

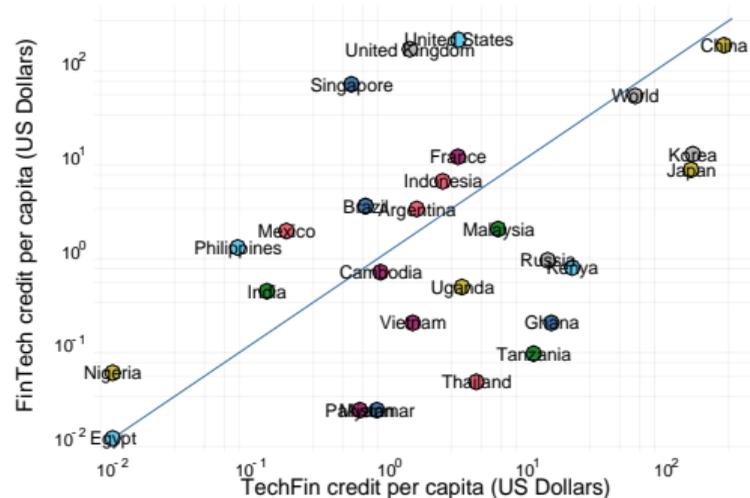
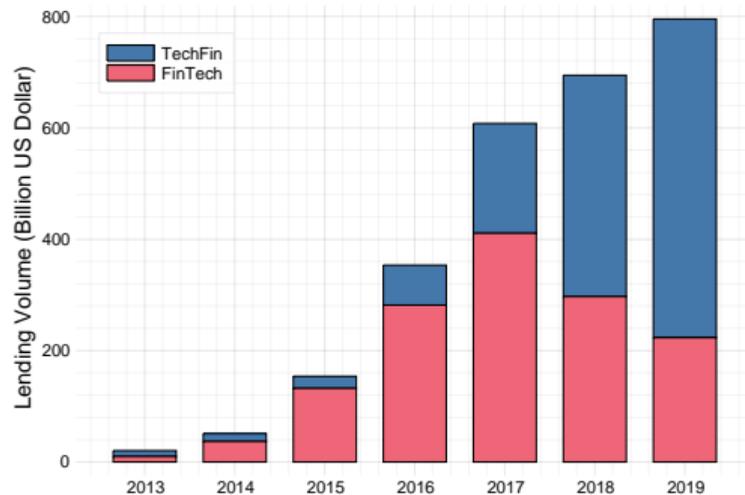
The Macroeconomics of TechFin

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Rise of New Financial Intermediaries



- **FinTech**: digital lending facilitated by online platforms (e.g., P2P, ...)
- **TechFin/BigTech**: large tech companies lend in the credit markets (e.g., Ant Group, WeBank, ...)
- a growing empirical literature, but theoretical implications?

Research Question: role of TechFin in macroeconomy

- **Existing literature: banks**
 - **key characteristic:** collateral-based borrowing constraint (“financial frictions”)
 - **macro implications:** aggregate productivity losses; financial accelerator mechanism
- **This paper**
 1. **what is the key difference between banks and BigTech in lending behaviors?**
 2. **how different are these macro implications with TechFin?**
- **why TechFin instead of FinTech:** TechFin is more bank-like (Stulz, 2019; King, 2019)

Bank v.s. TechFin: macro perspective

- **Banking sector**: collateral-based borrowing constraint
- **TechFin sector**: earnings-based borrowing constraint
- **microfoundation**:

tech advantages ⇒ **reduced cost of state verification**
⇒ **incomplete-collateralization contract**

empirical evidence: Gambacorta et al. (2020)

micro perspective: Thakor (2020); Stulz (2019)

Preview of Model and Results

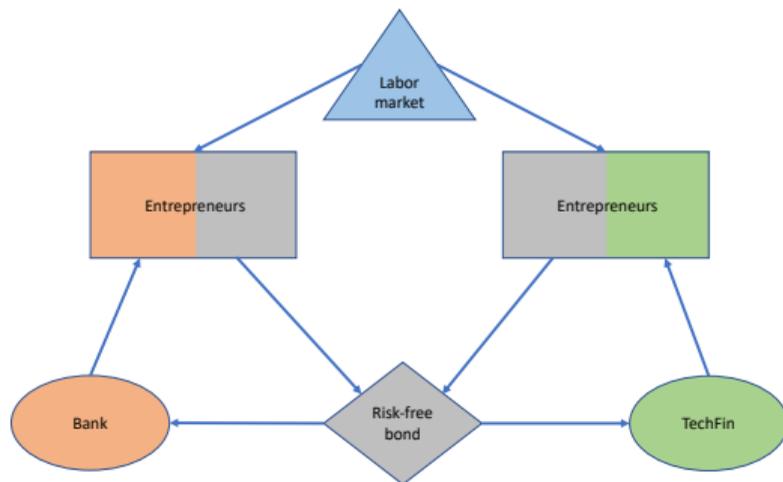
- **Key elements**

1. Heterogeneous agent model with incomplete markets
2. Two types of borrowing constraints
3. Two types of (temporary) economic fundamental shocks

- **Main conclusions** on the rise of TechFin

1. smaller aggregate productivity losses in steady-state
2. amplification and propagation of first-moment shocks are smaller
3. amplification and propagation of second-moment shocks are larger

Economic Environment



- **Three types of agents**

- a continuum of entrepreneurs borrowing from the banking sector **B**
- a continuum of entrepreneurs borrowing from the TechFin sector **F**
- \bar{L} hand-to-mouth workers

- **State of the economy**

$$\{\omega_F(t, a, z), \omega_B(t, a, z)\}$$

- **Caveats**

Model Setup

- Preference

$$\mathbb{E}_0 \int_0^{\infty} e^{-\rho t} \log c(t) dt$$

- Exogenous death shock

- each period an individual entrepreneur might exit from the market with probability χ
- his role is replaced by a new-born with the same z but the average wealth level of z

Technology

- **Production function**

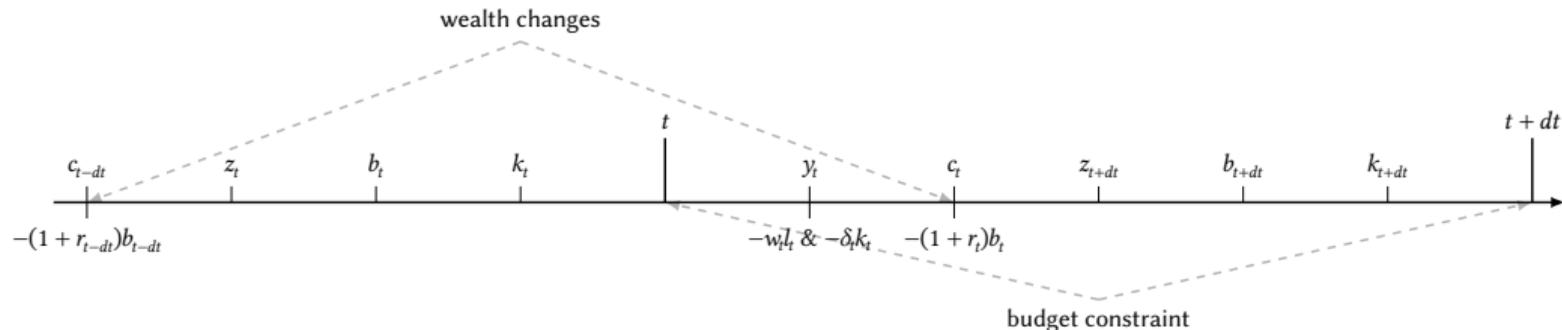
$$y = (zk)^\alpha l^{1-\alpha}$$

- **Modified Ornstein – Uhlenbeck productivity process**

$$d\log z_{i,j,t} = \theta(\bar{\mu} - \log z_{i,j,t}) + \sigma\sqrt{\theta}dW_{i,j,t}$$

- **Two types of (temporary) fundamental shocks**
 - shocks to common productivity component $\bar{\mu}$
 - shocks to micro-level uncertainty σ

Timeline



- **budget constraint from t to $t + dt$:**

$$c_t + k_{t+dt} - (1 - \delta)k_t + (1 + r_t)b_t + w_t l_t = y_t + b_{t+dt}$$

- **wealth definition:** $a \equiv k - b$
- **wealth changes from t to $t + dt$:**

$$da_t = (y_t - w_t l_t - \delta k_t - r_t b_t - c_t) dt$$

Two Types of Borrowing Constraints

- **Banking sector:** collateral-based borrowing constraint

$$(1 + r)b \leq \lambda_B k$$

- **TechFin sector:** earnings-based borrowing constraint

$$(1 + r)b \leq \lambda_F \pi = \lambda_F (y - wl)$$

▸ micro-foundation

▸ empirical evidence

Similarity and Difference

- Banking sector

$$b \leq \frac{\lambda_B}{1 + r - \lambda_B} a$$

- TechFin sector

$$b \leq \frac{\lambda_F \xi z}{1 + r - \lambda_F \xi z} a$$

where $\xi = \alpha \left(\frac{1-\alpha}{w} \right)^{\frac{1-\alpha}{\alpha}}$

debt capacity = ϕ × verifiable net worth

- ? “With cash flow-based lending and EBCs, we find that asset price feedback through firms’ balance sheets could diminish significantly.” (Lian and Ma, 2021)
- ? “This evidence implies that a greater use of big tech credit could reduce the importance of collateral in credit markets and potentially weaken the financial accelerator mechanism.” (Gambacorta et al., 2020)

Equilibrium Definition

- 1. Optimization:** given market prices $\{r(t), w(t)\}_{t=0}^{\infty}$, resource allocations $\{(l_{i,j}(t), k_{i,j}(t), b_{i,j}(t), c_{i,j}(t))_{i \in [0,1], j \in \{B,F\}}\}_{t=0}^{\infty}$ solves each entrepreneur's optimization problem given his constraints.
- 2. Market clearance:**

$$\begin{aligned}\iint l_B(t, a, z) \omega_B(t, a, z) da dz + \iint l_F(t, a, z) \omega_F(t, a, z) da dz &= \bar{L} \\ \iint b_B(t, a, z) \omega_B(t, a, z) da dz + \iint b_F(t, a, z) \omega_F(t, a, z) da dz &= 0 \\ C_F(t) + C_B(t) + C_L(t) + X_F(t) + X_B(t) &= Y_F(t) + Y_B(t)\end{aligned}$$

- 3. Stationary distribution:**

$$\frac{\partial \omega_B(t, a, z)}{\partial t} = \frac{\partial \omega_F(t, a, z)}{\partial t} = 0, \forall a, z$$

Optimal Policy Functions

- **Banking sector**

$$b_B(a, z) = \begin{cases} \frac{\lambda_B a}{1+r-\lambda_B} & z \geq \underline{z} \\ -a & z < \underline{z} \end{cases}$$

$$k_B(a, z) = \begin{cases} \frac{(1+r)a}{1+r-\lambda_B} & z \geq \underline{z} \\ 0 & z < \underline{z} \end{cases}$$

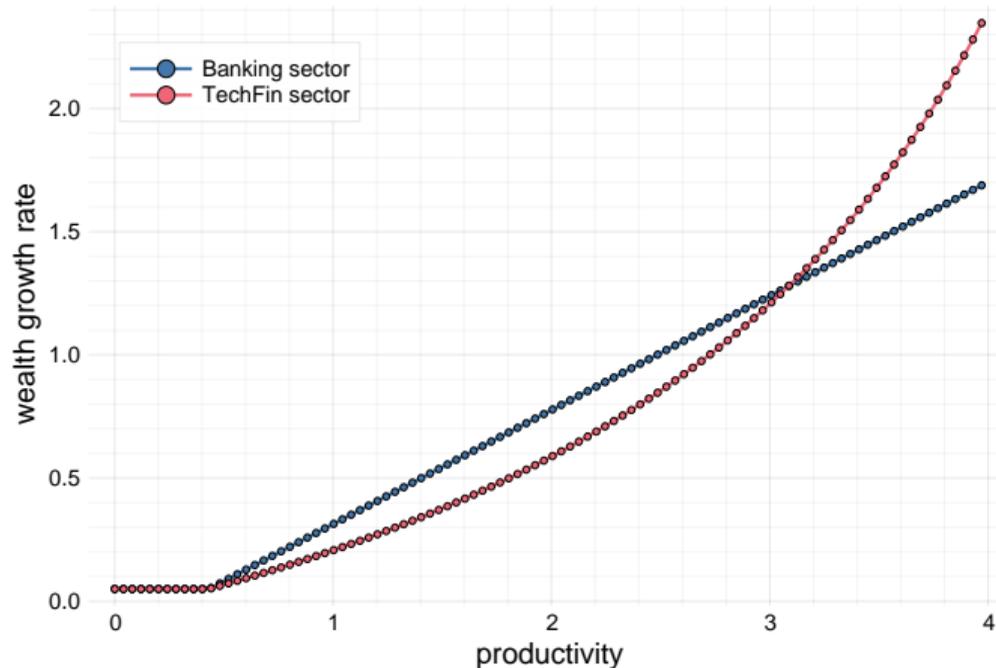
- **TechFin sector**

$$b_F(a, z) = \begin{cases} \frac{\lambda_F \xi^z a}{1+r-\lambda_F \xi^z} & z \geq \underline{z} \\ -a & z < \underline{z} \end{cases}$$

$$k_F(a, z) = \begin{cases} \frac{(1+r)a}{1+r-\lambda_F \xi^z} & z \geq \underline{z} \\ 0 & z < \underline{z} \end{cases}$$

where $\underline{z} = \frac{r+\delta}{\xi}$

Wealth Dynamics



$$da_B = \left\{ \mathbb{1}_{z \geq \underline{z}} \times \left[\frac{(1+r)(\xi z - r - \delta)}{1+r-\lambda_B} + r - \rho \right] + \mathbb{1}_{z < \underline{z}} \times (r - \rho) \right\} a_B dt \equiv \Gamma_B(z) a_B dt$$

$$da_F = \left\{ \mathbb{1}_{z \geq \underline{z}} \times \left[\frac{(1+r)(\xi z - r - \delta)}{1+r-\lambda_F \xi z} + r - \rho \right] + \mathbb{1}_{z < \underline{z}} \times (r - \rho) \right\} a_F dt \equiv \Gamma_F(z) a_F dt$$

Distribution Dynamics

$$\frac{\partial \omega_j(t, a, z)}{\partial t} = -\frac{\partial [\Gamma_j(z) a \omega_j(t, a, z)]}{\partial a} - \frac{\partial [\theta(\bar{\mu} - \log z) z \omega_j(t, a, z)]}{\partial z} + \frac{1}{2} \frac{\partial^2 [\theta \sigma^2 z^2 \omega_j(t, a, z)]}{\partial z^2} \text{ where } j \in \{B, F\}$$

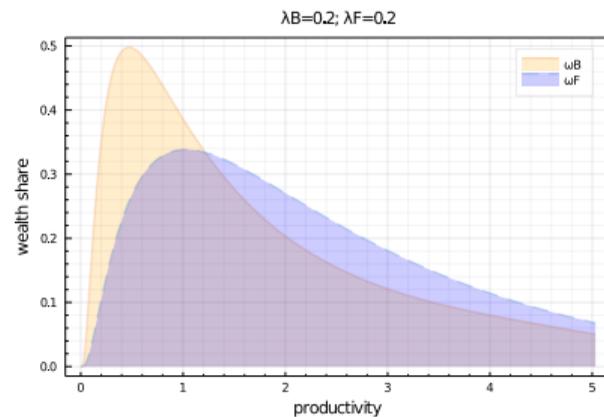
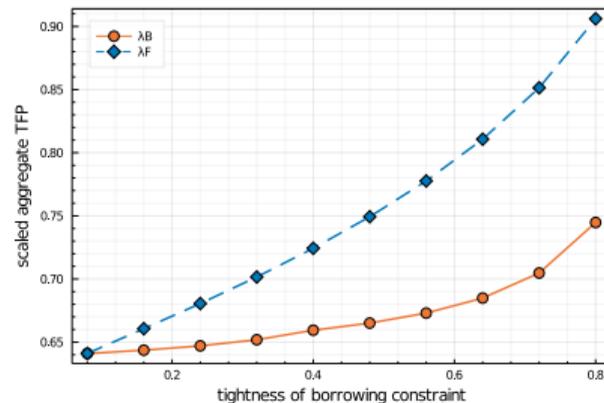
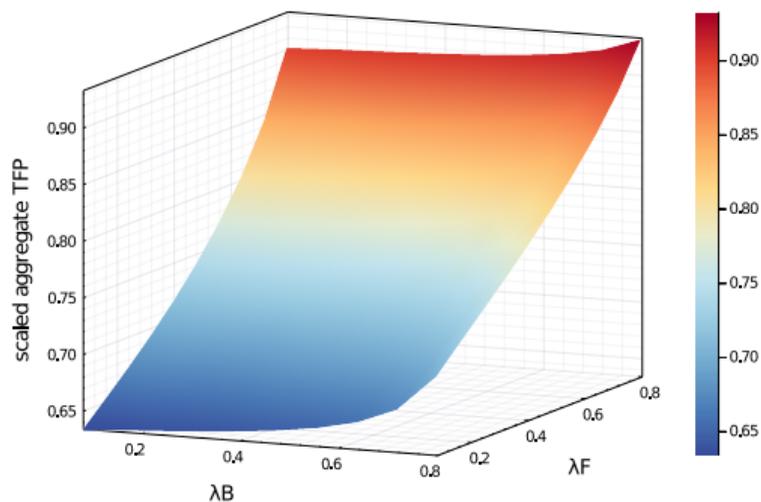
- ✗ **wealth share approach:** Caselli and Gennaioli (2013); Moll (2014); ...
- ✗ **(adaptive) sparse grid approach:** Brumm and Scheidegger (2017); ...
- ✓ **deep learning approach:** Han and E (2016); Raissi, Perdikaris and Karniadakis (2019); Fernandez-Villaverde et al. (2020); Chen, Didisheim and Scheidegger (2021); ...

Parametrization

Parameter	Description	Value	Source/Reference
ρ	rate of time preference	0.05	
α	capital share	0.33	Moll (2014)
\bar{L}	labor market size	1.0	
δ	capital depreciation rate	0.06	BEA-FAT
χ	death rate	0.05	Moll (2012)
$\bar{\mu}$	log idiosyncratic productivity mean	0.0	
θ	autocorrelation $e^{-\theta}$	0.16 (corr = 0.85)	Asker, Collard-Wexler and Loecker (2014)
σ	log idiosyncratic productivity s.d.	0.56	
$\bar{\phi}$	upper boundary for corporate leverage	10.0	

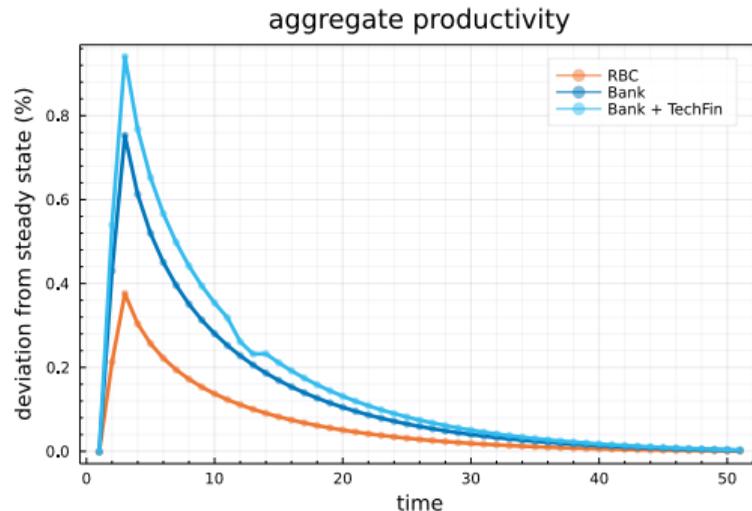
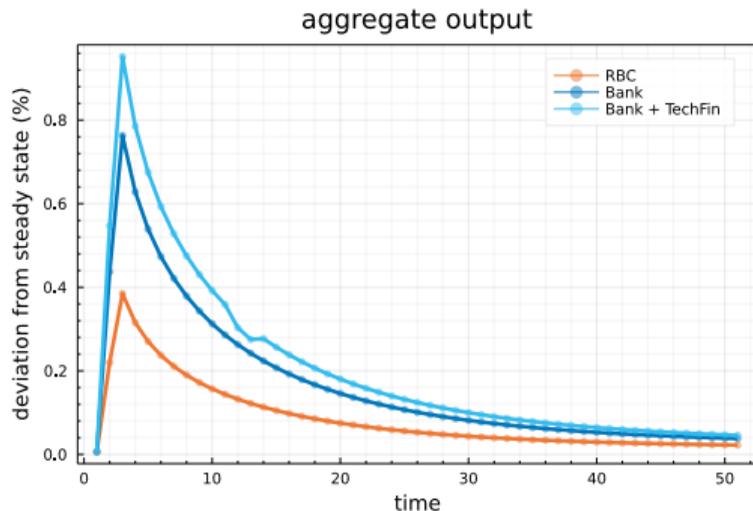
		Experimentation	Question
λ_B	tightness of constraint in banking	0 ~ 0.8	
λ_F	tightness of constraint in TechFin	0 ~ 0.8	1. steady-state TFP
$\Delta\bar{\mu}$	fundamental shocks to productivity	$\pm 0.1 \sim \pm 0.5$	2. business cycles
$\Delta\sigma$	fundamental shocks to micro uncertainty	$\pm 0.1\sigma \sim \pm 0.5\sigma$	

Productivity Losses in Steady-State



Business Cycles

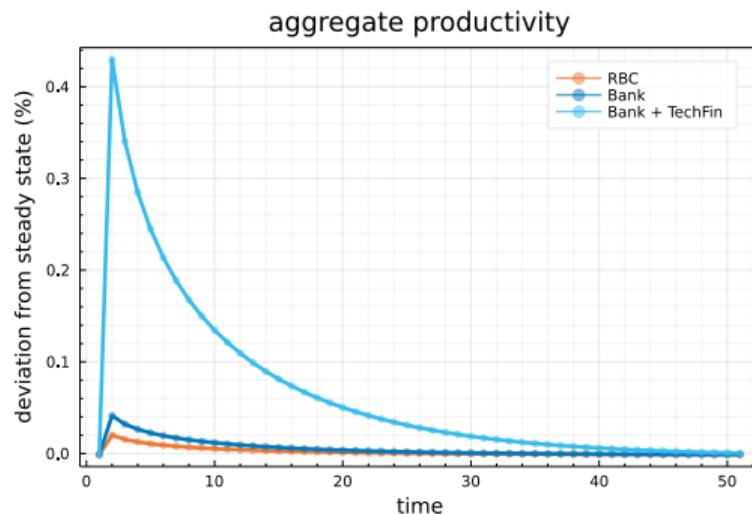
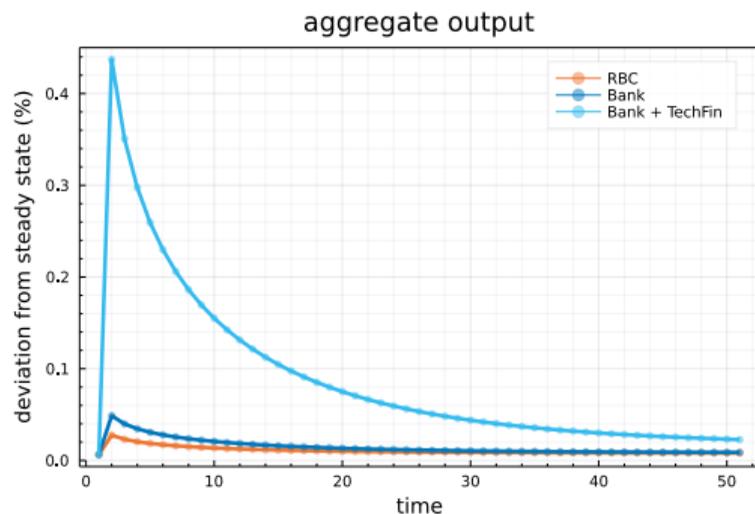
first-moment shocks: amplification and propagation



- $\Delta \bar{u} = \pm 0.1; \Delta \sigma = 0$

Business Cycles

second-moment shocks: amplification and propagation



- $\Delta \bar{u} = 0; \Delta \sigma = \pm 0.2\sigma$

▸ good firms principle

Conclusion



- **Goal:** introduce BigTech into the existing macro-finance literature
- **This paper:**
 - lending side only
 - a different type of borrowing constraint
- **Key take-away:**
 - two different credit systems
 - ⇒ two types of borrowing constraints
 - ⇒ two types of financial accelerator mechanism

Appendix

assumption

- **Key assumption:** technology, data, and platform advantages allow BigTech to **reduce the cost of state verification**
- **example:** 码商 (QR code merchants)



model setup

- entrepreneurs with capital k want to borrow b
 - exogenous interest rate r and liquidation value l
- **two possible outcomes**: entrepreneurs announce; lenders verify with cost f
 - good: $\pi_G = z_G k$ with probability p
 - bad: $\pi_B = z_B k$ with probability $1 - p$
 - $z_G > z_B > l > 0$
- **optimal contracts** \Rightarrow maximize utility and truth-telling

$$\max_{\{c_G, c_B^{nv}, c_B^v, q\}} \pi c_G + (1 - \pi) [p c_B^v + (1 - p) c_B^{nv}]$$

1. full-collateralization contract
2. incomplete-collateralization contract with stochastic verification

collateral v.s. earnings

1. full-collateralization contract: collateral-based borrowing constraint

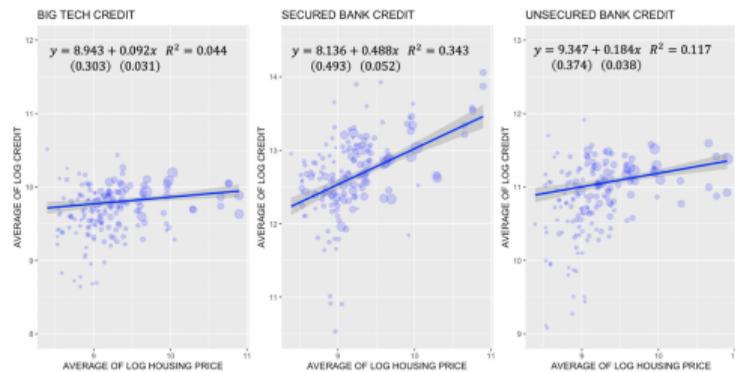
$$(1+r)b \leq \underbrace{lk}_{\text{collateral value}}$$

2. incomplete-collateralization contract: earnings-based borrowing constraint

$$(1+r)b \leq \underbrace{p\pi_G + (1-p)\pi_B}_{\text{expected earnings}} - \underbrace{(1-p)qf}_{\text{expected verification costs}} - pc_H - (1-p)[qc_L^y + (1-q)c_L^{nv}]$$
$$q = \frac{(1+r)b - z_B k}{p(z_G - z_B)k - (1-p)f} \in [0, 1]$$

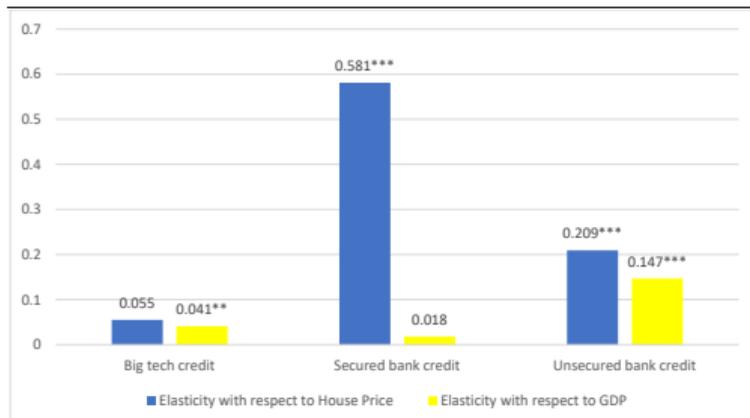
- cost of verification $f \Rightarrow$ whether cash flow-based lending is more attractive
 - either covenants or technology

Figure 5. Elasticity of credit with respect to house prices

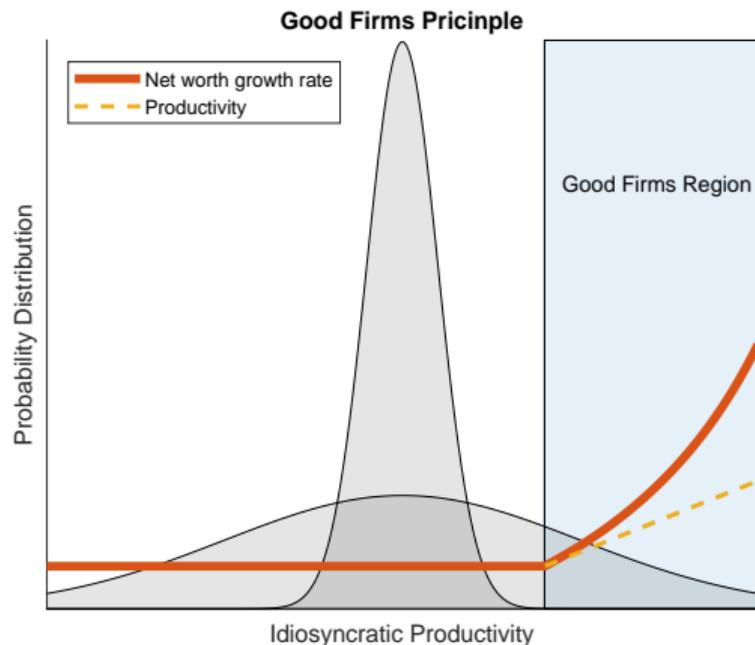


Note: Based on a 100,000 random sample of firms served by both MYbank and traditional banking. The dots in the figures indicate the average logarithm credit use (y-axis) and the average logarithm of housing price (x-axis) at the city-year level. Growth rates are approximated using first differences of log values. The left-hand panel plots big tech credit, the middle panel plots bank secured credit and the right hand panel plots bank unsecured credit. Linear trend lines are reported in each graph, together with 95% degree confidence bands. Standard errors in brackets.

Figure 6. Elasticity of credit with respect to house prices and GDP



Note: 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.



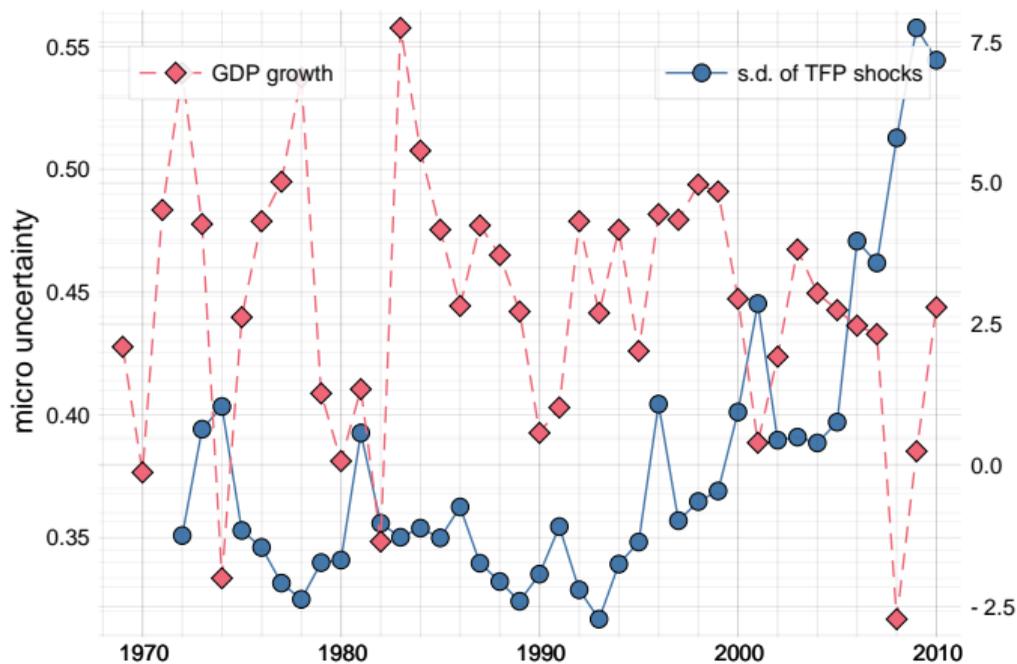
- **Positive impacts of uncertainty**

[◀ Back](#)

- **“Good Firms Principle”**: only good firms matter; best firms matter the most
- **“Good news principle”**(Bernanke, 1983): only good news matters in growth options because bad news is capped by closing down the project

Countercyclical Micro-Uncertainty

◀ Back



- **Data source:** Bloom et al. (2018)
- **Correlation:** -0.45

Related Literature

- **Empirical FinTech/TechFin:** Gambacorta et al. (2020); Tang (2019); Hau et al. (2018); Cornelli et al. (2020); ...
- **Financial frictions and macroeconomy:** Kiyotaki and Moore (1997); Bernanke and Gertler (1989); Brunnermeier and Sannikov (2014); Di-Tella (2017); He and Krishnamurthy (2013); Fernandez-Villaverde, Hurtado and Nuno (2019); ...
- **Distributional macro:** Moll (2014); Fernandez-Villaverde, Hurtado and Nuno (2019); Achdou et al. (Forthcoming); ...
- **Earnings-based borrowing constraint:** Lian and Ma (2021); Greenwald (2019); Drechsel (2019); ...

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