Access to Finance in Kosovo

October 13, 2022

1 Kosovo Firms before the credit guarantee scheme

According to the Tax Registry Data, in 2015, Kosovo had 37.3 thousand active firms, and more than 90% were classified as micro-enterprises. More than 70% of them did not have a credit history.[1] Their low productivity might be a factor that constrains their access to credit. The average sales per employee in micro-firms are three times lower than the one presented by small, medium, and large firms. In addition, micro-enterprises are more likely to stop their operations, which is seen as a high risk for the lenders. While more than 20% of the ones active in 2015 ended up closing between 2016 and 2018, 4% of medium and large firms did so (Table 1).

Table 1: Firms' characteristics by size, all active firms (2015)

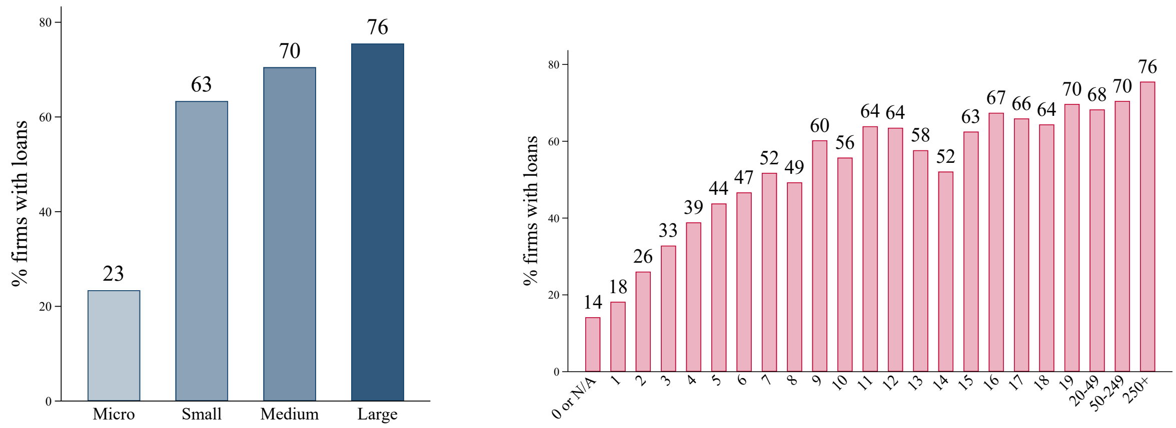
		Micro		Small		Medium		Large
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	N	Mean/SE
Sales, thousands 2021 EUR	27498	29.72	1766	867.28	269	4,765.28	46	38,882.36
		[0.30]		[21.37]		[291.32]		[6,312.43]
Num. employees	25452	2.35	1986	18.41	304	101.28	49	777.12
		[0.01]		[0.21]		[2.95]		[120.49]
Productivity, thousands 2021 EUR	15985	14.47	1609	43.91	237	46.03	41	48.46
		[0.10]		[0.88]		[2.46]		[5.79]
Stopped operating after 2015	35052	20.26	1995	10.03	305	4.92	49	0.00
		[0.21]		[0.67]		[1.24]		[0.00]
No credit history	34059	71.41	1965	33.54	303	26.73	49	22.45
		[0.24]		[1.07]		[2.55]		[6.02]

Source: Tax Registry and Credit Registry/Central Bank of Kosovo.

Figure 1 shows that the percentage of firms with loans increases with the number of employees. On average, less than 25% of micro-firms had access to credit in 2015, whereas the percentage reached more than 70% for medium and large firms.

[1] We define firms with credit history as the ones with at least one loan approved between 2010 (the first year of our panel) and the year before the one under analysis. Therefore, firms with a credit history in 2015 are the ones with at least one loan approved between 2010 and 2014.

Figure 1: % loans by firms' size, all active firms (2015)



(a) Firms' size (b) Employees

Source: Tax Registry. The label "0 or N/A" shows the percentage of loans registered by firms for which the variable *employees* in the Tax Registry is either 0 or missing, but the variable *firms' size* is micro-firm.

2 Determinants of Access to Credit

Using the Tax Registry Data, we define credit-constrained firms as the ones with no loans approved between 2010 and 2018. 98.5% of these firms are micro. In comparison to them, the micro-companies with loans approved in 2018 registered sales twice as high (58.8k versus 24k EUR) and productivity 40% higher (Table 2).[2]

Table 2: Firms' characteristics by access to credit (2018)

	Credit constrained firms Firms without loans 2010-2018				Firm with loan approved in 2018			
	mean	sd	min	max	mean	sd	min	max
Number employees	2.3	1.7	1	9	3.4	2.3	1	9
Sales, thousands 2021 EUR	24.1	41.9	0.0	288.7	58.9	69.2	0.0	289.6
Sales per employee, thousands 2021 EUR	13.3	12.3	1.5	65.1	18.6	14.8	1.5	65.1
Average wage, thousands 2021 EUR	2.2	0.7	0.6	4.0	2.4	0.7	0.6	4.0
Firm exports, %	2.4	15.3	0	100	7.2	25.9	0	100
Firm imports, %	21.0	40.7	0	100	50	50.0	0	100
Firms' age	6.7	5.4	0	17	7.7	5.2	0	15
Firm with credit history, %	0	0	0	0	61.4	48.7	0	100
Num. firms	17,874				7,277			

Source: Tax Registry and Credit Registry/Central Bank of Kosovo. The Table presents data only for micro-firms.

Lenders have at least two bottom lines: (1) improve the targeting of a program to either increase its efficiency or scale it up; and (2) produce well-calibrated credit scoring for the applicants to avoid discriminating against potential good borrowers. While these two objectives

[2] While we are waiting for the Government of Kosovo to share more recent data, we used the last Tax Registry information available, which is 2018.

are complementary, they are distinct.

In the first case, the lender is interested in identifying the set of *firms* it should target before expanding its lending operations. In the second case, the lender wants to find out the set of *variables* that best predict applicants' creditworthiness in order to lend to the highest number of borrowers without jeopardizing the quality of its portfolio.

To identify whether firms' observed characteristics help predict access to credit, we employ five machine learning models using information available in the Tax Registry and Central Bank database. The models compare the two groups of firms shown in Table 2. These models aim to identify the variables that explain the probability of firms accessing credit, therefore, the profile of successful borrowers so that the lender can improve the program's targeting if its expansion is under consideration.

The estimation of the ML models considers a rich vector of covariates with 96 variables. The model then selects the most important ones that predict the probability of firms obtaining credit. The results show that 10 out of the 96 variables do play an important role in the probability of getting a loan in year t. The variables are:

1. Credit history t. We use the number of loans accumulated between 2010 (the first year of the panel) and $t-1$ as a proxy for credit history.
2. The municipality where the firm is located.
3. Whether the municipality has a Serbian majority population.
4. History of the number of employees. The model selected the number of employees in $t-1$ and in $t-2$, as well as the squared value of the number of employees in $t-1$.
5. Total sales in $t-1$ and it's squared value.
6. Firms' age and its squared value.

The most important variable selected in the model is the credit history of the firm. Table 3 shows that all the performed models have an AUC-ROC close to 0.8. This means that the models perform very well in predicting whether the firm has a loan approved or not according to Hosmer et all (2013).[3] If the AUC-ROC were equal to one, it would mean that the models predict with a 100% of accuracy whether the firm has a loan or not based only on these observed characteristics. The score being lower than 1, suggests that the model in some cases attributes an approved loan to a firm that does not have it or vice-versa. As a consequence, there are firms without loans whose characteristics are similar to the ones with loans approved.

Table 3: AUC-ROC of the models that predict access to credit

	OLS	LASSO	KNN	Randon Forest	XGBoost
ROC-AUC out-of-sample	0.79	0.80	0.80	0.81	0.81

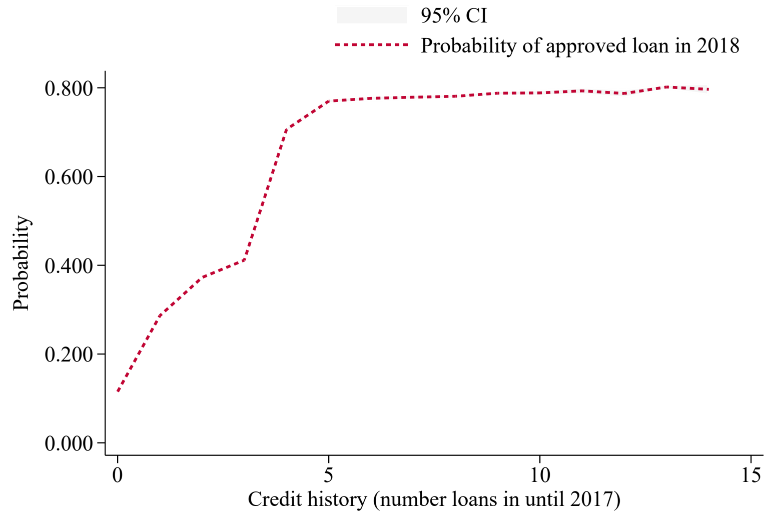
The machine learning models also calculate the probability of having a loan approved (loans not covered by KCGF and KCGF loans) according to the 10 selected variables. Figure 2 shows how this probability varies according to four of the selected variables. For instance, figure 2(a) shows two things. First, smaller firms (up to 10 employees) are more credit constrained, and second, the probability flattens as the firm size reaches 12 employees. Figures 2(b)-2(d) show similar patterns. Overall, these analyses show room for improving the targeting of programs aimed at easy firms' access to credit (e.g., by targeting smaller firms and not overemphasizing their credit history and productivity).[4]

[3] Applied Logistic Regression.

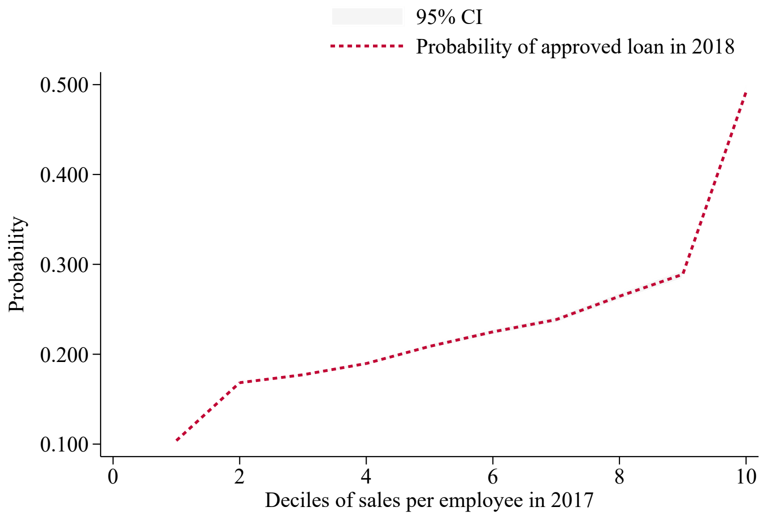
[4] Ideally, one would like to know what firms applied to credit, who got it and who didn't, and what drove the lenders' decision to either accept or reject a credit application. This information would enrich the empirical analyses by improving the identification of the applicant's profiles, and by revealing potential entry points for adapting (experimenting) the selection rules used by the lenders.

Figure 2: Probability of having a loan versus firms' characteristics, 2018

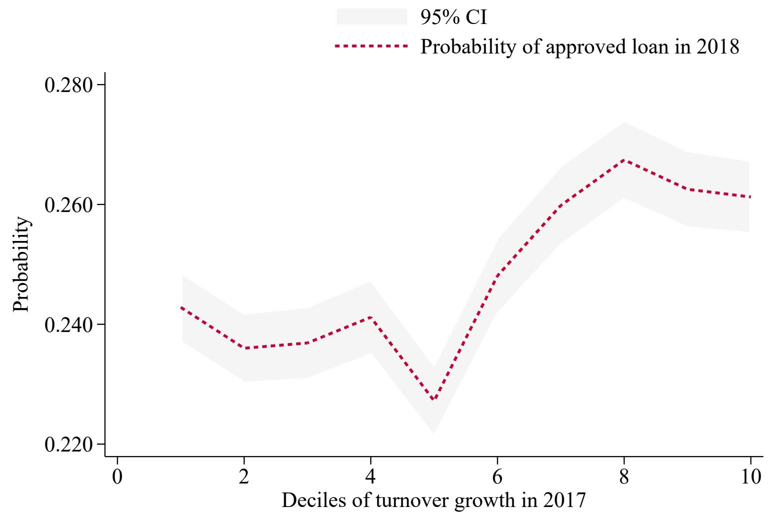
(a) Employees



(b) Credit history



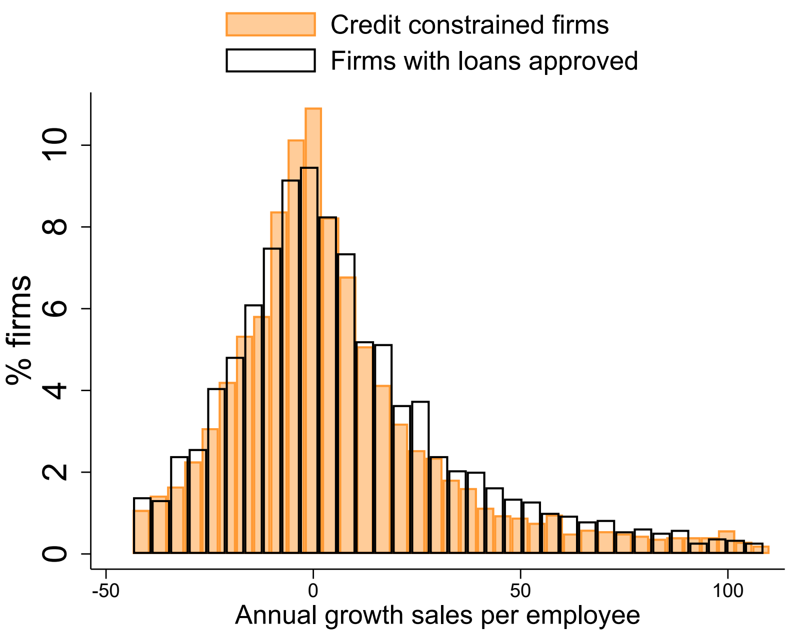
(c) Productivity



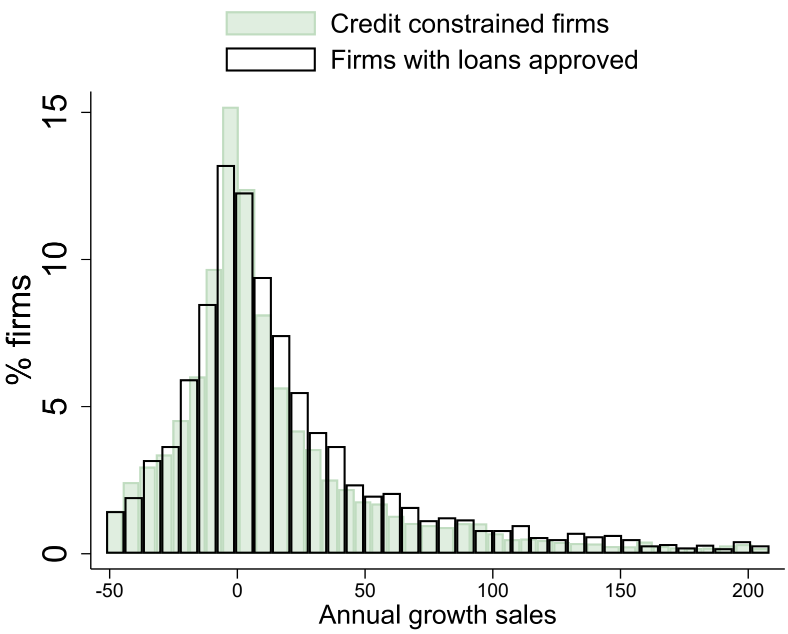
(d) Growth in turnover

Overall, our analysis indicates that there are firms with approved loans and firms without loans that are very similar. For example, Table 2 shows considerable overlap across the distribution of several firms' characteristics. Also, there is a significant number of firms in these two groups that look very similar in terms of annual growth sales per employee, and annual growth sales. Figure 3 points to a significant number of credit-constrained firms with annual growth in total sales and sales per employee as high as the ones observed for the firms with access to credit. If we use these variables as proxies for firms' capacity to pay the loan back, these credit-constrained firms have the potential to be borrowers as well.

Figure 3: Distribution of annual growth in sales and productivity of credit and non-credit constrained firms, 2015-2018



(a)



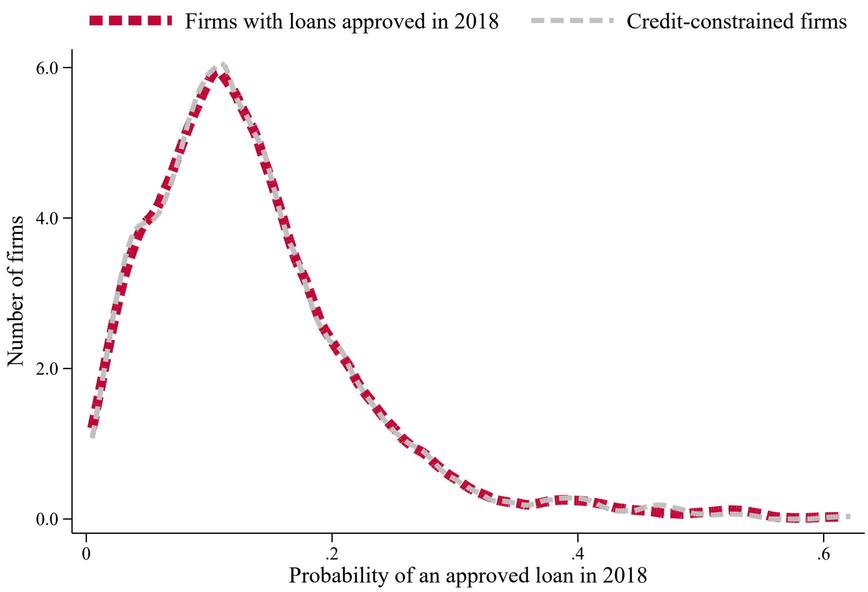
(b)

Source: Tax Registry and Credit Registry/Central Bank of Kosovo.

Therefore, one way of identifying a subset of credit-constrained firms that could be potential good borrowers is by matching this group of firms with the ones that had loans approved in 2018, using the 10 variables that most predict access to credit according to the machine learning models. The aim here is to find businesses with similar predicted probabilities of accessing credit. Figure 4 shows the distribution of the probability of the matched group of firms. From 17.8k credit-constrained firms, 2.5k were successfully matched to firms with loans approved. The matched firms are similar in observed characteristics except with respect to their access to the lending market. The matched sample could then be considered a potential subset of good borrowers.

This type of analysis is relevant because many credit-constrained firms do not have a credit history, perhaps the most commonly used information by the banks when looking at a loan request. The lender could use a similar analysis to contemplate more borrowers. And it could do so by expanding the access at the margin, i.e., by first targeting firms with the closest probability of accessing credit to firms with access to credit.

Figure 4: Distribution of the probability of having a loan approved, 2018



Source: DIME/World Bank calculation based on Tax Registry and Credit Registry/Central Bank of Kosovo.

3 KCGF

Table 4 shows firms' characteristics prior to the launch of KCGF. By comparing the firms before the fund was introduced, we can check the factors that might have played an important role when the banks decided on which firms to include in the fund.

We show data for three types of firms according to their access to credit between 2016-2018: the ones with no loans approved, the ones with loans not covered by the fund, and the ones with KCGF loans. We observe that the firms selected to be included in the fund were slightly smaller than the ones with other loans approved but bigger than the ones with no loans at all. Although smaller than firms with non-KCGF loans, firms included in the fund were significantly more productive. Also, their annual growth rates were at least twice as large as the ones registered by firms without loans approved.

The data indicate that financial institutions opted to include in the fund the companies that had more potential for growth and the ones that already had access to the lending market. More than 75% of KCGF firms had a credit history, whereas the percentage is less than 25% for firms without loans approved between 2016 and 2018.

Table 4: Firms' characteristics prior to KCGF according to their access to credit between 2016-2018

	1 KCGF loan (2016-2018)		2 No loan (2016-2018)		3 Other Loan (2016-2018)		Dif (1)-(2)	Dif (1)-(3)
	N	Mean/SE	N	Mean/SE	N	Mean/SE		
Firms' age'	911	6.20 [0.15]	24226	6.52 [0.03]	11892	6.69 [0.04]	-0.32**	-0.49***
Num. employees	810	4.23 [0.16]	16614	2.52 [0.03]	10014	5.11 [0.07]	1.72***	-0.87***
Micro-firm, %	911	92.10 [0.89]	24237	97.79 [0.09]	11899	88.34 [0.29]	-5.69***	3.75***
Sales micro-firms, thousands EUR 2021	665	60.14 [2.77]	18578	21.84 [0.29]	8255	44.99 [0.67]	38.29***	15.14***
Sales small-firms, thousands EUR 2021	71	809.19 [92.81]	451	643.86 [36.41]	1244	951.60 [26.42]	165.32*	-142.41
Productivity micro-firms, thousands EUR 2021	487	18.46 [0.68]	9775	13.01 [0.12]	5723	16.63 [0.18]	5.45***	1.83***
Productivity small-firms, thousands EUR 2021	65	45.45 [4.29]	396	34.83 [1.68]	1148	46.95 [1.05]	10.62**	-1.50
Average wage, thousands EUR 2021	627	2.47 [0.03]	11450	2.17 [0.01]	7703	2.50 [0.01]	0.30***	-0.03
Firm imports	911	56.09 [1.65]	24226	20.49 [0.26]	11892	48.57 [0.46]	35.60***	7.52***
Firm exports	911	6.70 [0.83]	24226	1.95 [0.09]	11892	6.72 [0.23]	4.74***	-0.02
Firm with access to credit between 2010-2015	911	76.73 [1.40]	24237	24.22 [0.28]	11899	73.44 [0.40]	52.51***	3.29**
Stopped operating after 2015	911	1.54 [0.41]	24237	23.44 [0.27]	11899	13.50 [0.31]	-21.90***	-11.96***
Annual average growth in productivity, %	339	6.12 [1.64]	5760	2.34 [0.38]	4245	4.73 [0.45]	3.78**	1.39
Annual average growth in employment, %	504	3.51 [0.54]	9159	1.17 [0.08]	6177	3.16 [0.15]	2.34***	0.36
Annual average growth in sales, %	475	10.94 [1.63]	11654	4.45 [0.33]	6275	9.42 [0.46]	6.48***	1.52

Source: Tax Registry and Credit Registry/Central Bank of Kosovo. The Table presents data only for micro and small firms.

Table 5 shows that the median of KCGF loans is 31k EUR, more than three times the median amount approved for non-KCGF loans (8.8k). As a consequence, the loan amount as a percentage of firms' sales reaches 13.5% for KCGF firms, whereas is 6% for companies with other loans. The interest rates are similar, but the duration of KCGF loans is three times longer.

Table 5: KCGF and non-KCGF loans (2016-2021)

KCGF , MSMEs

	Total amount million 2021 EUR	N. loans	Median loan 2021 EUR	Median interest rates	Median interest payments	Collateral 2021 EUR	Median duration in months	Loan as % of turnover	Class A %
2016	5.4	95	38,167	8.0	10,264		30	11.5	
2017	29.2	751	32,235	8.9	9,973		36	14.5	88.1
2018	59.5	1,440	31,900	8.9	8,648	69,581	36	15.4	92.7
2019	75.9	1,881	31,067	8.5	11,415	50,362	38	14.9	98.0
2020	73.0	2,003	25,838	8.5	8,091	46,146	36	15.3	-
2021	175.1	3,777	30,000	**7.9**	8,535	39,949	36	15.1	-
Total	**418.1**	**9,947**	**31,534**	**8.4**	**9,488**	**51,509**	**35**	**14.4**	**92.9**

Other loans , MSMEs

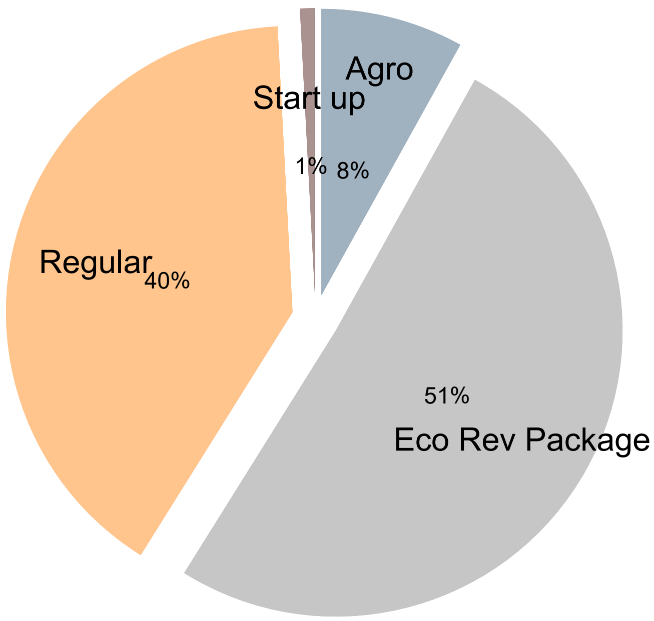
	Total amount million 2021 EUR	N. loans	Median loan 2021 EUR	Median interest rates	Median interest payments	Collateral 2021 EUR	Median duration in months	Loan as % of turnover	Class A %
2016	434	9,413	7,794	8.5	663	0	12	6.1	84.6
2017	465.3	9,377	10,745	8.5	913	4,051	12	6.3	91.0
2018	468.7	9,408	10,633	8	851	11,218	12	5.1	94.9
2019	312.1	6,732	10,356	8.5	880	15,825	13		97.5
Total	**1,680.1**	**34,930**	**9,882**	**8**	**827**	**7,773**	**12**	**6**	**92.0**

Source: Tax Registry and Credit Registry/Central Bank of Kosovo. The Table presents data only for MSMEs.

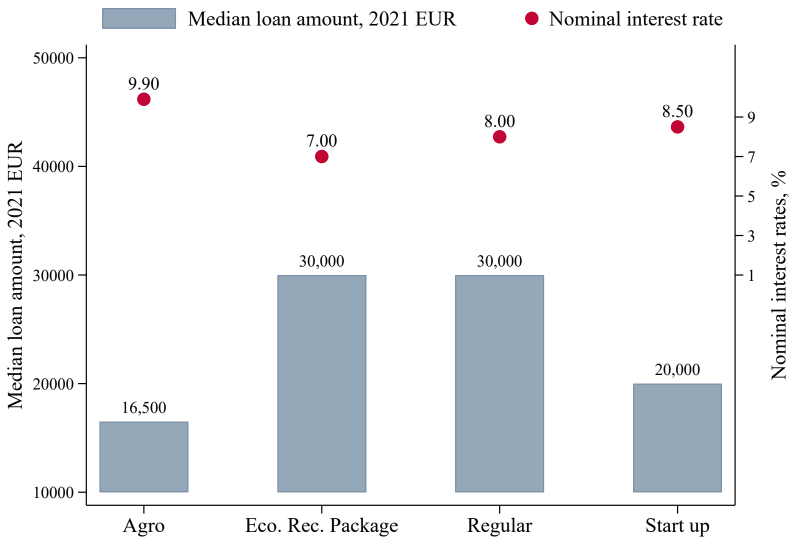
4 KCGF windows

In response to the pandemic situation from COVID-19, the Government of Kosovo has approved the Economic Recovery Package. The percentage of loans under this window reached more than 50% in 2021 (Figure 5). The median approved amount is the same as the regular window, but the interest rates are on average 1 pp lower. The median duration is the same across all windows (36 months).

Figure 5: KCGF windows, 2021



(a)



(b)

Source: Tax Registry and KCGF. Figure shows data for MSMEs.

Table 6 shows that on average firms included in the Economic Recovery Package are bigger than the ones included in the Regular Window. The difference in firms' productivity is associated to their size. Micro-firms included in the Recovery Package are less productive (91.4k versus 106.9k per employee), and medium firms tend to be more productive (48.8 k versus 21.6k). For small firms, there is no significant difference in their productivity.

have a higher % of the loan amount guaranteed and lower collateral.

Table 6: Balance test between KCGF Regular and Economic Recovery Package Windows, 2021

	(1) Economic Recovery Window		(2) Regular Window		t-test Difference
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
Micro-firms					
%	1978	79.22	1562	84.31	-5.09***
		[0.91]		[0.92]	
Sales, thousands 2021 EU	1238	213.11	1096	222.29	-9.18
		[4.57]		[4.81]	
Sales per employee, thousands 2021 EUR	1087	82.86	993	88.84	-5.99**
		[1.70]		[1.84]	
Collateral, 2021 EUR	986	48.87	1083	61.17	-12.30***
		[1.68]		[1.68]	
Guarantee, %	1567	72.91	1317	49.30	23.60***
		[0.36]		[0.11]	
Interest rate, %	1319	8.05	1210	8.87	-0.82***
		[0.05]		[0.07]	
Duration	1463	37.17	1204	36.62	0.55
		[0.41]		[0.44]	
Employees	962	3.61	747	3.51	0.10
		[0.05]		[0.06]	
Small-firms					
%	1,978	18.25	1,562	14.85	3.40***
		[0.87]		[0.90]	
Sales, thousands 2021 EU	318	893.69	215	859.72	33.97
		[42.54]		[46.99]	
Sales per employee, thousands 2021 EUR	322	52.80	210	53.14	-0.34
		[2.46]		[2.75]	
Collateral, 2021 EUR	212	139.47	168	161.32	-21.85
		[9.42]		[10.82]	
Guarantee, %	361	73.24	232	48.75	24.49***
		[0.80]		[0.36]	
Interest rate, %	302	6.84	207	7.53	-0.70***
		[0.07]		[0.09]	
Duration	327	34.50	210	28.02	6.47***
		[0.94]		[1.01]	
Medium-firms					
%	1,978	2.53	1,562	0.83	1.70***
		[0.35]		[0.23]	
Sales, thousands 2021 EU	42	3,876.21	13	2,209.82	1,666.40*
		[445.65]		[1,022.16]	
Sales per employee, thousands 2021 EUR	43	48.80	11	21.65	27.15**
		[6.34]		[5.36]	
Collateral, 2021 EUR	27	369.57	12	199.61	169.96
		[83.68]		[28.16]	
Guarantee, %	50	72.71	13	47.69	25.02***
		[1.98]		[2.31]	
Interest rate, %	46	6.00	11	6.86	-0.86***
		[0.13]		[0.35]	
Duration	44	34.64	13	30.00	4.64
		[2.87]		[5.43]	

Source: Tax Registry and KCGF. The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

5 Annex

5.1 Data inconsistencies

According to Tax Registry, average turnover reported by micro-firms a is 36 thousand EUR, whereas in KCGF dataset, the average turnover of this firms is 228 thousand EUR (Figure 6).

Figure 6: Turnover reported by micro-firms in Tax Registry versus KCGF Data (2018)

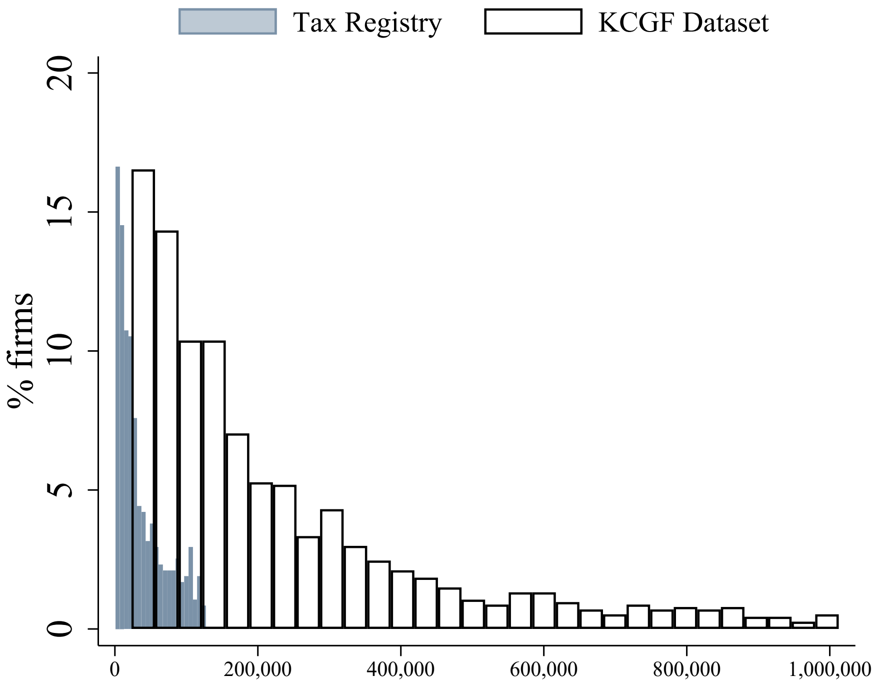


Table 7 shows a balance test between Tax Registry and KCGF data for micro and small firms. We aim to check whether the data presented in both datasets are consistent and we would expect no significant differences between them as they show descriptive statistics for the same set of firms.

However, for micro-firms, there are significant differences in the nominal interest rate, sales, number of employees, and, as a consequence, productivity. These differences suggest data issues that might affect the analysis of the impact of KCGF.

Table 7: Balance test between Tax Registry and KCGF data, 2021

Micro-firms	N	(1) Tax Registry Mean/SE	N	(2) KCGF Mean/SE	t-test Difference (1)-(2)
Sales, 2021 EUR	475	36,084.87	1137	228,701.15	-192,616.28***
		[1,518.29]		[6,366.84]	
Num. employees	662	3.45	1264	2.54	0.91***
		[0.09]		[0.05]	
Productivity, 2021 EUR	361	13,957.06	1036	98,181.83	-84,224.77***
		[518.52]		[2,215.21]	
Nominal interest rate	403	16.22	1239	8.75	7.47***
		[0.34]		[0.04]	

Small-firms	N	(1) Tax Registry Mean/SE	N	(2) KCGF Mean/SE	t-test Difference (1)-(2)
Sales, 2021 EUR	110	828,732.54	145	840,704.03	-11,971.49
		[61,979.04]		[53,522.57]	
Num. employees	120	17.01	161	16.79	0.22
		[0.67]		[0.63]	
Productivity, 2021 EUR	98	45,132.28	133	51,090.09	-5,957.81
		[3,574.00]		[3,021.38]	
Nominal interest rate	74	8.21	157	7.55	0.66***
		[0.29]		[0.10]	

Source: Tax Registry and KCGF. The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.