

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 affects the macroeconomy and the transmission of monetary policy. We first document a set of stylized facts on bigtech credit. We then rationalize this evidence through the lens of a model where Big Techs facilitate firms' matching on the trade platform and extend working capital loans, thus adding another source of finance 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) an increase in Big Tech's matching efficiency on the commerce platform raises the value for firms of trading in the platform and the availability of big tech credit, driving output closer to the efficient level; (ii) credit and output responds less to monetary policy due to the more muted response of firms' profits relative to physical collateral.

JEL classification: E44, E51, E52, G21, G23

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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 some relevance, and given the rise in e-commerce, has the potential to spread worldwide very rapidly (Cornelli et al. (2020)).¹

Changes in financial intermediation can 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, monetary policy will 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 the macroeconomy and on monetary policy transmission. We start by documenting some stylized facts on big tech credit. First, using existing evidence on China we document that big tech credit reacts by less to changes in asset prices and local economic conditions than bank credit. Second, because of their different characteristics these two forms of credit respond also very differently to a monetary policy shock. Specifically, using a simple panel-VAR analysis we document that while bank credit follows closely the response of house prices (typically used as collateral) and reacts very strongly

¹Available 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.

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 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. 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.

We obtain two sets of results. First, an expansion in Big Techs, as captured by an increase in matching efficiency on the commerce platform, raises the value for firms of trading in the platform and the availability of big tech credit. This in turn relaxes financing conditions and raises firms' output, driving aggregate output closer to the efficient level. Second, credit and output react less to monetary policy when firms have access to big tech credit. For given matching efficiency of Big Techs, this is due to a more muted response of firms' opportunity cost of default on big tech credit (future profits) compared to that on bank credit (physical collateral). Furthermore, as matching efficiency on Big Tech's commerce platform rises, the expansion in firms' profits leads to a higher value of trading in the platform and a larger share of big tech credit. The latter, coupled with the muted response of this new type of credit, leads to a weaker response of credit and output to monetary policy.

Our paper contributes to two broad strands of literature. The first is the "financial accelerator" literature where 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 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.²

Second, our paper contributes to the literature on financial inclusion by showing 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.

The paper proceeds as follows. Section 2 describes some stylised facts on big tech credit and reports some simple 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 3

²Furthermore, 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. Drechsel (2022), Lian and Ma (2021)).

describes our theoretical framework with a special focus on the dual role of the Big Tech firm as commerce platform and financial intermediary. Section 4 describes the parametrization of the model. Section 5 shows the steady-state equilibrium as a function of the matching efficiency between sellers and buyers on the commerce platform. Section 6 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 Some stylised facts on Big Tech credit and the transmission of monetary policy shocks

2.1 Expansion of big tech credit and e-commerce

Big tech platforms have expanded their lending around the world. Cornelli et al. (2020) estimates that the flow of these new forms of credit reached USD 572 billion in 2019, more than doubling traditional fintech credit (Figure 1, left-hand panel). While fintech credit models are built around decentralised platforms where individual lenders choose borrowers or projects to lend to in a market framework, big tech credit is based on a network activity that is developed mainly via e-commerce platforms. Big Techs can use large-scale micro-level data on users, often obtained from non-financial activities, to mitigate asymmetric information problems. There is substantial variation across countries, with the Big Tech credit equivalent to 3.5% of the stock of total credit in China, 2.0% in Kenya and around 1% in Korea. These figures have further expanded in recent years, especially during the Covid-19 pandemic due to the strong increase in e-commerce activity.

Since 2017, e-commerce revenues have risen from an estimated \$1.4 trillion to \$2.4 trillion, or about 2.7% of global output (Figure 2, left-hand panel). 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. Most of the activity is business-to-business (B2B) transactions (i.e. transactions between firms), which account for 80% of global online transactions (Figure 2, right-hand panel).

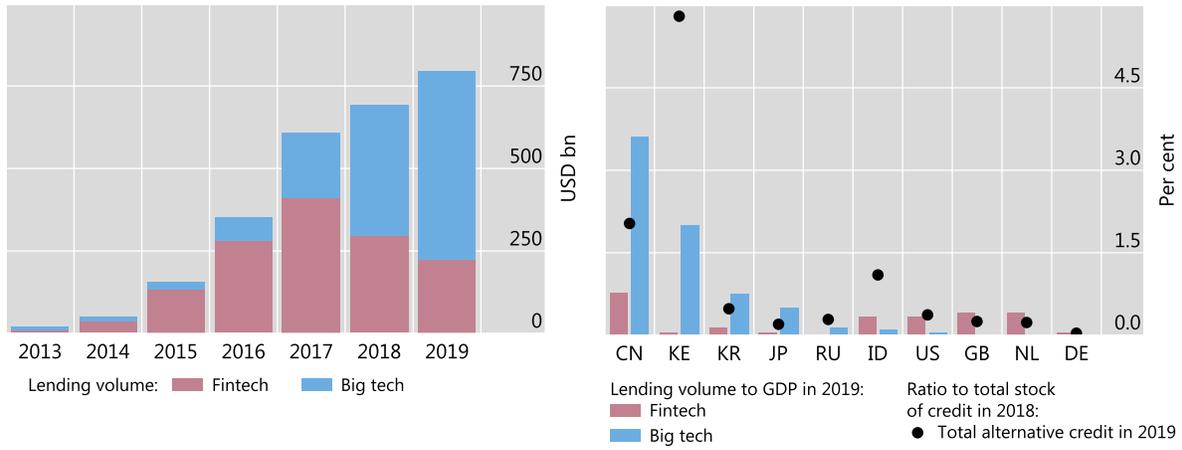


Figure 1: Upward trend in big tech credit

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. 2019 fintech lending volume figures are estimated for AU, CN, EU, GB, NZ and US. Sources: Cornelli et al. (2020).

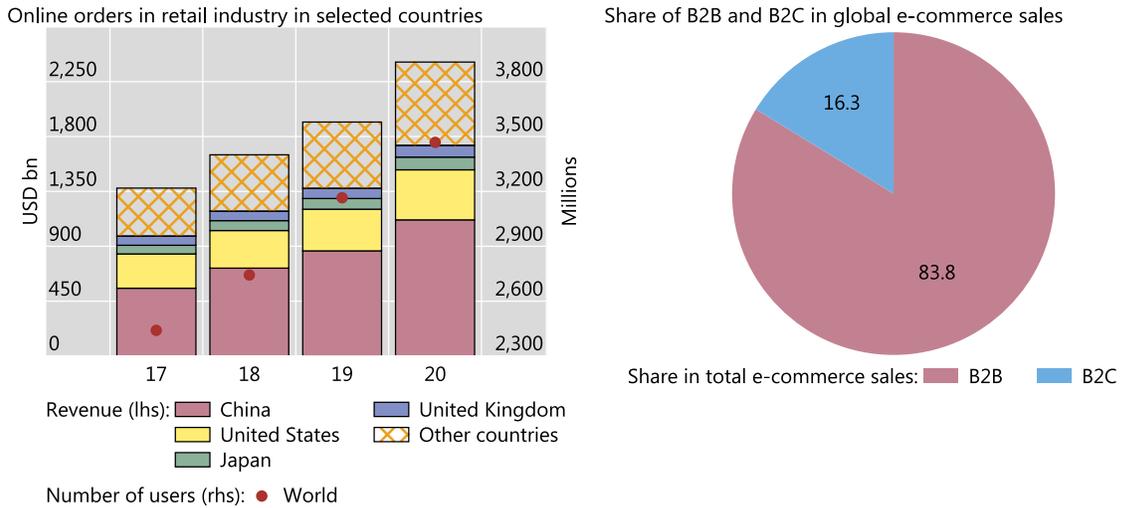


Figure 2: Upward trend in e-commerce, mostly via Big Tech platforms

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

2.2 Big tech credit vs bank credit

Big tech credit is not collateralised and it has a shorter maturity than bank credit. For the case of China, Gambacorta et al. (2022) show that the Big Tech credit has an average maturity of less than one year and it is typically renewed several times, as far as the credit approval remains in place. Often big tech credit assumes the form of a credit line. While two thirds of big tech credit has a maturity of one year or less this share drops to 43% for bank credit. Similar characteristics are detected for Mercado Libre in Mexico (Frost et al. 2019).

Due to lack of collateral big tech credit is less correlated with house prices. Moreover, as firms operate on e-commerce platforms the demand of big tech credit is less correlated with local business conditions (where the firms is headquartered). Figure 3 gives a summary of the results found by Gambacorta et al. (2022) comparing the elasticity between different credit types with respect to house prices and local GDP. In particular, the study compares big tech credit with unsecured (not collateralised) bank credit and secured (collateralised) bank credit. 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.

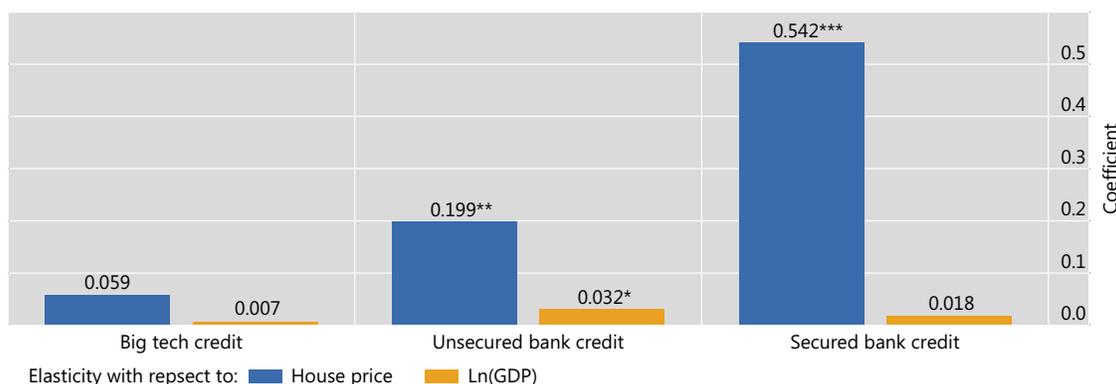


Figure 3: Elasticity of credit with respect to house prices and GDP

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).

2.3 Reactions of big tech and bank credit to a monetary policy shock

To get some preliminary evidence on the different behaviour of big tech and bank credit to a monetary policy shock we develop a simple panel VAR analysis on annual macroeconomic data for 19 countries over the period 2005 to 2020³. 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 (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.

Big tech credit comes from Cornelli et al. (2020)⁴ while the short term rate has been obtained from national central banks. Due to the presence of zero-lower bounds and unconventional monetary policies in some jurisdictions we have used the shadow rate for the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, Australia, and New Zealand⁵.

To avoid the problem of spurious correlations, we express all variables in first differences.⁶ The starting point of the multivariate analysis is:

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

where $z = [pk, Y, p, L, B, i]$ and $\epsilon_{i,t}$ is a vector of residuals, for $i = 1, \dots, N$, where N is the number of countries and $t = 1, \dots, T$. 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) criteria⁷.

³The 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.

⁴Big 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. Similar results are obtained using total alternative credit (the sum of fintech and big tech credit) in the PVAR analysis (results are available upon request).

⁵The methodology to calculate the shadow rates is reported in Krippner (2013, 2015), All shadow rates are available at <https://www.ljkmfa.com/visitors/>.

⁶Unit 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.

⁷The 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.

Figure 4 shows the dynamic responses of the variables to a monetary policy shock. We use a standard Cholesky decomposition and order the short term interest rate last (reacting to all remaining variables).⁸ The results suggest that bank credit and big tech 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 big tech credit. Importantly also, the response of bank credit follows closely the one of property prices, while this is not the case for big tech 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 -1.0 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 big tech credit at any horizon (bottom left panel).

Figure 4 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 A2 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 the credit channel of monetary policy by reducing the relevance of the “collateral channel”.

Next, we build a dynamic macroeconomic model featuring big tech and bank credit that matches the stylised facts documented above. We then use it to analyse the implications of the expansion of big tech credit for the macroeconomy and the transmission of monetary policy.

⁸Because 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%. The results do not change altering the order of the variables in the Cholesky decomposition.

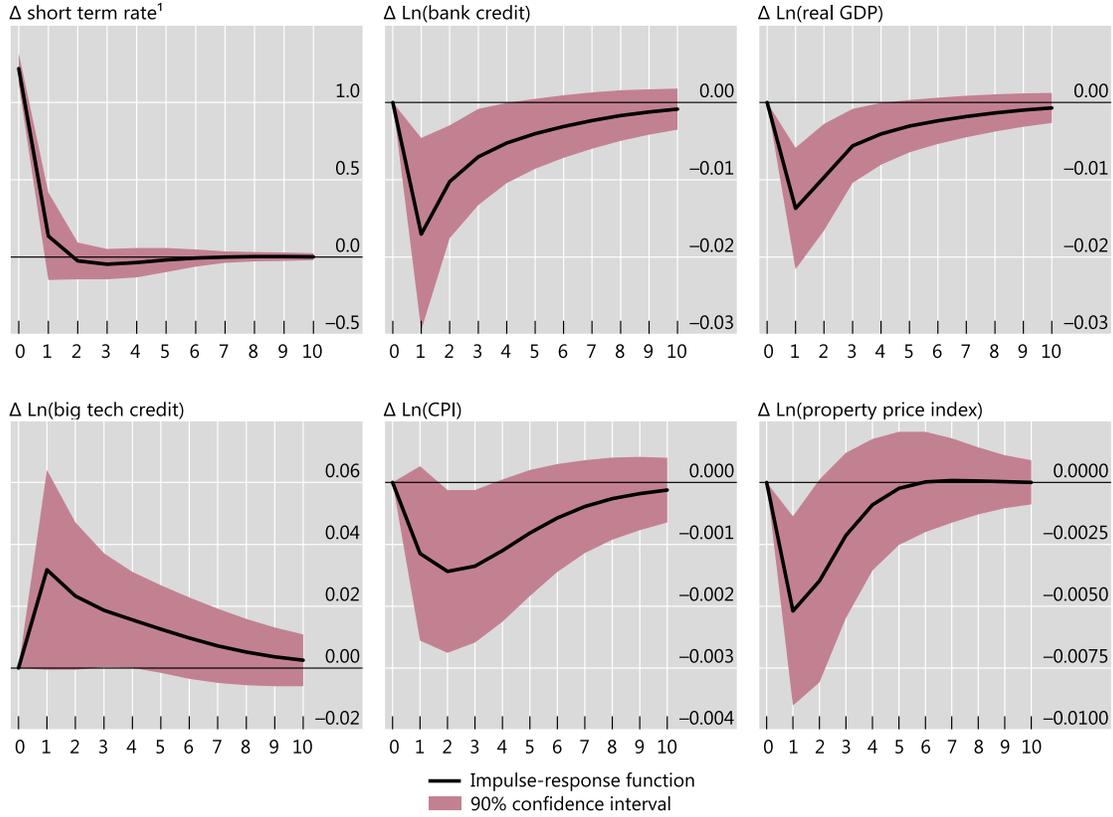


Figure 4: Estimated impulse responses to a monetary policy shock

Notes: The graphs show the impulse response function for a shock in the Δ short term rate. The horizontal axis reports the number of steps in the simulation. Due to the presence of zero-lower bounds and unconventional monetary policies in some jurisdictions we have used the shadow rate for the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, Australia and New Zealand.
 Source: Authors' calculations.

3 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.

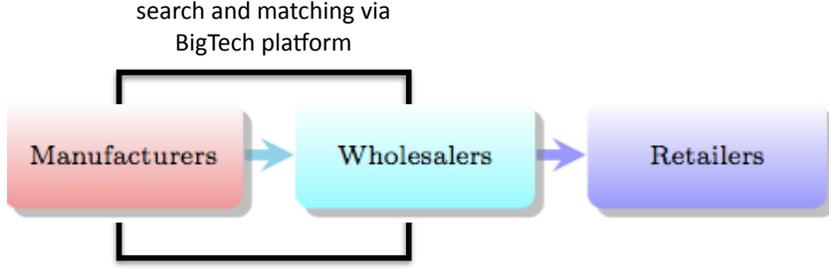


Figure 5: Three layer supply chain in the model

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 5). 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.

3.1 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 \mathcal{E}_t to maximize inter-temporal lifetime utility

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

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

$$P_t C_t + B_t^h + \mathcal{E}_t Q_t^e \leq W_t L_t + B_{t-1}^h (1 + i_{t-1}) + \mathcal{E}_t D_t^e + \mathcal{E}_{t-1} Q_t^e + \Upsilon_t^g + \Upsilon_t^p \quad (2)$$

for $t = 0, 1, 2, \dots$, where $P_t \equiv [\int_0^1 P_t(j)^{1-\varepsilon} dj]^{\frac{1}{1-\varepsilon}}$ 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 equity⁹, Υ_t^g are lump-sum net transfers by the government and Υ_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

⁹Equity investment is used to finance capital in the manufacturing sector. For tractability, capital enters production right away (see details in Section 3.3.2), and hence, dividends are paid in the same period when the equity investment is made.

use them to buy consumption goods. The maximization problem is subject to standard solvency constraints ruling out Ponzi schemes on bonds and equity

$$\lim_{T \rightarrow \infty} E_0 \left\{ \Lambda_{0,T} \frac{B_T^h}{P_T} \right\} \geq 0, \quad \lim_{T \rightarrow \infty} E_0 \left\{ \Lambda_{0,T} \frac{\mathcal{E}_T Q_T^e}{P_T} \right\} \geq 0, \quad (3)$$

where $\Lambda_{0,T} \equiv \beta^T \frac{C_T^{-\sigma}}{C_t^{-\sigma}}$. Household's optimality conditions write

$$\chi C_t^\sigma L_t^\varphi = \frac{W_t}{P_t}, \quad (4)$$

$$1 = E_t \left\{ \Lambda_{t,t+1} \Pi_{t+1}^{-1} (1 + i_t) \right\}, \quad (5)$$

$$Q_t^e = D_t^e + E_t \left\{ \Lambda_{t,t+1} \Pi_{t+1}^{-1} Q_{t+1}^e \right\}, \quad (6)$$

together with the sequence of budget constraints in (2) for $t = 0, 1, 2, \dots$, and the transversality conditions in (3), where $\Lambda_{t,t+1} \equiv \beta \frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}}$ is the real stochastic discount factor, $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ is the (gross) inflation rate between $t - 1$ and t .

3.2 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_t^b 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 χ_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 χ_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_t^b ,

$$B_t^b = N_t^b \tag{7}$$

and hence,

$$N_t^b = N_{t-1}^b(1 + i_{t-1}) + \chi_m P_t I_t + \chi_w P_t S_t \tag{8}$$

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 strictly larger than the incentive-compatible credit that is willing to extend, namely

$$\frac{N_t^b}{P_t} \gg \int_0^1 \mathcal{L}_t^b(j) dj \tag{9}$$

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.

3.3 Manufacturers

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

$$y_t^m(j) = \xi(k_t^m(j))^\gamma (l_t^m(j))^{1-\alpha}, \quad j \in [0, 1] \tag{10}$$

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 , ξ is an exogenous technology process, and $\gamma + (1 - \alpha) < 1$. In the current version

¹⁰A marginally small market power on the intra-temporal loan market would make equilibrium loan market rate strictly positive. In this case, the Big Tech would strictly prefer to lend its funds instead of keeping them idle (conditional on a strictly positive incentive-compatible demand for intra-temporal credit).

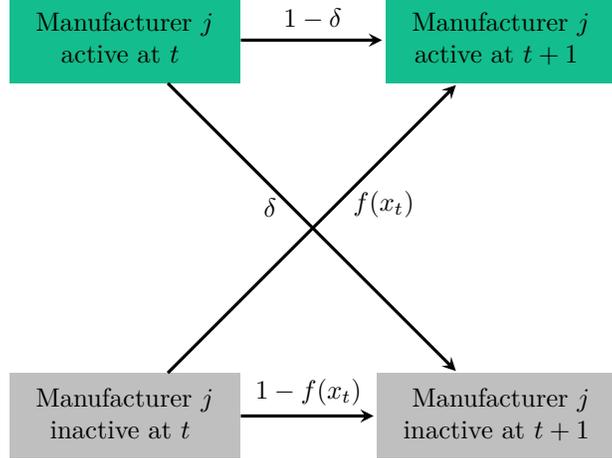


Figure 6: Manufacturers’ transition probabilities between the active and inactive states from period t to period $t + 1$

Notes: δ 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 $t + 1$

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 process¹¹.

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 δ , while new ones form with endogenous probability $f(x_t)$ (Figure 6). 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 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 χ_m to attract potential clients (or to maintain the advertisement if they were also inactive at $t - 1$).

¹¹With 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.

3.3.1 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 χ_m .

3.3.2 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 \mathcal{L}_t to hire labor l_t^m at price W_t and issues equity to buy capital k_t^m at price Q_t^k .¹³ For convenience, we assume that each manufacturer issues a number of claims equal to the number of units of capital acquired

$$\mathcal{E}_t = k_t^m \tag{11}$$

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, $Q_t^e = Q_t^k$.¹⁴ 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 $E_t \left\{ \Lambda_{t,t+1} \rho \left(\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right) \right\}$.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

¹²Note 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 .

¹³Since 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.

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

¹⁵The capital refurbishing cost is introduced to allow the credit constraint to bind for standard values of the collateral pledgeability ratio ν (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.

former equals:¹⁶

$$\begin{aligned} \mathcal{V}_t^A \equiv & \frac{p_t^m}{P_t} \xi_t (k_t^m)^\gamma (l_t^m)^{1-\alpha} - \frac{W_t}{P_t} l_t^m - \frac{Q_t^k}{P_t} k_t^m + E_t \left\{ \Lambda_{t,t+1} \rho \left(\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right) \right\} + \\ & + E_t \left\{ \Lambda_{t,t+1} \left[(1-\delta) \mathcal{V}_{t+1}^A + \delta \mathcal{V}_{t+1}^I \right] \right\} \end{aligned} \quad (12)$$

where $E_t \left\{ \Lambda_{t,t+1} \left[(1-\delta) \mathcal{V}_{t+1}^A + \delta \mathcal{V}_{t+1}^I \right] \right\}$ 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 δ 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

$$\mathcal{V}_t^I \equiv -\chi_m + E_t \left\{ \Lambda_{t,t+1} \left[f(x_t) \mathcal{V}_{t+1}^A + (1-f(x_t)) \mathcal{V}_{t+1}^I \right] \right\} \quad (13)$$

where $E_t \left\{ \Lambda_{t,t+1} \left[f(x_t) \mathcal{V}_{t+1}^A + (1-f(x_t)) \mathcal{V}_{t+1}^I \right] \right\}$ 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{V}_{t+1}^A , and with probability $1-f(x_t)$ will remain inactive and gain \mathcal{V}_{t+1}^I instead.

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

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

After replacing the expressions of \mathcal{V}_t^A from (12) and of \mathcal{V}_t^I from (13), and using manufacturer's production technology (10) to compute $l_t^m(y_t^m, k_t^m) = \left[\frac{y_t^m}{\xi_t (k_t^m)^\gamma} \right]^{\frac{1}{1-\alpha}}$, one may write S_t^m as a function of y_t^m , p_t^m and k_t^m as follows

$$\begin{aligned} S_t^m(p_t^m, y_t^m, k_t^m) = & \frac{p_t^m}{P_t} y_t^m - \frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) - \frac{Q_t^k}{P_t} k_t^m + E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} + \\ & + \chi_m + (1-\delta-f(x_t)) E_t \left\{ \Lambda_{t,t+1} [S_{t+1}^m(p_{t+1}^m, y_{t+1}^m, k_{t+1}^m)] \right\} \end{aligned} \quad (14)$$

For future reference, we define the “reservation return of a manufacturer” $\underline{\Omega}_t$ as the *minimum* gross

¹⁶In 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).

return required by a manufacturer, namely as the return value $\frac{p_t^m}{P_t} y_t^m$ for which its surplus S_t^m is 0:

$$\underline{\Omega}_t \equiv \frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) + \frac{Q_t^k}{P_t} k_t^m - E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} - \chi_w - \left(1 - \delta - f(x_t) \right) E_t \left\{ \Lambda_{t,t+1} \left[S_{t+1}^m \right] \right\} \quad (15)$$

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}_t^s is limited by the expected resale value of manufacturers' collateral. The latter is given by a share ν of physical capital value net of refurbishing costs, implying¹⁷

$$\mathcal{L}_t^s \leq \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} \quad (16)$$

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{V}_{t+1}):

$$\mathcal{L}_t^b \leq b \mathcal{V}_{t+1} \quad (17)$$

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

¹⁷If banks seized wholesaler's capital, they would need to pay themselves the maintenance costs before reselling it on the market.

products outside the Big Tech commerce platform¹⁸. 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

$$\mathcal{L}_t^b + \mathcal{L}_t^s \leq b\mathcal{V}_{t+1} + \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} \quad (18)$$

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

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \leq b\mathcal{V}_{t+1} + \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} \quad (19)$$

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

3.4 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_t^w with the following linear technology¹⁹

$$Y_t^w = \int_0^{A_t} y_t^m(j) dj$$

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 $\mathcal{V}_{t+1} - E_t \{ \Lambda_{t,t+2} V_{t+2} \}$.

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

where $y_t^m(j)$ 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

$$y_t^m(j) = y_t^m \quad \forall j \in [0, A_t],$$

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

$$Y_t^w = A_t y_t^m$$

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{I}_t^s (the subscript s denoting "search") which equals

$$\mathcal{I}_t^s \equiv -\chi_w + g(x_t) E_t \{ \Lambda_{t,t+1} \mathcal{I}_{t+1}^B \} \quad (20)$$

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

As long as the value of a search \mathcal{I}_t^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 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 $\mathcal{I}_t^s = 0$, namely for

$$\chi_w = g(x_t) E_t \{ \Lambda_{t,t+1} \mathcal{I}_{t+1}^B \} \quad (21)$$

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

$$\mathcal{I}_t^B = \frac{P_t^w}{P_t} y_t^w - \frac{p_t^m}{P_t} y_t^m + (1 - \delta) E_t \{ \Lambda_{t,t+1} \mathcal{I}_{t+1}^B \} \quad (22)$$

where $\frac{P_t^w}{P_t} y_t^w - \frac{p_t^m}{P_t} y_t^m$ are current real profits for the wholesaler from the relation with the supplier, and $(1 - \delta) E_t \{ \Lambda_{t,t+1} \mathcal{I}_{t+1}^B \}$ 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 \mathcal{I}_t^B in (22) further writes as

$$\mathcal{I}_t^B = \frac{P_t^w}{P_t} y_t^w - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_w(1-\delta)}{g(x_t)} \quad (23)$$

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

$$\frac{\chi_w}{g(x_t)} = E_t \left\{ \Lambda_{t,t+1} \left[\frac{P_{t+1}^w}{P_{t+1}} y_{t+1}^w - \frac{p_{t+1}^m}{P_{t+1}} y_{t+1}^m + \frac{\chi_w(1-\delta)}{g(x_{t+1})} \right] \right\} \quad (24)$$

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

$$S_t^w \equiv \mathcal{I}_t^B - \mathcal{I}_t^s \quad (25)$$

which, using the expression of \mathcal{I}_t^B in (23) and $\mathcal{I}_t^s = 0$, can be written in equilibrium as a function of p_t^m and y_t^m as follows

$$S_t^w(p_t^m, y_t^m) \equiv \frac{P_t^w}{P_t} y_t^w - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_w(1-\delta)}{g(x_t)} \quad (26)$$

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 $\frac{p_t^m}{P_t} y_t^m$ for which its surplus S_t^w is 0,

$$\bar{\Omega}_t \equiv \frac{P_t^w}{P_t} y_t^w + \frac{\chi_w(1-\delta)}{g(x_t)} \quad (27)$$

3.5 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 σ_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 δ 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 the manufactured goods market tightness (x_t) as the relative number of open searchers relative to the number of inactive manufacturers

$$x_t \equiv S_t/I_t \tag{28}$$

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 .

TABLE 1 Timeline operations – manufacturers and wholesalers

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

$$g(x_t) \equiv \frac{M(S_t, I_t)}{S_t} = \sigma_m \left(\frac{S_t}{I_t} \right)^{\eta-1} = \sigma_m x_t^{\eta-1} \quad (29)$$

Note that this probability decreases in x_t , implying that wholesalers find it 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

$$f(x_t) \equiv \frac{M(S_t, I_t)}{I_t} = \sigma_m \left(\frac{S_t}{I_t} \right)^\eta = \sigma_m x_t^\eta \quad (30)$$

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.

3.6 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

$$Y_t(i) = Y_t^w(i) \quad (31)$$

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

$$Y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\varepsilon} Y_t \quad (32)$$

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 θ^k . The optimality condition associated with the problem above takes the form (see e.g. Galí (2015)):

$$\sum_{k=0}^{\infty} \theta^k E_t \{ \Lambda_{t,t+k} Y_{t+k/t} (1/P_{t+k}) (P_t^* - \mathcal{M}(1 - \tau) P_{t+k}^w) \} = 0 \quad (33)$$

where $\mathcal{M} \equiv \frac{\varepsilon}{1-\varepsilon}$ 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.

3.7 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.

3.8 Central bank

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

$$1 + i_t = \frac{1}{\beta} \Pi_t^{\phi_\pi} \left(\frac{Y_t}{Y} \right)^{\phi_y} e^{\nu_t} \quad (34)$$

where Y is steady-state output and ν_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.

3.9 Government

The government issues the one period public nominal risk-free bonds held by households B_t^h and by the Big Tech firm B_t^b , subsidizes the purchase of wholesale goods by retailers at rate τ , and balances the budget with lump-sum transfers/taxes Υ_t^g :

$$B_t^h + B_t^b = \left(B_{t-1}^h + B_{t-1}^b \right) (1 + i_{t-1}) + \Upsilon_t^g + \tau P_t^m \int_0^1 Y_t^m(i) di \quad (35)$$

3.10 Market clearing

3.10.1 Retail goods market

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

$$C_t = Y_t, \quad (36)$$

where $Y_t \equiv \left[\int_0^1 Y_t(i)^{1-\frac{1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}}$. 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

$$P_t = \left[\theta (P_{t-1})^{1-\varepsilon} + (1-\theta) (P_t^*)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} \quad (37)$$

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

$$\Pi_t^{1-\varepsilon} = \theta + (1-\theta) \left(\frac{P_t^*}{P_{t-1}} \right)^{1-\varepsilon} \quad (38)$$

3.10.2 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:

$$\int_0^1 Y_t(i) di = Y_t^w \quad (39)$$

3.10.3 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 :

$$Y_t^w = A_t y_t^m \quad (40)$$

The quantity produced by each wholesaler y_t^m and the price of a manufactured good p_t^m are determined by period-by-period Nash-bargaining. The outcome of the latter process is described in detail in the next section.

3.10.4 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:

$$A_t k_t^m = \bar{K} \quad (41)$$

3.10.5 Labor market

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

$$A_t l_t^m = L_t \quad (42)$$

3.10.6 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:

$$B_t^h + B_t^b = B_t \quad (43)$$

3.10.7 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:

$$\mathcal{E}_t = A_t k_t^m \quad (44)$$

3.11 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_t^m and the manufactured output y_t^m , and it is subject to the manufacturers' credit and technology constraints. As a result, the set $\{p_t^m, y_t^m\}$ is given by the solution to the following bargaining problem²⁰:

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

subject to

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \leq b \mathcal{V}_{t+1} + \nu E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right] \right\} \quad (45)$$

where ϵ is the (relative) bargaining power of the active manufacturer. According to the credit constraint (45), the production cost cannot exceed the sum of the access value to the Big Tech platform \mathcal{V}_{t+1} and of the physical collateral value $\nu E_t \left\{ \rho \frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right\}$ 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

²⁰The optimal choices of p_t^m and y_t^m requires as well an appropriate choice of the capital stock k_t^m .

²¹ l_t^m 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.

shortly, the Nash bargaining model, in effect, is equivalent to one where y_t^m is chosen to maximize the joint surplus of the match, while p_t^m is set to split that surplus according to parameter ϵ .

The price p_t^m chosen by the match satisfies the optimality condition

$$\epsilon S_t^m = (1 - \epsilon) S_t^w \quad (46)$$

As mentioned above, this condition implies that the total surplus of a match is shared according to the parameter ϵ . Specifically, letting $S_t^T \equiv S_t^m + S_t^w$ denote the total surplus from a match, we obtain from (46) that $S_t^m = \epsilon S_t^T$ and $S_t^w = (1 - \epsilon) S_t^T$. Using the expressions of S_t^m from (14), and of S_t^w from (26), one may further write (46) as an equation in p_t^m as follows

$$\frac{P_t^m}{P_t} y_t^m = \epsilon \bar{\Omega}_t + (1 - \epsilon) \underline{\Omega}_t$$

We now turn to the determination of quantity y_t^m chosen by the match. The latter satisfies the following optimality condition

$$y_t^m : \epsilon S_t^w \left(\frac{W_t}{P_t} \frac{\partial l_t^m(y_t^m, k_t^m)}{\partial y_t^m} - \frac{p_t^m}{P_t} \right) = (1 - \epsilon) S_t^m \left(\frac{P_t^w}{P_t} - \frac{p_t^m}{P_t} - \frac{\lambda_t}{1 - \epsilon} \frac{W_t}{P_t} \frac{\partial l_t^m(y_t^m, k_t^m)}{\partial y_t^m} \left(\frac{S_t^w}{S_t^m} \right)^\epsilon \right)$$

where $\lambda_t \geq 0$ is the Lagrangian multiplier on a manufacturer's credit constraint²². Using (46), this optimality condition can be further simplified under our baseline calibration with $\epsilon = 1 - \epsilon$ as²³:

$$\frac{P_t^w}{P_t} = \frac{1}{1 - \alpha} \frac{W_t}{P_t} \frac{l_t^m}{y_t^m} \left[1 + \frac{\lambda_t}{1 - \epsilon} \right], \quad \lambda_t \geq 0 \quad (47)$$

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 λ_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

$$\frac{Q_t^k}{P_t} = \gamma \frac{P_t^w}{P_t} \frac{y_t^m}{k_t^m} + \left(1 + \frac{\nu \lambda_t}{\epsilon} \right) E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} \right] \right\} \quad (48)$$

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

²³The 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.

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 hence the nominal dividend paid to the household at time t on each equity claim equals

$$D_t^e = \gamma P_t^m \frac{y_t^m}{k_t^m} + \left(P_t \frac{\nu \lambda_t}{\epsilon} \right) E_t \left\{ \rho \Lambda_{t,t+1} \left[\frac{Q_{t+1}^k}{P_{t+1}} \right] \right\} \quad (49)$$

As credit constraints tighten (i.e. λ_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 (45), (46), (47), (48) and (49) describe the outcome of the bargaining process which determines λ_t , p_t^m , y_t^m , k_t^m and D_t^e . Without matching and credit frictions, the model nests the basic three-equations NK model.²⁴

4 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 β , curvature of consumption utility σ , curvature of labor disutility φ , labor share $1 - \alpha$, elasticity of substitution between retail goods ε , Calvo index of price rigidities θ). These parameters are set to their textbook values in Galí (2015), Chapter 3. The labor disutility parameter χ is also standard and chosen such that the efficient level of labor in steady state is one. Policy coefficients ϕ_π and ϕ_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 third group of structural parameters concerns the standard search and matching parameters – the relative bargaining power ϵ , the matching function parameter η and the probability to separate from an existing match δ . We choose to remain agnostic about the effects of the relative bargaining

²⁴This is also true without credit frictions only when $\gamma = \alpha$ (i.e. for constant returns to scale).

Table 2: Parametrization

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

Note: Values are shown in quarterly rates.

power ϵ and the relative contribution to matching η , 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 σ_m which takes values from 0 to 1, the fees perceived by the Big Tech network, χ_w and χ_m , set such that the matching probability $g(x) \in [0, 1]$ in steady-state for all $\sigma_m \in [0, 1]$, and the network value pledgeability ratio b set to 10%.

5 Big Tech efficiency and the macroeconomy: 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 affects 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 7, the availability of big tech credit increases total credit (left middle panel), relaxes credit constraints (middle right panel) and increases output approaching it to its efficient level (top left panel). These effects work via the binding borrowing constraint (45). Specifically, the availability of big tech credit allows manufacturers to pledge their future expected profits \mathcal{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 7), 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 (45), 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 8).

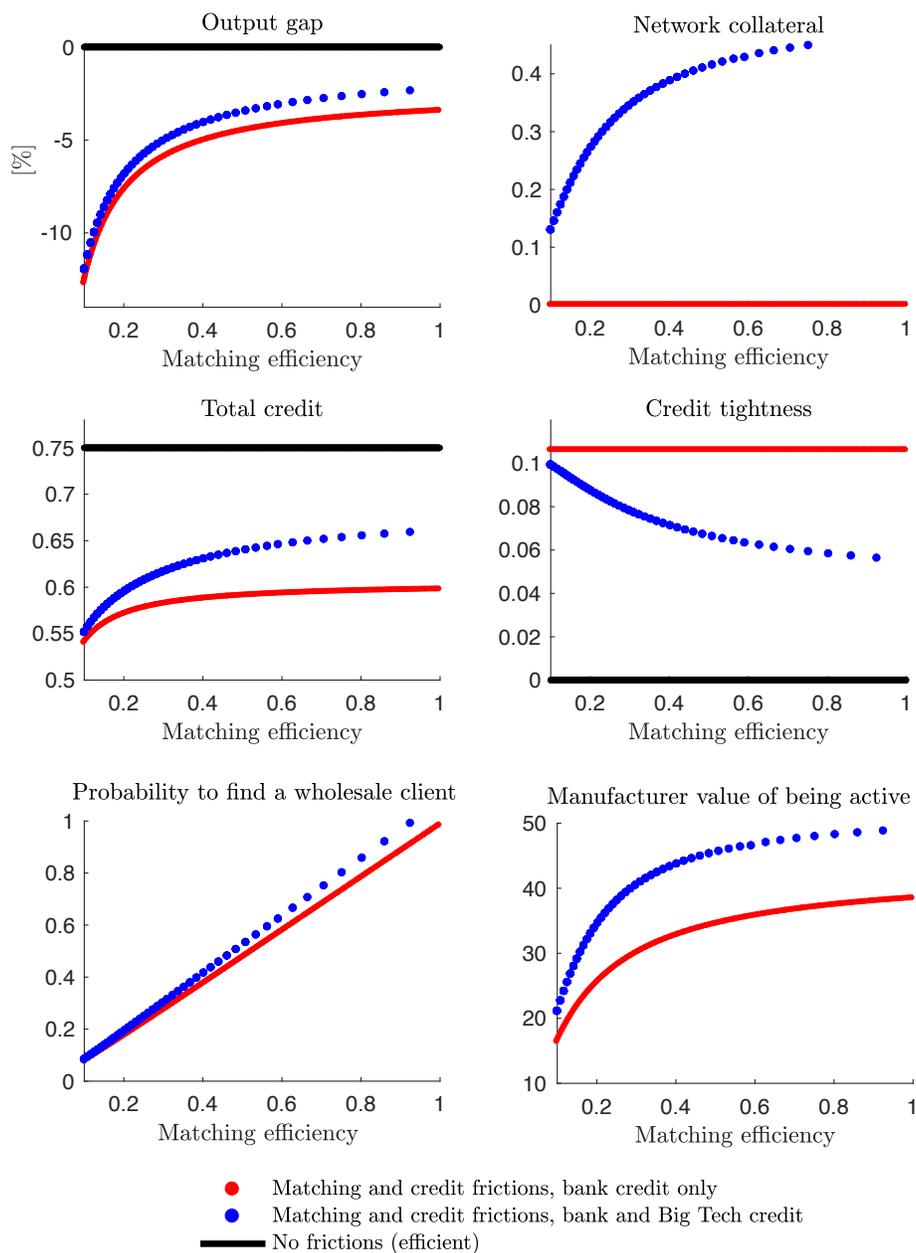


Figure 7: Steady-state equilibrium as a function of matching efficiency on the commerce platform

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 $b\mathcal{V}$. Total credit: Aggregate big tech credit and bank credit. Manufacturer value of being active: \mathcal{V}^a . Probability to find a wholesale client: $f(x)$. Matching efficiency: σ_m

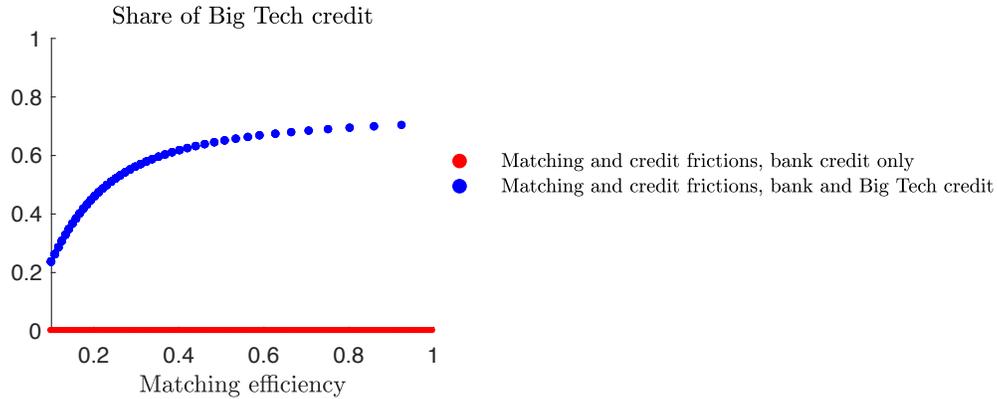


Figure 8: Steady-state share of big tech credit as the matching efficiency rises

Notes: Share of big tech credit: ratio of big tech credit and total credit. Matching efficiency: σ_m

6 Transmission of monetary policy: dynamic analysis

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 9 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 3 and A7 in the Appendix.

Figure 9 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.²⁶

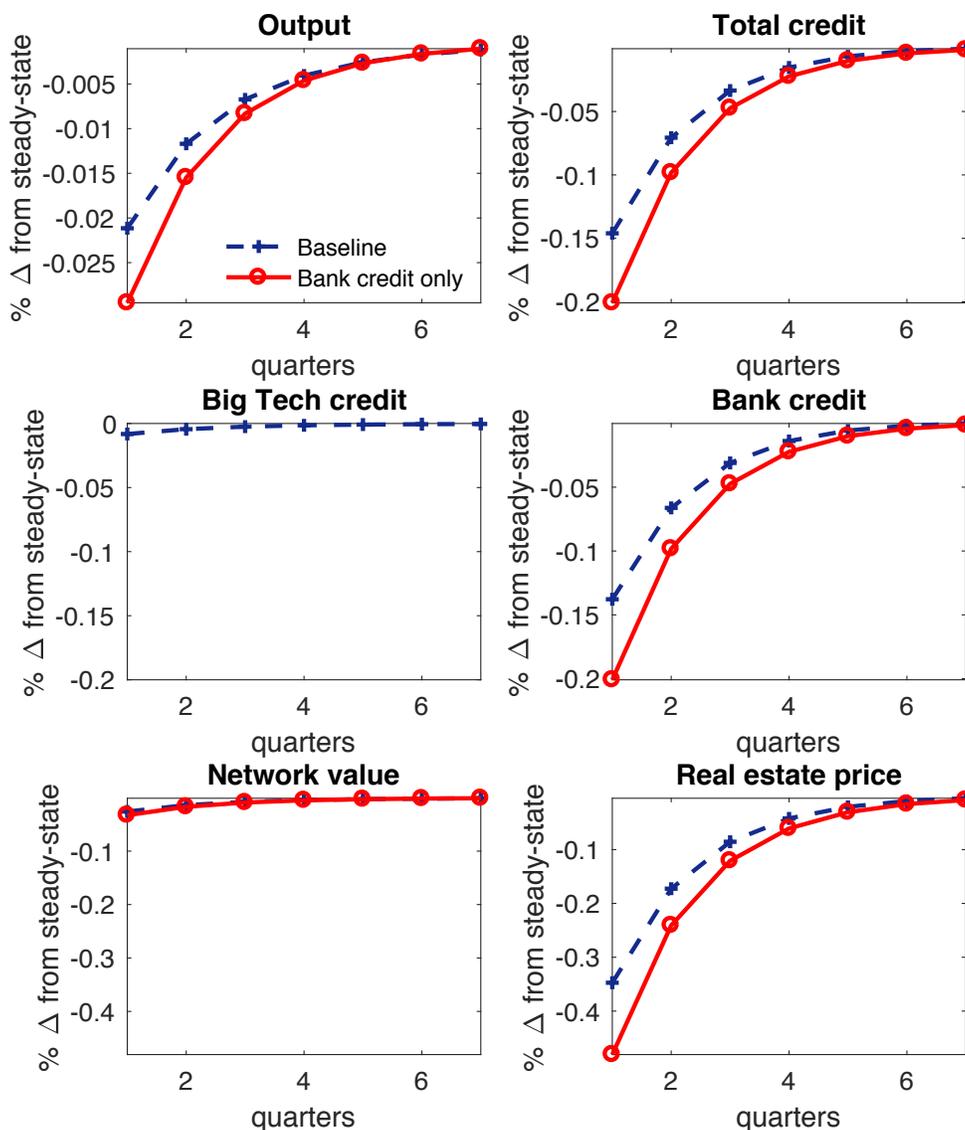


Figure 9: Dynamic responses to a monetary policy shock

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. Matching efficiency $\sigma_m \approx 0.178$ which gives an elasticity of big tech credit to network sales similar to current one estimated based on Chinese data by Gambacorta et al. (2022) (see figure A7 in the Appendix). In the specification with bank credit only, one needs a response coefficient to inflation higher than the coefficient of the simple Taylor rule (1993) (i.e. 3 instead of 1.5) to ensure equilibrium uniqueness. Thus, for comparison reasons, in both experiments the coefficient to inflation in the monetary policy rule is set to 3 instead of 1.5.

²⁶See Figure A3 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 A5 in the Appendix).

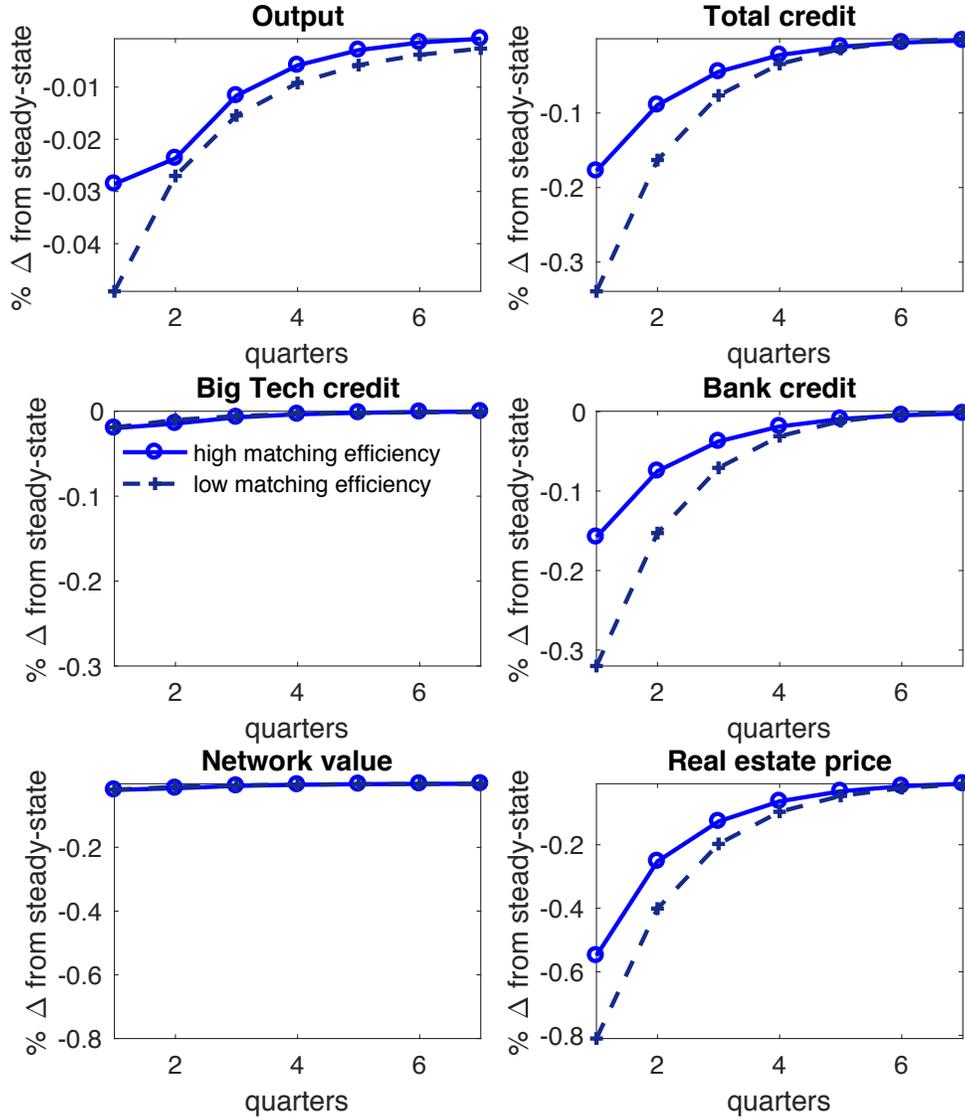


Figure 10: Dynamic responses to a monetary policy shock

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) (see figure A7 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 7 (blue solid line). The monetary policy regime is described by simple Taylor rule (1993).

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 9 (Figure 10, blue line), while no such differences exist in the absence of big tech credit (Figure A4 in the Appendix). This is because a higher share of total credit, the share of big tech credit, is less responsive to

monetary policy.

The quantitatively insignificant response of big tech credit and the strong response of bank credit in the middle panels in Figures 9 or 10 are broadly in line with the empirical estimates in section 2. 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.

7 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.

We obtain two sets of results. First, according to our model, an expansion in Big Techs, as captured by an increase in matching efficiency on the commerce platform, raises the value for firms of trading in the platform and the availability of big tech credit. This in turn relaxes financing conditions and raises firms' output, driving aggregate output closer to the efficient level. Second, 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.

8 References

Alfonso, V., Boar, C., Frost, J., Gambacorta, L., and Liu, J. (2021). "E-commerce in the pandemic and beyond". BIS Bulletin, 36.

Andrews, D. W., and Lu, B. (2001). "Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models". *Journal of econometrics*, 101(1), 123-164.

Bank for International Settlements (2019). "Big techs in finance: Opportunities and Risks", BIS Annual Economic Report, Ch. III, June.

Bahaj, S., Pinter G., Foulis A., and Surico, P. (2019). "Employment and the collateral channel of monetary policy", Bank of England Staff Working Paper 827.

Bazarbash, M. (2019). "FinTech in Financial Inclusion ? Machine Learning Applications in Assessing Credit Risk". IMF Working Paper, 109.

Bech, T., L. Gambacorta, Y. Huang, H. Qiu, and. Z. Li (2022). "Big techs, QR code payments and financial inclusion", BIS Working Papers, forthcoming.

Bernanke, B. (1983). "Nonmonetary effects of the financial crisis in the propagation of the great depression", *American Economic Review* 73(3): 257-276.

Branzoli, N., and Supino, I. (2020). "Fintech credit: A critical review of empirical research literature". Bank of Italy Occasional Paper, (549).

Cahuc, Pierre, Stane Carcillo, and André Zylberberg. *Labor economics*. MIT press, 2014.

Carstens, A., Claessens S., Restoy F. and, Shin H.S. (2021). "Regulating big techs in finance", BIS Bulletin no 45, August.

Calvo, Guillermo A. (1983). "Staggered prices in a utility-maximizing framework." *Journal of monetary Economics* 12, no. 3 (1983): 383-398.

Cornelli, G., Frost, J., Gambacorta, L., Rau, R., Wardop, R., and Ziegler, T. (2020). "Fintech and big tech credit: A new database", BIS Working Papers 887.

Croxson, K., Frost, J., Gambacorta, L., and Valletti, T. (2021). "Platform-based business models and financial inclusion". BIS Paper, forthcoming.

Del Negro, Marco, Gauti Eggertsson, Andrea Ferrero and Nobuhiro Kiyotaki. (2017). "The Great Escape? A Quantitative Evaluation of the Fed's Liquidity Facilities." *American Economic Review*, 107(3):824-57.

De Roure, C, L. Pelizzon, P. Tasca (2016). "How does P2P lending fit into the consumer credit market?". Deutsche Bundesbank Discussion Papers 30.

Drechsel, Thomas. (2022). "Earnings-based borrowing constraints and macroeconomic fluctuations." DP16975 .

De Fiore, Fiorella, and Oreste Tristani. (2013). "Optimal monetary policy in a model of the credit channel." *The Economic Journal* 123, no. 571 (2013): 906-931.

Galí, Jordi. "Monetary policy and unemployment." In *Handbook of Monetary Economics*, vol. 3, pp. 487-546. Elsevier, 2010.

Gambacorta, Leonardo, Yiping Huang, Zhenhua Li, Han Qiu, and Shu Chen. (2022) "Data vs collateral.", *Review of Finance*, forthcoming.

Gambacorta L., Y. Huang, H. Qiu, J. Wang (2019). "How do machine learning and nontraditional data affect credit scoring? New evidence from a Chinese fintech firm". *BIS Working Papers* 834.

Gertler, M., and. Gilchrist, S. (1994). "Monetary policy, business cycles, and the behavior of small manufacturing firms", *The Quarterly Journal of Economics* 109(2): 309–340.

Gertler, Mark, and Peter Karadi. (2011). "A model of unconventional monetary policy." *Journal of monetary Economics* 58, no. 1: 17-34.

Granger, C. W. (1969). "Investigating causal relations by econometric models and cross-spectral methods". *Econometrica: journal of the Econometric Society*, 424-438.

Feyen, E., Frost, J., L. Gambacorta, H. Natarajan and, M. Saal (2021). "Fintech and the digital transformation of financial services: Implications for market structure and public policy", *BIS Papers* 117.

Frost, J., L. Gambacorta, Y. Huang, H.S. Shin, and P. Zbinden (2019). "BigTech and the changing structure of financial intermediation", *Economic Policy* 34(100): 761-799.

Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai and A. Walther (2019). "The effect of machine learning on credit markets", *VoxEU*, 11 January.

Haddad, C., and Hornuf, L. (2019). "The emergence of the global fintech market: Economic and technological determinants". *Small business economics*, 53(1), 81-105.

Hau, H., Huang, Y., Shan, H., and Sheng, Z. (2021). "FinTech credit and entrepreneurial growth". *Swiss Finance Institute Research Paper*, (21-47).

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

trepreneurial growth”. Mimeo.

Ioannidou, V., Pavanini, N., and Peng, Y. (2022). ”Collateral and asymmetric information in lending markets”, *Journal of Financial Economics*, 144(1): 93-121.

Jagtiani, J., and Lemieux, C. (2019). ”The roles of alternative data and machine learning in fintech lending: evidence from the Lending Club consumer platform”. *Financial Management*, 48(4), 1009-1029.

Kiyotaki, N., J. Moore (1997). ”Credit cycles”. *Journal of political economy*, 105(2), 211- 248.

Krippner, L. (2013) ”Measuring the Stance of Monetary Policy in Zero Lower Bound Environments”. *Economics Letters*, 118, 135-138.

Krippner, L. (2015) ”Zero Lower Bound Term Structure Modeling: A Practitioner’s Guide”. Palgrave-Macmillan.

Lian, Chen, and Yueran Ma. (2021). ”Anatomy of corporate borrowing constraints.” *The Quarterly Journal of Economics* 136, no. 1 (2021): 229-291.

Manea, C. (2020): ”Monetary policy with financially constrained and unconstrained firms”, *Essays in Monetary Economics*, PhD Thesis, Universitat Pompeu Fabra.

Mian, A., and Sufi, A. (2011). ”House prices, home equity-based borrowing, and the US household leverage crisis”, *The American Economic Review* 101(5): 2132-56.

Mas-Colell, Andreu, Michael Dennis Whinston, and Jerry R. Green. *Microeconomic theory*. Vol. 1. New York: Oxford university press, 1995.

Ottonello, P., and, Winberry, T.. (2020). ”Financial heterogeneity and the investment channel of monetary policy”, *Econometrica*, 88(6): 2473-2502.

Restoy, F (2021). ”Fintech regulation: how to achieve a level playing field”, *FSI Occasional Papers*, 17, February.

Tang, H. (2019). ”Peer-to-peer lenders versus banks: substitutes or complements?” *Review of Financial Studies*, 32(5), 1900-1938.

Trigari, Antonella. (2009). ”Equilibrium unemployment, job flows, and inflation dynamics.” *Journal of money, credit and banking* 41, no. 1 (2009): 1-33.

9 Appendix

9.1 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.

	Observations	Mean	Std dev	Min	Max
$\Delta \text{Ln}(\text{property price index})$	274	0.05	0.05	-0.02	0.16
$\Delta \text{Ln}(\text{real GDP})$	304	0.01	0.09	-0.16	0.16
$\Delta \text{Ln}(\text{CPI})$	304	0.03	0.03	-0.00	0.10
$\Delta \text{Ln}(\text{banking credit})$	304	0.07	0.13	-0.32	0.46
$\Delta \text{Ln}(\text{big tech credit})$	304	0.29	1.17	-1.61	8.79
$\Delta \text{short term rate}$	304	-0.27	1.64	-9.50	7.77

Table A1: Summary statistics

Notes: The sample includes 19 countries over the period 2005-2020. Data winsorised at the 5th and 95th percentiles. Due to the presence of the zero lower bound and unconventional monetary policies in some jurisdictions we have used the shadow rate for the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, Australia and New Zealand. Sources: Cornelli et al. (2020); Krippner (2013) and (2015); BIS; IMF, World Economic Outlook; World Bank; national data; authors' calculations.

	ΔLn (property price index)		ΔLn (real GDP)		ΔLn (CPI)		ΔLn (banking credit)		ΔLn (Big Tech credit)		Δ (short term rate)	
	Stat	P- value	Stat	P- value	Stat	P- value	Stat	P- value	Stat	P- value	Stat	P- value
Inverse chi-squared (38)	81.05	0.00	134.28	0.00	104.65	0.00	204.68	0.00	63.08	0.01	206.43	0.00
Inverse normal	-3.91	0.00	-7.34	0.00	-5.78	0.00	-10.33	0.00	-4.3	0.00	-10.91	0.00
Inverse logit t(99)	-4.02	0.00	-8.15	0.00	-6.12	0.00	-12.84	0.00	-4.55	0.00	-13.02	0.00
Modified inv chi-squared	4.94	0.00	11.04	0.00	7.64	0.00	19.12	0.00	2.88	0.00	19.32	0.00

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. Due to the presence of zero-lower bounds and unconventional monetary policies in some jurisdictions we have used the shadow rate for the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, Australia and New Zealand. 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 minimized²⁷.

Lags	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.95	130.12	0.07	-446.33	-85.88	-231.63
2	0.98	76.71	0.33	-307.60	-67.29	-164.46
3	0.99	49.51	0.07	-142.64	-22.49	-71.08
4	0.98					

Table A3: Lag selection

Notes: The sample includes 19 countries over the period 2005-2020. Data winsorised at the 5th and 95th percentiles. Sources: 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 variables 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 big tech credit does not Granger cause the property price index, it Granger causes real GDP, banking credit and the short term rate.

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 A1 shows that

²⁷While 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).

Equation /excluded	ΔLn (property price index)			ΔLn (real GDP)			ΔLn (CPI)			ΔLn (banking credit)			ΔLn (big tech credit)			Δ short term rate		
	chi2	df	P-value	chi2	df	P-value	chi2	df	P-value	chi2	df	P-value	chi2	df	P-value	chi2	df	P-value
ΔLn (property price index)				0.16	1	0.69	13.44	1	0.00	0.71	1	0.40	0.45	1	0.51	17.9	1	0.00
ΔLn (real GDP)	0.31	1	0.58				0.05	1	0.83	0.73	1	0.39	0.01	1	0.92	3.1	1	0.08
ΔLn (CPI)	1.55	1	0.21	7.03	1	0.01				7.05	1	0.01	9.07	1	0.00	1.1	1	0.29
ΔLn (banking credit)	9.44	1	0.00	114.62	1	0.00	1.04	1	0.31				0.4	1	0.53	1.2	1	0.28
ΔLn (alternative credit)	0.01	1	0.92	3.37	1	<i>0.07</i>	1.86	1	0.17	5.95	1	0.02				6.4	1	0.01
Δ short term rate	4.2	1	0.04	8.2	1	0.00	1.8	1	0.18	5.25	1	0.02	2.59	1	0.11			
All	26.69	5	0.00	141.9	5	0.00	27.65	5	0.00	29.23	5	0.00	13.12	5	0.02	26.8	5	0.00

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. Due to the presence of zero-lower bounds and unconventional monetary policies in some jurisdictions we have used the shadow rate for the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, Australia and New Zealand. Sources: Authors' calculations.

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.

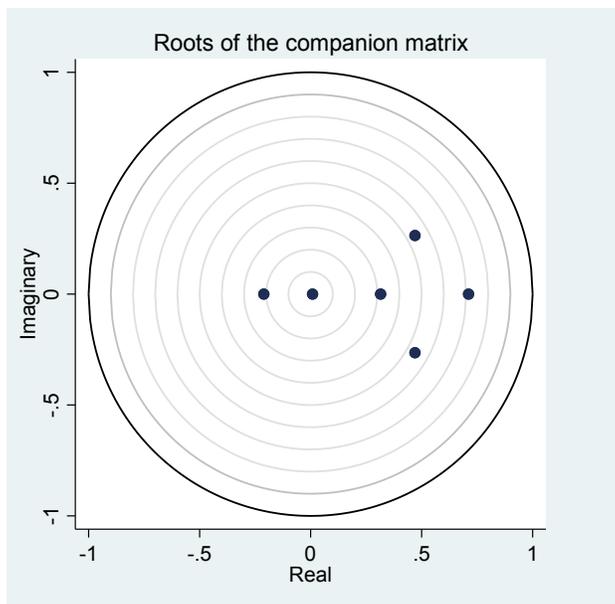


Figure A1: Roots of the companion matrix

Notes: Source: Authors' elaboration.

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 A2 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.

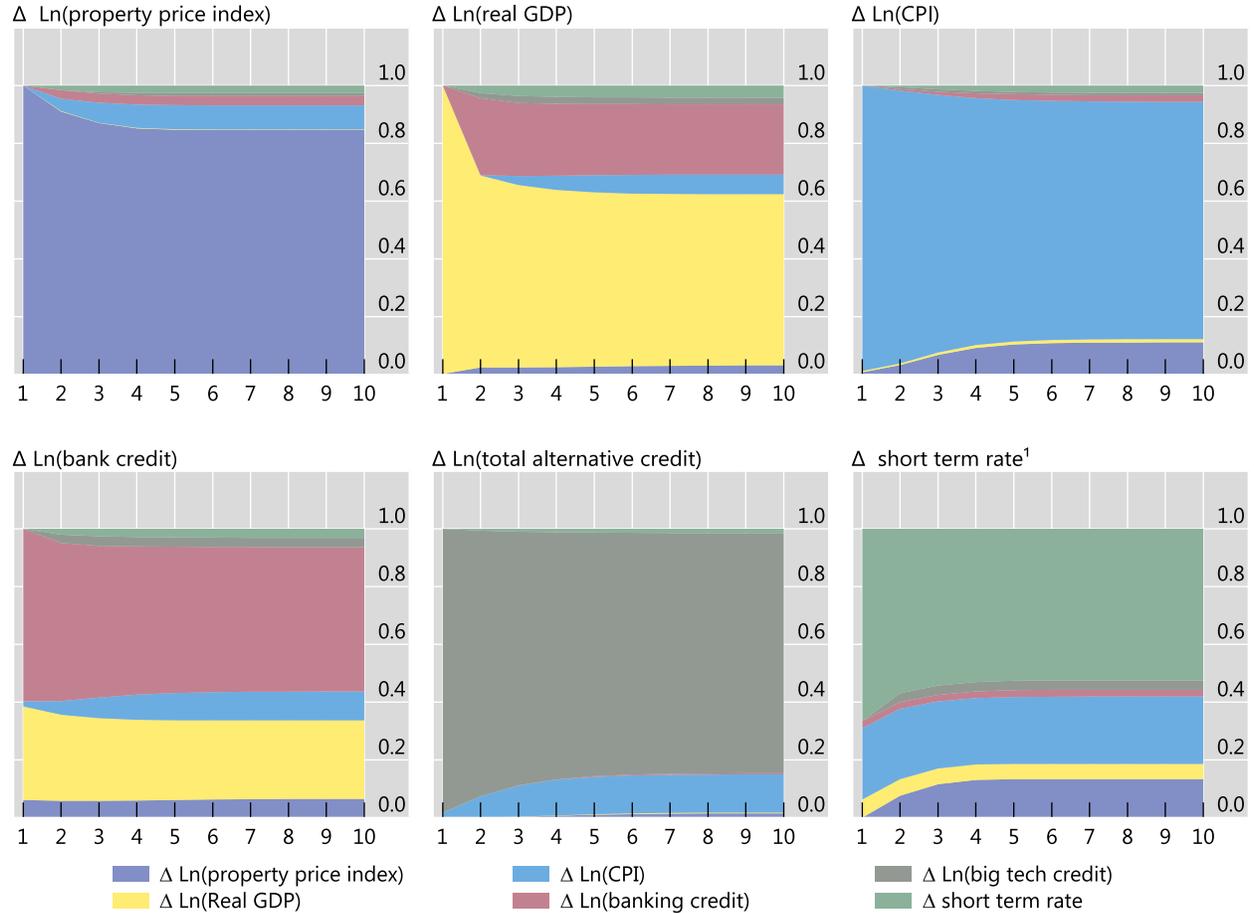


Figure A2: Forecast-error variance decomposition

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. Due to the presence of zero-lower bounds and unconventional monetary policies in some jurisdictions we have used the shadow rate for the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, Australia and New Zealand. Source: Cornelli et al (2020); Krippner (2013) and (2015); BIS; IMF, World Economic Outlook; World Bank; national data; authors' calculations.

9.2 Model-based dynamic responses to a monetary policy shock

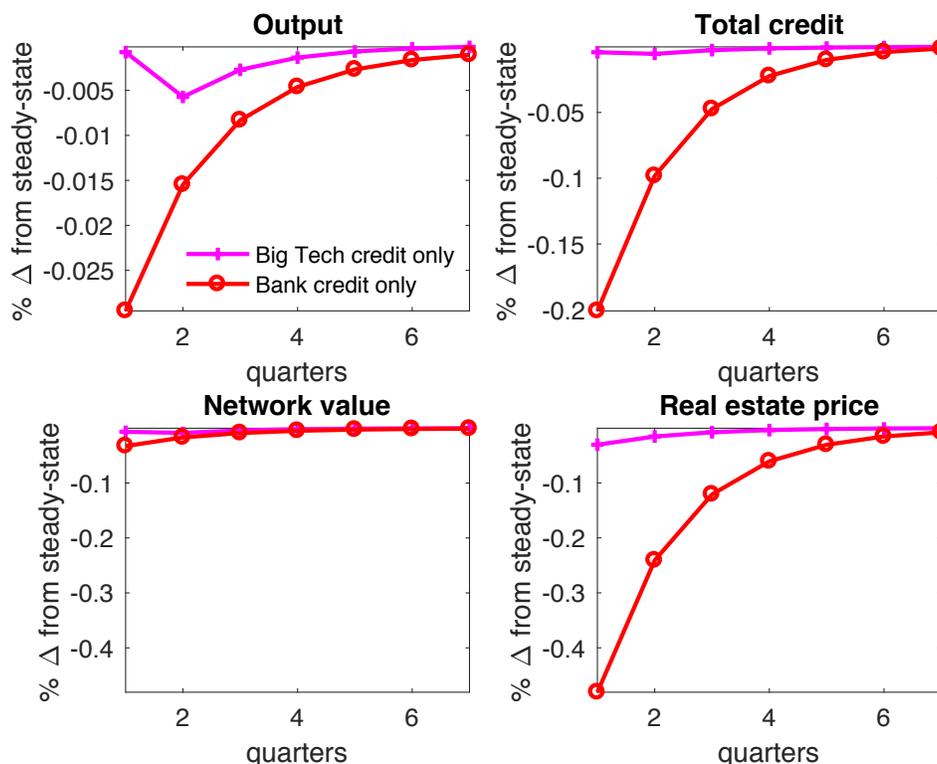


Figure A3: Dynamic responses to a monetary policy shock

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 7 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.

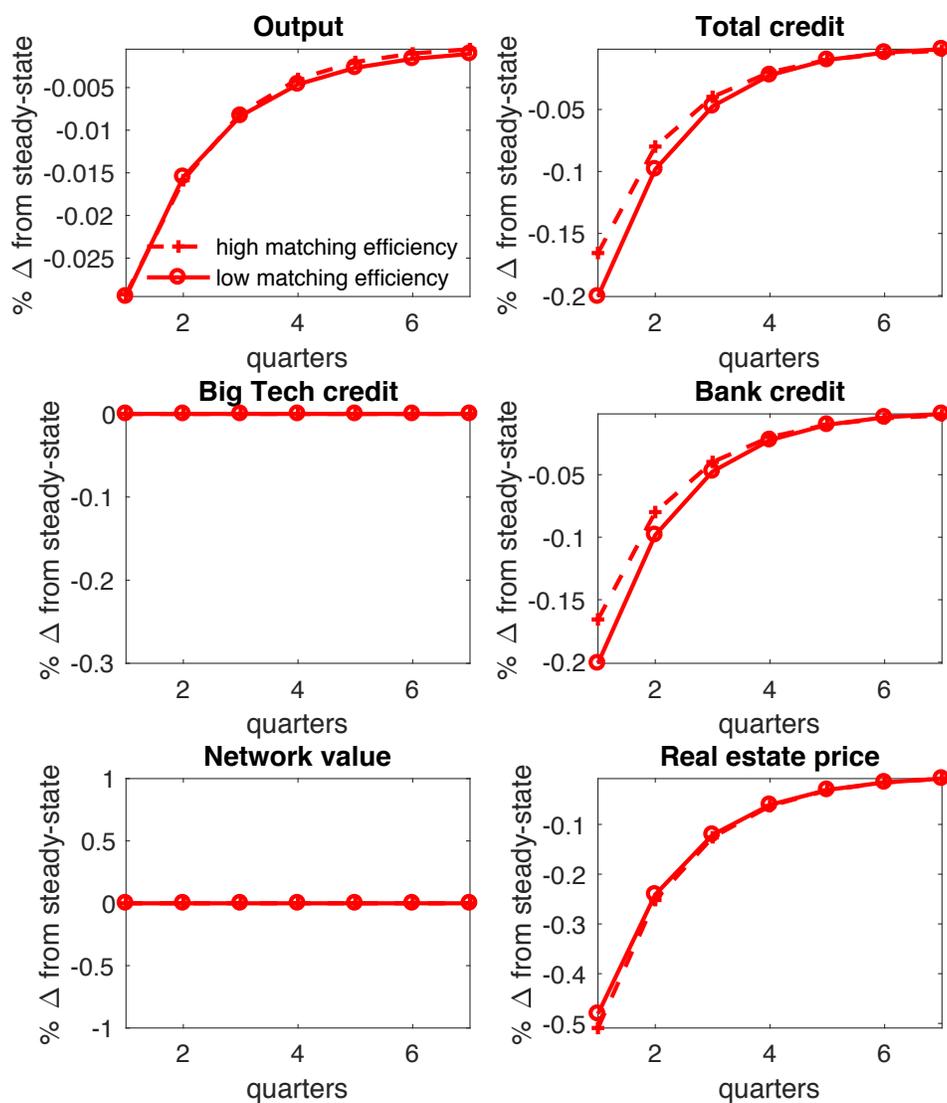


Figure A4: Dynamic responses to a monetary policy shock

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. The 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 7 (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.

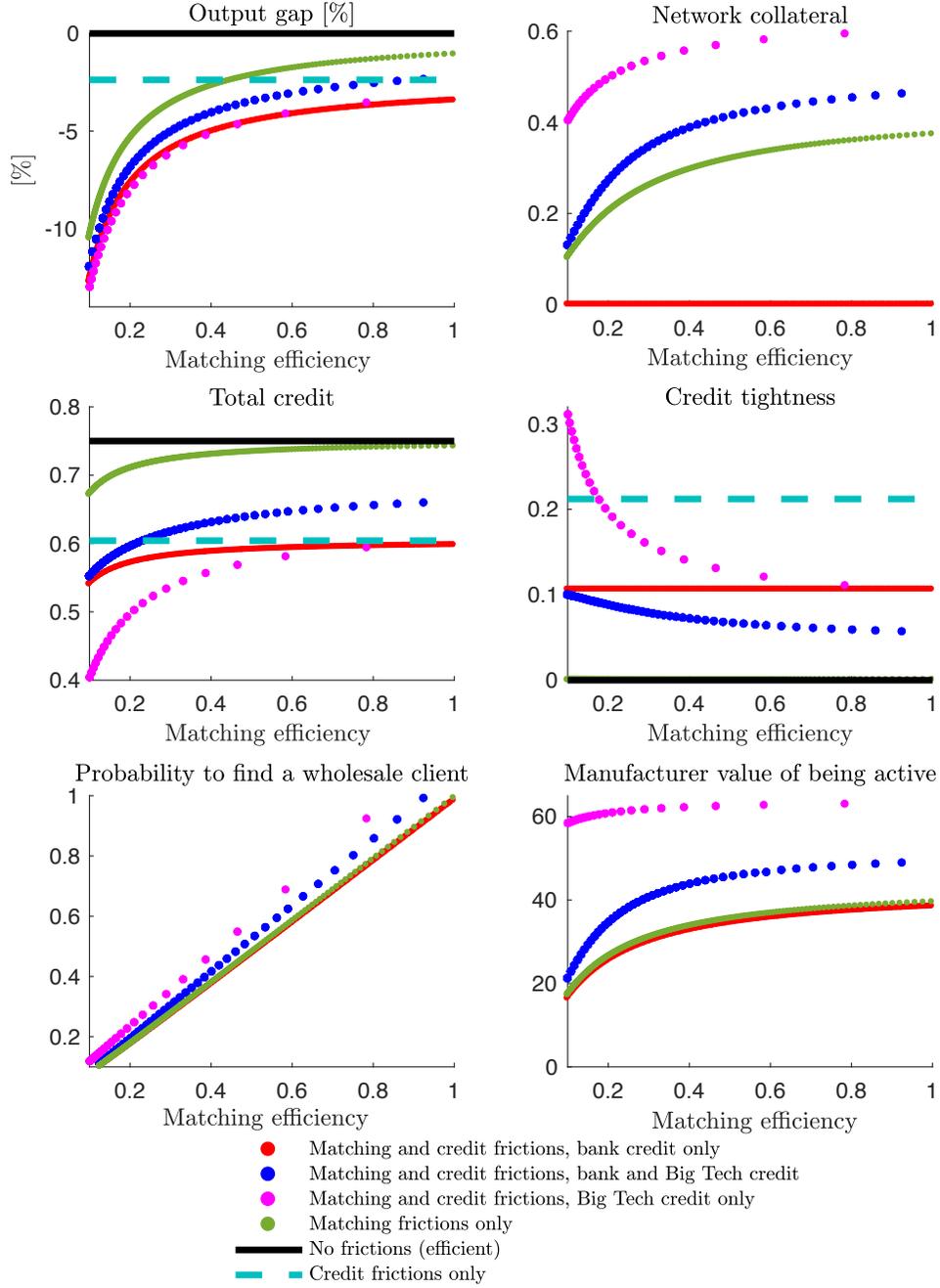


Figure A5: Steady-state equilibrium as a function of matching efficiency on the commerce platform

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 $b\mathcal{V}^a$. Total credit: Aggregate big tech credit and bank credit. Manufacturer value of being active: \mathcal{V}^a . Probability to find a wholesale client: $f(x)$. Matching efficiency: σ_m

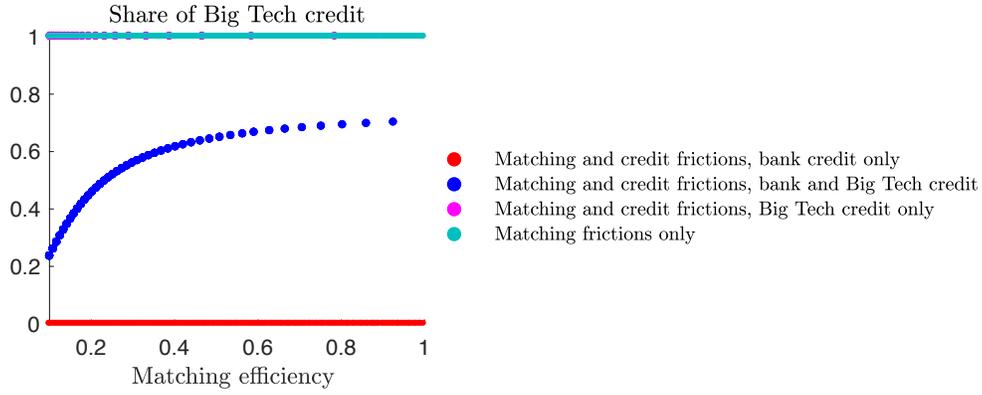


Figure A6: Steady-state and matching efficiency

Notes: Share of big tech credit: ratio of big tech credit and total credit. Matching efficiency: σ_m

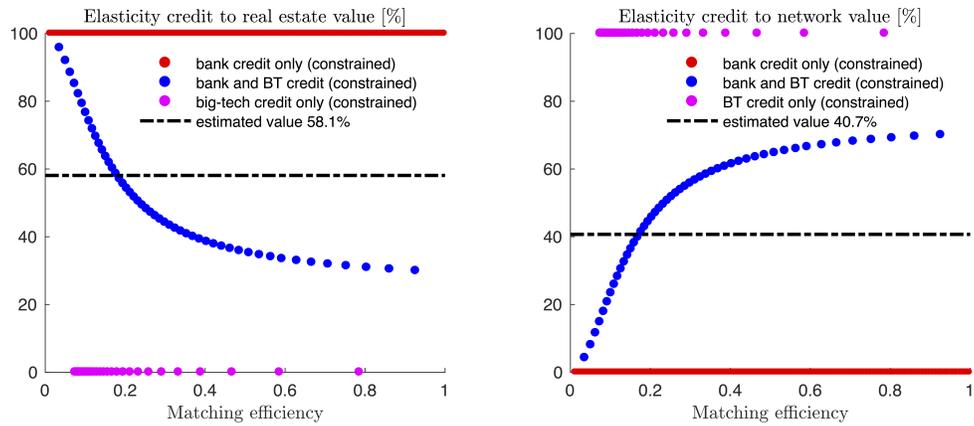


Figure A7: Steady-state and matching efficiency

Notes: Matching efficiency: σ_m