Bigtech in finance

SUMMARY

We consider the drivers and implications of the growth of 'BigTech' in finance – i.e. the financial services offerings of technology companies with established presence in the market for digital services. BigTech firms often start with payments. Thereafter, some expand into the provision of credit, insurance and money management products, either directly or in cooperation with financial institution partners. Focusing on credit, we show that BigTech firms lend more in countries with less competitive banking sectors and less stringent bank regulation. Analysing the case of Argentina, we find support for the hypothesis that BigTech lenders, by acquiring a vast amount of non-traditional information, have an advantage in credit assessment relative to a traditional credit bureau. They also serve unbanked borrowers, and may have an advantage in contract enforcement. It is too early to judge the extent of BigTech's eventual advance into the provision of financial services. However, the early evidence allows us to pose pertinent questions that bear on their impact on financial stability and overall economic welfare.

JEL codes: E51, G23, O31

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BigTech and the changing structure of financial intermediation

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1. INTRODUCTION

One of the most notable developments in recent years has been the entry of technology companies ('BigTech' or 'TechFins') with existing platforms into the provision of financial services.[1] The presence of BigTech in finance is perhaps most advanced in some business segments in China, with the activities of Ant Financial (part of Alibaba Group) Tencent, and Baidu, each of which is active across a broad range of financial services for retail and small business clients (Xie *et al.*, 2018). Less visibly but no less important, BigTech companies are becoming active in financial services in other regions, for instance, in East Africa, Egypt and India, through the entry into payment and banking-related services of Vodafone M-Pesa; in Latin America, with the growing financial activities of e-commerce platform Mercado Libre; in Asia, with the activities of Kakao Bank, KBank and Samsung Pay in Korea, Line and NTT Docomo in Japan and the payments and credit services of ride-hailing apps Go-Jek and Grab, operating in Indonesia, Malaysia, Singapore and elsewhere in Southeast Asia; in France, with the banking services offered by Orange; and in the United States, with the budding payment services offerings of Amazon, Apple, Facebook and Google (Zetzsche *et al.*, 2017).

To date, BigTech firms have pursued a well-worn strategy of broadening their activities in finance. They often start with payments, in many cases overlaying such services on top of existing payments infrastructures. Increasingly, thereafter, they have expanded beyond payments into the provision of credit, insurance and money management products, either directly or in cooperation with financial institution partners. In China, Ant Financial, Tencent's (part) subsidiary WeBank and Baidu's (part) subsidiary Du Xiaoman provide lending to millions of small and medium firms. To be sure, their activity is small in terms of total lending (less than 1% of total credit). There are also important differences in the strategy of BigTech firms. However, their growing footprint in areas that were previously unserved by the conventional banking sector suggests that there are important economic effects that deserve attention, including their role in financial inclusion (Luohan Academy Report, 2019). This may also apply for the provision of savings products. Yu'ebao, a money market fund investment product of Ant Financial, became the largest money market fund in the world in 2017 in terms of total assets, but 99% of its users are retail customers, often with small investments. Meanwhile, Tencent recently gained a license to operate mutual funds.

1 The term 'TechFin' was popularized by Jack Ma, co-founder and executive chairman of Alibaba Group, to refer to new business models to '*rebuild the [financial] system with technology*' (as quoted in Zen Soo, 'TechFin: Jack Ma Coins Term to Set Alipay's Goal to Give Emerging Markets Access to Capital', *South China Morning Post*, 2 December 2016). The term 'BigTech' is used in the financial press and in some international policy discussions to describe the direct provision of financial services or of products very similar to financial products by technology companies. In this paper, we use the term 'BigTech' to refer to such companies whose primary business is technology, in the context of their activities in financial services. See also Carstens (2018) and FSB (2019).

BigTech firms present a distinctive business model due to the combination of two key features, namely: (1) network effects (generated by e-commerce platforms, messaging applications, search engines, etc.)[2] and (2) technology (e.g. artificial intelligence using big data). BigTech firms can exploit their existing networks and the massive quantities of data generated by them. They can then process and use the data including through machine learning models. Because of their digital nature, their services can be provided at almost zero marginal cost, i.e. they are largely 'non-rival' (Metcalfe, 2013). The provision of credit lines and other services to small vendors is typically done without human intervention.

Although the activities of BigTech firms in credit provision are most pronounced in China, credit activity has also grown in other jurisdictions, although on a smaller scale. This is due perhaps to the presence of incumbent bank-based payment systems, and in some cases to regulation. In Korea, following the introduction of virtual banking licenses, the messaging company Kakao established Kakao Bank, which attracted 820,000 customers in its first 4 days of operation, and granted KRW 4.6 trillion (USD 4.1 billion) of loans over 2017.[3] In the United States, Amazon lent over $1 billion to small- and medium-sized businesses in 2017.[4] Amazon has also begun a partnership with Bank of America on small business lending and is reportedly in talks with banks about a checking account product.[5] In Latin America, Mercado Libre had outstanding credit of over $127 million in Brazil, Argentina and Mexico as of late 2017 and is making tentative entries into asset management and insurance products.

The activities of BigTech in finance can be considered a particular subset of broader FinTech innovations.[6] FinTech refers to technology-enabled innovation in financial services with associated new business models, applications, processes or products, all of which have a material effect on the provision of financial services (FSB, 2017*a*). In some cases, FinTech activity has gained a significant share in specific market segments. For instance, online lenders like Quicken Loans now account for about 8–12% of new mortgage loan originations in the United States (Buchak *et al.*, 2017; Fuster *et al.*, 2018) and became the largest US mortgage lender in terms of originations at the end of 2017. FinTech credit platforms accounted for 36% of the flow of personal unsecured loans in the United States in 2017 (Levitt, 2018, citing TransUnion data). Claessens *et al.* (2018) discuss the growth of FinTech credit and its drivers, such as income per capita, regulatory stringency and competition in the banking sector. We follow Claessens *et al.* but extend the focus to BigTech activities, both in credit and other activities.

2 For a discussion of network effects in technology, see Shapiro and Varian (1998).

3 Kakao (2018).

4 Amazon (2018); CBInsights (2018).

5 Glazer *et al.* (2018).

6 This paper does not consider the activities of BigTech in other industries, nor the public policy issues around data protection and privacy, international taxation, etc. It considers competition issues only in the specific context of financial services.

The term 'BigTech' refers in this paper to large existing companies whose primary activity is in the provision of digital services, rather than mainly in financial services. While FinTech companies operate primarily in financial services, BigTech companies offer financial products only as one part of a much broader set of business lines. In other words, BigTech does finance in parallel to non-financial activities.[7]

Understanding the growth and potential of BigTech activities in finance is important for several reasons. First of all, analysing the drivers of such growth helps shed light on changing market structure wrought by technology, allowing an initial assessment of the economic effects of changes, together with an assessment of the balance of risks and benefits. For instance, if the entry of BigTech is driven primarily by lower transaction costs than incumbent financial institutions, access to better information or a superior screening technology, this can mean that BigTech brings greater efficiency to the financial sector, as well as opening up financial services to customers who were previously unserved by the conventional financial institutions. On the contrary, if such entry is driven primarily by bundling or tying of products, or by market power due to network externalities and portfolio effects,[8] the consequences will be less desirable in welfare terms. The fact that both the benefits and risks arise from the same key features of the business model – network effects and informational advantage – makes the economic assessment a challenging one. If regulatory arbitrage or additional risk-taking were key drivers, this would also tilt the balance of the welfare effects towards the less desirable end. Therefore, the issues for public policy are multifaceted when it comes to BigTech, and a full understanding of all economic effects is important for policy purposes. A comparative analysis across countries may yield insights into how the drivers of the growth of BigTech in finance are similar or different across countries, and whether they can be replicable elsewhere. This is relevant both from a business model perspective and from the perspective of industrial organization.

The aim of this paper is to lay out the available empirical evidence on the drivers of the growth of BigTech in finance, and then address some of its implications. Due to data availability, our empirical analysis focuses primarily on these firms' credit activities or 'BigTech credit'. We analyse a few specific questions based on available evidence. More specifically, we address the following questions:

1. What are the economic forces that best explain the adoption of BigTech services in finance, especially BigTech credit?

7 BigTech companies may have different business priorities. Finance constitutes a core business component for some BigTech firms, especially those with main activities in e-commerce, while this does not apply to some other firms.

8 'Bundling' generally refers to the practice of selling two or more products together or at a discount relative to their individual prices. 'Tying' refers to a range of practices by which the purchaser of one product is required to purchase a second product. 'Portfolio effects' can refer to a range of relationships between firms that are not a traditional customer, supplier or competitor role. See Nalebuff (2003).

2. Do BigTech lenders have an information advantage from alternative data or processing methods, particularly in relation to credit scoring?

To answer the first question on the determinants of BigTech, we first provide a bird's eye view of the industrial organization of BigTech and its rapidly shifting contours, especially in its relationship with the existing financial intermediary sector. In particular, Section 2 considers several recent trends so as to lay out the potential drivers of the growth of BigTech in a range of financial services, including supply factors (e.g. technological advantage, lack of regulation, market power or concentration among incumbent banks) and demand factors (e.g. underserved market segments, consumer preferences). Section 3 then zooms in on BigTech credit, and empirically tests drivers with a simple cross-country regression analysis. Building on Claessens *et al.* (2018), we construct a unique dataset that includes BigTech credit as an additional category in broader FinTech credit. In particular, we find that the factors that explain FinTech credit in general seem to be even more important in those jurisdictions in which there is significant BigTech credit activity, such as banking sector competition and regulatory stringency measures. We also find evidence for some specific factors, such as a larger unbanked population (as measured by fewer bank branches relative to the adult population).

To answer the second question on the economic advantages of BigTech firms in their business, we look more deeply into credit assessment techniques adopted by BigTech companies. In particular, in Section 4, we analyse available evidence on the performance of BigTech credit ratings to date. In Argentina, the evidence to be presented later is that these credit scoring techniques, based on big data and machine learning, have so far outperformed credit bureau ratings in terms of predicting loss rates of small businesses. A key question here is whether this outperformance will persist through a full business and financial cycle. At the same time, the predictive power of the scoring system arises from exploiting the network structure between vendors and customers. For instance, fraudulent applications are detected by identifying isolated clusters of nodes that have limited connections with other businesses. For example, MYbank uses network analysis of transactions to evaluate if an entrepreneur separates personal funds from business funds, which is one of the basic principles for successful small business owners.[9] We show evidence that BigTech firms often serve unbanked borrowers and may have advantages in terms of contract enforcement in some cases.

Finally, Section 5 concludes with some policy considerations and avenues for future research.

9 Chataing and Kushnir (2018).

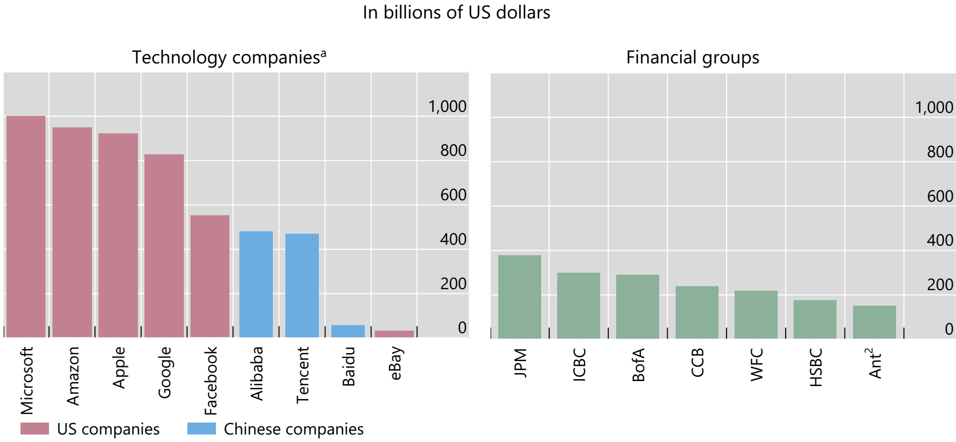

Figure 1. Market capitalization of major financial groups and BigTech firms.

[a]Stock market capitalization, 30 April 2019.

[b]The estimated value of Ant Financial was derived from the amount raised in the company's recent funding rounds times the stakes sold.

Ant, Ant Financial; BofA, Bank of America; CCB, China Construction Bank; ICBC, Industrial and Commercial Bank of China; JPM, JPMorgan Chase; WFC, Wells Fargo.

Sources: Thomson Reuters Eikon; company reports.

2. TRENDS AND POTENTIAL DRIVERS

BigTech companies are currently the largest companies in the world by market capitalization, with the largest seven technology companies all surpassing the largest global systemically important financial institutions (G-SIFIs) (Figure 1). The next section will briefly consider the growth of BigTech activities in financial services around the world, starting from payments and advancing to credit, insurance, and savings and investment. It then considers potential drivers of these developments. Section 2.2 will investigate what are the main drivers of BigTech in finance.

2.1. Trends in the growth of BigTech in finance

BigTech firms' core business is not in finance. Most of their profits derive from activities in communication services and advertising as well as information technology (i.e. cloud computing and data analysis). These account for 32% and 30% of their revenues, respectively (Figure 2, left-hand panel). Financial services represent only around 11%. While BigTech firms serve users globally, their operations are mainly located in Asia-Pacific and North America (Figure 2, right-hand panel). Their move into financial services has been most extensive in China, but activities have also been expanding rapidly in other emerging markets, notably in Southeast Asia, East Africa and Latin America.

The financial services activities of BigTech have grown rapidly in some economies, particularly in payments, lending to small and medium enterprises (SMEs), and other

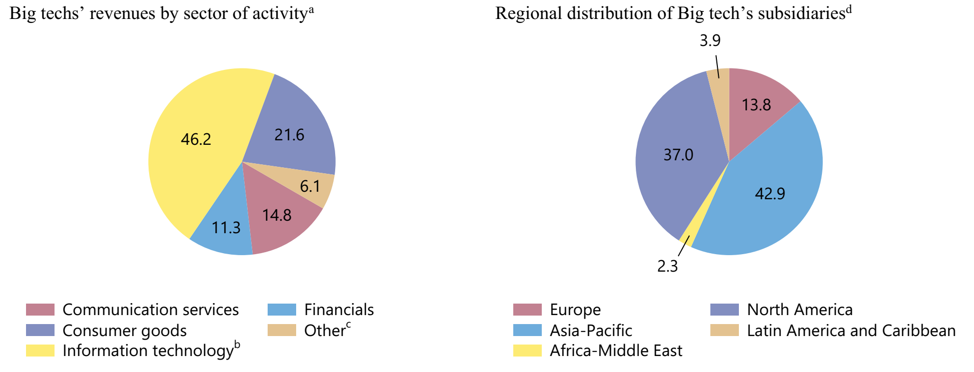

Figure 2. Sectorial and geographical distribution of BigTech business.

Notes: The sample includes Alibaba, Alphabet, Amazon, Apple, Baidu, Facebook, Grab, Kakao, Mercado Libre, Rakuten, Samsung and Tencent.

[a]Shares calculated on 2018 total revenues (where available) as provided by S&P Capital IQ. Where data were not available, data for 2017. Data accessed on 3 June 2019.

[b]Information technology might include some financials-related business.

[c]Other includes health care, real estate, utilities and industrials.

[d]Shares are calculated on the number of subsidiaries as classified by S&P Capital IQ. Data accessed on 3 June 2019.

Source: BIS (2019).

specific market segments. In fact, while most BigTech firms start in payments, often to facilitate their 'core' business (e-commerce, advertising, etc.), there is considerable diversity in the sequencing of business areas and how they conduct payments services.

In payments, available data suggest that China is by far the largest market, with BigTech mobile payments for consumption reaching RMB 14.5 trillion in 2017, or 16% of gross domestic product (GDP) (Figure 3). The United States, India and Brazil follow at a distance, with BigTech mobile payments of 0.3–0.6% of GDP. The key distinction is between the use of existing payments infrastructure, such as credit or debit cards or partner banks, or building a separate payments infrastructure. In countries where the incumbent bank-based payment infrastructure is dominant – such as the United States, Europe and Korea – innovations in payment services like Google Pay, Amazon Pay, Apple Pay, Samsung Pay and payments on Facebook messenger all rely on existing payment rails. The new credit card product by Apple and Goldman Sachs, announced in March 2019, will also operate through existing credit card infrastructure (Apple, 2019). This trend may relate to the high penetration of credit cards and bank accounts in the population and hence the ability to build on the network effects associated with well-developed payment infrastructures. By contrast, Ant Financial's Alipay, Tencent's WeChat Pay, Baidu's Du Xiaoman Pay (previously Baidu Wallet), Vodafone M-Pesa and Mercado Libre's Mercado Pago all involve a separate payments infrastructure that is integrated with these firm's related core products (namely a mobile e-commerce and services platform, a messaging and social media platform, mobile phone

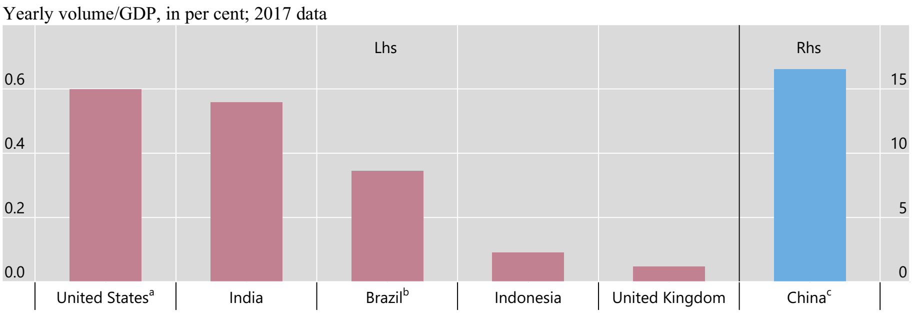

Figure 3. BigTech mobile payment services around the world.

Notes: Yearly volume/GDP, in percentage; 2017 data. The figure shows the annual volume of BigTech payment services in selected jurisdictions divided by GDP. China is displayed on a separate axis due to the large difference in scale to the other jurisdictions.

[a]2016 data are used for the United States.

[b]Estimate based on public data for Mercado Libre.

[c]Only mobile payments for consumption.

Sources: Forrester Research; GlobalData; iResearch; Mercado Libre; Nikkei; Worldpay; BIS.

credit and an e-commerce platform, respectively). The differences are revealing and may relate to the lack of credit card and other payments infrastructure in these markets (see below). Often, BigTech firms charge lower fees than incumbent providers, and operate with low margins. In a number of cases, such payments services may offer complementary benefits to their core business, and for this reason may even be cross-subsidized by other business lines of the firm.[10]

The penetration of these payment services has proceeded at a rapid pace. In China, Alipay (launched in 2004) and WeChat Pay (launched in 2011) have surpassed 500 million and 900 million monthly active users, respectively, or 36% and 65% of the overall population. Together, these two firms account for 94% of the mobile payments market in China. Both services have followed Chinese customers abroad and are also offered in a number of locations in other countries, although these services are offered in partnership with local banks and cross-border settlement takes place through the conventional correspondent banking network. In the United States, with a much smaller mobile payment volume of $112 billion, Apple Pay has 22 million users that made an in-store payment in the last 6 months, compared with 11.1 million for Google Pay and 9.8 million for Samsung Pay, according to eMarketer estimates.[11] As indicated by Chorzempa

10 For instance, one smartphone maker has noted in discussions that payments services are not meant to be profit-making, but simply to make the core product more attractive for users and to keep up with similar offerings by competitors.

11 The largest mobile payments company in the United States was actually Starbucks, with 23.4 million users. Because the primary business of Starbucks is coffee, not technology, it is not considered a BigTech company in our analysis.

(2018), the more limited development of these payment services in the United States may be attributable to the widespread use of credit and debit cards.

In East Africa, Egypt and India, M-Pesa has 32 million active monthly users, processing 6.5 billion transactions in 2017. In Latin America, Mercado Libre's payments service, Mercado Pago, has 12 million active monthly users. In Indonesia, Go-Jek's Go-Pay (established in 2016) now processes half of Go-Jek's 100 million monthly transactions. Finally, Grab's GrabPay is rapidly expanding its network of merchants in Indonesia, Malaysia, Singapore and the Philippines.

The activities of BigTech firms in finance thus started with payments, but are rapidly expanding into the provision of credit, insurance and even savings and investment products. Network effects allow the bundling of products and complementarity of services. Network effects are particularly strong in two-sided markets, where both same-side (e.g. customer-customer) and cross-side (e.g. customer-merchant) network effects operate. The economics of two-sided markets can give rise to complex interaction between consumers and sellers on a platform. For example, BigTech firms could exploit network externalities resulting in the creation of seemingly impenetrable barriers to market entry even by innovative companies (Rysman, 2009).

As noted already, BigTech credit activities are still small in aggregate terms compared with overall credit markets. In China, Ant Financial lends through three different services. MYbank, which started by lending to merchants on Alibaba's Taobao platform, had RMB 31.6 billion ($5 billion) in loans outstanding as of end-2017, primarily to SMEs (see Section 4). Ant Credit Pay and Ant Cash Now lend to consumers, e.g. for purchases of durable goods. In total, Ant Financial had lent RMB 654 billion ($95 billion) to consumers through Q1 2017. These compare to RMB 120 trillion ($19 trillion) loans outstanding of the banking sector as a whole.

Recently, Ant Financial's MYbank has also developed a partnership with an established traditional bank to better serve small off-line farmers (i.e. retailers not on the Taobao e-commerce platform). The partner bank already had established relationships with farmers, which MYbank could access (Chataing and Kushnir, 2018). However, the data (mainly sales or transaction history derived from bank accounts) was subject to manipulation and not sufficiently high-quality for calculating credit scores. Ant Financial moved off-line vendors on-line, by offering them use of Alipay services at no cost. Concretely, Ant Financial supplied the small vendors (farmers in rural areas) with QR code posters that allowed their customers to scan those codes and pay via their Alipay app. With the obtained transaction data, the firm was able to use the MYbank scoring system to offer credit to these customers, which typically cannot provide sufficient documentation to apply for regular bank credit. This generated substantial improvements in financial inclusion (Ding *et al.*, 2017).

In the Tencent ecosystem, WeBank (30% owned by Tencent) has established a large lending presence. Through its microloan and micro auto loan products, WeBank had RMB 47.7 billion ($8 billion) in credit to consumers outstanding as of late 2017, and cumulative lending of RMB 870 billion ($127 billion).

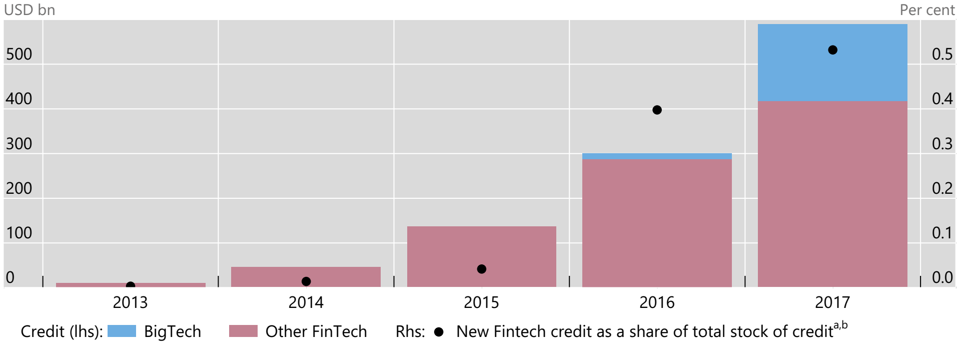

Figure 4. Global volume of new FinTech credit.

Notes: The bars indicate annual global lending flows by BigTech and other FinTech firms over 2013–17. Figure includes estimates.

[a]Total FinTech credit is defined as the sum of the flow of BigTech and other FinTech credit. This is then divided by the stock of total credit to the private non-financial sector.

[b]Calculated for countries for which data were available for 2013–17.

Sources: Cambridge Centre for Alternative Finance and research partners; BigTech companies' financial statements; authors' calculations.

BigTech firms are also lending elsewhere. In Korea, after the introduction of a virtual banking license in 2017, the online-only banks Kakao Bank (owned by internet company Kakao) and KBank (owned by Korea Telecom) lent, respectively, $4.1 billion and $0.7 billion by year-end. In Southeast Asia, Grab had a loan book of $700 million in Southeast Asia as of late 2017, with a focus on Indonesia (Russell, 2018). In Brazil, Argentina and Mexico, Mercado Libre lent $127 million over 2017 through its product Mercado Crédito. In Europe, telecom company Orange has a banking license for Orange Bank. In December 2018, Google acquired a Lithuanian banking license, but it has so far not engaged in large-scale lending.

While BigTech credit is rapidly growing, at the global level it remains quite limited compared with other forms of financing (see Figure 4). The total flow of FinTech credit in 2017 represents around 0.5% of total stock of private sector credit at the global level (including bank loans).

Network effects in BigTech allow for the bundling of products and complementarity of services. The most advanced BigTech players are indeed active not only in the supply of credit but also in related financial services like insurance and savings and investment.[12] Again, in China, Yu'ebao ('leftover treasure'), a mobile money market fund went online in June 2013 and was initially established to allow customers invest small cash amounts sitting in their Alipay payment account. The minimum investment was of 1 RMB. In 5 years' time, Yu'ebao reached RMB 1.7 trillion ($266 billion) assets under

12 Some FinTech players also offer a broad range of financial services; what distinguishes them is that these firms generally do not have non-financial services offerings.

management, making it the largest MMF in the world. Beyond Yu'ebao, Ant Fortune is a marketplace for other Ant Financial and third-party financial products, with 180 million users. In 2014, Tencent created Licaitong, a wealth management platform with over RMB 300 billion ($47 billion) in assets under management as of January 2018. Ant Financial and Tencent also offer insurance products on their platforms, both from third parties and from their own dedicated insurance offerings (Ant Insurance Services and WeSure Insurance). In the United Kingdom, Amazon has offered an insurance product for online purchases called Amazon Protect, but this is at a much lower scale than the offerings in China.[13] Mercado Libre is piloting insurance and savings products in some markets, but these activities are also still limited.

By entering a broad range of financial services, BigTech firms are increasingly competing with incumbent financial institutions. Yet there are also other forms of interaction. For example, BigTech firms are important third-party service providers to financial institutions. Amazon Web Services is the largest provider of cloud services in the world, including many financial institutions. Microsoft and Google are also large cloud services providers, while Ali Cloud (an affiliated company of Ant Financial in the Ali Group) is a dominant player in Asia. Many BigTech firms also offer specific tools using artificial intelligence and machine learning to corporate clients, including financial institutions. The activity of BigTech firms as both suppliers to, and competitors with financial institutions raises a number of potential conflicts of interest, at the same time that their dominant market power in some markets is coming under greater scrutiny (see e.g. Khan, 2017).

2.2. Drivers of BigTech in finance

The drivers of BigTech activity in finance, particularly beyond payments, may be similar to those of FinTech activity more generally, or there may be unique drivers. In the past few years, there is a growing body of research considering why investment in FinTech (e.g. Navaretti *et al.*, 2017) or FinTech credit have grown more in some jurisdictions than others (e.g. Davis and Murphy, 2016; CGFS and FSB, 2017; Rau, 2017; Claessens *et al.*, 2018). Broadly, these can be broken down into demand and supply factors.

On the demand side, important factors could be:

- *Unmet customer demand*: Where existing firms or consumers are underserved by banks, as visible in a low share of the population with a bank account or credit card, there may be an opportunity for more rapid growth of lending by BigTech. Hau *et al.* (2018) and Huang *et al.* (2018) find that BigTech credit in China fills unmet customer demand. Similar results have been found for Germany by De Roure *et al.* (2016), and for the United States by Tang (2019) and Jagtiani and Lemieux (2018*b*) with

13 CBInsights (2018).

regard to broader FinTech credit. In emerging market and developing economies, there may be large demand from the unbanked or underbanked population. A 2016 survey by Mercado Libre found that 70% of its on-platform merchants were interested in taking a loan to invest in their businesses, but that only 25% of them had access to bank loans.

- *Consumer preferences*: Consumers and small businesses are more likely to use the financial offerings of BigTech intermediaries when they are broadly comfortable with new technologies, especially if banks do not change their provision of financial services. Bain & Company and Research Now (2017) find in a survey that 91% of Indian respondents, 86% of Chinese respondents and 60% of US respondents would consider financial products from technology firms they already use. This interest is even higher among younger consumers (ages 18–34 years). These preferences may create a number of opportunities for cross-selling by BigTech firms. For instance, Chen (2016) argues that FinTech adoption is supported by integration of financial products with customer needs.

On the supply side, the most important factors may be the following:

- *Access to data*: BigTech firms have access to a wide range of customer data, which may give them superior information to assess the creditworthiness of borrowers and policyholders, leading either to more accurate credit and insurance assessments or to lower costs of the intermediation process. These advantages have been found for FinTech lenders (see Fuster *et al.*, 2018; Jagtiani and Lemieux, 2018*a*) but apply even more for companies whose primary business is e-commerce or data services.
- *Technological advantage*: Due to their extensive use of new technologies like artificial intelligence and machine learning, BigTech firms may be able to better process data, e.g. through a superior screening technology, relative to financial institutions with legacy systems. If this is the case, it should be reflected in lower default rates or to lower costs per loan granted, or lower costs on insurance.
- *Access to funding*: Securing adequate funding is one constraint for BigTech firms in expanding lending. For this reason, BigTech firms often partner with a bank or set up their own bank. One option, for example, is to establish an online bank. But in some countries, regulatory authorities restrict the opening of remote (online) bank accounts. One example is China, where the two Chinese BigTech banks (MYbank and WeBank) rely mostly on the interbank market funding rather than on traditional deposits. Another practice is loan syndication or an originate-to-distribute model – a framework already used by FinTech firms. Quicken Loans, the largest mortgage lender in the United States in terms of originations (Sharf, 2018), securitizes virtually all originated credit. Ant Financial's gross issuance of asset-backed securities (ABSs) accounted for almost a third of all ABS exchanged with non-banks in China throughout 2017 (18% considering interbank transactions which are dominant in China's ABS market). BigTech firms also issue bonds at relatively lower cost than

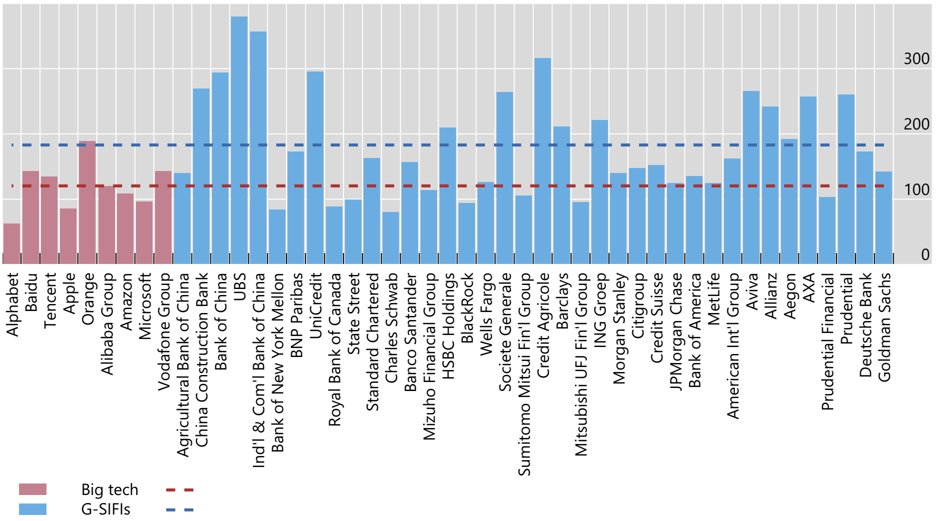

Figure 5. Average spread of active bonds to US Treasury bonds at issuance.

Notes: The bars represent the spread of each firm, and dashed horizontal lines indicate the simple average. All values are represented in basis points. Average spread of active bonds over US Treasury bonds at issuance as collected by Bloomberg SRCH function. Terminal accessed on 18 January 2019. Filters used are Corporates, Active Bonds, Issue Date >12/31/2013 and Issuer Name as listed in the graph above.

Sources: Bloomberg; authors' calculations.

G-SIFIs (see Figure 5), even if their main source of funding remains equity (the average equity to asset ratio of the BigTech firms reported in Figure 5 is 50.2%).

- *Lack of regulation*: If existing financial regulations, e.g. consumer protection rules or prudential requirements, do not apply equally to BigTech firms entering financial services, then this can lead to lower costs and a competitive advantage for BigTech. This may also lead to higher risk-taking. These factors vary widely by country, as regulatory frameworks for BigTech in finance are currently developing.[14]
- *Lack of competition*: Incumbent banks and non-bank lenders may be shielded from competition by regulation (caps on deposit interest rates) or by market power in the banking sector. Where the unit cost of finance is high (see Philippon, 2015), this may make entry by challengers, including BigTech firms, particularly attractive. BigTech entry may thus be more likely where banking sector markups are high.

Disentangling these factors at an aggregate level is an empirically challenging task. Moreover, over the period of analysis, there may be important macroeconomic and macrofinancial factors, which may work in unexpected ways.[15] As such, controlling for macro factors is important to understand BigTech's development.

14 BCBS (2018).

15 To give one example, for FinTech loans, Bertsch *et al.* (2016) find that in December 2015, Fed lift-off in the United States was associated with *lower* interest rates in the following hours, as it provided a positive signal about future borrower solvency.

Table 1. Percentage of FinTech users using other technology propositions

Column, %	Sharing economy (e.g. Airbnb, GoGet)	On-demand services (e.g. Uber, Menulog)	Online content streaming (e.g. Netflix, YouTube)	Messaging and video chat (e.g. WhatsApp, Snapchat, Skype)	Social media profile (e.g. Facebook, LinkedIn)
Daily	7	9	47	66	71
Weekly	17	31	29	15	14
Monthly	21	26	11	7	6
Rarely	17	13	6	5	3
Never	24	14	3	4	4
Yearly	14	7	4	4	2

Notes: The table shows the percentage of FinTech users from a survey of 22,535 individuals in 20 markets globally who also use other tech propositions. Survey respondents were given specific examples for each tech proposition (such as those listed in each column) that were tailored to each market.
Source: EY.

One key question is whether the experience in China is unique. EY (2017) finds in a survey that the share of the (digitally active) population that is a regular user of FinTech services (including BigTech) is quite heterogeneous across countries and reaches its maximum (69%) in China. FinTech services (including BigTech) are also widely used in India (52%), but are not widely used in countries as Belgium, the Netherlands and Japan (13–14%) where traditional banking services are quite well developed, especially for consumers. EY argues that the use of financial technology services is more popular among tech-literate but financially underserved populations. All the five emerging countries included in the survey (China, India, Brazil, Mexico and South Africa) are characterized by rapid economic growth and an expanding middle class, but without traditional financial infrastructure to support this new demand. Relatively high proportions of the population are underserved by existing financial services providers, while falling prices for smartphones and broadband services have increased the digitally active population that financial technology firms target. Notably, in many of these countries, and globally, FinTech users are also more likely to use other tech prepositions, such as online streaming content, messaging and video chat, and social media (Table 1).

Other studies note that Tencent and Ant Financial only expanded into financial services like lending and asset management after online payments were well entrenched (Chorzempa, 2018). One key lesson from China's experience is that the development of BigTech companies did not occur overnight. The relatively underdeveloped state of China's payment system infrastructure in the early 2000s was essential for the development of online payment systems. The lack of access to payments, e.g. through lack of credit cards, the limited use of online banking, and geographical restrictions on the use of debit cards allowed Tencent and Alibaba to develop their own payment systems to solve specific problems in their business. Tencent created its virtual currency 'Q' as early as 2002. Alibaba launched Alipay in 2004. It took years to develop this infrastructure and for enough consumers to trust technology companies with their finances, before

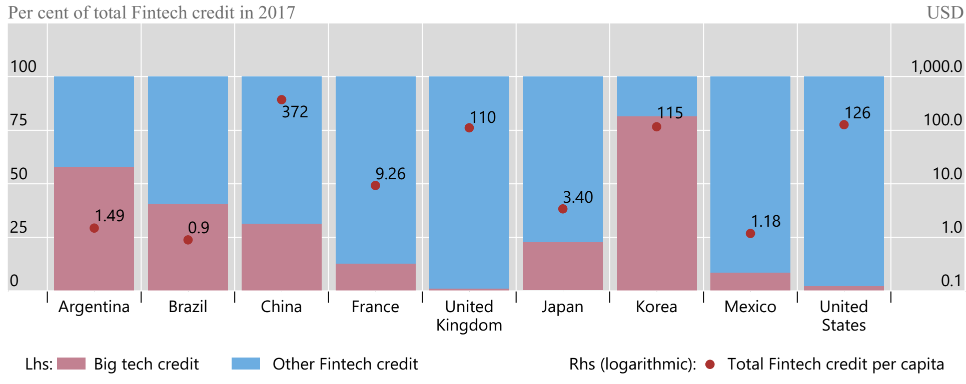

Figure 6. FinTech and BigTech credit in selected countries.

Note: The bars show the share of BigTech and other FinTech credit in selected jurisdictions in 2017, while dots show the total FinTech credit (sum of BigTech and other FinTech credit) per capita.

Sources: Cambridge Centre for Alternative Finance and research partners; BIS calculations.

such services took off (a standard 'S-curve effect'). Growth rates in other emerging markets may indicate that these countries are now following a similar path, but that it could take several years before services are similarly widespread.

3. BIGTECH CREDIT

Given data availability, and for comparability across jurisdictions, we focus our empirical analysis on BigTech credit, or credit provided by BigTech firms, which can be seen as a component of FinTech credit. FinTech credit can be broadly defined as credit activity facilitated by electronic (online) platforms that are not operated by commercial banks (CGFS and FSB, 2017). However, available statistics used by public sector authorities or private sector data providers for FinTech credit do not include BigTech credit. As such, we have hand-collected data on BigTech credit volumes for 17 economies from public data sources, with the help of contacts at several BigTech firms (see Appendix for further details). Based on these data, and existing data on FinTech credit ('loan-based alternative finance') from the Cambridge Centre for Alternative Finance (see e.g. CCAF, 2017, 2018), we have constructed a cross-section of *total* FinTech credit, which includes BigTech credit.

The volume of BigTech credit varies greatly across economies. We have already documented in Figure 4 that the flow of BigTech credit is growing fast but it is still small as compared with the total stock of credit to the private sector. Moreover, as visible in Figure 6, with the red shading, the share of BigTech credit in total FinTech credit is highest in Korea, Argentina and Brazil, each of which has relatively small FinTech credit markets. It is about 20% of overall FinTech credit volumes in the very large and deep FinTech credit markets in China – the world's largest market for FinTech and BigTech credit in both absolute and per capita terms. Finally, while moderately large in

Table 2. Descriptive statistics on BigTech and total FinTech credit volumes

Variable	Obs	Mean	Std. Dev.	Min	Max
Log of total FinTech credit per capita (in USD)[a]	64	0.316	2.474	–4.468	5.920
Log of BigTech credit per capita (in USD)[a]	64	–5.507	3.379	–7.183	4.766
Log of other FinTech credit per capita (in USD)	64	–0.007	2.576	–6.986	5.541
Log of BigTech credit share of total credit[a],[b]	64	–10.397	2.791	–15.174	–3.509
GDP per capita (in USD)[c]	64	21.139	16.460	0.737	62.790
Banking sector Lerner index (markup)[d]	64	0.266	0.131	–0.269	0.621
Normalized regulation index[e]	64	0.740	0.087	0.522	0.957
GDP growth (in %)[c]	64	3.596	2.022	–0.107	8.104
Crisis dummy (post-2006)	64	0.266	0.445	0.000	1.000
Credit growth[f]	64	7.231	7.085	–7.995	22.648
Mobile phones per 100 persons[g]	64	114.137	32.833	32.129	214.735
Bank branches per 100,000 adult population[d]	64	22.564	23.368	1.711	145.995
BigTech dummy	64	0.234	0.427	0.000	1.000

[a]2017 data.
[b]Sum of total FinTech credit and total credit to the private non–financial sector.
[c]Average from 2013 to 2016.
[d]Average from 2010 to 2015.
[e]In 2015.
[f]Total banking credit growth to the private non–financial sector (in %; average over the period 2010–16).
[g]2016 data.
Sources: (Laeven and Valencia, 2013)); Cambridge Centre for Alternative Finance and research partners; IMF, World Economic Outlook; World Bank, Bank Regulation and Supervision Survey; World Bank, Global Financial Development Database and World Development Indicators; International Telecommunication Union; authors' calculations.

absolute terms, BigTech credit is still quite small as a share of total FinTech credit in the United States and United Kingdom, and is only a moderate share of overall FinTech credit in Japan. The red dots in Figure 6 show that total FinTech credit per capita is highest in China, the United States and United Kingdom.

In order to understand the drivers of BigTech credit, we conduct an econometric analysis with cross-sectional regressions as in Claessens *et al.* (2018). The main difference is that here we consider separately BigTech and total FinTech credit per capita as our dependent variables. Key independent variables correspond to the drivers described in Section 2.2. Overall, we have data for 64 countries on total FinTech credit, of which 17 are known to have BigTech credit. Table 2 shows the descriptive statistics.

As a first step of the analysis, we run the following baseline linear probability model:

$$BT_i = \alpha + \beta_1 y_i + \beta_2 y_i^2 + \gamma LI_i + \delta RS_i + \mu BN_i + \sigma X_i + \varepsilon_i \tag{1}$$

where BT_i is a dummy that takes the value of 1 if BigTech credit has been extended in country i in 2017 and 0 elsewhere. The right-hand side includes a number of regressors: y_i is log of GDP per capita in economy i, and the variable y_i^2 is its quadratic term, to address the non-linear relationship between credit development and income levels; LI_i is the Lerner index of banking sector markups in economy i, reflecting market power by incumbent banks; RS_i is an index of regulatory stringency for the banking sector of economy i, as constructed by Navaretti *et al.* (2017) from World Bank data[16]; X_i is a vector of control variables, BN_i is the density of the bank branch network in country i (which may capture both the reach of the banking sector and its relative cost base) and ε_i is an error term. Additional control variables included in X_i are growth in GDP and total credit; a dummy for whether a country had suffered a financial crisis since 2006; mobile phone penetration (given the mobile-based nature of many platforms), and a dummy for advanced economies.

The results of the linear probability model are reported in the first column of Table 3. The existence of BigTech credit activity is positively associated with GDP per capita. Since GDP per capita is likely to be a proxy for many aspects of a country's stage of development (indeed, it is positively correlated with several of the possible explanatory variables we discussed in Section 2.2), this result confirms a positive relationship between a county's overall economic and institutional development and BigTech activity. The negative coefficient estimate on squared GDP per capita suggests that such effects become less important at higher levels of development.

The positive correlation with the Lerner index suggests that BigTech activity develops in those jurisdictions with a less competitive banking sector. This result could be explained by the notion that BigTech credit is offered at relatively lower costs and it is relatively more attractive to borrowers in these countries. It may also be that high margins make entry more attractive for the BigTech firms, themselves.

Similarly, the density of the bank branch network is negatively correlated with the development of BigTech credit. This is consistent with the view that BigTech credit serves clients in unbanked areas and therefore their credit supply is complementary to traditional bank credit.

The coefficient of the stringency of banking regulation is not significant: more stringent regulation is not significantly linked to less BigTech credit activity (though this changes for other specifications – see below – when we can exploit the cross-sectional heterogeneity in a larger number of countries with FinTech credit). The additional controls are generally not significant.

The results are largely confirmed when considering BigTech credit per capita or per unit of total credit as the dependent variable. The second and the third columns of Table 3 reports the results of linear models that estimate variations of Equation (1) where the BT dummy is replaced by two alternative dependent variables: the logarithm of BigTech credit per capita (second column) and the logarithm of BigTech credit per unit of total credit (third column). Results are qualitatively similar. In the latter case, GDP per capita is also not significant.

16 In practice, there are often specific rules that may prevent BigTech entry into banking, such as specific bank licensing requirements or (in the United States) the separation of banking and commerce. The existence of these rules may be correlated with overall banking sector stringency, but would not be explicitly captured by this measure.

Table 3. Drivers of BigTech and total FinTech credit volumes

Explanatory variables	Dependent variable						
	BigTech dummy (0/1) (I)	Ln(BigTech credit per capita[a]) (II)	Ln(BigTech credit per unit of total credit[a,b]) (III)	Ln(Total FinTech credit per capita)[c] (IV)	Ln(Total FinTech credit per capita)[c] (V)	Ln(Other FinTech credit per capita)[d] (VI)	Ln(Other FinTech credit per capita)[d] (VII)
GDP per capita[e]	0.038**	0.364***	–0.080	0.186***	0.142**	0.199***	0.147**
	(0.015)	(0.136)	(0.078)	(0.058)	(0.059)	(0.056)	(0.057)
GDP per capita squared[e]	–0.001**	–0.005**	0.000	–0.002***	–0.002**	–0.003***	–0.002**
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lerner index[f]	0.883**	9.588***	7.258***	3.795*	1.115	4.708**	1.365
	(0.435)	(3.132)	(2.219)	(2.068)	(1.532)	(2.305)	(1.480)
Normalized regulation index[g]	0.399	–2.161	–2.972	–8.754***	–5.968*	–10.309***	–6.029*
	(0.718)	(6.271)	(3.179)	(2.927)	(3.254)	(3.220)	(3.257)
Bank branches per 100,000 adult population[f]	–0.005**	–0.039**	–0.033***	0.001	0.004	0.001	0.003
	(0.002)	(0.016)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
BigTech dummy (BT)				1.557**	7.799*	0.226	10.256***
				(0.634)	(3.967)	(0.672)	(3.187)
Interactions with BigTech dummy							
BT*GDP per capita[e]					–0.157		–0.241***
					(0.139)		(0.085)
BT*GDP per capita squared[e]					0.004*		0.004***
					(0.002)		(0.001)
BT*Lerner index[f]					9.475*		10.911***
					(4.782)		(3.999)
BT*Normalized regulation index3					–9.994**		–16.920***
					(4.920)		(4.602)
BT*Bank branches per adult population[f]					–0.038		0.118
					(0.076)		(0.088)
Other controls[h]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	64	64	64	64	64	64	64
Estimation method	OLS	Tobit	Tobit	OLS	OLS	OLS	OLS
R^2 / Pseudo R^2	0.189	0.0520	0.1996	0.722	0.781	0.709	0.814

Note: Robust standard errors in parentheses. Tobit estimation with right-censoring variable.

***, ** and * denotes results significant at the 1, 5 and 10% level, respectively.

[a]Average from 2013 to 2016; GDP per capita, in USD thousands.

[b]Average from 2010 to 2015.

[c]n 2015.

[d]Other controls include a constant, GDP growth (in % average over the period 2010–16); a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere (post 2006); total banking credit growth to the private non–financial sector (in % average over the period 2010–16); Mobile phones per 100 persons (in 2016); and a dummy that takes the value of 1 for advanced economies and 0 elsewhere.

[e]BigTech credit is zero in 49 countries. To allow the computation of the log of the ratio (not defined for zero), BigTech credit has been rescaled summing an arbitrary constant (the minimum value).

[f]Sum of total FinTech credit and total credit to the private non–financial sector. More information on the database is provided in Appendix.

[g]The dependent variable is total FinTech credit per capita in 2017. Total FinTech is defined as the sum of BigTech and other FinTech credit.

[h]Other FinTech credit is defined as credit activity facilitated by electronic platforms that are not operated by commercial banks or BigTech firms. Data come from the Cambridge Centre for Alternative Finance and research partners, and correspond to the category 'debt-based alternative finance'.

In a second step of the analysis, we ty to understand if the drivers of BigTech credit are different from those of FinTech credit more generally. To do so, we conduct an econometric analysis with cross-sectional regressions as in Claessens *et al.* (2018). The main difference is that, we consider total FinTech credit per capita, including BigTech credit, as our dependent variable. Moreover, we control explicitly for economies in which there is BigTech credit activity with the simple dummy variable BT, and can test whether the drivers have a different impact in economies with BigTech credit by interacting the drivers with this variable.

Thus, our regression takes the form:

$$\ln(FT_i) = \alpha + \beta_1 y_i + \beta_2 y_i^2 + \gamma LI_i + \delta RS_i + \mu BN_i + \vartheta BT_i + \sigma X_i + \varepsilon_i \qquad (2)$$

where FT_i is the volume of total FinTech credit per capita in economy i (including BigTech credit), while the right-hand side regressors are the same included in Equation (1).

Our results are presented in the fourth column of Table 3. As in Claessens *et al.* (2018), FinTech credit volume per capita is positively associated with GDP per capita, but again with a negative coefficient estimate on squared GDP per capita. There is again a positive correlation with the Lerner index. We also confirm the result in Claessens *et al.* (2018) for FinTech credit that more stringent banking regulation is associated with less FinTech credit activity. This could have several possible explanations. It could suggest that regulation on FinTech in general and BigTech, in particular, is more liberal in jurisdictions where banking regulation is more liberal. Conversely, it may be more difficult to launch new lending activities in countries with relatively strict prudential and bank licensing regimes. This provides some evidence against the argument that regulatory arbitrage boosts FinTech activity in general.

The quantitative effects of regulation are also economically relevant. The regulatory stringency variable is constructed as an index (normalized between 0 and 1) based on the World Bank's Bank Regulation and Supervision Survey. The index takes a value between 0 (least stringent) and 1 (most stringent) based on 18 questions about bank capital requirements, disclosure, the legal powers of supervisory agencies, etc. The average of the index is 0.74 and the standard deviation is 0.087. Therefore, a country with an index that is one standard deviation lower in the cross-section (looser regulation) has a ratio of total FinTech credit per capita that is 0.9 percentage points higher.

The coefficient of the BigTech dummy is significant, showing that (ceteris paribus) these economies have higher overall FinTech credit volumes than economies without a BigTech credit presence. This result is quite mechanical as BigTech credit is a part of FinTech credit. Yet when interacting the BigTech dummy with the various drivers discussed above (see the fifth column of Table 3), a few interesting insight emerge: banking market power (Lerner index) and regulatory stringency are actually more important as drivers in economies where BigTech firms offer credit. Figure 7 shows the correlations on BigTech and other FinTech credit per capita in case of a one-standard deviation

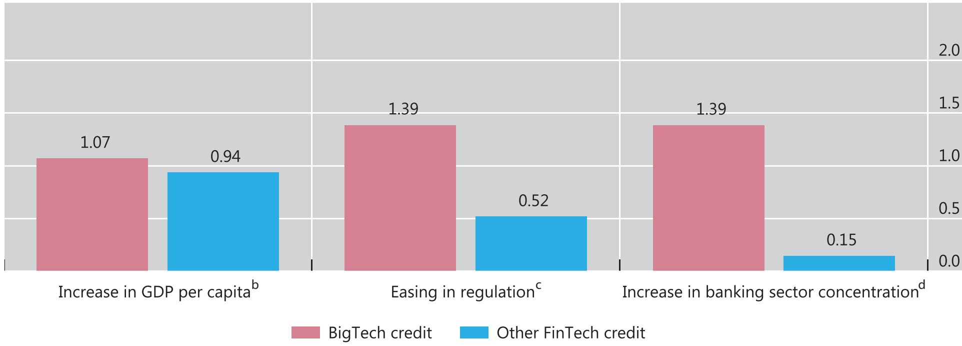

Figure 7. Drivers of BigTech and other FinTech credit volumes across jurisdictions[a].

Note: The bars visualize the estimated change in BigTech and other FinTech credit volumes from a change in the respective variables, based on the estimated coefficients displayed in the fifth column of Table 3.

[a]Change in BigTech credit and other FinTech credit per capita given a one-standard deviation change in the selected variables.

[b]Nominal GDP in USD over total population. Given the non-linearity of the relationship, the change is calculated at the average GDP per capita level.

[c]Regulatory stringency is constructed as an index based on the World Bank's Bank Regulation and Supervision Survey. The index takes a value between 0 (least stringent) and 1 (most stringent) based on 18 questions about bank capital requirements, the legal powers of supervisory agencies, etc.

[d]One-standard deviation increase in the banking Sector Lerner index (an indicator of bank markups and hence market power).

Source: Authors' calculations.

change in selected variables. Interestingly, BigTech credit sees more of a boost from easier financial regulation and increased banking sector concentration than FinTech credit.

The above results call for further investigation on the difference between BigTech credit and other forms of FinTech credit. Are these two forms of credit really that different? How do they influence each other? In the sixth column of Table 3, we run an additional regression using the logarithm of other FinTech credit per capita as the dependent variable but keeping the BigTech dummy as a regressor on the right-hand side. The coefficient on the BigTech dummy is in this case statistically not different from zero, indicating that the development of BigTech credit has no direct positive effect on other FinTech credit. This is consistent with the notion that BigTech firms offer a different financial service compared to FinTech firms. While BigTech firms offer credit to clients operating on their e-commerce or social media platforms, FinTech credit is supplied via an online (often P2P) platform that simply allows for matching between borrowers and lenders.

In the last column of Table 3, we replicate the results of the fifth column, using now the logarithm of other FinTech credit per capita as the dependent variable. The reason for this test is to evaluate whether the presence of BigTech firms impact on the elasticity of other FinTech credit to economic activity, regulation, competition and bank penetration. The results show that this is indeed the case. The interaction terms are qualitatively very similar to those reported in Column (V). These results confirm that both BigTech and FinTech credit react by more to banking market power (Lerner index) and regulatory stringency in jurisdictions in which BigTech credit is present. This is another indication that the correlation of these two forms of credit to economic and institutional factors is not so different, but they are simply stronger in those jurisdictions in which also BigTech credit is present.[17]

The results reported in this section offer first evidence on the drivers of BigTech credit and the main differences with respect to the factors that influence other FinTech credit volumes. However, in order to better understand more specific drivers, including the competitive and comparative advantages of BigTech, it is necessary to understand the lending model in more detail. In particular, we seek to understand how lending decisions based on machine learning and the processing of large quantities of information (big data) alter the lending relationship.

4. CREDIT ASSESSMENTS

To understand lending decisions better, we focus on one important aspect of lending, namely the credit screening of potential borrowers. We seek to assess whether BigTech lenders have an information advantage from data or processing methods in their credit assessment models. For this, we rely on available data from Mercado Libre, and its lending product Mercado Crédito.

Unlike banks, BigTech firms do not have a traditional branch distribution network to interact with borrowers and gain ‘soft’ information through, e.g. human loan officers. Instead, those that offer credit use proprietary data from online platforms. Notably, the loan origination process generally includes credit decisions based on predictive algorithms and machine learning.[18] Like FinTech credit platforms, BigTech firms may use alternative data sources including insights from e-commerce or social media activity (US Department of Treasury, 2016; Jagtiani and Lemieux, 2018*a*) and from users’ digital footprints (Berg *et al.*, 2018). They may also use machine learning methods to processes these data. This may allow them to lend to clients who are unserved by banks. Moreover, technology may allow additional contract enforcement methods.

Ant Financial, Mercado Libre and many peer-to-peer lending platforms state that their credit assessment involves a review of a large volume of customer data – often

17 As a final check, we have also regressed the ratio of BigTech credit over FinTech credit on the main economic and institutional factors. As BigTech credit is present in only 17 of the 64 countries of the sample, we have limited the number the regressors to GDP capitalization, the Lerner Index, the supervisory strength index and bank branches per adult population. The results (not reported for the sake of brevity) indicate that none of these variables correlate with the ratio, providing further support that the main economic and institutional determinants for FinTech and BigTech credit are similar.

18 For more on machine learning in finance, see FSB (2017*b*) and van Liebergen (2017). Machine learning algorithms often involve the use of big data.

more than 1,000 data points per borrower. This scoring approach could provide an advantage over traditional banks, where it is common practice to rely heavily on loan officer judgment alone to approve or reject a potential customer. The use of machine learning could have some advantages because the direct and fast assessment of credit risk improves the underwriting process, draws on information that is derived from relationships between customers, and could prevent, in some cases, human bias from entering the decision. The greater data resources could open up the possibility that BigTech lenders lend to borrowers who were previously shut out of the formal bank credit market.

Many SMEs in emerging market and developing economies do not meet the minimum requirements to complete a loan application, especially since they cannot provide audited financial statements to a bank and may lack other formal documentation. BigTech firms are able to overcome these limitations by exploiting the information provided by their core business, such as e-commerce, with no need for additional documentation from merchants. Data obtained directly from the platform include (1) transactions (sales volumes and average selling prices); (2) reputation (client reviews, claim ratio, handling time and complaints); and (3) industry-specific characteristics (sales seasonality, trend and macroeconomic sensitivity). This database can be also enriched by using additional data via social media and other channels. Because BigTech firms offer their clients a range of services, they may have data that banks would not have access to, and some enforcement methods that banks cannot access (see below).

Moreover, combining transactional data with machine learning techniques could help to expand the potential pool of borrowers who can receive credit. Such an expansion of the user base could facilitate financial inclusion in market niches where financing opportunities are scarce or where the loan application process is onerous for the borrower. Based on a unique dataset provided by Mercado Libre, we can calculate that if the credit decision process was based solely on local credit bureau information, 30% of the borrowers of Mercado Crédito in Argentina would be assessed as 'high risk' and therefore, excluded from bank loans.

Table 4 depicts a double-entry risk matrix with Mercado Libre's proprietary internal ratings and the local credit bureau ratings in Argentina. The table shows the loss rate, i.e. the volume of loans more than 30 days past due relative to the origination volume. In its use to date, the internal rating is better able to predict such losses. While both the internal rating and the credit bureau rating are continuous variables (between 0 and 1,000), they can be segmented into five different risk groups (A through E) versus three clusters identified by the credit bureau.

The different buckets are represented graphically in Figure 8. For a given bureau rating (i.e. low-risk), the expected loss rate is strictly monotonic with the internal rating (i.e. the patterns of the dots show that the internal rating orders expected loss). Conversely, given an internal rating (i.e. C, D or E), the loss rate is not strictly monotonic with the bank bureau risk. For example, the dot associated with internal rating D in the low-risk bureau category indicates a higher risk than the internal rating D in the medium-risk

Table 4. Loss rates by internal rating and credit bureau rating in Argentina

		Internal rating (%)					Total Bureau (%)	Portfolio Share (%)
		A	B	C	D	E		
Bureau rating	Low	0.0	0.3	0.9	3.3	8.4	0.7	25
	Medium	0.5	0.7	0.7	2.3	10.2	1.0	45
	High	2.2	3.3	3.3	3.3	4.0	2.8	30
Total internal rating		0.7	1.2	1.9	2.8	7.7	1.4	
Portfolio share		25	55	14	3	3		

Notes: Loss rates are defined as the volume of outstanding credit that is 30 days or more past due divided by origination amount. These are shown for different ranges of credit bureau and Mercado Libre internal ratings, over the period January to December 2017. The (continuous) internal ratings of Mercado Libre at origination are divided into five different risk groups (A through E), while the (continuous) scores of the credit bureau are divided into three corresponding to risk level (low, medium and high).
Source: Authors' calculations based on data from Mercado Libre.

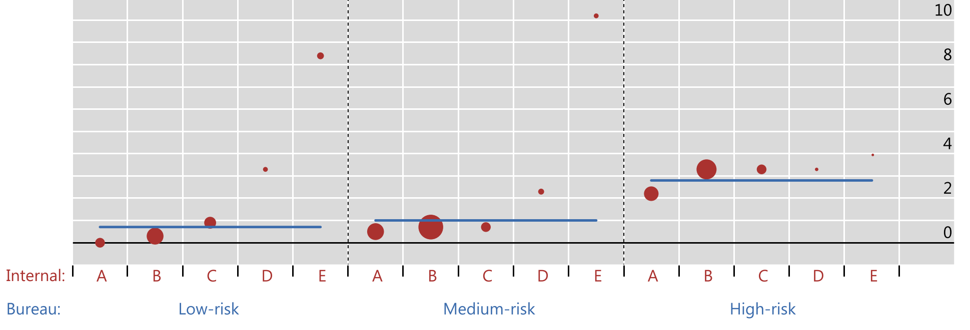

Figure 8. Loss rates by internal ratings of Mercado Libre versus credit bureau in Argentina.

Notes: The figure shows the loss rate, i.e. the volume of loans more than 30 days past due relative to the origination volume. In its use to date, the internal rating of Mercado Libre is better able to predict such losses. It segments the originations into five different risk groups (A through E) versus the three clusters identified by the credit bureau. For a given credit bureau rating (i.e. low), the expected loss rate is strictly monotonic with the internal rating (i.e. internal rating orders expected loss). Conversely, given an internal rating (i.e. C, D or E), the loss rate is not strictly monotonic with the credit bureau risk. The size of the dots is proportional to the share of the firms in the rating distribution.

Sources: Authors' calculations based on Mercado Libre data.

bureau category. Moreover, the internal rating has a broader range, covering losses from 0.0% to 10.2%; the bureau rating ranges from 0.7% to 2.8%. Most importantly, by using its proprietary scoring model, Mercado Libre is able to serve the profiles assessed as 'high risk' by the bureau. The size of the dots is proportional to the share of the firms in rating distribution. Similarly, the last column of Table 4 gives the portfolio share by bureau rating. As shown, 30% of the portfolio originated by Mercado Libre would fall into the 'high risk' cluster. Banks use a mix of credit bureau information and soft information from loan officers, but in general, would not lend to these borrowers in

Argentina.[19] With its more granular scoring model, Mercado Libre is able to offer credit and in turn, financially include these merchants. It is interesting to highlight that the loss rate for the 'high risk' segment is 2.8%, which is similar to the premium SME segment at traditional banks.

These simple statistics indicate that the internal rating system of Mercado Libre is more discriminating than a traditional credit bureau, and allows the firm to serve vendors that would be otherwise be excluded from the provision of credit. However, it remains to be verified if an internal rating system based on machine learning techniques and data obtained from the e-commerce platform can outperform (ex post) the more traditional models in predicting defaults over a full business and financial cycle.

In order to more formally test the differences between the credit bureau and Mercado Libre credit scoring, we estimate regressions for the rate of default based on three models: (1) a logistic regression with only the credit bureau score ($BS_{i,t}$) on firm i at time t as dependent variable; (2) a logistic regression with the credit bureau score and additional borrower characteristics ($X_{i,t}$); and (3) a machine learning model based only on the Mercado Libre internal rating ($r_{i,t}$).

In particular, we use the following models:

Model I: $$p(D_{i,t}) = \Phi(\alpha BS_{i,t} + \varepsilon_{i,t}) \tag{3}$$

Model II: $$p(D_{i,t}) = \Phi(\alpha BS_{i,t} + \beta X_{i,t} + \varepsilon_{i,t}) \tag{4}$$

Model III: $$p(D_{i,t}) = \Phi(\beta r_{i,t} + \varepsilon_{i,t}) \tag{5}$$

where $p(D_{i,t})$ indicates the probability for the borrower of a loan to default. Models I and II are estimated with logit models, which are preferable for a large sample size, while Model III is estimated using a machine learning technique. The borrower characteristics $X_{i,t}$ include the sales trend in the last 6 months, sales in the last 15 days, client reviews and monthly instalments/commitments over sales (a proxy for the debt to income ratio). $\varepsilon_{i,t}$ is an error term.

Table 5 summarizes the main results. In particular, the bottom of the table reports the area under the receiver operating characteristics (ROC) curve (AUROC) for every model. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. This is represented graphically in Figure 9. The TPR is also known as the hit rate or sensitivity. The FPR is also known as

19 Anecdotally, many Argentine banks use a cut-off and do not lend to borrowers with credit scores below 400.

Table 5. Default rate regressions

Explanatory variables	Dependent variable: default rate I Logistic Only Bureau score	II Logistic Bureau score and Borrowers' characteristics	III Machine Learning Only Mercado Libre credit score
Bureau score	−0.0022*** (30.92)	−0.0021*** (34.72)	
Mercado Libre credit score			0.4146*** (21.03)
Borrowers' characteristics[a]	N	Y	N
AUROC	0.640	0.680	0.764
Observations	7,300	7,300	7,300

Note: The table estimates the impact of the bureau score, borrowers' characteristics and Mercado Libre credit score on the loss rate (in percentage of origination volume) of a firm's loan.
aThese include sales trend in the last 6 months, sales in the last 15 days, client reviews, monthly sales versus instalments, city and time fixed effects. *T*-statistics are reported in the parentheses.
*** denotes statistical significance at 1% level.

the fall-out rate or probability of false alarms, and can be calculated as (1 − specificity). The AUROC ranges from 50% (purely random prediction) to 100% (perfect prediction). The predictive power of the model rises substantially for the model that uses a machine learning technique applied to the data from the e-commerce platform. The machine learning model (III) and the other two models (I and II) are statistically different from one another, as verified by the tests reported in Table 6. The mean AUROC for the machine learning model (III) is 0.764 and the standard deviation is 0.015. Assuming a normal distribution of the AUROC at a 95% confidence level, the confidence interval around the AUROC is (0.734; 0.793). This interval does not overlap with the 95% confidence interval of the AUROC of Model II, which is (0.662; 0.698).

The predictive power of the scoring system depends not only on the high granularity of the data for the vendor but also arises from exploiting the network structure between vendors and customers. For example, fraudulent applications could be detected by identifying isolated clusters of nodes that have limited connections with other businesses.[20]

These findings are broadly in line with Jagtiani and Lemieux (2018*a*), who compare loans made by a large FinTech lender and similar loans that were originated through traditional banking channels. Specifically, they use account-level data from LendingClub and Y-14M data reported by bank holding companies with total assets of $50 billion or more. They find a high correlation between interest rate spreads, LendingClub rating grades and loan performance. Interestingly, the correlations between the rating grades and FICO scores have declined from about 80% (for loans that were originated in 2007) to only about 35% for recent vintages (originated in 2014–15),

20 For the case of Ant Financial, see Chataing and Kushnir (2018).

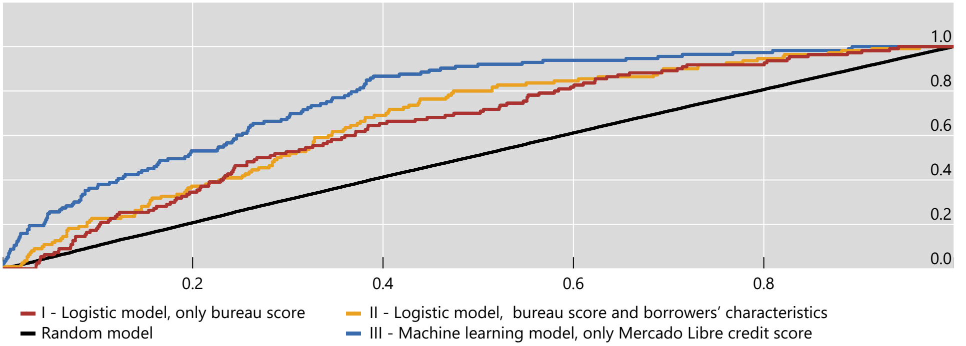

Figure 9. ROC curves for the different credit score models.

Notes: The figure shows TPRs versus FPRs for borrowers at different thresholds for three different models: (I) a logistic regression with only the credit bureau score on firm i at time t as dependent variable; (II) a logistic regression with the credit bureau score and additional borrower characteristic; and (III) a machine learning model based only on the Mercado Libre internal rating. A random model is included for comparison purposes. The ROC curve shows that the machine learning model has superior predictive power to both the credit bureau score only and the credit bureau score with borrower characteristics.

Sources: Mercado Libre; authors' calculations.

Table 6. A horse race between the three different models

	AUROC	Std. Err.	95% Confidence interval	
I. Logistic Only Bureau score	0.640	0.013	0.614	0.666
II. Logistic Bureau score and Borrowers' characteristics	0.680	0.009	0.662	0.698
III. Machine Learning Only Mercado Libre credit score	0.764	0.015	0.734	0.793

Note: The table reports detailed statistics on the AUROC for the three models described in Table 5. The confidence interval assumes a normal distribution of the AUROC at a 95% confidence level.

indicating that LendingClub has increasingly used non-traditional alternative data. Furthermore, they find that the rating grades (assigned based on alternative data) perform well in predicting loan performance over the 2 years after origination. The use of alternative data has allowed some borrowers who would have been classified as subprime by traditional criteria to be slotted into 'better' loan grades, which allowed them to get lower priced credit. In addition, for the same risk of default, consumers pay smaller spreads on loans from LendingClub than from credit card borrowing.

Hau *et al.* (2018) analyse credit scoring for the case of Ant Financial. Similarly to Mercado Libre, the key element of the credit evaluation process for Ant Financial combines historical default data on firm credit with sales and financial data mostly sourced from the e-commerce trading platforms. Potentially, the information can encompass not only the financial information of the borrower, but the relationships between the borrower and other participants of the e-commerce platform and the payment network.

The credit scoring model summarizes the credit evaluation in terms of a one-dimensional score ranging from 400 to 600.[21] Ant Financial evaluates credit eligibility on a monthly basis in an automated process. Vendors judged eligible for credit are automatically informed via the Taobao e-commerce web interface about the amount of their credit line. To use this credit, vendors fill out a single online contract form, which takes a few minutes. The credit is available immediately and the credit terms are similar to a credit card. The maturity of credit is usually 6–12 months, of which a minimum of 1/6 to 1/12 has to be repaid each month counting from the date the credit line is drawn on. If the credit score of the vendor drops below the credit score threshold of 480, the credit line is withdrawn.[22] Withdrawal of the credit line implies that no new credit is available, and the existing balance has to be repaid over the remaining maturity unless eligibility is granted again. According to MYbank financial statements, the default rate on Taobao credit is 1.2%, a percentage similar to what can be reported using data by Mercado Libre (see Table 4).

Low default rates can of course also relate to contractual enforcement advantages. One interesting characteristic of BigTech platforms is the strong relationship that the clients build with the platform, and the reliance on the platform not only for credit but other services. The threat of the BigTech firms excluding defaulting vendors from future use of their online trading platform can be quite powerful. In some cases, there are also technological possibilities to promote repayment. For instance, for Mercado Libre, there is a collection advantage as the payments of vendors go through a Mercado Pago account. As such, in the case of late payments, Mercado Libre is able to use those funds to repay the debt.[23] As a further example, one lender offering auto loans has noted it is able to remotely lock out drivers that do not repay. In this sense, BigTech players could benefit from better credit default sanctions and enforcement than traditional banks.

5. CONCLUSIONS

The entry of BigTech into financial services is proceeding rapidly. Having started with payments, BigTech companies in some jurisdictions have more recently expanded into lending, insurance and even money management products, either directly or with financial institution partners. Understanding the competitive and comparative advantages of

21 Parallel to the credit scoring model, Ant Financial also applies several additional criteria to exclude firms from credit approval. For example, if a firm has insufficient sales in three preceding months, it is not approved for credit even if the credit score is above 480. Most of the exclusion cases are a result of applying this criterion (Hau *et al.*, 2018).

22 This applies also in other situations such as selling of fake products or fraud.

23 This contrasts to traditional banks, where receivables are not necessarily processed by the lending institution (particularly for small vendors who collect cash payments). Furthermore, since the bank does not act as a marketplace, if the borrower does not meet the schedule payments, future income on a selling platform is not compromised.

BigTech in financial intermediation is a necessary first step for assessing the opportunities these technological developments may provide for enhancing financial intermediation, the role they may play for the real economy, and the challenges this may entail.

In this paper, we have considered the main drivers and the implications of the growth of the financial services offerings of BigTech, focusing in our empirical analysis on BigTech credit. We find that the drivers of BigTech credit are similar to those of FinTech credit (economic activity, financial regulation and competitiveness). We also show evidence that one BigTech lender has an information advantage in credit scoring relative to a traditional credit bureau.

While the preliminary evidence is encouraging and sheds some light on these developments, much remains to be done to address the larger economic questions. For example, what are the implications of BigTech for relationship lending? A bank acquires soft information from its clients by developing long-term relationships. By contrast, credit scoring with advanced analytics does not necessarily rely on long-term, one-to-one relationships, but exploits patterns of consumer preferences and behaviour using big data. Any judgement on the ability of these new credit scoring techniques to identify client characteristics and solve asymmetric information problems should be based on a complete cycle, evaluating the probability of these loans to go into default in stress situations. If borrowers can draw on both traditional banks and new lenders using alternative data, then the potential for strategic behaviour ('shopping around') could also be investigated.

Another set of questions relates to the relationship between financial technology firms and incumbents. To date, such relationships have been largely cooperative in nature, with banks relying on and benefiting from the provision of innovative technologies by third parties, including by acquiring such firms (FSB, 2019). Yet in other cases, BigTech appears to be a competitor to financial institutions or to offer similar services to largely unserved market segments. In yet other cases, BigTech is a third-party vendor to financial institutions, or both a third-party vendor and competitor. Will BigTech challenge banks in the future and, if so, in what roles?

Given large network effects and economies of scale and scope, BigTech could also lead to greater concentration. Examples of high concentration already exist in specific segments in some markets. With a greater reliance on third-party service providers, notably for data storage, transmission and analytics—markets that tend to be highly concentrated—operational failure or cyber events can more easily lead to systemic events. What risks could an operational incident at a BigTech firm that manages client data create for financial institutions?

The rapid growth of BigTech services in finance will undoubtedly bring changes that have both benefits and drawbacks, as well as possible risks to the financial system. BigTech firms may enhance competition and financial inclusion, particularly in emerging market and developing economies, and contribute to the overall efficiency of financial services. Conversely, such firms may further concentrate market power or even give rise to new systemic risks. Not least, it is important to understand how BigTech firms fit within current frameworks of financial regulation, and under which principles regulation should be organized. All these are relevant aspects for future research in this area.

APPENDIX: CONSTRUCTION OF BIGTECH CREDIT DATA SET

The data on BigTech credit volumes have been gathered from a range of public sources, including annual reports and other communications from respective firms. For instance, Ant Financial and WeBank have published cumulative lending volumes as of 31 December 2016 and 31 December 2017, from which total lending over 2017 can be calculated (Ant Financial, 2018 ; WeBank, 2018). Kakao Bank and KBank have communicated their overall lending over 2017 (Kakao, 2018; KT, 2018). Amazon communicated that it lent 'over $1 billion' in 2017 (Amazon, 2018). Amazon Lending is available in the United Kingdom and Japan, as well, but in the absence of any communication on these volumes, it has been assumed that lending volumes are proportional to revenues in these two countries in 2017. Mercado Libre has released data on its overall lending in 2017 (Mercado Libre, 2018), but not a breakdown by country; through contact with the firm, a rough breakdown was provided of the shares in Brazil, Argentina and Mexico.

In some cases, lending flows are not available, and as such the stock of outstanding lending has been used as a proxy. For instance, Grab noted in March 2018 that it had a loan book of $700 million in Southeast Asia, with a focus on Indonesia (Russell, 2018). This volume was distributed over Indonesia, Malaysia and Singapore in proportion to each country's GDP. Similarly, the total assets of Orange bank as of end-2017 are taken as a proxy for its lending in France over the year. For BigTech credit volumes in Kenya, Vodafone M-Pesa has provided a rough estimate based on the number of loans granted per month and the average loan size. All credit totals have been converted to US dollars at average market exchange rates over 2017. The data are available upon request.

Data on GDP per capita come from the IMF World Economic Outlook. Data on the Lerner Index of banking sector markups and bank branches relative to the adult population come from the World Bank Global Financial Development Database and World Development Indicators, respectively. The index of regulatory stringency is from the World Bank's Bank Regulation and Supervision Survey. Data on mobiles per adult come from the International Telecommunication Union.

Discussion

Alessandra Bonfiglioli

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The last decade has seen a worldwide boom in the provision of digital financial services using big data, which was labelled FinTech. While initially the firms engaging in these activities were mainly operating in the financial sector, more recently, other big players from different digital service sectors have joined the market: the BigTech firms. These companies expanded easily their activities into digital finance since, as part of their core business (e.g. e-commerce, messaging and search engines), they can count on a wide network of customers/providers and make use of artificial intelligence and big data.

BigTech firms are indeed big players, with the top 7 capitalizing more than the largest banks in the world. Given their global relevance, the present paper focuses on the diffusion of their financial activities and it addresses two main questions: (1) What drives cross-country differences in the diffusion of BigTech finance, especially credit? Are these factors the same for FinTech firms? (2) Are BigTech companies better lenders, and what makes them such?

To address the first question, the authors start by reporting a series of extremely interesting statistics on the geographical diffusion of BigTech finance and anecdotes on the business model and growth of some of the most notable players, especially in China, Korea and Latin America. This evidence, presented in Section 2, shows that BigTech firms tend to serve small customers, by providing them small loans alongside a wide range of other financial services, like payment instruments and insurance. While these companies are not banks, they often team up with financial institutions, which provide funds in exchange for other digital services.

Section 3 formally analyses the country-specific drivers of both BigTech and FinTech in general using data from a cross-section of 64 countries observed in 2017. In addition to the FinTech credit volumes from the Cambridge Centre for Alternative Finance, the authors use their newly hand-collected data on BigTech credit volumes for the 17 countries in which BigTech firms are known to operate. The results from OLS regressions of both series on a number of country-level characteristics show that both BigTech and FinTech credit are larger in richer – but not too rich – countries, which captures the importance of demand-side factors. Both series are also significantly correlated with supply-side conditions: BigTech and FinTech credit are larger where banks have more market power, the former is associated to scarcity of bank branches, while only FinTech credit is systematically larger in countries with less stringent banking sector's regulation. Moreover, FinTech is more strongly associated to all factors in countries where BigTech is also present.

Section 4 probes deeper in the sources of competitive edge of BigTech firms relative to the traditional credit institutions by focussing on the case of Mercado Libre and using confidential data on over 7,000 individual borrowers. The evidence suggests that BigTech firms are able to better predict loan defaults due to the more accurate credit ratings they can achieve using the wealth of data they can collect on borrowers. In so doing, they can also extend credit to those firms that are wrongly denied it based on credit bureau scores.

Overall, this paper addresses a timely and important topic and makes a number of novel contributions. First, it provides new data on BigTech credit; second, it highlights the importance of BigTech in the provision of credit to small borrowers who are less likely to borrow from traditional banks; third, it suggests BigTech credit to be less subject to default risk. These are important pieces of evidence both from an academic and a policy point of view, since they may have implications for welfare, growth and misallocations, financial stability and regulation. Yet, the analysis may be expanded to better understand (1) the role of countries' characteristics in shaping BigTech and FinTech credit, (2) why BigTech firms have better creditors and (3) whether BigTech firms provide their creditors better incentives in addition to credit.

Probing Deeper into the Determinants of BigTech and FinTech

Having only a cross-section of data, the present analysis cannot exploit variation in the evolution of digital financial services, which would allow us to gauge the reaction to changes in countries' income and conditions on the banking and financial sector, and to better account for omitted variables. Yet, with the data at hand, it would be possible to further explore the differences in the drivers of BigTech and FinTech by estimating tobit specifications like the ones in columns II and III of Table 3 for the ratio of BigTech to other FinTech credit.

Why Are BigTech Firms Better at Selecting Creditors?

Section 4 shows that firms' defaults on loans are better predicted by Mercado Libre's machine learning techniques applied to internal ratings than by the standard logit models using credit bureau scores and publicly available observations on firms' characteristics. However, to understand whether and to what extent the performance of BigTech could be matched by other technological companies, it would be important to know the relative importance of ratings and machine learning techniques. If the former are the main factor of success, then only BigTech companies, exploiting the wealth of their data on the history of network transactions, are able to assess credit risk so accurately. In this case, a concern may arise that BigTech may acquire market power in the market for small loans to consumers and SMEs, or increase it in the market for data generation and processing. A way of addressing this hypothesis could be to estimate a traditional logit for default probability using Mercado Libre's internal ratings and comparing its performance with the other three in the present paper.

Does BigTech Lending Provide More Than Funds?

Section 4 also shows that loans by BigTech firms are less subject to default than traditional credit for given types of borrower. This raises the question of whether this is entirely due to better selection and risk assessment or to the special relationship between BigTech firms and their borrowers. In particular, firms borrowing from Mercado Libre use the same platform to sell their products to final customers. This may generate a stronger incentive to repay, since default on credit would not only prevent the borrower from obtaining further credit in the future, but also, potentially, from continuing to sell on the e-commerce platform. Additionally, it may be the case that Mercado Libre itself increases the probability of debt repayment by helping borrowers to increase their sales through the platform. Investigating these mechanisms seems important to have a better understanding of the features that may distinguish BigTech from banks and FinTech companies. This would in turn provide interesting hints for policy, regulation and supervision.

Concluding Remarks

This paper provides an excellent discussion of the recent global trends in BigTech finance and very interesting insights on the country-specific factors behind its diffusion. It also gives an important initial contribution to the better understanding of some of the distinguishing features of BigTech credit. The results suggest that the diffusion of BigTech credit may bring opportunities in terms of better access to finance and better credit assessment and performance, but also threats to competition in financial markets, given the advantage that BigTech have in collecting and processing big data. Further analysis will be needed to better study these opportunities and risks.

Alexander Popov

European Central Bank

This paper is motivated by the increasing entry of technological firms into financial services in recent years. This has given rise to the term 'BigTech', which is understood as the provision of financial products by companies mainly specializing in digital services. These companies are some of the largest players in the digital sector: for example, each of the top six BigTech firms is bigger – in terms of market capitalization – than JP Morgan, the largest global financial institution. While initially BigTech firms populated the market for payments, in recent years they have also started extending credit to household and to a lesser extent to SMEs.

Against this background, this paper's goal is to map and analyse recent trends in the provision of financial services by BigTech firms in a global sample. The paper asks two main questions: What drives the adoption of BigTech services, and why are they very prevalent in some countries, but absent in others? And, what precisely is the advantage that BigTech firms have over more traditional financial market players, such as banks? To answer these questions, the authors analyse (both public and hand-collected) data on 64 economies, in 17 of which there is some measure of BigTech presence.

The main results of the paper are two-fold. First, the rise of financial intermediation by BigTech firms appears to be driven both by demand-side factors, such as economic development, and by supply-side factors, such as a low degree of competition in the banking sector. At the same time, the stringency of financial regulation does not appear to play a role. Second, by acquiring information on unbanked borrowers, BigTech firms appear to have information advantage in credit assessment over banks.

This is a timely and important paper that enhances our understanding of an important recent phenomenon that is increasingly a part of our lives. The documented trends have important policy implications with respect to, e.g. consumer welfare, financial stability, regulation and financial innovation. While the analysis is competently executed, some improvements are still possible in the direction of strengthening the causal analysis, thinking about the interaction between BigTech and public policy, and deepening the discussion of the welfare implications of the results.

Adoption of BigTech Financial Services

In Section 3, the authors perform a cross-sectional analysis of the association between a number of country-level factors and the provision of financial services by BigTech firms in 64 countries. Of course, a causal interpretation is unlikely in this set-up, something the authors are up-front about. An alternative would be to use an analytical framework which allows for the analysis of changes in the entry and/or extent of financial services by BigTech firms over time. This would allow for the inclusion of country fixed effects and would go a long way towards establishing causality. The authors could even think about an instrument for BigTech finance, such as the extent of country-specific regulation of such services.

Quality of Credit Assessment by BigTech Firms

In Section 4, the authors compare loan default probabilities based on different credit scoring, after accounting for borrower characteristics, in the case of Argentina. They find that the provision of credit by BigTech is associated with lower default probabilities, and that such firms are more likely to approach customers that do not have access to bank credit. The question still remains, however, what exactly is the advantage of BigTech over banks. Is it based on superior information, i.e. BigTech firms know more about the true default probability of the customer than banks do? Or is it based on collateral, i.e. BigTech firms are willing to serve customers that do not have the type of collateral that banks require? Which of the two is the right answer, has important implications for both the welfare benefit from and the regulation of financial intermediation by tech firms.

Impact of BigTech on Firm Performance

An important missing leg of the analysis is, how do firms compare – e.g. in terms of sales growth or investment – based on whether they get credit from banks or from BigTech firms? For instance, if a firm is equally likely to get credit from a bank and from a BigTech company, does it matter who ends up providing the credit? While it is possible that tech companies are better at screening customers, based on superior information, it would be interesting to know if they are also better at monitoring them, and even at adding value to their project. While there are both data and econometric issues associated with this approach, the benefits of getting closer to answering these questions are potentially large.

Discussion of Implications

While BigTech firms' focus has so far largely been on payment services, they are increasingly entering the market for credit provision. Plausibly, deposit collection by such firms will also grow. This raises non-trivial questions about the competition effect that BigTech firms will have on banks – and hence, about financial stability – and about the right approach to regulating BigTech. The authors could also extend their discussion on the difference between emerging markets and industrial economies. While BigTech firms have been acquiring ever larger shares in markets such as China and Brazil, their presence has been relatively muted in Europe. Should we expect this to change in the future, especially in more underbanked parts of the continent? And do policymakers in Europe face unique challenges in regulating the provision of financial services by BigTech firms?

Panel discussion

Beata Javorcik began the discussion by recommending that the authors focus more on specifying the question before establishing causality in the third exercise. She proposed several alternatives: that BigTech firms are better at screening for firm growth prospects; that credit in general stimulates growth; or that BigTech credit is better for future firm performance than ordinary credit. She recommended that the authors decide first on this before thinking about the appropriate counterfactual. She suggested that the speed of response may be one reason that BigTech credit is different, with small firms being better able to take advantage of short-term opportunities.

Nicolas Reigl asked why we do not see BigTech more in Estonia, suggesting that this could be linked to the size of the available data that firms can analyse which is limited in Estonia given its small population.

Guido Ascari noted that the authors spoke about the informational advantage coming from BigTech firms using artificial intelligence but pointed out that they cannot control for 'soft' information used by banks. He added that relationship lending by normal banks may be important, then asking whether BigTech algorithms can do better than the information coming from long-term relationships with banks.

Giacomo Calzolari noted that, from a micro perspective, BigTech is not just about data but also its platforms, suggesting that they source the money to provide credit from activities on other sides of the market. He inquired whether Amazon activity in a particular country could be a determinant of their ability to provide credit.

David HÕmous asked if there is anything that can be learnt from the diffusion of payment systems through BigTech and FinTech companies.

Thorsten Beck commented on the cross-country regressions which were run separately, suggesting that they could be combined using a tobit. He asked whether FinTech and BigTech are reliant on each other and proposed that this could be considered with a two-stage model, adding that BigTech firms could be catering more to less capital-intensive firms. He further noted that BigTech lending resembles transaction-based lenders rather than relationship-based lenders, asking whether they are catering to the same type of firms. He also raised the question of implications for the long run structure of the economy if BigTech firms crowd out the banking system.

Given the emergence of these BigTech companies in many developing countries where credit market imperfections seem to be particularly severe, Sebastian Axbard wondered what their role was in solving moral hazard issues as well as adverse selection, and whether the two sides can be disentangled.

Responding to comments, Leonardo Gambacorta explained that the phenomenon started very recently, reaching macroeconomically significant levels only in 2017, and therefore certain cross-country tests might need to wait a few years. He added that all observations started in similar years, so it is not possible to exploit different starting periods.

He clarified that the authors compare the performance of firms that used and did not use the credit line within the group that received the option of the credit line for the first time, seeing that the firms that used the credit performed better. He added that it is difficult to do a horse race with banks as BigTech is entering segments that are typically not served by banks, for example, serving small vendors, but noted that they could potentially serve other segments in the future.

He went on to discuss the fact that it is a challenge to work out how to regulate BigTech in the future to provide a level playing field, especially given that there are different regulations across countries. Regarding funding, he explained that although BigTech firms have a lot of cash it is not enough, and they would like to expand more. He went on to say that they have a comparative advantage in terms of low bond rates when going into the market for funding due to their good prospects. He further recognized that no relationship between the lender and borrower means no safety net where the bank wants to protect the borrowers in temporary challenging times for future business. Finally, Leonardo Gambacorta explained that the authors use a regression discontinuity design in another paper, getting good causal results but looking at a very small subset of firms, clarifying that this paper takes the opposite approach.

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