

A discussion of

Data vs. Collateral

(by Gambacorta, Huang, Li, Qiu, and Chen)

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Background

- Traditional banks no longer monopolize on lending or provide credit.
- Tech companies increasingly provide credit to firms especially those who operate on their platforms.
- There is usually no collateral required for tech credit.
- Tech can screen borrowers as well as monitor/enforce payments in ways that are different from banks.
- The authors have amazing and unique data from MYBank (Ant Group) with matched data about bank credit, allowing them to analyze the sensitivity of different types of credit to personal characteristics and macro indicators.
- The research represents one of the most exciting new directions in finance research.

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Objectives of research

- Broadly, “Data can replace collateral.”
- More specifically,
 - Do big tech and bank credit react differently to collateral value, local economic conditions and firm-specific characteristics?
 - How could the increased use of big data and machine learning in solving asymmetric information problems, in lieu of collateral, impact the collateral channel?
 - Are there differences between credit granted to firms that operate in the ecommerce platform (online) and credit granted to firms that operate on traditional business channels (offline)?

Question 1

- *Do big tech and bank credit react differently to collateral value, local economic conditions and firm-specific characteristics?*

This is the most thoroughly answered question.

Explanatory variables	Dependent variable: Log (MYbank credit) (I)	Dependent variable: Log (Secured bank credit) (II)	Dependent variable: Log (Unsecured bank credit) (III)
Log House Price	0.052 (0.047)	0.371** (0.151)	0.239* (0.138)
Log GDP	-0.028 (0.034)	0.053 (0.101)	0.229* (0.121)
Log Transaction Volume	0.064*** (0.001)	0.036*** (0.002)	0.064*** (0.001)
Log Network Score	0.465*** (0.004)	0.096*** (0.011)	0.128*** (0.008)
Age of the borrower	0.026*** (0.0003)	0.009*** (0.001)	0.037*** (0.001)
Middle income	0.569*** (0.003)	0.129*** (0.012)	0.075*** (0.007)
High income	1.281*** (0.005)	0.325*** (0.014)	0.312*** (0.008)
Time and City FE	Yes	Yes	Yes
Number of observations	6,299,630	91,767	365,344
Adjusted R-squared	0.242	0.098	0.115

Notes: Standard errors in brackets are clustered at the city-month level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Comments

- From data description, the regression samples seem to be conditional on credit granted, hence is about relationship on the intensive margin, and is where supply meets demand.
- The credit supply decision on the extensive margin—whether to extend credit at all—is arguably more important and informative than that on the intensive margin—how much credit to grant conditional on approval.
- Suggestions:
 - More discussions about the application-approval process. It could be that approval is near 100% with qualifications then it is an important difference from banks.
 - The relation tracks credit supply more closely on subsamples with tighter credit rationing—is there a way to sort it out?

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Question 2

- *How could the increased use of big data and machine learning in solving asymmetric information problems, in lieu of collateral, impact the collateral channel?*
- All results demonstrate how the amount of credit varies with underlying borrower/economic conditions differentially among tech, bank/unsecured, and bank/secured.
- But results do not directly speak to whether and how tech credit “impacts the collateral channel.”
- Has the growth of tech credit reduced the demand for bank secured credit for firms that could otherwise be eligible for bank secured credit?
- Has tech provided credit access to firms that were rejected by banks for lack of collateral?
- Has tech reduced the collateral value premium in certain assets?

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Comments

- Would be helpful to have discussions on a *priori* predictions with respect to the regression models.
- If data is “in lieu of collateral,” should tech credit behave more like bank secured debt than unsecured debt? E.g., tech credit should be less stringent on age/income/local economy than unsecured bank debt, but be more similar to secured debt?
- Results have shown tech vs. bank; could have more discussion on unsecured vs. secured.

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Question 3

- Are there differences between credit granted to firms that operate in the ecommerce platform (online) and credit granted to firms that operate on traditional business channels (offline)?

On the intensive margin, it seems that differences manifest themselves in credit demand rather than supply?

Explanatory variables	Dependent variable: Log (MYbank credit used)			Dependent variable: Log (MYbank credit line granted)		
	All (I)	Offline (II)	Online (III)	All (IV)	Offline (V)	Online (VI)
Log House Price	0.002 (0.038)	0.046 (0.047)	0.019 (0.042)	-0.041 (0.065)	-0.089 (0.066)	0.154 (0.096)
Log GDP	0.046** (0.019)	0.064*** (0.022)	-0.003 (0.027)	0.0004 (0.017)	-0.009 (0.017)	0.018 (0.030)
Log Transaction Volume	0.046*** (0.001)	0.021*** (0.0004)	0.160*** (0.002)	0.0005** (0.0002)	0.0003* (0.0002)	0.001** (0.001)
Log Network Score	0.567*** (0.012)	0.092*** (0.009)	0.818*** (0.010)	0.205*** (0.010)	0.193*** (0.010)	0.179*** (0.024)
Time FE (month)	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	7,096,381	4,885,482	2,210,899	1,354,461	1,254,503	163,025
Adjusted R-squared	0.635	0.642	0.619	0.918	0.917	0.930

Notes: Standard errors reported in brackets are clustered at the city-month level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

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The big question: Can data replace collateral?

- We learn more about the determinants of credit grant, separately for tech and bank; and separately for online and offline. They are mostly about data-driven credit scoring vs. traditional methods.
- The paper has the potential to go further on the substitutability between data and collateral in order to answer the headline question.
- The different sensitivity with respect to credit quality signals could be due to differential decision rule, but also to differential observability:
 - Income/credit score is observable for both secured and unsecured lenders. But secured lenders put less weight on them – decision rule.
 - Perhaps both tech and bank would like to use real-time, network information to the same extent, but the latter do not observe such information as timely or with the same detail. Hence, they need to weigh on coarser signals about individual credit quality, such as local economic condition – information sufficiency rule.
- How to test the channels for data to mitigate information asymmetry vs. moral hazard? This was discussed in the introduction, and would be nice to be reflected in and connected to the empirical tests.

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More connection to the literature

- “Digital Footprints as Collateral for Debt Collection,” by Dai, Han, Shi, and Zhang, is a closely related paper.
 - Fintech lender weighs more on “digital footprints,” which facilitates debt collection in the absence of collateral.
 - Importantly, in this analysis, digital footprints takes the position of collateral in analyzing delinquency and recovery.
- Theoretically, relate to “Open Banking: Credit Market Competition When Borrowers Own the Data” by He, Huang, and Zhou.
 - Borrower data could be shared between banks and Fintech lenders endogenously.
- Digital information could complement rather than substitutes for credit bureau information (Berg et al. (2020)).
- Integrate screening with ex post performance (“Fintech Borrowers: Lax Screening or Cream-Skimming?” by Di Maggio and Yao).
- Choice of venue by borrowers (Tang (2019))

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Summary

- How big data expand credit access, refine credit scoring, and shape credit quality is a BIG question.
- The evolving nature of information asymmetry.
- The paper offers many interesting results on credit scoring; and have the potential to address credit access and performance, and how data substitute collateral in both screening and enforcement.