Big Tech Credit and the Macroeconomy

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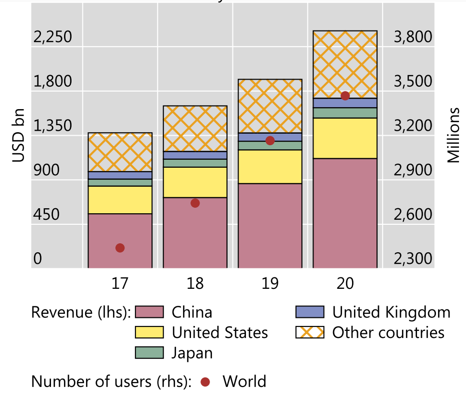
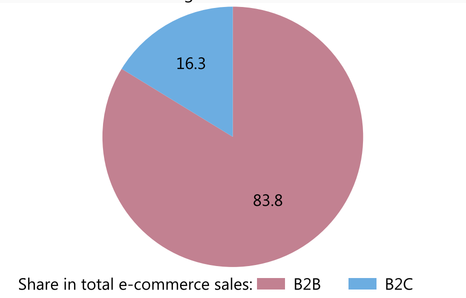
Global e-commerce sales are rising, and most of them are B2B transactions

Online orders in retail industry in selected countries

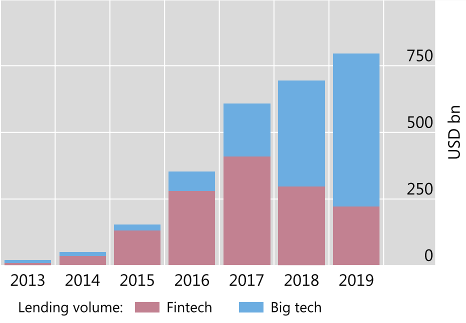


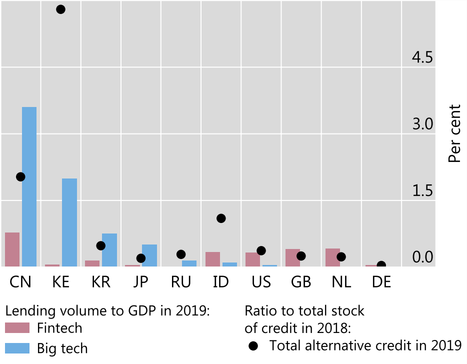
Share of B2B and B2C in global e-commerce sales



- Lion's share of e-commerce via big tech platforms

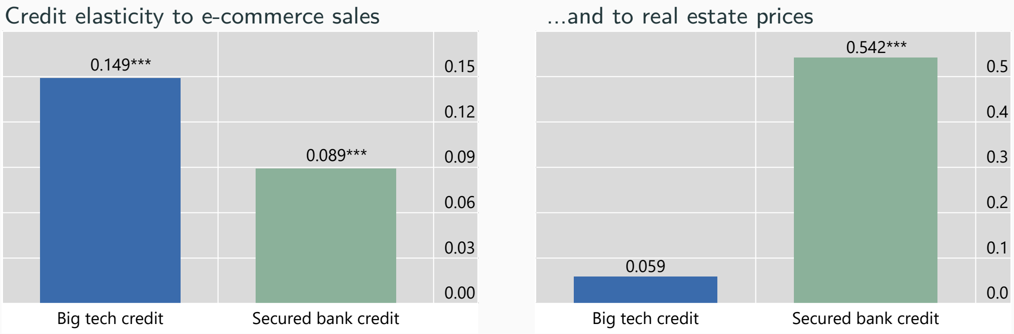
Big techs started to give credit to vendors on their e-commerce platforms





- Big tech credit has overtaken Fintech credit over time, doubling Fintech flows in 2019
- In China, big tech credit $\approx 3.5\%$ of total credit

Big tech credit: uncorrelated with property prices, correlated with sales



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)

- Granular data for 2 millions Chinese firms from 2017 to 2019
- Larger elasticity of big tech credit to e-commerce sales than to house prices
- The opposite is true for bank credit
- Similar patterns emerge based on macro data for both China and the US

Credit enforcement by big techs versus banks

- Big tech credit is not collateralised and of shorter maturity than bank credit, typically less than 1 yr
- Big techs screen firms' activity on the e-commerce platform using big data and machine learning
- Due to high switching costs, big techs may enforce repayment by simple threat of exclusion
- Banks don't have access to big techs' enforcement technology, and rely instead on physical collateral

Research questions

1. How does big techs' entry into finance affect the long run macroeconomic allocation?
2. How does big tech credit affect the transmission of business cycle shocks?

... through the lens of a New Keynesian (NK) model with big tech credit and B2B transactions

◂ IRFs to a MP shock

Main findings

1. **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
    - big techs' efficiency gains are limited by the distorsionary nature of their fees
2. **Big tech credit alters the nature of the financial accelerator and can mitigate the sensitivity of the macroeconomy to the business cycle (BC)**
    - BC shocks affect the borrowing limit on big tech credit via expected profits on the platform, instead of via physical collateral as in the case of secured bank credit
    - When matching efficiency is relatively low, expected profits on the platform are less sensitive to the BC $\Rightarrow$ big tech credit weakens the transmission of BC shocks

Roadmap

1. A NK model with big tech credit
2. Big tech credit and the long run macroeconomic allocation
3. Big tech credit and the response to business cycle shocks

A NK model with big tech credit

Basic New Keynesian model with sticky wages (e.g. Galí (2015))

- Two–layer supply chain **intermediate goods firms/retailers** instead of a single firm sector
- The two types of firms search and match on a big tech commerce platform
- Intermediate goods firms finance wages with both bank credit and big tech credit
  - If they don't repay big tech credit $\rightarrow$ exclusion from the platform
  - If they don't repay bank credit $\rightarrow$ loss of physical collateral

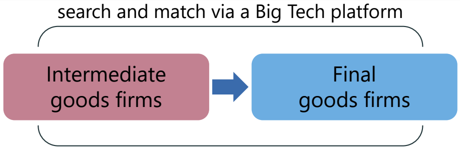


Figure 1: The two layer production chain and the big tech commerce platform

Agents

1. Households: work, consume, save in public bonds and equity, set sticky wages
2. Central bank: sets the nominal interest rate in the economy with a simple Taylor rule
3. Government: issues public bonds and collects lump sum taxes
4. Banks: extend loans secured against physical capital

5. Intermediate goods firms: produce with labor and capital, sell output to retailers
6. Retailers: use intermediate goods to produce final goods, sell output to households
7. Big tech: facilitates matching between firms and retailers, gives credit to the former

◂ Household ◂ Central bank ◂ Government

Big tech firm

- Dual role:

  (i) matches $1 - \mathcal{A}_t$ inactive intermediate firms with retailers posting $\mathcal{S}_t$ ads to buy goods

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

  (ii) gives loans and enforces repayment with the threat of exclusion from e-commerce platform

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

$$N_t^b = N_{t-1}^b \left(1 + i_{t-1}\right) + \chi_m P_t I_t + \tau^* P_t^m y_t^m A_t + \chi_r P_t S_t - \Upsilon_t^b$$

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

$$\frac{N_t^b}{P_t} = \int_0^1 \mathcal{L}_t^b(i)di$$

Intermediate goods firms – sellers on the big tech commerce platform

- $\mathcal{A}_t$ **active:** matched with retailers, issue equity to buy capital, Cobb-Douglas production

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

pay proportional fee τ^*, finance wages with bank and big tech credit; law of motion:

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

- $1 - \mathcal{A}_t$ **inactive:** no match, no production, add on the big tech platform at unit fee χ_m

- p_t^m and y_t^m are decided by Nash-bargaining between active intermediate firms and retailers

Timeline operations Transition probabilities

Active intermediate goods firm – surplus from a match

- **Surplus from a match for an active intermediate goods firm:**

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

- Value of being "active" at time t:

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

- 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 inactive intermediate firms to find a match at t, $x_t \equiv \frac{\mathcal{S}_t}{1-\mathcal{A}_t}$

Active intermediate goods firm – credit constraints

- **Bank credit**: opportunity cost of default is value of physical collateral

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

- **Big tech credit**: opportunity cost of default are expected profits on e-commerce platform

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

or, with finite κ exclusion periods:

$$\mathcal{L}_t^b \leq b \tilde{\mathcal{V}}_{t+1}, \quad \tilde{\mathcal{V}}_{t+1} = \mathcal{V}_{t+1} - E_t \left\{ \Lambda_{t,t+\kappa} \left[\mathcal{V}_{t+\kappa+1} \right] \right\} \tag{1}$$

$\Rightarrow$ Credit constraint:

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

Retailers – buyers on the big tech commerce platform

- A typical retailer produces Y_t using all active intermediate goods with linear technology

$$Y_t = \int_0^{\mathcal{A}_t} y_t^m(i)di$$

... and searches for $\mathcal{S}_t$ intermediate goods suppliers, paying a unit fee χ_r for each search

- Looks for additional suppliers until

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

Representative retailer – surplus from a match

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

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

- Value of an existing relation with an intermediate goods supplier at time t

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

- Value of searching for an intermediate goods supplier

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

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

Collective bargaining (period-by-period)

- Active intermediate firms and retailers set $\{p_t^m, y_t^m\}$ via period-by-period Nash bargaining:

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

subject to

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

where ϵ is the (relative) bargaining power of active intermediate goods firms.

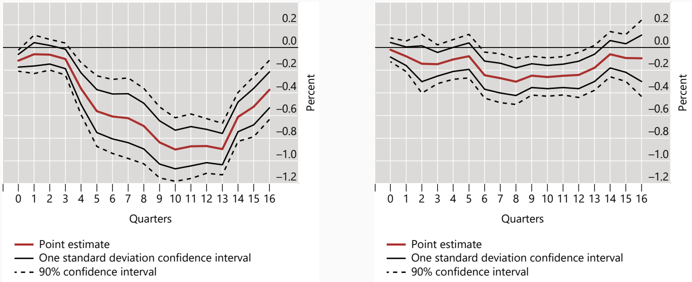
Optimality conditions

Parametrisation

- Standard parametrization Parametrization
- "Big tech parameters": $\chi_m = .05$, $\chi_r = .05$, $\tau^* = 8\%$ set to reflect average big tech fees
- ν set such that property prices respond significantly more than e-sales to a monetary policy shock in line with empirical estimates

Dynamic responses to a 25 bps monetary policy tightening:

(a) Commercial property prices (real) (b) E-commerce sales (real)



Big tech credit and the long run macroeconomic allocation

Macroeconomic impact of big tech credit expansion

- Higher matching efficiency (σ_m) leads to

  $\rightarrow$ higher expected profits on commerce platform $\tilde{\mathcal{V}}_{t+1}$

  $\rightarrow$ higher cost of default/limit on big tech credit

  $\rightarrow$ expansion in total credit supply

  $\rightarrow$ decline in credit constraints tightness

  $\rightarrow$ output closer to efficient level Steady-states

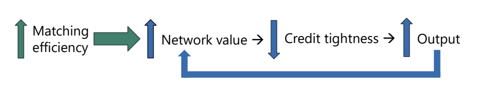
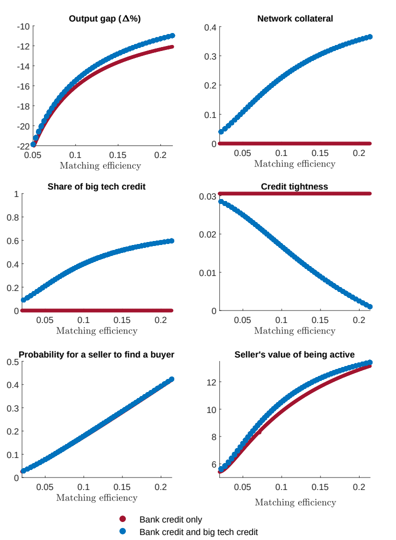


Figure 2: Feedback loop between network value, credit constraints and output

Steady state allocation as σ_m rises



Distortionary fees and limits to big techs' efficiency gains

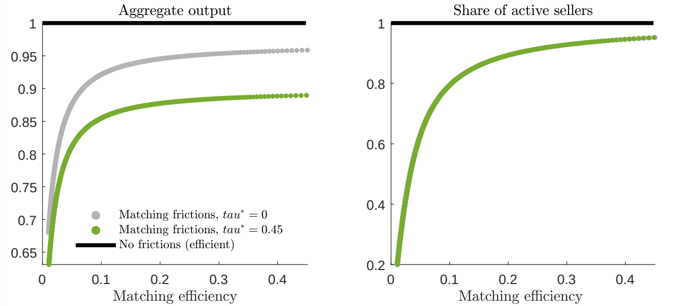


Figure 3: Distorsionary big tech fees and the steady-state allocation

Notes: Aggregate output: Y; Share of active sellers: $\mathcal{A}$. Matching efficiency: σ_m

Big tech credit and the response to business cycle shocks

Big tech credit alters the nature of the financial accelerator

- $\text{Credit}_t = \underbrace{b\tilde{\mathcal{V}}_{t+1}}_{\text{big tech credit}} + \underbrace{\nu E_t \left\{ \Lambda_{t,t+1} \left[\frac{Q^k_{t+1}}{P_{t+1}} k^m_t \right] \right\}}_{\text{bank credit}}$
- Business cycle shocks affect the borrowing limit on
  - big-tech credit via expected profits on the platform
  - bank credit via property prices

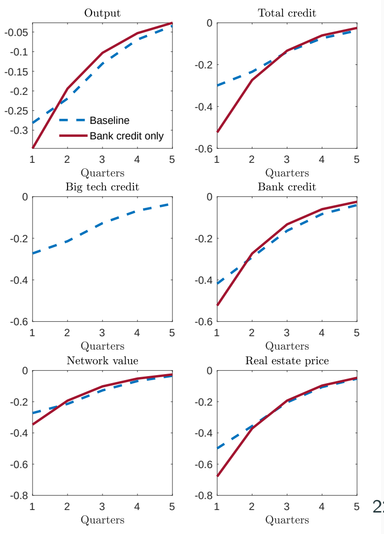
$\Rightarrow$ As big tech credit expands, the financial accelerator works more via expected profits on the e-commerce platform, and less via property prices

Low matching efficiency: big tech credit dampens real effect of BC shocks

- Matching frictions dampen the response of expected profits to business cycle shocks
  - Losses during "inactivity" (fixed fees, insensitive to shocks) count for a larger share of expected profits

- When matching efficiency is low, big tech credit
  - ⇒ reacts significantly less than bank credit
  - ⇒ dampens the reaction of total credit and output

Dynamic responses to a MP shock (25 bps)



As matching efficiency rises, big tech credit and output becomes more sensitive

	Baseline model with both types of credit				Bank credit only	
Matching efficiency/Variables	Big tech credit	Bank credit	Total credit	Output	Credit	Output
Low	-0.35	-0.42	-0.37	-0.26	-0.49	-0.31
Intermediate	-0.43	-0.46	-0.43	-0.29	-0.49	-0.30
High	-0.21	-0.21	-0.21	-0.21	-0.48	-0.30

Table 1: Matching efficiency and the effect of monetary policy shocks on credit and output

Notes: Effect on impact to a positive 25 basis points monetary policy surprise.

When matching efficiency high enough to push the economy into its credit frictionless limit, discrete drop in the sensitivity of big tech credit and output

	Baseline model with both types of credit				Bank credit only	
Matching efficiency/Variables	Big tech credit	Bank credit	Total credit	Output	Credit	Output
Low	-0.35	-0.42	-0.37	-0.26	-0.49	-0.31
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High	-0.21	-0.21	-0.21	-0.21	-0.48	-0.30

Table 2: Matching efficiency and the effect of monetary policy shocks on credit and output

Notes: Effect on impact to a positive 25 basis points monetary policy surprise.

Main takeaways

Takeaways

1. Macro shocks affect big tech credit via firms' profits and bank credit via physical collateral
   - The overall impact depends on the relative strength of the network collateral channel vs the physical collateral channel, which changes over time and across countries
2. A higher efficiency on big techs' e-commerce platforms:
   - raises firms' expected profits on the platform/opportunity cost of default on big tech credit, relaxes borrowing limits and approaches output to its efficient level
   - may push the economy into its credit frictionless limit and lead to a significant and discrete drop in the sensitivity of credit and real activity to the business cycle
3. Net efficiency gains on big techs' expansion are limited by the distortionary nature of fees

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)

Elasticity of credit to house prices and to e-commerce sales: macro data

	China	United States
Big tech credit to house price	0.56	0.18
Bank credit to house price	1.40***	1.02***
Big tech credit to e-commerce sales	5.39***	3.75***
Bank credit to e-commerce sales	0.39***	0.25***

Unconditional elasticities. Estimation period 2013-2020. *** Significance at the 1% level.
Sources: Cornelli et al (2020); Statista; BIS; authors' calculations.

- Elasticities based on macro data on e-commerce revenues for China confirm micro evidence
- Similar results emerge for the US

Typical household

$$E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma} - 1}{1-\sigma} - \chi \int_0^1 \frac{L_t(j)^{1+\varphi}}{1+\varphi} dj \right) \right\}$$

subject to the sequence of budget constraints

$$P_t C_t + B_t^h + \mathcal{E}_t Q_t^e \leq \int_0^1 W_t(j) L_t(j) dj + B_{t-1}^h (1 + i_{t-1}) + \mathcal{E}_t D_t^e + \mathcal{E}_{t-1} Q_t^e + \Upsilon_t^g + \Upsilon_t^p + \Upsilon_t^b$$

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

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Central bank

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

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

◂ Back to main

Government

- Issues nominal public bonds and sells them to households B_t^h and the big tech firm B_t^b
- Collects lump-sum taxes Υ_t^g to balance its period budget constraint:

$$B_t^h + B_t^b = \left(B_{t-1}^h + B_{t-1}^b\right)\left(1 + i_{t-1}\right) + \Upsilon_t^g$$

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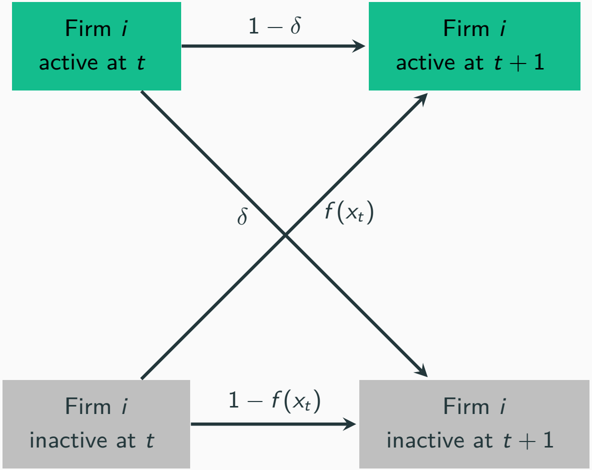
Intermediate firms: transition probabilities between active and inactive states



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

Bargaining – optimality conditions

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

$$\epsilon(1-\tau^*)S_t^m = (1-\epsilon)S_t^r$$

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

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

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

$$\frac{Q_t^k}{P_t} = \gamma\frac{y_t^m}{k_t^m}\left[\frac{1+\frac{\lambda_t}{\epsilon}\left(1-\tau^*\right)^{1-\epsilon}}{\frac{1}{1-\tau^*}+\frac{\lambda_t}{1-\epsilon}\left(\frac{1}{1-\tau^*}\right)^{\epsilon}}\right] + \left[1+\frac{\nu\lambda_t}{\epsilon}\left(1-\tau^*\right)^{1-\epsilon}\right]E_t\left\{\rho\Lambda_{t,t+1}\left[\frac{Q_{t+1}^k}{P_{t+1}}\right]\right\} \quad (2)$$

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Timeline operations – intermediate goods firms and retailers

Table 3 Timeline operations – intermediate goods firms and retailers

Period $t-1$	Each intermediate goods firm $i \in [0,1]$ finds out if it is active or inactive at t
Period t	**Intermediate goods firms:** intermediate goods firm $i \in [0,1]$: If active, produces and sells intermediate goods to retailers; 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, transfers the return on capital as dividend to equity investors and any remaining profits to the household, pays a fee τ^* to the big tech proportional to its sales on the commerce platform. If inactive, pays a fee χ_m to post an ad on the big tech platform, and transfers net period profit to the household. **Retailers:** A typical retailer : (i) buys inputs from all A_t active intermediate goods suppliers; (ii) searches for S_t intermediate goods suppliers for use at $t+1$, paying a unit fee equal to χ_r for each of these searches. **Matching:** Active intermediate goods firms and retailers bargain over the price p_t^m and the quantity y_t^m of intermediate goods.
Period $t+1$	If active at t, intermediate goods firm 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	0.99
σ	Curvature of consumption utility	1.6
φ	Curvature of labor disutility	2
χ	Labor disutility	0.75
$1-\alpha$	Elasticity of output to labor	0.75
ε_w	Elasticity of substitution of labor types	4.5
θ_w	Calvo index of wage rigidities	0.75
ϕ_π	Taylor coefficient inflation	1.5
ϕ_y	Taylor coefficient output	0.5/4
ρ_ν	Persistence monetary policy shock	0.5
ρ_z	Persistence demand preference shock	0.5
ρ_a	Persistence technology shock	0.9
ϵ	Relative bargaining power of the seller	0.5
η	Matching function parameter	0.5
δ	Probability to separate from an existing match	5%
$\bar{K}$	Fixed supply of capital (real estate)	1
γ	Elasticity of output to real estate	0.03
ν	Sensitivity working capital to physical collateral	1%
χ_m	Fixed big tech fee for intermediate goods firms	0.05
χ_r	Fixed big tech fee for retailers	0.05
τ^*	Variable big tech fee on intermediate goods sales	8%
b	Share of profits pledgeable as network collateral	30%
κ	Exclusion periods from the commerce platform	12
σ_m	Matching efficiency	$[0, \infty]$

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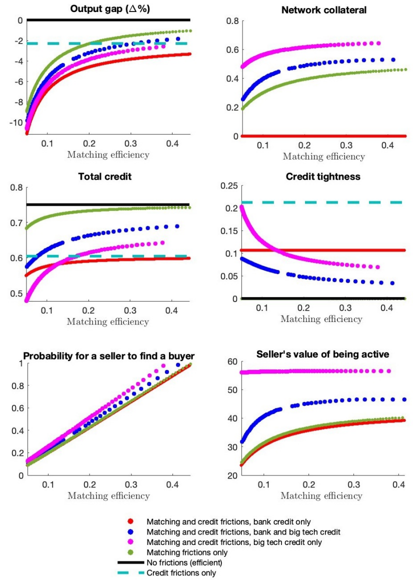
Steady-state and matching efficiency on the commerce platform



Effects of big tech credit amplified within a feedback loop

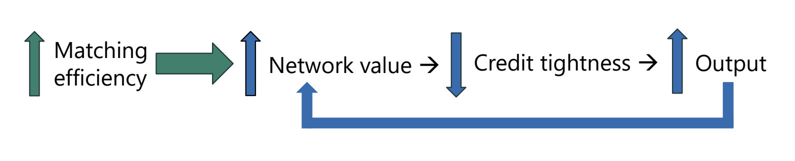


Figure 4: Feedback loop between network value, credit constraints and output

Persistence of monetary policy effects

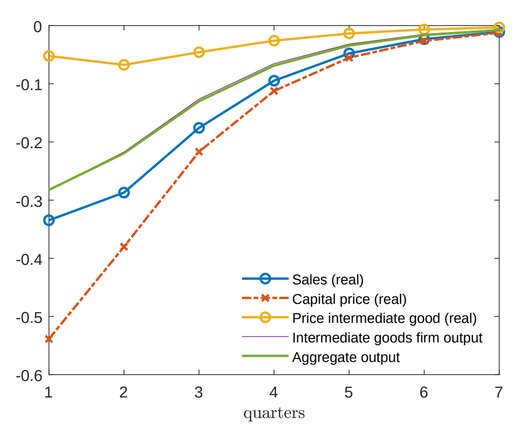


Figure 5: Dynamic responses to a monetary policy shock (25 bps)

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points.

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 $t = 1, ... T$ 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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