Big Techs and the Credit Channel of Monetary Policy

F. De Fiore[*] L. Gambacorta[†] C. Manea[‡§]

December 31, 2022

Preliminary draft

Abstract

We study how Big Techs' 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 reinforces credit repayment with the threat of exclusion from its ecosystem, while bank credit is secured against collateral. According to our model: (i) a rise in Big Techs' matching efficiency increases the value for firms of trading on the e-commerce platform and the availability of big tech credit, alleviating both matching and credit frictions; (ii) the reaction of aggregate credit and output to a monetary policy shock depends on the elasticity of firms' future profits from operating on the e-commerce platform relative to that of physical collateral value.

JEL classification: E44, E51, E52, G21, G23
Keywords: Big Techs, monetary policy, credit frictions

[*]Bank for International Settlements and CEPR. Email: Fiorella.DeFiore@bis.org.

[†]Bank for International Settlements and CEPR. Email: Leonardo.Gambacorta@bis.org.

[‡]Bank for International Settlements. Email: cristina.manea@bis.org.

[§]This research project was partially completed while C. Manea was working for the research center of the Deutsche Bundesbank. The views expressed in this paper are our own and should not be interpreted as reflecting the views of the Bank for International Settlements, the Deutsche Bundesbank or the Eurosystem. We thank K. Adam, F. Alvarez, J. Galí, R. Reis and H. Uhlig for useful discussions while developing the analytical framework of this project, to F. Smets and M. Bussière for discussing our paper at the CEBRA and the Annual SNB Monetary Economics Conference, as well as for useful comments to J. Benchimol, B. Bundick, P. Cavallino, K. Dogra, M. Gertler, A. Glover, M. Hoffmann, T. Holden, D. Lee, V. Lewis, M. Lombardi, G. Lombardo, Y. Ma, L. Melosi, E. Mertens, T. Mertens, E. Moench, M. Rottner, J. Sim, M. Spiegel, I. Vetlov, L. Zheng and seminar and conference participants at the Bank for International Settlements, Deutsche Bundesbank, Central Bank of Israel's VIMACRO seminar series, Kansas City Fed, BSE Summer Forum, IFRMP, Padova Macro, RAD, CEBRA and Oslo Macro conference. We are grateful to G. Cornelli for excellent research assistance, and to V. Shreeti for her analysis of fees on Big Techs' platforms.

1 Introduction

Large technology firms such as Alibaba, Amazon, Facebook or Mercado Libre (Big Techs) have recently started to provide loans to vendors on their commerce platforms and their presence in credit markets has expanded over the recent years. In 2019, Fintech credit reached USD 240 billion, while big tech credit volumes amounted 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 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. But given the dramatic rise in e-commerce - which has reached 2.7% of global output in 2020 - these alternative forms of credit have the potential to spread worldwide very rapidly (Cornelli et al. (2020)).

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 that big tech credit reacts by less to changes in asset prices and local economic conditions than bank credit. 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 going forward. 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 firms producing intermediate and final goods, and extends working capital loans to the former. Intermediate goods firms 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. Wages 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 with sticky wages[1]

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 constraints and raises firms' output, driving aggregate output closer to the efficient level. Second, the reaction of credit and output to a monetary policy shock crucially depends on the sensitivity of firms' opportunity cost of default on big tech credit (the stream of future profits from operating on the big tech platform) compared to that of defaulting on bank credit (the value of physical collateral). In our baseline calibration on US data, the introduction of big tech credit does not dramatically affect the response of aggregate credit and output to a monetary shock. This could however differ in countries like China, where we document that the sensitivity of big tech credit to e-commerce revenues is substantially larger than in the US.

Our paper contributes to the literature on the "financial accelerator," 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

[1]For simplicity, sticky wages are the only source of nominal rigidities. Apart from rendering monetary policy non-neutral, sticky wages generate a response of labor and output to a monetary policy shock as observed in the data, which also leads credit constraints to amplify the impact of the shock. The addition of sticky prices does not qualitatively change the results.

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) and Ioannidou et al. (2022)). Our paper contributes by analysing how Big Techs' use of big data for credit scoring and of "network collateral" instead of physical collateral affect the link between asset prices, credit and the business cycle.

In our setup, big tech credit supply is ultimately constrained by firms' expected profits. Our analysis therefore also relates to the literature on the macroeconomic effects of intangible or earnings-based borrowing constraints (e.g. Drechsel (2022), Lian and Ma (2021)).

Finally, our paper relates to a recent literature on financial innovation and inclusion by showing how a rise in matching efficiency between buyers and sellers on commercial platforms can lead to an overall expansion of credit supply. 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) documents that Lending Club has penetrated areas that are underserved by traditional banks. In Germany, De Roure et al (2016) shows 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. Our paper offers a complementary view by analysing the implications for macroeconomic efficiency and for the monetary transmission mechanism of the credit supply expansion offered by Big Techs.

The paper proceeds as follows. Section 2 describes the stylised facts on big tech credit. Section 3 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 7 concludes.

2 Stylised facts on Big Tech credit

Over the last decade, big tech platforms have expanded their activity globally and started venturing into credit activity.

2.1 Expansion of big tech credit and e-commerce

Cornelli et al. (2020) estimates that the flow of big tech 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. The relevance of big tech credit varies substantially across countries, with amounts corresponding to 3.5% of the stock of total credit in China, 2.0% in Kenya and around 1% in South Korea. These figures have further expanded in recent years, especially during the Covid-19 pandemic, due to the strong increase in e-commerce activity.

E-commerce revenues have risen from an estimated $1.4 trillion in 2017 to $2.4 trillion in 2020, which amounts to 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).

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 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

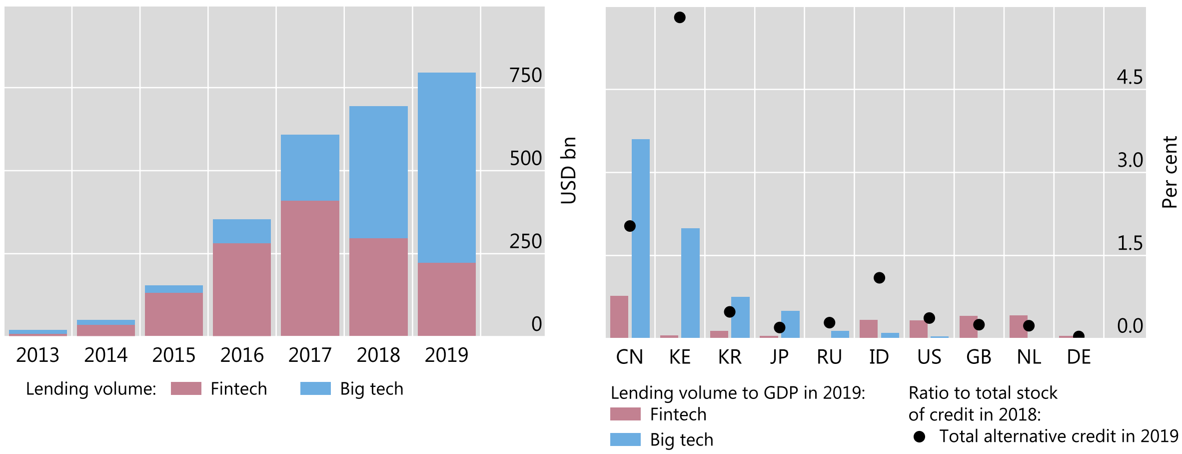

Figure 1: Upward trend in big tech credit

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).

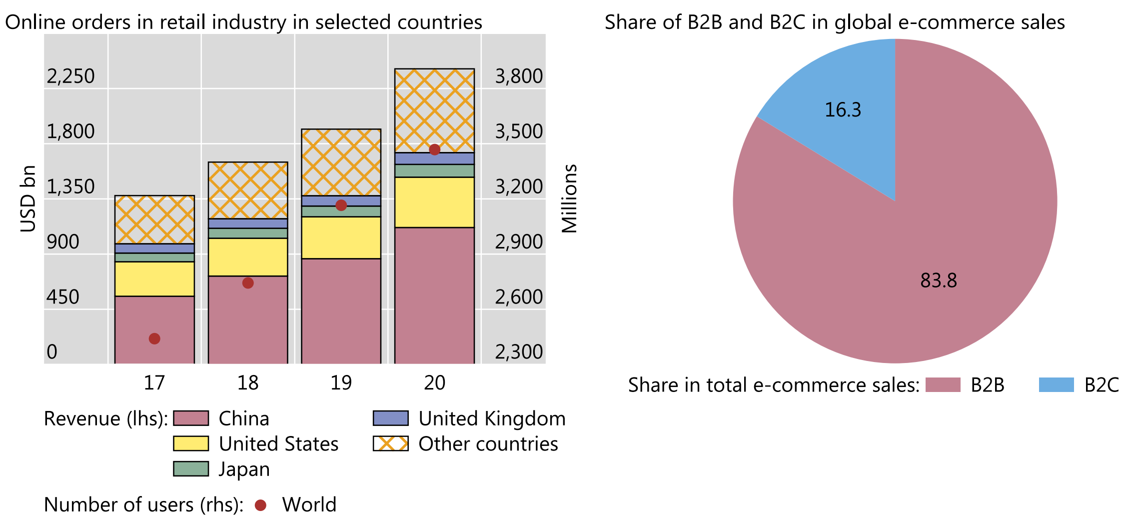

Figure 2: Upward trend in e-commerce, mostly via Big Tech platforms

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)

operate on e-commerce platforms, the demand of big tech credit is less correlated with local business conditions (where the firm is headquartered). Gambacorta et al. (2022) compare the elasticity of different credit types to house prices and local GDP. The main result (reported in Figure 3) is that big tech credit does not correlate with local business conditions and house prices when controlling for demand factors, while it 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.

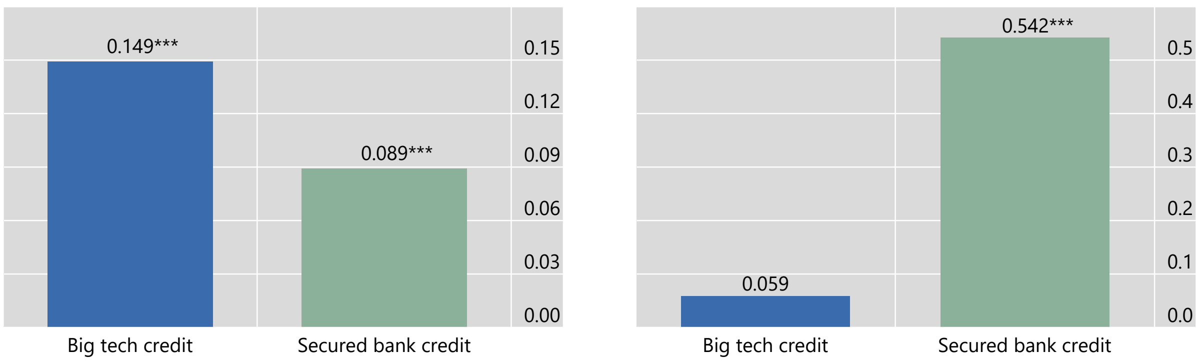

Figure 3: Credit elasticity to transactions on big tech platform (left) and house prices (right)

Notes: Significance level: $^{***}p < 0.01$. Quarterly panel data for over 2 million Chinese SMEs from 2017 to 2019 with access to both bank credit and big tech credit from the financial arm of Alibaba Group (AntGroup). Source: Gambacorta et al. (2022)

Extending the analysis to macroeconomic data for both China and the United States, we obtain similar patterns (Table 1). In both regions, bank credit reacts more strongly to house prices than big tech credit, while the converse is true for the reaction to e-commerce revenues. This evidence implies that a broader use of big tech credit could reduce the importance of the collateral channel.

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

Table 1: Credit elasticity to house prices and transactions on big tech platforms (macro data)

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

3 Model

The model is characterized by three main building blocks: credit frictions in the production sector, search and matching along the production chain, and nominal rigidities in the form of sticky wages. The model is populated by (1) a large number of identical households who consume, invest and work, (2) intermediate goods firms which produce using labor and physical capital, (3) final goods firms which use intermediate goods as inputs, (4) a Big Tech firm which facilitates transactions between intermediate goods and final goods firms, and extends credit to the former, (5) banks which give secured loans to intermediate goods firms, (6) a government which issues risk–free nominal bonds, and (7) a central bank which sets the nominal interest rate.

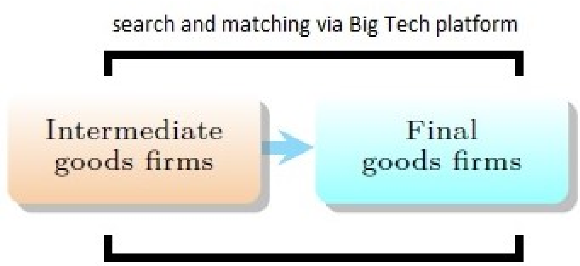

Figure 4: The two layer supply chain in the model

Intermediate goods firms sell products to final goods firms via a Big Tech commerce platform where buyers and sellers need to search for and match with one another (Figure 4). Intermediate goods firms 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 Households

The economy is populated by a large number of identical infinitely-lived households. Each household is made up of a continuum of members, each specialized in a different labor service, and indexed by $j \in [0,1]$. Income is pooled within each household, which thus acts as risk sharing mechanism. A typical household chooses each period how much to consume C_t and invest in nominal risk–free public bonds B_t and equity $\mathscr{E}_t$ to maximize its intertemporal utility,

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

subject to the sequence of budget constraints

$$P_tC_t + B_t^h + \mathscr{E}_tQ_t^e \leq \int_0^1 W_t(j)L_t(j)dj + B_{t-1}^h(1+i_{t-1}) + \mathscr{E}_tD_t^e + \mathscr{E}_{t-1}Q_t^e + \Upsilon_t^g + \Upsilon_t^p \qquad (1)$$

for $t = 0, 1, 2...$, taking employment choices $L_t(j)$ and labor income $\int_0^1 W_t(j)L_(j)dj$ as given. Individually, each household has no influence on nominal wage rates $W_t(j)$ set by unions, or employment levels $L_t(j)$ determined by firms. P_t is the price of a consumption good, Q_t^e is the unit price of equity, i_t is the nominal interest rate on public bonds, D_t^e is the dividend paid on equity, 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 intermediate goods firms and final goods firms)[2]. The household receives the wages for all types of labor services as bank deposits at the beginning of period t and uses them within the period to buy consumption goods. The maximization problem is subject to standard solvency constraints ruling out Ponzi schemes on bonds and equity

$$\lim_{T\to\infty} E_0\left\{\Lambda_{0,T}\frac{B_T^h}{P_T}\right\} \geq 0, \qquad \lim_{T\to\infty} E_0\left\{\Lambda_{0,T}\frac{\mathscr{E}_TQ_T^e}{P_T}\right\} \geq 0, \qquad (2)$$

where $\Lambda_{0,T} \equiv \beta^T\frac{C_T^{-\sigma}}{C_t^{-\sigma}}$. Households' optimality conditions concern the optimal intertemporal allocation of consumption described by the Euler equations

$$1 = E_t\left\{\Lambda_{t,t+1}\Pi_{t+1}^{-1}(1+i_t)\right\}, \qquad (3)$$

$$Q_t^e = D_t^e + E_t\left\{\Lambda_{t,t+1}\Pi_{t+1}^{-1}Q_{t+1}^e\right\}, \qquad (4)$$

together with the sequence of budget constraints in (1) for $t = 0, 1, 2, ...$, and the transversality conditions in (2), 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.

The wage setting problem and nominal wage rigidities are standard (see for instance Galí (2015), Chapter 6): each period workers specialized in a given type of labor (or the union representing them) set wages subject to the Calvo-type nominal rigidities. Specifically, workers specialised in any given labor type can reset their nominal wage only with probablity $1-\theta_w$ each period, independently of the time elapsed since they last adjusted their wage. Equivalently, each period the nominal wage for

[2]Equity 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. For computational reasons, search costs are rebated to the household.

workers of any given type remains unchanged with probability θ_w. In this environment, the wage dynamics are described up to a first-order log-linear approximation by

$$\pi_t^w = \beta E_t\{\pi_{t+1}^w\} - \lambda_w \widehat{\mu_t}^w \tag{5}$$

where π_t^w is wage inflation rate, $\lambda_w \equiv \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(1+\epsilon_w\varphi)}$, with ϵ_w the elasticity of substitution among labor types indexed by j, and $\widehat{\mu_t}^w \equiv \mu_t^w - \mu^w$ denotes the deviations of the economy's (log) average wage markup $\mu_t^w \equiv (w_t - p_t) - (log(\chi) + \sigma c_t + \varphi l_t)$ from its steady-state level μ^w.

3.2 Big Tech firm

The role of the Big Tech firm is twofold – one is to run an e-commerce platform which facilitates transactions between intermediate goods firms and final goods firms, the other is to extend credit to the former. We assume the Big Tech has the ability to collect data and process information about firms' characteristics, and uses it to gradually improve the matching efficiency on its e-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 levying fees from both sellers (intermediate goods firms) and buyers (final goods firms). Specifically, intermediate goods firms that are not matched with final goods firms at time t (a measure I_t) post advertisements on the platform at a unit real lump-sum cost χ_m, while those with a match (a measure A_t) pay a fee τ^* proportional to their transactions $\frac{P_t^m}{P_t} y_t^m$ on the platform. This implies a total real income for the Big Tech firm in period t from taxes levied on intermediate goods firms equal to $\chi_m I_t + \tau^* \frac{P_t^m}{P_t} y_t^m A_t$. Furthermore, each final good firm from the continuum of size one pays a unit real fee equal to χ_w for each of the S_t intermediate goods suppliers it searches. This results in an additional real income for the Big Tech firm in period t equal to $\chi_w S_t$[3]. The Big Tech invests its net worth at the end of each period in nominal risk–free government bonds B_t^b,

$$B_t^b = N_t^b \tag{6}$$

and hence,

$$N_t^b = N_{t-1}^b(1 + i_{t-1}) + \chi_m P_t I_t + \tau^* \frac{P_t^m}{P_t} y_t^m A_t + \chi_w P_t S_t \tag{7}$$

[3]In practice, e-commerce platforms such as Amazon, Shopify, E-bay or AliExpress perceive both variable and fixed fees, with variables fees ranging from 2% to 45% of sellers' transaction volumes.

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.[4] 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

$$\frac{N_t^b}{P_t} \gg \int_0^1 \mathscr{L}_t^b(j)dj \tag{8}$$

where $\mathscr{L}_t^b(j)$ is the real value of incentive-compatible credit extended to the intermediate goods firm $j \in [0,1]$. 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 users with the exclusion from the commerce platform.

In the model, we fix the fees set by the Big Tech. In reality, Big Techs' fees change over time. Industrial organisation models assume Big Techs' fee structure seeks to maximize the number of users on their platforms (e.g. Rochet and Tirole (2002)) which, given strong network effects, is equivalent to Big Techs' profit maximization in the long-run. In our analysis the number of sellers and buyers using the Big Tech commerce platform are both normalised to unity.

3.3 Intermediate goods firms

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

$$y_t^m(i) = \xi(k_t^m(i))^\gamma(l_t^m(i))^{1-\alpha}, \quad i \in [0,1] \tag{9}$$

where ξ is an exogenous technology process, $k_t^m(i)$ is the capital stock used in production by intermediate goods firm i, $l_t^m(i)$ is a CES index of labor input made of all labor types j hired by

[4] A marginally small market power in the credit market would make the 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).

intermediate goods firm i at aggregate wage rate W_t[5], and $\gamma + (1-\alpha) < 1$. In the current version of the model we assume decreasing returns to scale such that intermediate goods firms have strictly positive profits in equilibrium given the levels of y_t^m and p_t^m decided in the bargaining process[6].

Intermediate goods firms sell products to final goods firms. 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 5). Thus, at each point in time, the economy is populated with two types of intermediate goods firms: those matched with final goods firms which use technology (9) 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 intermediate goods firms' operations is summarized in Table 2. Intermediate goods firms found out in period $t-1$ their active or inactive status in period t. Active intermediate goods firms at time t produce and sell their output to final goods firms, 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 $t-1$).

3.3.1 Inactive intermediate goods firms

As already mentioned, the I_t intermediate goods firms that are not matched with final goods firms 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.

---

[5] The aggregate labor index and the wage index takes the standard CES expressions

$$l_t^m(i) \equiv \left(\int_0^1 l_t^m(i,j)^{1-\frac{1}{\epsilon_w}} dj \right)^{\frac{\epsilon_w}{\epsilon_w - 1}}$$
$$W_t \equiv \left(\int_0^1 W_t(j)^{1-\epsilon_w} dj \right)^{\frac{1}{1-\epsilon_w}}$$

where $l_t^m(i,j)$ denotes the quantity of type j labor employed by firm i in period t. The aggregate wage bill of any given firm can thus be expressed as the product of the wage index W_t and the firm's employment index $l_t^m(i)$:

$$\int_0^1 W_t(j) l_t^m(i,j) dj = W_t l_t^m(i)$$

[6] With constant returns to scale, the profits of active intermediate goods firms are negative given the price and quantities decided by Nash bargaining. An alternative way to make their profits positive would be to assume intermediate goods firms are monopolistically competitive.

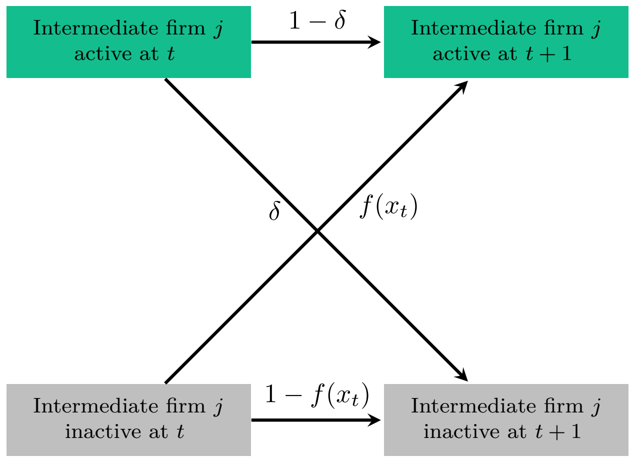

Figure 5: Intermediate goods firms' transition probabilities between the active and inactive states

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

3.3.2 Active intermediate goods firms

Since all A_t intermediate goods firms 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 intermediate goods firms and the final goods firms which are in a match at time t.[7]

Each intermediate goods firm producing at time t takes an intra-temporal loan $\mathscr{L}_t$ to hire labor l_t^m at price W_t and issues equity to buy capital k_t^m at price Q_t^k[8]. For convenience, we assume that each intermediate goods firm issues a number of claims equal to the number of units of capital acquired

$$\mathscr{E}_t = k_t^m \tag{10}$$

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, $Q_t^e = Q_t^k$.[9] We further assume that

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

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

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

intermediate goods firms 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 $E_t\Big\{\Lambda_{t,t+1}\rho\Big(\frac{Q^k_{t+1}}{P_{t+1}}k^m_t\Big)\Big\}$[10].

Two value functions on the intermediate goods firms' side play an important role in the Nash bargaining process: (i) the value for an intermediate goods firm of being "active" ($\mathscr{V}^A_t$), namely of being in a match, and (ii) the value for an intermediate goods firm of being "inactive" ($\mathscr{V}^I_t$), namely of being looking for a match. The former equals:[11]

$$\begin{aligned}\mathscr{V}^A_t \equiv &(1-\tau^*)\frac{p^m_t}{P_t}\xi_t(k^m_t)^\gamma(l^m_t)^{1-\alpha}-(1-\tau)\frac{W_t}{P_t}l^m_t-\frac{Q^k_t}{P_t}k^m_t+E_t\Big\{\Lambda_{t,t+1}\rho\Big(\frac{Q^k_{t+1}}{P_{t+1}}k^m_t\Big)\Big\}+\\ &+E_t\Big\{\Lambda_{t,t+1}\Big[(1-\delta)\mathscr{V}^A_{t+1}+\delta\mathscr{V}^I_{t+1}\Big]\Big\}\end{aligned}\tag{11}$$

where τ is an employment subsidy used to correct for market power distorsions on the labor market, $E_t\Big\{\Lambda_{t,t+1}\Big[(1-\delta)\mathscr{V}^A_{t+1}+\delta\mathscr{V}^I_{t+1}\Big]\Big\}$ is the expected value of the intermediate goods firm at $t+1$ when with probability $1-\delta$ will maintain its match with the final goods firm and gain $\mathscr{V}^A_{t+1}$, and with probability δ will lose this match and gain $\mathscr{V}^I_{t+1}$ instead.

The value for an intermediate goods firm of being inactive at time t and posting an advertisement equals

$$\mathscr{V}^I_t \equiv -\chi_m+E_t\Big\{\Lambda_{t,t+1}\Big[f(x_t)\mathscr{V}^A_{t+1}+(1-f(x_t))\mathscr{V}^I_{t+1}\Big]\Big\}\tag{12}$$

where $E_t\Big\{\Lambda_{t,t+1}\Big[f(x_t)\mathscr{V}^A_{t+1}+\Big(1-f(x_t)\Big)\mathscr{V}^I_{t+1}\Big]\Big\}$ is the expected value at $t+1$ when with (endogenous) probability $f(x_t)$ the intermediate goods firm will be matched with a final goods firm and gain $\mathscr{V}^A_{t+1}$, and with probability $1-f(x_t)$ will remain inactive and gain $\mathscr{V}^I_{t+1}$ instead.

The surplus of an active intermediate goods firm from an existing match is thus given by

$$S^m_t \equiv \mathscr{V}^A_t-\mathscr{V}^I_t,$$

[10]The 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.

[11]In our model, capital is chosen contemporaneously such that the value for an intermediate goods firm of being inactive in the network at time t is identical to the outside option for an active intermediate goods firm when it enters the bargaining process. If capital were chosen instead one period in advance once an intermediate goods firm found out that would be active in the following period, the two values would be different because inactive intermediate goods firms would not have capital, while active intermediate goods firms walking away from bargaining would be left with idle capital (and hence with the net capital gains).

After replacing the expressions of $\mathscr{V}_t^A$ from (11) and of $\mathscr{V}_t^I$ from (12), and using intermediate goods firm's production technology (9) 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

$$
\begin{aligned}
S_t^m(p_t^m, y_t^m, k_t^m) = & (1-\tau^*)\frac{p_t^m}{P_t} y_t^m - (1-\tau)\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) - \frac{Q_t^k}{P_t} k_t^m + E_t\Big\{\rho \Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big]\Big\} + \\
& + \chi_m + (1-\delta - f(x_t)) E_t\{\Lambda_{t,t+1}[S_{t+1}^m(p_{t+1}^m, y_{t+1}^m, k_{t+1}^m)]\}
\end{aligned} \tag{13}
$$

For future reference, we define the "reservation return of an intermediate goods firm" $\underline{\Omega}_t$ as the *minimum* gross return required by an intermediate goods firm, namely as the return value $(1-\tau^*)\frac{p_t^m}{P_t} y_t^m$ for which its surplus S_t^m is 0:

$$
\underline{\Omega}_t \equiv (1-\tau)\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) + \frac{Q_t^k}{P_t} k_t^m - E_t\Big\{\rho \Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big]\Big\} - \chi_w - \Big(1-\delta - f(x_t)\Big) E_t\Big\{\Lambda_{t,t+1}\Big[S_{t+1}^m\Big]\Big\} \tag{14}
$$

The production of intermediate goods 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 $\mathscr{L}_t^s$ is limited by the expected resale value of firms' collateral. The latter is given by a share ν of physical capital value net of refurbishing costs, implying[12]

$$
\mathscr{L}_t^s \le \nu E_t\Big\{\rho \Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big]\Big\} \tag{15}
$$

The amount of credit that the Big Tech firm is willing to extend to intermediate goods firms is also limited by moral hazard. The limit equals the expected gains for intermediate goods firms from retaining access to the Big Tech network in the following periods ($\mathscr{V}_{t+1}$):

$$
\mathscr{L}_t^b \le b \mathscr{V}_{t+1} \tag{16}
$$

where $\mathscr{V}_{t+1} \equiv E_t\Big\{\Lambda_{t,t+1}\Big[(1-\delta)\mathscr{V}_{t+1}^A + \delta \mathscr{V}_{t+1}^I\Big]\Big\}$ is the expected value of retaining access to the network if intermediate goods firms behave and repay their credit. This is because intermediate

[12] If banks seized final goods firm's capital, they would need to pay themselves the maintenance costs before reselling it on the market.

goods firms which default on big tech credit are automatically excluded from the e-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 intermediate goods firms to sell their products outside the Big Tech commerce platform[13]. 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 intermediate goods firms can get is limited by both collateral and incentives to remain in the Big Tech network, namely

$$\mathscr{L}_t^b + \mathscr{L}_t^s \leq b\mathscr{V}_{t+1} + \nu E_t\Big\{\rho\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\Big]\Big\} \tag{17}$$

Since credit is used to finance labor, intermediate goods firms' borrowing constraint can be written as

$$(1-\tau)\frac{W_t}{P_t}l_t^m(y_t^m, k_t^m) \leq b\mathscr{V}_{t+1} + \nu E_t\Big\{\rho\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\Big]\Big\} \tag{18}$$

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

[13]The 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 intermediate goods firms 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 intermediate goods firms lost access to the commerce platform for only one period in case of default, the credit limit would be given by $\mathscr{V}_{t+1} - E_t\big\{\Lambda_{t,t+2}V_{t+2}\big\}$.

3.4 Final goods firms

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. A typical final goods firm purchases intermediate goods from all A_t intermediate goods firms active at time t via the Big Tech commerce platform, and produces final goods Y_t with the following linear technology[14]

$$Y_t = \int_0^{A_t} y_t^m(i)di$$

where $y_t^m(i)$ is the quantity purchased from the active intermediate goods firm i decided by Nash–bargaining. The quantity purchased from each active intermediate goods firm is the same for all final goods firms

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

implying that the output of the representative final goods firm (and of the final goods sector as a whole) equals

$$Y_t = A_t y_t^m$$

Each period a typical final goods firm actively searches on the Big Tech commerce platform for S_t intermediate goods firms for use in the following period (see the timeline in Figure 2). We denote the value of a search by $\mathcal{I}_t^s$ (the subscript s denoting "search") which equals

$$\mathcal{I}_t^s \equiv -\chi_w + g(x_t)E_t\{\Lambda_{t,t+1}\mathcal{I}_{t+1}^B\} \tag{19}$$

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 intermediate goods 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, final goods firms will look for new suppliers until the marginal value of an open search is

[14] We implicitly assume that at each date the active intermediate goods firms are indexed on the interval $[0, A_t]$.

zero. Thus, the equation describing the number of searches S_t is obtained for $\mathcal{I}_t^s = 0$, namely for

$$\chi_w = g(x_t) E_t\{\Lambda_{t,t+1} \mathcal{I}_{t+1}^B\} \tag{20}$$

The value of an existing relation with an intermediate goods supplier at time t equals

$$\mathcal{I}_t^B = y_t^w - \frac{p_t^m}{P_t} y_t^m + (1-\delta) E_t\Big\{\Lambda_{t,t+1} \mathcal{I}_{t+1}^B\Big\} \tag{21}$$

where $y_t^w - \frac{p_t^m}{P_t} y_t^m$ are current real profits for the final goods firm 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 (20) holds in equilibrium, the expression of $\mathcal{I}_t^B$ in (21) further writes as

$$\mathcal{I}_t^B = y_t^w - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_m (1-\delta)}{g(x_t)} \tag{22}$$

One may write expression (22) for $t+1$, and combine it with equation (20) to obtain the *intermediate goods supplier–search equation*

$$\frac{\chi_w}{g(x_t)} = E_t\Big\{\Lambda_{t,t+1}\Big[y_{t+1}^w - \frac{p_{t+1}^m}{P_{t+1}} y_{t+1}^m + \frac{\chi_w(1-\delta)}{g(x_{t+1})}\Big]\Big\} \tag{23}$$

The surplus for a typical final goods firm from an existing match is thus given by

$$S_t^w \equiv \mathcal{I}_t^B - \mathcal{I}_t^s \tag{24}$$

which, using the expression of $\mathcal{I}_t^B$ in (22) and $\mathcal{I}_t^s = 0$, can be written in equilibrium as a function of p_t^m and y_t^m as follows

$$S_t^w(p_t^m, y_t^m) \equiv y_t^w - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_w(1-\delta)}{g(x_t)} \tag{25}$$

For future reference, we define the "reservation cost of a final goods firm" $\bar{\Omega}_t$ as the *maximum* amount that a typical final goods firm can pay for an additional intermediate goods supplier, namely the value of $\frac{p_t^m}{P_t} y_t^m$ for which its surplus S_t^w is 0,

$$\bar{\Omega}_t \equiv y_t^w + \frac{\chi_w(1-\delta)}{g(x_t)} \tag{26}$$

3.5 Matching

Final goods firms search each period for inactive intermediate goods firms in the network. That is, final goods firms cannot buy their inputs instantaneously. Rather, intermediate goods suppliers need to be found first through a costly and time–consuming search process. If a match is formed at time t, intermediate goods firms 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 intermediate goods firms which post advertisements (and do not produce) closing a deal with the final goods sector at time t. σ_m 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 its 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 intermediate 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 intermediate goods firms which split with their client and need to post an advertisement. Hence, the number of intermediate goods firms 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) intermediate goods firms 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 intermediate goods firm to find a match $f(x_t)$, and for an open search to be filled by an intermediate goods firm $g(x_t)$. We first

Table 2 Timeline operations – intermediate goods firms and final goods firms

Period $t-1$	Each intermediate goods firm $i \in [0,1]$ finds out if it is active or inactive at t
Period t	**Intermediate goods firms:** Intermediate goods firm $i \in [0,1]$: If active, produces and sells its output to final goods firms; to do so: (i) at the beginning of the period, issues equity $\mathscr{E}_t$ to buy capital k_t^m, gets working capital loan $\mathscr{L}_t$ to hire labor l_t^m, and produces y_t^m; (ii) at the end of the period, repays the working capital loan and transfers the return on capital as dividend to equity investors and any remaining profits to the household. If inactive, pays a fee χ_m to post an ad on the Big Tech platform, and transfers net period profit to the household. **Final goods firms:** A typical final goods firm: (i) buys inputs from all A_t active intermediate goods suppliers; (ii) searches for S_t intermediate goods suppliers for use at $t+1$, paying a unit fee equal to χ_w for each of these searches. **Matching:** Active intermediate goods firms and final goods firms bargain over the price p_t^m and the quantity y_t^m of intermediate goods.
Period $t+1$	If active at t, intermediate goods firm j sells capital k_t^m and pays the household back the value of its equity investment $Q_t^e \mathscr{E}_{t-1}$.

define the the intermediate goods market tightness (x_t) as the relative number of open searchers relative to the number of inactive intermediate goods firms

$$x_t \equiv S_t / I_t \tag{27}$$

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

The probability that an open search is filled with an inactive intermediate goods firm, $g(x_t)$

equals

$$g(x_t) \equiv \frac{M(S_t, I_t)}{S_t} = \sigma_m \left(\frac{S_t}{I_t}\right)^{\eta-1} = \sigma_m x_t^{\eta-1} \tag{28}$$

Note that this probability decreases in x_t, implying that final goods firms find it more difficult to find an intermediate goods supplier when the intermediate goods market is tight. Similarly, the probability that any inactive intermediate goods firm is matched with an open search at time t, $f(x_t)$, is given by

$$f(x_t) \equiv \frac{M(S_t, I_t)}{I_t} = \sigma_m \left(\frac{S_t}{I_t}\right)^{\eta} = \sigma_m x_t^{\eta} \tag{29}$$

and increases in x_t. This implies that inactive intermediate goods firms find final goods clients more easily when the intermediate goods market is tighter, that is, when the number of inactive intermediate goods firms is low relative to the one of open searches by final goods firms.

3.6 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.

3.7 Central bank

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

$$1 + i_t = \frac{1}{\beta} \Pi_t^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_y} e^{\nu_t} \tag{30}$$

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.

3.8 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 employment at rate $\tau = \frac{1}{\epsilon_w}$, and balances the budget with lump–sum transfers/taxes Υ_t^g:

$$B_t^h + B_t^b = \left(B_{t-1}^h + B_{t-1}^b\right)\left(1 + i_{t-1}\right) + \Upsilon_t^g + \tau W_t \int_0^{A_t} l_t^w(i)di \tag{31}$$

3.9 Market clearing

3.9.1 Final goods market

Market clearing requires aggregate demand for final goods by households to equal their aggregate supply:

$$C_t = Y_t \tag{32}$$

3.9.2 Intermediate goods market

Market clearing requires aggregate demand for intermediate goods by final goods firms to equal aggregate supply by all active intermediate goods firms at time t:

$$Y_t = A_t y_t^m \tag{33}$$

The quantity produced by each intermediate goods firm y_t^m and the price of an intermediate 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.

3.9.3 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 intermediate goods firms to equal its aggregate supply:

$$A_t k_t^m = \bar{K} \tag{34}$$

3.9.4 Labor market

Market clearing requires aggregate demand for all labor types by all active intermediate goods firms to equal its supply by households:

$$\int_0^{A_t} \int_0^1 l_t^m(i,j) dj di = L_t$$
$$\Delta_{w,t} A_t l_t^m = L_t \tag{35}$$

where $\Delta_{w,t} \equiv \int_0^1 \left(\frac{W_t(j)}{W_t}\right)^{-\epsilon_w}$ is equal to 1 up to a first order log-linear approximation.

3.9.5 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:

$$B_t^h + B_t^b = B_t \tag{36}$$

3.9.6 Equity market

Market clearing requires that the demand for equity claims by the representative household to equal their supply by active intermediate goods firms wiling to finance physical capital:

$$\mathscr{E}_t = A_t k_t^m \tag{37}$$

3.10 Bargaining

In equilibrium, the final goods firms and intermediate goods firms which are in a match obtain a total return that is strictly higher than the expected return of unmatched final goods firms and intermediate goods firms. The reason is that if a intermediate goods firm and a final goods firm 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 p_t^m of an intermediate good and the output y_t^m of an intermediate good producer, and it is subject to the intermediate goods firms' credit and technology constraints. As a result, the set $\{p_t^m, y_t^m\}$ is given by the solution to the following bargaining problem[15]:

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

subject to

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \leq b\mathscr{V}_{t+1} + \nu E_t\Big\{\rho\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big]\Big\} \tag{38}$$

where ϵ is the (relative) bargaining power of the active intermediate goods firm. According to the credit constraint (38), the wage bill cannot exceed the sum of the access value to the Big Tech platform $\mathscr{V}_{t+1}$ and of the physical collateral value $\nu E_t\Big\{\Lambda_{t,t+1}\Big[\rho\frac{Q_{t+1}^k}{P_{t+1}} k_t^m\Big]\Big\}$[16]. Because the two parties bargain simultaneously over the price and individual quantity of intermediate goods, the outcome is (privately) efficient and the price of intermediate goods plays only a distributive role. As shown 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

$$\epsilon S_t^m = \frac{(1-\epsilon)}{1-\tau^*} S_t^w \tag{39}$$

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 (39) 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 (13), and of S_t^w from (25), one may further write (39) as an equation in p_t^m as follows

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

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

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

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

[16]l_t^m is substituted in the bargaining problem using the technology constraint, so the constraint entering the bargaining problem is a combination of the borrowing and technology constraints.

where $\lambda_t \geq 0$ is the Lagrangian multiplier on an intermediate goods firm's credit constraint. Using (39), this optimality condition can be simplified under our baseline calibration with $\epsilon = 1 - \epsilon$ as[17]:

$$1 = \frac{1}{1-\alpha}\frac{W_t}{P_t}\frac{l_t^m}{y_t^m}\Big[\frac{1}{1-\tau^*} + \frac{\lambda_t}{1-\epsilon}\Big(\frac{1}{1-\tau^*}\Big)^{\varepsilon}\Big], \;\; \lambda_t \geq 0 \tag{40}$$

In the absence of credit frictions, this condition implies that the real return for a final goods producer on an intermediate good equates its marginal production cost at the intermediate goods firm 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. Note how the proportional fee τ^* levied by the Big Tech distorts firms' price and quantity decisions.

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

$$\frac{Q_t^k}{P_t} = \gamma\frac{y_t^m}{k_t^m}\left[\frac{1+\frac{\lambda_t}{\epsilon}\Big(1-\tau^*\Big)^{1-\epsilon}}{1+\frac{\lambda_t}{1-\epsilon}\Big(\frac{1}{1-\tau^*}\Big)^{\epsilon}}\right] + \left[1+\frac{\nu\lambda_t}{\epsilon}\Big(1-\tau^*\Big)^{1-\epsilon}\right]E_t\Big\{\rho\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}\Big]\Big\} \tag{41}$$

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

$$D_t^e = \gamma P^w\frac{y_t^m}{k_t^m}\left[\frac{1+\frac{\lambda_t}{\epsilon}\Big(1-\tau^*\Big)^{1-\epsilon}}{1+\frac{\lambda_t}{1-\epsilon}\Big(\frac{1}{1-\tau^*}\Big)^{\epsilon}}\right] + \left(P_t\frac{\nu\lambda_t}{\epsilon}\Big(1-\tau^*\Big)^{1-\epsilon}\right)E_t\Big\{\rho\Lambda_{t,t+1}\Big[\frac{Q_{t+1}^k}{P_{t+1}}\Big]\Big\} \tag{42}$$

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 (38), (39), (40), (41) and (42) 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 with sticky wages.[18]

[17]The relative bargaining power of sellers and buyers may play an important role for the equilibrium allocation. In this analysis however we remain agnostic about such effects and give both equal bargaining power. This allows also to simplify the equilibrium expressions.

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

4 Parametrization

We parameterize our model at quarterly frequency. One may split structural parameters of the model in four groups (Table 3). 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 labor types ε_w, Calvo index of wage rigidities θ_w). These parameters are set to their textbook values in Galí (2015), Chapter 6. The labor disutility parameter χ is 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.

Table 3: 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_w	Elasticity of substitution of labor types	9
θ_w	Calvo index of wage 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-ρ	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/real search costs for intermediate goods firms	0.05
χ_m	Big tech fee/ real search costs for final goods firms	0.05
τ^*	Variable big tech fees	8%
b	Pledgeability ratio of network value	1.25%
σ_m	Matching efficiency	$[0, \infty]$

Note: Values are shown in quarterly rates.

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% of 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 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 the value of 0.178 in our baseline calibration but is then moved to analyse the impact of increasing levels of Big Techs' matching efficiency[19]; the network value pledgeability ratio b, which is set at 1.25%; the fees perceived by the Big Tech platform, χ_w and χ_m, which are set at 0.05; and the variable fee τ^*, which is set at 8% to reflect current sample average.[20].

5 Big Tech efficiency and the macroeconomy: comparative statics

This section studies how the provision of big tech credit affects the steady-state allocation, and how these effects vary with the matching efficiency between sellers and buyers on the Big Tech's e-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.[21] 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

[19]The value $\sigma_m = 0.178$ gives an elasticity of big tech credit to network sales similar to the one estimated based on chinese data by Gambacorta et al. (2022).

[20]The assumed network value pledgeability ratio proxies for a finite period exclusion from the commerce platform in case of default, as well as for an outside retail option available to the intermediate goods firm (not observed in equilibrium).

[21]Figure B1 in the appendix further disentangles the channels driving our results by considering various nested versions of the model, ie the models with matching frictions and only bank credit, with only big tech credit, or with both sources of credit; the model with matching frictions but no financial frictions; the model with financial frictions but no matching frictions; and the frictionless model.

acquire more data on their clients, and are able to match more efficiently sellers with buyers on their commerce platforms.

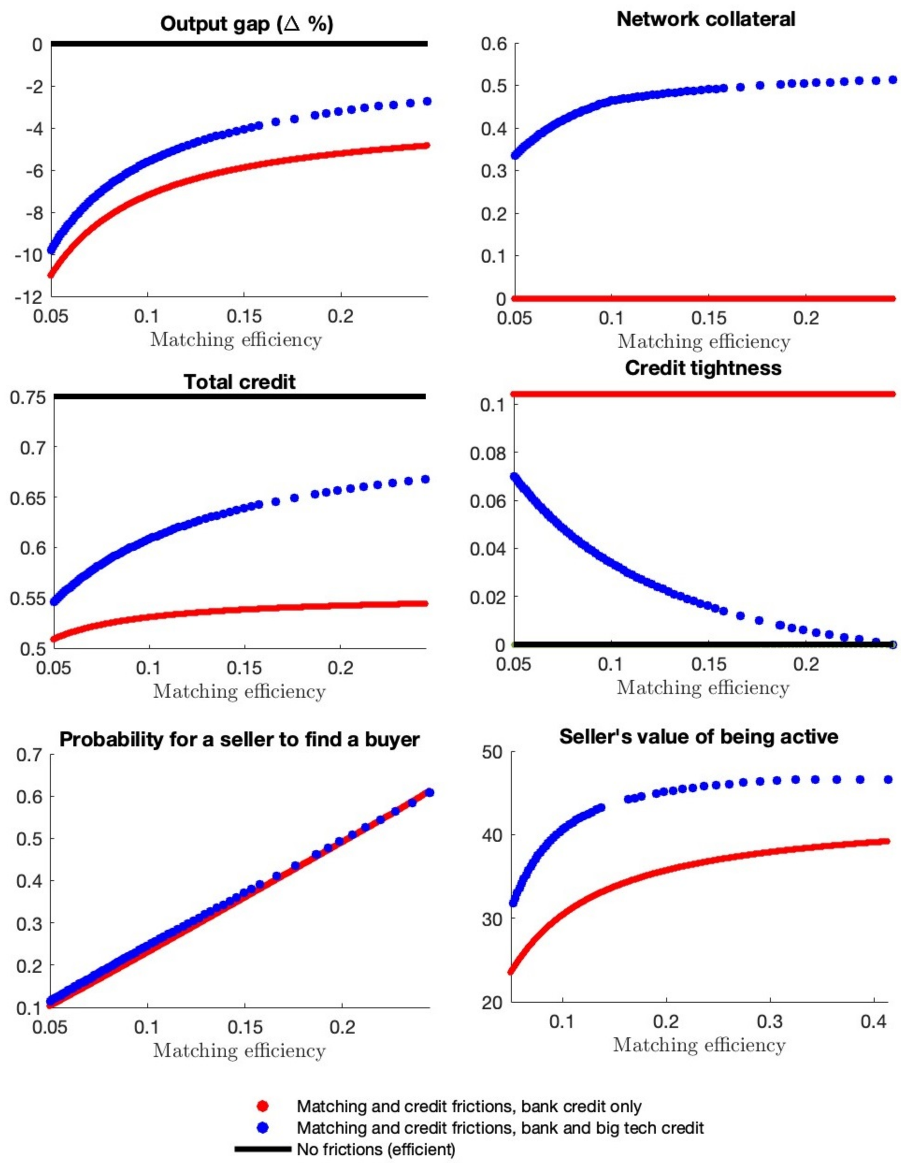

Figure 6: Steady-state equilibrium and matching efficiency on the e-commerce platform

Notes: Output gap: % deviation of output from its efficient level $(Y - Y^e)/Y^e$. Network collateral: expected profits that sellers on the platform would lose in case of default $b\mathscr{V}$. Total credit: aggregate big tech credit and bank credit. Sellers' value of being active: $\mathscr{V}^a$. Probability for a seller to find a buyer on the commerce platform: $f(x)$. Matching efficiency: σ_m

According to the results reported in Figure 6, 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 (38). Specifically, the availability of big tech credit allows intermediate goods firms to pledge their future expected profits $\mathscr{V}_{t+1}$ (top right panel) as "network collateral" alongside physical capital. Everything else equal, the higher collateral allows intermediate goods firms 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 intermediate goods firms 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 intermediate goods firms' 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 e-commerce platform rises. A higher matching efficiency increases the probability for an intermediate goods firm to find a client (bottom left panel in Figure 6), and leads to higher expected profits, a higher value of being active on the e-commerce platform (top right panel), and ultimately a larger "network collateral" (right top panel). Everything else equal, the higher network collateral allows intermediate goods firms to borrow more (38), and hire more labor. This relaxes to a larger extent the tightness of the borrowing constraints relative to the case with bank credit only (middle right panel) and translates in larger effects on total credit and output. Under our baseline calibration, the rise in matching efficiency may reduce the tightness of credit constraints up to point where the economy enters the credit–frictionless region. The increased relevance of big tech credit is also reflected in its higher share in total credit (Figure 7).

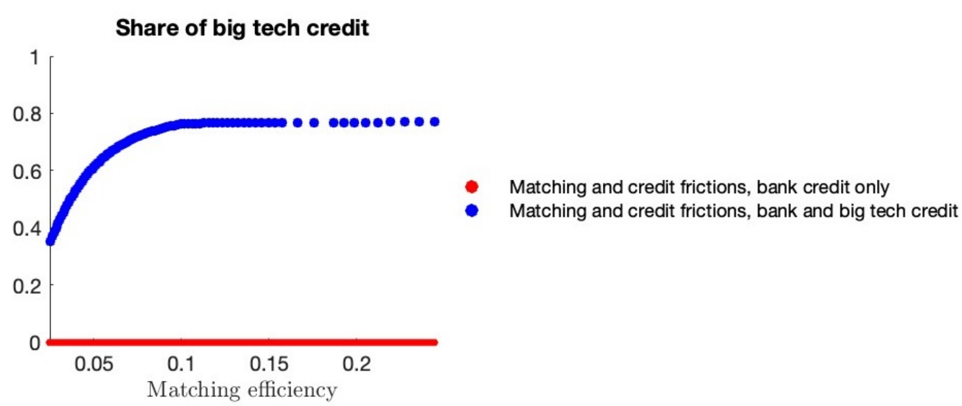

Figure 7: Steady-state share of big tech credit and matching efficiency

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 responses to monetary policy in our baseline economy with those in a counterfactual economy with bank credit only. 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.

Figure 8 shows the dynamic macroeconomic responses in our model economy in the case with bank credit only. The matching efficiency on the e-commerce platform is set in this experiment at a relatively low level (0.178) to proxy for the initial stage of development of e-commerce. The magnitude of the response of aggregate output in the model is very much in line with empirical estimates of a 25 bps monetary policy shock, as obtained using local projections on US data (reported in the appendix, figure A1). The responses of commercial real-estate prices and e-commerce sales are also in line with the empirical estimates (as shown in figures A2 and A3 of the appendix). This suggests that our baseline calibration proxies well the case without big tech credit for the US.

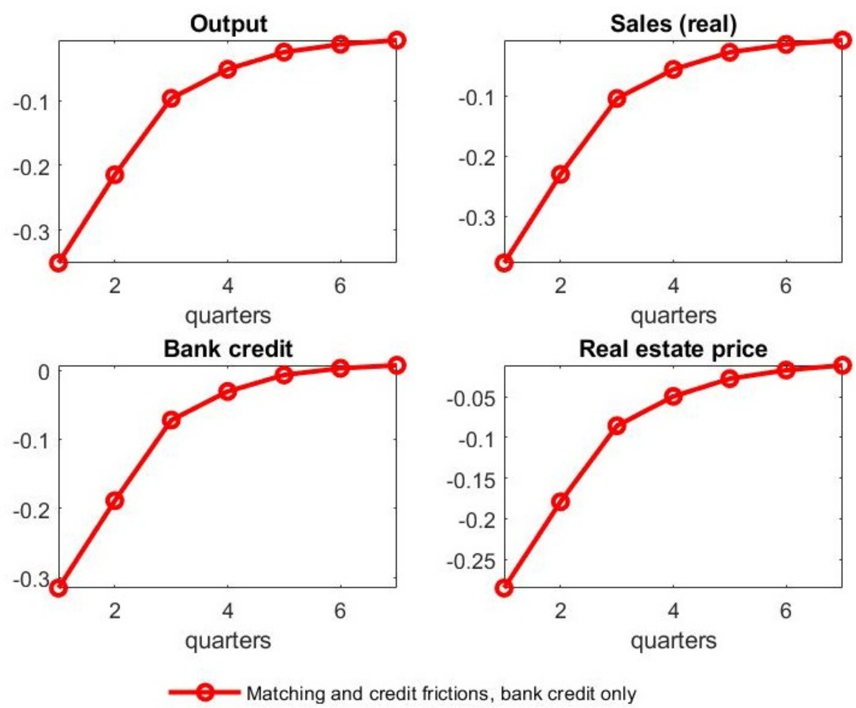

Figure 8: Impulse responses to a monetary policy shock in en economy with bank credit only

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

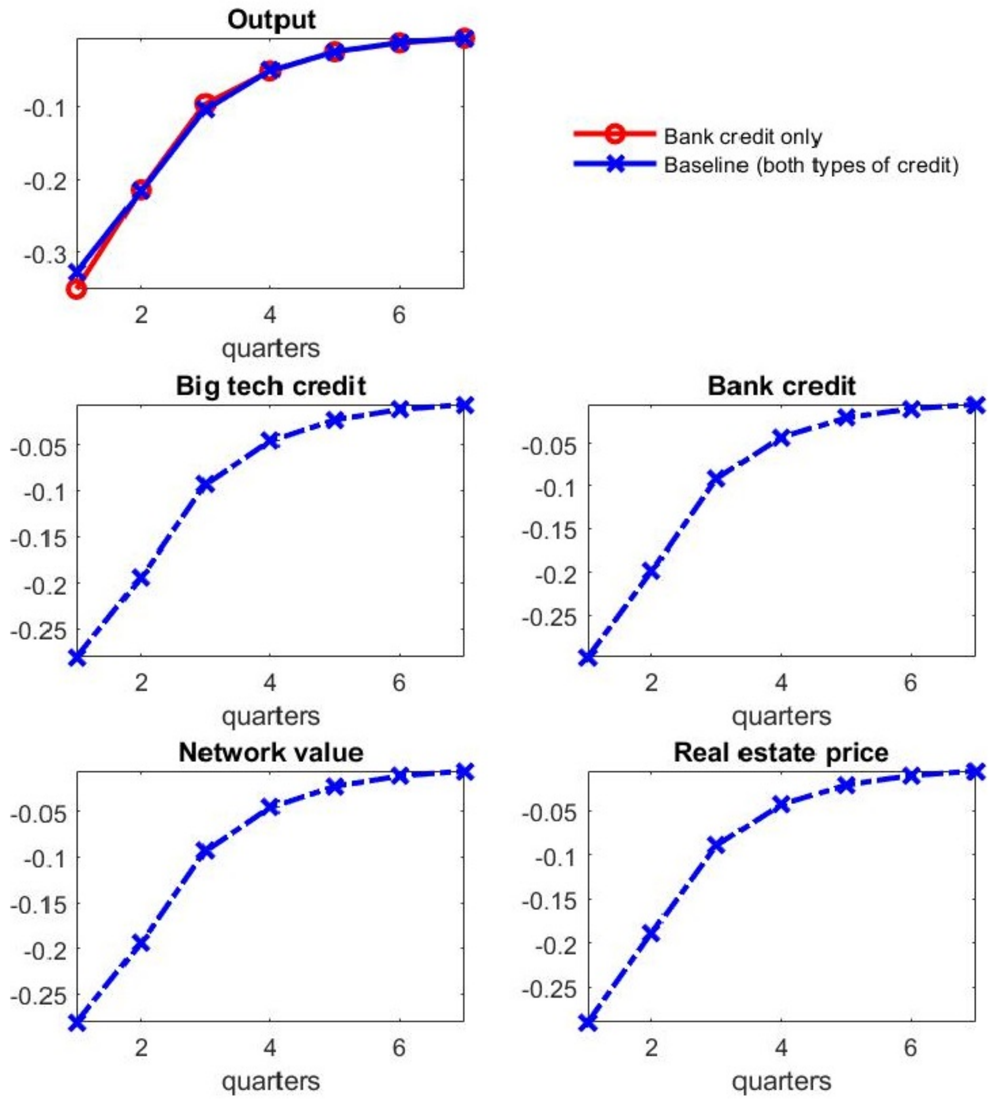

Figure 9: Impulse responses to a monetary policy shock in an economy with both types of credit

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. Matching efficiency $\sigma_m \approx 0.178$, Y-axis: $\%\Delta$ from steady-state.

We study next how the availability of big tech credit affects the results. Figure 9 shows that big tech credit and secured bank credit (middle panels) respond similarly to a monetary policy tightening.[22] In the model, these responses can be traced to similar sensitivities of "network collateral" (i.e. expected profits on the Big Tech platform, bottom left panel) and physical collateral (i.e. real estate values pledged as collateral, bottom right panel) to a monetary policy shock. With the strength of the credit channel unchanged, the response of output (in percentage terms) is affected

[22]This result is consistent with the empirical estimates for China in Huang et al. (2022).

little by the availability of big tech credit (top panel) under our baseline calibration. Notably, the overall impact of a monetary policy shock on the different sources of finance, as well as on aggregate credit and output, depends on the sensitivities of network and physical collateral to a monetary policy shock. These can differ across countries, also depending on the level of financial development and on the efficiency of the e-commerce platforms. [23]

Finally, figure 10 shows that, under our baseline calibration, as matching efficiency on the e-commerce platform increases and the economy gradually converges to its credit-frictionless counterpart, the financial accelerator fades away and real activity becomes less sensitive to monetary policy.

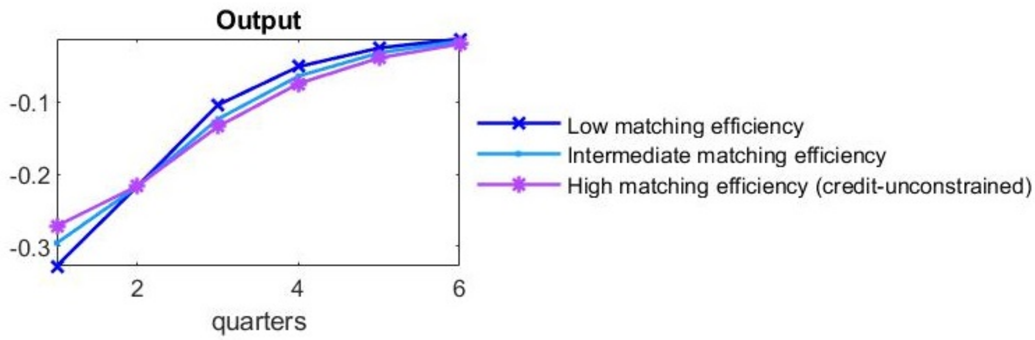

Figure 10: Dynamic responses to a monetary policy shock for different levels of matching efficiency

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

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 local property prices 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 intermediate goods firms and final goods firms and extends working capital loans

[23] Figures C1 and C2 in the Appendix illustrate a case where network collateral is less sensitive to monetary policy than physical collateral. In that economy, big tech credit responds less to monetary policy than secured bank credit, and the availability of the new type of credit dampens the strength of the credit channel and the overall reaction of real activity to monetary policy.

to the former subject to limited commitment. Firms have access to both big tech credit and secured bank credit. Nominal wages are rigid and monetary policy affects real economic outcomes.

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 e-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, under our calibration based on US data, big tech credit and bank credit react similarly to a monetary policy tightening, due to the similar 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, 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. Thus, as matching efficiency on the e-commerce platform increases and the economy gradually converges to its credit-frictionless counterpart, the financial accelerator fades away and real activity becomes less sensitive to monetary policy.

Possible future extensions of our framework include business-to-consumer (B2C) transactions and household credit, Big Techs' financing constraints, complementarity or substitutability between big tech credit and bank credit, Big Tech's market power, and 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.

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, Stéphane 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.

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 entrepreneurial growth". Mimeo.

Huang, Y., L. Xiang, H. Qiu and C. Yu (2022), "BigTech Credit and Monetary Policy Transmission: Micro-Level Evidence from China". Available at SSRN: https://ssrn.com/abstract=4176100 or http://dx.doi.org/10.2139/ssrn.4176100

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.

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.

Rochet, J.-C., and Tirole, J. (2003), "Platform Competition in Two-sided Markets", Journal of the European Economic Association, 1(4), 990–1029.

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.

A Estimated responses to a monetary policy shock in the US

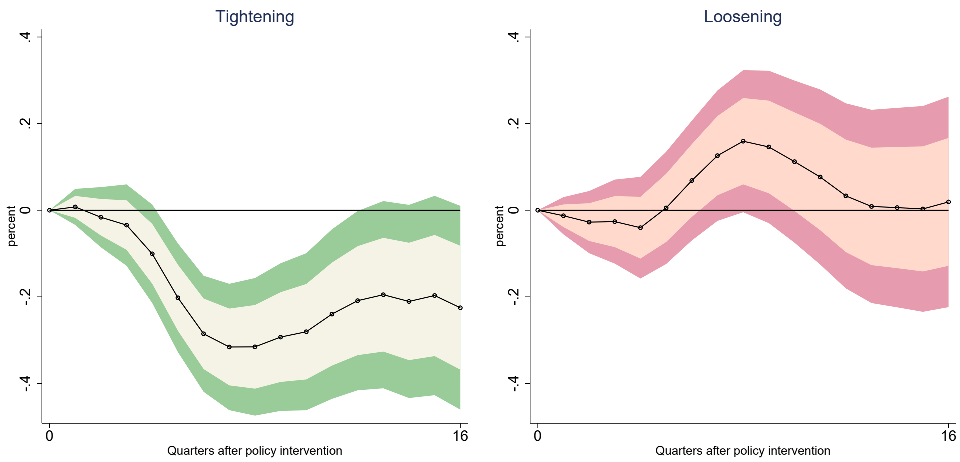

Figure A1: Estimated response of real GDP to a 25 basis points monetary policy shock

Notes: Estimation using local projections on a quarterly sample from 1994Q4 to 2016Q2 for the US. Data source: FRED, Jarosinski and Karadi (2020)

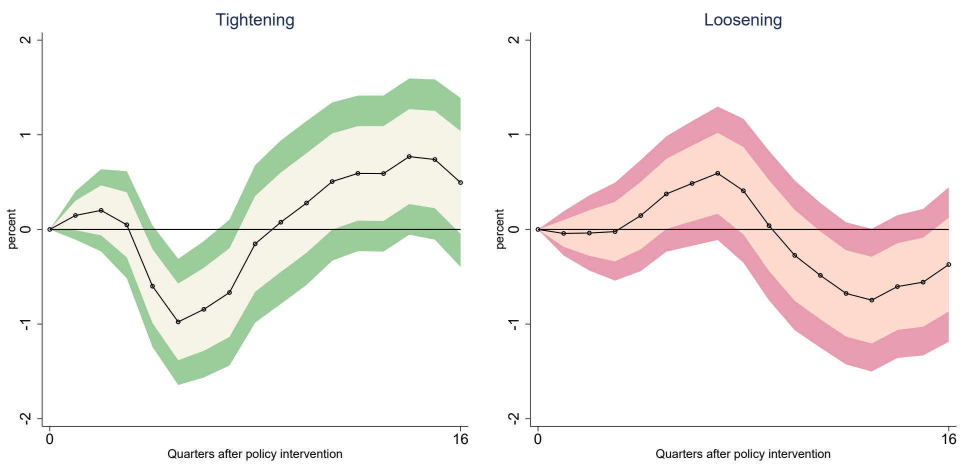

Figure A2: Estimated response of real commercial property prices to a 25 basis points monetary policy shock

Notes: Estimation using local projections on a quarterly sample from 1994Q4 to 2016Q2 for the US. Data source: FRED, Jarosinski and Karadi (2020)

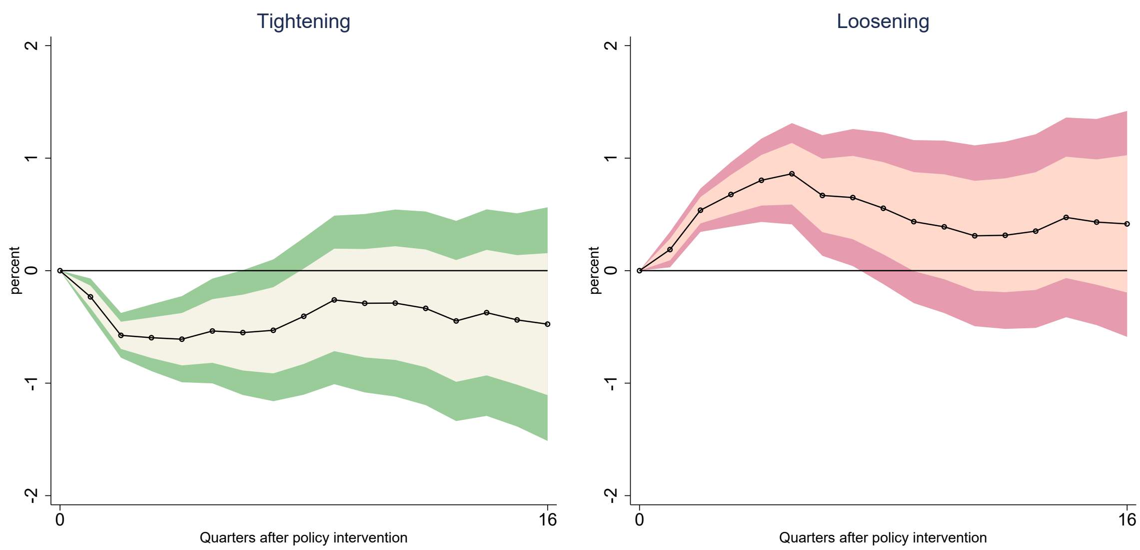

Figure A3: Estimated response of real e-commerce sale to a 25 basis points monetary policy shock

Notes: Estimation using local projections on a quarterly sample from 1994Q4 to 2016Q2 for the US. Data source: US Census data, Jarosinski and Karadi (2020)

B Steady-state analysis: disentangling the channels

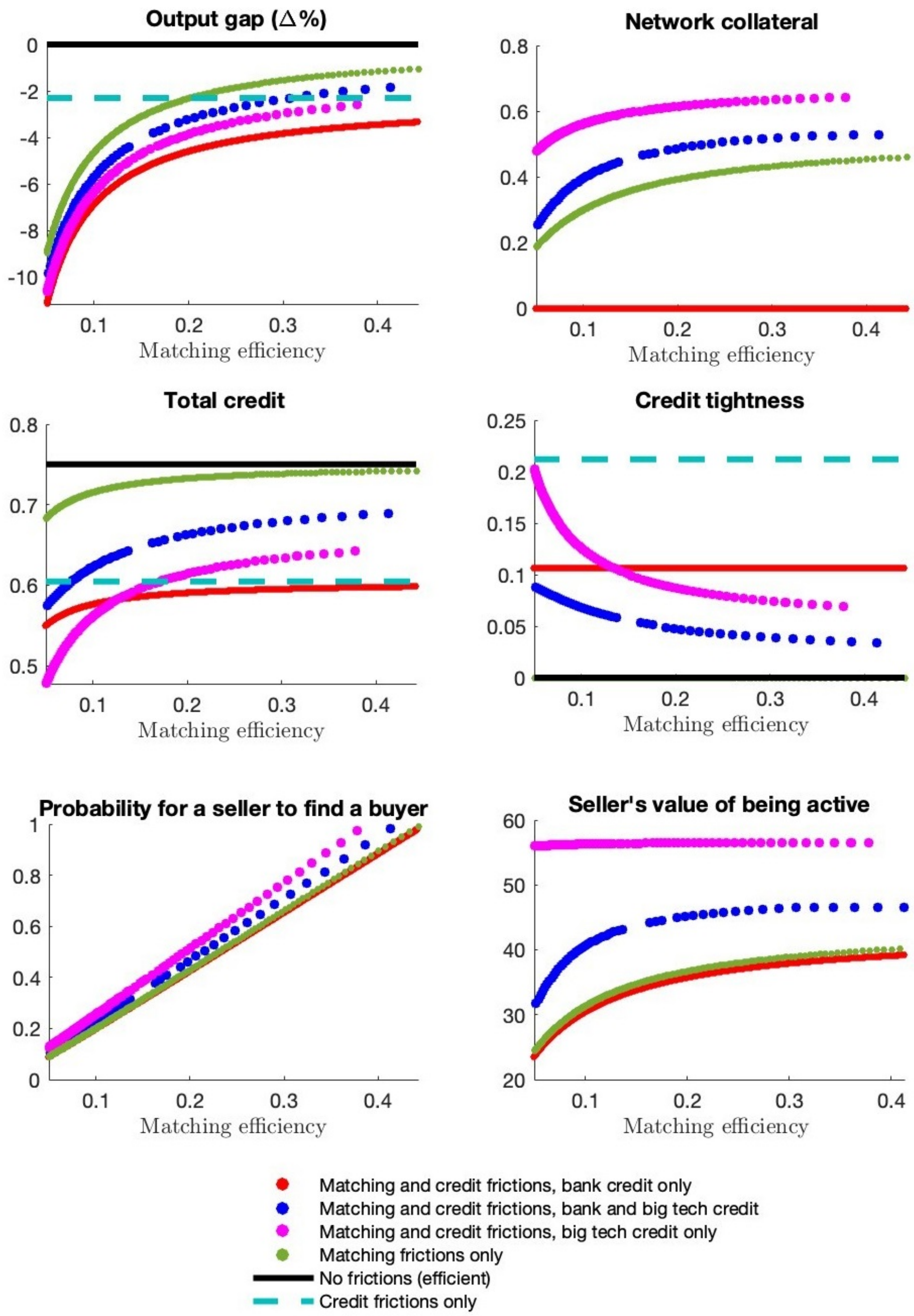

Figure B1: Steady-state equilibrium and matching efficiency on the e-commerce platform

Notes: Case without variable fees ($\tau^* = 0$). Output gap: % deviation of output from its efficient level $(Y - Y^e)/Y^e$. Network collateral: expected profits that sellers on the platform would lose in case of default $b\mathscr{V}^a$. Total credit: aggregate big tech credit and bank credit. Sellers' value of being active: $\mathscr{V}^a$. Probability for a seller to find a buyer: $f(x)$. Matching efficiency: σ_m

C Dynamic analysis under low elasticity of e-commerce sales

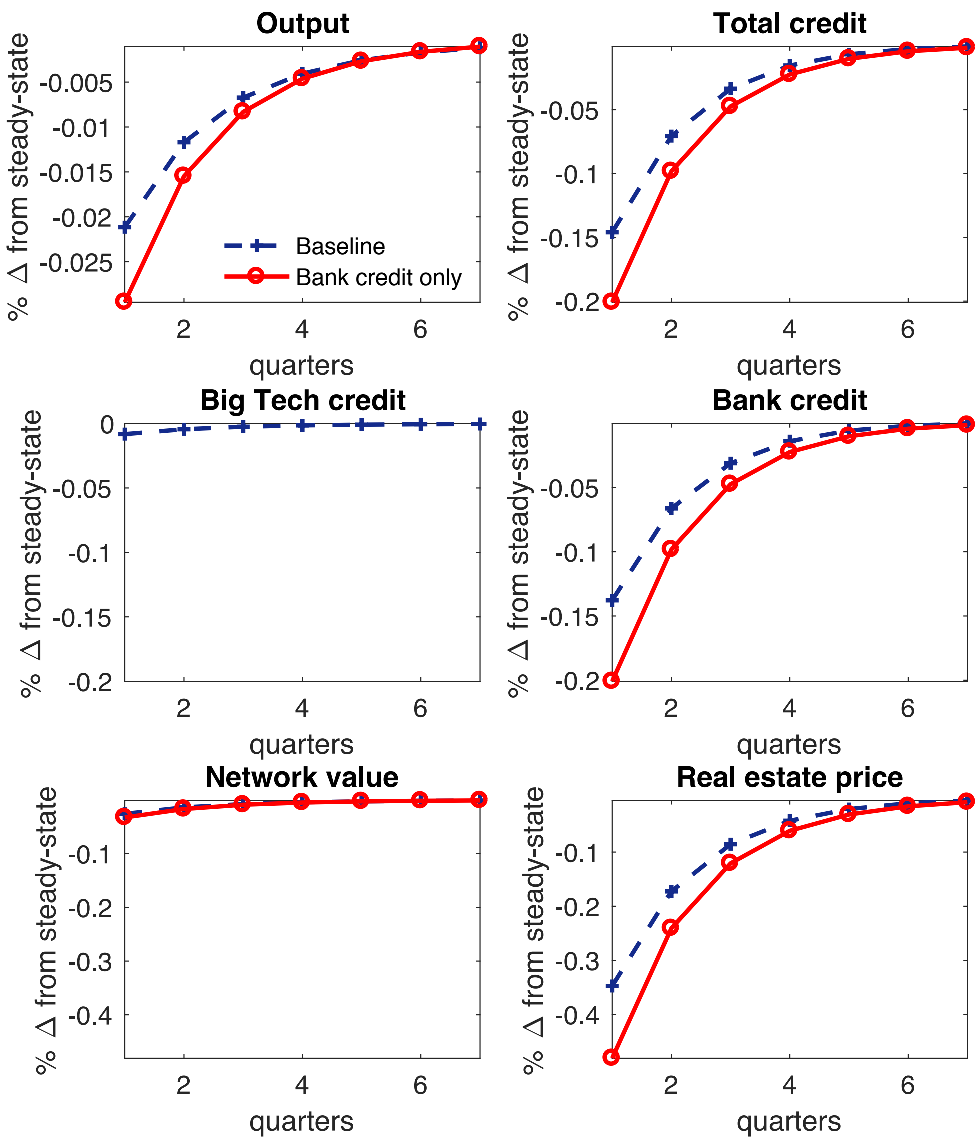

Figure C1: Impulse responses to a monetary policy shock under low elasticity of e-commerce sales

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. Matching efficiency is $\sigma_m \approx 0.178$, which gives an elasticity of big tech credit to network sales similar to the one estimated based on Chinese data by Gambacorta et al. (2022). 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.

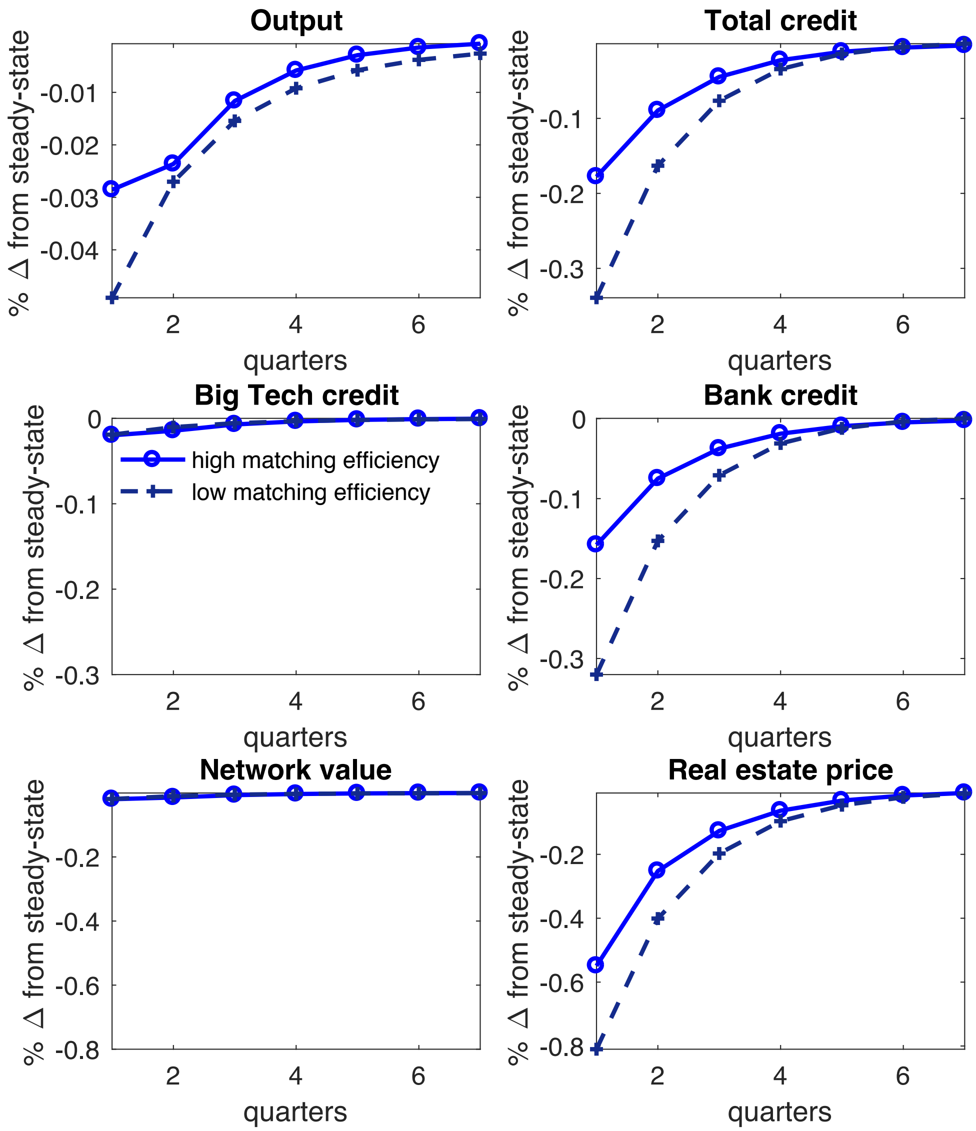

Figure C2: Impulse responses to a monetary policy shock under low elasticity of e-commerce sales, for low vs high matching efficiency

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 **??** in the Appendix). The high level of efficiency corresponds to $\sigma_m \approx 0.93$ and characterizes the highest matching efficiency when both type of credit are available in Figure 6 (blue solid line). The monetary policy regime is described by simple Taylor rule (1993).