Big Techs and the Credit Channel of Monetary Policy

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BSE Summer Forum – Workshop on Monetary Policy and Central Banking – 9 June 2022

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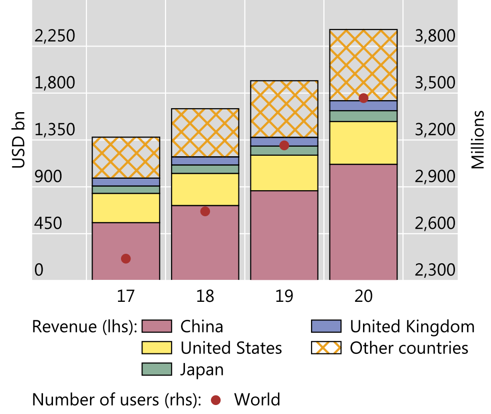
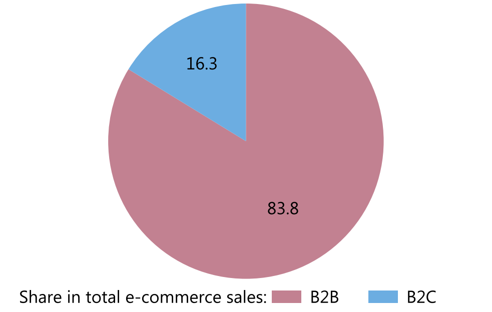
Global e-commerce sales are rising, and most of them are B2B transactions

Online orders in retail industry in selected countries

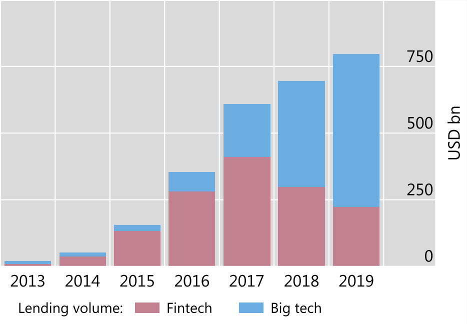


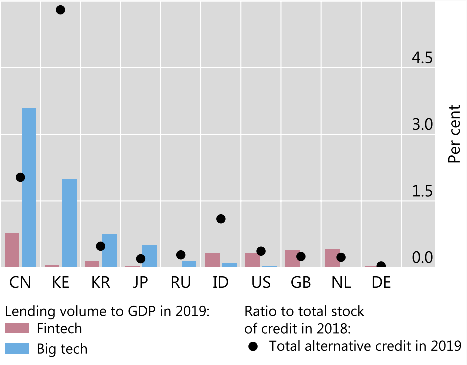
Share of B2B and B2C in global e-commerce sales



Source: V. Alfonso, C. Boar, J. Frost, L. Gambacorta and J. Liu (2021): E-commerce in the pandemic and beyond, BIS Bulletins, no 36, January (left panel); UNCTAD with shares corresponding to averages calculated over the period 2017-19 (right panel)

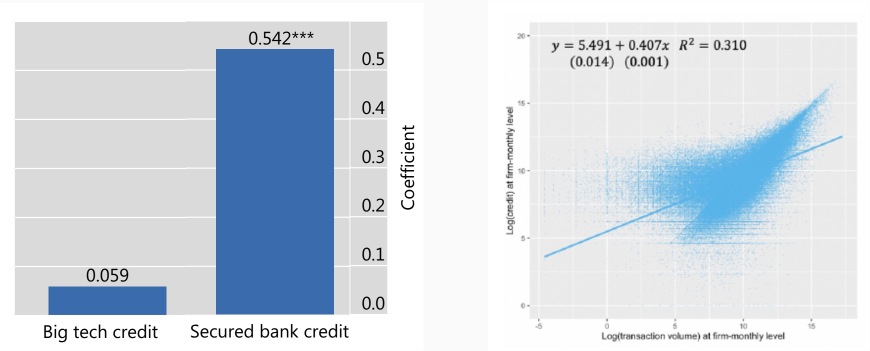
Big Techs started to give credit to vendors on their e-commerce platforms





Notes: Figures include data for China (CN), Kenya (KE), Korea (KR), Japan (JP), Russia (RU), Indonesia (ID), United States (US), United Kingdom (UK), Netherlands (NL), Australia (AU). 2019 fintech lending volume figures are estimated for AU, CN, EU, GB, NZ and US. Sources: Cornelli et al. (2020)

Big tech credit uncorrelated with property prices, but correlated with transaction volumes on the commerce platform



Credit elasticity with respect to house prices (left) and transaction volume on big tech platform (right)

Notes: Significance level: $^{***}p < 0.01$. Quarterly panel data for over 2 million Chinese SMEs from 2017 to 2019 with access to both bank credit and big tech credit from the financial arm of Alibaba Group (AntGroup). Source: Gambacorta et al. (2022)

Big Tech credit enforcement technologies

$\Rightarrow$ Unlike banks, Big Techs do not rely on physical collateral to enforce credit repayment

- Instead, because of high switching costs between Big Tech platforms, they may enforce it by the simple threat of exclusion from their ecosystem

Research questions

1. What is the macroeconomic impact of BigTechs' entry into finance?
2. How does big tech credit affect the transmission of monetary policy (MP)?

... through the lens of a NK model with big tech credit and B2B transactions

◂ Related literature ◂ IRFs to a MP shock

Main findings

1. **Big tech credit and the macroeconomy**
   - big tech credit relaxes credit constraints and approaches output to its efficient level
   - $\uparrow$ matching efficiency $\Rightarrow$ $\uparrow$ expected profits on the platform $\Rightarrow$ $\uparrow$ opportunity cost of default on big tech credit $\Rightarrow$ $\uparrow$ borrowing limit $\Rightarrow$ $\uparrow$ effect on credit constraints/output
2. **Big tech credit and MP transmission**
   - MP affects the borrowing limit on big tech credit via expected profits in the network, instead of via physical collateral as in the case of secured bank credit
   - if expected profits react less than property prices to MP, a larger share of big tech credit will mute out the reaction of credit and output to variations in the policy rate

Roadmap

1. NK model with big tech credit
2. Macroeconomic impact of Big Techs' expansion
3. Big tech credit and monetary policy transmission
4. Main takeaways

NK model with big tech credit

Basic New Keynesian model

- Supply chain: manufacturers (M) – wholesalers (W) – retailers $\Rightarrow$ matching M with W
- Working capital paid in advance and limited commitment for M $\Rightarrow$ M face credit constraints
- A Big Tech firm (i) facilitates matching of M with W, (ii) extends working capital loans
- Capital in fixed aggregate supply $\Rightarrow$ bank credit secured against real estate

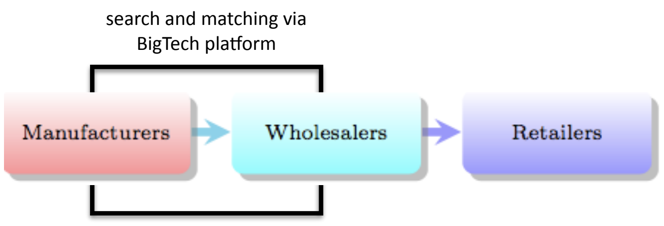


Figure 1: Three layer supply chain in the model

Agents

1. Household (representative): works, consumes, saves in public bonds and equity
2. Central bank: sets the nominal interest rate in the economy with a simple Taylor rule
3. Retailers: monopolistic, differentiate wholesale goods, set prices subject to nominal rigidities
4. Government: issues public bonds and collects (net) lump sum taxes
5. Bank (representative): extends (intratemporal) loans secured against physical capital

6. Manufacturers: competitive, use labor and capital to produce, sell output to wholesalers
7. Wholesalers: competitive, use manufactured goods as input, sell output to retailers
8. BigTech: facilitates matching between manufacturers and wholesalers, gives credit to former

◂ Household ◂ Central bank ◂ Retailers ◂ Government

Big Tech firm

- **Dual role:** (i) match manufacturers without a match $1 - \mathcal{A}_t$ with wholesalers' postings $\mathcal{S}_t$

$$M(\mathcal{S}_t, 1 - \mathcal{A}_t) = \sigma_m \mathcal{S}_t^{\eta} (1 - \mathcal{A}_t)^{1-\eta}, \quad \sigma_m : \text{matching efficiency}$$

(ii) give loans and enforces repayment with the threat of exclusion from commerce platform

- Builds net worth N_t^b with fees from sellers/buyers on the platform, which it invests in bonds

$$N_t^b = N_{t-1}^b \left(1 + i_{t-1}\right) + \chi_m P_t \left(1 - \mathcal{A}_t\right) + \chi_w P_t S_t$$

- ... and uses to finance incentive-compatible credit $\int_0^1 \mathcal{L}_t^b(j) dj$ on the commerce platform

$$\frac{N_t^b}{P_t} \gg \int_0^1 \mathcal{L}_t^b(j) dj$$

Manufacturers – sellers on the Big Tech commerce platform

- $\mathcal{A}_t$ **active:** matched with wholesalers, produce with a Cobb-Douglas technology

$$y_t^m = \xi_t (k_t^m)^\gamma (l_t^m)^{1-\alpha},$$

pay wage bill in advance of sales with bank and big tech credit, issue equity to buy capital;

- Price p_t^m and output y_t^m are decided by collective Nash-bargaining between active M and W
- $1 - \mathcal{A}_t$ **inactive:** no match, no production, add on the Big Tech platform at unit fee χ_m
- Active manufacturers at time $t+1$ (determined at t) equal

$$\mathcal{A}_{t+1} = (1-\delta)\mathcal{A}_t + M(\mathcal{S}_t, \mathcal{I}_t)$$

◂ Timeline operations ◂ Transition probabilities

Active manufacturers – credit constraints

- Opportunity cost of default on bank credit: value of physical collateral

$$\mathcal{L}_t^s \le \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\}$$

- Opportunity cost of default on big tech credit: expected profits on the commerce platform

$$\mathcal{L}_t^b \le b \mathcal{V}_{t+1}, \quad \mathcal{V}_{t+1} \equiv E_t \left\{ \Lambda_{t,t+1} \left[(1-\delta) \mathcal{V}_{t+1}^A + \delta \mathcal{V}_{t+1}^I \right] \right\}$$

$\Rightarrow$ Total credit (equal to the wage bill) is limited by the value of physical and network collateral

$$\frac{W_t}{P_t} l_t^m (y_t^m, k_t^m) \le \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} + b \mathcal{V}_{t+1}$$

Active manufacturers – surplus from a match

- **Surplus for an active manufacturer** from being in a match is given by

$$S_t^m \equiv \mathcal{V}_t^A - \mathcal{V}_t^I$$

- Value of being "active" at time t:

$$\mathcal{V}_t^A \equiv \frac{p_t^m}{P_t}\xi_t (k_t^m)^\gamma (l_t^m)^{1-\alpha} - \frac{W_t}{P_t} l_t^m - \frac{Q_t^k}{P_t} k_t^m + E_t\left\{\Lambda_{t,t+1}\rho\left(\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\right)\right\} + \\ + E_t\left\{\Lambda_{t,t+1}\left[(1-\delta)\mathcal{V}_{t+1}^A + \delta \mathcal{V}_{t+1}^I\right]\right\}$$

- Value of being "inactive" at time t:

$$\mathcal{V}_t^I \equiv -\chi_m + E_t\left\{\Lambda_{t,t+1}\left[f(x_t)\mathcal{V}_{t+1}^A + (1-f(x_t))\mathcal{V}_{t+1}^I\right]\right\},$$

$f(x_t)$ endogenous probability for an inactive manufacturer at t to find a match, $x_t \equiv \frac{\mathcal{S}_t}{1-\mathcal{A}_t}$

Representative wholesaler – buyer on the Big Tech commerce platform

- Produces Y_t^w using all active manufactured goods with linear technology

$$Y_t^w = \int_0^{\mathcal{A}_t} y_t^m(j)dj$$

... and searches for $\mathcal{S}_t$ manufacturing suppliers, paying a unit fee χ_w for each search

- Looks for additional suppliers until

$$\mathcal{I}_t^s = 0$$

Representative wholesalers – surplus from a match

- **Surplus for each wholesaler** from a match

$$S_t^w \equiv \mathcal{I}_t^B - \mathcal{I}_t^s$$

- Value of an existing relation with a manufacturing supplier at time t

$$\mathcal{I}_t^B = \frac{P_t^w}{P_t} y_t^m - \frac{p_t^m}{P_t} y_t^m + (1-\delta) E_t \left\{ \Lambda_{t,t+1} \mathcal{I}_{t+1}^B \right\}$$

- Value of searching a manufactured goods supplier

$$\mathcal{I}_t^s \equiv -\chi_w + g(x_t) E_t \{ \Lambda_{t,t+1} \mathcal{I}_{t+1}^B \},$$

where $g(x_t)$ is the endogenous probability for wholesalers to find a match

Collective bargaining (period-by-period)

- Active M and W collectively set p_t^m and y_t^m via period-by-period Nash bargaining:

$$\{p_t^m, y_t^m, k_t^m\} = argmax\left[S_t^m(p_t^m, y_t^m, k_t^m)\right]^{\epsilon}\left[S_t^w(p_t^m, y_t^m)\right]^{1-\epsilon}, \quad 0 < \epsilon < 1$$

subject to

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \leq b\mathcal{V}_{t+1} + \nu E_t\left\{\rho\Lambda_{t,t+1}\left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\right]\right\}$$

where ϵ is the (relative) bargaining power of active manufacturers.

◂ Optimality conditions

Macroeconomic impact of Big Techs' expansion

A higher matching efficiency leads to an expansion in big tech credit ...

- Higher matching efficiency (σ_m) leads to
  - $\longrightarrow$ higher profits on commerce platform $\mathcal{V}_{t+1}$
  - $\longrightarrow$ higher cost of default on big tech credit
  - $\longrightarrow$ higher borrowing limit on big tech credit
  - $\longrightarrow$ expansion in credit supply

$$\uparrow \text{Credit}_t = \underbrace{\uparrow b\mathcal{V}_{t+1}}_{\text{big tech credit}} \underbrace{+\nu E_t\left\{\rho\Lambda_{t,t+1}\left[\frac{Q^k_{t+1}}{P_{t+1}}k^m_t\right]\right\}}_{\text{bank credit}}$$

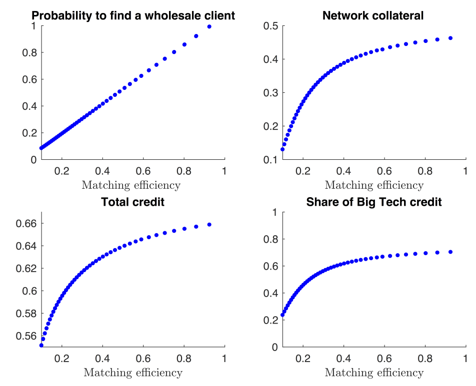


Figure 2: Steady-state allocation and matching efficiency

◂ Parametrization

… which relaxes credit constraints and approaches output to its efficient level

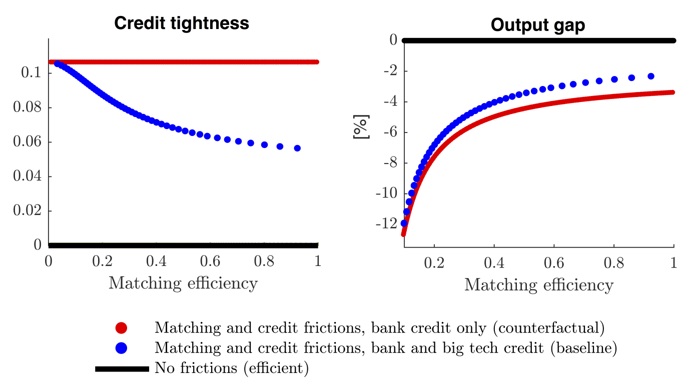


Figure 3: Steady-state allocation and matching efficiency

Big tech credit and monetary policy transmission

Effect of big tech credit: low and high matching efficiency

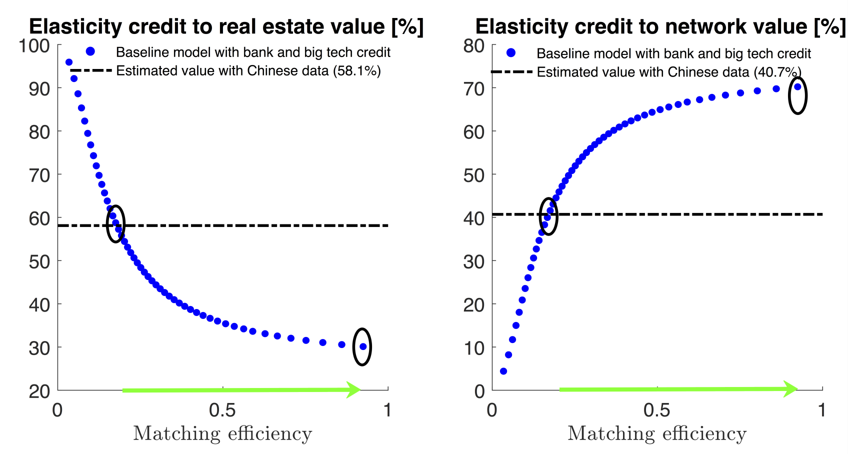


Figure 4: Parametrization for low and high matching efficiency in our experiments

Notes: Elasticities of bank credit and big tech credit for the baseline matching efficiency are the ones in Gambacorta et al.(2022)

With big tech credit, total credit and output respond less to MP...

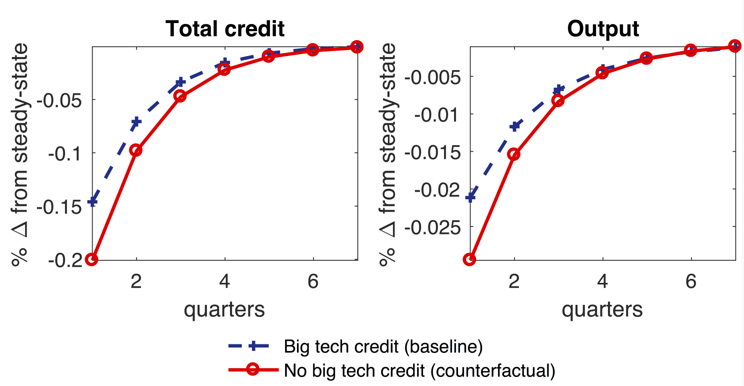


Figure 5: Dynamic responses to a monetary policy shock (25 basis points)

Notes: Calibration with matching efficiency $\sigma_m \approx 0.178$ which gives an elasticity of big tech credit to network sales, and of bank credit to property prices similar to the ones estimated based on Chinese data by Gambacorta et al. (2022).

… because this additional source of credit reacts less than bank credit

- $\text{Credit}_t = \underbrace{b\mathcal{V}_{t+1}}_{\text{big tech credit}} + \underbrace{\nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q^k_{t+1}}{P_{t+1}} k^m_t \right] \right\}}_{\text{bank credit}}$

S

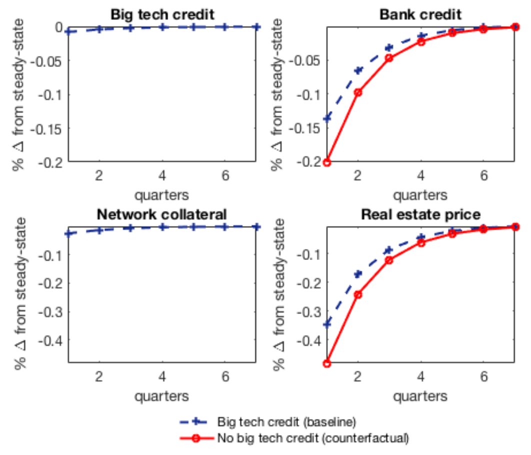


Figure 6: Dynamic responses to the MP shock

Polar cases

Estimated irfs

… because this additional source of credit reacts less than bank credit

- $\text{Credit}_t = \underbrace{b\mathcal{V}_{t+1}}_{\text{big tech credit}} + \underbrace{\nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q^k_{t+1}}{P_{t+1}} k^m_t \right] \right\}}_{\text{bank credit}}$
- With bank credit only ($b = 0$):
  - all credit linked to real estate prices …
  - … which are very responsive to MP

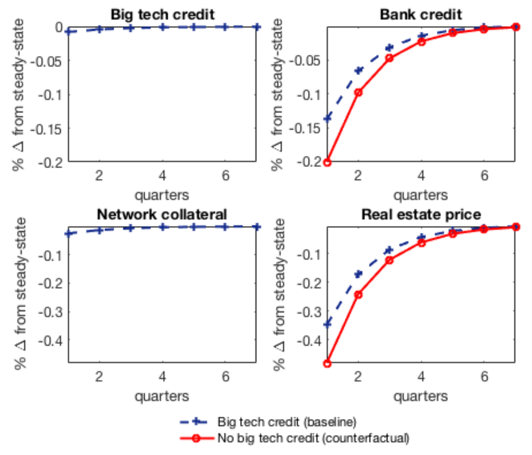


Figure 6: Dynamic responses to the MP shock

S

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- $$\text{Credit}_t = \underbrace{b\mathcal{V}_{t+1}}_{\text{big tech credit}} \underbrace{+\nu E_t\left\{\rho\Lambda_{t,t+1}\left[\frac{Q^k_{t+1}}{P_{t+1}}k^m_t\right]\right\}}_{\text{bank credit}}$$
- With bank credit only ($b = 0$):
  - all credit linked to real estate prices …
  - … which are very responsive to MP
- When we add big tech credit ($b \neq 0$):
  - a credit share is linked to expected profits
  - … which respond less to MP

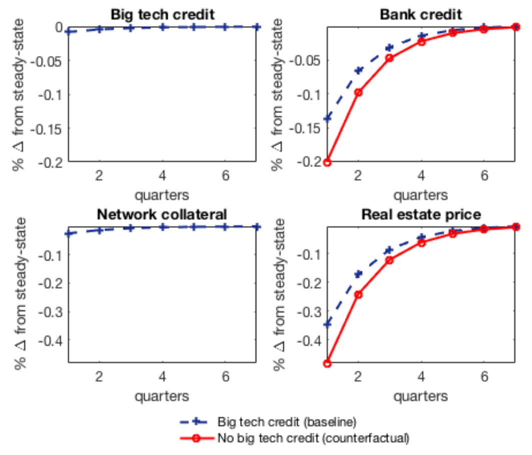

Figure 6: Dynamic responses to the MP shock

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◂ Estimated irfs

◂ Polar cases

… because this additional source of credit reacts less than bank credit

- $$\text{Credit}_t = \underbrace{b\mathcal{V}_{t+1}}_{\text{big tech credit}} \underbrace{+\nu E_t\left\{\rho\Lambda_{t,t+1}\left[\frac{Q^k_{t+1}}{P_{t+1}}k^m_t\right]\right\}}_{\text{bank credit}}$$
- With bank credit only ($b = 0$):
  - all credit linked to real estate prices …
  - … which are very responsive to MP
- When we add big tech credit ($b \neq 0$):
  - a credit share is linked to expected profits
  - … which respond less to MP

$\Rightarrow$ Total borrowing limit reacts less

$\Rightarrow$ Total credit reacts less

$\Rightarrow$ Output reacts less

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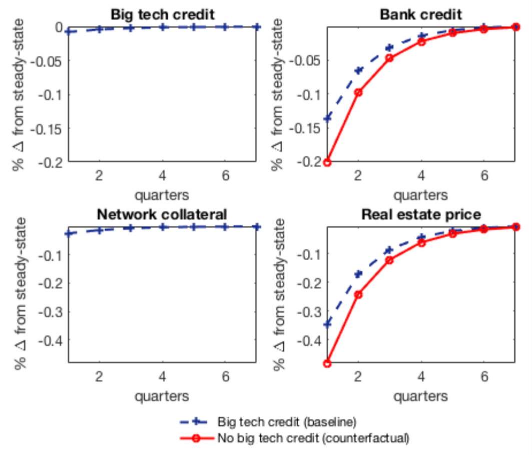

Figure 6: Dynamic responses to the MP shock

Estimated irfs

Polar cases

As matching efficiency rises, output responds less to MP

- A higher matching efficiency leads to a higher share of big tech credit

$$\text{Credit}_t = \underbrace{\overbrace{b\mathcal{V}_{t+1}}^{\uparrow\text{share}}}_{\text{weak response to MP}} + \underbrace{\nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q^k_{t+1}}{P_{t+1}} k^m_t \right] \right\}}_{\text{strong response to MP}}$$

$\Rightarrow$ Total credit responds less

$\Rightarrow$ Output responds less

◂ Complete set IRFs ◂ IRFs bank credit only

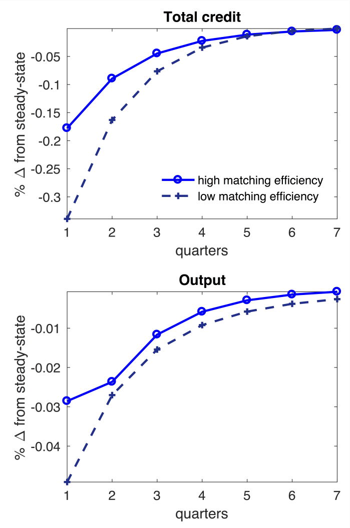

Figure 7: Dynamic responses to the MP shock

Main takeaways

Main takeaways

Through the lens of the model,

1. MP affects the borrowing limit on big tech via firms' expected profits, while they affect the limit on secured bank credit via physical collateral values

2. a higher matching efficiency on Big Tech's commerce platform:

- raises firms' opportunity cost of default on big tech credit, expands borrowing limits via big tech credit, and approaches output to its efficient level

- the higher share of big tech credit makes credit and output less responsive to MP

Backup slides

Related literature

1. **Credit channel of MP**: Bernanke and Gertler (1994), De Fiore and Tristani (2013), Drechsel (2022), Iacoviello (2006), Manea (2020), Ottonello and Winberry (2020)

2. **Financial inclusion due to big tech credit:** Bazarbash (2019), Haddad and Hornuf (2019), Cornelli et al. (2020), Frost et al. (2019)

3. **Tangible vs. intangible collateral**: Chatelain and Ralf (2010), Nikolov (2012)

4. **Collateral vs. earnings–based credit constraints**: Lian and Ma (2021), Drechsel (2022)

◂ Back to main

Panel SVAR analysis

- Data: annual macro data for 19 countries over the period 2005 to 2020[1]
- Six variables: property price index (pk), real GDP(Y), consumer price index (p), bank lending (L), big tech credit and fintech credit, hereafter called total alternative credit (B), short term interest rate/shadow rate (i).[2]
- Econometric specification:

$$z_{i,t} = \mu + \sum_{k=1}^{p} \phi_k z_{i,t-k} + \epsilon_{i,t}$$

for $t = 1, \ldots T$ where $z = [pk, Y, p, L, B, i]$ and $\epsilon_{i,t}$ is a vector of residuals.

[1] The 19 countries are: Austria, Brasil, Canada, Switzerland, Chile, China, Euro Area, Great Britain, Indonesia, Israel, India, Japan, South Korea, Mexico, Russia, Thailand, Turkey, US, South Africa.
[2] Apart from the short term interest rate, all variables are in logarithm.

Estimated impulse responses to a monetary policy shock

- The response of alternative credit (big tech and fintech credit) is statistically insignificant
- The response of bank credit mirrors the strong response of property prices

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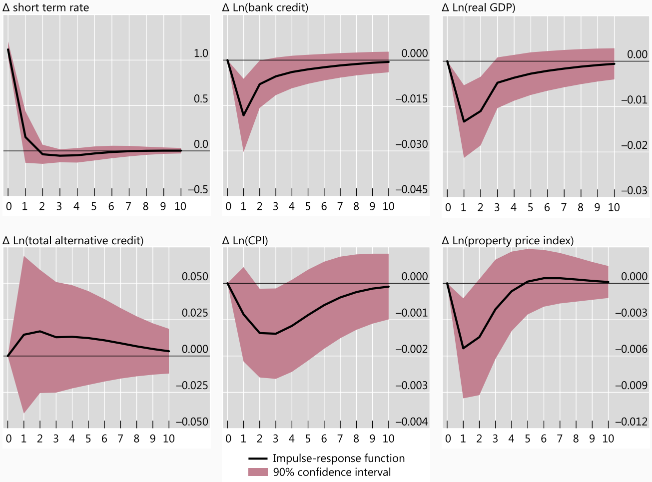

Representative household

$$\max E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \chi \frac{L_t^{1+\varphi}}{1+\varphi} \right) \right\} \text{ subject to}$$

$$P_t C_t + B_t^h + \mathcal{E}_t Q_t^e \leq W_t L_t + B_{t-1}^h (1 + i_{t-1}) + \mathcal{E}_t D_t^e + \mathcal{E}_{t-1} Q_t^e + \Upsilon_t^g + \Upsilon_t^p, \ \ \forall t$$

$$\lim_{T\to\infty} E_0 \left\{ \Lambda_{0,T} \frac{B_T^h}{P_T} \right\} \geq 0, \qquad \lim_{T\to\infty} E_0 \left\{ \Lambda_{0,T} \frac{\mathcal{E}_T Q_T^e}{P_T} \right\} \geq 0$$

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Central bank

Sets the nominal interest rate i_t in line with a simple Taylor rule:

$$1 + i_t = \frac{1}{\beta} \Pi_t^{\phi_\pi} \left(\frac{Y_t}{Y} \right)^{\phi_y} e^{\nu_t}$$

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Government

- Issues nominal bonds and sells them to households B_t^h and the Big Tech firm B_t^b
- Subsidizes purchase of wholesale goods at rate τ[3]
- Collects lump-sum taxes Υ_t^g to balance its period budget constraint:

$$B_t^h + B_t^b = \left(B_{t-1}^h + B_{t-1}^b\right)\left(1 + i_{t-1}\right) + \Upsilon_t^g + \tau P_t^m \int_0^1 Y_t^m(i)di$$

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[3] The subsidy corrects for monopolistic power distortions in the retail sector

Retailers

- Use a linear production function to differentiate wholesale goods

$$Y_t(i) = Y_t^w(i)$$

- Set prices in the presence of Calvo type adjustment costs subject to their demand constraint

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\varepsilon} Y_t$$

- Their price setting decision is standard

$$\sum_{k=0}^{\infty} \theta^k E_t\{\Lambda_{t,t+k} Y_{t+k/t}(1/P_{t+k})(P_t^* - \mathcal{M}(1-\tau)P_{t+k}^w\} = 0$$

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Bargaining – optimality conditions

- With respect to the price of a manufactured goods p_t^m:

$$\epsilon S_t^m = (1-\epsilon) S_t^w$$

- With respect to the quantity produced by an active manufacturing firm y_t^m:

$$\frac{P_t^w}{P_t} = \frac{1}{1-\alpha} \frac{W_t}{P_t} \frac{l_t^m}{y_t^m} \left[1 + \frac{\lambda_t}{1-\epsilon}\right], \quad \lambda_t \geq 0$$

- With respect to the capital chosen by an active manufacturing firm k_t^m:

$$\frac{Q_t^k}{P_t} = \gamma \frac{P_t^w}{P_t} \frac{y_t^m}{k_t^m} + \left(1 + \frac{\nu \lambda_t}{\epsilon}\right) E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}}\right] \right\}$$

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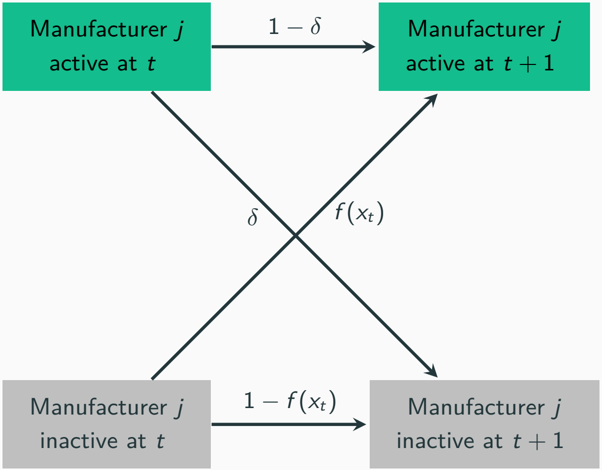
Manufacturers – transition probabilities between active and inactive states



Notes: δ is the exogenous probability that a manufacturer active at time t becomes inactive at time $t+1$, while $f(x_t)$ is the endogenous probability that a manufacturer inactive at t becomes active at $t+1$.

Timeline operations – manufacturers and wholesalers

Period $t-1$	Each manufacturer $j \in [0,1]$ finds out if it is active or inactive at t
Period t	**Manufacturers:** Manufacturer $j \in [0,1]$: If active, produces and sells its output to wholesalers; to do so: (i) at the beginning of the period, issues equity $\mathcal{E}_t$ to buy capital k_t^m, gets working capital loan $\mathcal{L}_t$ to hire labor l_t^m, and produces y_t^m; (ii) at the end of the period, repays the working capital loan and transfers the return on capital as dividend to equity investors and any remaining profits to the household. If inactive, pays a fee χ_m to post an ad on the Big Tech platform, and transfers net period profit to the household **Wholesalers:** The representative wholesaler: (i) buys inputs from all A_t active manufacturing suppliers (ii) searches for S_t manufacturing suppliers for use at $t+1$, paying a unit fee equal to χ_w for each of these searches **Matching:** Active manufacturers and wholesalers bargain over the price p_t^m and the quantity y_t^m of manufactured goods
Period $t+1$	If active at t, manufacturer j sells capital k_t^m and pays the household back the value of its equity investment $Q_t^e \mathcal{E}_{t-1}$.

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Parametrisation

Parameter	Description	Value
β	Discount factor	0.995
σ	Curvature of consumption utility	1
φ	Curvature of labor disutility	5
χ	Labor disutility	0.75
$1-\alpha$	Labor share	0.75
ε	Elasticity of substitution of goods	9
θ	Calvo index of price rigidities	0.75
ϕ_π	Taylor coefficient inflation	1.5
ϕ_y	Taylor coefficient output	0.5/4
$\bar{K}$	Fixed supply of capital (real estate)	1
γ	Elasticity of output to real estate	0.03
1-ρ	Capital refurbishing cost (% from capital value)	15%
ν	Pledgeability ratio of capital as collateral	0.7
ϵ	Relative bargaining power of the seller	0.5
η	Matching function parameter	0.5
δ	Probability to separate from an existing match	5%
χ_w	Big tech fees for manufacturers	0.1
χ_m	Big tech fees for wholesalers	0.3
b	Pledgeability ratio of network value	0.1
σ_m	Matching efficiency	[0, 1]

Note: Values are shown in quarterly rates.

Feedback loop

- Higher network value $\mathcal{V}$ loosens credit constraints and leads to higher output
- Higher output leads to a further rise in $\mathcal{V}$

$\Rightarrow$ Macroeconomic effect amplified via a feedback loop

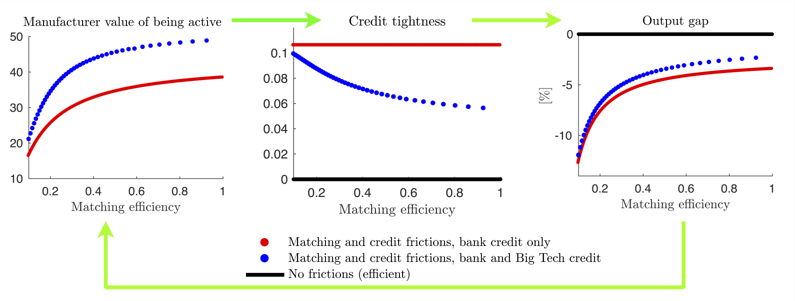
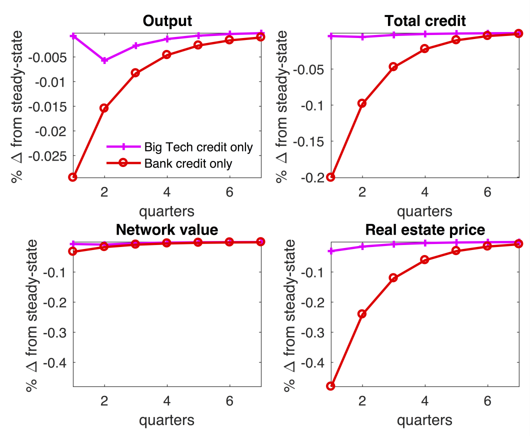


Figure 8: Steady-state allocation and matching efficiency

Dynamic responses to a monetary policy shock – polar cases



Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. The two polar cases are compared at given credit–to–output ratio (which is equivalent in the model to a given tightness of the credit constraint). In the specification with bank credit only, one needs a response coefficient to inflation higher than 3 (when the response to output is set as in the Taylor rule) to ensure equilibrium uniqueness. Thus, for comparison reasons, the monetary policy rule assumed in this experiment has a response coefficient to inflation equal to 3 instead of the one in the simple Taylor rule (1993) equal to 1.5.

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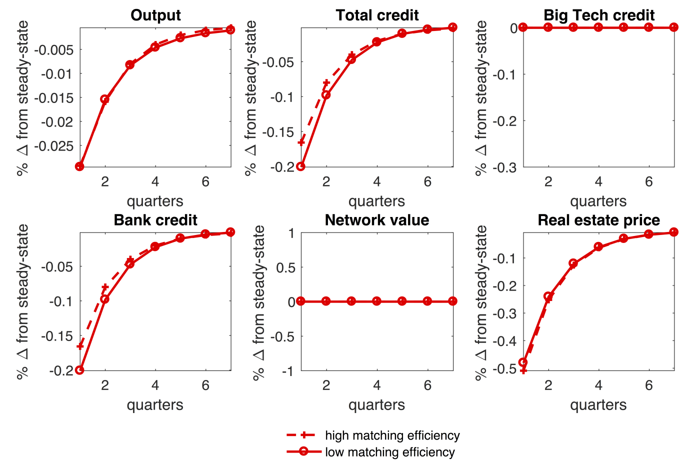
Dynamic responses to a monetary policy shock - bank credit only



Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. The low level of matching efficiency corresponds to $\sigma_m \approx 0.178$ which gives an elasticity of big tech credit to network sales similar to current one estimated based on Chinese data by Gambacorta et al. (2020). The high level of efficiency corresponds to $\sigma_m \approx 0.93$ and characterizes the highest matching efficiency when both type of credit are available. In the specification with bank credit only, one needs a response coefficient to inflation higher than 3 (when the response to output is set as in the Taylor rule) to ensure equilibrium uniqueness. Thus, for comparison reasons, the monetary policy rule assumed in this experiment has a response coefficient to inflation equal to 3 instead of the one in the simple Taylor rule (1993) equal to 1.5.

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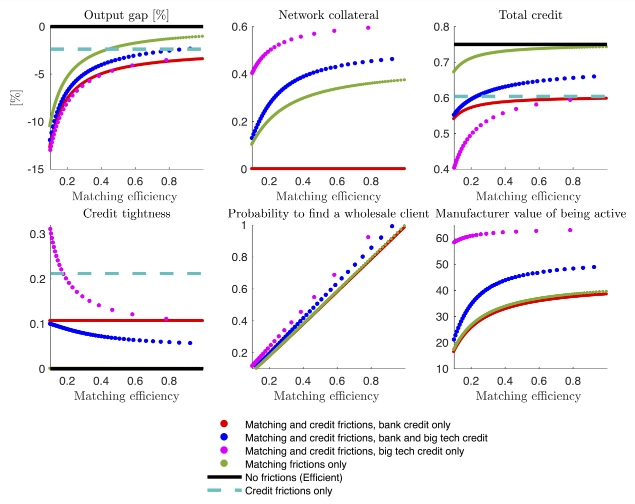
Steady-state and matching efficiency on the commerce platform



Notes: Output gap: the % deviation of output from its efficient level $(Y - Y^e)/Y$. Network collateral: expected profits that manufacturers would lose in case of default $b\mathcal{V}^a$. Total credit: big tech credit and bank credit. Manufacturer value of being active: $\mathcal{V}^a$. Probability to find a wholesale client: $f(x)$. Matching efficiency: σ_m

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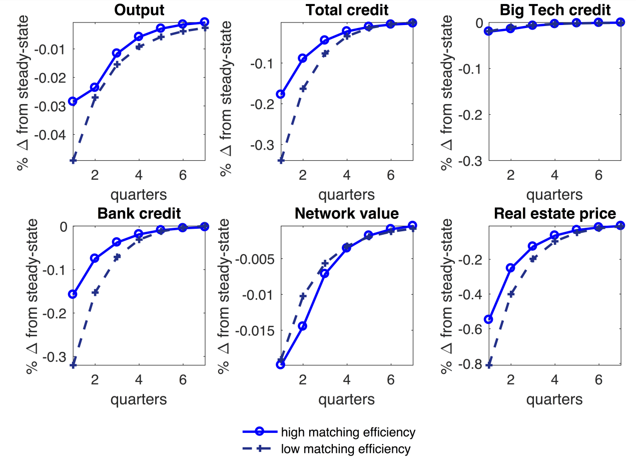
Dynamic responses to a monetary policy shock and matching efficiency



Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. The low level of matching efficiency corresponds to $\sigma_m \approx 0.178$ which gives an elasticity of big tech credit to network sales similar to current one estimated based on Chinese data by Gambacorta et al. (2020). The high level of efficiency corresponds to $\sigma_m \approx 0.93$ and characterizes the highest matching efficiency when both type of credit are available. The monetary policy regime is described by simple Taylor rule (1993).