Big Tech Credit and the Macroeconomy

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

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Abstract

We document the recent advent of big techs in finance and study the macroeconomic impact of these developments. To this end, we build a model where big techs facilitate matching between sellers and buyers on a e-commerce platform and extend loans to firms. Big techs reinforce credit repayment with the threat of exclusion from the platform, while bank credit is secured against collateral. Our calibrated model suggests that: (i) a rise in big techs' matching efficiency boosts firms' expected profits on the e-commerce platform, expands the supply of big tech credit, and approaches output to its efficient level, with the effects being amplified in a positive feedback loop; (ii) gains generated by big techs' improved efficiency are limited by the distortionary nature of fees collected from users; (iii) big tech credit can mitigate the transmission of business cycle shocks – most notably monetary policy shocks – to real activity.

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

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*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.

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1 Introduction

Large technology firms such as Alibaba, Amazon, Facebook or Mercado Libre (big techs) have recently ventured in financial markets by 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 pace of increase in big tech credit can be expected to exceed 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 may affect macroeconomies in multiple ways. For instance, big tech credit can change the nature of the financial accelerator and the propagation of macroeconomic shocks. 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 (Frost, Gambacorta, Huang, Shin, and Zbinden (2019)). In addition, 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 (Gambacorta, Huang, Li, Qiu, and Chen (2022)). As the share of big tech credit rises, the financial accelerator will thus affect credit supply less via asset prices (the traditional "physical collateral channel" à la Kiyotaki and Moore (1997)), and more via repayment incentive compatibility constraints within big techs' ecosystems (the novel "network collateral channel" that we highlight).

To study the impact of big tech credit on the macroeconomy we develop a model where 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. Our focus on business-to-business (B2B) transactions (i.e. transactions between firms) reflects the evidence that such transactions account for the lyon share of big tech trade, ie around 84% of global online e-commerce sales. In the model, 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 real estate collateral. In contrast, those that default on big tech credit lose access to big techs' e-commerce platform, and hence lose their future profits from trading on that platform. An incentive compatible contract thus limits the total amount of credit to the sum of physical and network collateral. We calibrate the model as to replicate two key empirical facts we document about big techs' credit provision and e-commerce trade. First, using macro data for China and the US, and extending previous evidence based on Chinese micro data, we show that big tech credit does not react to changes in asset prices and local economic conditions, unlike bank credit. Second, using local projections, we show that commercial property prices respond more strongly than e-commerce sales to a monetary policy shock.

We use the model to evaluate how the advent of big tech credit will affect the macroeconomy both in the long-run, as well as at business cycle frequency. We obtain three sets of results. First, we find that an expansion in big techs, as captured by a rise in the matching efficiency on the e-commerce platform, boosts the value for firms of trading in the platform and the willingness of big techs to extend credit. This in turn relaxes financing constraints, increases production and further raises firms' value, unleashing a positive feedback loop which amplifies the initial effects of the supply of big tech credit on firms' output and employment possibilities.

Second, the gains from big techs' improved efficiency are limited by the distortionary nature of the fees collected from their users. Specifically, most big tech fees are proportional to transactions on the platform, and hence, they act *de facto* as sales taxes and distort the equilibrium allocation.

Third, the impact of big tech credit on business cycle fluctuations crucially depends on two factors. One is the difference between the reaction to business cycle shocks 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 on bank credit (the value of physical collateral). The other is the share of big tech credit. Matching frictions dampen the reaction of expected profits, and hence of network collateral, to business cycle shocks in our framework. This is because when matching efficiency on the e-commerce platform is low, a relative large share of firms' expected profits are linked to components insensitive to the business cycle such as fixed big tech fees and search costs. Thus, in the low matching efficiency region, network collateral is less sensitive to macroeconomic shocks than physical collateral. For this reason, provided the share of big tech credit is high enough, this novel type of credit can initially mitigate the responses of total credit and output to business cycle shocks.

Later on, as the matching efficiency between sellers and buyers on the platform rises, the relative importance of search frictions for expected profits decreases. As a result, expected profits become more sensitive to business cycle shocks, network collateral becomes more procyclical, the financial accelerator associated to big tech credit intensifies, and the mitigation effect of big tech credit weakens. Finally, once matching efficiency becomes high enough to push the economy into its credit-frictionless limit, the financial accelerator fades away and the sensitivity of real activity to business cycle shocks drops sharply. These channels are at play when considering monetary policy shocks, as well as demand preference shocks and technology 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), Kiyotaki and Moore (1997), Iacoviello (2005)). A rise in physical 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, Foulis, Pinter, and Surico (2022), Ottonello and Winberry (2020) and Ioannidou, Pavanini, and Peng (2022)). Our paper contributes to this literature by analysing how big techs' use of big data for credit scoring and of network collateral instead of physical collateral to enforce credit repayment affect the link between asset prices, credit and the business cycle.

In our setup, the supply of big tech credit is ultimately constrained by firms' expected profits. Our analysis therefore also relates to the literature on the macroeconomic effects of intangible collateral (e.g. Amable, Chatelain, and Ralf (2010), Nikolov (2012)), as well as of earnings-based borrowing constraints (e.g. Drechsel (2023), Ivashina, Laeven, and Moral-Benito (2022), Lian and Ma (2021), Holmstrom and Tirole (1997)). One distinguishing feature of borrowing limits on big tech credit compared to those imposed by earnings or intangible collateral is their link to the level of matching efficiency on the e-commerce platform. Specifically, our analysis shows that the way big tech credit affects the macro-economy depends on the matching efficiency on the platform which will evolve over time as big techs acquire more data on their users and expand their activities.

The paper further connects 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 credit and big tech credit are growing where the current financial system is not meeting demand for financial services (Bazarbash (2019), Haddad and Hornuf (2019), Croxson, Frost, Gambacorta, and Valletti (2023), Hau, Huang, Shan, and Sheng (2021)). Beck, Gambacorta, Huang, Li, and Qiu (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. Similar findings are uncovered by Frost, Gambacorta, Huang, Shin, and Zbinden (2019) using data from Mercado Credito, which provides credit lines to small firms in Argentina on the e-commerce platform Mercado Libre.

Finally, our paper belongs to the novel literature on the impact of new financial technologies on the transmission of monetary policy shocks. In contrast to our paper, contributions to this literature have been so far empirical and have focused on China. In particular, Hasan, Kwak, and Li (2023) estimate an interacted panel-VAR with monetary policy shocks and regional macroeconomic data for China, and conclude, inter alia, that the provision of credit by AntGroup, the financial arm of the big tech company Alibaba, has relaxed firms' financial constraints, and has made real activity and inflation less sensitive to monetary policy. In another recent paper, Huang, Li, Qiu, and Yu (2023) estimate that for firms already using actively both bank credit and big tech credit from AntGroup, the two types of credit are equally sensitive to the interbank rate. Finally, Cornelli, De Fiore, Gambacorta, and Manea (2024) focus more generally on fintech credit which covers all credit activity facilitated by electronic (online) platforms that are not operated by commercial banks. Based on a cross-country panel-VAR analysis, they find that fintech credit has not shown the strong and significant response to monetary policy observed with traditional bank credit.

The paper proceeds as follows. Section 2 presents some 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 e-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 e-commerce platform. Section 6 studies how big tech credit shapes the transmission of business cycle shocks and the credit channel of monetary policy. 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 provision.

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, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2023)). The expansion has been particularly strong during the Covid-19 pandemic, due to the increase in e-commerce activity that has also increased 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) used e-commerce platforms in 2022. China is the largest market, followed by the United States, Japan, the United Kingdom and Germany. More than 80% of global online transactions (Figure 1, right-hand panel) are business-to-business (B2B) (i.e. transactions between firms).

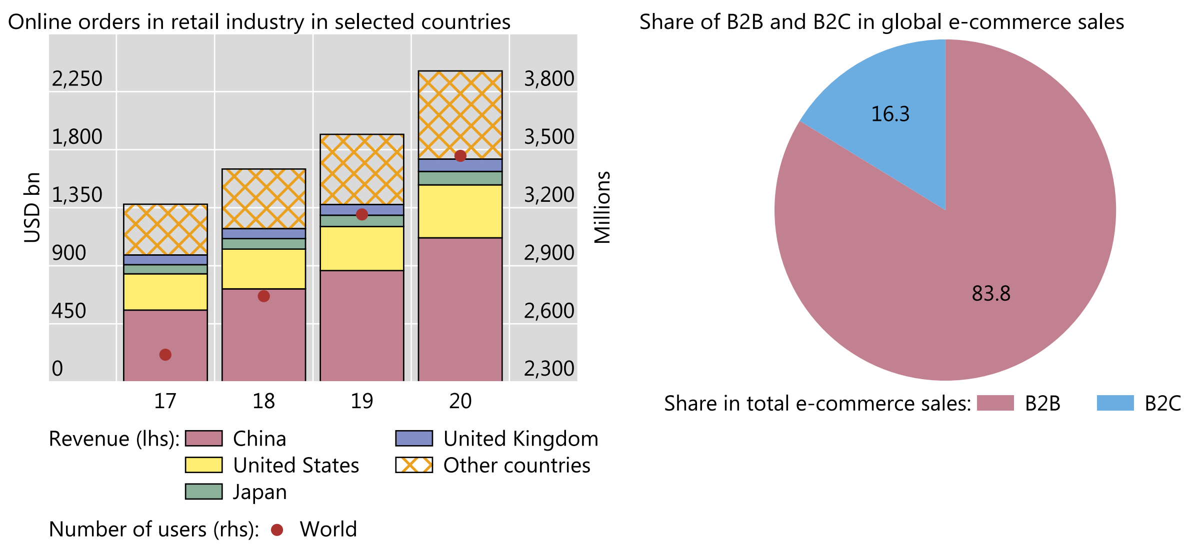

Figure 1: Upward trend in e-commerce, mostly via big tech platforms

Notes: B2B denotes "business-to-business" transactions (transactions between firms), while B2C denotes "business-to-consumer" transactions (transactions between firms and consumers). Source: Alfonso, Boar, Frost, Gambacorta, and Liu (2021) (left panel); UNCTAD: 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, Ehlers, Gambacorta, and Shin (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 around 8%.

				Fixed	Variable		
E-commerce platform	Fixed Fee	Variable Fee	Other Fees	Average	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 1: E-commerce platform fees

Big techs' rapid expansion in credit provision 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. Gambacorta, Khalil, and Parigi (2022) 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 profits 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 secured against physical collateral 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 (Beck, Gambacorta, Huang, Li, and Qiu (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, Gambacorta, Huang, Shin, and Zbinden (2019)).

Due to lack of physical 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, Huang, Li, Qiu, and Chen (2022) use micro data for Chinese firm to compare the elasticity of different credit types to house prices and local GDP. The main result is that big tech credit does not correlate with local business conditions and house prices when controlling for demand factors, 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.

We obtain similar findings using macroeconomic data for both China and the United States (Table 2). In both regions, we find that over the period 2013-2020 bank credit is more correlated to house prices than big tech credit, whereas the opposite is true for e-commerce sales. This evidence suggests that a wider use of big tech credit might decrease the significance of the physical collateral channel of monetary policy.

3 Model

The model is characterized by three main building blocks: credit frictions in the production sector, search and matching along the supply chain, and nominal rigidities in the form of sticky wages[1].

[1]See Cahuc, Carcillo, and Zylberberg (2014) for a description of search and matching frameworks applied to labor markets, and Trigari (2009) and Galí (2010) for monetary (New Keynesian) models incorporating them. See De Fiore and Tristani (2013), Bernanke, Gertler, and Gilchrist (1999), Iacoviello (2005) or Manea (2020) for New-Keynesian models studying how credit frictions affect the transmission of monetary policy and of business cycle shocks. As in Manea (2020), since credit is only used to finance working capital, sticky wages are necessary for credit frictions to

	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 sales	5.39	3.75
Bank credit to e-commerce sales	0.39	0.25

Table 2: Credit elasticity to house prices and to e-commerce sales (macro data)

Notes: Unconditional elasticities. Estimation period 2013-2020. *** Significance at the 1% level. Sources: data on big techs are from Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2023), on e-commerce sales are from Statista and on house prices are from the BIS.

When search frictions and credit frictions are set to zero, the model collapses to the basic three equation New Keynesian (NK) model with sticky wages.[2]

The model economy is populated with: (1) a large number of identical households who consume, invest and work, (2) intermediate goods firms which produce using labor and capital, (3) final goods producers ("retailers") which use intermediate goods as inputs, (4) a big tech firm which facilitates transactions between intermediate goods firms and retailers, and extends credit to the former, (5) banks which provide loans secured against physical capital to firms, (6) a government which issues risk–free nominal bonds, and (7) a central bank which sets the nominal interest rate.

Firms sell intermediate goods to retailers via a big tech e-commerce platform where buyers and sellers need to search for and match with one another. 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 indexed by j $[0, 1]$. Income is pooled within each household. A typical household chooses each period how much to consume C_t and how much to invest in nominal risk–free public bonds B_t and equity E_t to

amplify the response of output to business cycle shocks, and hence, for the model to feature a financial accelerator.

[2]For simplicity, we assume that sticky wages are the only source of nominal rigidities in the model. One could write a version of the model with sticky wages and prices, but that version will entail adding an additional sector of monopolistic firms setting prices subject to nominal rigidities or assuming Nash-Bargaining with staggered price setting in the intermediate goods market à la Gertler, Sala, and Trigari (2008) or Gertler and Trigari (2009).

maximize intertemporal utility,

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

subject to the sequence of budget constraints

$$P_t C_t + B_t^h + E_t Q_t^e \leq \int_0^1 W_t(j) L_t(j) dj + B_{t-1}^h (1 + i_{t-1}) + E_t D_t^e + E_{t-1} Q_t^e + \Upsilon_t \tag{1}$$

for $t = 0, 1, 2...$, taking employment choices $L_t(j)$ and labor income $\int_0^1 W_t(j) L_t(j) dj$ 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 final consumption good, Q_t^e is the unit price of equity, i_t is the nominal interest rate on public bonds bought at t, 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. Z_t is a demand preference shock which follows the exogenous process $log(Z_t) = \rho_z log(Z_{t-1}) + \varepsilon_t^z$, with $\rho_z \in [0, 1)$. The household receives the wages for all types of labor services in the form of bank deposits at the beginning of period t and uses them within the period to buy final goods. The maximization problem is subject to standard solvency constraints ruling out Ponzi schemes on bonds and equity

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

where $\Lambda_{0,T} \equiv \beta^T \frac{C_T^{-\sigma}}{C_t^{-\sigma}} \frac{Z_T}{Z_t}$.

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 (1) for $t = 0, 1, 2, \ldots$, and the transversality conditions (2), where $\Lambda_{t,t+1} \equiv \beta \frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}} \frac{Z_{t+1}}{Z_t}$ is the real stochastic discount factor, and $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ is the (gross) inflation rate between $t-1$ and t.

The wage setting problem and nominal wage rigidities are standard: each period workers specialized in a given type of labor (or the union representing them) set wages subject to the Calvo (1983)-type nominal rigidities. Specifically, workers specialised in any given labor type can reset their nominal wage only with probability $1 - \theta_w$ each period, independently of the time elapsed since they last adjusted their wage. In this environment, 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 $\pi_t^w \equiv log(W_t) - log(W_{t-1})$ is wage inflation rate, $\lambda_w \equiv \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(1+ \ {}_w\phi)}$, with $\ {}_w$ 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 $\mu_t^w \equiv (w_t - p_t) - (log(\chi) + \sigma c_t + \phi l_t)$ from its steady-state level μ^w[3].

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 search and matching between sellers and buyers of intermediate goods; the other is to provide credit to the sellers on its e-commerce platform. Its operating costs are normalized to zero.

The big tech firm makes profits and builds net worth N_t^b by levying fees from both sellers and buyers on its commerce platform. Specifically, intermediate goods producers 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 defined in terms of the bundle of final goods. Furthermore, those with a match (a measure A_t) pay a fee τ proportional to their sales $\frac{p_t^m}{P_t} y_t^m$ on the platform, where y_t^m is the quantity of intermediate goods sold by an individual firm and p_t^m is the unit price of such goods. 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 a continuum of size one pays a unit real fee equal to χ_r for each of its S_t searches for intermediate goods suppliers, with the fee defined in terms of the bundle of final goods. 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) nominal lump-sum transfer to the latter equal to Υ_t^b. The big tech invests its net worth at the

[3]For the derivation of the wage setting relation (5) see for instance Chapter 6 in Galí (2015).

end of each period in nominal risk–free public bonds B_t^b,

$$B_t^b = N_t^b$$

and hence,

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

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 e-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 lump-sum transfer Υ_t^b is such that the net worth of the big tech firm is equal to the incentive-compatible credit that is willing to extend, namely

$$\frac{N_t^b}{P_t} = \int_0^1 L_t^b(i) di$$

where $L_t^b(i)$ is the real value of incentive-compatible credit extended to the intermediate goods firm $i \in [0, 1]$, ensuring that the big tech firm is never financially–constrained. Unlike banks, the big tech can exclude sellers from its e-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 credit repayment by threatening its users with the exclusion from the platform[5].

In the model, the fee structure is taken as given and assumed to be determined by the big tech firm so as to maximize the number of platform users (as in Rochet and Tirole (2003)). Accordingly, the fees are invariable to business cycle fluctuations. The number of sellers and buyers in our model are both normalised to unity.

[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).

[5] 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)).

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

$$y_t^m(i) = \xi_t (k_t^m(i))^{\gamma} (l_t^m(i))^{1-\alpha}, \quad i \in [0,1], \tag{6}$$

where ξ_t represents the level of technology assumed to be common to all firms and to evolve exogenously over time according to the process

$$log(\xi_t) = \rho_{\xi} log(\xi_{t-1}) + \epsilon_t^{\xi},$$

with $\rho_{\xi} \in [0,1]$. $k_t^m(i)$ 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 the intermediate goods firm i at aggregate wage rate W_t[6] .The production function is characterised by decreasing returns to scale, that is $\gamma + (1-\alpha) < 1$, and hence implies that for a given amount of inputs, aggregate output is higher when production takes place in multiple production units than in a single one[7]. In the context of our analysis focused on small and medium enterprises – the ones most likely financially constrained and targeted by big techs' credit provision services in practice – such a technology speaks to congestion effects and diminishing marginal productivity observed as firms scale up production within fixed production capacities (which are relatively inelastic in the short run).

Intermediate goods firms sell their output to retailers. To do so, they need to match with the latter via big tech's e-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 2). For

[6]The CES index of labor input $l_t^m(i)$ and the aggregate wage rate W_t take 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]This implies increasing marginal costs for firms. Similarly, in the labor market search and matching framework worker's marginal disutility of labour (the corespondent of the marginal cost in our setup) is increasing in labor.

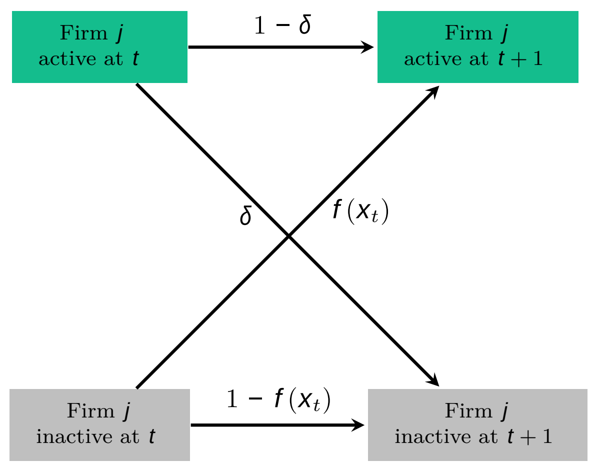

Figure 2: Intermediate goods firms' transition probabilities between the active and inactive states

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 $t+1$

this reason, at each date t, the economy is populated with two types of intermediate goods firms: those matched with retailers which use technology (6) to produce (a share A_t), and those without a match at time t 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 3. Intermediate goods firms found out in period $t-1$ their active or inactive status in period t.

3.3.1 Inactive firms

Inactive firms are not matched with retailers at time t. They neither produce, nor sell goods. They post instead advertisements on the big tech e-commerce platform at a fixed unit (real) cost χ_m to attract potential clients (or to maintain the advertisement if they were also inactive at $t-1$).

3.3.2 Active firms

Active firms at time t produce and sell their output to retailers. Since all A_t intermediate goods firms active at date t produce the same quantity in equilibrium, we drop the index i 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 retailers which are in a match at time t.[8]

Each intermediate goods firm producing at time t takes an intra-temporal loan L_t to hire labor l_t^m at unit price W_t, and issues equity to buy capital k_t^m at unit 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

$$E_t = k_t^m,$$

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]

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" (V_t^A), namely of being in a match, and (ii) the value for an intermediate goods firm of being "inactive" (V_t^I), namely of being looking for a match. The former equals:[11]

$$\begin{aligned} V_t^A \equiv\ & (1-\tau)\frac{p_t^m}{P_t}\xi(k_t^m)^{\gamma}(l_t^m)^{1-\alpha} - \frac{W_t}{P_t}l_t^m - \frac{Q_t^k}{P_t}k_t^m + E_t\left[\Lambda_{t,t+1}\left(\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\right)\right] + \\ & + E_t\left[\Lambda_{t,t+1}\left((1-\delta)V_{t+1}^A + \delta V_{t+1}^I\right)\right] \end{aligned} \tag{7}$$

where $E_t\left[\Lambda_{t,t+1}\left((1-\delta)V_{t+1}^A + \delta V_{t+1}^I\right)\right]$ is the expected value for an active firm at $t+1$ when with probability $1-\delta$ will maintain its match and gain V_{t+1}^A, and with probability δ will lose the match and gain V_{t+1}^I instead. This is also the expected value for an active firm of retaining access to the e-commerce platform from $t+1$ onward and will play a key role in our analysis. For future reference, we thus further denote the expected value of profits on the platform by

$$V_{t+1} \equiv E_t\left[\Lambda_{t,t+1}\left((1-\delta)V_{t+1}^A + \delta V_{t+1}^I\right)\right] \tag{8}$$

[8]Note that the aggregate output by intermediate goods firms is *not* predetermined at time t: even though the number of firms producing at time t (A_t) is 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 with equity rather than with credit.

[10]A similar simplifying assumption is used in the literature by Gertler and Karadi (2011).

[11]In our model, capital is chosen contemporaneously such that the value for a firm of being inactive in the network at time t is identical to the outside option for an active firm if it were to split from its match during bargaining.

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

$$V_t^I \equiv -\chi_m + E_t\left\{\Lambda_{t,t+1}\left[f(x_t)V_{t+1}^A + (1 - f(x_t))V_{t+1}^I\right]\right\} \tag{9}$$

where $-\chi_m$ are the net period losses incurred as it posts the advertisement, while $E_t\left\{\Lambda_{t,t+1}\left[f(x_t)V_{t+1}^A + \left(1 - f(x_t)\right)V_{t+1}^I\right]\right\}$ is the expected value at $t+1$ for an inactive firm when with (endogenous) probability $f(x_t)$ will be matched with a retailer and gain V_{t+1}^A, and with probability $1 - f(x_t)$ will remain inactive and gain V_{t+1}^I instead.

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

$$S_t^m \equiv V_t^A - V_t^I$$

After replacing the expressions of V_t^A from (7) and of V_t^I from (9), and using intermediate goods firms' production technology (6) to compute $l_t^m = \left(\frac{y_t^m}{(k_t^m)^\gamma}\right)^{\frac{1}{1-\alpha}}$, one may write the surplus S_t^m as a function of y_t^m, p_t^m and k_t^m as follows:

$$\begin{aligned} S_t^m(p_t^m, y_t^m, k_t^m) = &(1 - \tau)\frac{p_t^m}{P_t}y_t^m - \frac{W_t}{P_t}l_t^m(y_t^m, k_t^m) - \frac{Q_t^k}{P_t}k_t^m + E_t\left\{\Lambda_{t,t+1}\left[\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\right]\right\} + \\ &+ \chi_m + (1 - \delta - f(x_t))E_t\{\Lambda_{t,t+1}[S_{t+1}^m(p_{t+1}^m, y_{t+1}^m, k_{t+1}^m)]\} \end{aligned} \tag{10}$$

The production of intermediate goods is subject to credit 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 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, implying:

$$L_t^s \leq \nu E_t\left\{\Lambda_{t,t+1}\left[\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\right]\right\} \tag{11}$$

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

$$L_t^b \leq b\tilde{V}_{t+1}$$

This is because intermediate goods firms which default on big tech credit are automatically excluded from the e-commerce platform in the following period. If credit exceeded the expected gain of remaining on the platform, firms would be better off defaulting and running away with the funds. Anticipating this, the big tech creditor does not extend credit above what firm borrowers would get if they absconded such that the latter always have an incentive to repay.

We assume that only a share strictly lower than one of future profits, $b \in [0, 1)$, can be pledged as network collateral. This accounts for alternative retail options that intermediate goods firms can use to sell products other than the big tech e-commerce platform, as well as switching costs between those alternative options and the e-commerce platform. In particular, if firms had the alternative to sell products outside the e-commerce platform, and chose to default, they would then lose the *difference* between the expected profits on the big tech e-commerce platform and those earned with the alternative retail option, net of switching costs to those alternative options. To the extent that this difference is (roughly) proportional to a share of expected profits on the e-commerce platform, setting $b < 1$ accounts for this dimension.

We further assume that firms are excluded from the platform for a finite number of periods. The rationale of this assumption has to do with big tech's incentives: the big tech may not want to exclude intermediate goods firms forever from the e-commerce platform because it would lose a substantial amount of fees. Denoting by κ the number of exclusion periods, we obtain

$$\tilde{V}_{t+1} = V_{t+1} - E_t\left[\Lambda_{t,t+\kappa}\left(V_{t+\kappa+1}\right)\right] \tag{12}$$

where $V_{t+\kappa+1} \equiv E_t\left[\Lambda_{t+\kappa,t+\kappa+1}\left((1-\delta)V^A_{t+\kappa+1} + \delta V^I_{t+\kappa+1}\right)\right]$ is the expected value at time $t+\kappa$ of regaining access to the platform from $t+\kappa+1$ onward, and $\Lambda_{t,t+\kappa} \equiv \beta^\kappa \frac{C_{t+\kappa}^{-\sigma}}{C_t^{-\sigma}}$ is the stochastic real discount factor at time t of consumption units at time $t+\kappa$. For instance, if intermediate goods firms lost access to the commerce platform for one period (i.e. $\kappa = 1$) in case of default, the credit limit would equal $\tilde{V}_{t+1} \equiv V_{t+1} - E_t\left[\Lambda_{t,t+1}V_{t+2}\right]$.

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

$$L_t^b + L_t^s \leq b\tilde{V}_{t+1} + \nu E_t\left[\Lambda_{t,t+1}\left(\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\right)\right]$$

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

$$\frac{W_t}{P_t}l_t^m \leq b\tilde{V}_{t+1} + \nu E_t\left[\Lambda_{t,t+1}\left(\frac{Q_{t+1}^k}{P_{t+1}}k_t^m\right)\right] \tag{13}$$

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

3.4 Retailers

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

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

where $y_t^m(i)$ is the quantity purchased from the active intermediate goods firm $i \in [0, A_t]$ decided by Nash–bargaining. Retailers purchase the same quantity from each active intermediate goods firm i

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

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 Table 3). The value of a search $\mathcal{I}_t^s$ (the subscript s denoting "search") equals

$$\mathcal{I}_t^s \equiv -\chi_r + g(x_t)E_t\{\Lambda_{t,t+1}\mathcal{I}_{t+1}^B\} \tag{14}$$

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

As long as the value of a search 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, 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 $I_t^s = 0$, namely for

$$\chi_r = g(x_t) E_t\{\Lambda_{t,t+1} I_{t+1}^B\} \tag{15}$$

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

$$I_t^B = y_t^m - \frac{p_t^m}{P_t} y_t^m + (1-\delta) E_t \left\{ \Lambda_{t,t+1} I_{t+1}^B \right\} \tag{16}$$

where $y_t^m - \frac{p_t^m}{P_t} y_t^m$ are current real profits for the retailer from the relation with a supplier, and $(1-\delta)E_t\{\Lambda_{t,t+1} I_{t+1}^B\}$ is the expected value of the match at $t+1$ when with probability $1-\delta$ it will be maintained. Since (15) holds in equilibrium, the expression of I_t^B in (16) further writes as

$$I_t^B = y_t^m - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_r (1-\delta)}{g(x_t)} \tag{17}$$

One may write expression (17) for $t+1$, and combine it with equation (15) to obtain the intermediate goods supplier–search equation

$$\frac{\chi_r}{g(x_t)} = E_t \left\{ \Lambda_{t,t+1} \left[y_{t+1}^m - \frac{p_{t+1}^m}{P_{t+1}} y_{t+1}^m + \frac{\chi_r (1-\delta)}{g(x_{t+1})} \right] \right\} \tag{18}$$

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

$$S_t^r \equiv I_t^B - I_t^s$$

which, using the expression of I_t^B in (17) and $I_t^s = 0$, can be written in equilibrium as a function of p_t^m and y_t^m as follows

$$S_t^r(p_t^m, y_t^m) \equiv y_t^m - \frac{p_t^m}{P_t} y_t^m + \frac{\chi_r (1-\delta)}{g(x_t)} \tag{19}$$

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

$$M(S_t, I_t) = \sigma_m S_t^{\eta} I_t^{1-\eta}, \eta \quad (0,1) \tag{20}$$

gives the number of inactive 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. The parameter captures the ability of the big tech to collect data and process information about firms' characteristics. The higher the volume of available data, the more efficiently the big tech firm can match sellers with buyers on the e-commerce platform. The matching function is increasing in its arguments and satisfies constant returns to scale.

Existing matches on the intermediate goods market might also 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 define the intermediate goods market tightness (x_t) as the relative number of open searchers

Table 3 Timeline of operations – intermediate goods firms and retailers

Period $t-1$	Each intermediate goods firm finds out if it is active or inactive at t
Period t	**Intermediate goods firm i $[0,1]$:** If active, produces and sells intermediate goods to retailers; to do so: (i) at the beginning of the period, issues equity E_t to buy capital k_t^m, gets (real) working capital loan 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. **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 search. **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 i sells capital k_t^m and pays the household back the market value of its equity investment $Q_t^e E_{t-1}$.

relative to the number of inactive intermediate goods firms

$$x_t \equiv S_t / I_t \tag{21}$$

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, $g(x_t)$, decreases in x_t, and equals

$$g(x_t) \equiv \frac{M(S_t, I_t)}{S_t} = \sigma_m \left(\frac{S_t}{I_t}\right)^{\eta-1} = \sigma_m x_t^{\eta-1} \tag{22}$$

Similarly, the probability that any inactive intermediate goods firm is matched with an open search at time t, $f(x_t)$, increases in x_t, and is given by

$$f(x_t) \equiv \frac{M(S_t, I_t)}{I_t} = \sigma_m \left(\frac{S_t}{I_t}\right)^{\eta} = \sigma_m x_t^{\eta} \tag{23}$$

Thus, inactive intermediate goods firms will find final goods clients more easily when the intermediate goods market is tighter, that is, when inactive intermediate goods producers are scarce relative to the 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 buy final goods by 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

$$1 + i_t = \frac{1}{\beta} \Pi_t^{\varphi_\pi} \left(\frac{Y_t}{Y}\right)^{\varphi_y} e^{\nu_t} \tag{24}$$

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

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

where $\rho_\nu \in [0, 1)$. A positive (negative) realization of ε_t^ν should be interpreted as a contractionary (expansionary) monetary policy surprise. By arbitrage, the risk-free interest rate on public 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:

$$B_t^h + B_t^b = \left(B_{t-1}^h + B_{t-1}^b\right)\left(1 + i_{t-1}\right) + \Upsilon_t^g \tag{25}$$

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:

$$C_t = Y_t \tag{26}$$

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:

$$Y_t = A_t y_t^m \tag{27}$$

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 bargaining process is described in detail in the next section.

3.9.3 Capital market

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

$$A_t k_t^m = \bar{K} \tag{28}$$

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:

$$\int_0^{A_t}\int_0^1 l_t^m(i,j)\,dj\,di = L_t$$
$$\Delta_{w,t} A_t l_t^m = L_t \tag{29}$$

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 public bonds by the household and by the big tech firm to equal their supply by the government:

$$B_t^h + B_t^b = B_t \tag{30}$$

3.9.6 Equity market

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

$$E_t = A_t k_t^m \tag{31}$$

3.10 Bargaining

In equilibrium, the retailers and the 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 match needs to share this pure economic rent 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 between each retailer and its suppliers. 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 firm, and it is subject to the technology and credit constraints of intermediate goods firms described by equations (6) and (13), respectively. Since all retailers are identical, active intermediate good firms will sell the same quantity y_t^m at the same price p_t^m to all its customer retailers. The optimal choices of p_t^m and y_t^m implicitly 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:

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

subject to

$$\frac{W_t}{P_t} l_t^m(y_t^m, k_t^m) \leq bV_{t+1} + \nu E_t \left[\Lambda_{t,t+1} \left(\frac{Q_{t+1}^k}{P_{t+1}} k_t^m \right) \right] \tag{32}$$

where η is the (relative) bargaining power of the active intermediate goods firms.[12]

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

$$(1 - \tau)\eta S_t^r = (1 - \eta) S_t^m \tag{33}$$

where both surpluses S_t^m and S_t^r are a function of p_t^m, y_t^m and k_t^m.

The optimality condition with respect to y_t^m writes

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

where $\lambda_t \geq 0$ is the Lagrangian multiplier on a intermediate goods firm's credit constraint. Using (33), this optimality condition can be simplified under our baseline calibration with $\eta = 1 - \eta$ as:[13]

$$1 = \frac{1}{1 - \alpha} \frac{W_t}{P_t} \frac{l_t^m}{y_t^m} \left[\frac{1}{1 - \tau} + \frac{\lambda_t}{1 - \eta} \left(\frac{1}{1 - \tau} \right) \right], \quad \lambda_t \geq 0 \tag{34}$$

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. 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

[12] 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.

[13] 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 $\eta = 1 - \eta = 0.5$.

chosen to maximize the joint surplus of the match, while p^m_t is set to split that surplus according to the parameter . 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 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, it also impairs it by financing credit with fees that distort the production choices of firms active on the platform. Furthermore, 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 (34) with both credit constraints and variable fees (i.e. when $\lambda_t > 0$ and $\tau > 0$), the magnitude of the wedge depends on both types of frictions.

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

$$\frac{Q^k_t}{P_t} = \gamma \frac{y^m_t}{k^m_t}\left[\frac{1+\frac{\lambda_t}{\,}\left(1-\tau\right)^{1-}}{\frac{1}{1-\tau}+\frac{\lambda_t}{1-}\,\frac{1}{1-\tau}}\right] + \left(1+\frac{\nu\lambda_t}{\,}\left(1-\tau\right)^{1-}\right) E_t\left[\Lambda_{t,t+1}\frac{Q^k_{t+1}}{P_{t+1}}\right] \tag{35}$$

In the absence of credit frictions and of the variable fee, the optimality condition above defines a standard capital demand equation where the price of capital equals its marginal return plus the discounted value of its future expected market value.[14] In the general case with a binding credit constraint ($\lambda_t > 0$), firms take into account the contribution of capital as collateral.

To sum up, equations (32), (33), (34) and (35) describe the outcome of the bargaining process which determines λ_t, p^m_t, y^m_t, and k^m_t.

4 Parametrization

We parameterize our model at quarterly frequency using data for the US economy. In our model, the impact of big tech lending on the responses of credit and real activity to business cycle fluctuations crucially depends on the strength of the network channel relative to the physical collateral channel.

[14] Setting $\lambda_t = 0$ and $\tau = 0$ in (35), we get:

$$\frac{Q^k_t}{P_t} = \gamma \frac{y^m_t}{k^m_t} + E_t\left[\Lambda_{t,t+1}\frac{Q^k_{t+1}}{P_{t+1}}\right]$$

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

We discipline the model by choosing parameters that replicate the estimated reaction of commercial property prices and e-commerce activity to monetary policy[15]. We show next our empirical results, and then turn to our parametrization strategy.

4.1 Estimated effects of monetary policy

We estimate the dynamic responses of log-transformed real e-commerce sales and log-transformed real commercial property prices to monetary policy using Jordà (2005)'s local projection method. That is, for each forecast horizon $h = 0, .., H - 1$ we run a distinct regression for a given dependent variable y (either the log-transformed real commerce sales, or the log-transformed real commercial property prices) on a high-frequency identified monetary policy surprise (mps_t) and a vector of control variables $\mathbf{x}_t$[16]:

$$y_{t+h} = \alpha_h + \beta_h \cdot mps_t + \mathbf{A_h} \cdot \mathbf{x}_t + e_{t+h}, \tag{36}$$

where the forward term y_{t+h} captures the value of the dependent variable h periods after the monetary policy shock, the coefficient β_h gives the response of the dependant variable at time $t + h$ to a shock at time t, $\mathbf{A_h}$ is the coefficient matrix of control variables at horizon h (to be described shortly), and e_{t+h} is the regression residual at horizon h. We report Newey-West standard errors to account for serial correlation.

Following Ramey (2016), we include in the vector of control variables $\mathbf{x}_t$ lags of the dependant variable, lags of the monetary policy surprise, contemporaneous and lagged values of the log-transformed CPI, of the unemployment rate, of the log-transformed industrial production, the Wu-Xia shadow federal funds rate, and further add to this list the Gilchrist and Zakrajšek (2012) equity finance premium as suggested by Caldara and Herbst (2019). The number of lags is chosen optimally according to the SBIC information criteria and equals one. Our estimation period runs from 1999:Q4-2016:Q2 because the series of e-commerce sales series begins in 1999:Q4 and that of

[15]Ideally, one would like to estimate the direct impact of monetary policy on vendors' profits. However, long enough series for such variables are not yet publicly available for the US.

[16]Commercial property prices are the commercial real estate prices for the United States available in the FRED database of the Federal Reserve Bank of St. Louis. E-commerce sales are the retail sales (total excluding food services, current prices) for the United States from the U.S. Census Bureau Data. Both series are quarterly, seasonally adjusted and deflated using the 2010 CPI. We use the high frequency identified monetary policy surprises derived by Jarociński and Karadi (2020). These monetary policy surprises are constructed from surprises in the 3-month fed funds futures to measure changes in expectations about short term interest rates around Federal Open Market Committee (FOMC) announcements, and are corrected for "information channel" biases using sign restrictions. The high frequency monetary policy surprises are converted to quarterly series by summing observations within each quarter.

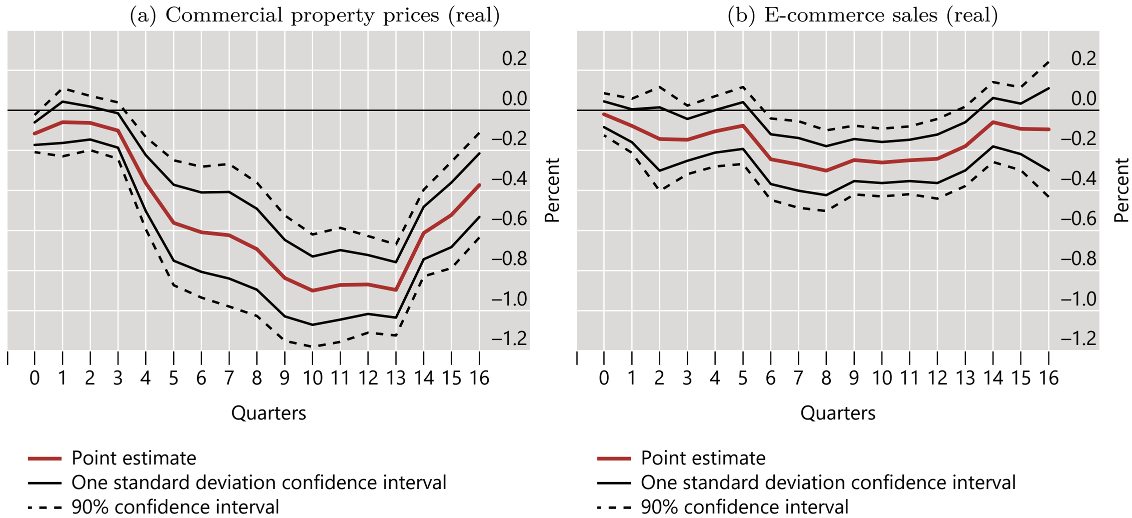

Figure 3: Estimated dynamic responses to an unexpected monetary policy tightening

Notes: Shown are the coefficients β_h in the local projection regression (36) for $h = 0, ..., 16$. The unexpected monetary tightening is an unexpected 25 basis points rise in the policy rate.

high-frequency monetary policy surprises ends in 2016:Q2.

Figure 3 reports the dynamic responses of real commercial property prices (left panel) and e-commerce sales (right panel) to a monetary policy shock in the US. The estimates show higher responsiveness on impact of commercial property prices relative to e-commerce sales. The stronger reaction of commercial property prices compared to that of real activity is consistent with estimates based on FAVAR models (e.g. Eickmeier and Hofmann (2013)).

4.2 Parametrization strategy

It is convenient to split the structural parameters of the model in four groups (Table 4).

The first group includes the standard parameters of the basic NK model. The discount factor β, the curvature of labor disutility ϕ, the labor share $1 - \alpha$, the elasticity of substitution between labor types ε_w, the Calvo index of wage rigidities θ_w and the persistence of shocks are all set to standard textbook values (see Galí (2015)). The labor disutility parameter χ is set to obtain an efficient level of labor equal to one in steady state, while the monetary policy coefficients φ_π and φ_y describe the Taylor (1993) rule. The curvature of consumption utility σ is set larger than one such that property prices respond more than e-commerce sales to monetary policy in the model in line with our empirical findings. The higher $\sigma > 1$, the larger the reaction of capital price above that

Table 4: Parametrization

Parameter	Description	Value
β	Discount factor	0.99
σ	Curvature of consumption utility	1.6
ϕ	Curvature of labor disutility	2
χ	Labor disutility	0.75
$1-\alpha$	Elasticity of output to labor	0.75
ε_w	Elasticity of substitution of labor types	4.5
θ_w	Calvo index of wage rigidities	0.75
φ_π	Taylor coefficient inflation	1.5
φ_y	Taylor coefficient output	0.5/4
ρ_v	Persistence monetary policy shock	0.5
ρ_z	Persistence demand preference shock	0.5
ρ_a	Persistence technology shock	0.9
	Relative bargaining power of the seller	0.5
η	Matching function parameter	0.5
δ	Probability to separate from an existing match	5%
$\bar{K}$	Fixed supply of capital (real estate)	1
γ	Elasticity of output to real estate	0.03
ν	Sensitivity working capital to physical collateral	1%
χ_m	Fixed big tech fee for intermediate goods firms	0.05
χ_r	Fixed big tech fee for retailers	0.05
τ	Variable big tech fee on intermediate goods sales	8%
b	Share of profits pledgeable as network collateral	30%
κ	Exclusion periods from the commerce platform	12
σ_m	Matching efficiency	$[0, \infty]$

Note: Values are shown in quarterly rates.

of sales[17]. We choose $\sigma = 1.6$ which is the maximum value for which we don't run into nominal determinacy issues in the credit constrained region of the model economy under the conventional Taylor (1993) monetary policy rule[18].

[17]This is true with and without big tech credit. Since the average share of big tech credit in the US during the estimation period is negligible, the empirical estimates roughly speak to the dynamics in the absence of big tech credit (i.e. $b = 0$).

[18]The value we chose for σ lies in the standard parameter space of basic NK models without credit frictions (e.g. $\sigma = 1$ in Galí (2015) and $\sigma = 2$ in Woodford (2003)). Setting $\sigma > 1$ is also necessary for credit frictions to amplify

The second group of parameters captures the search and matching frictions. We choose to remain agnostic about the effects of the relative bargaining power and the relative contribution to matching η by setting both parameters to 0.5[19]. The probability to separate from a match δ is set to 5% which implies an average supplier relation duration of five years consistent with median values within supply chains reported by Cen, Dasgupta, and Sen (2016) based on US Compustat firm level data[20].

The third group of parameters concerns physical capital. The fixed aggregate supply of capital is normalized to 1 and its index of decreasing returns γ equals 0.03 as in Iacoviello (2005). Conditional on $\sigma > 1$, the capital pledgeability ratio (for working capital credit) ν is a key determinant for how much more the price of capital responds to monetary policy than e-commerce sales when the credit constraint (32) binds: the lower ν, the larger the response of capital price relatively to that of sales. To match the magnitude of the estimated effects of the monetary shock on sales and property prices in Figure 3, one needs to set ν below the range of empirically plausible values[21]. In doing so however, we face a downward limit: since ν affects the volume of big tech credit in equilibrium, a low value implies a low volume of bank credit in the credit constraint region of the economy, and hence, a very steep rise in the share of big tech credit as matching efficiency increases. Faced with these constraints, we set $\nu = 1\%$ [22].

The forth and final group of parameters concern the big tech platform. Ideally, one would like to use micro-level evidence to set the values of these parameters. However, aside from variable big tech fees, such evidence is not yet available. We thus set the variable big tech fee τ roughly equal to average values in the data (Table 1), choose plausible values for the other variables, and then check the robustness of our findings around these plausible values. In particular, we set the share of vendors' profits pledgeable as network collateral b to 30%, the number of exclusion periods from the platform in case of default on big tech credit κ to 12 (that is, three years) and the fixed big

the response of output to monetary policy (alongside wage stickiness), and hence for the model to feature a financial accelerator.

[19]These values are standard in the search and matching labor market literature and also simplify the solution of the highly non-linear steady state of the model.

[20]Cen, Dasgupta, and Sen (2016) report a median (mean) supplier relationship duration of 4.9 (5.6) years.

[21]With a working capital credit constraint, one needs a low capital pledgeability ratio to embed a strong financial accelerator in the the basic New Keynesian model with capital in fixed aggregate supply (see Manea (2020)).

[22]Adding the share of physical capital financed with collateralised debt as opposed to equity as an extra parameter in the model would strengthen the financial accelerator at each level of the capital pledgeability ratio ν (see Manea (2020)). This would allow us to replicate the empirical findings in Figure 3 for higher values of ν.

tech fees, χ_m and χ_r, to 0.05[23]. Finally, the matching efficiency on the e-commerce platform σ_m is set initially to a low value (0.01) and is then varied to see how its increase affects the long run allocation and the transmission of business cycle shocks.

5 Big tech credit and the long-run allocation

This section studies how the availability of big tech credit affects the long run (steady-state) allocation, and how these effects vary with the matching efficiency between sellers and buyers on the big tech e-commerce platform. With this exercise, our goal is twofold. First, we aim to shed light on how the entry of big techs into finance may shape the long-run macroeconomic allocation. Second, we study how these effects may change as big tech companies acquire more data on their clients and are able to match more efficiently sellers with buyers on their e-commerce platforms.

To do so, we solve the steady-state of the model as a function of the matching efficiency σ_m. For simplicity, we assume a steady-state with zero inflation and zero growth. Main findings are reported in Figure 4. To disentangle the effect of big tech credit, we study the difference between steady state outcomes with both types of credit (blue line) and those with bank credit only (red line).

Given a matching efficiency level σ_m, we observe that the availability of big tech credit expands total credit and relaxes credit constraints (middle right panel) relative to an economy with bank credit only. The expansion in credit supply boosts aggregate output approaching it to its efficient level (top left panel). These effects work via the binding borrowing constraint (32). Specifically, the availability of big tech credit allows intermediate goods firms to additionally pledge a share of their future expected profits $\tilde{V}_{t+1}$ as network collateral (top right panel) alongside physical capital. All else equal, the higher collateral allows intermediate goods firms to increase their borrowing and to hire more labor. This relaxes credit constraints and leads to the higher aggregate output.

Notably, the higher output resulted from the credit expansion further translates into a higher value for intermediate goods firms to be active in the network (bottom right panel). Thus, at a given matching efficiency, expected profits and network collateral (blue line) are even higher than in the absence of big tech credit (red line). As a result, a feedback loop emerges between the volume of big tech credit and intermediate goods firms' output which works to amplify the initial effect of

[23]Setting instead the exclusion period to two, four or five years, or the share of pledgeable profits to 20% or 40% would not change qualitatively our conclusions.

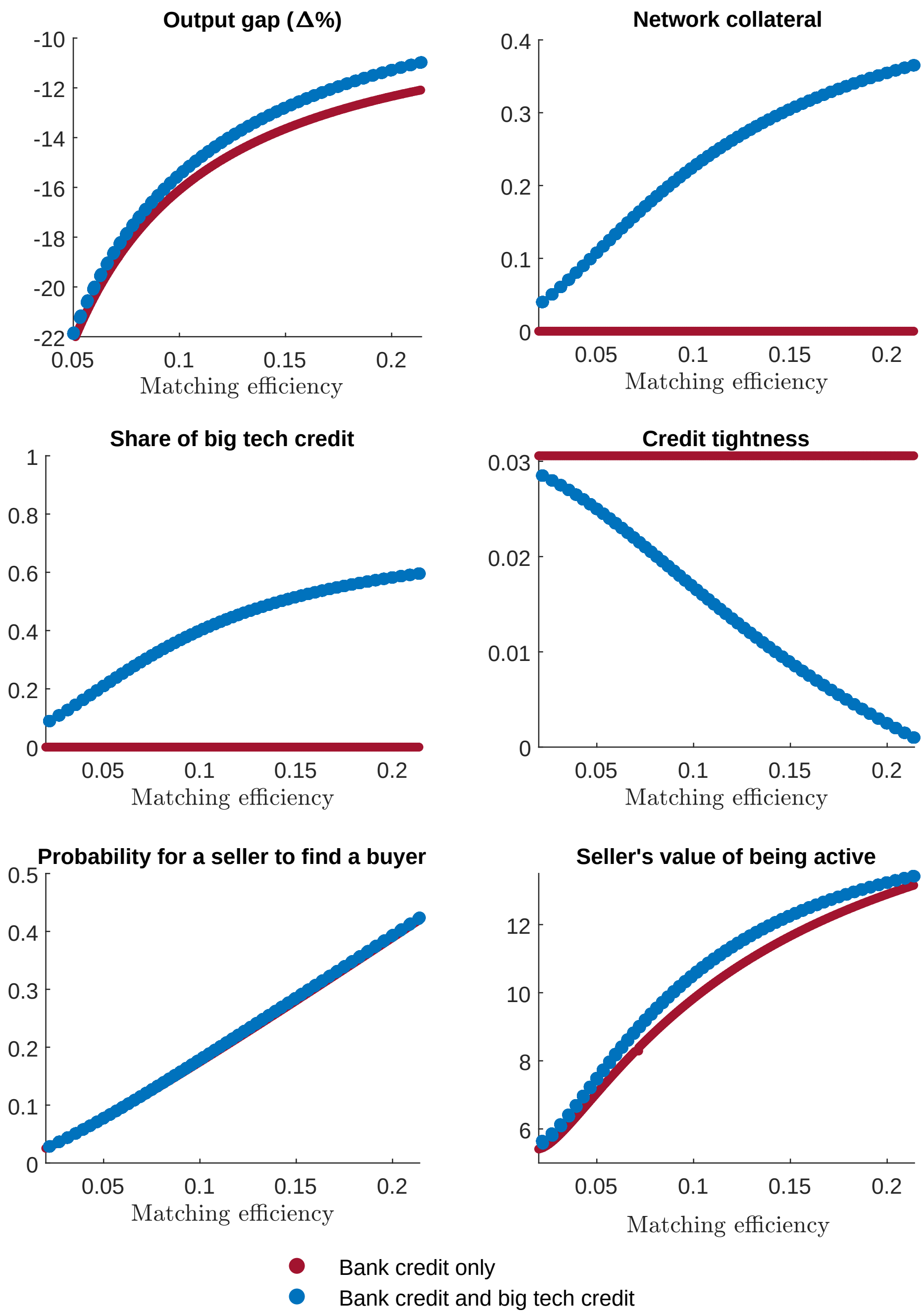

Figure 4: Steady-state equilibrium and matching efficiency on the e-commerce platform

Notes: Output gap: percentage deviation of output Y from its efficient level. Network collateral: expected profits that vendors on the platform would lose in case of default $b(1-\beta^k)V$. Credit tightness: λ. Probability for a vendor to find a client: $f(x)$. Vendors' value of being active: V^a.

this new type of credit on the macroeconomy (Figure 5).

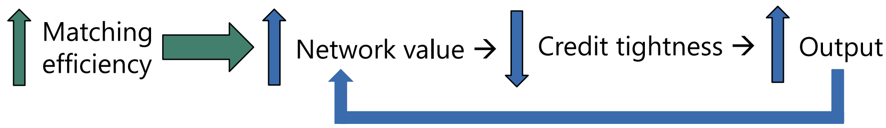

Figure 5: Feedback loop between network value, credit constraints and output

The higher the matching efficiency σ_m, the stronger is the effect of big tech credit on the steady-state allocation. This is reflected in Figure 4 by the larger differences between the blue and red lines for higher values of σ_m. A higher matching efficiency increases the probability for an intermediate goods firm to find a client $f(x)$ both directly by making a match more likely and indirectly by raising the intermediate goods market tightness x (equations (21) and (23))[24]. The higher probability to find a client (bottom left panel) boosts the expected profits of intermediate goods firms in inactive and active contingencies (equations (7) and (9)) and translates in higher network collateral $\tilde{V}$ (equation (12))[25]. Everything else equal, the higher network collateral allows intermediate goods firms to borrow more and hire more labor. This relaxes by more borrowing constraints relative to the case with bank credit only and boosts by more total credit and output.

According to our findings, when big tech credit is available, as the matching efficiency on the e-commerce platform rises, not only matching, but also credit frictions are progressively corrected. So, provided firms can pledge a high enough share of their expected profits on the platform, the increase in matching efficiency can reduce the tightness of credit constraints up to the point where the economy enters its credit–frictionless region ($\lambda \to 0$ as σ_m increases, middle right panel)[26].

Since the rise in total credit is driven by the expansion in big tech credit, the share of big tech credit in total credit steadily increases as matching efficiency improves (middle left panel). Notably, the rise in the share of big tech credit used by firms on the platform is further reinforced by a slight decline in the supply of bank credit. The shrinkage in bank credit is due to the loosening of credit constraints (middle right panel) which makes physical capital less valuable as collateral, and consequently, reduces its price (equation (35)). As a result, as matching efficiency on the

[24] The rise in intermediate goods market tightness is due to the decline in the number of inactive intermediate goods firms I, as more of these firms become active on the platform.

[25] The value of network collateral in steady-state equals $\tilde{V} = b(1-\beta^k)V$.

[26] The same applies to the number of exclusion periods from the platform in case of default κ.

e-commerce platform improves, the rise in big tech credit slightly crowds out bank credit, and the two types of credit become (net) strategic substitutes in equilibrium.

Notably, the efficiency gains associated to the use of the big tech platform are limited by the distortionary nature of their fees. Figure 6 shows that in the absence of credit frictions, variable fees distort the allocation via the firm level output (a pure sales tax effect), without affecting the matching process (i.e. the equilibrium level of active sellers). The higher the fees levied in proportion to sales on the big tech platform τ , the larger the "sales-tax" distorsions (see equation (34)), and the lower the net efficiency gains associated to the expansion of transaction on the big tech e-commerce platform.

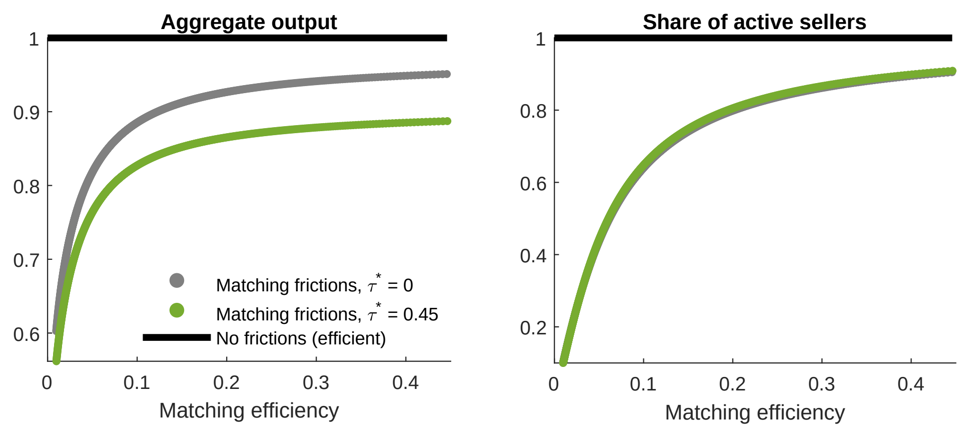

Figure 6: Distorsionary big tech fees and the steady-state allocation

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

6 Big tech credit and business cycle fluctuations

How does big tech credit affect the propagation of business cycle shocks in the economy? Similarly to the long-run effects studied in the previous section, the answer to this question depends on the matching efficiency on the e-commerce platform.

The borrowing constraint on big tech credit (equation (12)) shows that the financial accelerator characterising this new type of credit is different from that characterising bank credit. Specifically, when credit constraints bind, big tech credit amplifies business cycle fluctuations via a feedback loop between output and future profits on the e-commerce platform (network collateral). This feedback loop (equation (11)) is different from the conventional one characterising bank credit which works via property prices (physical collateral) as opposed to future profits.

The quantitative impact of big tech credit on the responses of total credit and output to business cycle shocks thus ultimately depends on two factors: the gap between the responses of network collateral and physical collateral – that is, the strength of the financial accelerator associated to big tech credit compared to that associated to bank credit – and the share of this new type of credit. Notably, our analysis shows that these two factors are affected by the matching efficiency between sellers and buyers on the e-commerce platform. Consequently, the overall impact of big tech credit on macroeconomic fluctuations varies with this structural parameter.

	Baseline model with both types of credit				Bank credit only	
Matching efficiency/Variables	Big tech credit	Bank credit	Total credit	Output	Credit	Output
Low	-0.35	-0.42	-0.37	-0.26	-0.49	-0.31
Intermediate	-0.43	-0.46	-0.43	-0.29	-0.49	-0.30
High	-0.21	-0.21	-0.21	-0.21	-0.48	-0.30

Table 5: Matching efficiency and the effect of monetary policy shocks on credit and output

Notes: Effect on impact to a positive 25 basis points monetary policy surprise.

Under our baseline calibration, when matching efficiency on the e-commerce platform is low, the introduction of big tech credit mitigates the sensitivity of credit and output to business cycle shocks. Such a situation may characterise the relatively early development stages of big tech platforms. Table 5 summarises results in the particular case of a monetary policy shock. Similar findings apply more generally to technology (Table 6 in the Appendix) and demand preference shocks[27]. Columns two to five in Table 5 show the responses on impact of big tech credit, bank credit, total credit and output to a 25 basis points contractionary monetary policy shock for different levels of the matching efficiency σ_m in the baseline economy where firms have access to both types of credit. For ease of comparison, to disentangle the effect of big tech credit, columns six and seven further show the corresponding responses of credit and output in a counterfactual economy with bank credit only.

[27]Dynamic responses of output and credit to a demand preference shock ${}^{z}_{t}$ of -0.5 percentage points are identical to those to a 25 basis points monetary policy shock. In fact, given the normalization of the shock, the response of all variables excluding the nominal and real interest rate is identical to that describing the effects of a monetary tightening. Formally, the reason for this is that $(1 - \rho_z) log(Z_t)$ and ν_t enter symmetrically (though with opposite sign) in the log-transformed version of the Euler equation (3).

According to Table 5, when matching efficiency is relatively low (row one), big tech credit (column two) responds significantly less on impact than bank credit to the monetary shock (column three) in the baseline economy. For example, when $\sigma_m = 0.02$, big tech credit drops by -0.35 percent, while bank credit drops by -0.42 percent. As a result, provided the share of big tech credit is high enough, in this low matching efficiency region, the supply of credit by big techs works to dampen the response of total credit to monetary policy. In particular, at that level of matching efficiency, total credit drops by -0.37 percent in the baseline economy with both types of credit (column four) instead of -0.49 percent in the counterfactual economy with bank credit only (column six). With total credit reacting less, the response of output in the baseline economy (column five) is also mitigated relatively to the case with bank credit only (column seven) – for instance, in our previous example, it drops by -0.26 percent instead of -0.31 percent.

Figure 7 compares the dynamic responses to a 25 basis points unexpected monetary policy tightening in the baseline economy (blue line) to those in an economy with bank credit only (red line) at a low level of the matching efficiency[28]. The figure shows that in the baseline economy, big tech credit (middle left panel, blue line) responds less than bank credit (middle right panel, blue line) because pledgeable profits on the platform (bottom left panel, blue line) react less than property prices (bottom right panel, blue line). As a result, total credit (right top panel) and output (left top panel) react less in the baseline economy (blue lines) than in the case with bank credit only (red lines) implying that big tech credit mitigates the response of the macroeconomy to the shock.

Notably, the dynamic responses in Figure 7 show that big tech credit dampens the effect of the shock on output (top left panel) not only because it reacts less than bank credit (middle panels), but also because it mitigates the reaction of bank credit. Specifically, bank credit (right middle panel) responds less in the baseline economy (blue line) than in the case with bank credit only (red line). This is because big tech's additional supply of credit in the baseline economy loosens credit constraints relative to the case with bank credit only, thereby weakening the financial accelerator[29].

As the matching efficiency on the e-commerce platform rises (Table 5, rows one versus two), big tech credit (column two) starts reacting more to the shock in the baseline economy (but still less than bank credit (column three)). This is explained by a higher sensitivity of network collateral to

[28] The share of big tech credit is an increasing function of the matching efficiency (Figure 4, left middle panel).

[29] In our current setup, this is true only on impact. We are currently adding consumption habits to match the persistent stronger reaction of real estate prices to monetary policy relatively to sales observed in the data, so as to generalise our theoretical findings to longer horizons.

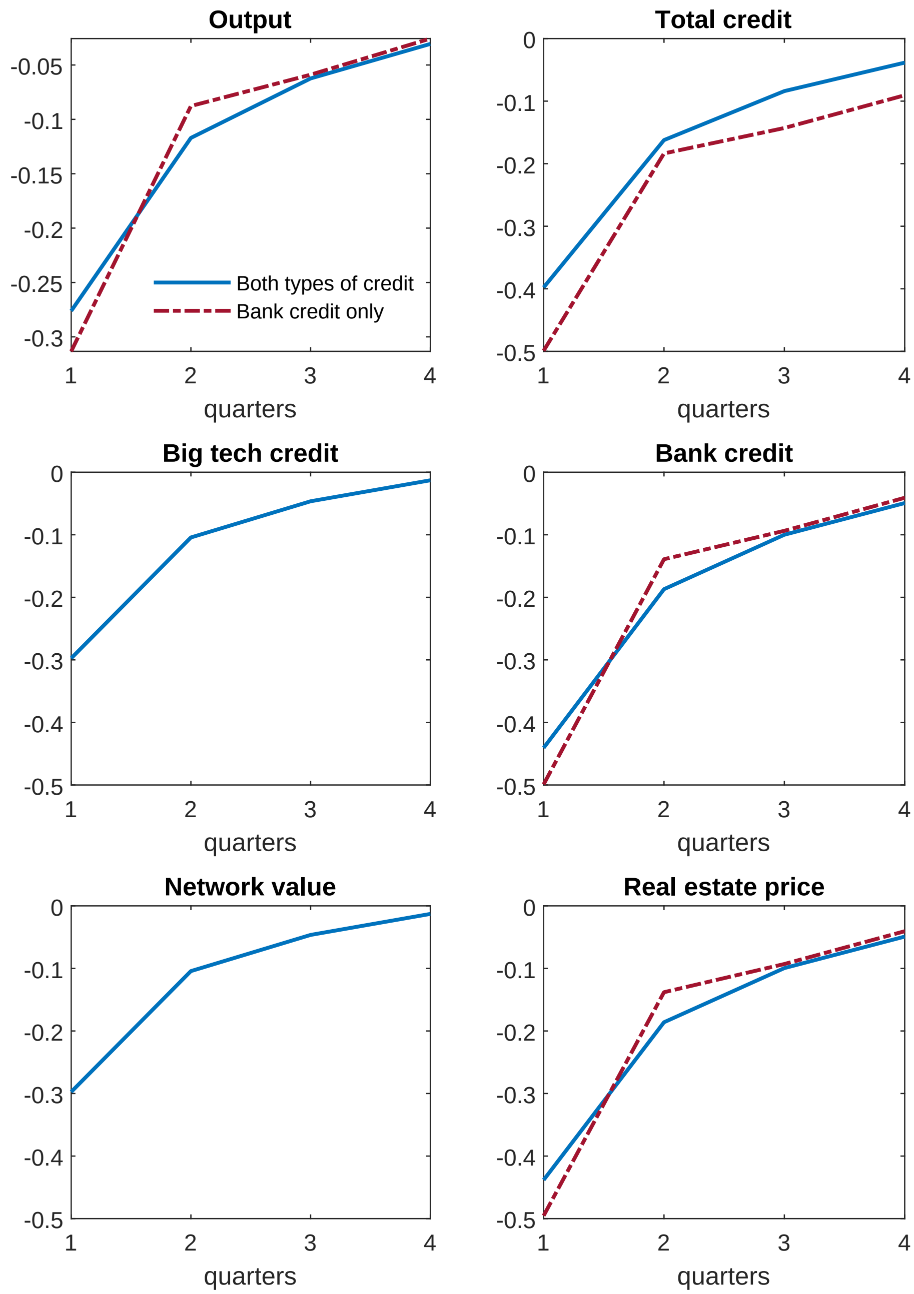

Figure 7: Dynamic responses to a monetary policy shock

Notes: The monetary policy shock is due to a monetary surprise $^{v}_{t}$ of 25 basis points. Low matching efficiency $\sigma_m = 0.02$. Share of big tech credit: 30%. Y-axis: percentage deviation from steady-state.

the shock as matching frictions subside. With less matching frictions, the average probability for a firm to become active once inactive $f(x)$ is higher, implying that network collateral V_t (equation (8)) becomes closer tied to the value of being active V_t^a (equation (7)), and hence to period profits and capital return earned on the platform which are sensitive to the business cycle as opposed to net losses while inactive which equal fixed fees and hence are not sensitive to shocks (equation (9)).

The implications of enhanced sensitivity of big tech credit are twofold. First, total credit (column four) and output (column five) start reacting more to the shock in the baseline economy (rows one versus two). Second, the gaps between the reactions in the baseline economy and those in the case with bank credit only narrow, implying that the mitigation effect of big tech credit on the propagation of business cycle shocks weakens as matching efficiency on the commerce platform rises.

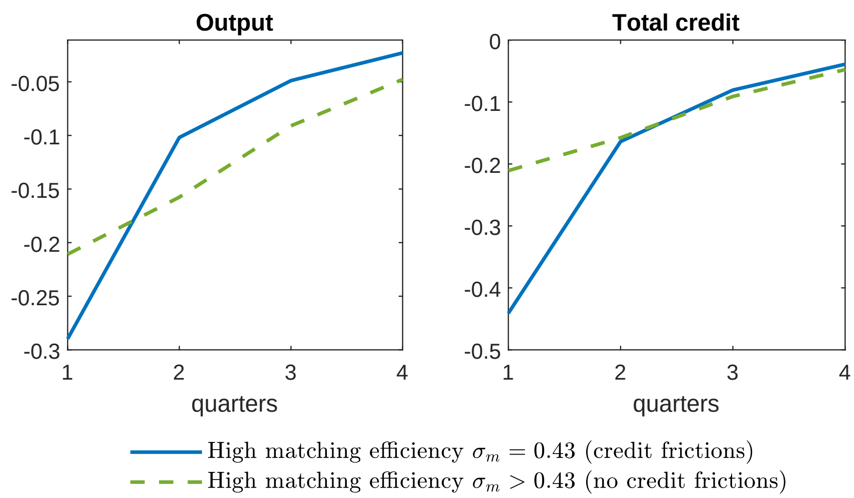

Figure 8: Dynamic responses to a monetary policy shock: transition to the credit frictionless limit
<u>Notes:</u> The monetary policy shock is due to a monetary surprise $^{\nu}_{t}$ of 25 basis points. Y-axis: percentage deviation from steady-state.

Eventually, once matching efficiency becomes sufficiently high to push the economy beyond its credit frictionless limit, the financial accelerator vanishes and the reactions of credit and output to business cycle shocks drop sharply. In particular, Table 5 shows that the drop on impact in output in response to the monetary shock goes from -0.29 percent (row five, column five) to merely -0.21 percent (row six, column five) as the economy enters its credit-frictionless region. This is illustrated in Figure 8 with the impulse response of output and credit to the shock, when the credit frictions are operating (blue solid lines) and when they are absent (dashed green lines). Notably, the economy with bank credit only, where the tightness of firms' credit constraints is not affected by the matching efficiency on the e-commerce platform, does not experience such a discrete drop in the sensitivity of real activity to the shock (Table 5, column seven, row five versus row six).

7 Conclusions

Motivated by the recent advent of big tech companies into finance, we provide an analytical framework to study how these structural changes in financial intermediation might affect the macroeconomy.

We obtain three sets of results. First, according to our model, an expansion in big techs' activity, as captured by a rise in the matching efficiency on the e-commerce platform, increases the value for firms of trading on the platform and the availability of big tech credit. This in turn relaxes financing constraints and raises firms' output, driving production closer to its efficient level.

Second, big techs' macroeconomic efficiency gains are limited by the distortionary nature of the fees collected from their platform users. Specifically, as most big tech fees are proportional to transactions on the platform, they act *de facto* as sales taxes and distort the equilibrium allocation.

Third, under our baseline calibration, when matching efficiency on the e-commerce platform is relatively low, big tech credit reacts less than bank credit to busines cycle shocks due to a more muted response of firms' opportunity cost of default on this new type of credit (future profits) compared to that on bank credit (real estate collateral). Thus, at relatively low matching efficiency levels, this novel type of credit can work to mitigate the responses of total credit and output to business cycle fluctuations. As matching efficiency on the e-commerce platform rises and the effect of matching frictions vanishes, network collateral becomes more sensitive to macroeconomic shocks and the mitigation effect of big tech credit weakens. Eventually, once matching efficiency becomes sufficiently high to push the economy into its credit-frictionless region, the financial accelerator fades away and the sensitivities of total credit and real activity to business cycle shocks drop sharply.

Our results suggest that the sensitivities of network and physical collateral to business cycle shocks, as well as the overall impact of the latter on the different sources of finance, credit and output, will likely differ across countries, depending on the level of financial development and the efficiency of the e-commerce platforms.

Looking forward, possible extensions of our framework include the analysis of big techs' financing constraints, optimal interest rate and fee setting by big techs, big techs' market power and regulation.

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8 Appendix

A Big tech credit and technology shocks

	Baseline model with both types of credit				Bank credit only	
Matching efficiency/Variables	Big tech credit	Bank credit	Total credit	Output	Credit	Output
Low	2.34	2.59	2.39	1.63	2.85	1.79
Intermediate	2.52	2.65	2.52	1.66	2.82	1.77
High	1.17	1.17	1.17	1.17	2.81	1.76

Table 6: Matching efficiency and the effect of technology shocks on credit and output

Notes: Effect on impact to a positive one standard deviation technology shock