit denials varies across our dataset.

Overall, we find that very young businesses appear to consistently face credit rejections from the lenders, compared to older SMEs. This result is stable to different model specifications and is confirmed even after addressing – via the Heckman probit model – the potential selection bias that may affect our estimates. Moreover, our additional tests highlight that young SMEs located in the Southern and Central countries of the Euro area are 4% more likely to face credit denials than older enterprises; whereas young businesses in Northern Europe do not seem to suffer similar issues. Finally, results also highlight that – among the various sectors of economic activity – new businesses operating in the “Trade” industry are the ones that, compared to older peers, face the highest probability (i.e., 8%) of being credit constrained.

In sum, our results suggest that actions from the policy maker could be desirable to ease the flow of credit and, thus, ensure the growth of young SMEs in the Euro area. Alternatively, in the absence of a decisive policy action, credit constrained businesses might find it beneficial to rely on the new channels of finance offered by the FinTech industry, whose relevance to the economy is massively increasing even in Europe.

REFERENCES

Andrieu, G., R. Staglianò, and P. van der Zwan. 2017. Bank Debt and Trade Credit for SMEs in Europe: Firm-, Industry-, and Country-level Determinants. *Small Business Economics*, forthcoming. DOI: https://doi.org/10.1007/s11187-017-9926-y

Ayadi, R., and S. Gadi. 2013. Access by MSMEs to Finance in the Southern and Eastern Mediterranean: What Role for Credit Guarantee Schemes? European Commission, MEDPRO Technical Report No. 35/2013.

Baum, C.F. 2006. *An Introduction to Modern Econometrics Using Stata*. College Station, Texas: Stata Press.

Beck, T., L.F. Klapper, and J.C. Mendoza. 2010. The Typology of Partial Credit Guarantee Funds around the World. *Journal of Financial Stability* 6, 10–25.

Bonnet, J., S. Cieply, and M. Dejardin. 2016. Credit Rationing or Overlending? An Exploration into Financing Imperfection. *Applied Economics* 48 (57), 5563–5580.

Diamond, D.W. 1989. Reputation Acquisition in Debt Markets. *Journal of Political Economy* 97 (4), 828–862.

European Commission. 2017. Annual Report on European SMEs 2016/2017 – Focus on Self-employment. Available at: http://ec.europa.eu/growth/smes/business-friendly-environment/performance-review-2016_en#annual-report

Ferrando, A., A. Popov, and G.F. Udell. 2017. Sovereign Stress and SMEs' Access to Finance: Evidence from the ECB's SAFE Survey. *Journal of Banking and Finance* 81, 65–80.

Ferrando, A., A. Popov, and G.F. Udell. 2018. Do SMEs Benefit from Unconventional Monetary Policy and How? Micro-Evidence from the Eurozone. *Journal of Money, Credit, and Banking, forthcoming*.

Galli, E., D.V. Mascia, and S.P.S. Rossi. 2018. Does Corruption Influence the Self-Restraint Attitude of Women-led SMEs towards Bank Lending? *CESifo Economic Studies, forthcoming*. DOI: https://doi.org/10.1093/cesifo/ifx021

Hyytinen, A., and M. Pajarinen. 2008. Opacity of Young Businesses: Evidence from Rating Disagreements. *Journal of Banking and Finance* 32, 1234–1241.

Mac an Bhaird, C., J.S. Vidal, and B. Lucey. 2016. Discouraged Borrowers: Evidence for Eurozone SMEs. *Journal of International Financial Markets, Institutions and Money* 44, 46–55.

Mascia, D.V., and S.P.S. Rossi. 2017. Is There a Gender Effect on the Cost of Bank Financing? *Journal of Financial Stability* 31, 136–153.

Moro, A., M. Fink, and D. Maresch. 2015. Reduction in Information Asymmetry and Credit Access for Small and Medium-Sized Enterprises. *The Journal of Financial Research* 38 (1), 121–143.

Moro, A., D. Maresch, and A. Ferrando. 2016. Creditor Protection, Judicial Enforcement and Credit Access. *The European Journal of Finance*, DOI: http://dx.doi.org/10.1080/1351847X.2016.1216871

Moro, A., T.P. Wisniewski, and G.M. Mantovani. 2017. Does a Manager's Gender Matter when Accessing Credit? Evidence from European Data. *Journal of Banking and Finance* 80, 119–134.

Polzin, F., H. Toxopeus, and E. Stam. 2017. The Wisdom of the Crowd in Funding. Information Heterogeneity and Social Networks of Crowdfunders. *Small Business Economics*, forthcoming. DOI: https://doi.org/10.1007/s11187-016-9829-3

Shaban, M., M. Duygun, and J. Fry. 2016. SME's Lending and Islamic Finance. Is It a "Win-Win" Situation? *Economic Modelling* 55, 1–5.

Stiglitz, J.E., and A. Weiss. 1981. Credit Rationing in Markets with Imperfect Information. *The American Economic Review* 71 (3), 393–410.

Van de Ven, W.P.M.M., and Van Pragg, B.M.S. 1981. The Demand for Deductibles in Private Health Insurance: A Probit Model with Sample Selection. *Journal of Econometrics* 17, 229–252.

Vermoesen, V., M. Deloof, and E. Laveren. 2013. Long-Term Debt Maturity and Financing Constraints of SMEs During the Global Financial Crisis. *Small Business Economics* 41, 433–448.

Vos, E., A.J. Yeh, S. Carter, and S. Tagg. 2007. The Happy Story of Small Business Financing. *Journal of Banking and Finance* 31, 2648–2672.

Yoshino, N., and F. Taghizadeh-Hesary. 2014. Analytical Framework on Credit Risks for Financing Small and Medium-sized Enterprises in Asia. *Asia-Pacific Development Journal* 21 (2), 1–21.

Zhang, Y., 2015. The Contingent Value of Social Resources: Entrepreneurs' Use of Debt-Financing Sources in Western China. *Journal of Business Venturing* 30, 390–406.

APPENDIX

Table A1: Variable Descriptions and Sources

Variables	Description	Source
Dependent variable		
Fear	Dummy variable that equals one if a firm applied for bank credit but was rejected during the past six months.	ECB: SAFE
Key variables		
Young Enterprises	Dummy variable that equals one if a firm is less than 2 years old.	ECB: SAFE
Firm-level controls		
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
Micro	Dummy variable that equals one if the firm has between 1 and 9 employees.	ECB: SAFE
Small	Dummy variable that equals one if the firm has between 10 and 49 employees.	ECB: SAFE
Medium	Dummy variable that equals one if the firm has between 50 and 249 employees.	ECB: SAFE
Large	Dummy variable that equals one if the firm has 250 employees or more.	ECB: SAFE
Industry	Dummy variable that equals one if the firm's main activity is industry.	ECB: SAFE
Construction	Dummy variable that equals one if the firm's main activity is construction.	ECB: SAFE
Trade	Dummy variable that equals one if the firm's main activity is trade.	ECB: SAFE
Services	Dummy variable that equals one if the firm's main activity is services.	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
Country-level controls		
GDP Growth	The annual growth rate of real GDP based on averages of quarterly data for each survey round.	OECD
Inflation	The annual inflation rate based on averages of quarterly data for each survey round.	OECD
Unemployment	The annual unemployment rate based on averages of quarterly data for each survey round.	Eurostat
Concentration	The Herfindahl index (HI) of total assets concentration (for the banking sector).	ECB: Data Warehouse
Credit standards	The bank credit standards (in the previous three months) based on averages of quarterly data for each survey round.	ECB: Bank Lending Survey