Big Techs and the Credit Channel of Monetary Policy

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Abstract

We document some stylized facts on big tech credit and rationalize them through the lens of a model where big techs facilitate matching on the e-commerce platform and extend loans. The big tech reinforces credit repayment with the threat of exclusion from the platform, while bank credit is secured against collateral. Our model suggests that: (i) a rise in big techs' matching efficiency increases the value for firms of trading on the platform and the availability of big tech credit; (ii) big tech credit mitigates the initial response of output to a monetary shock, while increasing its persistence; (iii) the efficiency gains generated by big techs are limited by the distortionary fees collected from users.

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

1 Introduction

Large technology firms such as Alibaba, Amazon, Facebook or Mercado Libre (big techs) have recently ventured in financial markets and started providing loans to vendors on their e-commerce platforms. Big tech credit has rapidly expanded over the recent years, reaching volumes of USD 530 billion in 2019, up from only around USD 11 billion in 2013. The increase in big tech credit can be expected to outpace that of bank credit in some countries. For instance, during 2020-21, big tech credit in China recorded an average annual growth rate of 37%, compared to 13% for bank credit.

These 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' creditworthiness with more precision than traditional credit bureau ratings (Frost et al. (2020)). Moreover, the threat of being banned from the e-commerce platform or even of having one's reputation tarnished serves as an extra-legal but highly effective means of contract enforcement for big tech companies (Gambacorta, Khalil and Parigi (2022)). The crucial role of data in the credit scoring process and the threat of exclusion from the big tech ecosystem reduce the need for firms to pledge collateral in loan contracts. This explains why big tech credit is uncorrelated with real estate values, but it is highly correlated 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 develop a model that can replicate two empirical facts we document about big tech. First, extending previous results based on micro data for China to a longer sample and set of countries, we show that unlike bank credit, big tech credit does not react to changes in asset prices and local economic conditions. Second, using local projections to analyse the response to a monetary policy shock, we show that commercial property prices respond more strongly than e-commerce sales, although less persistently. Our model is consistent with this evidence and can be used to predict how the advent of big tech credit will

impact the monetary policy transmission going forward.

Our analysis focuses on business-to-business (B2B) transactions (i.e. transactions between firms), which account for 80% of global online transactions.[1] In our framework, a big tech platform facilitates the search and matching between intermediate goods firms and final goods firms, and extends working capital loans to the former.[2] 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 crucial 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 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.[3]

We obtain three 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 mitigates the initial responses of aggregate credit and output to a monetary shock, but increases the persistence of the effect of monetary policy on the macroeconomy. Third, big techs' macroeconomic efficiency gains are limited by the distorsionary nature of the fees collected from their users.

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[1]According to the United Nations Conference on Trade and Development (UNCTAD), the average share of B2B in global e-commerce sales over the period 2017-19 was equal to 83.8%.

[2]Big techs' business model is characterized by a mutually reinforcing data-network-activity feedback loop which helps increase the speed and accuracy with which the platform is able to connect buyers and sellers. The higher the matching efficiency, the more seamless and convenient the platform is for users, and the more likely they are to use the platform for their transactions (Boissay et al. (2021)).

[3]For simplicity, sticky wages are the only source of nominal rigidities in the model. Apart from rendering monetary policy non-neutral, sticky wages are necessary for credit constraints to amplify the impact of monetary policy shocks.

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 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 collateral (Amable, Chatelain and Ralf (2010), Nikolov (2012)) and earnings-based borrowing constraints (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)). Bech et al. (2022) find that creating a digital payment footprint enables small firms to access credit from big tech companies, and that this has spillover effects for their ability to access bank credit as well. Frost et al. (2020) 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 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. Section 7 concludes.

2 Stylised facts on big techs

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

Big tech credit has rapidly expanded in the last years becoming macroeconomically relevant in China, Kenya and Indonesia (Cornelli et al. (2022)). The expansion has been particularly strong during the Covid-19 pandemic, due to the increase in e-commerce activity that has also expanded the demand for credit. 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 1, left-hand panel). Recent estimates indicate that 3.5 billion individuals globally (about 47% of the population) use e-commerce platforms in 2022. 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 1, right-hand panel).
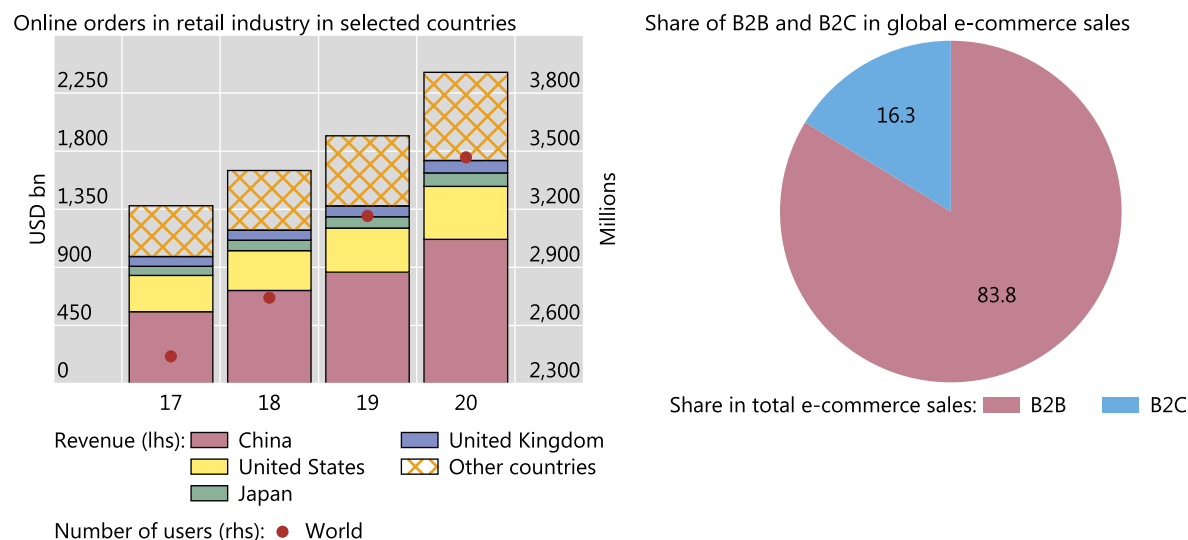

Figure 1: Upward trend in e-commerce, mostly via Big Tech platforms

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)

The fee structure of big techs generates around one third of their total revenues (Boissay et al. (2021)). These fees can be charged for different services, including platform access fees for third-party merchants and consumers, subscription fees for premium services, and advertising fees for reaching a wider audience. E-commerce platform fees are typically divided in a fixed component and a variable one. The fixed fees cover a number of services provided by the platform for product advertisement and are often negligible or absent for merchants. The variable fee is a percentage of the sale price charged by big techs to third-party merchants for using their platforms to reach customers. For example, Amazon charges third-party sellers a referral fee, which ranges from 6% to 45% of the sale price, depending on the product category. Table A1 in the Appendix reports the structure of the e-commerce platform fees for a selected number of big techs. The average variable platform fee is 8.5%.

Big techs' rapid expansion in the provision of credit mirrors the evolution of their revenues. Due to their large profits big techs have a substantial amount of liquidity that can be used to finance lending to firms and consumers. Boissay et al. (2020) show that big tech firms are more profitable and capitalised than global systemically important financial institutions (G-SIFIs) and have a larger amount of assets in liquid form. Prior to the Covid shock, the average earning-to-asset ratio for big techs was 24%, against 4% for G-SIFIs. The larger amount of profit was also reflected in a higher equity-to-total asset ratio (52% against 8%) and cash-to-total asset ratio (11% and 7%, respectively).

2.2   Big tech credit vs bank credit

Big tech credit is not collateralised and has a shorter maturity than bank credit. For the case of China, big tech credit has an average maturity of less than one year and is typically renewed several times, as far as the credit approval remains in place (Gambacorta et al., 2022). 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., 2020).

Due to lack of collateral big tech credit is less correlated with house prices than bank credit. Moreover, as firms operate on e-commerce platforms, the demand for 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 2) 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.
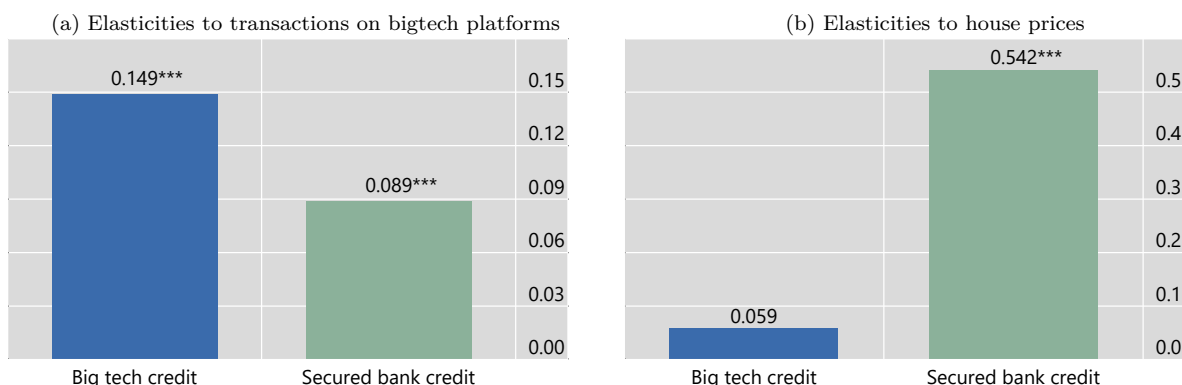

Figure 2: Credit elasticity to transactions on big tech platform (left) and house prices (right)

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)

When we extend the analysis to macroeconomic data for both China and the United States, we uncover similar patterns (Table 1). In both regions, bank credit is more correlated to house prices than big tech credit, whereas the opposite is true for e-commerce revenues. This evidence suggests that a wider use of big tech credit might decrease the significance 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 to e-commerce revenues (macro data)

Notes: Unconditional elasticities. Estimation period 2013-2020. *** Significance at the 1% level. Sources: Cornelli et al (2022a); 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 capital, (3) retailers which produce final goods using intermediate goods as inputs, (4) a big tech firm which facilitates transactions between firms and retailers, and extends credit to the former, (5) banks which give secured loans to firms, (6) a government which issues risk–free nominal bonds, and (7) a central bank which sets the nominal interest rate.

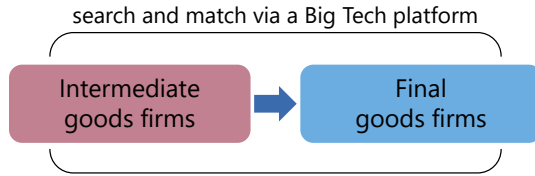search and match via a Big Tech platform

Figure 3: The two layer production chain and the big tech commerce platform

Firms sell intermediate goods to retailers via a big tech commerce platform where buyers and sellers need to search for and match with one another (Figure 3). Intermediate goods firms finance their working capital in advance of sales with both secured bank credit and big tech credit.

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,

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

subject to the sequence of budget constraints

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

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, $\Upsilon_t \equiv \Upsilon_t^g + \Upsilon_t^p + \Upsilon_t^b$ are aggregate (net) lump-sum transfers received by the households, where Υ_t^g are lump-sum net transfers by the government, Υ_t^p are lump-sum net pay–outs by the private sector (i.e. by intermediate goods firms and retailers) and Υ_t^b are lump-sum net transfers by the big tech firm.[4] 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

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

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

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

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

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 workers of any given type remains unchanged with probability θ_w. In this environment, the wage

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[4]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.

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   The 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 retailers, 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 matching efficiency is captured by a scaling parameter σ_m in its matching technology (27). 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 (retailers) on its commerce platform. Specifically, intermediate goods firms that are not matched with retailers 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 retailer from the continuum of size one pays a unit real fee equal to χ_r for each of the S_t searches for intermediate goods suppliers. This results in an additional real income for the big tech firm in period t equal to $\chi_r S_t$. The big tech firm is owned by the household, and each period pays a (net) lump-sum transfer to the latter equal to Υ_t^b. 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,

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

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.[5] The lump-sum transfer Υ_t^b is such that the net worth value of the big tech firm is equal to the incentive-compatible credit that is willing to extend, namely

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

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, and hence, shut down their sales options, 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, the fees set by the big tech are taken as given. The fee structure is assumed to be determined by the big tech in a separate optimization problem so as to maximize the number of platform users (as in industrial organisation models, e.g. Rochet and Tirole (2003)).The number of sellers and buyers are both normalised to unity in our analysis.

3.3 Intermediate goods firms

The economy is populated with a continuum of perfectly competitive intermediate goods firms indexed on the unit interval. Intermediate goods are produced with a Cobb Douglas 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

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[5]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,[6] 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.[7]

Intermediate goods firms sell their output to retailers. 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 4). Thus, at each point in time, the economy is populated with two types of intermediate goods firms: those matched with retailers 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 firms at time t produce and sell their output to retailers, 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 firms

As already mentioned, the I_t firms that are not matched with retailers at time t do not produce and do not sell goods, and post instead advertisements on the big tech commerce platform at a fixed unit (real) cost χ_m.

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[6]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 $l_t^m(i)$:

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

[7]With constant returns to scale, the profits of active 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.
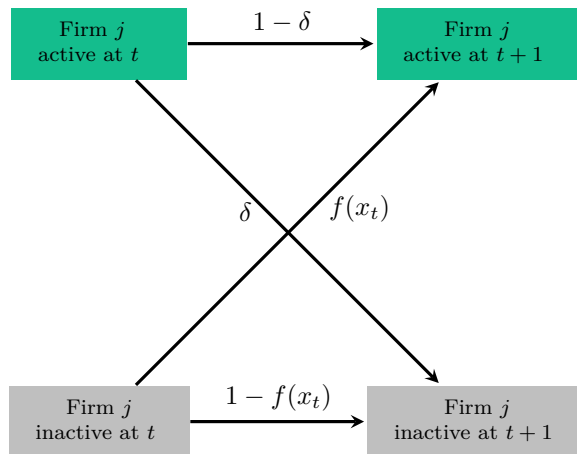
Figure 4: Intermediate goods firms' transition probabilities between the active and inactive states

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

3.3.2 Active 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 firms and the retailers which are in a match at time t.[8]

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.[9] For convenience, we assume that each 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, $Q_t^e = Q_t^k$.[10] We further assume that 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

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[8]Note that the aggregate intermediate goods 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.

[9]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.

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

resale value of capital net of refurbishment costs equals $E_t\left\{\Lambda_{t,t+1}\rho\left(\frac{Q^k_{t+1}}{P_{t+1}}k^m_t\right)\right\}$.[11]

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:[12]

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

where $E_t\left\{\Lambda_{t,t+1}\left[(1-\delta)\mathscr{V}^A_{t+1} + \delta\mathscr{V}^I_{t+1}\right]\right\}$ is the expected value of the intermediate goods firm at $t+1$ when with probability $1-\delta$ will maintain its match with the retailer 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 posting an advertisement equals

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

where $E_t\left\{\Lambda_{t,t+1}\left[f(x_t)\mathscr{V}^A_{t+1} + \left(1-f(x_t)\right)\mathscr{V}^I_{t+1}\right]\right\}$ is the expected value at $t+1$ when with (endogenous) probability $f(x_t)$ the intermediate goods firm will be matched with a retailer 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

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

After replacing the expressions of $\mathscr{V}^A_t$ from (11) and of $\mathscr{V}^I_t$ from (12), and using intermediate goods firm's production technology (9) to compute $l^m_t(y^m_t, k^m_t) = \left[\frac{y^m_t}{\xi_t(k^m_t)^\gamma}\right]^{\frac{1}{1-\alpha}}$, one may write S^m_t as a

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[11]The capital refurbishing cost is introduced to allow the credit constraint to bind for standard values of the collateral pledgeability ratio ν. 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 parametrizations of the model.

[12]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).

function of y_t^m, p_t^m and k_t^m as follows:[13]

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

For future reference, we define the "reservation return of an intermediate goods firm" $\underline{\Omega}_t$ as the *minimum* 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:[14]

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

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:[15]

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

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 ($\mathscr{V}_{t+1}$):

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

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

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[13]Firms will negotiate over p_t^m and y_t^m, but will only get a share of total sales when the big tech levies a strictly positive variable fee τ^*.

[14]Notably, $\underline{\Omega}_t$ is not affected by the variable fee τ^*.

[15]If banks seized the capital of intermediate goods producers, they would need to pay themselves the maintenance costs before reselling it on the market.

default on big tech credit are automatically excluded from the e-commerce platform from next period onward.[16] 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 only a share strictly lower than unity $b \in [0, 1)$ 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 that intermediate goods firms can use to sell their products other than the big tech commerce platform.[17] 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

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

Since credit is used to finance labor, intermediate goods firms' borrowing constraint implies

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

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

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[16]Numerous documented cases from China show that when a vendor defaults on Alibaba credit, their digital stores in Taobao (Alibaba) is permanently shut down and he has difficulties to switch to other big tech platforms because of reputation effects (https://business.sohu.com/20130717/n381836247.shtml (in Chinese)).

[17]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 $\mathscr{V}_{t+1} - E_t \left\{ \Lambda_{t,t+2} V_{t+2} \right\}$.

3.4 Retailers

There is a continuum of size one of such firms. They are all identical and perfectly competitive. A typical retailer 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:[18]

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

where $y_t^m(i)$ is the quantity purchased from the active intermediate goods firm i, which is decided by Nash–bargaining. All retailers purchase the same quantity from each active intermediate goods firm i

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

implying that the output of a typical retailer (and of the final goods sector as a whole) equals

$$Y_t = A_t y_t^m$$

Each period a typical retailer actively searches on the big tech commerce platform for S_t intermediate goods suppliers for use in the following period (see the timeline in Figure 2). The value of a search $\mathcal{I}_t^s$ (the subscript s denoting "search") equals

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

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 $\mathcal{I}_{t+1}^B$ denotes 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, retailers will add new searches. As the number of searches increases, the probability $g(x_t)$ that any open search gets matched with 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, retailers 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

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

$\mathcal{I}_t^s = 0$, namely for

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

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

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

where $Y_t - \frac{p_t^m}{P_t}y_t^m$ are current real profits for the retailer from the relation with a 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

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

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

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

The surplus of a typical retailer from an existing match is thus given by

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

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

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

For future reference, we define the "reservation cost of a retailer " $\bar{\Omega}_t$ as the *maximum* amount that a typical retailer 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^r is 0,

$$\bar{\Omega}_t \equiv Y_t + \frac{\chi_r(1-\delta)}{g(x_t)} \tag{26}$$

3.5 Matching

Retailers search each period for inactive intermediate goods firms on the e-commerce platform. That is, retailers 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 inputs to retailers at time $t + 1$. The matching function

$$M(S_t, I_t) = \sigma_m S_t^\eta I_t^{1-\eta}, \eta \in (0, 1) \tag{27}$$

gives the number of intermediate goods firms which post advertisements (and do not produce) closing a deal with the retail sector at time t. σ_m is the 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

TABLE 2   Timeline operations – intermediate goods firms and retailers

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Period $t-1$ Each intermediate goods firm $i \in [0,1]$ finds out if it is active or inactive at t

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Period t **Intermediate goods firms:** intermediate goods firm $i \in [0,1]$:

If active, produces and sells intermediate goods to retailers; 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, transfers the return on capital as dividend to equity investors and any remaining profits to the household, pays a fee τ^* to the big tech proportional to its sales on the commerce platform.

If inactive, pays a fee χ_m to post an ad on the big tech platform, and transfers net period profit to the household.

Retailers: A typical retailer :

(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_r for each of these searches.

Matching:

Active intermediate goods firms and retailers 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 $Q_t^e \mathscr{E}_{t-1}$.

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

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

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

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

Note that this probability decreases in x_t, implying that retailers 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

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

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 retailers.

3.6   Banks

Banks finance intra-period secured loans by issuing intra-period deposits. 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 Taylor-type rule

$$1 + i_t = \frac{1}{\beta} \Pi_t^{\phi_\pi} \left(\frac{Y_t}{Y} \right)^{\phi_y} e^{\nu_t} \tag{31}$$

where Y is steady-state output, and ν_t is a monetary policy shock following an AR(1) process:

$$\nu_t = \rho_\nu \nu_{t-1} + \epsilon_t^{\nu}$$

where $\rho_\nu \in [0, 1)$. A positive (negative) realization of ϵ_t^{ν} should be interpreted as a contractionary (expansionary) monetary policy shock, leading to a rise (decline) in the nominal interest rate, *given* inflation and output. 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, and balances the budget with lump–sum (net) transfers Υ_t^g:

$$B_t^h + B_t^b = \left(B_{t-1}^h + B_{t-1}^b\right)\left(1 + i_{t-1}\right) + \Upsilon_t^g \tag{32}$$

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 by retailers:

$$C_t = Y_t \tag{33}$$

3.9.2   Intermediate goods market

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

$$Y_t = A_t y_t^m \tag{34}$$

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:

$$A_t k_t^m = \bar{K} \tag{35}$$

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:

$$\int_0^{A_t} \int_0^1 l_t^m(i,j)djdi = L_t$$
$$\Delta_{w,t} A_t l_t^m = L_t \tag{36}$$

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:

$$B_t^h + B_t^b = B_t \tag{37}$$

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:

$$\mathscr{E}_t = A_t k_t^m \tag{38}$$

3.10 Bargaining

In equilibrium, the retailers and intermediate goods firms which are in a match obtain a total return that is strictly higher than the expected return of unmatched retailers and intermediate goods firms. The reason is that if the two firms 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 the 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 goods

producer, and it is subject to the credit and technology constraints of intermediate goods firms. The optimal choices of p_t^m and y_t^m require an appropriate choice of the capital stock k_t^m. The set $\{p_t^m, y_t^m, k_t^m\}$ is given by the solution to the following bargaining problem:

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

subject to

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \le b\mathcal{V}_{t+1} + \nu E_t \Big\{ \rho \Lambda_{t,t+1} \Big[\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \Big] \Big\} \tag{39}$$

where ϵ is the (relative) bargaining power of the active intermediate goods firms. According to the credit constraint (39), the wage bill cannot exceed the sum of the access value to the big tech platform $\mathcal{V}_{t+1}$ and of the physical collateral value $\nu E_t \Big\{ \Lambda_{t,t+1} \Big[\rho \frac{Q_{t+1}^k}{P_{t+1}} k_t^m \Big] \Big\}$.[19]

The optimality condition with respect to y_t^m writes

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

where $\lambda_t \ge 0$ is the Lagrangian multiplier on a intermediate goods firm's credit constraint. Using (44), this optimality condition can be simplified under our baseline calibration with $\epsilon = 1 - \epsilon$ as:[20]

$$1 = \frac{1}{1-\alpha} \frac{W_t}{P_t} \frac{l_t^m}{y_t^m} \left[\frac{1}{1-\tau^*} + \frac{\lambda_t}{1-\epsilon} \left(\frac{1}{1-\tau^*} \right)^\epsilon \right], \quad \lambda_t \ge 0 \tag{40}$$

In the absence of credit frictions and of the variable big tech fee (i.e. when $\lambda_t = 0$ and $\tau^* = 0$), this condition implies that the real return for a retailer on an intermediate good equates its marginal production cost at the intermediate goods firm level. In this special case, the outcome is (privately) efficient and the price of intermediate goods plays only a distributive role: the Nash bargaining model, 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. In the absence of credit frictions, the variable fee τ^* levied by the big tech distorts firms' production decisions similar to a proportional sales tax. The higher the variable fee, the larger the wedge between the marginal production cost

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[19]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.

[20]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 $\epsilon = 1 - \epsilon = 0.5$. This allows also to simplify the equilibrium expressions.

of an intermediate good and its marginal return, and the lower the level of intermediate goods. Thus, while the big tech improves the aggregate allocation by allowing firms to match in a more efficient way (via A_t), it also impairs it by financing credit provision with fees that distort the production choices by firms active on the platform (via y_t^m and p_t^m). Similarly, credit frictions taken individually distort firms' production decisions introducing a wedge between the marginal revenue and the marginal production cost of intermediate goods. The tighter the credit constraint, the higher this wedge. In the general case (40) with both credit constraints and variable fees (i.e. when $\lambda_t > 0$ and $\tau^* > 0$), the magnitude of the wedge depends on the three types of frictions.

The optimality condition with respect to capital for $\epsilon = 1 - \epsilon$ writes

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

Subsequently, the marginal nominal return on capital, and hence the nominal dividend paid to the household at time t on each equity claim, equals

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

In the absence of credit frictions and of the variable fee, the optimality condition with respect to capital (43) defines a standard capital demand equation where the price of capital equals its marginal return plus the discounted value of its future expected value.[21] In the general case with a binding credit constraint ($\lambda_t > 0$), firms take into account the contribution of capital as collateral. Capital stock affects the tightness of the credit constraint via two opposing channels. One channel is the value financed against collateral: the higher the capital stock k_t^m, the higher the production level y_t^m, and the tighter the credit constraint. The other channel is the collateral value: the higher the capital stock, the higher the collateral value, and the looser the credit constraint. Since firms choose jointly their output and capital stock subject to the binding credit constraint, both effects are taken into account. In equilibrium, in the general case with a binding credit constraint (43),

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[21]Setting $\lambda_t = 0$ and $\tau^* = 0$ in(43), we get:

$$\frac{Q_t^k}{P_t} = \gamma \frac{y_t^m}{k_t^m} + E_t\left\{ \rho \Lambda_{t,t+1}\left[\frac{Q_{t+1}^k}{P_{t+1}}\right] \right\} \qquad (43)$$

The same optimality condition is satisfied in the case with a variable big tech fee, but no credit frictions.

the price of capital increases as the credit constraint tightens (i.e. λ_t increases), suggesting that its marginal value as collateral and hence, its marginal contribution in production increases.

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

$$\epsilon (1 - \tau^*) S_t^r = (1 - \epsilon) S_t^m \tag{44}$$

where both surpluses S_t^m and S_t^r are a function of p_t^m given the levels of y_t^m and k_t^m determined by the previous two optimality conditions (see equations (13) and (25)). Using the expressions of S_t^m from (13), and of S_t^r from (25), one may further write (44) as an equation in p_t^m as follows

$$\frac{p_t^m}{P_t} y_t^m = \frac{\epsilon \bar{\Omega}_t + (1 - \epsilon) \underline{\Omega}_t}{1 - \tau^*(1 - \epsilon)} \tag{45}$$

where $\bar{\Omega}_t$ and $\underline{\Omega}_t$ depend on y_t^m and k_t^m, but not on p_t^m. Note that the chosen price p_t^m will depend on both the reservation values $\bar{\Omega}_t$ and $\underline{\Omega}_t$ and the variable fee τ^*.[22] Given $\bar{\Omega}_t$ and $\underline{\Omega}_t$, the higher the variable fee τ^*, the higher the price level p_t^m.[23]

To sum up, equations (39), (44), (40), (43) 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.[24]

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[22]In the limit case when intermediate goods firms have full market power (i.e. $\epsilon = 1$), the price will be set at the maximum level which can be paid by retailers (the level at which the surplus of the latter is zero):

$$\frac{p_t^m}{P_t} y_t^m = \bar{\Omega}_t$$

Alternatively, when retailers have full market power, $1 - \epsilon = 1$, the price will be set at the minimum level acceptable by intermediate goods firms, namely the level at which the surplus of the latter is zero:

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

[23]In the absence of the variable fee (i.e. $\tau^* = 0$), the total surplus $S_t^T \equiv S_t^m + S_t^r$ from a match does not depend on p_t^m. In this special case, 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 and k_t^m are chosen to maximize the joint surplus of the match, while p_t^m is set to split that surplus according to parameter ϵ. This is because the two parties bargain simultaneously over the price and individual quantity of intermediate goods. In particular, letting $S_t^T \equiv S_t^m + S_t^r$ denote the total surplus from a match, we obtain from (44) that $S_t^m = \epsilon S_t^T$ and $S_t^r = (1 - \epsilon) S_t^T$, and hence the total surplus of a match is shared via p_t^m according to the parameter ϵ. In the case with a variable fee, this is no longer the case since the total surplus depends as well on p_t^m. In the general case, $(1 - \tau^* \epsilon) S_t^m = \epsilon(1 - \tau^*) S_t^T$ and $(1 - \tau^* \epsilon) S_t^r = (1 - \epsilon) S_t^T$. When intermediate goods producers have full market power $\epsilon = 1$, they get the whole match surplus ($S_t^m = S_t^T$). In the other limit case when final goods producers have all the market power $1 - \epsilon = 1$, they got the whole surplus ($S_t^r = S_t^T$).

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

4 Empirical evidence and parameterization

We parameterize our model at quarterly frequency. It is convenient to split the structural parameters of the model in four groups (Table 3).

The first group includes the standard parameters 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, persistence of the monetary policy shock ρ_ν). 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.

The second group of structural parameters concerns the 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 third group of parameters concerns physical capital and is key to determine the reaction of bank credit and big tech credit to a monetary policy shock. To discipline the model, we first use US data to estimate the dynamic responses of e-commerce sales and commercial property prices to a monetary policy shock. We use the local projection method of Jorda (2005). That is, for each forecast horizon $h = 0, .., H$ a distinct regression is run for a given dependent variable y (either the log of commerce sales, or the log of commercial property prices) on the high-frequency identified monetary policy shocks (mps), as well as controls $\mathbf{Y}$:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h^T \cdot mps_t \cdot \mathbb{1}\{mps_t > 0\} + \beta_h^{NT} \cdot mps_t \cdot \mathbb{1}\{mps_t \leq 0\} + A_h \sum_{\tau=1}^{6} \mathbf{Y}_{t-\tau} + e_{t+h}, \quad (46)$$

where the lagged term y_{t-1} captures the value of the dependent variable one period before the shock, while y_{t+h} capture its value h periods after the shock. In our regressions we allow the effect on the dependent variable to depend on the sign of the shock. $\mathbb{1}\{MP_t > 0\}$ is an indicator variable which equals one if the shock is strictly positive at time t (i.e. the shock is an unexpected monetary tightening) and $\mathbb{1}\{MP_t \leq 0\}$ is an indicator variable which equals one if the shock is negative or zero. β_h^T for $h = 0, .., H$ are the coefficients of interest, and e_{t+h} is the regression residual. Commercial real

estate price are the commercial real estate prices for United States available in the FRED database at the Federal Reserve Bank of St. Louis. E-commerce sales are the retail sales (total excluding food services, current prices) for United States from the U.S. Census Bureau Data. Both series are quarterly, seasonally adjusted and deflated using the 2010 CPI. The high frequency identified monetary policy shocks are taken from Jarocinski and Karadi (2020). These shocks are constructed from surprises in bond/futures prices around Federal Open Market Committee announcements, and are corrected for "information channel" biases using sign-restrictions. Controls, $\mathbf{Y}_t$, include six lags of the dependant variable. Our sample period for the estimation runs from 1999:Q4-2016:Q2 because our e-commerce sales data begin in 1999:Q4 and the high-frequency *mps* data ends in 2016:Q2. Figure 5 reports the dynamic responses of real commercial property prices (left panel) and e-commerce sales (right panel) to a monetary policy shock, and show that commercial property prices respond more strongly than e-commerce sales, although less persistently[25].

(a) Commercial property prices (real) (b) E-commerce sales (real)

— Point estimate
— One standard deviation confidence interval
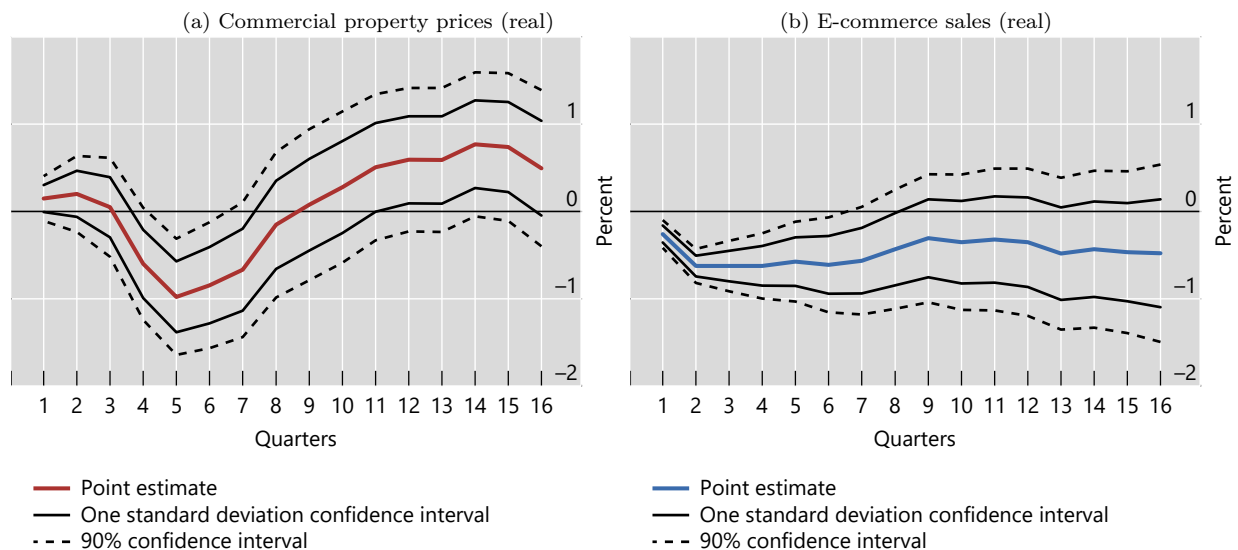- - - 90% confidence interval

Figure 5: Estimated dynamic responses to an unexpected monetary policy tightening

Notes: The unexpected monetary policy tightening is an unexpected 25bp rise in the policy rate. Dynamic responses estimated using local projections on a quarterly sample from 1994Q4 to 2016Q2 for the US. Specifications include six lags of the dependent variable and allow for asymmetric responses to a monetary policy tightening versus loosening. Data source: FRED, US Census, Jarocinski and Karadi (2020)

As a second step, we set the capital pledgeability ratio ν and the capital refurbishing costs ρ as to replicate in the model the estimated reaction of e-commerce sales and property prices to the

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[25]Since the average share of big tech credit during this period was 0.001%, we use these results to discipline dynamics in the version of the model without big tech credit (i.e. for $b = 0$)

same 25 basis points monetary policy shock. The corresponding value for the capital pledgeability ratio is 0.2 and for the capital refurbishing costs is 85% of the capital market value. [26] The index to decreasing returns to capital (real estate) is set as in Iacoviello (2005) and fixed capital aggregate supply is normalized to 1.

Table 3: Parametrization

Parameter	Description	Value
β	Discount factor	0.99
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	4.5
θ_w	Calvo index of wage rigidities	0.75
ρ_ν	Persistence monetary policy shock	0.5
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
$1\text{-}\rho$	Capital refurbishing cost (% from capital value)	85%
ν	Pledgeability ratio of capital as collateral	0.2
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_m	Big tech fees/real search costs for intermediate goods firms	0.05
χ_r	Big tech fee/ real search costs for retailers	0.05
τ^*	Variable big tech fees	8.5%
b	Pledgeability ratio of network value	2%
σ_m	Matching efficiency	$[0,\infty]$

Note: Values are shown in quarterly rates.

The forth and final group of parameters plays a key role in our model and is composed by:

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[26]A capital pledgeability ratio of 20% could be justified for instance by a loan to value ratio of 40% and a capital pledgeability ratio as collateral of 50%.

the matching efficiency σ_m, which takes the value of 0.1441 in our baseline calibration but is then varied to analyse the impact of increasing levels of big techs' matching efficiency; the network value pledgeability ratio b, which is set at 2% such that the steady-state allocation converges gradually to its credit frictionless limit[27]; the fees perceived by the big tech platform, χ_r and χ_m, are set at 0.05; the variable fee τ^* is set at 8.5% to reflect the sample average of observed variable fees (see Table A1 in the Appendix).[28]

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.[29] 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 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 (39). Specifically, the availability of big tech credit allows intermediate goods firms 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 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

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[27]The higher b, the faster the credit-frictionless limit is reached as the matching efficiency increases.

[28]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).

[29]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.
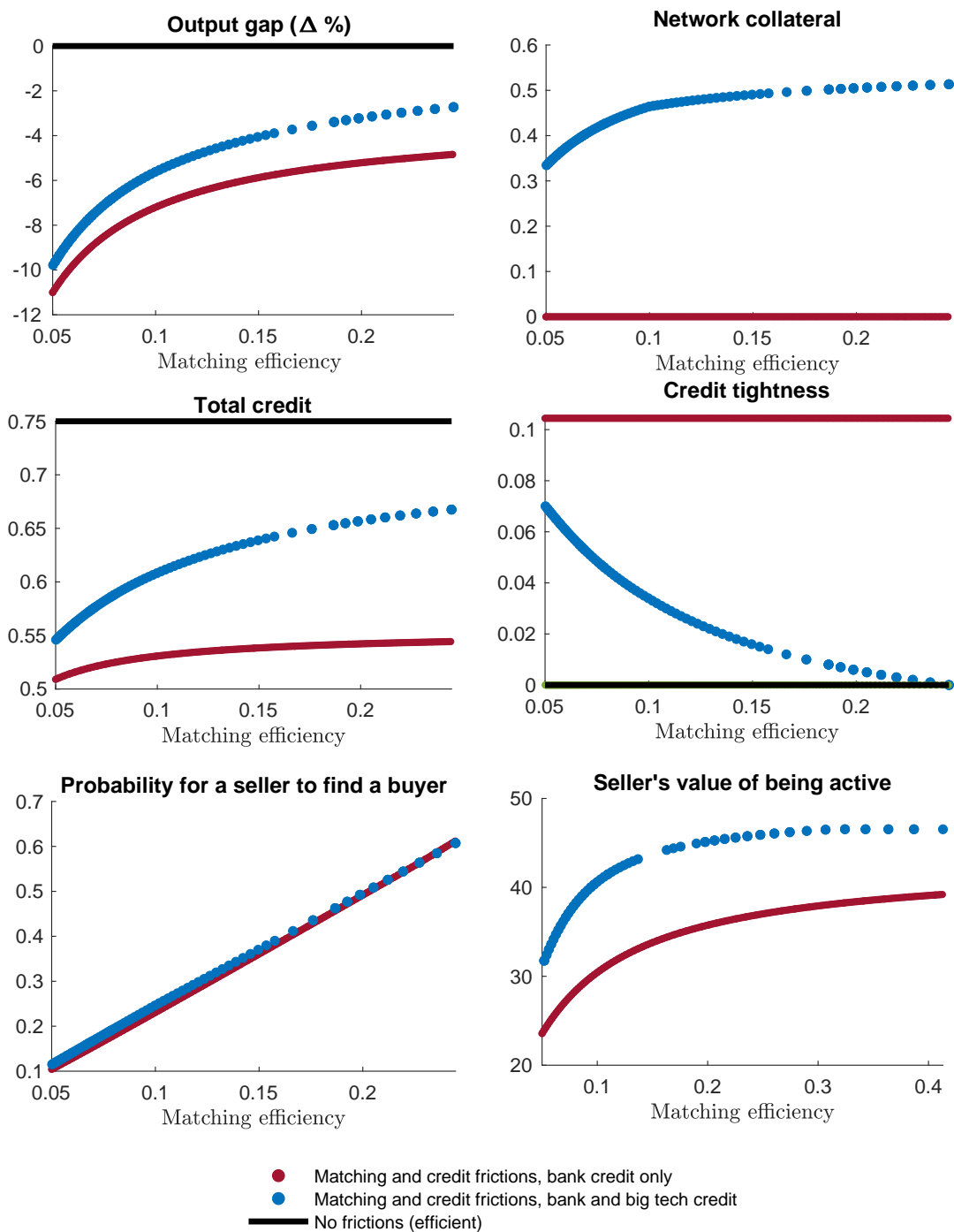
Figure 6: Steady-state equilibrium and matching efficiency on the e-commerce platform

Notes: Output gap: percentage deviation of output Y from its efficient level. 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

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 (Figure B2). This feedback loop is in assent with the Data-Network-Activity (DNA) amplification mechanism frequently underscored by policy discussions regarding big tech activity (Boissay et al. (2022)).

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 a 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 (39), 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 B3).
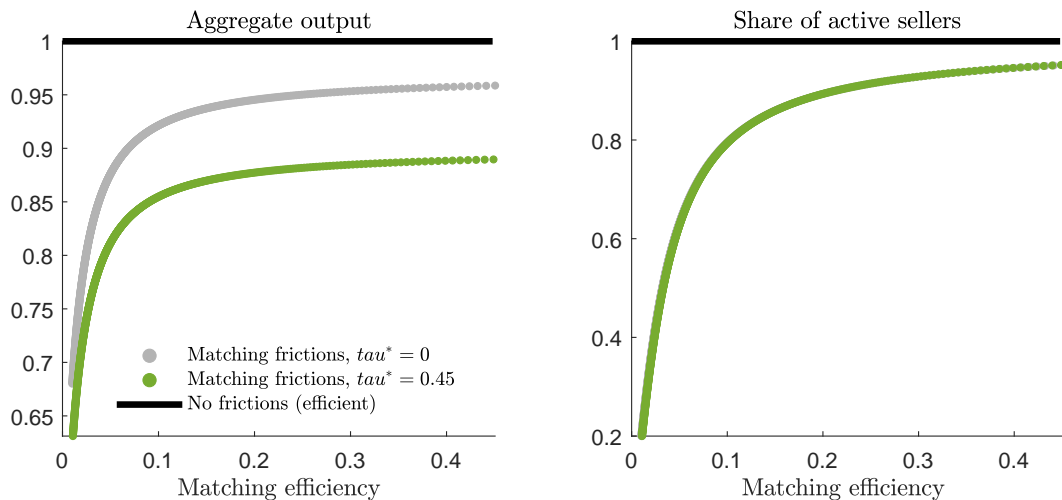

Figure 7: Distorsionary big tech fees and the steady-state allocation

Notes: Output (aggregate): Y. Share of active sellers on the commerce platform: $\mathscr{A}$. Matching efficiency: σ_m

The efficiency gains associated to the use of the big tech platform are limited by the distortionary nature of fees. The higher the fees levied in proportion to sales on the big tech platform τ^*, the larger the "sales-tax" distorsions (see equation (40)), and the lower the net efficiency gains associated to the big tech commerce platform. Figure 7 shows that in the absence of credit frictions, variable fees distort the allocation exclusively via the firm -level output (a pure sales tax effect), without affecting the matching process (i.e. the equilibrium level of active sellers).

6   Transmission of monetary policy: dynamic analysis

How does big techs' entry into finance affect the transmission of monetary policy? We now turn 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.

The red solid lines in Figure 8 show 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 (0.1441) to proxy for the initial stage of development of e-commerce. The peak response of aggregate output in the model with bank credit only is very much in line with its empirical counterpart estimated for the US (Figure A1). Notably, under the specification with bank credit only, the response of commercial real-estate prices is stronger on impact, but less persistent than that of e-commerce sales, in line with empirical estimates reported in Figure 5.

We study next how the availability of big tech credit affects the results. Figure 8 shows that big tech credit responds less on impact than secured bank credit to a monetary policy tightening (middle panels). In the model, these responses can be traced to a lower sensitivity to monetary policy of "network collateral" (i.e. expected profits on the big tech platform, bottom left panel) than that of physical collateral (i.e. real estate values pledged as collateral, bottom right panel). With the strength of the credit channel weaker on impact, the initial response of output (in percentage terms) is mitigated by the availability of big tech credit (top panel) under our baseline calibration.
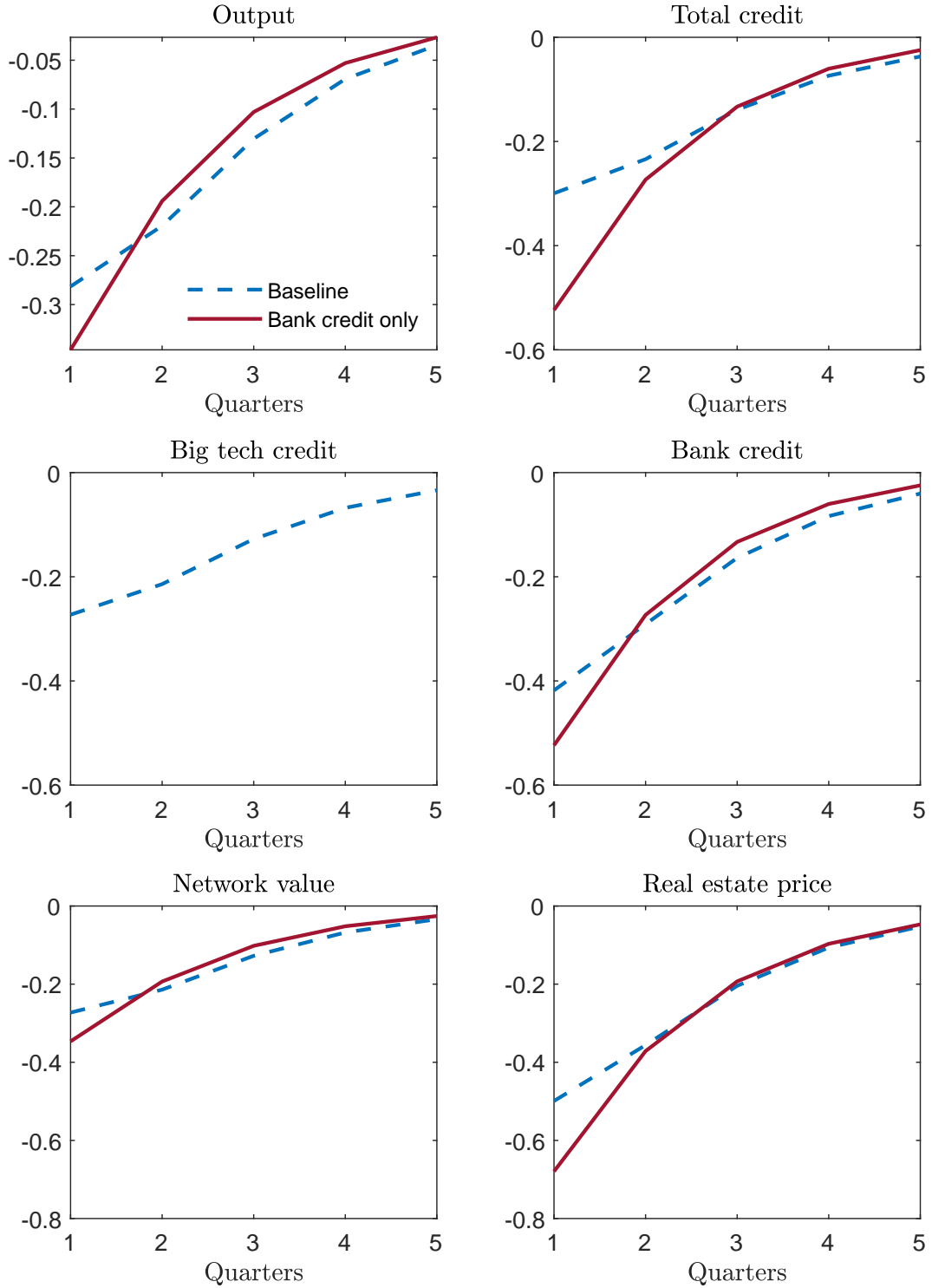
Figure 8: Dynamic responses to a monetary policy shock

The greater persistence of the response of e-commerce sales and profits to monetary policy renders however the credit channel more persistent in the presence of big tech credit. Through the lenses of our model, this greater persistence is due to the sluggish adjustment of prices of goods sold on the e-commerce platform (Figure 9).
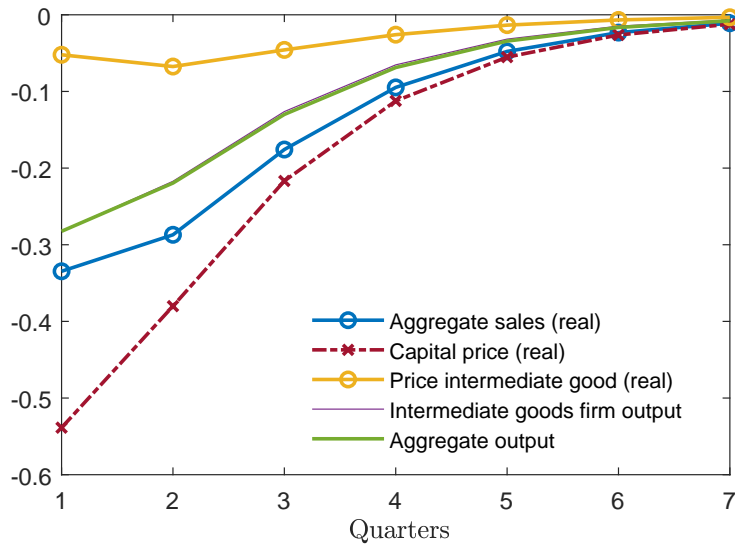

Figure 9: Dynamic responses to a monetary policy shock

<u>Notes:</u> The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. Baseline: bank credit and big tech credit. Matching efficiency $\sigma_m = 0.1441$. Y-axis: percentage deviation from steady-state

Under our baseline calibration, as matching efficiency on the e-commerce platform increases and the economy gradually converges to its credit-frictionless limit, the financial accelerator fades away and real activity becomes less sensitive to monetary policy. More generally, 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.

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 credit and bank credit respond very differently to local property prices and e-commerce sales, 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 more than 80% of global online transactions. In our framework, a big tech firm intermediates the search and matching between intermediate goods firms and final goods firms, and extends working capital loans to the former subject to limited commitment. Intermediate goods firms have access to both big tech credit and secured bank credit. Nominal wages are rigid and monetary policy affects the real economy.

We obtain three 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 reacts on impact less than bank credit to a monetary policy tightening, 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, 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 rises and the economy gradually converges to its credit-frictionless limit, the financial accelerator fades away and real activity becomes less sensitive to monetary policy. Finally, according to our third finding, big techs' macroeconomic efficiency gains are limited by the distorsionary nature of the fees collected from their users.

Possible future extensions of our framework include the analysis of business-to-consumer (B2C) transactions and household credit, big techs' financing constraints, complementarity or substitutability between big tech credit and bank credit, interest rate setting on big tech credit, big techs' market power, payment services provided by big techs, the trade-off between efficiency and privacy, or big techs' regulation.

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9 Appendix

A E-commerce platform fees

E-commerce platform	Fixed Fee	Variable Fee	Other Fees	Fixed	Average	Min	Max
Amazon	$0-$39	6% to 45%, average seller pays 15% of selling price, varies with category of product	Amazon might charge if the seller uses its logistics services (minimum of $3.43), also sometimes pays a shipping credit	19.5	15	6	45
AliExpress	0	5-10% of selling price, depends on product category	Offers shipping at additional costs, cheaper than other shipping services but longer delivery times	0	7.5	5	10
Shopify	$5 to $299	2.4% to 5% + 30c per sale		150	3.7	2.4	5
E-bay	First 250 items free, then $0.35 per item	2% to 12.25% of total price (selling price + shipping, handling cost)		0	7.25	2	12.5
Etsy	$0.20 per item	6.5% of total price (selling price + shipping, handling costs)	Etsy Plus subscription at $10 a month	0	6.5	6.5	6.5
Walmart	0	6% to 15%		0	10.5	6	15
					8.4	2	45

Table A1: E-commerce platform fees

B Baseline calibration

(a) Estimated

(b) Model-based (bank credit only)

- Point estimate
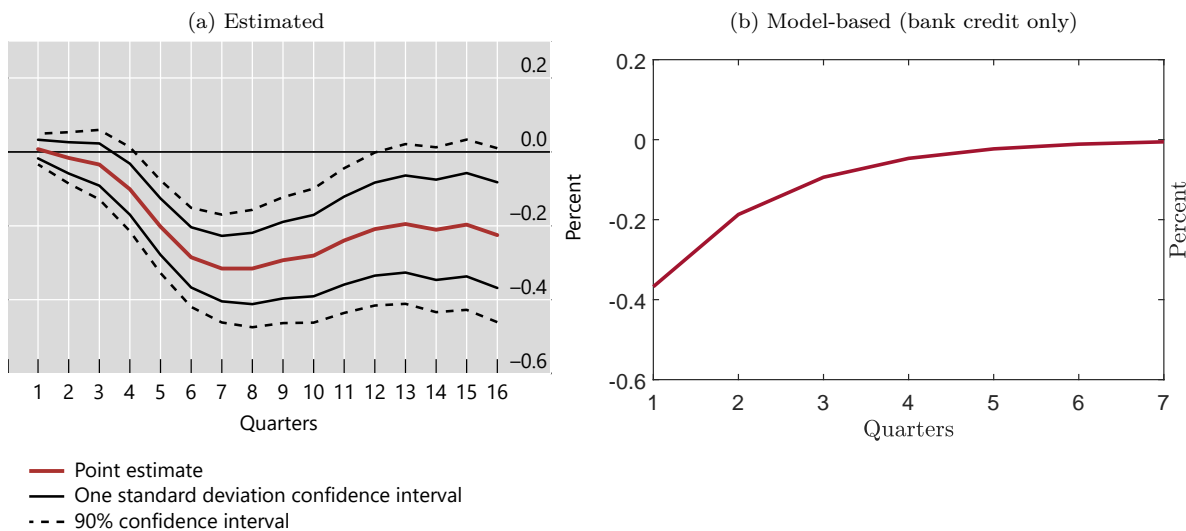- One standard deviation confidence interval
- 90% confidence interval

Figure A1: Dynamic response of real GDP to a monetary policy shock

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. Dynamic responses estimated using local projections on a quarterly sample from 1994Q4 to 2016Q2 for the US. Specifications including six lags of the dependent variable and allowing for asymmetric responses to a monetary policy tightening and loosening. Data source: FRED, Jarocinski and Karadi (2020)
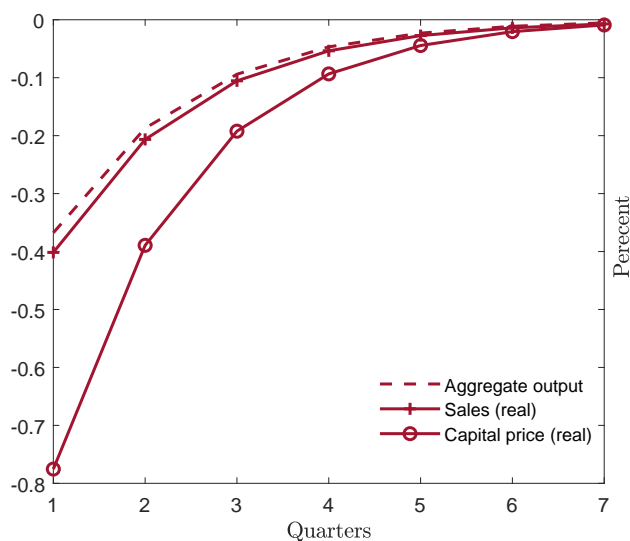

Figure A2: Dynamic responses to a monetary policy shock in an economy with bank credit only

Notes: The monetary policy shock is an unexpected rise in the policy rate of 25 basis points. Matching efficiency level $\sigma_m = 0.1441$. Y-axis: percentage deviation from steady-state

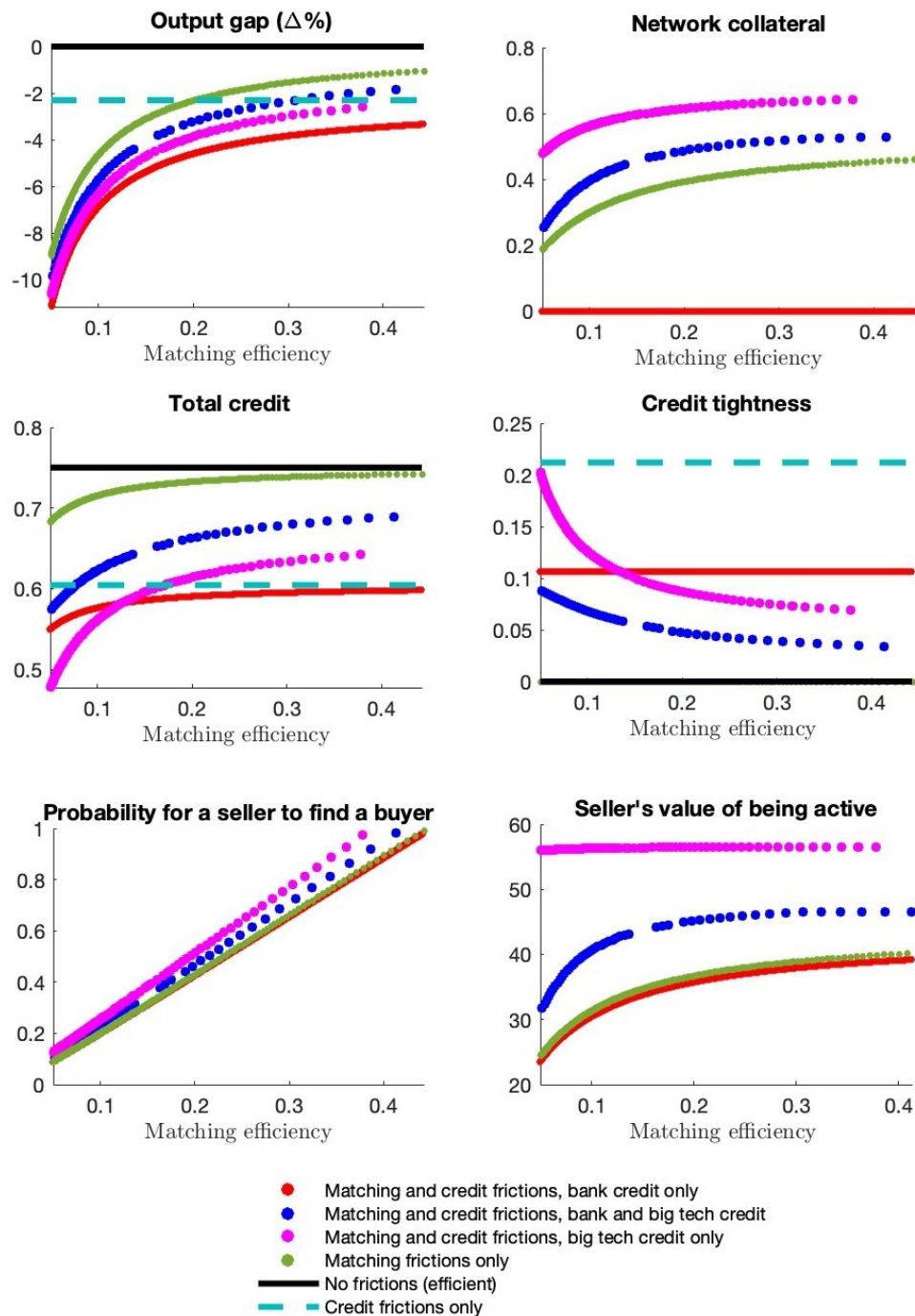# C Steady-state analysis – disentangling the effect of frictions

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

<u>Notes:</u> Case without variable fees ($\tau^* = 0$). Output gap: percentage deviation of output Y from its efficient level. 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

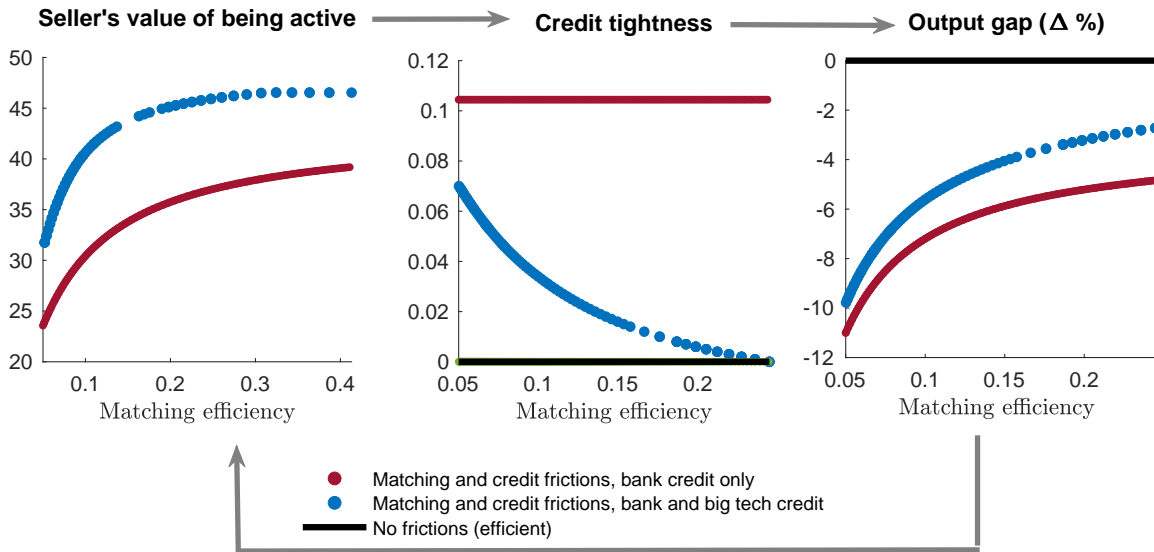# D   Feedback loop: network value, credit tightness, and output

Figure B2: Steady-state allocation and matching efficiency

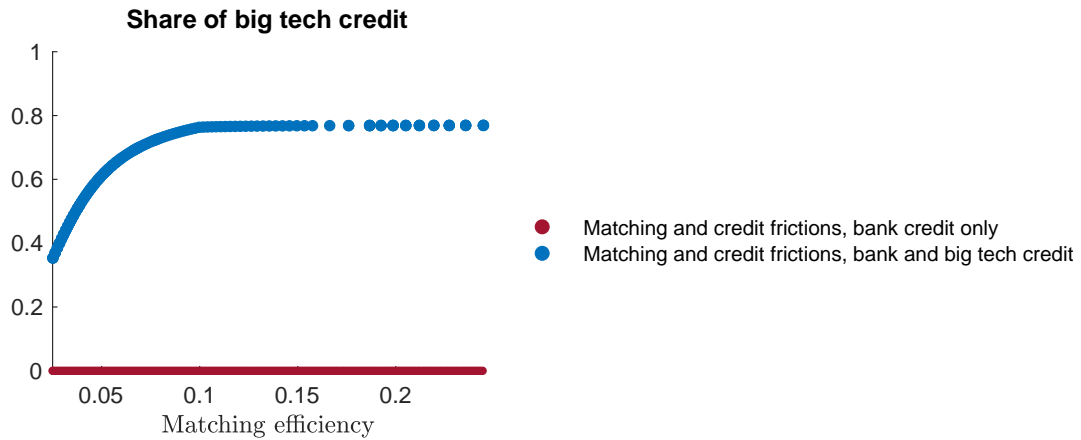# E   Share of big tech credit and matching efficiency

Figure B3: Steady-state and matching efficiency

<u>Notes:</u> Share of big tech credit: ratio of big tech credit and total credit. Matching efficiency: σ_m