Access to Finance in Kosovo

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DIME/World Bank

October 13, 2022

Kosovo Firms in 2018

Using the last Tax Registry Data we had access to (2018)

90% of the firms are micro:

- 37.1 thousand firms.
- Almost 70% of these micro firms do not have a credit history history.[1]
- Low productivity might be a factor that constrains access to credit:
  - Sales per employee are 3 times lower in micro firms compared to small, medium, and large firms.
- Micro firms are more likely to stop their operations.
  - 20% of active micro firms in 2015 closed between 2016-2018.
  - The percentages are 10% for small, 5% for medium, and 0% for large.

[1] We define firms with credit history as the ones with approved loans between 2010-2017.

The % of firms with loans increases significantly with firms' size:

- More than **50%** of firms with more than 10 employees have loans.
- Among all the firms without loans in the country, **98.5%** are micro.

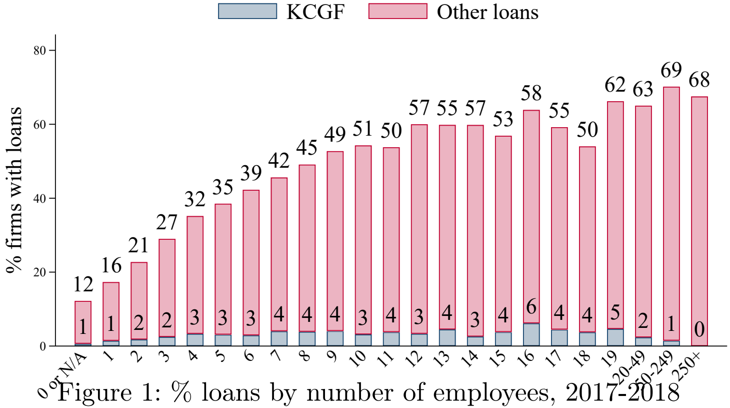


Figure 1: % loans by number of employees, 2017-2018

Micro-firms with access to credit versus the credit-constrained ones:

- The micro firms with approved loans: **sales 3 times** $\uparrow$ and are **40%** more productive.
- Still, there are several overlaps $\rightarrow$ it can help us to identify potential borrowers.

Table 1: Firms' characteristics by access to credit, micro firms (2018)

	Credit constrained firms Firms without loans 2010-2018				Firm with loan approved in 2018			
	mean	sd	min	max	mean	sd	min	max
Employees	2.3	1.7	1	9	3.4	2.3	1	9
Sales, k 2021 EUR	24.1	41.9	0.0	288.7	58.9	69.2	0.0	289.6
Sales/employee,	13.3	12.3	1.5	65.1	18.6	14.8	1.5	65.1
Wage, k 2021 EUR	2.2	0.7	0.6	4.0	2.4	0.7	0.6	4.0
Exports, %	2.4	15.3	0	100	7.2	25.9	0	100
Imports, %	21.0	40.7	0	100	50	50.0	0	100
Age	6.7	5.4	0	17	7.7	5.2	0	15
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.

Determinants of Access to Credit

What are the firms' characteristics that help to predict their access to credit?

We employ an ML model to identify firms' characteristics that help to predict access to credit:

Among the **96** variables used in the analysis, the model selects **10**:

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

Significant ↑ probability of a loan for firms with > 10 employees

The more the number of previous loans approved for the firm, the higher the probability of having a loan approved in 2018.

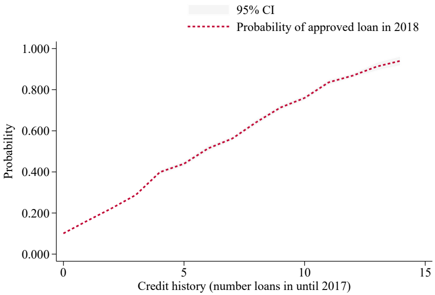


Figure 2: Probability of loan versus credit history

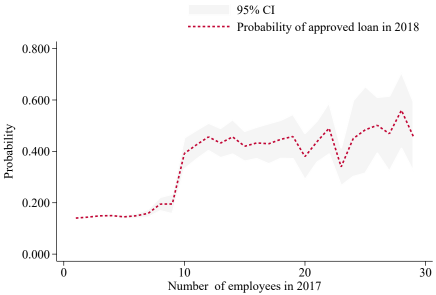


Figure 3: Probability of loan versus n.employees

The model predicts very well whether the firm has a loan approved:

Table 2: AUC-ROC of the models that predict access to credit

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

Source: Authors' estimate based on Tax Registry and Credit Registry.

- If ROC-AUC $= 1 \rightarrow 100\%$ accuracy in the probability of loan.
- If ROC-AUC $< 1 \rightarrow$ the model in some cases attributes an approved loan to a firm that does not have it or vice-versa.
- This means that there are firms without loans whose characteristics are similar to the ones with loans approved.

There are credit-constrained firms that are very similar to firms with approved loans:

- Similar annual growth in sales per employee, and annual growth in sales.
- Proxies for firms' capacity to pay the loan back → these credit-constrained firms have the potential to be borrowers as well.

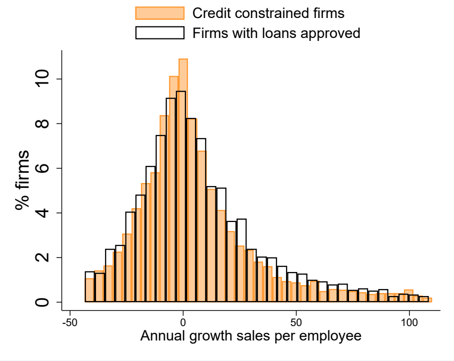


Figure 4: Annual growth in productivity

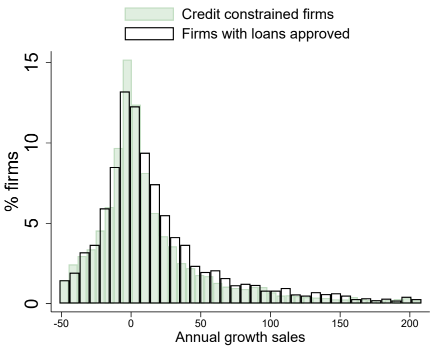
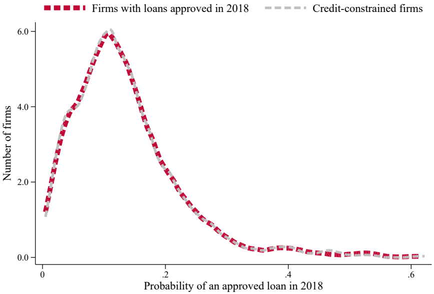


Figure 5: Annual growth in sales

To identify the subset of credit-constrained firms that could be potential good borrowers:

- We match this group of firms with the ones with approved loans in 2018
- We the 10 variables that most predict access to credit.
- We then find businesses with similar predicted probabilities of accessing credit.
- 17.8k credit-constrained firms, 2.5k were successfully matched to firms with loans approved → a potential subset of good borrowers).

Figure 6: Probability of having a loan approved, 2018



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

KCGF

Using the last KCGF Data from 2019-2021

The loans under the Recovery Package represent more than 50% of KCGF loans in 2021:

- The median approved amount is the same as the regular window.
- The interest rates are on average 1 pp lower.

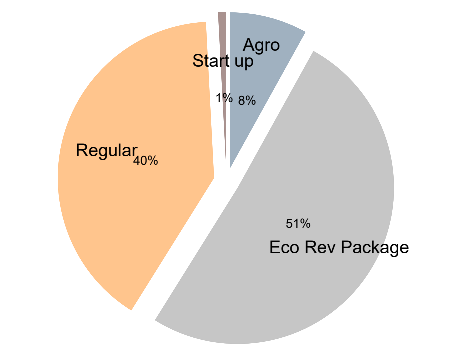


Figure 7: KCGF Windows

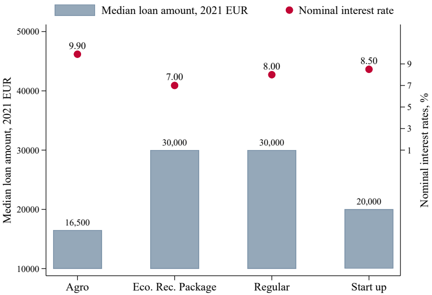


Figure 8: Loan amount and interest rates

Micro-firms included in the Recovery Package are on average less productive than the Regular Window:

Table 3: KCGF Regular and Recovery Package Windows, 2021

	(1) 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, k 2021 EU	1238	213.11	1096	222.29	-9.18
		[4.57]		[4.81]	
Sales/employee	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]	