Big Tech, Financial Intermediation and the Macroeconomy

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Federal Reserve Bank of Boston 68th Economic Conference
Boston - 16 November 2024

Motivation

- Large increase in market share of nonbanks since the GFC, including fintech and big tech
- Big tech exploits synergies across businesses and data collection to expand activities
- Recent expansion into provision of financial services
- Shift from initial focus on payment services to financial management and personal finance
- Increasing relevance of big tech as source of funding, but heterogeneous across countries

Questions

1. What is the macroeconomic impact of big tech's entry into finance?
2. Does the provision of big tech credit affect the transmission of monetary policy?
3. Can it shield the economy from adverse shocks and contribute to financial stability?

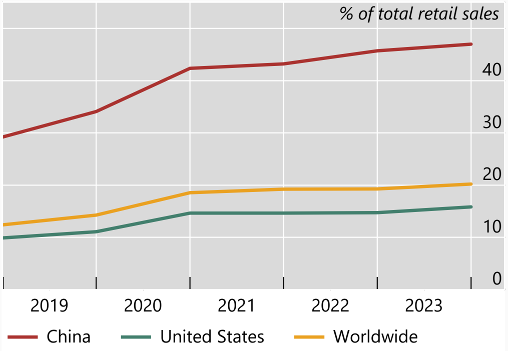
Roadmap

1. Big tech and the evolving financial system
2. A DSGE model with e-commerce trade and big tech credit
3. Numerical results: impact of big tech credit on
   - the macroeconomy
   - the transmission of monetary policy
   - financial stability

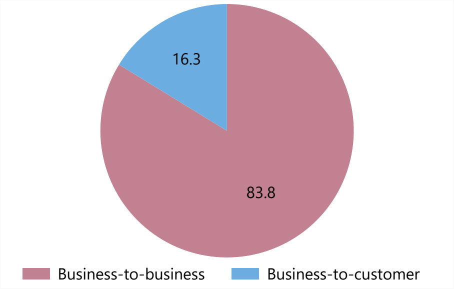
Big tech and the evolving financial system

E-commerce sales

Retail e-commerce sales



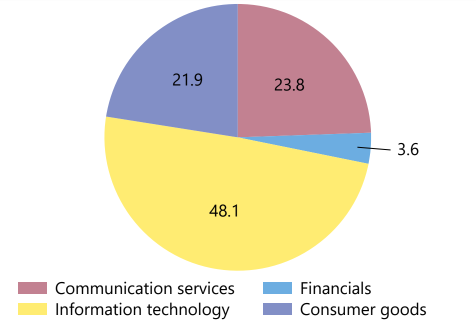
Share of B2B in e-sales



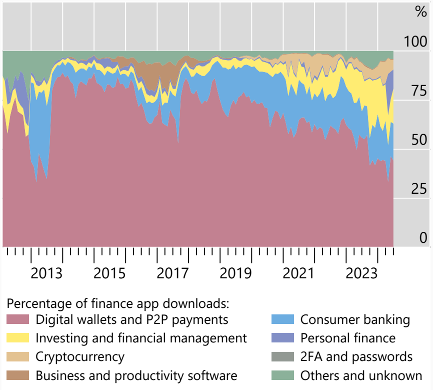
- Steadily rising e-commerce sales: 12% of global retail sales in 2019, 20% in 2023
- 84% of e-commerce sales are B2B
- Lion's share of e-commerce takes place on big tech platforms

Big tech business and financial services

Big tech revenues by sector of activity

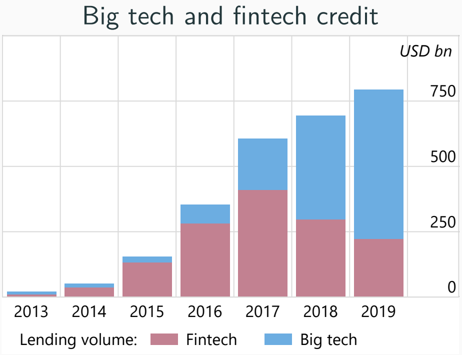


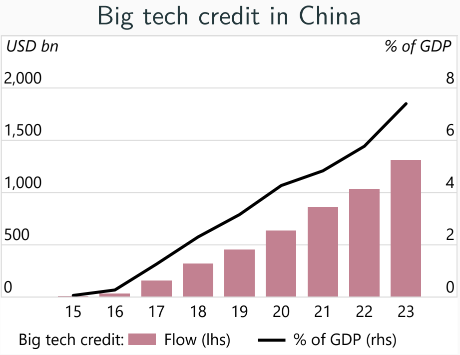
Demand of big tech financial apps



- Big tech's core business is IT. In 2022, financial services accounted for only 4%.
- But demand for big tech's financial services has been growing faster than for other products
- Largest growth in apps for 'Personal finance' and 'Investing and financial management'

Big tech's expansion into financial intermediation





- Big tech credit has rapidly expanded, overtaking fintech credit over time
- In China, big tech credit grew from 0% in 2015 to 7.5% of GDP (estimated) in 2023
- Tiny amounts and flat profile in US (and other AEs) due to stringent regulation

Big tech's revenues and liquid assets

Fees on e-commerce platform

			Fixed	Variable (%)		
E-commerce platform	Fixed Fee	Variable Fee	Average	Average	Min	Max
Amazon	\$0-\$39	6% to 45%	19.5	15	6	45
AliExpress	0	5-10% of selling price	0	7.5	5	10
Shopify	\$5 to \$299	2.4% to 5% + 30c per sale	150	3.7	2.4	5
E-bay	250 items free then \$0.35 each	2% to 12.25% of price	0	7.25	2	12.5
Etsy	\$0.20 per item	6.5% of price	0	6.5	6.5	6.5
Walmart	0	6% to 15%	0	10.5	6	15
Average				**8**	**2**	**45**

- Big tech is more profitable than G-SIFIs; uses a larger share of liquid assets to finance loans
- Pre-Covid, big tech's earning-to-asset ratio was 24%, against 4% for G-SIFIs
- Large part of big tech's revenues comes from fees

Big tech credit vs bank credit

Unconditional elasticities

	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***

Notes: Estimation period 2013-2020. *** Significance at the 1% level.

- Big tech credit is uncorrelated with property prices but correlated with e-commerce sales
- Conversely, bank credit is more correlated with property prices than with e-commerce sales

Credit enforcement by big tech versus banks

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

A DSGE model with big tech credit and B2B transactions

The model

- Two-layer production chain with **intermediate goods firms** and **retailers**
- The two types of firms search and match on the **big tech** e-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
- Other agents: households, a government and a central bank
- Nominal rigidities: sticky wages

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

- Uses N_t^b to finance credit offered to firms on the commerce platform

Intermediate goods firms – sellers on the big tech commerce platform

- $\mathcal{A}_t$ **active:** matched with retailers, pay proportional fee τ^*; issue equity to buy capital, finance wages with credit; Cobb-Douglas production; 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, ad 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

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:

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

- Value of being ”inactive” at time t:

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

$f(x_t)$ 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

$$\mathcal{L}_t^b \leq b \tilde{\mathcal{V}}_{t+1}$$

$\Rightarrow$ Credit constraint:

$$\frac{W_t}{P_t} l_t^m \leq \mathcal{L}_t^s + \mathcal{L}_t^b$$

Retailers – buyers on the big tech commerce platform

- A typical retailer produces Y_t using all active intermediate goods with a linear technology
- It searches for $\mathcal{S}_t$ intermediate goods suppliers, paying a unit fee χ_r for each search
- Looks for additional suppliers until the value of that search is zero, $\mathcal{I}_t^s = 0$

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

- 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.

Numerical results

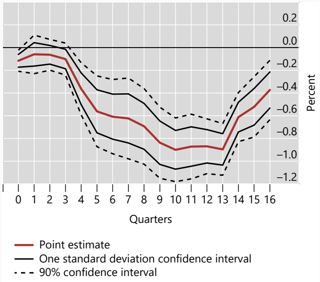
Key mechanism for the response of credit to shocks

- $\frac{W_t}{P_t} l_t^m = \underbrace{b\tilde{\mathcal{V}}_{t+1}}_{\text{big tech credit}} + \underbrace{\nu E_t \left\{ \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\}}_{\text{bank credit}}$
- Aggregate shocks affect the borrowing limit on
  - big-tech credit via expected profits on the platform
  - bank credit via property prices
- When matching efficiency is low,
  - Losses during "inactivity" (fixed fees, insensitive to shocks) count more
  - Big tech credit reacts significantly less than bank credit
- As big tech credit expands
  - Fixed fees play a lower role, expected profits react more
  - Big tech credit becomes more reactive to shocks

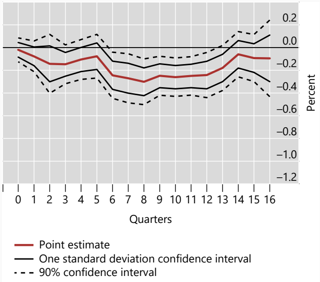
Calibration

- Local projections: dynamic responses to a 25 bps monetary policy tightening

(a) Commercial property prices (real)



(b) E-commerce sales (real)



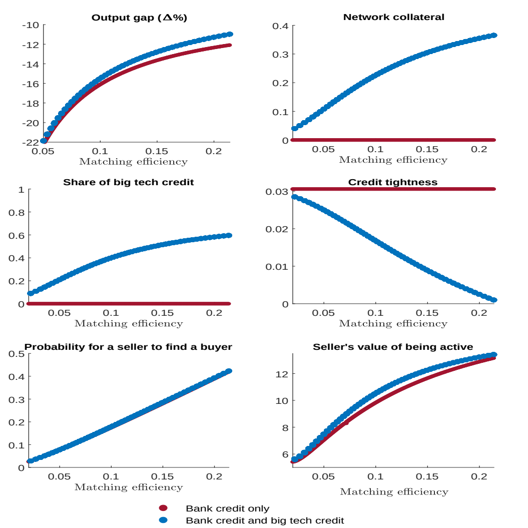
- Standard parametrization for new-keynesian block of the model
- Big tech fees: $\chi_m = .05$, $\chi_r = .05$, $\tau^* = 8\%$ to reflect evidence
- $b = 0$ to capture negligible share of big tech credit in the US
- $\sigma = 1.5$ and $\nu = .01$ to replicate evidence on impulse response of property prices and e-sales

Big tech and the macroeconomy

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
- Big techs' efficiency gains are limited by big tech's distortionary fees

Steady state allocation as σ_m rises

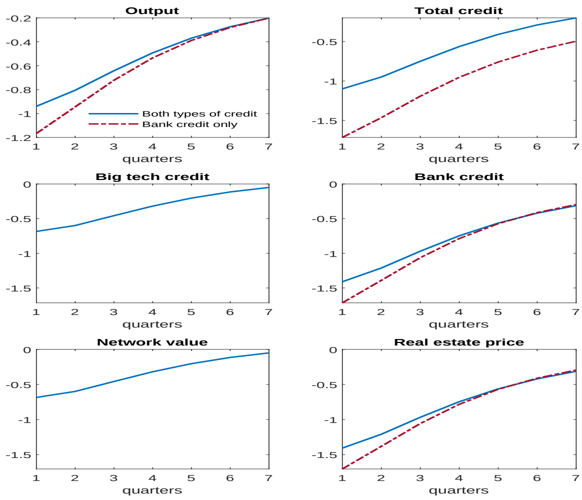


Big tech and the transmission of monetary policy

Low matching efficiency: response to a monetary policy shock

- Big tech dampens reaction of total credit and output
  - Big tech credit reacts less than bank credit
  - Reduced credit friction lowers the sensitivity of the price of capital and the reaction of bank credit

Dynamic responses to a MP shock (25 bps)



Mitigation effect depends non-linearly on matching efficiency

Impact of a positive 25 basis points monetary policy surprise

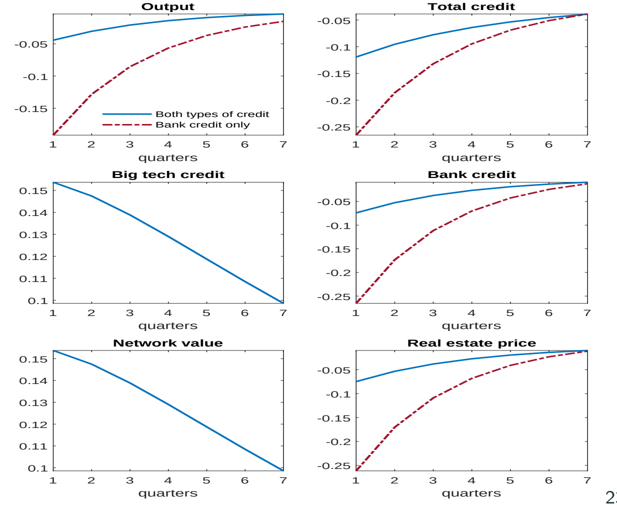
	Baseline model with both types of credit				Bank credit only	
Matching efficiency/Variables	Big tech credit	Bank credit	Total credit	Output	Credit	Output
Low	-0.68	-1.41	-1.09	-0.93	-1.71	-1.16
Intermediate	-1.31	-1.49	-1.31	-1.01	-1.71	-1.16
High	-0.84	-0.84	-0.84	-0.84	-1.71	-1.16

Big tech and financial stability

Dynamic responses to an adverse financial shock

- Surprise decline in ν_t, ie resale value of firms' capital
- Baseline (red): collateral value of capital and bank credit contract
- Big tech credit (blue): lower price of capital boosts firm profits and big tech credit
  - Higher credit sustain demand and price of capital. Bank credit contracts less.
- Big tech credit acts as 'spare tyre'

Dynamic responses to a financial shock (25 bps)



Conclusions

1. An expansion of big tech due to improved matching efficiency raises the value for firms of trading on the platform and big tech credit
   - Output closer to the efficient level but gains are limited by distortionary nature of the fees
2. Big tech credit mitigates the response of output to a monetary policy shock
   - But mitigation depends non-linearly on the platform's matching efficiency
3. Big tech credit provides a 'spare tyre' in response to shocks to the supply of bank credit
   - Milder output contraction due to increase in big tech credit and smaller decline in bank credit
4. Big tech's expansion into financial services also creates financial stability risks
   - Reliance of the financial sector on highly concentrated clouding services
   - Inter-linkages with banks, ie large deposits at banks of big tech's MMFs

Backup slides

Households

Maximize

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

subject to the sequence of budget constraints

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

and transversality conditions:

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

Central bank

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

$$1 + i_t = \frac{1}{\beta}\left(1 + i_{t-1}\right)^{\phi_i}\left[\Pi_t^{\phi_\pi}\left(\frac{Y_t}{Y}\right)^{\phi_y}\right]^{(1-\phi_i)} e^{\mu_t}$$

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:

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

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:

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

Parametrisation

Parameter	Description	Value
β	Discount factor	0.99
σ	Curvature of consumption utility	1.5
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_i	Taylor interest rate smoothing	0.8
ϕ_π	Taylor coefficient inflation	1.5
ϕ_y	Taylor coefficient output	0.5/4
ρ_μ	Persistence monetary policy shock	0.5
ρ_ν	Persistence financial shock	0.9
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	[0; 0.3]%
κ	Exclusion periods from the commerce platform	12
σ_m	Matching efficiency	$[0.01, \infty]$