Relationship lending in Peru

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Abstract

This paper studies whether the *strength* of bank-firm relationships has an impact on credit conditions, particularly during a stress scenario such as COVID-19 crisis. Using the Peruvian credit registry, we find that firms get better credit conditions (higher credit line and loan size growth, lower interest rate growth) in the institution where they have a stronger bond, measured by years of relationship, geographical proximity to a branch and share of credit. Furthermore, those effects are stronger compared to a pre-COVID scenario and heterogeneous depending on firm characteristics. We also find a positive effect of our *relationship lending* indices on the probability of getting *Reactiva* loans and loan rescheduling, and on the growth rate of the number of employees.

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1 Introduction

The backbone of Peruvian economy are micro-, small and medium-sized enterprises (MSMEs). Roughly 99.5% of Peruvian firms are MSMEs, which employ about 90% of the private sector's workforce; nonetheless, more than 80% of these jobs are informal and those firms contribute to only 25% of GDP [Produce (2021), OECD (2022)]. On the other hand, financial inclusion (i.e. the access to bank loans) is growing among Peruvian businesses. According to Ministry of Production, in 2019 the number of formal firms[1] was 2.4 million; at the same time, 2.3 million Peruvians had a credit line or an outstanding loan for micro-business use (1.7 million in 2015).[2] This suggests the existence of a huge number of informal small businesses with some credit record, as indicated by Lahura (2016).[3]

After this brief overview, it is reasonable to think that the so-called *relationship lending* could have a particular relevance regarding credit allocation in Peru. Indeed, the adoption of relationship lending is mainly related to small business lending: while large enterprises can present audited financial statements and make use of bonds or equity, this is generally not the case for small and micro-firms. In this sense, we can define *relationship lending* as a tool adopted by financial institutions and their borrowers (in this paper, firms), such that the former acquire proprietary information over time through contact with the latter, and use this information in their decisions about credit conditions, such as availability and cost. Hence, relationship lending exploit soft information which can mitigate information asymmetries. In opposition, we talk about *transactional lending* if the financial institution is focused on the singular transaction and takes decisions based only on current hard information. [Duqi, Tomaselli, and Torluccio (2018), Degryse and Van Cayseele (2000), Boot (2000)].

The following paper studies relationship lending in Peruvian economy; to the best of our knowledge, this is the first paper to explore this topic in Peru. In particular, we focus on a stress scenario, such as the first year of COVID-19 pandemic crisis. In order to do that, we use the universe of Peruvian nonfinancial private firms, including both juridical and natural persons, which are customers of Peruvian lending institutions (banks, saving banks, microfinance companies, etc). Following related literature, we work with three drivers of relationship lending: (1) length or duration of the relationship between lender and borrower, in quarters; (2) geographical proximity between lender branches and borrower location; and (3) share of total debt of the borrower with the lender, in percentage level. Using these three variables, we can calculate *relationship lending* indices and test several hypothesis.

The main hypothesis to test is whether firms get better credit conditions (such that a credit line increase, a loan size increase and a loan rate decrease) in the financial institution where they have a

[1]A formal firm has a tax ID number (RUC). This RUC number can be assigned to a juridical entity or to a natural person with business activity.

[2]We can only refer to formal loans, so we exclude informal (and illegal) loans from our analysis.

[3]In fact, the majority of micro-business loans are registered under a National ID, but not under a formal Tax ID.

stronger tie —this is, with the *relationship lender*. We also compare our findings from the pandemic crisis period with the ones from a pre-pandemic period (2018-2019). In addition to that, we want to check if firms have a higher chance of getting loan rescheduling and *Reactiva* government-backed loans with the relationship lender. In the subsequent section, using information from the Peruvian tax authority (SUNAT), we estimate the impact of a firm *credit relationship duration* index on the number of employees of the firm. To conclude, we provide a brief excursus about *switching loans* [i.e. firms that get loans from "new" banks, see Ioannidou and Ongena (2010)].

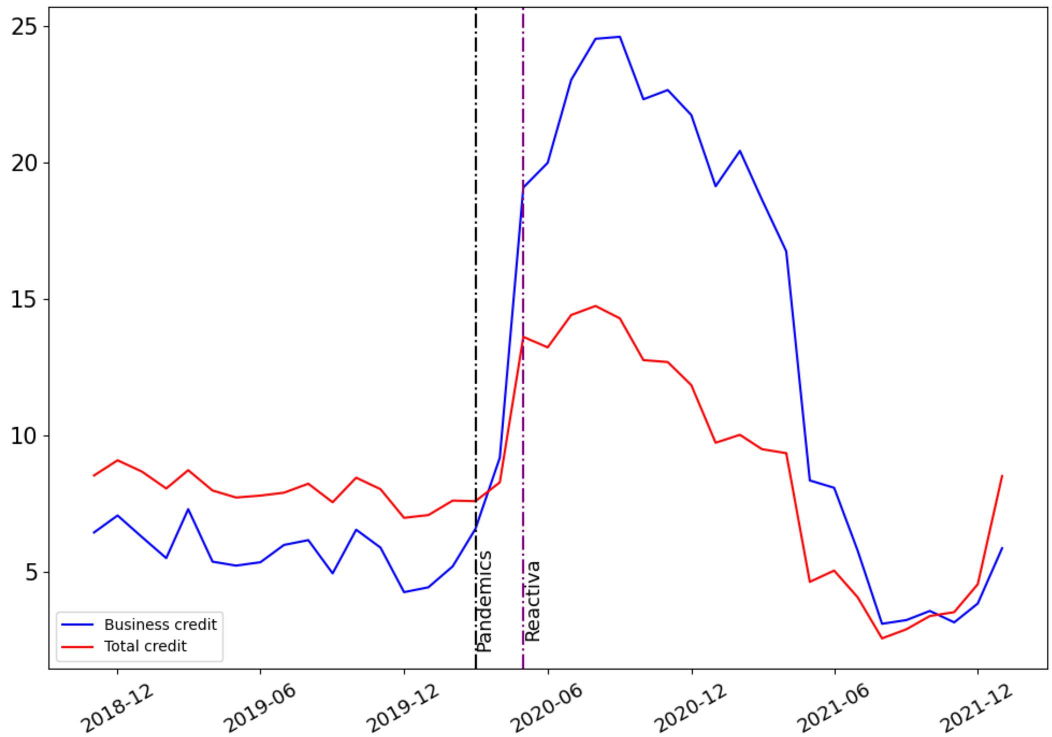
Since we are comparing year-end credit information between 2019 and 2020 (i.e. December registries), the context of this study coincides, roughly, with the first year of COVID-19 pandemics. Notice that business credit growth rates (see Figure 1), during the 12 months period before March 2020[4], oscillated between 4 and 7%. Nonetheless, in May 2020, the growth rate reached a notable 19%, followed by a peak on September (24,6%). To a great extent, we can attribute this credit boom to *Reactiva Perú* government-backed loans which, at the end of 2020, allocated around 58 000 PEN millions in business loans at low interest rates. Furthermore, BCRP used a wide range of tools to provide liquidity to the financial sector and ensure financial stability.[5] See for instance, Figure 2, which shows BCRP monetary policy (reference) rate flexibilization and our estimated median lending rates, that exhibit a decline between 2019 and 2020. Hence, unlike related papers such as Banerjee, Gambacorta, and Sette (2021) or Sette and Gobbi (2015), we do not explore a negative liquidity shock and a financial crisis (such as 2007-08 crisis), but a real negative shock (COVID-19 pandemics) with a rapid policy response that provided abundant liquidity across the financial system. As a matter of fact, 49% of *Reactiva* funds were allocated to corporate firms, but 98% of *Reactiva* loans were allocated to small enterprises, which suggest that this liquidity provision helped private sector both in intensive and extensive margins, across firm size distribution.

We find that firms exhibit an additional growth of credit line (+3.6%) and loan size (+3%), and a larger loan rate decrease (-6.4%) with the relationship lender, compared to the rest of banks where the business is also a customer. Among other results, we also observe a stronger effect of relationship lending during pandemic crisis, compared to normal times, and a heterogeneous intensity depending on firm characteristics; furthermore, there is a higher chance of getting a *Reactiva* loan (+8.1% additional probability) and a loan rescheduling (+11%) from the relationship lender. These results suggest that relationship lending is an important tool for credit allocation in Peruvian economy.

[4]State of emergency in Peru, due to COVID-19 outbreak, started on March 16th, 2020.

[5]We can mention, among others: the decline of policy rate (from 2.25 to 0.25%), flexibilization of reserve requirements, use of repurchase agreements, FX intervention.

Figure 1: Annual growth rate (%) of total and business credit in Peru



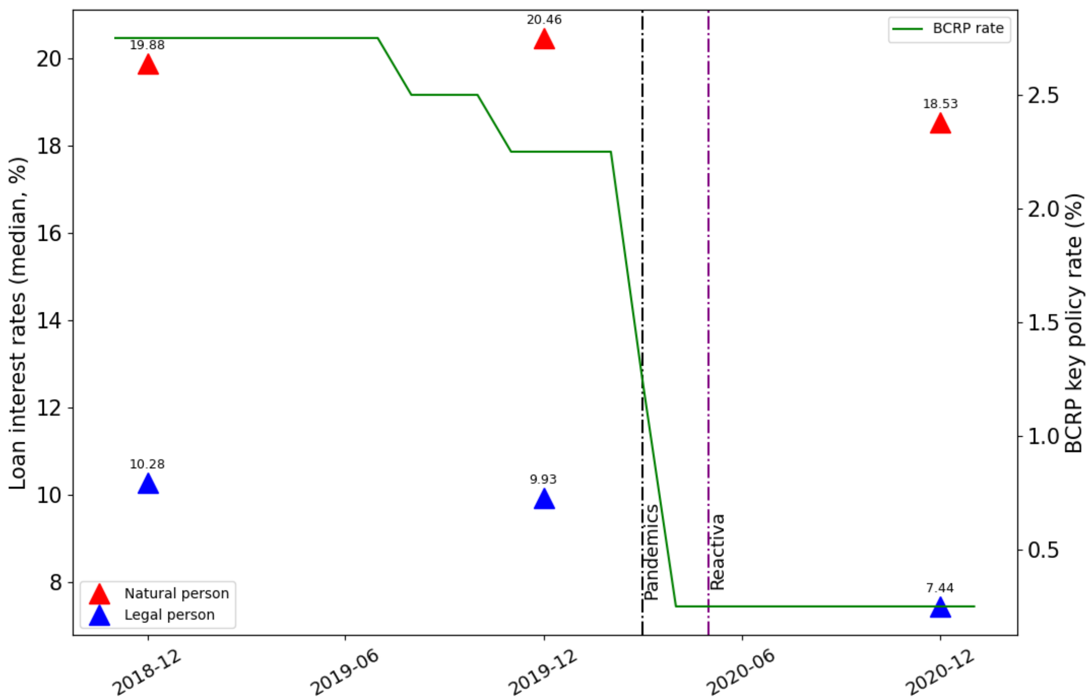
2 Related literature

The literature about relationship lending is huge. An interesting review was recently made by Duqi, Tomaselli, and Torluccio (2018); an important older review is Boot (2000). The findings have been somewhat mixed, and it is not easy to establish under what conditions relationship lending can be beneficial or harmful for both sides. On one hand, relationship lending can mitigate information asymmetries, particularly for small firms, and help those firms to signal their quality in order to get better credit conditions; on the other hand, relationship lending can foster opportunistic behaviors, such as moral hazard (firm side) or a debtor capturing which could translate into higher loan interest rates (bank side). At the same time, it is clear that relationship lending *drivers* are multidimensional: geographical distance, relationship duration, exclusivity, market competition, firm and bank structure, among many others. For instance, Degryse and Ongena (2005) find that loan rates decrease with the distance between the firm and the lending bank, while Berger and Udell (1995) find that small firms with a long relationship with a bank get there lower spreads on loan interest rates and fewer collateral requests. We highlight below some relevant result from related papers.

Sette and Gobbi (2015) is a closely related paper that studies relationship lending in Italy. They find that relationship lending mitigated the transmission of the Lehman default shock to the supply of credit in Italy; in particular, firms got better credit conditions with the relationship lender (4.6% higher credit line growth, and 0.5% lower cost of credit) compared with the transactional lender. These results are heterogeneous: the positive effect is greater on smaller borrowers, and the support provided by relationship lenders is related with their exposure to the financial crisis and the strength of their borrowers. Their identification strategy follows Khwaja and Mian (2005), since they focus on firms borrowing from at least two banks and include firm fixed effects.

Another close paper is Banerjee, Gambacorta, and Sette (2021), which also studies the effects of relationship lending on Italian firms following Lehman default shock, but here the focus is on the real effects. They find that banks offered more favourable continuation lending terms to firms with which they had stronger relationships, with a positive effect on firm investment and employment. Their empirical strategy make use of a *relationship duration* weighted index, and they also employ an instrumental variable that exploit a wave of bank mergers and acquisitions.

Figure 2: Median business loan rates and BCRP reference rate (%)



Regarding bank credit supply shocks, an interesting paper is Degryse et al. (2019). A relevant issue of identification methods à la Khwaja-Mian is that they rely strictly on multi-bank firms and ignore firms borrowing from only one bank, which are often the majority of firms in an economy. In this sense, they implement an alternative industry–location–size–time fixed effect that allows to include all the types of businesses. Using data from Belgium, they find that firms borrowing from banks with negative credit supply shocks exhibit lower financial debt growth, asset growth, and investments.

A recent paper that is worth reviewing is Acosta-Henao, Pratap, and Taboada (2022), which studies relationship lending in Chile. They characterize relationship lending in this country between 2012-2019, using several duration and concentration indices. Among other results, they find that relationship duration has been procyclical during normal times, positively correlated with loan amounts, and negatively correlated with interest loan rates; yet, these results could be hindered depending on the phase of the business cycle. To conclude this section, we also make reference to Ioannidou and Ongena (2010), which studies *switching loans*; this is, loans that a firm get from a bank with which it did not have a lending relationship during the previous 12 months. They find that those loans carries a loan rate that is lower than the rates on comparable new loans from the firm's current banks; nonetheless, this *switching premium* fades as time passes, and after 3 years the loan rate from the *new* bank equals the one obtained from the *old* bank.

3 Data

We have used four main datasets. The first one is the Peruvian credit registry, at monthly frequency, for the period between June 2004 and December 2020. The second dataset is the SUNAT firm register (January 2021), which includes business sector, firm location (district code), and firm age.[6] The third dataset is the branch register of financial institutions in Peru, which includes the opening (closing) date and the location (district) of every branch. The last dataset is the employment register (*Planilla Electrónica* SUNAT) between 2019 and 2021. Those four datasets were merged at individual identifier level (tax or national ID number[7]).

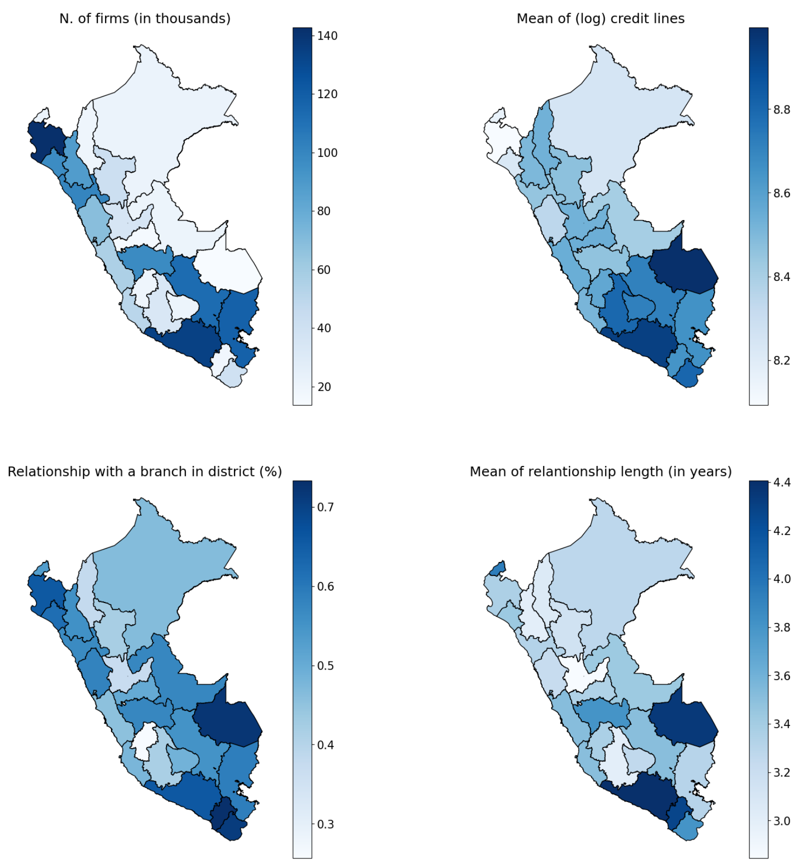
The database includes the universe of Peruvian active, non-financial, and privately held businesses with some credit relationship between December 2019 and December 2020.[8] In order to compare our results with a pre-COVID period, we also collect credit information of those firms for December 2018 (only for Section 4.3). The primary dataset is structured at firm-institution level, so we have 2 263 926 observations, 1 855 821 unique businesses[9] and 50 lending institutions (banks, *cajas municipales*, *cajas rurales*, *EDPYME*, *financieras*, among others). Roughly 43% of firms have at least one bank relationship, while 80% of firms have at least one relationship with a non-bank lending institution. We can observe several variables for each firm-institution-month combination, such as the outstanding

[6]The administrative SUNAT dataset we had access to mostly includes legal persons (*personas jurídicas*); we complemented the information from natural persons (*personas naturales*) using web-scraping tools and credit registry data.
[7]Recall that Tax ID is called *RUC*. National ID is called *DNI*.
[8]In other words, these firms appear in Peruvian credit registry and have non-zero credit lines between December 2019 and 2020. We exclude firms with non-performing loans (bad credit score) on December 2019.
[9]Note that a firm can also be a natural person (in this case, the business credit is identified by a DNI number).

loan amount[10], line of credit, accrued interest amount[11], credit score, reschedulings, and *Reactiva* loan amount.[12] See Table 11 in the Appendix for further statistics.

Figure 3 illustrates the regional heterogeneity of Peruvian firms, excluding the Province of Lima and Callao, at the end of 2019. For instance, Piura Region in Northern Peru has the highest amount of firms in Peru (about 142 000), but its average credit line is the smallest (8.09, in log scaled PEN). On the other hand, the region with the highest lending relationship duration, on average, is Arequipa (4.4 years); the lowest value belongs to Huánuco region (2.84 years). Furthermore, while 73% of lending relationships in Moquegua region are established in an institution that has a branch in the same district where the business operates, this value is only of 25% in Huancavelica region. These statistics suggest that the strength of borrower-lender connections are correlated with geographical features, demographics and local development. This heterogeneity is also observable if we focus on Province of Lima and Callao districts (see Figure 4 in the Appendix).

Figure 3: Maps of Peruvian regions (excluding Lima and Callao)



[10]The currency of loans and credit lines can be USD or PEN. We work with PEN denomination: USD amounts get converted to PEN using a unique exchange rate from December 2019 (3.31), and then collapse loan accounts at firm-institution-time level.

[11]While we do not observe contractual loan rates, we can calculate estimated rates dividing annual accruals by the average monthly loan amount. We trim these rates at 5-95 level to remove extreme values.

[12]It is worth mentioning that, since *Reactiva* funds were PEN-denominated, this policy strongly reduced business credit dollarization (from 37% to 27%, between 2019 and 2020). Here we will not focus on currency substitution.

Despite our dataset includes the universe of Peruvian (borrower) firms, our main empirical method (see Section 4) make use of a particular sample. In the spirit of Khwaja and Mian (2008), we select businesses with two or more lending relationships. This leaves us with 738 505 observations (335 629 unique firms and 50 lending institutions). Note that 54% of firms have more than one credit relationship (see Table 12 in the Appendix). Table 1 shows that, in about half of lending relationships, firms got a lower interest rate between December 2019 and December 2020. Nevertheless, if we separate this by type of lending institution, note that the interest rate went down about 71% of times in banks, but only 42% in non-bank institutions. Regarding credit line dynamics, we also have consistent statistics: more than a half of credit lines in banks increased, while 60% of non-bank credit lines decreased. Finally, as expected, we have better credit conditions in firms registered with RUC (*personas jurídicas*) than in firms registered with DNI (*personas naturales*). See Table 14 and Table 16 in the Appendix. To conclude the section, we describe the sample of firms with available employees information (see Table 16 in Appendix). This includes 63 120 firms, with an average of 13.7 workers (16.1 if we also consider *outsourced* workers). Furthermore, the mean age of these firm is 10.7 years, 74% got a *Reactiva* loan and 40% a loan rescheduling. On the other hand, in a context of COVID crisis and anti-firing laws[13], we have an annual variation of (extended) employees numbers of -2.9% (0.55%), on average.

Table 1: Summary statistics

	mean	p25	p50	p75	sd
Δ credit line	10.33	-37.40	-2.31	61.39	96.63
Δ int. rate	78.80	-13.17	-0.01	22.57	226.28
Δ loan size	13.14	-37.95	-3.12	66.45	107.94
relationship length	3.94	0.75	2.50	5.75	4.07
close branch	0.65	0.00	1.00	1.00	0.48
share	45.31	23.29	42.86	65.66	26.47
n. credit rel.	3.01	2.00	3.00	4.00	1.06
log(credit line)	9.09	7.73	8.95	10.34	1.87
log(credit)	9.01	7.64	8.86	10.28	1.85
int. rate	22.86	9.92	19.27	32.64	16.81
Observations	738505				

[13]See, for instance, Nº 038-2020 Decree (about *suspensión perfecta de labores*).

4 Empirical strategy and results

4.1 On main credit outcomes

The main empirical method follows Sette and Gobbi (2015). We select firms with two or more lending relationships, so we can exploit heterogeneity at firm-institution level. The main regression to estimate, for a private non-financial firm i and a lending institution j:

$$\Delta Y_{ij} = \alpha_i + \gamma_j + \beta RelationshipLender_{ij} + \ln CreditLine_{ij} + UsageRatio_{ij} + \epsilon_{ij} \tag{1}$$

where $Y = \{CreditLine, LoanSize, InterestRate\}$. In other words, we estimate the effect of a relationship strength index on the annual variation[14] (December 2019 - December 2020) of a credit outcome. On the other hand, *RelationshipLender* is a dummy variable equal to 1 if the relationship between firm i and institution j is the strongest, among all the institutions where the firm is also a customer. In order to measure the *strength* of a relationship, we perform a Principal Component Analysis (PCA) with three variables:

1. Length or duration of the relationship, in years. Since we track this variable quarterly, it can be a decimal number. For instance, if firm X opened a line of credit in Bank Y for the first time in June 2016, then (on December 2019) this length is 3.5 years.

2. Presence of a branch of the lending institution in the same district where the firm has its main office. This is a dummy variable.

3. Share of total credit of the firm in the lending institution, in percentage level.

Then, we define $RelationshipLender_{ij}$ index equal to 1 for the institution j with the highest value of the first principal component, among the set of lending institutions for firm i. The regression also includes fixed effects[15] at bank- and firm-level, and two controls at relationship-level: the (log) size of credit line and the credit line usage (in percentage level). Note that firm fixed effects allow us to control for all firm observed and unobserved characteristics; meanwhile, bank fixed effects control for general lending policies and for liquidity shocks (such as the positive liquidity supply shock from *Reactiva* program) during pandemics.

We show in Table 2, 3, and 4 the effects of relationship lending indices on credit line, loan size and interest rate[16]. Note that all coefficients are already converted to percentage points. In every

[14] Defined as a log-difference: $\Delta Y_{ij} = \ln Y_{dec20,ij} - \ln Y_{dec19,ij}$. Hence, we should interpret every coefficient as an additional effect on Y (outcome) *growth* rate.

[15] For simplicity, we refer to *institution fixed effect* as *bank FE*.

[16] Note that Table 4 includes less observations due to the algorithm we use to estimate interest rates. On the other hand, our estimated rates show a good match with public data on interest rates published by SBS.

regression, we double-cluster standard errors (at institution and firm level) in order to account for potential correlation between residuals within clusters. We find that one additional year in lending relationship duration increases credit line (0.68%) growth and loan size growth (0.22%) and decrease interest rate variation (-0.96%); moreover, if the lending institution has a branch in the same district of the firm, there is an additional growth on credit line and loan size (2.77% and 3.17%, respectively). Conversely, we find a small negative effect of credit share on line (-0.25%) and loan (-0.55%) variation. The impact of our *relationship lender* dummy[17] on credit outcome is the one we expected: on average, a firm has a higher line and size, and a lower interest rate growth (3.55%, 2.99% and -6.42%, respectively) with the relationship lender, compared with the rest of institution where it is also a customer.

Potential identification issues

Note that our identification strategy *à la* Khwaja-Mian has two related shortcomings: (1) we can only use firms with two or more lending relationships, which means that we lose the firms with only one relationship. Those firms could be very significant for our economy (and indeed, 45% of Peruvian businesses in our dataset falls into this category) and may be structurally different from those with multiple relationship. And (2) we need to assume that firm credit demand across banks is homogeneous, so our firm fixed effect (α_i) fully controls for firm credit demand.

We will try to address these concerns. Regarding (1), we could use an industry–district–firm type fixed effect, instead of a firm fixed effect. Here, we use the industry code (ISIC) up to three digits, and define two types of firm (natural or juridical person). The robustness check get favorable results (see Table 17 and Table 18 in Appendix). Regarding (2), we attempt a falsification test in the spirit of Sette and Gobbi (2015): we regress our relationship lending indices on the variation of line usage ratio. Insignificant estimators would suggest that there is not a specific firm-bank credit demand; we also find favorable results (see Table 19 in Appendix).

Alternative variables

Another way to check the robustness of our results is to study alternative measures for relationship strength. In particular, relationship *duration* (or length) could be replaced with relationship *intensity*, which is defined as the number of "meetings" between a firm and a lending institution in the last 15 years[18]. It is also possible to define alternative measures of *intensity*, such as counting only the meetings during the last 2 or 5 years, which can give a better idea of how much borrower and lender have been connected during recent times. In addition, we can consider an *intensity* measure that

[17] Recall that we used PCA to summarize our three drivers. We find that the three variables have positive loadings.

[18] In other words, we count how many times (between 2004 and 2019, at quarterly frequency) the firm and the lending institution had an active credit relationship (i.e. an active credit line). We divide this number by four, to make the values comparable with relationship length measure in years.

only counts borrower-lender encounters where the borrower had the best credit score possible[19], again, during the prior 2 or 5 years. Regarding geographical dimension, let's define a more lenient *closeness* dummy: instead of being determined at district level, this time it is at province level.[20]

The results are shown in the Appendix. Relationship intensity and geographical closeness at province level have both a positive and significant coefficient on line of credit (1.04 and 4.16 pp respectively) and negative and significant on loan interest rate (-1.25 and -5.67 pp); see Table 20. Furthermore, an additional borrower-lender meeting in the last 2 (5) years increase credit line by 1.20% (0.52%) and decrease loan rate growth by 2.19% (0.76%), as shown in Table 21. We get similar results from Table 22, using relationship intensity-quality measures. Finally, we again perform PCA to build *RelationshipLender* dummy, but this time using our alternative variables (intensity and province-closeness) in Table 23: the coefficient we get are almost the same as the ones from Table 2, 3, and 4. This suggest that our results are robust to different relationship lending metrics.

Table 2: Effect on credit line

	(1)	(2)	(3)	(4)	(5)
	Δ line	Δ line	Δ line	Δ line	Δ line
relationship length	0.675***			0.690***	
	(8.52)			(9.53)	
close branch		2.765***		2.092***	
		(4.24)		(3.48)	
share			-0.230***	-0.235***	
			(-4.84)	(-4.98)	
relationship lender					3.551***
					(9.48)
line usage	0.180***	0.171***	0.320***	0.332***	0.178***
	(3.96)	(3.71)	(4.53)	(4.77)	(3.98)
log(credit line)	-30.73***	-30.58***	-24.35***	-24.40***	-30.77***
	(-11.66)	(-11.69)	(-7.70)	(-7.70)	(-11.68)
firm FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	738505	738505	738505	738505	738505
R^2	0.526	0.526	0.526	0.527	0.526

SE double clustered at Firm and Bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[19]Consider that credit score is a categorical variable (1-5, from best to worst score, plus a "no opinion" score. Here we only count meetings with a score of 1.

[20]Several firms, while not located in the same district as a branch of their lender, could still be close to another bureau (e.g. if there is a branch in an adjacent district). So it is reasonable to also define *closeness* at province level.

Table 3: Effect on loan size

	(1)	(2)	(3)	(4)	(5)
	Δ loan	Δ loan	Δ loan	Δ loan	Δ loan
relationship length	0.222**			0.272**	
	(2.02)			(2.60)	
close branch		3.172***		3.099***	
		(3.62)		(3.32)	
share			-0.555***	-0.557***	
			(-5.48)	(-5.51)	
relationship lender					2.989***
					(7.74)
firm FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes
N	738505	738505	738505	738505	738505
R^2	0.507	0.507	0.509	0.509	0.507

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect on interest rate

	(1)	(2)	(3)	(4)	(5)
	Δ rate	Δ rate	Δ rate	Δ rate	Δ rate
relationship length	-0.955***			-0.935***	
	(-5.46)			(-5.22)	
close branch		-3.738		-2.692	
		(-1.48)		(-1.05)	
share			0.0109	0.0183	
			(0.21)	(0.35)	
relationship lender					-6.423***
					(-6.55)
firm FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes
N	694798	694798	694798	694798	694798
R^2	0.616	0.616	0.616	0.616	0.616

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Heterogeneity

This section shows that our main results, depending on firm and lending institution features, may vary. In Table 5 we introduce interactions of *relationship lender* dummy variable with new explanatory variables. Here we have (1) natural person, a dummy equal to one if the borrower got its credit using a DNI[21]; (2) population size of the district where the firm main office is located, in hundreds of thousands[22]; and (3) firm age[23] in years. Regarding credit lines, we find that the relationship lending *premium* is smaller (-2.33%) if the borrower is a natural person, and it is decreasing to district population (-0.33% for 100 000 additional people) and also to firm age (-0.18% for one additional year). See Table 24 in Appendix for a similar table with loan size as dependent variable.

[21]In general, we expect that these kind of firms are informal or undercapitalized. Big (formal) firms tends to get credit using their RUC identification number.

[22]We use Peruvian Census data (2017).

[23]Column (4) includes less observations since we do not have firm age for natural persons.

Regarding interest rate (Table 6) we find that our results are driven by natural persons (-8.93%) and, for the sample with firm age information, that our *relationship lender premium* is decreasing on age (0.37%). To conclude this section, we split the sample across two dimensions: firm type (RUC or DNI) and lending institution type (bank or non-bank). Table 25 in Appendix shows a stronger effect on non-bank credit from natural persons (-5.81% on interest rate variation).[24]

Table 5: Effect on credit line, heterogeneity

	Baseline	By type	By pop.	By age
	(1)	(2)	(3)	(4)
	Δ line	Δ line	Δ line	Δ line
relationship lender	3.551***	5.658***	4.107***	4.339***
	(9.48)	(5.40)	(10.28)	(3.37)
relationship lender × natural person		-2.330**		
		(-2.28)		
relationship lender × district pop.			-0.334***	
			(-2.74)	
relationship lender × firm age				-0.180*
				(-1.92)
firm FE	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes
N	738505	738505	738497	72160
R^2	0.526	0.526	0.526	0.416

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[24]Note the average interest rate variation is negative only for the *RUC/Bank* sample, which suggests that the transmission channel of monetary policy is more effective across this category (i.e. formal firms linked with banks).

Table 6: Effect on interest rate, heterogeneity

	Baseline	By type	By pop.	By age
	(1)	(2)	(3)	(4)
	Δ rate	Δ rate	Δ rate	Δ rate
relationship lender	-6.423***	1.761	-6.974***	-5.734***
	(-6.55)	(0.76)	(-8.32)	(-3.09)
relationship lender × natural person		-8.926***		
		(-3.62)		
relationship lender × district pop.			0.322	
			(1.02)	
relationship lender × firm age				0.367***
				(3.28)
firm FE	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes
N	694798	694798	694790	59305
R^2	0.616	0.616	0.616	0.549

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 What about normal times?

Our previous results came from a COVID pandemics scenario, since we compared December 2019 to the same month in 2020. We suggest that pandemic crisis, a large and unexpected shock, could have amplified relationship lending importance for credit allocation. In this sense, it is relevant to compare Section 4.1 results from a crisis period with a *normal* scenario. In this section, we track our set of firms with multiple credit relationship and include their information from December 2018 in the dataset. With an additional point in time, we now have a proper panel data[25] and regression (1) can be modified to:

[25]This is, we can compare 2018-2019 to 2019-2020 outcome changes at firm × institution level. Then, t = {1, 2}

$$\Delta Y_{ijt} = \alpha_{it} + \gamma_{jt} + \beta RelationshipLender_{ijt} + \ln CreditLine_{ijt} + UsageRatio_{ijt} + \epsilon_{ijt} \quad (2)$$

where α_{it} and γ_{jt} are firm-time and bank-time fixed effects, respectively. These time-varying intercepts help to account for the impact of pandemic crisis for each business and lending institution. Furthermore, since we want to compare normal with pandemic times, it is useful to include the interaction term *RelationshipLender* $\times$ *pandemics*, where *pandemics* is a dummy variable which value is equal to 1 if $t = 2$ (COVID crisis observations). Results are shown in Table 7. In columns (1), (2) and (3), reported coefficients from relationship lending drivers are similar to respective Section 4.1 coefficients. The interaction term estimated effect is positive and significant for line of credit [1.40 additional pp, see column (4)] and negative and significant for interest rate [-5.76 additional pp, see column (6)]. This confirms that, while relationship lending tool is relevant even during normal times[26], its importance increases during crisis times. This result is consistent with Sette and Gobbi (2015) findings.[27]

Table 7: Effects including 2018 data

	(1) Δ line	(2) Δ loan	(3) Δ rate	(4) Δ line	(5) Δ loan	(6) Δ rate
relationship length	0.706***	0.493***	-0.560***			
	(9.20)	(3.99)	(-5.20)			
close branch	2.634***	3.739***	-1.509			
	(5.31)	(4.17)	(-1.02)			
share	-0.293***	-0.744***	0.0297			
	(-5.79)	(-7.48)	(0.96)			
relationship lender				2.448***	2.474***	-0.234**
				(6.08)	(5.19)	(-2.13)
rel. lender $\times$ pandemics				1.401***	0.839	-5.758***
				(4.11)	(1.37)	(-6.40)
firm $\times$ time FE	Yes	Yes	Yes	Yes	Yes	Yes
bank $\times$ time FE	Yes	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1291832	1291832	1195903	1291832	1291832	1195903
R^2	0.549	0.508	0.635	0.547	0.505	0.635

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[26] Note that *relationship lending* coefficients in columns (4), (5), (6) have the expected signs and are significant.

[27] They find that relationship lending effects are amplified during a financial crisis (2008) in Italy.

4.4 Reactiva loans and rescheduling

We now study whether our *relationship lending* indices are increasing on the probability of (1) getting a *Reactiva* government-backed loans[28]; (2) getting a loan rescheduling.[29]. Hence, we now estimate regression (1) on a dummy equal to one if the firm i got a *Reactiva* loan at institution j; in other words, we have a linear probability model; we repeat this exercise using a dummy equal to one if the firm got a loan rescheduling. In the first (second) set of estimations we select the sample of firms with at least one *Reactiva* loan (loan rescheduling). We find (Table 8) a positive impact of relationship duration, closeness of branch and share of credit on the chance of getting a *Reactiva* loan. Furthermore, the firm is 8.07% more likely to get *Reactiva* with the relationship lender. At the same time, firms have an higher chance of getting a loan rescheduling with their relationship lender (10.85%). We perform a robustness check (see Table 28, Appendix) using additional fixed effects, which confirm our findings.

Table 8: Effect on Reactiva and rescheduling probability

	(1)	(2)	(3)	(4)
	P(reactiva)	P(reactiva)	P(reschedule)	P(reschedule)
relationship length	0.136**		-0.0870***	
	(2.30)		(-2.69)	
close branch	1.458***		-0.178	
	(3.59)		(-0.86)	
share	0.277***		0.516***	
	(6.69)		(52.98)	
relationship lender		8.067***		10.85***
		(5.26)		(19.73)
firm FE	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes
N	547953	552654	1612803	1614781
R^2	0.592	0.584	0.689	0.659

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line.

Coefficients in percentage points.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[28] *Reactiva Peru* was not the only government relief program for businesses during pandemics (e.g. we also have *FAE-Mype*), but it was by far the largest and most important. We will focus on *Reactiva* loans.

[29] Recall that Peruvian government have also used extraordinary funds to facilitate loan rescheduling during pandemics (*Programa de Garantías COVID-19)* See *Ley N. 31050*.

4.5 On workers

Here we study the effect of a *relationship duration* index on a real variable, such as the number of employees of the firm. We use two definitions of employees: (1) *workers*, which are the main employees (defined as *trabajadores* in SUNAT register); and (2) *extended workers*, which are the sum of workers and outsourced workers (*prestadores de servicios*). Due to limited data availability, we can only use a sample of 62 939 firms. Recall that $\Delta workers$ (i.e. the variation of employees number between January 2020 and January 2021) is negative, on average (-2.90%), while it is slightly positive for $\Delta ext\_workers$ (0.55%). Following Banerjee, Gambacorta, and Sette (2021), we estimate the regression:

$$\Delta L_i = \beta RelationshipLength_i + Industry_i + District_i + \Omega X_i + \epsilon_i \tag{3}$$

where $L = \{Workers, ExtendedWorkers\}$. Unfortunately, in this regression, we cannot exploit heterogeneity at firm-bank level, since we have one observation per business. Here, *RelationshipLength* firm index is defined as a weighted sum of firm-institution relationship durations: in other words, $\Sigma Share_{ij} * RelationshipLength_{ij}$. Note that $Share_{ij}$ is the share of total credit of the firm i in the institution j. We also includes district and industry fixed effects, and a vector of firm controls X_i (credit line size, firm age, credit score, firm size, collaterals, number of credit relationships). Results from Table 9 shows a small positive effect (between 0.12-0.13%) of relationship length on growth rates of both variables, using two sets of fixed effects.

Table 9: Effect on workforce

	(1)	(2)	(3)	(4)
	Δ workers	Δ workers	Δ ext_workers	Δ ext_workers
relationship length	0.132**	0.129**	0.120***	0.129***
	(2.52)	(2.86)	(4.15)	(4.70)
industry FE	Yes	No	Yes	No
district FE	Yes	No	Yes	No
industry × district FE	No	Yes	No	Yes
controls	Yes	Yes	Yes	Yes
N	62939	61849	62939	61849
R^2	0.113	0.150	0.114	0.152

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line.

Coefficients in percentage points.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6 A brief exploration on loan switching

Our previous results indicate that strong lender-borrower connections can decrease the cost of credit, particularly during an economic shock. But, while we suggest that relationship lending (compared to transaction lending) can be beneficial for firms, we still have not discussed the fact that businesses could *strategically* switch[30] lenders. Following Ioannidou and Ongena (2010), we define a *switching loan* as a new loan from a bank where the business did not have a credit relationship during the previous 12 months. In this sense, an interesting exercise would be to compare the interest rate of a switching loan against the rate of a non-switching loan. We estimate the following regression[31]:

$$LoanRate_{ij} = \alpha_i + \gamma_j + \beta SwitchingLoan_{ij} + \Omega X_{ij} + \epsilon_{ij} \tag{4}$$

where $LoanRate_{ij}$ is the loan interest rate for firm i in lending institution j and $SwitchingLoan_{ij}$ is a dummy variable (see the definition of *switching loan* above). Similarly to previous sections, we include fixed effects and a vector of control variables at firm- and relationship-level[32]. Table 10

[30]Note that by "switching" we refer to the creation of new credit relationships (i.e. a firm becoming a new customer of a lending institution). We do not specifically focus on *substitution* of lenders.
[31]We are working with data from December 2020
[32]See Table 29 in Appendix for the extended list of variables.

shows a negative and significant coefficient for *SwitchingLoan* dummy.[33] This result is consistent with Ioannidou and Ongena (2010) study with Bolivian data, where they also find that turning to a new bank leads to a drop in the loan interest rate.[34]

Table 10: Effect of loan switching on interest rate

	(1)	(2)	(3)
	int. rate	int. rate	int. rate
switching loan	-26.49***	-26.07***	-4.726***
	(-3.95)	(-4.01)	(-2.84)
bank FE	Yes	Yes	Yes
industry FE	Yes	No	No
district FE	Yes	No	No
industry × district FE	No	Yes	No
firm FE	No	No	Yes
controls	Yes	Yes	Yes
N	2797841	2777697	1195772
R^2	0.167	0.182	0.610

SE double clustered at (Firm Bank) Industry-District and Bank level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusions

Our preliminary results confirm that lending institutions, during COVID-19 crisis, have made use of relationship lending tools to allocate loans. Furthermore, not only relationship lenders provided additional growth rates for credit lines (3.55 pp) and loans (2.99 pp) compared to transactional lenders, but also with a lower cost (i.e. an additional -6.42 pp on loan rate variation). On the other hand, the size of this *relationship lending* premium is heterogeneous, depending on borrower features, such as age,

[33]Note the huge discrepancy in size (but not in sign) between the coefficient of columns (1)-(2) and (3), which includes firm fixed effect. Unobservables at firm level could explain this difference. In fact, even if we restrict the sample to column (3) observations and use columns (1)-(2) specifications, we get huge negative coefficients (-24%)

[34]They use matching methods in order to build counterfactuals for switching loans, and find a decrease of 0.80% in the loan rate at switching time.

firm size or geographical location. Moreover, we find that relationship lending technology is important even during normal (i.e. pre-pandemics) times and, consistent with literature, it is stronger during a crisis. The results are robust to alternative specifications and measures of relationship lending.

As expected, the allocation of *Reactiva* government-backed loans had a higher chance of occurrence across the most solid lending relationships. We also find a slightly positive impact of a relationship lending duration index on labor input growth rate. And finally we provided a brief excursus on loan switching, and suggest that firms could have a strategic advantage if they establish new credit relationships, where they can get lower interest loan rates. Further research should include a more detailed study on lending institution market (such as local banking concentration) and a broader set of variables at firm level (such as investments or ROA) in order to explore better the effects of relationship lending on the real economy.

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6 Appendix

6.1 Appendix A

Figure 4: Maps of Lima and Callao districts

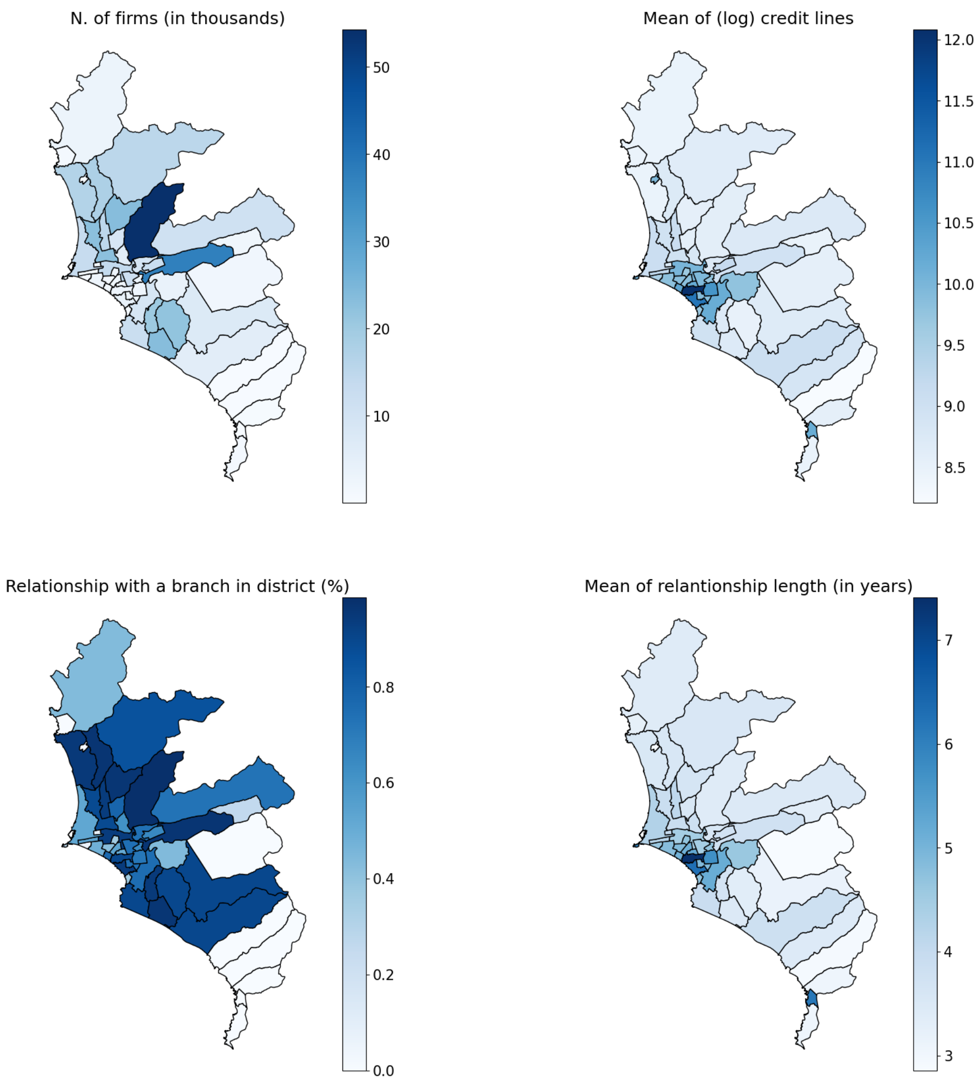

Table 11: Summary statistics

	mean	p25	p50	p75	sd
Δ line	17.46	-35.06	3.58	75.13	98.57
Δ rate	43.22	-15.48	-0.86	15.85	144.80
Δ loan	20.39	-35.16	6.16	81.68	105.93
relationship length	3.51	0.75	2.25	4.75	3.79
close branch	0.63	0.00	1.00	1.00	0.48
share	79.13	57.46	100.00	100.00	30.63
n. credit rel.	2.14	1.00	2.00	3.00	1.20
log(credit line)	8.61	7.33	8.45	9.81	1.76
log(credit)	8.52	7.26	8.35	9.72	1.75
int. rate	24.03	10.52	20.45	34.70	17.82
Observations	2177072				

Table 12: Firms, by number of relationships

	Freq.	Percent	Cumul.
1	852769	45.95	45.95
2	526149	28.35	74.30
3	283966	15.30	89.60
4	130398	7.026	96.63
5	46128	2.486	99.12
6	12674	0.683	99.80
7	2951	0.159	99.96
8	610	0.0329	99.99
9	126	0.00679	100.00
10	30	0.00162	100.00
11	9	0.000485	100.00
12	6	0.000323	100.00
13	2	0.000108	100.00
14	1	0.0000539	100.00
15	2	0.000108	100.00
Total	1855821	100.00	

Table 13: Summary statistics, by type of institution

	mean	p25	p50	p75	sd
non-bank					
Δ credit line	6.56	-38.98	-5.99	56.25	92.94
Δ int. rate	113.86	-11.50	0.93	56.70	262.37
Δ loan size	6.23	-39.63	-6.40	56.66	97.28
relationship length	3.35	0.50	2.00	4.75	3.75
close branch	0.60	0.00	1.00	1.00	0.49
share	44.91	23.31	42.47	64.83	25.97
n. credit rel.	2.97	2.00	3.00	4.00	1.00
log(credit line)	8.63	7.53	8.52	9.77	1.49
log(credit)	8.62	7.53	8.52	9.75	1.48
int. rate	24.53	11.64	21.00	34.69	17.05
bank					
Δ credit line	17.84	-33.86	0.59	72.52	103.17
Δ int. rate	9.01	-15.58	-3.14	2.21	93.79
Δ loan size	26.89	-34.40	3.68	90.73	125.37
relationship length	5.13	1.50	4.25	7.75	4.41
close branch	0.73	0.00	1.00	1.00	0.44
share	46.11	23.25	43.68	67.36	27.42
n. credit rel.	3.08	2.00	3.00	4.00	1.16
log(credit line)	10.01	8.40	10.10	11.41	2.19
log(credit)	9.79	8.11	9.89	11.23	2.21
int. rate	19.52	7.36	15.63	27.93	15.79
Observations	738505				

Table 14: Summary statistics, by type of firm

	mean	p25	p50	p75	sd
DNI					
Δ credit line	9.83	-38.08	-3.49	61.32	96.58
Δ int. rate	85.67	-14.00	-0.00	27.67	234.85
Δ loan size	12.23	-38.04	-3.83	65.51	103.86
relationship length	3.76	0.75	2.50	5.25	3.94
close branch	0.63	0.00	1.00	1.00	0.48
share	45.51	23.87	43.24	65.64	26.09
n. credit rel.	2.99	2.00	3.00	4.00	1.02
log(credit line)	8.79	7.60	8.70	9.97	1.57
log(credit)	8.73	7.57	8.62	9.91	1.56
int. rate	23.87	11.01	20.41	33.97	16.89
RUC					
Δ credit line	15.40	-29.78	0.38	62.16	96.99
Δ int. rate	9.34	-7.12	-0.49	2.42	77.21
Δ loan size	22.37	-36.93	3.10	76.01	142.40
relationship length	5.85	1.50	4.75	9.25	4.83
close branch	0.85	1.00	1.00	1.00	0.36
share	43.32	17.61	38.29	65.84	30.03
n. credit rel.	3.14	2.00	3.00	4.00	1.33
log(credit line)	12.14	11.19	11.92	13.08	1.98
log(credit)	11.86	10.92	11.74	12.90	2.08
int. rate	12.64	4.24	9.35	17.78	11.73
Observations	738505				

Table 15: Summary statistics, Lima-Callao vs Rest of Peru

	mean	p25	p50	p75	sd
Rest of Peru					
Δ line	11.15	-36.68	-1.90	62.46	96.45
Δ rate	85.66	-13.59	-0.00	27.64	234.51
Δ loan	13.94	-36.87	-2.49	67.28	105.63
relationship length	3.80	0.75	2.50	5.25	3.92
close branch	0.58	0.00	1.00	1.00	0.49
share	45.52	23.70	43.20	65.75	26.27
n. credit rel.	2.93	2.00	3.00	3.00	0.99
log(credit line)	8.90	7.61	8.75	10.14	1.69
log(credit)	8.83	7.59	8.69	10.07	1.68
interest_y_201912	23.62	10.50	20.03	33.77	17.08
Lima and Callao					
Δ line	7.93	-39.89	-3.36	58.32	97.12
Δ rate	58.51	-12.15	-0.53	11.64	198.60
Δ loan	10.78	-41.53	-4.70	63.91	114.44
relationship length	4.37	0.75	2.75	6.75	4.48
close branch	0.85	1.00	1.00	1.00	0.36
share	44.71	22.11	41.76	65.38	27.05
n. credit rel.	3.22	2.00	3.00	4.00	1.20
log(credit line)	9.67	8.05	9.54	11.04	2.21
log(credit)	9.56	8.01	9.44	10.89	2.17
interest_y_201912	20.61	8.45	17.16	29.26	15.76
Observations	738505				

Table 16: Summary statistics (2)

	mean	p25	p50	p75	sd
Δ workers	-2.90	-18.23	0.00	0.00	55.04
Δ ext. workers	0.55	-22.31	0.00	22.31	60.64
firm age (years)	10.74	5.00	10.00	15.00	6.94
got Reactiva	0.74	0.00	1.00	1.00	0.56
got rescheduling	0.40	0.00	0.00	1.00	0.72
workers	13.71	2.00	3.00	8.00	87.69
extended workers	16.14	2.00	4.00	11.00	90.14
Observations	63120				

6.2 Appendix B

Table 17: Effect on credit variables, additional FE

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ line	Δ loan	Δ rate	Δ line	Δ loan	Δ rate
relationship length	1.087***	0.428***	-1.447***	1.171***	0.545***	-1.483***
	(33.28)	(11.49)	(-33.01)	(37.29)	(15.21)	(-33.56)
close branch	1.984***	2.374***	-3.935***	1.398***	1.725***	-3.695***
	(4.75)	(4.93)	(-5.74)	(3.30)	(3.58)	(-5.33)
share	-0.142***	-0.243***	-0.204***	-0.139***	-0.241***	-0.207***
	(-44.53)	(-61.79)	(-43.16)	(-43.44)	(-60.37)	(-43.69)
bank FE	Yes	Yes	Yes	Yes	Yes	Yes
district × industry FE	Yes	Yes	Yes	No	No	No
district × industry × type FE	No	No	No	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2208672	2208672	2162099	2204138	2204138	2157470
R^2	0.155	0.107	0.186	0.161	0.113	0.188

SE double clustered at Industry-District and Bank level. Controls: line usage ratio, log credit line
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Effect on credit variables, additional FE

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ line	Δ loan	Δ rate	Δ line	Δ loan	Δ rate
relationship lender	7.380***	5.135***	-19.36***	7.322***	5.050***	-19.38***
	(36.83)	(22.33)	(-51.62)	(36.58)	(21.99)	(-51.60)
bank FE	Yes	Yes	Yes	Yes	Yes	Yes
district × industry FE	Yes	Yes	Yes	No	No	No
district × industry × type FE	No	No	No	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2208672	2208672	2162099	2204138	2204138	2157470
R^2	0.153	0.104	0.186	0.158	0.110	0.188

SE double clustered at Industry-District and Bank level. Controls: line usage ratio, log credit line
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Test, using usage ratio

	(1)	(2)
	Δ usage	Δ usage
relationship length	0.0277	
	(3.54)	
close branch	-0.00523	
	(-0.03)	
share	-0.319**	
	(-46.74)	
relationship lender		0.595
		(3.88)
log(credit line)	10.05**	0.740**
	(22.61)	(47.08)
firm FE	Yes	Yes
bank FE	Yes	Yes
N	738505	738505
R^2	0.535	0.474

SE double clustered at Firm and Bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Effect on credit outcomes: alternative RL drivers

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ line	Δ loan	Δ rate	Δ line	Δ loan	Δ rate
relationship intensity	1.040***	0.265	-1.252***			
	(7.60)	(1.09)	(-4.63)			
close branch (province)				4.164***	5.750***	-5.672*
				(4.83)	(4.92)	(-1.78)
firm FE	Yes	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	738505	738505	694798	738505	738505	694798
R^2	0.526	0.507	0.616	0.526	0.507	0.616

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Effect on credit outcomes: relationship intensity

	(1) Δ line	(2) Δ loan	(3) Δ rate	(4) Δ line	(5) Δ loan	(6) Δ rate
relationship intensity (last 2 years)	1.196***	1.066***	-2.191***			
	(7.36)	(4.58)	(-5.49)			
relationship intensity (last 5 years)				0.522***	0.290**	-0.763***
				(7.83)	(2.31)	(-5.27)
firm FE	Yes	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	738505	738505	694798	738505	738505	694798
R^2	0.526	0.507	0.616	0.526	0.507	0.616

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Effect on credit outcomes: relationship intensity with highest quality

	(1) Δ line	(2) Δ loan	(3) Δ rate	(4) Δ line	(5) Δ loan	(6) Δ rate
rel. intensity w/ top score (last 2y)	1.265***	1.086***	-2.162***			
	(7.68)	(4.58)	(-5.43)			
rel. intensity w/ top score (last 5y)				0.546***	0.294**	-0.750***
				(7.93)	(2.25)	(-5.34)
firm FE	Yes	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	738505	738505	694798	738505	738505	694798
R^2	0.526	0.507	0.616	0.526	0.507	0.616

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Effect on credit outcomes: alternative RL indices

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ line	Δ loan	Δ rate	Δ line	Δ loan	Δ rate
relationship lender (I)	3.919***	2.884***	-7.047***			
	(8.61)	(4.54)	(-7.11)			
relationship lender (II)				4.199***	2.873***	-7.518***
				(8.92)	(4.01)	(-6.23)
firm FE	Yes	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	738505	738505	694798	738505	738505	694798
R^2	0.526	0.507	0.616	0.526	0.507	0.616

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

Columns (1)-(3) use rel. intensity instead of rel. duration to perform PCA.

Columns (4)-(6) use rel. intensity and branch closeness at province (instead of district) level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Effect on credit, heterogeneity

	Baseline	By type	By pop.	By age
	(1)	(2)	(3)	(4)
	Δ loan	Δ loan	Δ loan	Δ loan
relationship lender	2.982***	9.906***	3.543***	7.733**
	(7.77)	(4.38)	(7.01)	(2.45)
relationship lender × natural person		-7.642***		
		(-3.37)		
relationship lender × district pop.			-0.334	
			(-1.67)	
relationship lender × firm age				-0.404
				(-1.60)
firm FE	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes
N	738505	738505	738497	72160
R^2	0.507	0.507	0.507	0.434

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Effect on interest rate, splitting samples

	All	DNI/Bank	DNI/Nonbank	RUC/Bank	RUC/Nonbank
	(1)	(2)	(3)	(4)	(5)
	Δ rate	Δ rate	Δ rate	Δ rate	Δ rate
relationship lender	-6.429***	-0.681**	-5.810***	-0.769***	-2.260
	(-6.55)	(-2.31)	(-4.00)	(-4.79)	(-0.46)
firm FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes
Y Mean	80.06	5.144	161.4	-2.214	86.33
X Mean	0.453	0.466	0.473	0.393	0.471
N	694798	34960	332820	50260	5419
R^2	0.616	0.659	0.616	0.469	0.643

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Effects including 2018 data. Alternative FE

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ line	Δ loan	Δ rate	Δ line	Δ loan	Δ rate
relationship lender	6.092***	7.427***	-2.570***	5.786***	3.196**	-11.22***
	(9.63)	(7.80)	(-9.89)	(5.09)	(2.11)	(-3.88)
firm × time FE	Yes	Yes	Yes	No	No	No
bank × time FE	Yes	Yes	Yes	Yes	Yes	Yes
district × industry × type × time FE	No	No	No	Yes	Yes	Yes
controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1291832	1291832	1195903	4037891	4037891	3922310
R^2	0.548	0.500	0.645	0.162	0.107	0.218

SE double clustered at (Firm Bank) Industry-District Bank level. Controls: line usage ratio, log credit line
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27: Reactiva and rescheduling - Logit, marginal effects

	(1)	(2)	(3)	(4)
	reactiva	reactiva	reschedule	reschedule
relationship length	0.0340***		-0.00702***	
	(0.00111)		(0.000903)	
close branch	0.606***		0.0731***	
	(0.0135)		(0.0101)	
share	0.000999***		0.00756***	
	(0.000142)		(0.000128)	
relationship lender		0.193***		0.0894***
		(0.00609)		(0.00496)
N	544548	549227	1476744	1478714

Marginal effects; Standard errors in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28: Effect on Reactiva and rescheduling probability - Linear model, additional FE

	(1)	(2)	(3)	(4)
	P(reactiva)	P(reactiva)	P(reschedule)	P(reschedule)
relationship lender	8.507***	7.999***	12.26***	12.28***
	(30.41)	(29.11)	(97.73)	(97.60)
firm FE	Yes	Yes	Yes	Yes
district × bank FE	Yes	No	Yes	No
district × bank × industry FE	No	Yes	No	Yes
controls	Yes	Yes	Yes	Yes
N	539837	531163	1599795	1590472
R^2	0.611	0.630	0.672	0.676

SE double clustered at Firm and Bank level. Controls: line usage ratio, log credit line. Coefficients in pp.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29: Effect of loan switching on interest rate

	(1)	(2)	(3)
	int. rate	int. rate	int. rate
switching loan	-26.49***	-26.07***	-4.726***
	(-3.95)	(-4.01)	(-2.84)
log(loan size)	-3.061	-3.000	-4.728***
	(-1.23)	(-1.20)	(-2.99)
good credit score	-7.396***	-7.404***	
	(-3.23)	(-3.25)	
natural person	5.919*	6.036**	
	(1.89)	(2.06)	
n. of credit rel.	5.270***	5.324***	
	(3.26)	(3.27)	
relationship length	-0.957***	-0.954***	-0.393***
	(-3.71)	(-3.74)	(-5.17)
close branch	-0.491	-0.474	0.0975
	(-0.59)	(-0.52)	(0.08)
share	-0.0471**	-0.0446**	0.162***
	(-2.36)	(-2.20)	(5.32)
bank FE	Yes	Yes	Yes
industry FE	Yes	No	No
district FE	Yes	No	No
industry × district FE	No	Yes	No
firm FE	No	No	Yes
N	2797841	2777697	1195772
R^2	0.167	0.182	0.610

SE double clustered at (Firm Bank) Industry-District and Bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$