Data vs Collateral

Leonardo Gambacorta*, Yiping Huang⁺, Zhenhua Li^{*}, Han Qiu⁺ and Shu Chen^{*}

* Bank for International Settlements and CEPR, [†]Institute of Digital Finance, National School of Development, Peking University, ^{*}Ant Group.

Banca d'Italia and Federal Reserve Board Joint Conference on "Nontraditional Data & Statistical Learning with Applications to Macroeconomics", 11 November 2020

Disclaimer

The views in this paper are those of the authors only and do not necessarily reflect those of the Bank for International Settlements nor Ant Group. The authors highlight that the data and analysis reported in this paper may contain errors and are not suited for the purpose of company valuation or to deduce conclusions about the business success and/or commercial strategy of Ant Group or other firms. All statements made reflect the private opinions of the authors and do not express any official position of Ant Group and its management. The analysis was undertaken in strict observance of the Chinese law on privacy. Gambacorta, Huang and Qiu declare that they have no relevant or material financial interests that relate to the research described in this paper. Zhenhua Li and Shu Chen disclose having an employment relationship in Ant Group. Ant Group did not exercise any influence on the content of this paper, but has ensured confidentiality of the (raw) data.

Outline of the presentation

Motivation and research questions

□ Main results

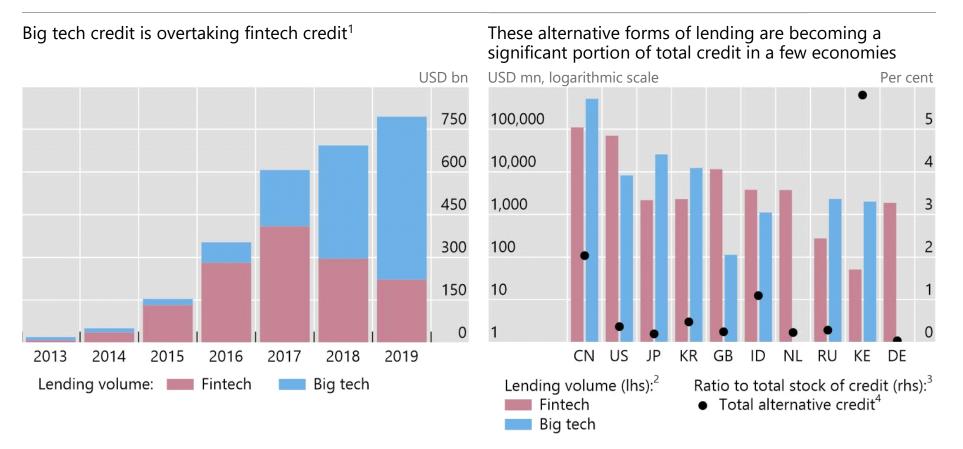
Conclusions





Motivation and research questions

Big tech credit is booming



Figures include estimates. CN = China, US = United States, JP = Japan, KR = Korea, GB = Great Britain, ID = Indonesia, NL = Netherlands, RU = Russia, KE = Kenya, DE = Germany.

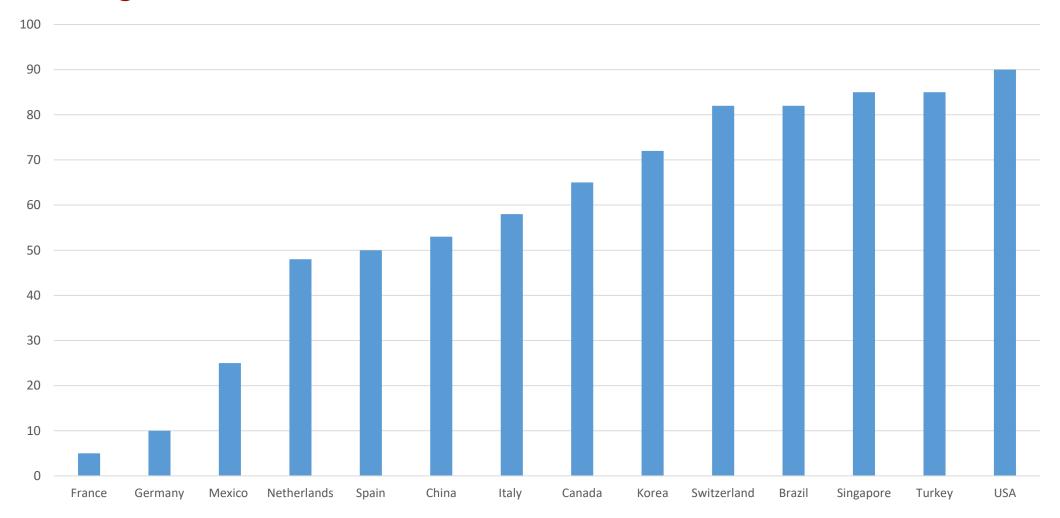
¹ 2019 fintech lending volume figures are estimated on AU, CN, EU, GB, NZ and US. ² Data for 2019. ³ Domestic credit provided by the financial sector. Data for 2018. ⁴ Total alternative credit is defined as the sum of fintech and big tech credit. Data for 2019.

Source: Cornelli et al (2020), "Fintech and big tech credit: a new database", BIS WP 887.

Data can replace collateral

- Big techs could address AI problems differently from banks (Hau et al, 2018)
- They can use machine learning and big data to infer the credit quality of a borrower more precisely in real time (Bazarbash, 2019; Frost at al 2019)
- Banks usually require their borrowers to pledge tangible assets, such as real estate, to:
 - lessen ex-ante adverse selection problems (Bester 1985, Chan and Kanatas, 1985; Besanko and Thakor, 1987)
 - as a way to reduce ex-post frictions, such as: i) moral hazard; ii) costly state verification; iii) imperfect contract enforcement

Percentage of bank loans to SMEs that is collateralised



Note: Data for 2017. For Italy, the SME aggregate refers to bank loans to firms with <20 employees. For Spain, the data comes from Spanish Mercantile Registers, which covers around 45% of the total population of SMEs (in terms of number of firms and number of employees). For China, the data comes from OECD (2019) Source: FSB questionnaire on SME financing. See FSB (2019). OECD (2019).

Research questions and data

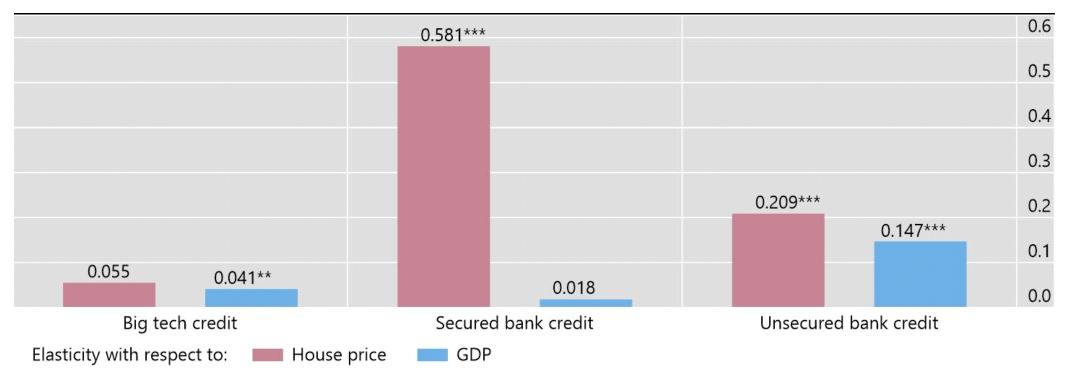
- How the use of big data changes the financial intermediation process
 - Is big tech credit less pro-cyclical than bank credit?
 - How could big techs entry in finance affect the monetary policy transmission mechanism?
- Data reduce the importance of collateral in solving asymmetric information problems in credit markets, especially for SMEs
- Random sample of more than 2 million Chinese firms that have received credit from Ant Group and traditional banks
- Compared three types of credit:
 - Big tech credit (short term)
 - Secured bank credit (mortgages)
 - Unsecured bank credit (credit lines)



Main results

Big tech credit reacts less to changes in house prices and local GDP

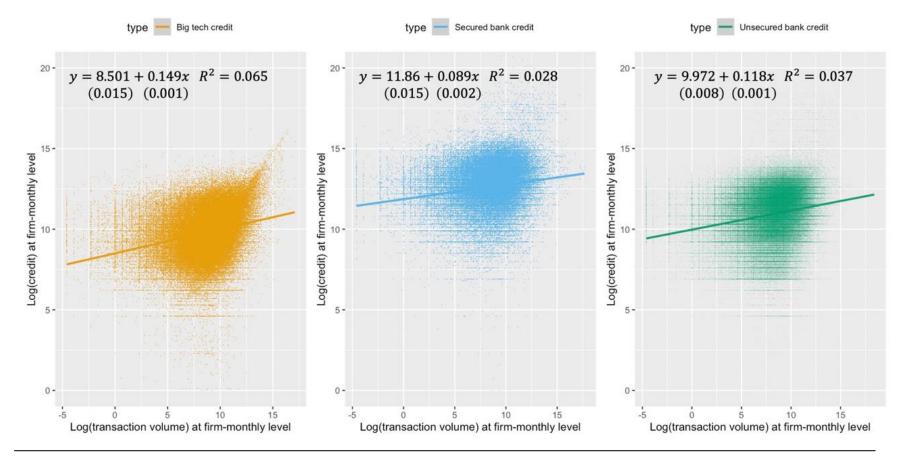
Elasticity of credit with respect to house prices and GDP



The figure reports the coefficient of three different regressions (one for each credit types) in which the log of credit is regressed with respect to the log of house prices at the city level, the log of GDP at the city level and a complete set of time dummies. Significance level: ** p < 0.05; *** p < 0.01.

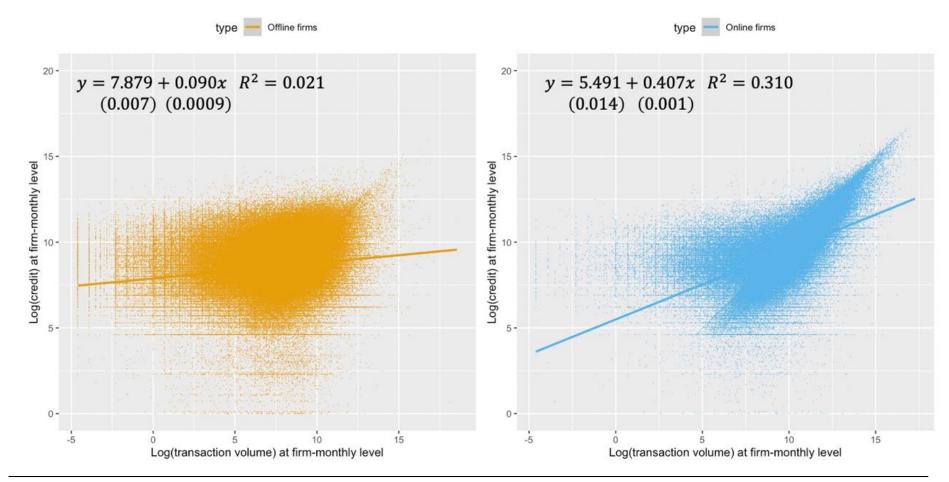
Source: Gambacorta, L, Y Huang, Z Li, H Qiu, and S Chen (2020): "Data vs collateral." BIS Working Paper, no 881, September.

Elasticity between credit and transaction volumes



Note: Based on a 100,000 random sample of firms served by both MYbank and traditional banking. The dots in the figure indicates the log of credit use (y-axis) and the log of transaction volume (x-axis) at the firm-month level. The left-hand panel plots big tech credit, the middle panel plots secured credit and the right hand panel plots unsecured bank credit. Linear trend lines are reported in the graphs, together with 95% degree confidence bands. Standard errors in brackets.

Elasticity between big tech credit and transaction volume: offline vs online firms



Note: Based on a 100,000 random sample of firms that received credit by MYbank. The dots in the figure indicates the log of credit use (y-axis) and the log of transaction volume (x-axis) at the firm-month level. The left-hand panel plots credit to offline firms and the right hand panel plots credit to online firms. Linear trend lines are reported in both graphs, together with 95% degree confidence bands. Standard errors in brackets.



Conclusions

Main takeaways

- Big tech credit react less to house prices and changes in local GDP conditions, but reacts strongly to firm characteristics.
- Big tech credit to online firms, fully integrated in the e-commerce platform, is more strongly correlated with transaction volumes and network scores than it is in the case of offline firms. Big tech credit to offline firms shows some sign of correlation with local demand conditions.
- An increased use of big tech credit could weaken the financial accelerator mechanism. Credit becomes less pro-cyclical.