Real effects of imperfect bank-firm matching

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Disclaimer: The views expressed herein are those of the authors and should not be attributed to the Bank of Italy, the Banco de Portgual, their management, or policies.

Motivation

- Disruptions in credit markets have large consequences on economic activity.
- In the Great Recession and during the EU debt crisis a $\Downarrow$ in firm's credit turned into a $\Downarrow$ in firm's employment and investment.
- During "bad" times, relationship lending (especially for SMEs) can mitigate the negative effects by smoothing fluctuations in credit.
- If relationships are terminated firms may struggle to find new banks.
- If the new bank-firm match is less efficient then the firm might have restricted access to credit and lower growth.

Motivation

- A large literature studies the importance of lending relationships:
  - Existence: Easing in loans terms & conditions
  - Termination: Loss of "soft" information
  - Firm's outcomes: Smoothing fluctuations in credit
- BUT little is known about:
  1. Determinants of bank-firm matches
  2. How matches in place and newly formed matches during crises differ from those in pre-crises times
  3. Consequences of "worse" matches in terms of firms' access to credit and associated real effects (investment, employment, prob of default)

In this paper

Open the "black-box" of bank-firm matches *for SMEs and Micro Firms*:

1. Rely on unique granular dataset on the universe of bank-firm matches from the Portuguese credit and firm registers.
2. Provide evidence on the drivers of bank-firm matches; firm-bank characteristics that are more conducive to the formation.
3. Compare matches in crisis times to matches pre-crisis (when frictions were less binding). Create a match quality index measuring how much the former differ from the latter.
4. Analyze whether the match quality index explains access to credit and firm's real outcomes.

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Preview of the results

A. Matches are more likely to occur in pre-crisis time if:

- Larger bank network: Branch in the same post-code with firm's location
- Banks have higher capital: Tier 1
- Firms are less risky: CB Prob(D)

B. Variation in the match quality index in crisis period stems from:

- Deterioration in the bank and firm fundamentals
- New bank-firm matches are on average worse

Preview of the results (2)

C. Firm's real effects of the match-quality index during crisis

- Lower match-quality: Contraction in credit
- Lower match-quality: Higher unemployment
- Lower match-quality: Lower investments
- Lower match-quality: Higher Prob(D)

Mechanism: The above results are driven by small firms because bigger firms can smooth fluctuations between banks.

Relevant literature

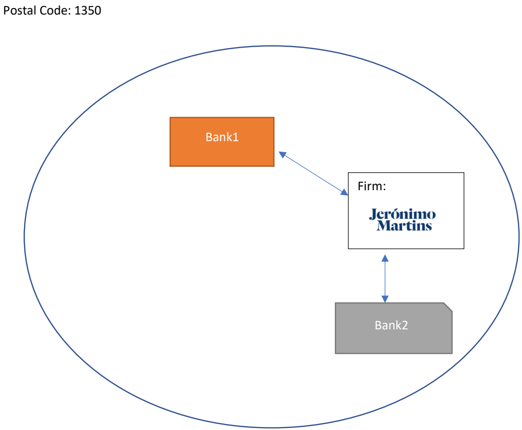
- Theories on bank-firm matching formation: Holmstorm & Tirole (97), Diamond & Rajan (01), Allen et al. (11), among others
  Our Contribution: We test empirically the relevance of the different drivers of bank-firm matches
- Bank capital as the driver of bank-firm matches: Schwert (18)
  Our Contribution: Look at both banks and firms characteristics and to a sample that includes mostly SMEs and Micro-Firms.
- Relationship lending in crisis times: Sette and Gobbi (15), Bolton et al. (16), Beck et al. (18)...
  Our Contribution: Matching is the input of relationship lending, go beyond traditional measures of duration or exposure (main bank)
- Real effects of bank shocks: Duchin et al. (10), Darmouni (20)...
  Our Contribution: Go beyond the anticipated loss of information and analyze the deterioration of relative bank-firm characteristics.

Data description

- We use the *Central Credit Register* (CR) of Banco de Portugal from 2006 to 2015. *Reporting threshold: €50*
- Firms' BS and IS are taken from the Central Balance Sheet which covers the entire universe of Portuguese non-financial firms.
- Bank BS data come from the MFI Statistics and regulatory ratios are obtained from prudential reports.
- The firm's *prob(default)* on bank debt within one-year horizon from the Banco de Portugal.

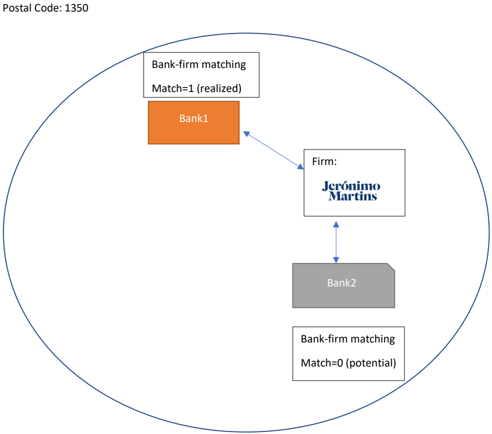
Definition of bank-firm matching

Example



Definition of bank-firm matching

Example (2)



Results

Part A: Determinants of bank-firm matching

Bank-firm matching: Reduced-form regression

$$Prob(Matching_{b,f,l,t}) = \alpha_0 + \lambda_1 * (F\ Size_{f,l,t} * B\ Size_{b,l,t})$$
$$+\lambda_2 * Capital\ ratio_{b,t} + \lambda_3 * HHI_{b,l,t} + \lambda_4 * Prob(d)_{f,t-1} + \epsilon_{b,f,l,t}$$

$$Matching_{b,f,l,t} = \begin{cases} \mathbb{1}, & \text{if bank } b \text{ and firm } f \text{ in a 4-d post code } l \\ & \text{at time } t \text{ are in the Credit Registry} \\ 0, & \text{Otherwise} \end{cases}$$

- $Prob(d)$: Firm's probability of default.
- α_0 : Firm, bank, year, location, bank*year, firm*year, bank*firm fixed effects.
- ϵ is the stochastic disturbance.

Results on the Determinants

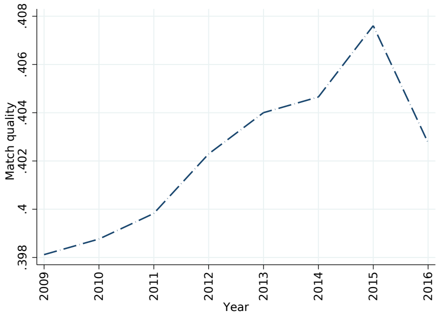
1. Both large and small firms are more likely to form a match with a big bank, within a 4 digit postcode.
2. Banks that are better capitalized are more likely to form credit relationships.
3. Better capitalized banks are more likely to match with riskier firms, pointing to an allocation of risk toward banks that have a higher risk-bearing capacity.
4. Overall, results are qualitatively and quantitatively similar across different sets of fixed effects.

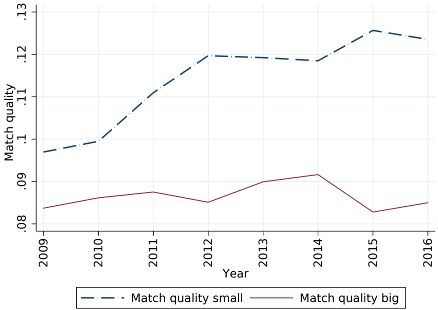
Part B: imperfect match index

Imperfect match index

- We estimate the model in the pre-crisis (2006-2008) period to predict matches out of sample in the crisis period (2009-2015). Figures
- We define the index as $(Realized - Predicted)^2$ and ranges from [0,1].
- Higher values of the index indicate that the relative bank-firm characteristics in pre-crisis matching (fewer frictions) are not aligned with the crisis period. $(0 -- >$ NO deviation)
- For this reason we use the label "**imperfect match index**".

Evolution of the imperfect match index





Part C: Decomposition in the imperfect match index

Sanity check 1: Loan-level

Table 1: Dependent Variable: Ln(Outstanding amt)

	I	II	III	IV	V
Imperfect Match	-4.563***	-0.340***	-0.706***	-1.429***	-1.427***
# of bank-branches					0.058
Observations	258,627	130,398	31,043	38,698	38,698
R-squared	0.108	0.651	0.704	0.708	0.708
Year FE	Y	Y		Y	Y
Bank FE	Y	Y			
Firm FE		Y			
Locations FE		Y	Y	Y	Y
Firm*Year FE			Y		
Bank*Year FE			Y		
Firm*Bank FE				Y	Y
SE	Robust	Robust	Robust	Robust	Robust

1. Larger values of the index lead to a significant deterioration in credit in the post-crisis period.

2. 1 std worsening in match quality is associated with a drop in credit between 263,000 and 657,000 €, depending on the specification.

Index decomposition at the Firm-Year

Table 2: Decomposition of the changes in the imperfect match index

Decomposition of the change in the imperfect match index between 2009 and 2016		
Mean of imperfect match index (Year=2009): 0.160 *Mean of imperfect match index (Year=2016): 0.190*		
Components	Absolute difference	Proportion (%)
Firm and Bank characteristics (Block 1)	0.0272	87.37
Changes in the share of credit (Block 2)	-0.0000	-0.09
New relations opened (Block 3)	0.0042	13.52
Relationships closed (Block 4)	-0.0002	-0.80
Overall	0.0312	100

1.Overall, the index changes from 0.160 in 2009 to 0.190 in 2016, indicating a worsening of match quality during the crisis years.

2.Variation comes mainly from changes in bank and firm characteristics (block 1) and from the opening of new bank-firm relationships (block 3).

3.Relationships opened during the crisis period are on average worse

Part D: Firm's real effect

Firm-level regressions: Weighed by share of credit

- *Instrument*: Unexpected EBA shocks after the default of Banco Espirito Santo, e.g., Blattner et al. 18; Gropp et al. 19
- IV estimation for supply-driven changes in the match quality index:

$$Imperfect\ Match_{f,t} = \alpha_0 + \rho * EBA\ borrowing\ share_{f,t} + \gamma * F_{f,t} + \eta_{f,t}$$

$$Y_{f,t} = \alpha_0 + \boxed{\beta_1 * \widehat{Imperfect\ Match}_{f,t}} + \beta_2 * F_{f,t} + \mu_f + \mu_t + \epsilon_{f,t}$$

- $EBA\ borrowing\ share_{f,t} = \frac{\sum_{EBA} Outstanding\ amount_{f,t}}{\sum_{All\ bank} Outstanding\ amount_{f,t}}$

Table 3: Imperfect match index and real effects

	Panel A: First stage					
	I	II	III	IV	V	VI
Dependent variable	Imperfect Match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.003***	0.004***	-0.009	0.001***	0.001**	-0.003

	Panel B: Second stage					
	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{\textit{Imperfect Match}}$	-5.300***	-5.339***	0.292	-16.318***	-16.767***	-0.407
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	134,267	115,359	21,297	131,204	112,528	20,967
R-squared	0.936	0.935	0.254	0.908	0.908	0.258
Year & Firm FE	Y	Y	Y	Y	Y	Y
SE	Robust	Robust	Robust	Robust	Robust	Robust

1.Imperfect match exerts a negative and highly significant effect on firm employment. 1 standard deviation worsening in match quality is associated with a drop in firms' employment of 0.9 per cent (90 per cent of std).

2.The effect is entirely driven by firms with single relationships.

Sample: Firms that switch lenders

Table 4: Distribution of new matches and real effects

	Panel A: First stage					
	I	II	III	IV	V	VI
Dependent variable	Imperfect Match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.003***	0.003***	0.001***	0.002***	0.003***	0.001***

	Panel B: Second stage					
	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{\textit{Imperfect Match}}$	-3.441***	-3.380***	-5.313***	-6.932***	-7.465***	-6.242**
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	57,909	50,149	7,734	58,071	50,325	7,723
R-squared	0.292	0.313	0.202	0.247	0.269	0.249
Year & Year FE	Y	Y	Y	Y	Y	Y
SE	Robust	Robust	Robust	Robust	Robust	Robust

Additional tests

Further tests:

- Determinants of bank-firm matching: Results Table
- Determinants of matching: Single VS multiple lending Table
- Heterogeneous effects on bank-firm matching Table
- OLS estimates for the real effects Table
- Analysis for switching lenders and terminating relationships Table
- Firm's probability of default Table
- Results on EBA and outstanding amount Table

Sensitivity tests:

- Alternative definitions for the bank-firm matching
- Alternative calculation for the imperfect match index
- Exclude Lisbon and Porto Table
- Results with bootstrap SE Table
- Industry-location-size FEs Table

Conclusions

- In this paper we open the "black-box" of bank-firm matches
- We study how imperfect matches between firms and banks affect firms' access to credit and real decisions during periods of adverse economic events.
- Imperfect matches reduces firm credit, employment, investment, and increases the probability of default.
- Results hold also for firms that manage to keep the same number of relationships, showing that the relative characteristics of banks and firms in a credit relationship matter.
- Relative characteristics between a bank and a firm matter and go beyond the standard proxies for relationship lending.

Thank you!

Appendix

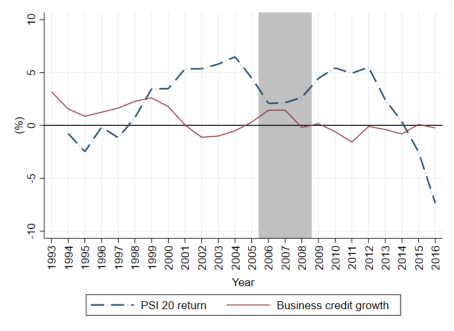
Table A1: Bank-firm matching : Single versus multiple lending

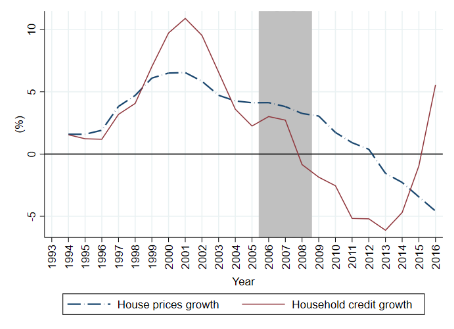
	I	II	III
	Full sample	Single lending	Multiple lending
Large_large	0.031***	0.031***	0.042***
Small_large	0.012***	0.039***	-0.009
Small_small	-0.015***	-0.009***	-0.002
Capital ratio	0.003***	0.013***	-0.018***
HHI	-0.012***	0.004**	-0.019*
Prob(default)	-0.060***	0.005	-0.070**
Observations	5,011,739	4,173,031	838,653
R-squared	0.099	0.061	0.175
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Bank FE	Y	Y	Y
Locations FE	Y	Y	Y
SE	Robust	Robust	Robust

Other Tests

Business & Household credit growth

Greenwood, Hanson, Shleifer and Sorensen (2020)





Pre-crisis period (2006-2008) is characterized by moderate credit growth and the absence of credit or housing bubbles. Matching index

Table A2: Bank-firm matching: Heterogeneous effect

	I	II	III
Large_large	0.032***	0.032***	0.023***
Small_large	0.011***	0.003**	-0.009***
Small_small	-0.016***	-0.024***	-0.026***
Capital ratio	-0.001	0.003**	-0.029***
HHI	-0.013***	-0.012***	-0.012***
Prob(default)	-0.061***	-0.134***	0.084***
Small_firm * Capital_ratio	0.008***		
Small_firm * Prob(default)		0.172***	
Large_firm * Prob(default)			-0.185***
Large_firm * High_capital			-0.005***
High_capital * Prob(default)			-0.082***
Large_firm * High_capital * Prob(default)			0.025**
Observations	5,011,739	5,011,739	5,011,739
R-squared	0.099	0.099	0.099
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Bank FE	Y	Y	Y
Locations FE	Y	Y	Y
SE	Robust	Robust	Robust

Other Tests

Table A3: Bank-firm matching: Alternative tests

	I	II	III	IV	V
Large_large	0.032***	0.114***	0.031***	0.031***	0.023***
Small_large	0.023***	0.003	0.012***	0.015***	0.004***
Small_small		-0.196***	-0.015***	-0.012***	-0.015***
Capital ratio		0.149***	0.003***	0.004***	0.006***
HHI		-0.032***	-0.012***	-0.013***	-0.013***
Prob(default)		0.197***	-0.060***	-0.057***	-0.060***
Ln(turnover)				-0.001**	
Ln(total expenses)				0.008***	
Ln(deposits)					0.006*
Bank cash					0.000***
Observations	5,645,040	4,977,513	5,011,739	4,616,007	5,011,739
R-squared	0.097		0.099	0.100	0.099
X-sq (Probit)		203174			
Year FE	Y	Y	Y	Y	Y
Firm FE	Y		Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Locations FE	Y	Y	Y	Y	Y
Industry*Location*Size*Year FE	Y				
SE	Robust	Robust	Bank*Firm	Robust	Robust

Other Tests

Table A4: Imperfect match index: Bootstrap SE

	I	II	III	IV	V
Imperfect match	-4.563***	-0.340***	-0.760**	-1.429***	-1.427***
# of bank-branches					0.058
Observations	258,627	130,398	31,043	38,698	38,698
R-squared	0.104	0.651	0.704	0.708	0.708
Year FE	Y	Y		Y	Y
Bank FE	Y	Y			
Firm FE		Y			
Locations FE		Y	Y	Y	Y
Firm*Year FE			Y		
Bank*Year FE			Y		
Firm*Bank FE				Y	Y
Cluster SE	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Other Tests

Table A5: EBA exercise and outstanding credit

	I	II
Dependent Variable:	Ln (Credit)	Ln (Credit)
EBA exercise	-0.571***	-0.614**
Capital ratio	0.493	1.965***
HHI	-0.024	-0.008
Ln(deposits)	-0.000	-0.001*
Bank size	-0.336**	0.020
Observations	407,556	407,553
R-squared	0.020	0.046
Year FE	Y	Y
Bank FE		Y
Cluster SE	Bank	Bank

Other Tests

Table A6: Imperfect-match index and real effects: Excluding Lisbon and Porto

	Panel A: First stage					
	I	II	III	IV	V	VI
Dependent variable	Imperfect match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.002***	0.002***	0.000	0.002***	0.002***	0.000

	Panel B: Second stage					
	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{\textit{Imperfect Match}}$	-8.470***	-8.742***	-59.992	-32.894***	-34.067***	-107.162
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	115,346	99,243	18,056	112,683	96,799	17,777
Year & Firm FE	Y	Y	Y	Y	Y	Y
SE	Robust	Robust	Robust	Robust	Robust	Robust

Other Tests

Table A7: Imperfect-match index and real effects: Firm-level OLS estimates

	I	II	III	IV	V	VI
Dependent variable	Ln(# of employees)			Ln(fixed tangible assets)		
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
Imperfect match	-5.581***	-6.074***	-4.394***	-11.736***	-12.816***	-8.026***
	[-136.321]	[-136.138]	[-36.860]	[-143.236]	[-141.528]	[-37.357]
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	279,000	257,691	21,309	267,530	246,548	20,982
R-squared	0.119	0.136	0.085	0.146	0.164	0.109
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Cluster SE	Robust	Robust	Robust	Robust	Robust	Robust

Other Tests

Sanity check: Loan-Level

Table A8: Switching lenders and terminating relationships

	I	II	III	IV	V	VI
Dependent variable	Prob(Switching lender)			Prob(Termination of lending)		
Imperfect Match	0.019***	0.054***	0.053***	0.057***	0.101***	0.100***
Observations	297,301	252,610	252,567	297,301	252,610	252,567
R-squared	0.443	0.452	0.455	0.435	0.444	0.448
Control Variables	Y	Y	Y	Y	Y	Y
Year FE	Y			Y		
Firm FE	Y			Y		
Bank FE	Y	Y		Y	Y	
Locations FE	Y	Y	Y	Y	Y	Y
Firm*Year FE		Y	Y		Y	Y
Bank*Year FE			Y			Y
SE	Robust	Robust	Robust	Robust	Robust	Robust

Higher quality matches are less likely to be associated with either a switch or an outright termination.

Other Tests

Table A9: Imperfect-match index and the probability of default

	I	II	III	IV	V	VI
	Panel A: First stage					
	All firms			*Only for firms that switched lenders*		
Dependent variable	Imperfect match					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
EBA borrowing share	0.001***	0.001***	0.000	0.001***	0.001***	0.001

	I	II	III	IV	V	VI
	Panel B: Second stage					
	All firms			*Only for firms that switched lenders*		
Dependent variable	Prob(default)					
Group	Full sample	Single	Multiple	Full sample	Single	Multiple
$\widehat{\textit{Imperfect Match}}$	0.274***	0.269***	-0.854	0.203***	0.194***	3.113
Firm control variables	Y	Y	Y	Y	Y	Y
Observations	148,238	128,056	22,543	55,172	47,092	9,736
R-squared	0.697	0.685	0.0647	0.708	0.719	0.118
Year & Firm FE	Y	Y	Y	Y	Y	Y
SE	Robust	Robust	Robust	Robust	Robust	Robust

1 std increase int he imperfect match index increases the firm Prob(D) by 4% (Column II). This increase represents 72% of the sample mean (5.5%).

Other Tests

Table A10: Bank-firm matching: Determinants

	I	II	III	IV	V	VI	VII
Large_large	0.119***	0.102***	0.031***	0.031***	0.033***	0.017***	0.013***
Small_large	0.089***	0.083***	0.012***	0.012***	0.026***		0.012***
Small_small	-0.025***	-0.015***	-0.015***	-0.015***		-0.018***	-0.038***
Capital ratio	-0.024***	-0.012***	0.003***	0.003***	0.004***		0.012***
HHI	-0.016***	-0.014***	-0.012***	-0.012***		-0.008***	-0.014***
Prob(default)	0.044***	-0.060***	-0.060***	-0.060***		-0.060***	-0.060***
Observations	5,013,829	5,011,739	5,011,739	5,011,739	5,010,697	5,011,739	3,049,146
R-squared	0.038	0.082	0.099	0.099	0.118	0.111	0.467
Year FE	Y	Y	Y	Y			Y
Firm FE		Y	Y	Y		Y	
Bank FE			Y	Y	Y		
Locations FE				Y	Y	Y	Y
Firm*Year FE					Y		
Bank*Year FE						Y	
Firm*Bank FE							Y
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust

1.Both large and small firms are more likely to form a match with a big bank, within a 4 digit postcode.

2.The relative size matching is not just a mechanical effect driven by big banks having more branches.

Overall, results are qualitatively and quantitatively similar across different sets of fixed effects.

Other Tests