Big Techs and the Credit Channel of Monetary Policy

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PRELIMINARY DRAFT

Abstract

We study how Big Tech’s entry into finance may affect the credit channel of monetary policy. Our empirical analysis suggests that big tech credit and bank credit react very differently to monetary policy. We rationalize these findings through the lens of a new framework where Big Techs facilitate matching in the supply chain and extend working capital loans, thus adding an additional source of finance relative to bank loans. The Big Tech firm reinforces credit repayment with the threat of exclusion from its ecosystem, while bank credit is secured against collateral. According to our model: (i) big tech credit reacts less to monetary policy due to a more muted response of firms’ profits as opposed to physical collateral; (ii) as matching efficiency on Big Tech’s commerce platform rises, the expansion in firms’ profits leads to a higher share of big tech credit, and hence, to weaker responses of credit and output to monetary policy.

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1 Introduction

Large technology firms such as Alibaba, Amazon, Facebook or Mercado Libre (Big Techs) have recently started to provide credit to vendors on their commerce platforms. This new type of credit has already gained quantitative relevance in China, Kenya or Indonesia (Figure 1), and given the rise in e-commerce (Figure 2), has the potential to spread worldwide very rapidly.

These changes in financial intermediation will likely shape the transmission of monetary policy in notable ways. The business model of Big Techs relies on the collection and use of vast troves of data rather than collateral to solve agency problems between lenders and borrowers. Credit scoring generated using machine learning and big data are able to identify firms’ characteristics with more precision than traditional credit bureau ratings (Frost et al. (2020)). Moreover, due to network effects and the presence of high switching costs between Big Tech platforms, Big Techs can enforce loan repayments by the simple threat of an exclusion from their ecosystem if the firm defaults. This explains why big tech credit is uncorrelated with real estate values, but it is highly correlated instead with firm-specific characteristics, such as transaction volumes on the Big Tech e-commerce platform (Gambacorta et al. (2022)). As the share of big tech credit rises, one thus expects monetary policy to affect credit supply less via asset prices (via the traditional "collateral channel" à la Kiyotaki and Moore (1997)), and more via repayment incentive compatibility constraints within Big Techs’ ecosystems.

Our paper aims to shed some light on the effects of Big Techs’ entry into finance on monetary policy transmission. We start by documenting that big tech credit and bank credit respond very differently to a monetary policy shock. Specifically, our panel–VAR analysis suggests that while bank credit follows closely the response of house prices (typically used as collateral) and reacts very strongly to monetary policy, the response of big tech credit is not statistically significant. Motivated by our empirical findings, we develop a model to help rationalize them and predict how the advent

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1 Available data and estimates show that fintech credit volumes reached USD 240 billion in 2019, while big tech credit volumes surged to USD 530 billion. This represents a dramatic increase since 2013, when volumes were only USD 9.9 billion and 10.6 billion, respectively. There is substantial variation across countries, with the sum of fintech and big tech credit flows (“total alternative credit”) equivalent to 5.8% of the stock of total credit in Kenya, 2.0% in China and 1.1% in Indonesia. In other major markets like the United States, Japan, Korea and the UK, fintech and big tech lending flows are less than 1% of the stock of total credit. Since 2017, e-commerce revenues have risen from an estimated 1.4 trillion to 2.4 trillion in 2020, or about 2.7% of global output (Figure 2 left-hand panel). More recent estimates are that 3.5 billion individuals globally (about 47% of the population) use e-commerce platforms today. China is the largest market, followed by the United States, Japan, the United Kingdom and Germany. In countries where Big tech firms are prohibited by law from direct lending (e.g. Indonesia), big tech credit activities are performed in partnership with financial institutions.
Figure 1: Upward trend in big tech credit

Notes: Figures include estimates. CN = China, KE = Kenya, KR = Korea, JP = Japan, RU = Russia, ID = Indonesia, US = United States, GB = United Kingdom, NL = Netherlands, AU = Australia. (1) 2019 fintech lending volume figures are estimated on AU, CN, EU, GB, NZ and US. (2) Data for 2019. (3) Domestic credit provided by the financial sector. Data for 2018. (4) Total alternative credit is defined as the sum of fintech and big tech credit. Data for 2019. Sources: Cornelli et al. (2020).

Figure 2: Upward trend in e-commerce, mostly via Big Tech platforms

of big tech credit may impact monetary policy transmission in the near future. The analysis focuses on business-to-business (B2B) transactions (i.e. transactions between firms), which account for 80% of global online transactions (Figure 2, right panel). In our framework, a Big Tech platform facilitates the search and matching between manufacturers and wholesalers, and extends working capital loans to the former. Manufacturers may finance their working capital with both secured bank credit and big tech credit, but cannot commit to repay their loans. The central difference between big tech credit and bank credit relates to borrowers’ opportunity cost of default. Firms that default on bank credit lose their collateral (real estate). In contrast, those that default on big tech credit lose access to Big Tech’s e-commerce platform, and hence their future profits ("network collateral"). An incentive compatible contract thus limits the total amount of credit to the sum of physical and network collateral. Nominal prices are sticky, and monetary policy affects the real economy. When search frictions in the goods markets and credit frictions in the financial markets are set to zero, the model collapses to the basic New Keynesian model.

According to our model, big tech credit reacts less to monetary policy due to a more muted response of firms’ opportunity cost of default on this type of credit (future profits) compared to that of bank credit (physical collateral). Furthermore, as matching efficiency on Big Tech’s commerce platform rises, our analysis shows that the expansion in firms’ profits leads to a higher opportunity cost of default on big tech credit, a higher borrowing limit, looser credit constraints and, ultimately, a higher share of big tech credit. The latter, coupled with the muted response of this new type of credit, leads to weaker responses of credit and output to monetary policy when matching efficiency on Big Tech’s commerce platform is higher.

The paper proceeds as follows. Section 2 outlines the contributions of our paper to the literature. Section 3 shows empirical evidence that bank credit and big tech credit respond very differently to a monetary policy shock due to a distinct effectiveness of the collateral channel. Section 4 describes our theoretical framework with a special focus on the dual role of the Big Tech firm as commerce platform and financial intermediary. Section 5 describes the parametrization of the model. Section 6 shows the steady-state equilibrium as a function of the matching efficiency between sellers and buyers on the commerce platform. Section 7 studies the effects of big tech credit on the dynamic responses to a monetary policy shock, and how these effects vary with the matching efficiency on the commerce platform. Section 8 concludes.
2 Literature review

Our paper contributes to three broad strands of literature. The first is the “financial accelerator” literature which argues that physical collateral plays a crucial role in the amplification of macroeconomic fluctuations and the transmission of monetary policy (e.g. Gertler and Gilchrist, 1994). A rise in collateral values during the expansionary phase of the business cycle typically fuels a credit boom, while their subsequent fall in a crisis weakens both the demand and supply of credit, leading to a deeper recession. The “collateral channel” was a relevant driver of the Great Depression (Bernanke (1983)), and of the more recent financial crisis (Mian and Sufi (2011), Bahaj et al. (2019), Ottonello and Winberry (2020)). Using a structural model, Ioannidou et al. (2022) shows that a 40% drop in collateral values would lead almost a quarter of loans to become unprofitable, a reduction in average demand by 16% and a drop in banks’ expected profits of 25%. Our paper contributes to this stream of the literature by analysing theoretically how Big Techs’ use of big data for credit scoring and of “network collateral” instead of physical collateral could attenuate the link between asset prices, credit and the business cycle. Further, since ultimately big tech credit supply is constrained in our setup by firms’ expected profits, our analysis is also related to the literature on the macroeconomic effects of earnings-based borrowing constraints (e.g. Drechel (2022), Lian and Ma (2021)).

Second, our paper contributes to the literature on financial inclusion by showing with the help of a model how a rise in matching efficiency between buyers and sellers on commercial platforms can lead to an expansion of credit supply. Overall, the empirical evidence suggests that Fintech and big tech credit are growing where the current financial system is not meeting demand for financial services (Bazarbash (2019), Haddad and Hornuf (2019)). For the case of China, Hau et al. (2021) show that Fintech credit mitigates supply frictions (such as a large geographic distance between borrowers and the nearest bank branch), and allows firms with a lower credit score to access credit. In the United States, Tang (2019) finds that Fintech credit complements bank lending for small-scale loans. Jagtiani and Lemieux (2018) find that Lending Club has penetrated areas that are underserved by traditional banks. In Germany, De Roure et al (2016) find that Fintech credit serves a slice of the consumer credit market neglected by German banks. Cornelli et al. (2020) find that Fintech and big tech credit are higher where banking sector mark-ups are higher, where there are fewer bank branches and where banking regulation is less stringent. Frost et al. (2019) use data for Mercado Credito, which provides credit lines to small firms in Argentina on the e-commerce
platform Mercado Libre. They find that, when it comes to predicting loss rates, credit scoring
techniques based on big data and machine learning have so far outperformed credit bureau ratings.

Third, our paper contributes to the literature on how to regulate Big Techs. Big Techs’ expansion
into financial services can bring competition, efficiency and inclusion benefits, particularly in emerging
market and developing economies, but it also gives rise to important policy issues (Feyen et al.
(2021)). Specifically, it has intensified concerns around a level playing field with banks, operational
risk and too-big-to-fail issues (Carstens (2021), Restoy (2021)), and it raises challenges for antitrust
rules and consumer protection (Croxon et al. (2021)). Using data on US mortgages, Fuster et al.
(2019) find that Black and Hispanic borrowers are disproportionately less likely to gain from the
introduction of machine learning in credit scoring models, suggesting that the algorithm may develop
differential effects across groups and increase inequality. By studying also the macroeconomic
implications of the entry of Big Tech in finance our paper aims to inform this policy debate.

3 Evidence on the response of Big Tech and bank credit to a
monetary policy shock

3.1 Data description

The VAR is based on annual macroeconomic data for 19 countries over the period 2005 to 2020.
The interaction between monetary policy, the credit market and economic activity is analyzed by
means of the following variables: i) the property price index (pk); ii) real GDP (Y); iii) the consumer
price index (p); iv) bank lending (L); v) big tech credit and Fintech credit, hereafter called total
alternative credit (B); vi) the short term interest rate (i). Apart from the short term interest rate,
all variables are in logarithm. The property price index and the banking credit data are taken from
the BIS Statistics Warehouse, while the real GDP and the CPI come from the IMF World Economic
Outlook database. The short term rate has been obtained from national central banks and the total
alternative credit (Big Tech and Fintech credit) comes from Cornelli et al. (2020).

3 The 19 countries/currency areas are: Austria, Brasil, Canada, Switzerland, Chile, China, Euro Area, Great Britain,
Indonesia, Israel, India, Japan, South Korea, Mexico, Russia, Thailand, Turkey, US, South Africa.

4 Total alternative credit is defined as the sum of fintech and big tech credit. Fintech credit corresponds to digital
lending models such as peer-to-peer (P2P)/marketplace lending and invoice trading which is facilitated by online
platforms rather than traditional banks or lending companies. Big tech credit is defined as credit disbursed either
directly or in partnership with financial institutions by large companies whose primarily business is technology. For
more details, please see Cornelli et al. (2020). Summary statistics of all the variables used in the analysis are reported
in Table A1 in the Appendix.
3.2 The VAR Model

We model a six-variable VAR system. To avoid the problem of spurious correlations, we express all variables in first differences. The starting point of the multivariate analysis is:

$$z_t = \mu + \sum_{k=1}^{p} \phi_k z_{t-k} + \epsilon_t$$

(1)

for \( t = 1, \ldots, T \) where \( z_t = [pk, Y, p, L, B, i] \) and \( \epsilon_t \) is a vector of residuals. The deterministic part of the model includes a constant, while the number of lags (p) has been set equal to 1 according to the Andrews and Lu (2001) criteria.

Figure 3 shows the dynamic responses of the variables to a monetary policy shock. The results suggest that bank credit and alternative credit respond very differently to monetary policy: while a one percentage point increase in the monetary policy rate has a negative effect on bank credit, it has no significant effect on total alternative credit. Importantly also, the response of bank credit follows closely the one of property prices, while this is not the case for alternative forms of credit. Precisely, a one percentage point unexpected increase in the monetary policy rate affects significantly the nominal interest rate for two consecutive years (top left panel). During these two years, asset prices decline by 0.5 per cent after the first year and by 0.4 in the second year (bottom right panel), bank credit drops by -1.8 per cent after one year, and by -0.8 per cent after two years (top centre panel). The effect of the monetary policy tightening becomes statistically insignificant from the third year onwards.

By contrast, the monetary policy shock does not significantly affect total alternative credit at any horizon (bottom left panel). The results are consistent with Gambacorta et al. (2022) who find that big tech credit does not correlate with house prices when controlling for demand factors, but reacts strongly to changes in firm characteristics, such as transaction volumes and network scores.

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5Unit root Phillips–Perron tests for all variables show that the null hypothesis that variables contain unit roots is always largely rejected. The results for the unit root Phillips–Perron tests for all variables in first differences are shown in Table A2 in the Appendix.

6The choice of the deterministic component (constant versus trend) has been verified by testing the joint hypothesis of both the rank order and the deterministic component (so-called Pantula principle). The lag selection procedure is described in Table A3 in the Appendix.

7Because the ordering of the variable is likely to affect orthogonalized IRFs and the interpretation of the results, we follow the theory and order the interest rate last so it reacts to all variables within one year. This choice is in line with the literature that analyses the effectiveness of monetary policy shocks using VAR models. Confidence intervals are calculated using Monte Carlo simulation with p-value bands of 90%.
Figure 3: Estimated impulse responses to a monetary policy shock

Notes: The graphs show the impulse response function for a shock in the ∆ short term rate. The horizontal axis reports the number of steps in the simulation. Confidence intervals are calculated using Monte Carlo simulation with p-value bands of 90%.
Source: Authors’ calculations.

used to calculate firm credit ratings\textsuperscript{8}

Figure 3 also shows that the monetary tightening induces a decline in the real GDP (top right panel), and the CPI index. According to the forecast error variance decomposition, a substantial part of the variability in real GDP, namely almost one quarter, is explained by bank credit, suggesting the importance of the credit channel of monetary policy transmission (see Figure A3 in the Appendix). The significant negative effect on the price level arrives with some delay (after one year and half) and vanishes from the middle of the third year (bottom centre panel), in line with previous estimates.

Overall, our empirical exercise suggests that the use of big tech credit alters the effectiveness of

\textsuperscript{8}Figure A1 in the Appendix, taken from Gambacorta et al. (2020), presents the elasticities of different forms of credit (big tech credit, unsecured bank credit, and secured bank credit) with respect to house prices and GDP. We will use the value of these elasticities to evaluate some the results in our dynamic analysis.
the credit channel of monetary policy by reducing the relevance of the “collateral channel”. In what follows, we build a model to rationalize these findings and study how monetary policy transmission may change as big tech credit becomes macro-economically relevant.

4 Model

The model is characterized by three main building blocks: search and matching along the production chain, credit frictions in the production sector, and nominal price rigidities. The model is populated by (1) a representative household who consumes, invests and works, (2) competitive manufacturers which produce using labor and physical capital, (3) competitive wholesalers which use manufactured goods as inputs, (4) monopolistic retailers which buy goods from wholesalers, differentiate them, and set prices subject to nominal rigidities, (5) a Big Tech firm which facilitates transactions between manufacturers and wholesalers, and extends credit to the former, (6) banks which give secured loans to manufacturers, (7) a government which issues risk–free nominal bonds, and (8) a central bank which sets the nominal interest rate.

Manufacturers sell products to wholesalers via a Big Tech commerce platform where buyers and sellers need to search for and match with one another (Figure 4). Manufacturers finance their working capital in advance of sales with both secured bank credit and big tech credit, and may end up financially constrained in equilibrium.

Figure 4: Three layer supply chain in the model
4.1 Representative household

The household is infinitely-lived, and chooses each period how much to work \( L_t \), consume \( C_t \) and invest in nominal risk-free public bonds \( B_t \) and equity \( E_t \) to maximize inter-temporal lifetime utility

\[
E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left( \frac{C_1 - \sigma}{1 - \sigma} - \chi_L \frac{L_1 + \varphi}{1 + \varphi} \right) \right\}
\]

where \( C_t = \int_0^1 C_t(j)^{1-\epsilon} \frac{dj}{1-\epsilon} \) is a standard Dixit-Stiglitz consumption index of differentiated goods with \( \epsilon \) a measure of substitutability among them. The representative household maximization problem is subject to the sequence of budget constraints

\[
P_t C_t + B_t^h + \varepsilon_t Q_t^e \leq W_t L_t + B_{t-1}^h (1 + i_{t-1}) + \varepsilon_t D_t^e + \varepsilon_{t-1} Q_{t-1}^e + \Upsilon_t^q + \Upsilon_t^p
\]

for \( t = 0, 1, 2, \ldots \), where \( P_t = \int_0^1 P_t(j)^{1-\epsilon} \frac{dj}{1-\epsilon} \) is the unit price of the consumption basket, \( W_t \) is the nominal revenue per unit of labour, \( Q_t^e \) is the unit price of equity, \( i_t \) is the nominal interest rate on public bonds, \( D_t^e \) is the dividend paid on equity, \( \Upsilon_t^q \) are lump-sum net transfers by the government and \( \Upsilon_t^p \) are lump-sum net pay-outs by the private sector (i.e. by manufacturers, wholesalers and retailers). The household receives their wage as bank deposits at the beginning of period \( t \), and use them to buy consumption goods. The maximization problem is subject to standard solvency constraints ruling out Ponzi schemes on bonds and equity

\[
\lim_{T \to \infty} E_0 \left\{ \Lambda_{0,T} \frac{B_T^h}{P_T} \right\} \geq 0, \quad \lim_{T \to \infty} E_0 \left\{ \Lambda_{0,T} \frac{\varepsilon_T Q_T^e}{P_T} \right\} \geq 0
\]

where \( \Lambda_{0,T} = \beta^T \frac{C_T^{1-\sigma}}{C_T} \). Household’s optimality conditions write

\[
\chi C_t^\sigma L_t^e = \frac{W_t}{P_t} ;
\]

\[
1 = E_t \left\{ \Lambda_{t,t+1} \Pi_{t+1}^{-1} (1 + i_t) \right\} ;
\]

\[
Q_t^e = D_t^e + E_t \left\{ \Lambda_{t,t+1} \Pi_{t+1}^{-1} Q_{t+1}^e \right\} ;
\]

\[\text{Equity investment is used to finance capital in the manufacturing sector. For tractability, capital enters production right away (see details in Section [3,2]), and hence, dividends are paid in the same period when the equity investment is made.}\]
together with the sequence of budget constraints in (2) for \( t = 0, 1, 2, \ldots \), and the transversality conditions in (3), where \( \Lambda_{t,t+1} \equiv \beta \frac{C_{t+1}}{C_t} \) is the real stochastic discount factor, \( \Pi_t \equiv \frac{B_t}{P_{t-1}} \) is the (gross) inflation rate between \( t - 1 \) and \( t \).

### 4.2 Big Tech firm

The role of the Big Tech firm is twofold – one is to run a commerce platform which facilitates transactions between manufacturers and wholesalers, the other is to extend credit to manufacturers. We assume the Big Tech has the ability to collect data and process information about firms’ characteristics, and use it to gradually improve the matching efficiency on its commerce platform. The operating costs of the Big Tech firm are normalized to zero.

The Big Tech firm makes profits and builds net worth \( N^b_t \) by hosting the advertisements of sellers (manufacturers) on its commerce platform, and by perceiving a registration fee from buyers (wholesalers). Specifically, manufacturers that are not matched with wholesalers at time \( t \) (a measure \( I_t \)) post advertisements on the platform at a unit real cost \( \chi_m \). This implies a total real income for the Big Tech firm in period \( t \) from hosting the advertisements of manufacturers equal to \( \chi_m I_t \).

Furthermore, each wholesaler from the continuum of size one pays a unit real fee equal to \( \chi_w \) for each of the \( S_t \) wholesale suppliers it searches. This results in an additional real income for the Big Tech firm in period \( t \) equal to \( \chi_w S_t \). The Big Tech invests its net worth at the end of each period in nominal risk–free government bonds \( B^b_t \),

\[
B^b_t = N^b_t
\]

and hence,

\[
N^b_t = N^b_{t-1} (1 + i_{t-1}) + \chi_m P_t I_t + \chi_w P_t S_t
\]

Within each period, the Big Tech firm has the option to either keep funds idle, or to use them to extend intra–temporal loans to firms selling products on its commerce platform. Since the bond market opens only at the end of each period, a priori, the Big Tech is indifferent between keeping funds idle within period (and getting a zero return) or using them to extend credit (and getting the competitive intra-period loan interest rate which equals zero). For simplicity, we assume they prefer the latter option.\(^{10}\) The model is calibrated such that the net worth value of the Big Tech firm is

\(^{10}\) A marginally small market power on the intra-temporal loan market would make equilibrium loan market rate
strictly larger than the incentive–compatible credit that is willing to extend, namely

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

where \( \mathcal{L}_t^b(j) \) is the real value of incentive-compatible credit extended to manufacturer \( j \in [0, 1] \). The latter assumption implies that the Big Tech firm is not financially–constrained. Unlike banks, the Big Tech can exclude the sellers from its commerce platform in case of default. Thus, as described later on, while banks need to ask for physical collateral, the Big Tech can enforce repayment by threatening its clients with the exclusion from the commerce platform.

4.3 Manufacturers

The economy is populated with a continuum of perfectly competitive manufacturers indexed on the unit interval with access to an identical production technology

\[
y_t^m(j) = \xi(k_t^m(j))^\gamma(l_t^m(j))^{1-\alpha}, \quad j \in [0, 1]
\]

where \( k_t^m(j) \) is the capital stock used in production by manufacturer \( j \), \( l_t^m(j) \) is the labor hired by manufacturer \( j \), \( \xi \) is an exogenous technology process, and \( \gamma + (1-\alpha) < 1 \). In the current version of the model we assume decreasing returns to scale such that manufacturers have strictly positive profits in equilibrium given the levels of \( y_t^m \) and \( p_t^m \) decided in the bargaining process\(^{11}\).

Manufacturers sell products to wholesalers. To do so, they need to match with the latter via the Big Tech’s commerce platform. Every period, some of the existing matches split with exogenous probability \( \delta \), while new ones form with endogenous probability \( f(x_t) \) (Figure 5). Thus, at each point in time, the economy is populated with two types of manufacturers: those matched with wholesalers which use technology (10) to produce (a share \( A_t \)), and those without a match which do not produce and do not sell (a share \( I_t = 1 - A_t \)). The latter post instead an advertisement on the Big Tech platform to signal their availability to supply goods in the next period. For ease of exposition, hereafter, we’ll call the former “active”, and the latter “inactive”. The timeline of manufacturers’ operations is summarized in Table 1. Manufacturers found out in period \( t-1 \) their

\(^{11}\)With constant returns to scale, the profits of active manufacturers are negative given the price and quantities decided by Nash bargaining. An alternative way to make their profits positive would be to assume manufacturers are monopolistically competitive.
active or inactive status in period $t$. Active manufacturers at time $t$ produce and sell their output to wholesalers, while inactive ones post instead an advertisement at a unit price $\chi_m$ to attract potential clients (or to maintain the advertisement if they were also inactive at $t-1$).

### 4.3.1 Inactive manufacturers

As already mentioned, the $I_t$ manufacturers that are not matched with wholesalers at time $t$ do not produce and do not sell goods, and post instead ads on the Big Tech commerce platform at a fixed unit (real) cost $\chi_m$.

### 4.3.2 Active manufacturers

Since all $A_t$ manufacturers active at date $t$ produce the same quantity in equilibrium, we drop the index $j$ while describing their individual behaviour. The unit price $p_{t}^{m}$ and the quantity sold $y_{t}^{m}$ by each of them are determined each period in a decentralized manner via period-by-period collective Nash bargaining between the manufacturers and the wholesalers which are in a match at time $t$.[12]

Each manufacturer producing at time $t$ takes an intra-temporal loan $L_{t}$ to hire labor $l_{t}^{m}$ at

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[12] Note that the aggregate wholesale production is not predetermined at time $t$: even though the number of manufacturers producing at time $t$ ($A_t$) was decided at $t-1$, the quantity produced by each of them is decided at $t$. 

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Figure 5: Manufacturers’ transition probabilities between the active and inactive states from period $t$ to period $t+1$

Notes: $\delta$ is the probability that a manufacturer active at time $t$ becomes inactive at time $t+1$, while $f(x_t)$ is the probability that a manufacturer inactive at $t$ becomes active at $t+1$.
price $W_t$ and issues equity to buy capital $k_t^m$ at price $Q_t^k$ for convenience, we assume that each manufacturer issues a number of claims equal to the number of units of capital acquired

$$\mathcal{E}_t = k_t^m$$

(11)

and pays the marginal return on capital as dividend. Under this assumption, the price of each equity claim $Q_t^e$ equals in equilibrium the price of capital $Q_t^k$, namely, $Q_t^e = Q_t^k$.

We further assume that manufacturers incur capital refurbishment costs before reselling capital on the market, and that these costs equal a share $1 - \rho$ of the future capital value. This implies that the expected resale value of capital net of refurbishment costs equals $E_t\{\Lambda_{t,t+1}\rho(\frac{Q_{t+1}^k k_{t+1}^m}{P_{t+1}})\}$

(15)

Two value functions on the manufacturers’ side play an important role in the Nash bargaining process: (i) the value for a manufacturer of being “active” ($\mathcal{V}_t^A$), namely of being in a match, and (ii) the value for a manufacturer of being “inactive” ($\mathcal{V}_t^I$), namely of being looking for a match. The former equals

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

(12)

where $E_t\{\Lambda_{t,t+1}\left[(1 - \delta)\mathcal{V}_{t+1}^A + \delta \mathcal{V}_{t+1}^I\right]\}$ is the expected value of the manufacturing firm at $t + 1$ when with probability $1 - \delta$ will maintain its match with the wholesaler and gain $\mathcal{V}_{t+1}^A$, and with probability $\delta$ will lose this match and gain $\mathcal{V}_{t+1}^I$ instead.

The value for a manufacturer of being inactive at time $t$ and posting an advertisement equals

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

(13)

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13 Since firms’ capital is pledged as collateral for commercial bank loans, firms need to own their capital (rather than rent it). Therefore, we assume they buy it via equity rather than by using loans.

14 A similar simplifying assumption has been used in the literature for instance in Gertler and Karadi (2011).

15 The capital refurbishing cost is introduced to allow the credit constraint to bind for standard values of the collateral pledgeability ratio $\nu$ (equal to 70% under our baseline calibration). Without refurbishing cost, since capital is in fixed aggregate supply (and hence, does not depreciate), its real price significantly exceeds the value of the wage bill for plausible parameterizations of the model.

16 In our model, capital is chosen contemporaneously such that the value for a manufacturer of being inactive in the network at time $t$ is identical to the outside option for an active manufacturer when it enters the bargaining process. If capital were chosen instead one period in advance once a manufacturer found out that would be active in the following period, the two values would be different because inactive manufacturers would not have capital, while active manufacturers walking away from bargaining would be left with idle capital (and hence with the net capital gains).
where $E_t\{\Lambda_{t,t+1} [f(x_t) \mathcal{Y}^A_{t+1} + (1 - f(x_t)) \mathcal{Y}^I_{t+1}]\}$ is the expected value at $t+1$ when with (endogenous) probability $f(x_t)$ the manufacturer will be matched with a wholesaler and gain $\mathcal{Y}^A_{t+1}$, and with probability $1 - f(x_t)$ will remain inactive and gain $\mathcal{Y}^I_{t+1}$ instead.

The surplus of an active manufacturer from an existing match is thus given by

$$S^m_t \equiv \mathcal{Y}^A_t - \mathcal{Y}^I_t,$$

After replacing the expressions of $\mathcal{Y}^A_t$ from (12) and of $\mathcal{Y}^I_t$ from (13), and using manufacturer’s production technology (10) to compute $l_t^{m}(y_t^{m}, k_t^{m}) = \left[\frac{y_t^{m}}{\xi_t(k_t^{m})}\right]^{\frac{1}{1-\alpha}}$, one may write $S^m_t$ as a function of $y_t^{m}$, $p_t^{m}$ and $k_t^{m}$ as follows

$$S^m_t(p_t^{m}, y_t^{m}, k_t^{m}) = p_t^{m} - \frac{W_t l_t^{m}(y_t^{m}, k_t^{m})}{P_t k_t^{m}} + E_t\{\rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^{k} k_t^{m}}{P_{t+1}}\right]\} + \chi_m + (1 - \delta - f(x_t)) E_t\{\Lambda_{t,t+1} \left[S^m_{t+1}(p_{t+1}^{m}, y_{t+1}^{m}, k_{t+1}^{m})\right]\}$$

For future reference, we define the “reservation return of a manufacturer” $\Omega_t$ as the minimum gross return required by a manufacturer, namely as the return value $\frac{p_t^{m} y_t^{m}}{P_t}$ for which its surplus $S^m_t$ is 0:

$$\Omega_t = \frac{W_t l_t^{m}(y_t^{m}, k_t^{m})}{P_t} + \frac{Q_t^{k} k_t^{m}}{P_t} - E_t\{\rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^{k} k_t^{m}}{P_{t+1}}\right]\} - \chi_w - (1 - \delta - f(x_t)) E_t\{\Lambda_{t,t+1} \left[S^m_{t+1}\right]\}$$

Manufacturing activity is subject to financial frictions. A firm producing at time $t$ needs to finance the wage bill in advance of sales. The firm starts with no net worth and distributes profits each period to the household. It thus needs to finance the wage bill with an intra-temporal loan.

There are two sources of credit available: secured bank credit and big tech credit. Both types of credit are limited. Bank credit $\mathcal{L}^s_t$ is limited by the expected resale value of manufacturers’ collateral. The latter is given by a share $\nu$ of physical capital value net of refurbishing costs, implying\footnote{If banks seized wholesaler’s capital, they would need to pay themselves the maintenance costs before reselling it on the market.}

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

The amount of debt that manufacturers can issue to the Big Tech firm is also limited by moral hazard. This limit equals the expected gains for manufacturers from retaining access to the Big
Tech network in the following periods ($\mathcal{R}_{t+1}$):

$$L^b_t \leq b\mathcal{R}_{t+1}$$

(17)

where $\mathcal{R}_{t+1} \equiv E_t\left\{ \Lambda_{t,t+1} \left[ (1-\delta)\mathcal{Y}_{t+1}^A + \delta \mathcal{Y}_{t+1}^I \right] \right\}$ is the expected value of retaining access to the network if manufacturers behave and repay their credit. This is because manufacturers which default on big tech credit are automatically excluded from the commerce platform from next period onwards. If credit exceeded the expected gain of staying in the network, they would be better off defaulting and running away with the funds. Anticipating this, their creditors do not extend credit above what borrowers would get if they absconded such that the latter always have an incentive to repay.

In the current version, we assume that a share $b < 1$ of these future profits can be pledged as network collateral. The reason is twofold – first, as a short-cut for assuming that access is lost for a finite number of periods, and second, to account for alternative ways for manufacturers to sell their products outside the Big Tech commerce platform. In particular, if firms had the alternative to sell their products outside the commerce platform as well, and chose to default, they would then lose the *difference* between the expected profits on the Big Tech commerce platform and those with the alternative retail option. To the extent that that this difference is (roughly) proportional to a share of the expected profits on the commerce platform, setting $b < 1$ accounts for this additional dimension as well.

Given the two credit constraints, the total amount of credit that manufacturers can get is limited by both collateral and incentives to remain in the Big Tech network, namely

$$L^b_t + L^s_t \leq b\mathcal{R}_{t+1} + \nu E_t\left\{ \rho\Lambda_{t,t+1} \left[ \frac{Q_{t+1}^k}{P_{t+1}^k} k_m^t \right] \right\}$$

(18)

Since credit is used to finance labor, manufacturers’ borrowing constraint can be written as

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

(19)

---

18The rationale of assuming that the exclusion applies only to a finite number of periods has to do with Big Tech’s incentives. Specifically, the Big Tech may not want to exclude manufacturers forever from the commerce platform because it may lose in this case a substantial amount of fees. Alternatively, we could choose to tailor the expression of the network value to a particular number of finite exclusion periods. For instance, if manufacturers lost access to the commerce platform for only one period in case of default, the credit limit would be given by $\mathcal{R}_{t+1} - E_t\left\{ \Lambda_{t,t+2} V_{t+2} \right\}$. 

Note that a binding constraint on manufacturers’ credit ultimately limits manufacturers’ output, and hence, the aggregate supply of goods in the economy.

4.4 Wholesalers

There is a continuum of size one of such firms. They are all identical and perfectly competitive. Their behavior can thus be described by the decisions of a representative firm. The representative wholesaler purchases manufactured goods from all $A_t$ manufacturers active at time $t$ via the Big Tech commerce platform, and produces wholesale goods $Y^w_t$ with the following linear technology\textsuperscript{19}

$$ Y^w_t = \int_0^{A_t} y^m_t(j) dj $$

where $y^m_t(j)$ is the quantity purchased from the active manufacturer $j$ decided by Nash–bargaining. The quantity purchased from each active manufacturer is the same for all wholesalers

$$ y^m_t(j) = y^m_t \forall j \in [0, A_t], $$

implying that the output of the representative wholesaler (and of the wholesale sector as a whole) equals

$$ Y^w_t = A_t y^m_t $$

Each period the representative wholesaler actively searches on the Big Tech commercial platform for $S_t$ manufacturers for use in the following period (see the timeline in Figure \[1\]). We denote the value of a search by $\mathcal{S}^{s}$ (the subscript $s$ denoting "search") which equals

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

(20)

where $g(x_t) E_t \{ A_{t,t+1} \mathcal{S}^{B}_{t+1} \}$ is the expected gain of finding a supplier. Here, $g(x_t)$ denotes the probability to find one (to be defined shortly) and $\mathcal{S}^{B}_{t+1}$ its state–contingent value at $t + 1$ (where $B$ stands for "business" relation).

As long as the value of a search $\mathcal{S}^{s}$ is strictly positive, firms will add new searches. As the number of searches increases, the probability $g(x_t)$ that any open search finds a suitable manufacturing supplier decreases. A lower probability of filling an open search reduces the attractiveness of looking

\textsuperscript{19}We implicitly assume that at each date the active manufacturers are indexed on the interval $[0, A_t]$. 

17
for an additional supplier, and decreases the value of an open search. Thus, in equilibrium, at each
date t, wholesalers will look for new suppliers until the marginal value of an open search is zero.
Thus, the equation describing the number of searches $S_t$ is obtained for $s_t = 0$, namely for

$$
\chi_w = g(x_t) E_t \{ \Lambda_{t,t+1} s_{t+1}^B \} \tag{21}
$$

The value of an existing relation with a manufacturing supplier at time $t$ equals

$$
J_t^B = \frac{P^w_p}{P_t} y^w_t - \frac{p^m_t}{P_t} y^m_t + (1 - \delta) E_t \{ \Lambda_{t,t+1} J_{t+1}^B \} \tag{22}
$$

where $\frac{P^w_p}{P_t} y^w_t - \frac{p^m_t}{P_t} y^m_t$ are current real profits for the wholesaler from the relation with the supplier, and $(1 - \delta) E_t \{ \Lambda_{t,t+1} J_{t+1}^B \}$ is the expected value of the match at $t+1$ when with probability $1 - \delta$ it will be maintained. Since (21) holds in equilibrium, the expression of $J_t^B$ in (22) further writes as

$$
J_t^B = \frac{P^w_p}{P_t} y^w_t - \frac{p^m_t}{P_t} y^m_t + \frac{\chi_m (1 - \delta)}{g(x_t)} \tag{23}
$$

One may write expression (23) for $t+1$, and combine it with equation (21) to obtain the manufacturing supplier–search equation

$$
\frac{\chi_t}{g(x_t)} = E_t \{ \Lambda_{t,t+1} [ \frac{P^w_{t+1}}{P_{t+1}} y^w_{t+1} - \frac{p^m_{t+1}}{P_{t+1}} y^m_{t+1} + \frac{\chi_w (1 - \delta)}{g(x_{t+1})} ] \} \tag{24}
$$

The surplus for the representative wholesaler from an existing match is thus given by

$$
S^w_t = J_t^B - s_t^s \tag{25}
$$

which, using the expression of $J_t^B$ in (23) and $s_t^s = 0$, can be written in equilibrium as a function of $p^m_t$ and $y^m_t$ as follows

$$
S^w_t(p^m_t, y^m_t) = \frac{P^w_p}{P_t} y^w_t - \frac{p^m_t}{P_t} y^m_t + \frac{\chi_w (1 - \delta)}{g(x_t)} \tag{26}
$$

Using the expression above, one may simply rewrite (24) as:

$$
\frac{\chi_t}{g(x_t)} = E_t \{ \Lambda_{t,t+1} [ S^w_{t+1} ] \} \tag{27}
$$

For future reference, we define the “reservation cost of a wholesaler” $\bar{\Omega}_t$ as the maximum amount
that the representative wholesaler can pay for an additional manufactured goods supplier, namely
the value of \( \frac{w^m}{P_t} y_t^m \) for which its surplus \( S_t^w \) is 0,

\[
\bar{\Omega}_t \equiv \frac{P_t^w y_t^w}{P_t y_t} + \frac{\chi w(1 - \delta)}{g(x_t)}
\]  

(28)

4.5 Matching

Wholesalers search each period for inactive manufacturers in the network. That is, wholesalers
cannot buy their inputs on the manufactured goods market instantaneously. Rather, manufactured
goods suppliers need to be found first through a costly and time-consuming search process. If a
match is formed at time \( t \), manufacturers start producing and selling goods at time \( t + 1 \). The
matching function

\[ M(S_t, I_t) = \sigma_m S_t^\eta I_t^{1-\eta}, \eta \in (0, 1) \]

gives the number of manufacturers which post advertisements (and do not produce) closing a deal
with the wholesale sector at time \( t \). \( \sigma_m \in (0, 1) \) is a scale parameter reflecting the efficiency of the
matching process. As previously mentioned, we link the efficiency of the matching process \( \sigma_m \)
to the volume of data available to the Big Tech. The higher such volume, the more efficiently can the Big
Tech firm match sellers with buyers on the commerce platform. Notice that the matching
function is increasing in its arguments and satisfies constant returns to scale.

Since client-searching and matching is a time-consuming process, matches formed in \( t - 1 \) only
start producing in \( t \). Furthermore, existing matches on the manufactured goods market might be
severed for exogenous reasons at the beginning of any given period, so that the stock of active
matches is subject to continual depletion. We denote with \( \delta \) the exogenous fraction of the active
manufacturers which split with their client and need to post an advertisement. Hence, the number
of manufacturers active at time \( t + 1 \) (determined at \( t \)) evolves according to the following dynamic
equation

\[ A_{t+1} = (1 - \delta) A_t + M(S_t, I_t), \]

which simply says that the number of matched (active) manufacturers at the beginning of period
$t + 1, A_{t+1},$ is given by the fraction of matches in $t$ that survives to the next period, $(1 - \delta)A_t,$ plus the newly-formed matches at time $t,$ $M(S_t, I_t).$

We can now compute the endogenous probabilities for an inactive manufacturer to find a match $f(x_t),$ and for an open search to be filled by a manufacturer $g(x_t).$ We first define the manufactured goods market tightness $(x_t)$ as the relative number of open searchers relative to the number of inactive manufacturers

$$x_t \equiv \frac{S_t}{I_t}$$

(29)

The manufactured goods market is tight (the value of $x_t$ is high) when there are very few inactive manufacturers $I_t$ relative to the number open searches $S_t.$

The probability that an open search is filled with an inactive manufacturer, $g(x_t)$ equals

$$g(x_t) \equiv \frac{M(S_t, I_t)}{S_t} = \sigma_m \left( \frac{S_t}{I_t} \right)^{-\eta-1} = \sigma_m x_t^{-\eta-1}$$

(30)

Note that this probability decreases in $x_t,$ implying that wholesalers find its more difficult to find a manufactured goods supplier when the wholesale market is tight. Similarly, the probability that any inactive manufacturer is matched with an open search at time $t,$ $f(x_t),$ is given by

$$f(x_t) \equiv \frac{M(S_t, I_t)}{I_t} = \sigma_m \left( \frac{S_t}{I_t} \right)^{\eta} = \sigma_m x_t^{\eta}$$

(31)

and increases in $x_t.$ This implies that inactive manufacturers find wholesale clients more easily when the wholesale market tightness is high, that is, when the number of inactive manufacturers is low relative to the one of open searches by wholesalers.
### Table 1  Timeline operations – manufacturers and wholesalers

<table>
<thead>
<tr>
<th>Period</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t-1$</td>
<td>Each manufacturer $j \in [0,1]$ finds out if it is <strong>active</strong> or <strong>inactive</strong> at $t$</td>
</tr>
<tr>
<td>$t$</td>
<td><strong>Manufacturers:</strong> Manufacturer $j \in [0,1]$:</td>
</tr>
<tr>
<td></td>
<td>If <strong>active</strong>, produces and sells its output to wholesalers; to do so:</td>
</tr>
<tr>
<td></td>
<td>(i) at the beginning of the period, issues equity $E_t$ to buy capital $k^m_t$, gets working capital loan $L_t$ to hire labor $l^m_t$, and produces $y^m_t$;</td>
</tr>
<tr>
<td></td>
<td>(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.</td>
</tr>
<tr>
<td></td>
<td>If <strong>inactive</strong>, pays a fee $\chi_m$ to post an ad on the Big Tech platform, and transfers net period profit to the household</td>
</tr>
<tr>
<td>$t+1$</td>
<td><strong>Wholesalers:</strong> The representative wholesaler:</td>
</tr>
<tr>
<td></td>
<td>(i) buys inputs from all $A_t$ active manufacturing suppliers</td>
</tr>
<tr>
<td></td>
<td>(ii) searches for $S_t$ manufacturing suppliers for use at $t+1$, paying a unit fee equal to $\chi_w$ for each of these searches</td>
</tr>
<tr>
<td></td>
<td><strong>Matching:</strong></td>
</tr>
<tr>
<td></td>
<td>Active manufacturers and wholesalers bargain over the price $p^m_t$ and the quantity $y^m_t$ of manufactured goods</td>
</tr>
<tr>
<td>$t+1$</td>
<td>If <strong>active</strong> at $t$, manufacturer $j$ sells capital $k^m_t$ and pays the household back the value of its equity investment $Q^e_t E_{t-1}$.</td>
</tr>
</tbody>
</table>

### 4.6 Retailers

Retailers are monopolistically competitive and each produces a differentiated good $i \in [0,1]$. Each retailer $i$ buys wholesale goods, differentiate them with the technology

$$Y_t(i) = Y^w_t(i)$$ (32)
which transforms one unit of wholesale good into one unit of retail good, and then re-sells them to the household. Each retailer $i$ is subject to a downward sloping demand schedule

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

and sets its price in the presence of nominal rigidities à la Calvo (1983). Specifically, in any given period each retailer can reset its price with a fixed probability $1 - \theta$ that is independent of the time elapsed since the last price adjustment. Forward-looking retailers choose their price to maximize expected future discounted profits given the demand for the goods they produce and under the hypothesis that the price they set at date $t$ applies at date $t + k$ with probability $\theta^k$. The optimality condition associated with the problem above takes the form (see e.g. Galí (2015)):

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

where $M \equiv \varepsilon_1 / (1-\varepsilon)$ is the optimal markup in the absence of constraints on the frequency of price adjustment, and $\tau = \frac{1}{\varepsilon}$ a subsidy on the purchase of intermediate goods. This subsidy corrects for market power distortions in the flexible price version of the model (and, hence also in steady-state) and is financed with lump-sum taxes. With this subsidy, there are three remaining frictions in the model: nominal rigidities, matching frictions and credit frictions.

### 4.7 Banks

Banks finance intra-period secured loans by issuing intra-period deposits (used in transactions). These deposits are received by households at the beginning of the period and used to purchase consumption goods at the end of the period.

### 4.8 Central bank

The central bank sets the nominal risk–free policy rate $i_t$ in line with the simple rule

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

where $Y$ is steady-state output and $\nu_t$ is a monetary policy shock following an AR(1) process. By arbitrage, the risk-free interest rate on government bonds equals the policy rate in equilibrium.
4.9 Government

The government issues the one period public nominal risk–free bonds held by households $B^h_t$ and by the Big Tech firm $B^b_t$, subsidizes the purchase of wholesale goods by retailers at rate $\tau$, and balances the budget with lump–sum transfers/taxes $\Upsilon^g_t$:

$$B^h_t + B^b_t = (B^h_{t-1} + B^b_{t-1})(1 + \iota_{t-1}) + \Upsilon^g_t + \tau P^m_t \int_0^1 Y^m_t(i) \, di$$  \hspace{1cm} (36)

4.10 Market clearing

4.10.1 Retail goods market

Market clearing implies $C_t(i) = Y_t(i), \; \forall i \in [0, 1]$ and hence,

$$C_t = Y_t,$$ \hspace{1cm} (37)

where $Y_t = \int_0^1 Y_t(i)^{1 - \frac{1}{\epsilon}} \frac{d}{d}^\epsilon$. Using the definition of the aggregate price level and the fact that all firms resetting prices will choose an identical price $P^*_t$, we obtain that aggregate price dynamics in this environment are described by

$$P_t = \left[ \theta(P_{t-1})^{1-\epsilon} + (1 - \theta)(P^*_t)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}$$  \hspace{1cm} (38)

After dividing both sides by $P_{t-1}$, the expression above is equivalent to

$$\Pi_t^{1-\epsilon} = \theta + (1 - \theta) \left( \frac{P^*_t}{P_{t-1}} \right)^{1-\epsilon}$$  \hspace{1cm} (39)

4.10.2 Wholesale goods market

Market clearing requires aggregate demand for wholesale goods by all retailers $i \in [0, 1]$ to equal their aggregate supply by wholesalers:

$$\int_0^1 Y_t(i) \, di = Y^w_t$$  \hspace{1cm} (40)
4.10.3 Manufactured goods market

Market clearing requires aggregate demand for manufactured goods by wholesalers to equal their aggregate supply by all active manufacturers at time $t$:

$$Y^w_t = A_t y^m_t$$

The quantity produced by each wholesaler $y^m_t$ and the price of a manufactured good $p^m_t$ are determined by period–by–period Nash–bargaining. The outcome of the latter process is described in detail in the next section.

4.10.4 Capital market

Capital is in fixed aggregate supply $\bar{K}$ and does not depreciate (“real estate”). Market clearing requires aggregate demand for capital by all active manufacturers to equal its aggregate supply:

$$A_t h^m_t = \bar{K}$$

4.10.5 Labor market

Market clearing requires aggregate demand for labor by all active manufacturers to equal its supply by the representative household:

$$A_t l^m_t = L_t$$

4.10.6 Bond market

Market clearing requires that demand for government bonds by the household and by the Big Tech firm to equal their supply by the government:

$$B^h_t + B^b_t = B_t$$

4.10.7 Equity market

Market clearing requires that the demand for equity claims by the representative household to equal their supply by active manufacturers willing to finance physical capital:

$$E_t = A_t k^m_t$$
4.11 Bargaining

In equilibrium, the wholesalers and manufacturers which are in a match obtain a total return that is strictly higher than the expected return of unmatched wholesalers and manufacturers. The reason is that if a manufacturer and a wholesaler separate, each will have to go through an expensive and time-consuming process of search before meeting another partner. Hence, a realized job match needs to share this pure economic rent which is equal to the sum of expected search costs for two parties.

We assume that this rent is shared through period–by–period collective Nash bargaining. That is, the outcome of the bargaining process maximizes the weighted product of the parties’ surpluses from the match according to the parties’ relative bargaining power. Bargaining takes place along two dimensions, the price of a manufactured good $p^m_{it}$ and the manufactured output $y^m_{it}$, and it is subject to the manufacturers’ credit and technology constraints. As a result, the set $\{p^m_{it}, y^m_{it}\}$ is given by the solution to the following bargaining problem:

$$\{p^m_{it}, y^m_{it}, k^m_{it}\} = \arg\max \left[ S^m_t(p^m_{it}, y^m_{it}, k^m_{it}) \right]^{\epsilon} \left[ S^w_t(p^m_{it}, y^m_{it}) \right]^{1-\epsilon}, \quad 0 < \epsilon < 1$$

subject to

$$\frac{W^m_t}{\tilde{P}^i_t} (y^m_{it}, k^m_{it}) \leq b \mathcal{H}_{t+1} + \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[ Q^m_{t+1} \bar{k}^m_{t+1} \right] \right\}$$

(46)

where $\epsilon$ is the (relative) bargaining power of the active manufacturer. According to the credit constraint (46), the production cost cannot exceed the sum of the access value to the Big Tech platform $\mathcal{H}_{t+1}$ and of the physical collateral value $\nu E_t \left\{ \rho \Lambda_{t,t+1} \left[ Q^m_{t+1} \bar{k}^m_{t+1} \right] \right\}$ (21). Because the two parties bargain simultaneously over the price and individual quantity of manufactured goods, the outcome is (privately) efficient and the price of manufactured goods plays only a distributive role. As shown shortly, the Nash bargaining model, in effect, is equivalent to one where $y^m_{it}$ is chosen to maximize the joint surplus of the match, while $p^m_{it}$ is set to split that surplus according to parameter $\epsilon$.

The price $p^m_{it}$ chosen by the match satisfies the optimality condition

$$\epsilon S^m_t = (1 - \epsilon) S^w_t$$

(47)

---

20The optimal choices of $p^m_{it}$ and $y^m_{it}$ requires as well an appropriate choice of the capital stock $k^m_{it}$.

21$q^m_{it}$ is substituted in the bargaining problem using the technology constraint, and that the constraint entering the bargaining problem is a combination of the borrowing and technology constraints.
As mentioned above, this condition implies that the total surplus of a match is shared according to the parameter $\epsilon$. Specifically, letting $S^T_t \equiv S^m_t + S^w_t$ denote the total surplus from a match, we obtain from (47) that $S^m_t = \epsilon S^T_t$ and $S^w_t = (1 - \epsilon)S^T_t$. Using the expressions of $S^m_t$ from (14), and of $S^w_t$ from (26), one may further write (47) as an equation in $p^m_t$ as follows

\[
\frac{p^m_t}{P_t} y^m_t = \epsilon \bar{\Omega}_t + (1 - \epsilon)\Omega_t
\]

We now turn to the determination of quantity $y^m_t$ chosen by the match. The latter satisfies the following optimality condition

\[
y^m_t : \epsilon S^w_t \left( \frac{W_t \partial l^m_t(y^m_t, k^m_t)}{P_t} - \frac{p^m_t}{P_t} \right) = (1 - \epsilon)S^m_t \left( \frac{P^w_t}{P_t} - \frac{p^m_t}{P_t} - \frac{\lambda_t}{1 - \epsilon} \frac{W_t \partial l^m_t(y^m_t, k^m_t)}{\partial y^m_t} \frac{S^w_t}{S^m_t} \right)
\]

where $\lambda_t \geq 0$ is the Lagrangian multiplier on a manufacturer’s credit constraint. Using (47), this optimality condition can be further simplified under our baseline calibration with $\epsilon = 1 - \epsilon$ as

\[
\frac{P^w_t}{P_t} = \frac{1}{1 - \alpha} \frac{W_t y^m_t}{P_t} \left[ 1 + \frac{\lambda_t}{1 - \epsilon} \right], \quad \lambda_t \geq 0
\]

In the absence of credit frictions, this condition implies that the real return for a wholesaler on a manufactured good equates its marginal production cost at the manufacturer level. With credit frictions, tighter credit constraints (i.e. higher $\lambda_t$) translate in higher marginal production costs and hence in upward pressures on inflation.

Finally, the optimality condition with respect to capital for $\epsilon = 1 - \epsilon$ writes as

\[
\frac{Q^k_t}{P_t} = \gamma \frac{P^w_t}{P_t} y^m_t + \left( 1 + \frac{\nu \lambda_t}{\epsilon} \right) E_t \left\{ \rho \Lambda_{t+1} \left[ \frac{Q^k_{t+1}}{P_{t+1}} \right] \right\}
\]

In the absence of credit frictions, this condition defines a standard capital demand equation where the price of capital equals its marginal return and the discounted value of its future expected value.

Note that with credit frictions capital demand accounts for how capital affects the tightness of the credit constraint via the collateral value. Subsequently, the marginal nominal return on capital, and

---

22 Note that the optimization problem is rephrased such that $\lambda_t \geq 0$.

23 The relative bargaining power of sellers and buyers may play an important role for the equilibrium allocation. In this analysis however we remain agnostic about such effects and give both equal bargaining power. This allows also to simplify the equilibrium expressions.
hence the nominal dividend paid to the household at time $t$ on each equity claim equals

$$D^e_t = \gamma P_{t^m}^y \frac{y^m_t}{k^m_t} + \left( P_t \frac{\nu \lambda_t}{\epsilon} \right) E_t \left\{ \frac{\rho \Lambda_{t,t+1}}{P_{t+1}} \left[ \frac{Q^k_{t+1}}{P_{t+1}} \right] \right\} \quad (50)$$

As credit constraints tighten (i.e. $\lambda_t$ increases), the price of capital increases. This is because its marginal value as collateral asset (and hence, its marginal contribution in production) increases. To sum up, equations (46), (47), (48), (49) and (50) describe the outcome of the bargaining process which determines $\lambda_t$, $p^m_t$, $y^m_t$, $k^m_t$ and $D^e_t$. Without matching and credit frictions, the model nests the basic three-equations NK model.\textsuperscript{24}

5 Parametrization of the model

We parametrize our model at quarterly frequency. One may split structural parameters of the model in four groups (Table 2). The first group includes the standard of the basic New Keynesian model (i.e. discount factor $\beta$, curvature of consumption utility $\sigma$, curvature of labor disutility $\varphi$, labor share $1 - \alpha$, elasticity of substitution between retail goods $\varepsilon$, Calvo index of price rigidities $\theta$). These parameters are set to their textbook values in Galí (2015), Chapter 3. The labor disutility parameter $\chi$ is also standard and chosen such that the efficient level of labor in steady state is one. Policy coefficients $\phi_{\pi}$ and $\phi_{y}$ are set to describe the Taylor (1993) policy rule.

The second group of parameters concerns physical capital. In this group, the index to decreasing returns to capital (real estate) is set as in Iacoviello (2005), capital pledgeability ratio is set to 0.7, fixed capital aggregate supply is normalized to 1, and refurbishing costs are set to 15% from capital market value. The latter are introduced to make the credit constraint bind in steady-state.

The third group of structural parameters concerns the standard search and matching parameters – the relative bargaining power $\epsilon$, the matching function parameter $\eta$ and the probability to separate from an existing match $\delta$. We choose to remain agnostic about the effects of the relative bargaining power $\epsilon$ and the relative contribution to matching $\eta$, by setting both to 0.5. The probability to separate from an existing match is set to 5%.

The final group of parameters plays a key role in the parametrization of our model. This category is composed by: the matching efficiency $\sigma_m$ which takes values from 0 to 1, the fees perceived by

\textsuperscript{24}This is also true without credit frictions only when $\gamma = \alpha$ (i.e. for constant returns to scale).
Table 2: Parametrization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Discount factor</td>
<td>0.995</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Curvature of consumption utility</td>
<td>1</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>Curvature of labor disutility</td>
<td>5</td>
</tr>
<tr>
<td>$\chi$</td>
<td>Labor disutility</td>
<td>0.75</td>
</tr>
<tr>
<td>$1 - \alpha$</td>
<td>Labor share</td>
<td>0.75</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Elasticity of substitution of goods</td>
<td></td>
</tr>
<tr>
<td>$\theta$</td>
<td>Calvo index of price rigidities</td>
<td>0.75</td>
</tr>
<tr>
<td>$\phi_\pi$</td>
<td>Taylor coefficient inflation</td>
<td>1.5</td>
</tr>
<tr>
<td>$\phi_y$</td>
<td>Taylor coefficient output</td>
<td>0.5/4</td>
</tr>
<tr>
<td>$\bar{K}$</td>
<td>Fixed supply of capital (real estate)</td>
<td>1</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Elasticity of output to real estate</td>
<td>0.03</td>
</tr>
<tr>
<td>$1 - \rho$</td>
<td>Capital refurbishing cost (% from capital value)</td>
<td>15%</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Pledgeability ratio of capital as collateral</td>
<td>0.7</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Relative bargaining power of the seller</td>
<td>0.5</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Matching function parameter</td>
<td>0.5</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Probability to separate from an existing match</td>
<td>5%</td>
</tr>
<tr>
<td>$\chi_w$</td>
<td>Big tech fees for manufacturers</td>
<td>0.1</td>
</tr>
<tr>
<td>$\chi_m$</td>
<td>Big tech fees for wholesalers</td>
<td>0.3</td>
</tr>
<tr>
<td>$b$</td>
<td>Pledgeability ratio of network value</td>
<td>0.7</td>
</tr>
<tr>
<td>$\sigma_m$</td>
<td>Matching efficiency</td>
<td>[0, 1]</td>
</tr>
</tbody>
</table>

Note: Values are shown in quarterly rates.

the Big Tech network, $\chi_w$ and $\chi_m$, set such that the matching probability $g(x) \in [0, 1] \forall \sigma_m \in [0, 1]$ in steady-state $\forall \sigma_m \in [0, 1]$, and the network value pledgeability ratio $b$ set to 10%. The latter parameter value proxies for a finite period exclusion from the commerce platform in case of default, as well as for an outside retail option available to the manufacturer (not observed in equilibrium).

6 Comparative statics

This section studies how the provision of big tech credit affects steady-state allocation, and how these effects vary with the matching efficiency between sellers and buyers on Big Tech’s commerce platform. To do so, we solve for the steady-state of the model as a function of the matching efficiency
σ_m. To disentangle the effect of big tech credit, we compare results in our baseline case (blue line) with those in a counterfactual economy without big tech credit (red line), i.e. with bank credit only. With this exercise, we aim to shed some light on how Big Techs’ entry into finance has already started to affect the macroeconomy, and how these effects may change as these companies acquire more data on their clients, and are able to match more efficiently sellers with buyers on their commerce platforms.

According to our results reported in Figure 6, the availability of big tech credit increases total credit (left middle panel), relaxes credit constraints (middle right panel) and reduces the output gap (top left panel). These effects work via the binding borrowing constraint (46). Specifically, the availability of big tech credit allows manufacturers to pledge their future expected profits V_{t+1} (top right panel) as “network collateral” alongside physical capital. Everything else equal, the higher collateral allows manufacturers to borrow more, and to hire more labor. This leads to higher output and a relaxation of credit constraints.

Notably, the higher output translates in a higher value for manufacturers to be active in the network (bottom right panel), and hence, to even higher expected profits than in the absence of big tech credit. As a result, a key feedback loop emerges between the volume of big tech credit and manufacturers’ output which works to amplify the effect of this new type of credit on the macroeconomy.

The effect of big tech credit is magnified as the matching efficiency on the commerce platform rises. A higher matching efficiency increases the probability for a manufacturer to find a client (bottom left panel in Figure 6), and leads to higher expected profits, a higher value of being active on the commerce platform (top right panel), and ultimately a larger “network collateral” (right top panel). Everything else equal, the higher network collateral allows manufacturers to borrow more (46), and hire more labor. This relaxes to a larger extent the tightness of borrowing constraints relative to the case with bank credit only (middle right panel) and translates in larger effects on total credit and output (gap). The increased relevance of big tech credit is also reflected in its higher share in total credit (Figure 7).
Figure 6: Steady-state equilibrium as a function of 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 \(b Y\). Total credit: Aggregate big tech credit and bank credit. Manufacturer value of being active: \(V\). Probability to find a wholesale client: \(f(x)\). Matching efficiency: \(\sigma_m\)
7 Dynamic analysis: response to a monetary policy shock

How does Big Techs’ entry into finance affect the transmission of monetary policy? We turn now to our core research question by comparing the dynamic responses to monetary policy in our baseline economy with those in a counterfactual economy without big tech credit. As in the previous section, we look first at the effect of big tech credit at a given matching efficiency, and then study how this effect varies as the matching efficiency on Big Tech’s commerce platform increases. For the first experiment, we parametrize the matching efficiency to match the steady-state elasticities of bank credit to real estate and of big tech credit to network profits to the ones estimated by Gambacorta et al. (2022) in China.²⁵

Figure 8 shows that access to big tech credit dampens the response of output to monetary policy, and that the effect works via the credit channel. Specifically, in the baseline case with both types of credit (dark blue line), output (top left panel) responds less to monetary policy than in the counterfactual economy with bank credit only (red line). The figure shows that the weaker response of output is associated with a weaker response of total credit (top right panel), explained by a low sensitivity of big tech credit compared to that of secured bank credit (middle panels). The lower sensitivity of big tech credit can be further traced to the significantly lower sensitivity of “network collateral” (i.e. expected profits on the Big Tech platform, bottom left panel) compared to that of physical collateral (i.e. real estate values pledged as collateral, bottom right panel). The findings in

²⁵See Figures A1 and A8 in the Appendix.
Figure 8 are corroborated by the comparison of the dynamic responses to monetary policy in the (counterfactual) polar economies with big tech credit only and, respectively, with bank credit only.\footnote{See Figure A4 in the Appendix. For comparison reasons, the level of matching efficiency is set such that the two polar economies are characterized by the same output to credit ratio and the same credit constraint tightness (i.e. at the intersection of the violet and red lines in Figure A6 in the Appendix.)}
The effects of big tech credit on monetary policy transmission are found to be even stronger for higher levels of matching efficiency. Specifically, the effect of monetary policy on output is weaker if the matching efficiency is higher than the baseline efficiency considered in Figure 8 (Figure 9, blue line), while no such differences exist in the absence of big tech credit (Figure A5 in the Appendix). This is because a higher share of total credit, the share of big tech credit, is less responsive to monetary policy.

![Figure 9: Dynamic responses to a monetary policy shock](image)

**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) (see figure A8 in the Appendix). 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 Figure 6 (blue solid line). The monetary policy regime is described by simple Taylor rule (1993).
The quantitatively insignificant response of big tech credit and the strong response of bank credit in the middle panels in Figures 8 or 9 are broadly in line with the empirical estimates in section 3. Thus, overall, our empirical and analytical results point to a dampening of the effect of monetary policy on credit and output as the matching efficiency of Big Tech platforms and the share of big tech credit rise.

8 Conclusions

Motivated by the recent advent of Big Tech companies into finance, we study how this may shape the transmission of monetary policy. We first document that Big Tech and bank credit respond very differently to monetary policy, and then develop a model to rationalize our findings and help make predictions for the future. Our model focuses on the interaction between firms on the e-commerce platforms and on business-to-business (B2B) transactions, which account for 80% of global online transactions. In our framework, a Big Tech platform intermediates the search and matching between manufacturers and wholesalers and extends working capital loans to the former subject to limited commitment. Firms have access to both big tech credit and secured bank credit. Nominal prices are rigid and monetary policy affects real economic dynamics.

According to our model, big tech credit reacts less to monetary policy due to a more muted response of firms’ opportunity cost of default on this type of credit (future profits) compared to that of bank credit (physical collateral). Furthermore, as matching efficiency on Big Tech’s commerce platform rises, our analysis shows that the expansion in firms’ profits leads to a higher opportunity cost of default on big tech credit, a higher borrowing limit, looser credit constraints and, ultimately, a higher share of big tech credit. The latter, coupled with the muted response of this new type of credit, leads to weaker responses of credit and output to monetary policy when matching efficiency on Big Tech’s commerce platform is higher.

Going forward, one may extend our analysis to include interalia, business-to-consumer (B2C) transactions and household credit, Big Techs’ financing constraints, complementarity/substitutability between big tech credit and bank credit, Big Tech’s market power, or a trade-off between efficiency and privacy.
9 References


Hau, H., Y. Huang, H. Shan, Z. Sheng (2018). Fintech credit, financial inclusion and en-


10 Appendix

10.1 Empirical evidence on the elasticities of big tech credit

![Figure A1: Elasticity of credit with respect to house prices and GDP](image)

Notes: 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. Source: Gambacorta et al. (2022).

We evaluate some of the results in our dynamic analysis taking into consideration evidence in the existing empirical literature. Using a unique dataset of more than 2 million Chinese firms that received credit from both an important Big Tech firm (Ant Group) and traditional commercial banks, Gambacorta et al. (2022) investigates how different forms of credit correlate with local economic activity, house prices and firm characteristics. Figure A1 gives a summary of the results reporting the elasticity between the different credit types with respect to house prices and local GDP. The main result is that big tech credit does not correlate with local business conditions and house prices when controlling for demand factors, but reacts strongly to changes in firm characteristics, such as transaction volumes and network scores used to calculate firm credit ratings. By contrast, both secured and unsecured bank credit react significantly to local house prices, which incorporate useful information on the environment in which clients operate and on their creditworthiness. This evidence implies that the wider use of big tech credit could reduce the importance of the collateral channel.
10.2 Additional information on the VAR analysis

This section reports some additional information on the VAR analysis. In particular Table A1 reports the summary statistics of the variables used in the regression, while Table A2 shows the results for the unit root Phillips–Perron tests for all variables in first differences.

<table>
<thead>
<tr>
<th>Observations</th>
<th>Mean</th>
<th>Std dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Ln(property price index)</td>
<td>274</td>
<td>0.05</td>
<td>0.05</td>
<td>-0.02</td>
</tr>
<tr>
<td>Δ Ln(real GDP)</td>
<td>304</td>
<td>0.01</td>
<td>0.09</td>
<td>-0.16</td>
</tr>
<tr>
<td>Δ Ln(CPI)</td>
<td>304</td>
<td>0.03</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Δ Ln(banking credit)</td>
<td>304</td>
<td>0.07</td>
<td>0.13</td>
<td>-0.32</td>
</tr>
<tr>
<td>ΔLn(total alternative credit)</td>
<td>304</td>
<td>0.38</td>
<td>0.73</td>
<td>-0.22</td>
</tr>
<tr>
<td>Δ Ln(big tech credit)</td>
<td>304</td>
<td>0.29</td>
<td>1.17</td>
<td>-1.61</td>
</tr>
<tr>
<td>Δ Ln(fintech credit)</td>
<td>304</td>
<td>0.39</td>
<td>1.22</td>
<td>-4.29</td>
</tr>
<tr>
<td>Δ short term rate</td>
<td>304</td>
<td>-0.23</td>
<td>1.56</td>
<td>-9.50</td>
</tr>
</tbody>
</table>

Table A1: Summary statistics

Notes: The sample includes 19 countries over the period 2005-2020. Data winsorised at the 5th and 95th percentiles. Total alternative credit is defined as the sum of fintech- and big tech credit. Sources: Cornelli et al. (2020); BIS; national data; authors’ calculations.

<table>
<thead>
<tr>
<th>Δ Ln (property price)</th>
<th>Δ Ln (real GDP)</th>
<th>Δ Ln (CPI)</th>
<th>Δ Ln (banking credit)</th>
<th>ΔLn (alternative credit)</th>
<th>ΔLn (Big Tech)</th>
<th>Δ Ln (fintech credit)</th>
<th>Δ (short term)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stat</td>
<td>P-value</td>
<td>Stat</td>
<td>P-value</td>
<td>Stat</td>
<td>P-value</td>
<td>Stat</td>
<td>P-value</td>
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<td>Inverse chi-squared (38)</td>
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<td>134.3</td>
<td>0.00</td>
<td>104.6</td>
<td>0.00</td>
<td>7.1</td>
</tr>
<tr>
<td>Inverse normal</td>
<td>-4.0</td>
<td>0.00</td>
<td>-7.3</td>
<td>0.00</td>
<td>-5.8</td>
<td>0.00</td>
<td>-4.3</td>
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<tr>
<td>Inverse logit (99)</td>
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<td>Modified inv chi-squared</td>
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<td></td>
<td>100.1</td>
<td>0.00</td>
<td>203.5</td>
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</table>

Table A2: Unit root tests

Notes: Based on Phillips-Perron tests. The null hypothesis is that all panels contain unit roots. The sample includes 19 countries over the period 2005-2020. Data winsorised at the 5th and 95th percentiles. Sources: authors’ calculations.

The lag selection has been based on a number of tests. Below Table A3 presents results from the first-, second-, third-, and fourth-order panel VAR models using the first four lags of the endogenous variables as instruments. For the fourth-order panel VAR model, only the coefficient of determination (CD) is calculated because the model is just-identified. Based on the three model-selection criteria by Andrews and Lu (2001), the first-order panel VAR is the preferred model because this has the
smallest MBIC, MAIC, and MQIC. For a lag equal to 1 also the CD is minimized.\textsuperscript{27}

<table>
<thead>
<tr>
<th>Lags</th>
<th>CD</th>
<th>J</th>
<th>J pvalue</th>
<th>MBIC</th>
<th>MAIC</th>
<th>MQIC</th>
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<tr>
<td>1</td>
<td>0.86</td>
<td>133.59</td>
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<td>-92.41</td>
<td>-228.16</td>
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<td>2</td>
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<td>0.92</td>
<td>-328.17</td>
<td>-87.87</td>
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<td>3</td>
<td>0.98</td>
<td>22.23</td>
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<td>-169.92</td>
<td>-49.77</td>
<td>-98.35</td>
</tr>
<tr>
<td>4</td>
<td>0.96</td>
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<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table A3: Lag selection

Notes: The sample includes 19 countries over the period 2005-2020. Data winsorised at the 5th and 95th percentiles. Sources: Cornelli et al. (2020); BIS; national data; authors’ calculations.

After fitting the reduced-form panel VAR, it is useful to understand whether past values of a variable, say, $x$, are useful in predicting the values of another variable $y$, conditional on past values of $y$, that is, whether $x$ "Granger-causes" $y$ (Granger (1969)). This is implemented as separate Wald tests with the null hypothesis that the coefficients on all the lags of an endogenous variable are jointly equal to zero; thus the coefficients may be excluded in an equation of the panel VAR model.

Table A4 below shows the test on whether the coefficients on the lags of each variable are zero. For example, the tests that the changes in banking credit or monetary policy interest rates do not Granger-cause the change in the logarithm of the property price index are rejected at the 95% confidence level. Interestingly, while total alternative credit does not Granger cause the property price index, it Granger causes CPI prices, banking credit and the short term rate. Total alternative credit marginally Granger causes real GDP (p-value 0.13) also in consideration of its still limited macroeconomic impact.

The coefficients on the reduced-form panel VARs cannot be interpreted as causal influences without imposing identifying restrictions on the parameters. If the fitted VAR model is stable, it can be reformulated as an infinite-order VMA, on which assumptions about the error covariance matrix may be imposed. Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs) have known interpretation when the panel VAR model is stable. Figure A2 shows that our PVAR is stable because all the moduli of the companion matrix are smaller than one and the roots of the companion matrix are all inside the unit circle.

\textsuperscript{27}While we also want to minimize Hansen’s J statistic, it does not correct for the degrees of freedom in the model like the MMSC by Andrews and Lu (2001).
<table>
<thead>
<tr>
<th>Equation /excluded</th>
<th>$\Delta \text{Ln}$ (property price index)</th>
<th>$\Delta \text{Ln}$ (real GDP)</th>
<th>$\Delta \text{Ln}$ (CPI)</th>
<th>$\Delta \text{Ln}$ (banking credit)</th>
<th>$\Delta \text{Ln}$ (alternative credit)</th>
<th>$\Delta$ short term rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{Ln}$ (property price index)</td>
<td>chi2</td>
<td>df</td>
<td>P-value</td>
<td>chi2</td>
<td>df</td>
<td>P-value</td>
</tr>
<tr>
<td>$\Delta \text{Ln}$ (real GDP)</td>
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<td>0.91</td>
<td>13.2</td>
<td>1</td>
<td>0.00</td>
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<td>$\Delta \text{Ln}$ (CPI)</td>
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<td>0.71</td>
<td>0.0</td>
<td>1</td>
<td>0.97</td>
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<tr>
<td>$\Delta \text{Ln}$ (banking credit)</td>
<td>2.5</td>
<td>1</td>
<td>0.12</td>
<td>6.9</td>
<td>1</td>
<td>0.01</td>
</tr>
<tr>
<td>$\Delta \text{Ln}$ (alternative credit)</td>
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<td><strong>0.01</strong></td>
<td>109.9</td>
<td>1</td>
<td>0.00</td>
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<tr>
<td>$\Delta$ short term rate</td>
<td>0.0</td>
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<td>0.89</td>
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<tr>
<td>All</td>
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<td>0.00</td>
<td>145.6</td>
<td>5</td>
<td>0.00</td>
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</table>

Table A4: PVAR Granger test

Notes: The null hypothesis of the test is that the excluded variable does not Granger-cause the equation variable. The sample includes 19 countries over the period 2005-2020. Data winsorised at the 5th and 95th percentiles. Sources: Cornelli et al. (2020); BIS; national data; authors’ calculations.
Now that we have established that the panel VAR model is stable, we can calculate orthogonalized IRFs and FEVDs. Orthogonalized IRFs and FEVDs may change depending on how the endogenous variables are ordered in the Cholesky decomposition. Specifically, the ordering constrains the timing of the responses: shocks on variables that come earlier in the ordering will affect subsequent variables contemporaneously, while shocks on variables that come later in the ordering will affect only the previous variables with a lag of one period.

In order to evaluate how much of the variability of the real GDP is driven by changes in banking credit and total alternative credit, we have computed the forecast error variance decomposition (FEVD) for different variables. This exercise helps us to get a sense of the amount of information coming from each variable in the formation of the forecasts. The top centre panel of Figure A3 shows that a substantial part of the variability of real GDP is explained by bank credit. This could be due to the importance of the credit channel in the financing of consumption and investment. Almost one quarter of the real GDP variability can be attributed to the bank credit variable. Changes in interest rates explain about 5% of the GDP variability, while changes in the CPI explain another 7%. Asset price movements contribute only for 3%, while the impact of total alternative forms of credit contribute for less than 2%, due to the still limited macroeconomic footprint of this form of credit.
Figure A3: Forecast-error variance decomposition

Notes: The graphs show the forecast-error variance decomposition. The response variable is indicated in the panel title and the impulse variable in the legend. The horizontal axis reports the number of steps in the simulation. Source: Authors’ calculations.
10.3 Model-based dynamic responses to a monetary policy shock

Figure A4: Dynamic responses to a monetary policy shock

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). As shown in the middle panel in Figure 6 by the red and the magenta lines, this obtains for $\sigma_m \approx 0.85$. 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.
Figure A5: Dynamic responses to a monetary policy shock

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 Figure 6 (blue solid line). 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.
Figure A6: Steady-state equilibrium as a function of 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 \(bY^a\). Total credit: Aggregate big tech credit and bank credit. Manufacturer value of being active: \(Y^a\). Probability to find a wholesale client: \(f(x)\). Matching efficiency: \(\sigma_m\).
Figure A7: Steady-state and matching efficiency

Notes: Share of big tech credit: ratio of big tech credit and total credit. Matching efficiency: $\sigma_m$

Figure A8: Steady-state and matching efficiency

Notes: Matching efficiency: $\sigma_m$