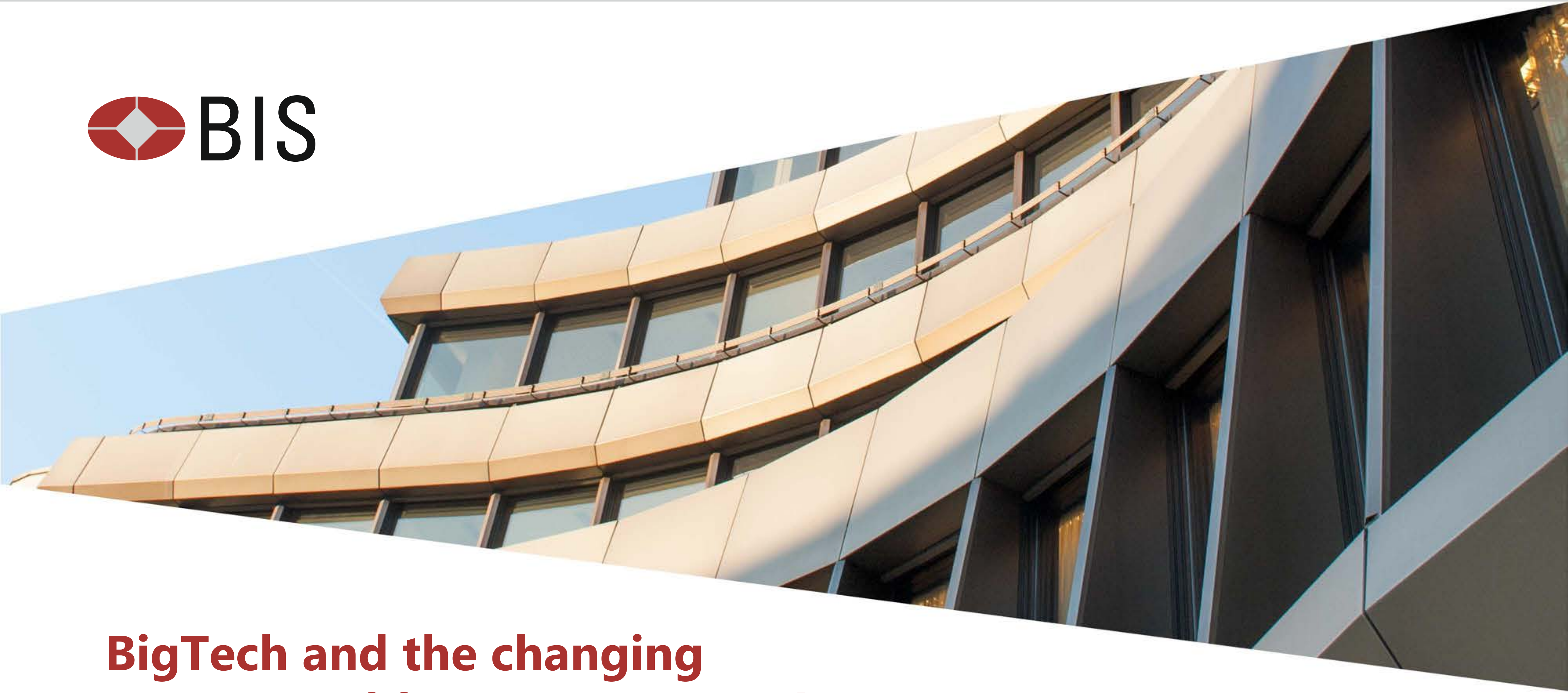

BigTech and the changing structure of financial intermediation

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The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. Pablo Zbinden discloses having an employment relationship and financial investments in Mercado Libre. Ant Financial and Mercado Libre did not exercise any influence on the content of this paper, but requires confidentiality of the (raw) data.

Outline of the presentation

- Introduction
- Trends and potential drivers
- BigTech credit
- Credit ratings
- Credit use and firms’ performance
- Conclusions

Introduction

BigTech expansion (1)

- BigTech firms' primary activity is in technology, rather than financial services. Their extensive networks and existing business in areas like e-commerce or social media offer them potential to make inroads into finance
- The activities of BigTech in finance started with payments, in many cases overlaying such services on top of existing payments infrastructures
- Increasingly, thereafter, they have expanded beyond payments into the provision of credit, insurance, and toward savings products, either directly or in cooperation with financial institution partners

BigTech expansion (2)

- The main advantage of Big Tech is the ability to exploit their existing networks and the massive quantities of data generated by their existing business lines

- BigTech firms should be distinguished from narrow FinTech firms. “FinTech companies digitise money, while BigTech firms monetise data” (Zetsche et al, 2017)

- The growth of BigTech in finance raises a host of questions for public policy (Carstens, 2018; BIS, 2019)

Three questions

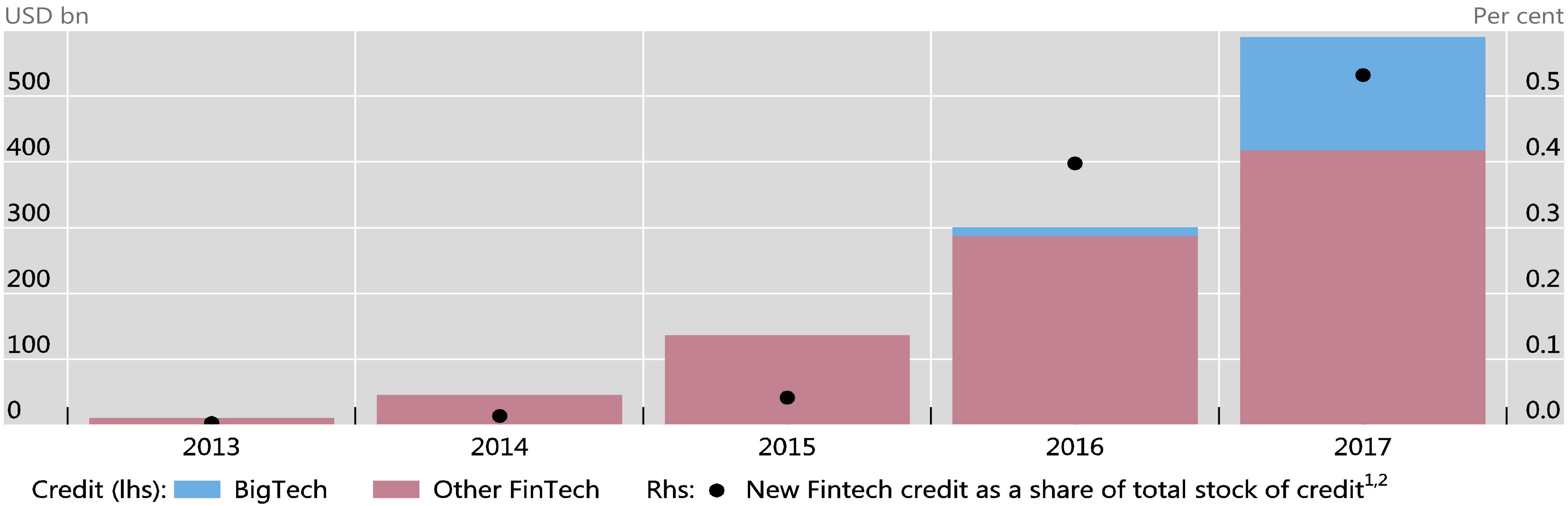
1. What are the economic forces that best explain the adoption of BigTech services in finance, especially BigTech credit?

2. Do BigTech lenders have an information advantage from alternative data or processing methods, particularly in relation to credit scoring?

3. Are there differences in the performance of firms that receive BigTech credit?

Trends and potential drivers

Global volume of new FinTech credit

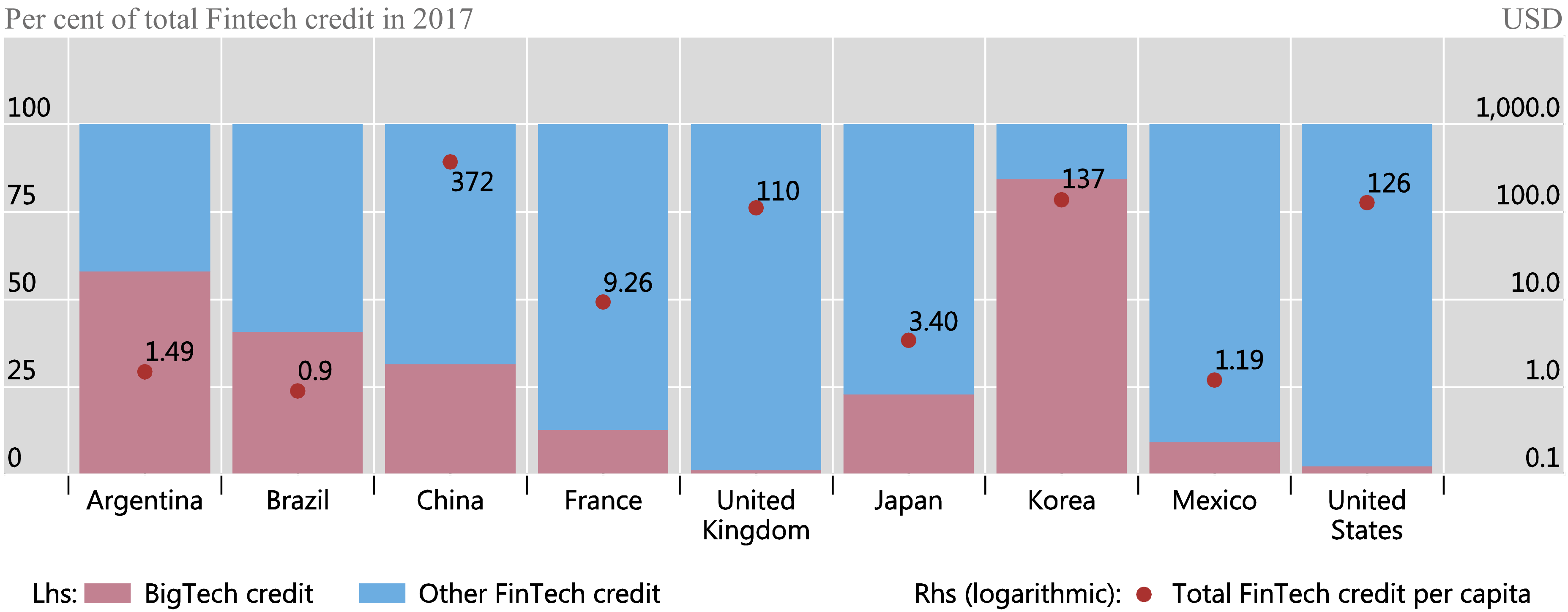


The bars indicate annual global lending flows by FinTech and BigTech firms over 2013-2017. Figures includes estimates.

[1] Total FinTech credit, defined as the sum of the flow of BigTech and other FinTech credit divided by the stock of total credit to the private non-financial sector. [2] Calculated on a selected set of countries for which data was available for the period 2015–2017.

Sources: Cambridge Centre for Alternative Finance and research partners; BigTech companies' financial statements; authors' calculations.

FinTech and BigTech credit



The bars show the share of BigTech and other FinTech credit in selected jurisdictions in 2017, while dots show total FinTech credit per capita.

Sources: Cambridge Centre for Alternative Finance and research partners; BIS calculations. Data for WeBank are taken from the public balance sheet: https://render.mybank.cn/p/s/render/404.

Potential drivers of BigTech in finance

- On the demand side:
  - Unmet customer demand (Hau et al. 2018 for China; De Roure et al. 2016 for Germany, Tang 2018 for US)
  - Consumer preferences (Bain & Company and Research Now, 2017)

- On the supply side:
  - Access to data (Jagtiani and Lemieux, 2018; Fuster et al., 2018 for FinTech lenders)
  - Technological advantage (van Liebergen, 2017)
  - Lack of regulation (Buchak et al., 2017 for FinTech)
  - Lack of competition (as alluded to in Philippon, 2015)

BigTech credit

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log of total FinTech credit per capita (in USD)[1]	64	0.3124	2.4745	–4.4677	5.9197
Log of BigTech credit per capita (in USD)[1]	64	-5.7353	3.2314	-7.183	4.7657
Log of BigTech credit share of total credit[1,2]	64	-10.539	2.7633	-15.17	-3.508
GDP per capita (in USD)[3]	64	21.139	16.4602	0.7367	62.7902
Banking sector Lerner index (mark-up)[4]	64	0.2663	0.1309	–.02688	0.6209
Normalized regulation index[5]	64	0.7405	0.0869	0.5217	0.9565
GDP growth (in %)[3]	64	3.5959	2.0216	–0.1074	8.1037
Crisis dummy (post 2006)	64	0.2656	0.4452	0.0000	1.0000
Credit growth[6]	64	7.2312	7.0855	–7.9948	22.6478
Mobile phones per 100 persons[7]	64	114.1372	32.8330	32.1285	214.7349
Bank branches per adult population[8]	64	22.5640	23.36794	1.7106	145.9949
BigTech dummy	64	0.20313	0.4055	0.0000	1.0000

[1] 2017 data. [2] Sum of total FinTech credit and total credit to the private non-financial sector. [3] Average from 2013 to 2016. [4] Average from 2010 to 2016. [4] Average from 2010–15. [5] In 2015. [6] Total banking credit growth to the private non-financial sector (in % average over the period 2010–2016). [7] 2016 data. [8] Average from 2013 to 2015.

Sources: Laeven and Valencia (2012); Cambridge Centre for Alternative Finance and research partners; IMF, World Economic Outlook; World Bank, Bank Regulation and Supervision Survey; World Bank, Global Financial Development Database and World Development Indicators; International Telecommunication Union; authors' calculations.

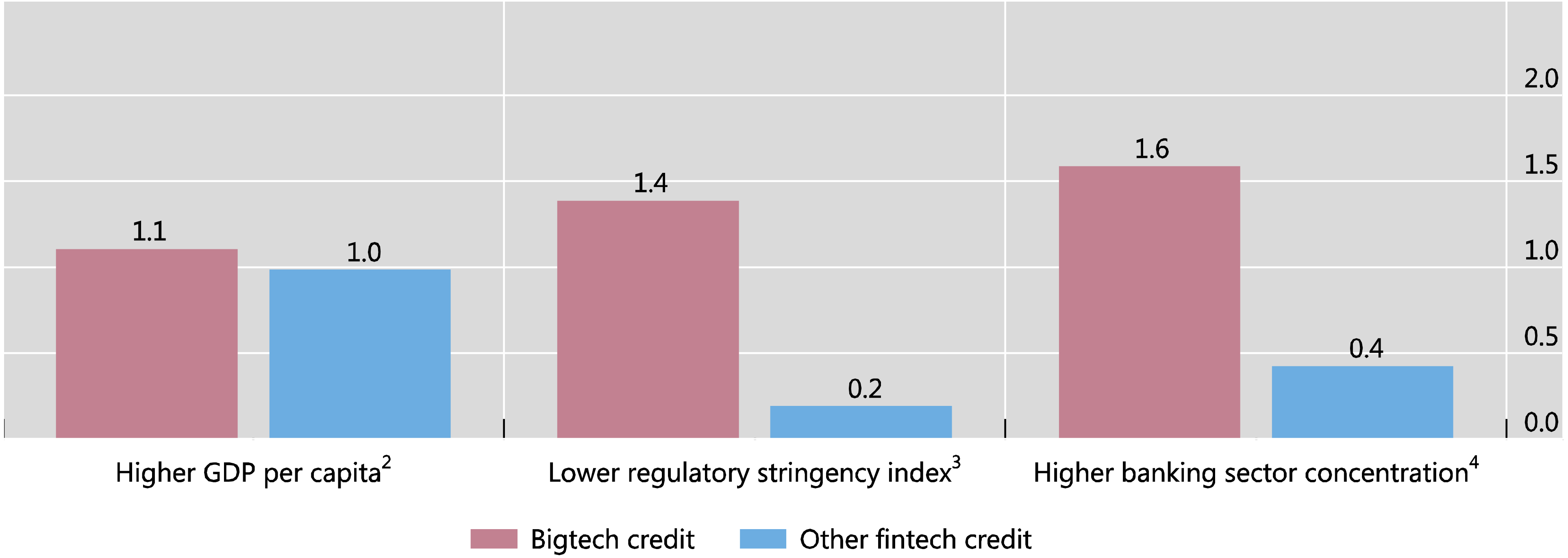
Regression results

Explanatory variables	BigTech dummy (0/1)	Ln(BigTech credit per capita)	Dependent variable: Ln(BigTech credit per unit of total credit[6])	Ln(Total FinTech credit per capita)[5]	Ln(Total FinTech credit per capita)[5]
	(1)	(2)	(3)	(4)	(5)
GDP per capita[1]	0.0416***	0.3890***	0.0641	0.1893***	0.1443**
	(0.0132)	(0.1258)	(0.0738)	(0.0637)	(0.0608)
GDP per capita squared[1]	-0.0005***	-0.0051***	-0.0001	-0.0026***	-0.0020**
	(0.0002)	(0.0018)	(0.0010)	(0.0009)	(0.0008)
Lerner index[2]	0.9440**	9.9783***	7.5166***	3.9099*	1.2220
	(0.4263)	(2.9311)	(2.1127)	(2.1254)	(1.4734)
Normalised regulation index[3]	-0.1197	-5.9459	-5.3582*	-8.0262**	-4.8756
	(0.6025)	(5.5436)	(3.0774)	(3.0553)	(3.1879)
Bank branches per population[2]	-0.0045**	-0.0386**	-0.0325***	0.0001	0.0032
	(0.0020)	(0.0150)	(0.0081)	(0.0061)	(0.0061)
BigTech dummy (BT)				1.3533*	9.8183**
				(0.7029)	(4.1396)
Interactions with BigTech dummy					
BT*GDP per capita[1]					-0.1575
					(0.1637)
BT*GDP per capita squared[1]					0.0039
					(0.0026)
BT*Lerner index[2]					9.3670**
					(4.2551)
BT*Normalised reg index[3]					-13.3597**
					(5.2568)
BT*Bank branches per pop[2]					-0.0211
					(0.0802)
Other controls[4]	Yes	Yes	Yes	Yes	Yes
No. of observations	64	64	64	64	64
Estimation method	OLS	Logit	Logit	OLS	OLS
R^2 / Pseudo R^2	0.1848	0.0592	0.1911	0.7054	0.7769

Main results

- BigTech drivers are similar to those of FinTech firms (Claessens et al., 2018)
- However, two institutional characteristics seems more relevant in economies where BigTech firms offer credit:
  - **Banking market power:** credit activity is higher in those jurisdictions with a less competitive banking sector. This results could be explained by the notion that BigTech credit is offered at relatively lower costs and it is relatively more convenient in these countries
  - **Regulatory stringency:** importance of light regulation for industry to develop new technology at initial stage

Estimated coefficients for BigTech and other FinTech credit



The bars visualise the estimated change in BigTech and other FinTech credit volumes from a change in the respective variables, based on the estimated coefficients displayed in the last column of Table 3.

[1] Change in BigTech credit and other FinTech credit per capita given a one-standard deviation change in the selected variables. [2] Nominal GDP in USD over total population. Given the non-linearity of the relationship, the change is calculated at the average GDP per capita level. [3] Regulatory stringency is constructed as an index based on the World Bank's Bank Regulation and Supervision Survey. The index takes a value between 0 (least stringent) and 1 (most stringent) based on 18 questions about bank capital requirements, the legal powers of supervisory agencies, etc. [4] One-standard deviation increase in the banking Sector Lerner index (an indicator of bank mark-ups and hence market power).

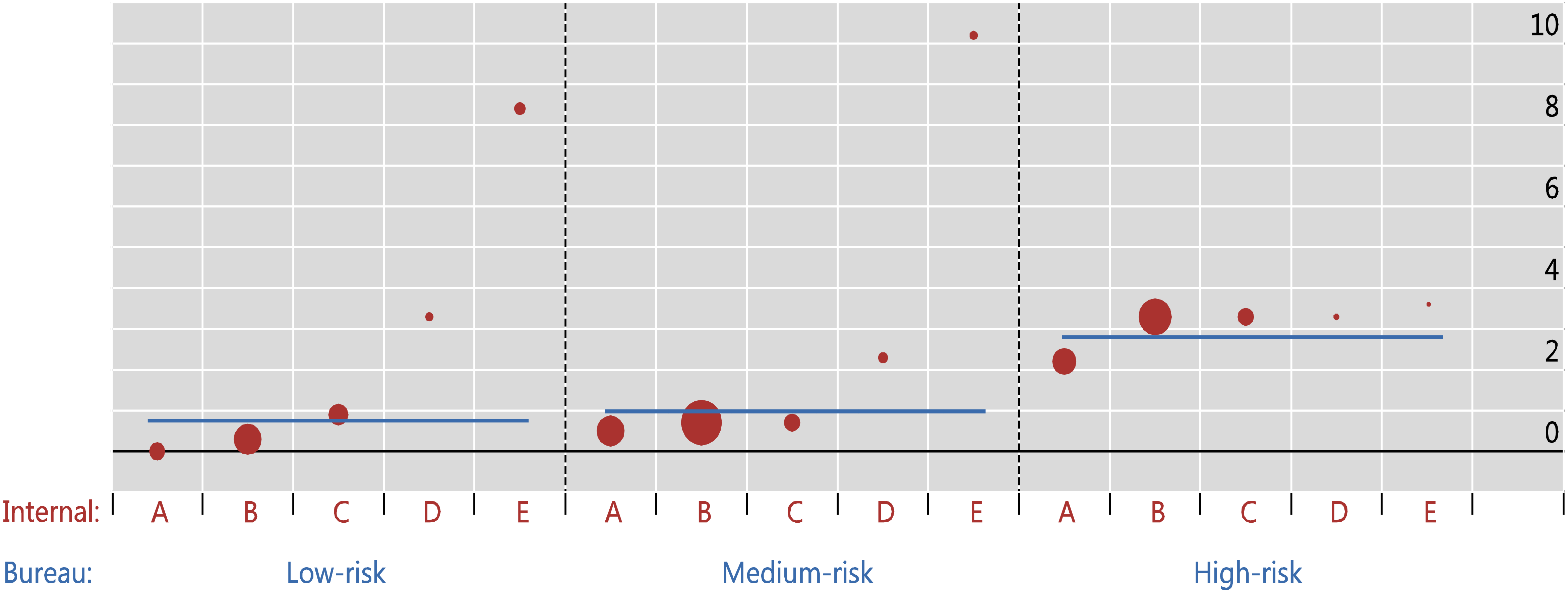
Source: authors' calculations.

Credit assessments

BigTech vs banks

- In contrast to banks, BigTech firms do not have a traditional branch distribution network to interact with their customers
- Advantage on proprietary data obtained from their online platforms and other alternative sources including from e-commerce, social media activity and from users' digital footprints (Berg et al, 2018)
- Notably, the loan origination processes generally include credit decisions based on predictive algorithms and machine learning techniques
- Analysis based on credit scoring by Mercado Libre in Argentina

Loss rates by ML internal ratings vs. credit bureau in Argentina



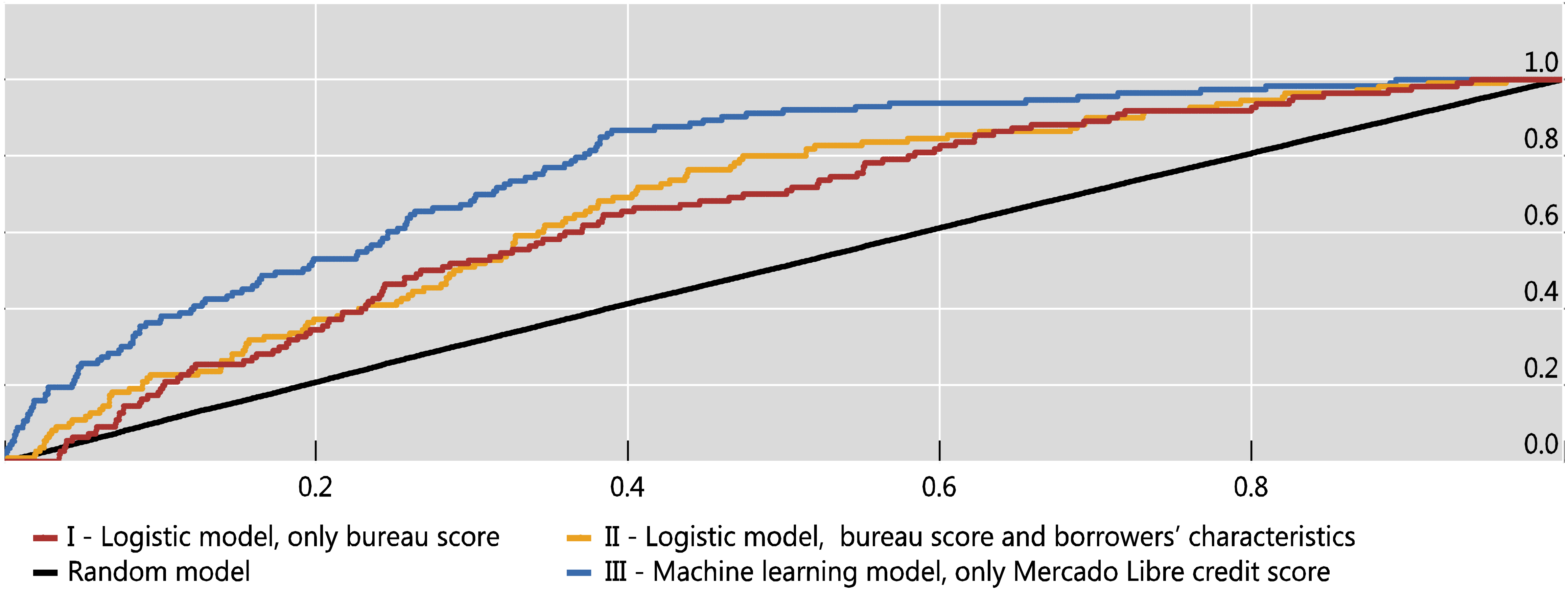
The figure shows the loss rate, i.e. the volume of loans more than 30 days past due relative to the origination volume. In its use to date, the internal rating of Mercado Libre is better able to predict such losses. It segments the originations into five different risk groups (A through E) versus the three clusters identified by the bank bureau. For a given bureau rating (i.e. low), the expected loss rate is strictly monotonous with the internal rating (i.e. internal rating orders expected loss). Conversely, given an internal rating (i.e. C, D or E), the loss rate is not strictly monotonous with the bank bureau risk. The size of the dots is proportional to the share of the firms in rating distribution. Sources: authors' calculation on Mercado Libre data.

Default rate regressions

	Dependent variable: Default Rate		
Explanatory variables	I Logistic Only Bureau score	II Logistic Bureau score and Borrowers' characteristics	III Machine Learning Only Mercado Libre credit score
Bureau score	-0.0022*** (30.92)	-0.0021*** (34.72)	
Mercado Libre Credit Score			Y
Borrowers' characteristics[1]	N	Y	N
AUROC	0.64	0.68	0.76
Observations	7,300	7,300	7,300

Note: The table estimates the impact of bureau score, borrowers' characteristics and Mercado Libre credit score on the loss rate (in % of origination volume) of a firm's loan. [1] They include sales trend in the last 6 months, sales in the last 15 days, client reviews, monthly sales vs instalments, city and time fixed effects. T-statistics are reported in the parentheses. *, ** and *** denotes for statistical significance at 10%, 5% and 1% respectively.

ROC curves for the different credit scores models



The figure shows true positive rates versus false positive rates for borrowers at different thresholds for three different models: (I) a logistic regression with only the credit bureau score on firm i at time t as dependent variable; (II) a logistic regression with the credit bureau score and additional borrower characteristic; and (III) a machine learning model based only on the Mercado Libre internal rating. A random model is included for comparison purposes. The ROC curve shows that the machine learning model has superior predictive power to both the credit bureau score only and the credit bureau score with borrower characteristics.

Sources: Mercado Libre; authors' calculations.

Credit use on firms' performance

Evidence from Mercado Libre: products offered and value of sold products

	Dependent variable: Annual growth rate of the number of offered products		Dependent variable: Annual growth rate of the value of a firm's sold products	
	(1)	(2).	(3)	(4)
D[Credit Use]	0.726***	0.793***	0.706***	0.747***
	(19.22)	(21.55)	(19.63)	(19.76)
Controls[1]	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Adjusted R^2	0.259	0.265	0.216	0.204
Number of obs.	81,045	40,762	81,045	40,762
Treatment and control groups	The treatment group includes those firms that have access to and used the credit line for the first time (Sample II in Table 6), while the control group includes those firms that have not used the credit line (Sample III and IV in Table 6).	The treatment group includes those firms that have access to the credit line for the first time (Sample II in Table 6), while the control group includes those firms that were eligible for the credit line but did not have not used it (Sample III in Table 6)	The treatment group includes those firms that have access to an used the credit line for the first time (Sample II in Table 6), while the control group includes those firms that have not used the credit line (Sample III and IV in Table 6).	The treatment group includes those firms that have access to the credit line for the first time (Sample II in Table 6), while the control group includes those firms that were eligible for the credit line but did not have not used it (Sample III in Table 6)

Note: The table reports the coefficient for the credit use variable in estimations of the annual growth rate of a firm's number of products (columns 1 to 2) and the firm's value of sold products (columns 3 to 4). [1] Controls include the credit score of the borrower, gender, and age. Columns differ in their use of product/industry and time fixed effects (FE). Standard errors are clustered at the firm level. All the dependent variables are winsorized at 1%. T-statistics are reported in the parentheses. *, ** and *** denotes for statistical significance at 10%, 5% and 1% respectively.

Evidence from Ant Financial: number of firms' online products

	Dependent variable: Annual growth rate of the number of offered online products			
	(1) Industry FE	(2) Industry and time FE	(3) Industry FE	(4) Industry and time FE
D[Credit Used]	0.1589***	0.1301***	0.0818***	0.0863***
	(44.03)	(36.03)	(47.80)	(49.58)
Controls[1]	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Time FE	N	Y	N	Y
Adjusted R^2	0.0211	0.0272	0.0256	0.0285
Number of observations	2,177,364	2,177,364	2,177,364	2,177,364
Treatment and control groups	The treatment group includes firms that have access to the credit line for the first time and used it (sample II in Table 7), while the "control" group includes firms that do not use the credit line (sample III and IV in Table 7).		The treatment group includes firms that have access to the credit line for the first time (samples II and III in Table 7), while the control group includes those firms that are not eligible for the credit line (sample IV in Table 7).	

Note: The growth rate of a firm's online products is calculated on an annual basis after the firm had access to the credit line. [1] Controls include the credit score of the borrower and characteristics such as gender, education level, age, marriage status and property ownership. Columns differ in their use of product/industry and time fixed effects. Standard errors are clustered at the firm level. All the dependent variables are winsorized at 1%. T-statistics are reported in the parentheses. *, ** and *** denotes for statistical significance at 10%, 5% and 1% respectively.

Conclusions

Main takeaways

- Drivers of BigTech credit are similar to those of FinTech credit. Activity is higher in those jurisdictions with:
  - less competitive banking sector (financial inclusion)
  - less stringent regulation (important for the industry to develop new technologies and products at initial stage)

- BigTech lenders appear to have an information advantage from alternative data, particularly in credit scoring, as illustrated by the example of Mercado Libre in Argentina

- Finally, based on data for Argentina and China, we show evidence that firms that use BigTech credit have offered more products and had higher sales than firms without credit