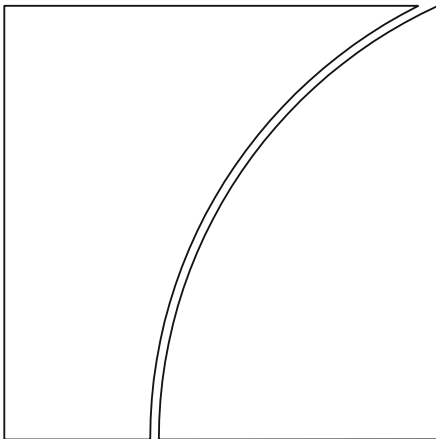BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers
No 779

BigTech and the changing structure of financial intermediation

by Jon Frost, Leonardo Gambacorta, Yi Huang, Hyun Song Shin and Pablo Zbinden

Monetary and Economic Department

April 2019

BIS Working Papers are written by members of the Monetary and Economic Department of the Bank for International Settlements, and from time to time by other economists, and are published by the Bank. The papers are on subjects of topical interest and are technical in character. The views expressed in them are those of their authors and not necessarily the views of the BIS.

This publication is available on the BIS website (www.bis.org).

BigTech and the changing structure of financial intermediation[*]

Jon Frost[♦], Leonardo Gambacorta[§], Yi Huang[†], Hyun Song Shin[§], and Pablo Zbinden[‡]

[♦]Financial Stability Board, [§]Bank for International Settlements, [†]Graduate Institute, Geneva, and [‡]Mercado Libre

Abstract

We consider the drivers and implications of the growth of "BigTech" in finance – ie 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 savings and investment 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 regulation. Analysing the case of Argentina, we find support for the hypothesis that BigTech lenders have an information advantage in credit assessment relative to a traditional credit bureau. For borrowers in both Argentina and China, we find that firms that accessed credit expanded their product offerings more than those that did not. 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.

Keywords: BigTech, FinTech, credit markets, data, technology, network effects, regulation.

JEL Codes: E51, G23, O31.

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) and Tencent, 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 savings and investment products, either directly or in cooperation with financial institution partners. In China, both Ant Financial and Tencent's (part) subsidiary WeBank 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.

BigTech firms present a distinctive business model due to the combination of two key features, namely: i) network effects (generated by e-commerce platforms, messaging applications, search engines, etc.)[2]; and ii) technology (eg 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, ie they are largely "non-rival"

---

[1] The term "TechFin" was popularised 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).

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

(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 four days of operation, and granted KRW 5.2 trillion (USD 4.5 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, 2017a). 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 U.S. 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 US 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.

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

---

[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.
[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.

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 other hand, 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 toward the less desirable end. Therefore the issues for public policy are multi-faceted when it comes to BigTech, and a full understanding of all economic effects are 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 organisation.

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:

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

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

iii) Are there differences in the performance of firms that receive BigTech credit?

To answer the first question on the determinants of BigTech, we first provide a bird's eye view of the industrial organisation of Big Tech 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 (eg technological advantage, lack of regulation, market power, or concentration among incumbent banks) and demand factors (eg 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.

---

[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).

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]

To answer our third question on the performance of borrowing firms, we focus on detailed micro data from Mercado Libre and Ant Financial for a comparison of borrowers and their performance after accessing BigTech credit. In particular, we assess how sales and the number of offered products have changed in the year following a loan. In contrast to the study by Hau et al. (2018), who focus on sales and transactions growth and use a regression discontinuity approach, we draw from the whole population of firms, and do not attempt to demonstrate causality. We find that firms in Argentina and China that used credit increased the number of online products offered in the following year. BigTech borrowers in Argentina also had higher sales. Additional robustness checks find that the results hold considering as control groups: i) firms that were eligible for the credit line but did not use it; ii) all firms that did not use the credit line (including those that were not eligible). These findings could result from the use of credit to fund growth, or from BigTech credit going to firms with higher growth prospects. For Ant Financial, we find similar results for a treatment sample those firms that had access to the credit line but did not necessarily use it.

Finally, section 6 concludes with some policy considerations and avenues for future research.

2. TRENDS AND POTENTIAL DRIVERS

BigTech companies are currently the largest companies in the world by market capitalisation, with the largest 6 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.

---

[9] Chataing and Kushnir (2018).

2.1. Trends in the growth of BigTech in finance

The financial services activities of BigTech have grown rapidly in some economies, particularly in payments, lending to small and medium enterprises (SMEs), and other 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 GDP (figure 2). 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 payments infrastructures. By contrast, Ant Financial's Alipay, Tencent's WeChat Pay, 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 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-subsidised 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 payments 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

---

[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.

Chorzempa (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 (eg customer-customer) and cross-side (eg 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, eg 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 (ie 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 transactions 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 micro loan 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).

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 $4.5 billion and $1.3 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, telecoms 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 3). 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 five years' time, Yu'ebao reached RMB 1.7 trillion ($266 billion) assets under 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 WeMin Insurance Agency). In the UK, 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 to 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 eg Khan, 2017).

---

[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.
[13] CBInsights (2018).

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 (eg Navaretti et al., 2017) or FinTech credit have grown more in some jurisdictions than others (eg Davis and Murphy, 2016; Rau, 2017; CGFS and FSB, 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 US by Tang (2018) and Jagtiani and Lemieux (2018b) with 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). 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 Jagtiani and Lemieux, 2018a; Fuster et al., 2018) 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, eg 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 an own bank. 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), securitises virtually all originated credit. Ant Financial's gross issuance of asset-backed securities (ABS) accounted for almost a third of all ABS exchanged with non-banks in China throughout 2017 (18% considering interbank transactions which is dominant in China's ABS market). BigTech firms also issue bonds at relatively lower cost than G-SIFIs (see Figure 4), even if their main source of funding remains equity (the average equity to asset ratio of the BigTech firms reported in Figure 4 is 50.2%).

- Lack of regulation: If existing financial regulations, eg 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 mark-ups 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.

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 characterised 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

---

[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 US was associated with *lower* interest rates in the following hours, as it provided a positive signal about future borrower solvency.

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, eg 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 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 15 economies from public data sources, with the help of contacts at several BigTech firms (see annex 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 eg 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 3 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 5, with the red shading, the share of BigTech credit in total FinTech credit is highest in Korea, Argentina and Brazil, each of which have 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 absolute terms, BigTech credit is still quite small as a share of total FinTech credit in the US and UK, and is only a moderate share of overall FinTech credit in Japan. The red dots in figure 5 show that total FinTech credit per capita is highest in China, the US and the UK.

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 15 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:

$$BT_i = \alpha + \beta_1 y_i + \beta_2 y_i^2 + \gamma LI_i + \delta RS_i + \mu BN_i + \sigma X_i + \varepsilon_i \qquad (1)$$

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 include 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 mark-ups 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 negative but not significant: more stringent regulation is not significantly linked to less BigTech credit activity (though this changes for other specifications – see below). The additional controls are generally 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.

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, where BigTech credit is scaled by total credit, regulatory stringency is significantly negative, while GDP per capita is not significant.

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 here, 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 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. Yet when interacting the BigTech dummy with the various drivers discussed above (see the fifth column of Table 3), an interesting insight emerges: banking market power (Lerner index) and regulatory stringency are actually more important as drivers in economies where BigTech firms offer credit. Figure 6 shows the correlations on BigTech and other FinTech credit per capita in case of a one-standard deviation 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 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 eg 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.[17] 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, 2018a) and from users' digital footprints (Berg et al., 2018). They may also use machine learning methods to processes these data.

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 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: i) transactions (sales volumes and average selling prices); ii) reputation (claim ratio, handling time and complaints); and iii) 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.

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

---

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

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 were based solely on local credit bureau information, 30% of the target audience for Mercado Credito in Argentina would be assessed as "high risk" and therefore, excluded from the credit program.

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, ie 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, they can be segmented into five different risk groups (A through E) versus three clusters identified by the bank bureau.

The different buckets are represented graphically in Figure 7. For a given bureau rating (ie low-risk), the expected loss rate is strictly monotonic with the internal rating (ie the patterns of the dots show that the internal rating orders expected loss). Conversely, given an internal rating (ie 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 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. Because banks use a mix of credit bureau information and soft information from loan officers, this segment may have much less access to traditional banking services. 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: i) a logistic regression with only the credit bureau score ($BS_{i,t}$) on firm i at time t as dependent variable; ii) a logistic regression with the credit bureau score and additional borrower characteristics ($X_{i,t}$); and iii) a machine learning model based only on the Mercado Libre internal rating ($r_{i,t}$).

In particular we use the following models:

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

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

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

where $p(D_{i,t})$ indicates the probability for the borrower of a loan to default. Model 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 summarises the main results. In particular, the bottom of the table reports the area under the receiver operating characteristics (ROC) curve 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 8. The TPR is also known as the hit rate or sensitivity. The false-positive rate is also known as the fall-out rate or probability of false alarms, and can be calculated as $(1 - \text{specificity})$. The area under the ROC curve (AUROC) ranges from 50% (purely random prediction) to 100% (perfect prediction). The predictive power of the model rises substantially for the model that use a machine learning technique applied to the data from the e-commerce platform.[18] 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.[19]

These findings are broadly in line with Jagtiani and Lemieux (2018a), 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 2014–2015), 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 two 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

---

[18] The cross-validation process for the optimal parameters to be used in the machine learning model indicated a good stability of the predictive power. The AUROC has a mean of 0.76, and in a cross-validation process, values range between 0.74 and 0.78.

[19] For the case of Ant Financial see Chataing and Kushnir (2018).

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.[20] 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 to 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.[21] 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). One interesting characteristic of BigTech platforms is the strong relationship that the vendor builds with the platform. While the low level of defaults depends on the higher predictive power of credit scoring techniques based on the use of machine learning techniques, low default rates could also result from the threat of the BigTech firms excluding defaulting vendors from future use of their online trading platform. For 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. CREDIT USE AND FIRMS' PERFORMANCE

If BigTech firms are able to use wider sources of information and employ more advanced credit scoring methods to better assess credit risk, a key question remains what this means for the nature of financial intermediation and the longer-term interests of customers. To shed some light on the larger welfare questions, our third research question relates to differences in the performance of firms that receive BigTech credit relative to other firms. In this section we use available information from two unique datasets to assess whether first-time access to and use of online credit is associated with higher firm performance.

In particular, we compare this across Mercado Libre in Argentina and Ant Financial in China – noting differences in data availability and sample. In contrast with Hau et al. (2018) who exploit a discontinuity in the score-based lending rule of Ant Financial (see also Hahn et al., 2001; Lee and Lemieux, 2010; Malenko and Shen, 2016), we analyse the relationship between the extension of a credit line and firm performance for the whole firm population. Moreover, while Hau et al. focus on credit market segmentation and effect of credit on vendor's sales and transactions

---

[20] 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).

[21] This applies also in other situations such as selling of fake products or fraud.

growth, we analyse the evolution of the volume of firms' online products.[22] For Mercado Libre, we provide novel analysis on credit provision and firms' performance (number and value of product sales). The comparison between Ant Financial and Mercado Libre provides the first international comparison that we are aware of between the micro lending of two BigTech firms. While we cannot compare the effects directly to other forms of external financing, such as bank loans, nor fully explore causality, we can give some insights on the magnitude relative to no such financing (relevant for underbanked or underserved firms).

5.1. Data

To perform these tests we use monthly statistics on vendors selling on the Mercado Libre platform in Argentina over January to December 2017, and Alibaba's trading platform Taobao in China during the period September 2014 to July 2016 with available information on online products. The data set and subsamples are summarised in Tables 6 and 7.

For Mercado Libre, the database has about 81,000 sellers, and we have data on the number of products offered and the value of products sold, as well as the credit bureau rating and Mercado Libre internal rating (see Table 6). For Ant Financial, the database includes more than 2.1 million firms on the Taobao platform undergoing a credit analysis. We have access to firm credit information and firm performance recorded at the end of each quarter for a total of more than 3.4 million observations (see Table 7). In both databases, we have access to information on the credit approval during the calendar month, as well as data on most owner and firm characteristics. Both tables are divided into different samples, namely: (I) for all firms; (II) firms that used the credit line for the first time; (III) firms that are eligible but did not use the credit line; (IV) firms that are not eligible to use the credit line. For Mercado Libre all numbers are converted to US dollars, and are rounded to the nearest $50 for confidentiality reasons. For Ant Financial all value numbers are expressed in Renminbi.

For Mercado Libre (Table 6), we see that credit lines are granted for 45% of all borrowers, but were used only in 5.4% of the firm-months.[23] Firms in sample II sold on average 79 different products at an average value of $5,000, while those that were eligible but did not use credit (sample III) had on average 49 products at a value of $3,050. Firms that were not eligible (sample IV) sold only 45 products on average, at a value of $2,900. The average credit line is of $13,000 and the average use is 80%.

The database for Ant Financial (Table 7) is constructed as a balanced panel between firms that are eligible for the credit line and those that are not. For this reason the credit approval (*Credit Approval* = 1) is exactly 50% of all firm-month observations.[24] From sample II+III we can see

---

[22] The results in this paper for Ant Financial are different to Hau et al. (2018) in several respects. In addition to the differences in the sample and the dependent variable, this paper uses regressions with industry and time fixed effects rather than a discontinuity-based approach. This simple estimation method allows for an international comparison. Finally, it includes an alternative specification with a different control group to show the robustness of the results.

[23] The overall annual adoption rate for Mercado Libre is 25%, which means that 1 out of 4 eligible merchants takes a loan in a 1-year window.

[24] It is worth noting that this working hypothesis broadly reflects the actual composition of the Ant Financial population where around 48% of firms are granted access to credit. Interestingly this share is not too different from what was observed from Mercado Libre where credit is granted to 45% of the firm population.

that the average credit line offered amounts to RMB 13,625 ($2,040), which is not very different with respect to firms that used the credit line (RMB 15,109 ($2,260)). This indicates that in the majority of the cases Ant Financial provides micro credit, with an average value of the credit line that is 1/6 of those offered by Mercado Libre. Indeed, the average loan in the last decile of the distribution is RMB 100,000 ($14,300) similar to the average offered by Mercado Libre. Taobao firms that are offered credit use the credit line in about 6% of the observations (sample II+III), a value very similar to those reported by Mercado Libre. The credit line is used for 83% of the available funds in the case of Ant Financial and 80% in the case of Mercado Libre (sample II).

5.2. Empirical framework

In this section we aim to test if firms that have access to credit for the first time develop by more. In particular, using data from Mercado Libre and Ant Financial we would like to verify if first-time use of online credit can boost firms' sales and product online offer. The econometric analysis is challenging because it is difficult to perfectly identify the causal effect of credit use on firms' performance. A firm that is eligible for credit and uses it (treatment group) could indeed have better investment opportunities a priori: a higher ex-post performance could be simply the reflection of a good ex-ante selection by the BigTech firms based on their credit scoring methodology. For this reason we will evaluate the robustness of the results by considering different control groups: i) all firms that did not use the credit line, including those that were eligible but did not use it (baseline for both Ant Financial and Mercado Libre); ii) only firms that were eligible but did not use it (for Mercado Libre). For Ant Financial, we also present an alternative test for "access to credit" (treatment group), considering as control group all firms that do not have access to credit.

In particular, we use the following baseline model:

$$Y_i = \alpha_{i,} + \alpha_{t,} + \beta_1 C_{i,t} + \gamma X_{i,t} + \varepsilon_i \qquad (6)$$

where Y_i refers to the number of products offered or value of products sold by firm i on the Mercado Libre platform, or the number of online products by firm i for borrowers from Ant Financial, $C_{i,t}$ is the credit use dummy, $X_{i,t}$ are borrower specific controls including the credit score in order to limit the "sorting effect"; $\alpha_{i,}$ and $\alpha_{t,}$ are industry and time fixed effects; and ε_i is an error term. Standard errors are clustered at the firm level.

5.3. Results

Table 8 shows the results for firms operating on the Mercado Libre platform. The left part of the table (columns 1 and 2) considers as dependent variable the annual growth rate of the number of offered products; the right part (columns 3 and 4) considers the annual growth rate of the value of a firm's sold products. The results are then cross-checked by considering different treatment and control groups. In particular, in columns 1 and 3, the treatment group includes those firms that have access to and used the credit line for the first time (Sample II in Table 6), while the control group includes those firms that have not used the credit line (Sample III and IV in Table

6). Given concerns around the sorting effect mentioned before, in columns 2 and 4 we replicate the results considering a different control group that includes only those firms that were eligible for the credit line but did not have not used it (Sample III in Table 6).

Overall, we find quite stable results. Firms that used credit saw the number of products offered rise by 71-73 percentage points more in the following year than borrowers that did not use credit, when considering different control groups. Moreover, these borrowers saw the value of products sold increase by 75-79 percentage points more. The results are also stable in different models with alternative combinations of time and industry effects (not reported for the sake of brevity).

Table 9 shows the results for Ant Financial. The dependent variable is the annual growth rate of a firm's online products, while the dummy refers to the firm's use to the credit line. Also in this case the results are verified considering different treatment and control groups. In particular, in columns 1 and 2, the treatment group includes those firms that used the credit line for the first time and used it (Sample II in Table 7), while the control group includes those firms that did not use the credit line (Sample III and IV in Table 7).

These findings could result from the use of credit to fund growth. However, we also find similar results considering as treatment sample those firms that had access to the credit line (but not necessarily used it). In columns 3 and 4 we replicate the results considering as treatment group all firms that received access to the credit line (Sample II and III) and as a control group only those firms that were not eligible (Sample IV in Table 7).

In particular, we find that firms that used the credit line increased their supply of online products by 13 to 15%, depending on the model used (columns 1 and 2 in Table 9). When we consider access to credit the effect is somewhat smaller at 8-9% (see columns 3 and 4 in Table 9).

It should be noted that, despite the large number of controls used, these results cannot be interpreted as a causal effect of credit on firms' performance, and we cannot completely rule out endogeneity issues. While it is possible that use of (access to) credit allowed firms to expand their product offering and sales, it is also possible that Mercado Libre and Ant Financial offered credit to those firms that they expected to grow, and that those firms that expected to grow drew on credit. The use of different controls group is only able to partially mitigate these problems. Disentangling causality is a promising avenue for further research.

6. 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 savings and investment products, either directly or with financial institution partners. Understanding the competitive and comparative advantages of 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. Finally, based on data for Mercado Libre in Argentina and Ant Financial in China, we show evidence that BigTech credit can support firms' sales and supply of online products.

While the preliminary evidence sheds some light on these devleopments, 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 which 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 organised. All these are relevant aspects for future research in this area.

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

In billions of US dollars

Technology companies

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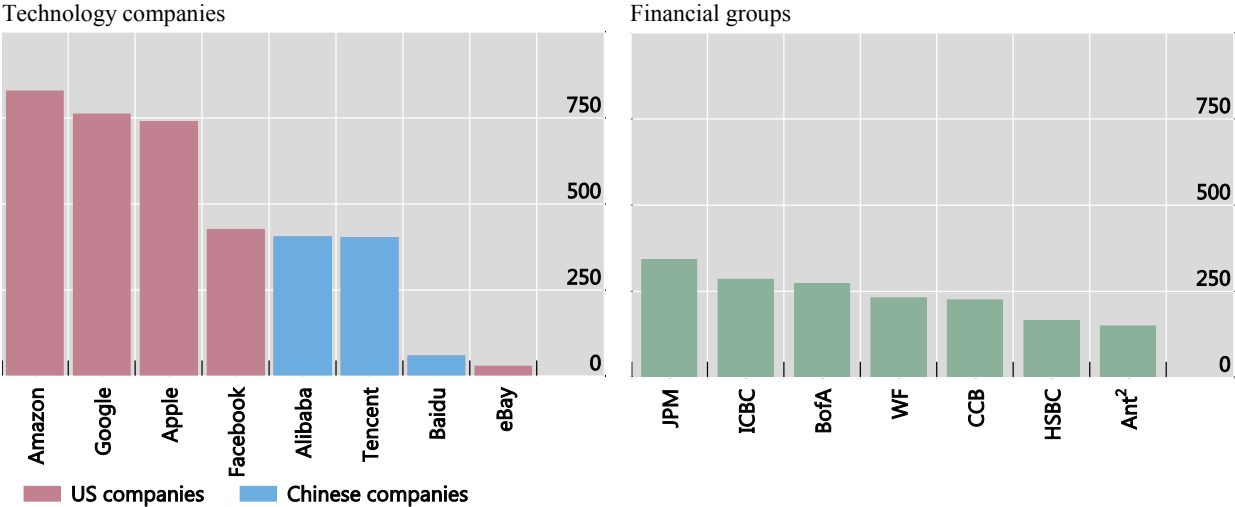
Ant = Ant Financial; BofA = Bank of America; CCB = China Construction Bank; ICBC = Industrial and Commercial Bank of China; JPM = JPMorgan Chase; WF = Wells Fargo.

[1] Stock market capitalisation, 18 January 2019.   [2] The estimated value of Ant Financial was derived from the amount raised in the company's recent funding rounds times the stakes sold.

Sources: Thomson Reuters Eikon; company reports.

Figure 2. BigTech mobile payment services around the world

Yearly volume/GDP, in per cent; 2017 data
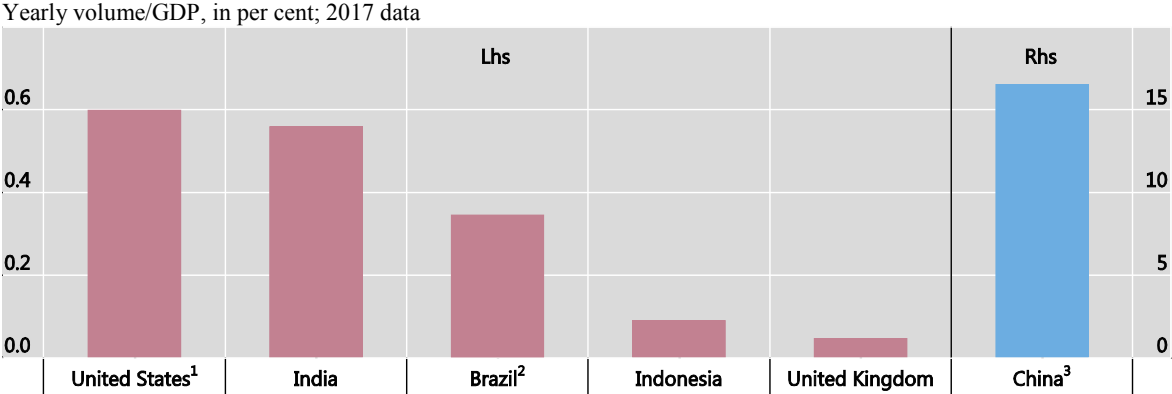
[1] 2016 data are used for US.   [2] Estimate based on public data for Mercado Libre.   [3] Only mobile payments for consumption.
The figure shows the annual volume of BigTech payment services in selected jurisdictions divided by GDP. China is displayed on a separate axis due to the large difference in scale to the other jurisdictions.

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

Figure 3. Global volume of new FinTech credit
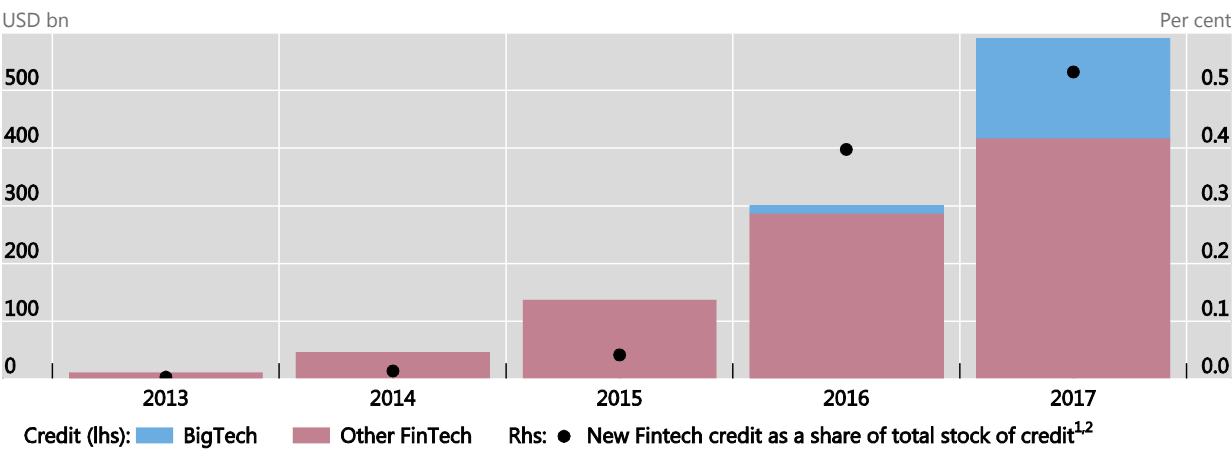
The bars indicate annual global lending flows by BigTech and other FinTech firms over 2013-2017. Figure includes estimates.

[1] 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.   [2] Calculated for countries for which data were available for 2013–2017.

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

Figure 4. Average spread of active bonds to US Treasury bonds at issuance
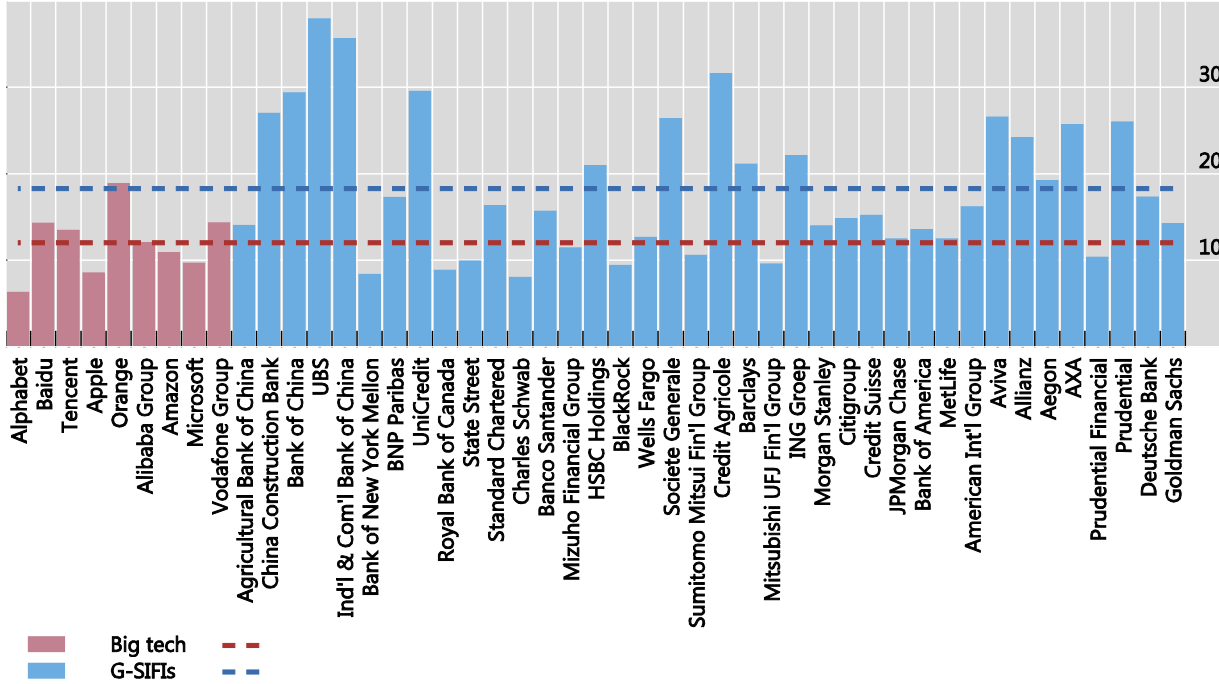
The bars represent the spread of each firm, and dashed horizontal lines indicate the simple average.

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 Jan 2019. Filters used: Corporates, Active Bonds, Issue Date >12/31/2013 and Issuer Name as listed in the graph above.

Sources: Bloomberg; authors' calculations.

Figure 5. FinTech and BigTech credit in selected countries

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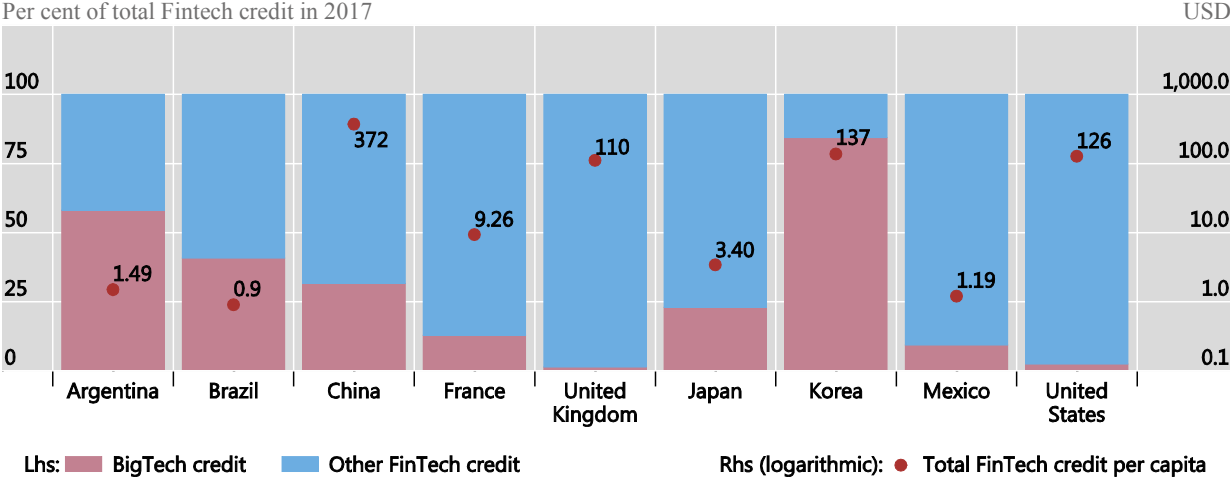
The bars show the share of BigTech and other FinTech credit in selected jurisdictions in 2017, while dots show the total FinTech credit (sum of BigTech and other FinTech credit) per capita.

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

Figure 6. Drivers of BigTech and other FinTech credit volumes across jurisdictions[1]
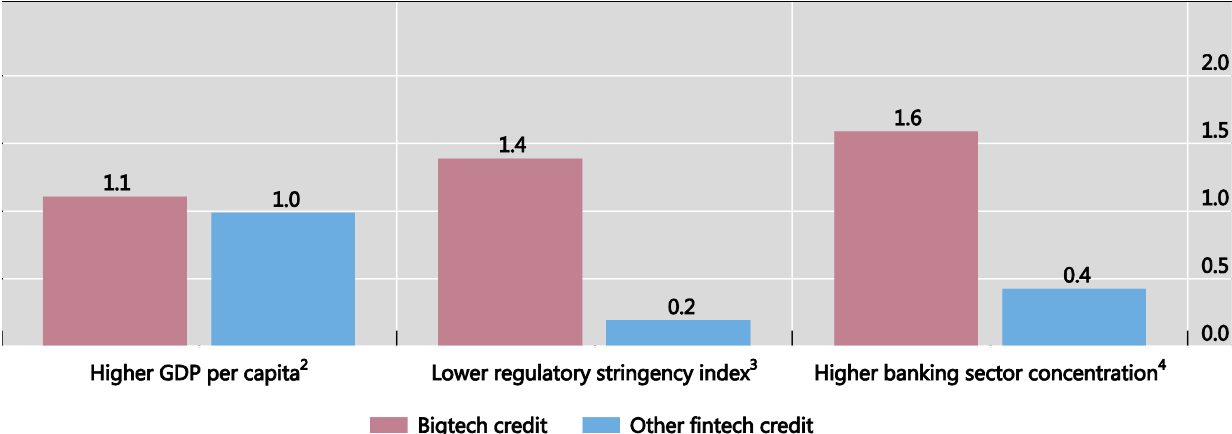

The bars visualise the estimated change in BigTech and other FinTech credit volumes from a change in the respective variables, based on the estimated coefficients displayed in the last column of Table 3.

[1] Change in BigTech credit and other FinTech credit per capita given a one-standard deviation change in the selected variables. [2] 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. [3] 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. [4] One-standard deviation increase in the banking Sector Lerner index (an indicator of bank mark-ups and hence market power).

Source: authors' calculations.

27

Figure 7. Loss rates by internal ratings of Mercado Libre vs. credit bureau in Argentina
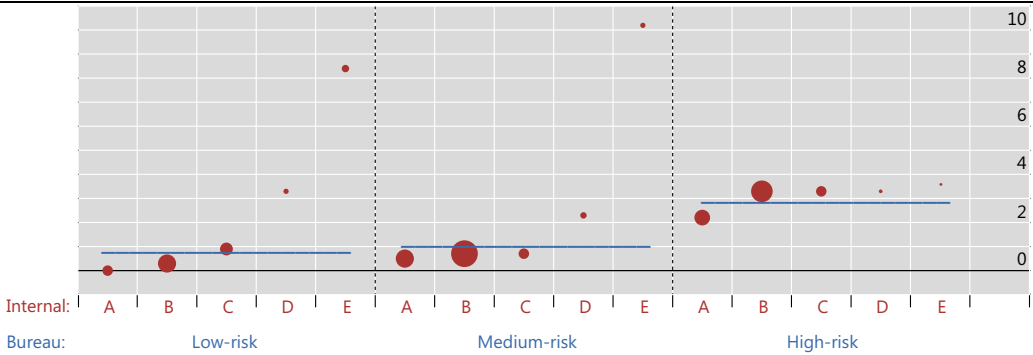
The figure shows the loss rate, ie the volume of loans more than 30 days past due relative to the origination volume. In its use to date, the internal rating of Mercado Libre is better able to predict such losses. It segments the originations into five different risk groups (A through E) versus the three clusters identified by the credit bureau. For a given credit bureau rating (ie low), the expected loss rate is strictly monotonic with the internal rating (ie internal rating orders expected loss). Conversely, given an internal rating (ie 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.

Figure 8. ROC curves for the different credit score models

- I - Logistic model, only bureau score
- II - Logistic model, bureau score and borrowers' characteristics
- Random model
- III - Machine learning model, only Mercado Libre credit score
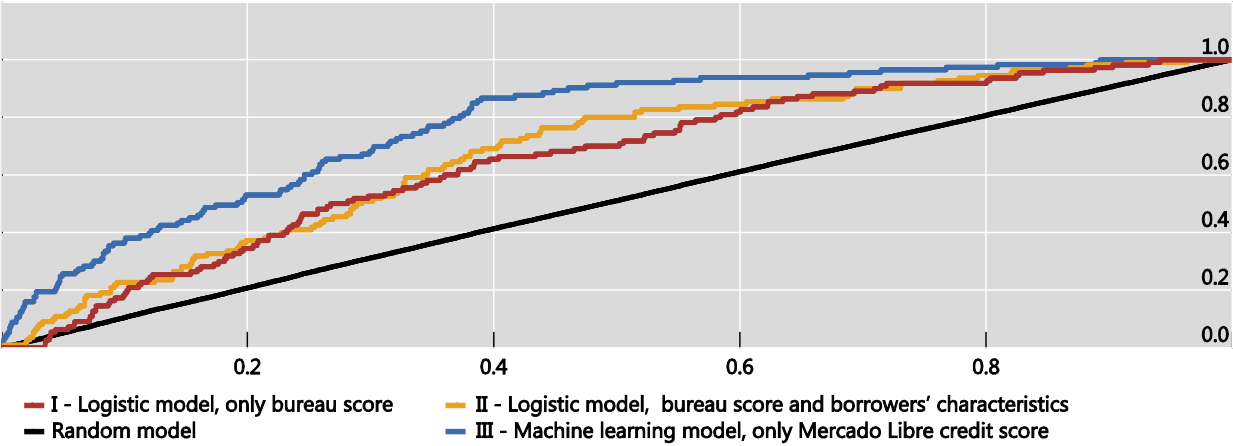
The figure shows true positive rates versus false positive rates for borrowers at different thresholds for three different models: (I) a logistic regression with only the credit bureau score on firm i at time t as dependent variable; (II) a logistic regression with the credit bureau score and additional 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 1. Percentage of FinTech users using other technology propositions

Column %	Sharing economy (eg, Airbnb, GoGet)	On demand services (eg, Uber, Menulog)	Online content streaming (eg, Netflix, YouTube)	Messaging and video chat (eg, Whatsapp, Snapchat, Skype)	Social media profile (eg, 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

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.

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)[1]	64	0.3124	2.4745	−4.4677	5.9197
Log of BigTech credit per capita (in USD)[1]	64	-5.7353	3.2314	-7.183	4.7657
Log of BigTech credit share of total credit[1,2]	64	-10.539	2.7633	-15.17	-3.508
GDP per capita (in USD)[3]	64	21.139	16.4602	0.7367	62.7902
Banking sector Lerner index (mark-up)[4]	64	0.2663	0.1309	−.02688	0.6209
Normalized regulation index[5]	64	0.7405	0.0869	0.5217	0.9565
GDP growth (in %)[3]	64	3.5959	2.0216	−0.1074	8.1037
Crisis dummy (post 2006)	64	0.2656	0.4452	0.0000	1.0000
Credit growth[6]	64	7.2312	7.0855	−7.9948	22.6478
Mobile phones per 100 persons[7]	64	114.1372	32.8330	32.1285	214.7349
Bank branches per adult population[8]	64	22.5640	23.36794	1.7106	145.9949
BigTech dummy	64	0.20313	0.4055	0.0000	1.0000

[1] 2017 data.   [2] Sum of total FinTech credit and total credit to the private non-financial sector.   [3] Average from 2013 to 2016.   [4] Average from 2010 to 2016.   [4] Average from 2010–15.   [5] In 2015.   [6] Total banking credit growth to the private non-financial sector (in % average over the period 2010–2016).   [7] 2016 data.   [8] Average from 2013 to 2015.

Sources: Laeven and Valencia (2012); 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.

Table 3. Drivers of BigTech and total FinTech credit volumes

	Dependent variable:				
Explanatory variables	BigTech dummy (0/1)	Ln(BigTech credit per capita)	Ln(BigTech credit per unit of total credit[6])	Ln(Total FinTech credit per capita)[5]	Ln(Total FinTech credit per capita)[5]
	(1)	(2)	(3)	(4)	(5)
GDP per capita[1]	0.0416***	0.3890***	0.0641	0.1893***	0.1443**
	(0.0132)	(0.1258)	(0.0738)	(0.0637)	(0.0608)
GDP per capita squared[1]	-0.0005***	-0.0051***	-0.0001	-0.0026***	-0.0020**
	(0.0002)	(0.0018)	(0.0010)	(0.0009)	(0.0008)
Lerner index[2]	0.9440**	9.9783***	7.5166***	3.9099*	1.2220
	(0.4263)	(2.9311)	(2.1127)	(2.1254)	(1.4734)
Normalised regulation index[3]	-0.1197	-5.9459	-5.3582*	-8.0262**	-4.8756
	(0.6025)	(5.5436)	(3.0774)	(3.0553)	(3.1879)
Bank branches per adult population[2]	-0.0045**	-0.0386**	-0.0325***	0.0001	0.0032
	(0.0020)	(0.0150)	(0.0081)	(0.0061)	(0.0061)
BigTech dummy (BT)				1.3533*	9.8183**
				(0.7029)	(4.1396)
Interactions with BigTech dummy					
BT*GDP per capita[1]					-0.1575
					(0.1637)
BT*GDP per capita squared[1]					0.0039
					(0.0026)
BT*Lerner index[2]					9.3670**
					(4.2551)
BT*Normalised regulation index[3]					-13.3597**
					(5.2568)
BT*Bank branches per adult population[2]					-0.0211
					(0.0802)
Other controls[4]	Yes	Yes	Yes	Yes	Yes
No. of observations	64	64	64	64	64
Estimation method	OLS	Logit	Logit	OLS	OLS
R^2 / Pseudo R^2	0.1848	0.0592	0.1911	0.7054	0.7769

Robust standard errors in parentheses; ***/**/* denotes results significant at the 1/5/10% level.

[1] Average from 2013–16; GDP per capita, in USD thousands.   [2] Average from 2010–15.   [3] In 2015.   [4] Other controls include: a constant, GDP growth (in % average over the period 2010–2016); 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 2010–2016); Mobile phones per 100 persons (in 2016); a dummy that takes the value of 1 for advanced economies and 0 elsewhere.   [5] The dependent variable is total FinTech credit per capita in 2017. Total FinTech is defined as the sum of FinTech and BigTech credit.   [6] Sum of total FinTech credit and total credit to the private non-financial sector. More information on the database are provided in the annex.

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%		

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.

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***	-0.0021***	
	(30.92)	(34.72)	
Mercado Libre Credit Score			Y
Borrowers' characteristics[1]	N	Y	N
AUROC	0.64	0.68	0.76
Observations	7,300	7,300	7,300

The table estimates the impact of the bureau score, borrowers' characteristics and Mercado Libre credit score on the loss rate (in % of origination volume) of a firm's loan. [1] They include sales trend in the last 6 months, sales in the last 15 days, client reviews, monthly sales vs instalments, city and time fixed effects. T-statistics are reported in the parentheses. *, ** and *** denotes for statistical significance at 10%, 5% and 1% respectively.

Table 6. Summary statistics for Mercado Libre borrowers

	I) All firms		II) Firms that used the credit line for the first time		III) Firms that are eligible but did not used the credit line		IV) Firms that are not eligible to use the credit line	
	Obs (1)	Mean (2)	Obs (3)	Mean (4)	Obs (5)	Mean (6)	Obs (7)	Mean (8)
Panel A: Firm credit information								
Credit Approval[1]	81,045	0.45	4,366	1	32,030	1	44,649	0
Credit Use[2]	81,045	0.054	4,366	1	32,030	0	44,649	0
Credit Line (volume USD)	4,366	13,000	4,366	13,000	n.a.	n.a.	n.a.	n.a.
Credit Use/ Credit Line	4,366	0.80	4,366	0.80	n.a.	n.a.	n.a.	n.a.
Credit Score	81,045	485	4,366	392	32,030	520	44,649	468
Panel B: Firm performance								
Number of products	81,045	48	36,396	79	4,366	49	44,649	45
Value of products (USD)	81,045	3,100	36,396	5,000	4,366	3,050	44,649	2,900

The table reports the number of available firm-month observations and the mean values. Data refer to the period January through December 2017 Sample I includes all firms on the Mercado Pago e-commerce platform that are included in the analysis. Sample II considers the subsample of firms that used a credit line for the first time in the period under analysis (*Credit line use* = 1). Sample III considers the subsample of firms that did not use the credit line in the period (*Credit line use* = 0). Sample IV considers the subsample of firms that are not eligible to use the credit line (*Credit approval* = 0). [1] Dummy that takes the value of 1 for those firms that had access to a credit line (ie firms to which Mercado Libre offered a credit line) and zero elsewhere. [2] Dummy that takes the value of 1 for those firms that used the credit line and zero elsewhere.
Source: Mercado Libre; authors' calculations.

Table 7. Summary Statistics for Ant Financial data

	I. All firms		II. Firms that use the credit line for the first time		III. Firms that are eligible but do not use the credit line (Sample III)		II+III. Firms that are eligible for the credit line for the first time		IV. Firms that are not eligible to use the credit line	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Firm credit information										
Credit Approval[1]	3,388,488	0.5	98,615	1.00	1,595,629	1.00	1,694,244	1.00	1,694,244	0.00
Credit Use[2]	3,388,488	0.03	98,615	1.00	1,595,629	0.00	1,694,244	0.06	1,694,244	0.00.
Credit Line (volume, RMB)	3,388,488	n.a.	98,615	15,109	1,595,629	13,533	1,694,244	13,625	n.a.	n.a.
Credit Use/ Credit Line	3,388,488	n.a.	98,615	0.83	1,595,629	0.0	1,694,244	0.05	n.a.	n.a.
Credit Score	3,388,488	515	98,615	513	1,595,629	520	1,694,244	519	1,694,244	512
Panel B: Firm performance										
Number of shop's online products	3,388,488	110	98,615	146	1,595,629	179	1,694,244	177	1,694,244	43

The table reports the number of available firm-month observations and the mean values. Data refer to the period September 2014 to July 2016. Sample I includes all firms on the Taobao e-commerce platform that are included in the analysis. Sample II considers the subsample of firms that used a credit line for the first time in the period under analysis (*Credit line use* = 1). Sample III considers the subsample of firms that are eligible but did not use the credit line in the period (*Credit Approval=1; Credit line use* = 0). Sample IV considers the subsample of firms that are not eligible to use the credit line (*Credit approval* = 0). [1] Dummy that takes the value of 1 for those firms that had access to a credit line (ie firms to which Ant Financial offered a credit line) and zero elsewhere. [2] Dummy that takes the value of 1 for those firms that used the credit line and zero elsewhere. Source: Ant Financial; authors' calculations.

Table 8. Use of credit and firm growth: Firm's products offered and value of sold products for Mercado Libre

	Dependent variable: Annual growth rate of the number of offered products		Dependent variable: Annual growth rate of the value of a firm's sold products	
	(1)	(2).	(3)	(4)
D[Credit Use]	0.726***	0.793***	0.706***	0.747***
	(19.22)	(21.55)	(19.63)	(19.76)
Controls[1]	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Adjusted R^2	0.259	0.265	0.216	0.204
Number of obs.	81,045	40,762	81,045	40,762
Treatment and control groups	The treatment group includes those firms that have access to and used the credit line for the first time (Sample II in Table 6), while the control group includes those firms that have not used the credit line (Sample III and IV in Table 6).	The treatment group includes those firms that have access to the credit line for the first time (Sample II in Table 6), while the control group includes those firms that were eligible for the credit line but did not use it (Sample III in Table 6)	The treatment group includes those firms that have access to an used the credit line for the first time (Sample II in Table 6), while the control group includes those firms that have not used the credit line (Sample III and IV in Table 6).	The treatment group includes those firms that have access to the credit line for the first time (Sample II in Table 6), while the control group includes those firms that were eligible for the credit line but did not use it (Sample III in Table 6)

The table reports the coefficient for the credit use variable in estimations of the annual growth rate of a firm's number of products (columns 1 to 2) and the firm's value of sold products (columns 3 to 4). [1] Controls include the credit score of the borrower, gender, and age. Columns differ in their use of product/industry and time fixed effects (FE). Standard errors are clustered at the firm level. All the dependent variables are winsorized at 1%. T-statistics are reported in the parentheses. *, ** and *** denotes for statistical significance at 10%, 5% and 1% respectively.

Table 9. Use of credit and firm growth: Number of firms' online products for Ant Financial

	Dependent variable: Annual growth rate of the number of offered online products			
	(1) Industry FE	(2) Industry and time FE	(3) Industry FE	(4) Industry and time FE
D[Credit Used]	0.1589***	0.1301***	0.0818***	0.0863***
	(44.03)	(36.03)	(47.80)	(49.58)
Controls[1]	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Time FE	N	Y	N	Y
Adjusted R^2	0.0211	0.0272	0.0256	0.0285
Number of observations	2,177,364	2,177,364	2,177,364	2,177,364
Treatment and control groups	The treatment group includes firms that have access to the credit line for the first time and used it (sample II in Table 7), while the "control" group includes firms that did not use the credit line (sample III and IV in Table 7).		The treatment group includes firms that have access to the credit line for the first time (samples II and III in Table 7), while the control group includes those firms that are not eligible for the credit line (sample IV in Table 7).	

The growth rate of a firm's online products is calculated on an annual basis after the firm had access to the credit line. [1] Controls include the credit score of the borrower and characteristics such as gender, education level, age, marriage status and property ownership. Columns differ in their use of product/industry and time fixed effects. Standard errors are clustered at the firm level. All the dependent variables are winsorized at 1%. T-statistics are reported in the parentheses. *, ** and *** denotes for statistical significance at 10%, 5% and 1% respectively.

REFERENCES

Amazon (2018): "Small Business Impact Report", 3 May.

Apple (2019): "Introducing Apple Card, a new kind of credit card created by Apple", 25 March.

Bain & Company and Research Now (2017): "Evolving the customer experience in banking", November.

Basel Committee on Banking Supervision (2018): "Sound practices: Implications of fintech developments for banks and bank supervisors", February.

Berg, T, V Burg, A Gombović and M Puri (2018): "On the rise of fintechs – credit scoring using digital footprints", NBER Working Papers, no 24551, April.

Bertsch, C, I Hull and X Zhang (2016): "Fed liftoff and subprime loan interest rates: evidence from the peer-to-peer lending market", Sveriges Riksbank.

Buchak, G, G Matvos, T Piskorski and A Seru (2017): "FinTech, regulatory arbitrage, and the rise of shadow banks", NBER Working Papers, no 23288, March.

Cambridge Centre for Alternative Finance (2017): "Sustaining momentum: the second European alternative finance report", September.

--- (2018): "The third Asia Pacific region alternative finance report", November.

Carstens, A (2018): "Big tech in finance and new challenges for public policy", speech to FT Banking Summit, 2 December.

CBInsights (2018): "Everything You Need To Know About What Amazon Is Doing In Financial Services", June.

Chataing, M and K Kushnir (2018): "How Is Ant Financial Closing the SME Finance Gap in China?", 7 June.

Chen, L (2016): "From Fintech to Finlife: the case of Fintech Development in China", *China Economic Journal*, 9, 3, 225–39.

Chorzempa M. (2018): "How China leapfrogged ahead of the United States in the FinTech rate?, PIIE, China Economic Watch.

Claessens, S, J Frost, G Turner, and F Zhu (2018): "Fintech credit markets around the world: size, drivers and policy issues", BIS Quarterly Review, September.

Committee on the Global Financial System and Financial Stability Board (2017): "FinTech credit: Market structure, business models and financial stability implications", June.

Davis, K, and J Murphy (2016): "Peer-to-peer lending: structures, risks and regulation", *The Finsia Journal of Applied Financ*e, 3, 37–44.

De Roure, C, L Pelizzon and P Tasca (2016): "How does P2P lending fit into the consumer credit market?" Deutsche Bundesbank Discussion Papers, no 30/2016.

Ding G, Chong G, Kuo Chuen D L and Cheng TL (2017): "From Ant Financial to Alibaba's Rural Taobao Strategy – How Fintech Is Transforming Social Inclusion", mimeo.

EY (2017): "EY fintech adoption index 2017: the rapid emergence of fintech".

Financial Stability Board (2017a): "Financial stability implications from FinTech: regulatory and supervisory issues that merit authorities' attention", June.

——— (2017b): "Artificial intelligence and machine learning in financial services: Market developments and financial stability implications", November.

——— (2019): "FinTech and market structure in financial services: market developments and potential financial stability implications", February.

Fuster, A, M Plosser, P Schnabel and J Vickery (2018): "The role of technology in mortgage lending", Federal Reserve Bank of New York Staff Report, no 836, February.

Glazer, E, L Hoffman and L Stevens (2018): "Next Up for Amazon: Checking Accounts", Wall Street Journal, 8 March.

Hahn, J, P Todd, and W Van der Klaauw (2001): "Identification and estimation of treatment effects with a regression-discontinuity design", *Econometrica*, 69, 201-209.

Hau, H, Y Huang, H Shan and Z Sheng (2018): "Fintech credit, financial inclusion and entrepreneurial growth", Working Papers.

Huang Y, C Lin, Z Sheng and L Wei (2018), "FinTech Credit and Service Quality", mimeo.

Jagtiani, J and C Lemieux (2018a): "The Roles of Alternative Data and Machine Learning in Fintech Lending: evidence from the Lending Club Consumer Platform", Federal Reserve Bank of Philadelphia Working Paper, no 18–15.

Jagtiani, J and C Lemieux (2018b): "Do fintech lenders penetrate areas that are underserved by traditional banks", Federal Reserve Bank of Philadelphia Working Paper, no 18–13.

Kakao (2018): "Operating Results Q1 2018", March.

Khan, L (2017): "Amazon's Antitrust Paradox", *Yale Law Journal* 126(3).

KT (2018): "Annual Report", March.

Lee, DS and T Lemieux (2010): "Regression discontinuity designs in economics", *Journal of Economic Literature* 48, 281-355.

Levitt, H (2018): "Personal Loans Surge to a Record High", Bloomberg, 3 July.

Luohan Academy Report (2019), "Digital Technology and Inclusive Growth", Shenzhen.

Malenko, N, and Y Shen (2016): "The role of proxy advisory firms: Evidence from a regression discontinuity design", *The Review of Financial Studies* 29: 3394-3427.

Mercado Libre (2018): "Q4 2018 Overview Presentation", December.

Metcalfe, B (2013): "Metcalfe's law after 40 years of Ethernet", *IEEE Computer*.Nalebuff, B (2003): "Bundling, tying, and portfolio effects", DTI Economics Paper.

Navaretti, G, G Calzolari, and A Pozzolo (2017): "FinTech and Banks: Friends or Foes?", *European Economy: Banks, Regulation, and the Real Sector*, December.

Philippon, T (2015): "Has the US finance industry become less efficient? On the theory and measurement of financial intermediation", *The American Economic Review,* 105 (4), 1408–38.

Rau, R (2017): "Law, trust, and the development of crowdfunding", University of Cambridge Woking Paper.

Russell, J (2018): "Grab, Uber's Southeast Asia rival, now offers micro-loans and other services", Tech Crunch, March.

Rysman, M (2009): "The Economics of Two-Sided Markets", *Journal of Economic Perspectives*, 23 (3), 125-43.

Shapiro, C and H Varian (1998): *Information Rules: A Strategic Guide to the Network Economy*, Harvard Business School Press.

Sharf, S (2018): "Quicken loans overtakes Wells Fargo as America's largest mortgage lender", Forbes, 5 February.

Tang, H (2018): "Peer-to-peer lenders versus banks: substitutes or complements?", *Review of Financial Studies*, forthcoming.

US Department of Treasury (2016): "Opportunities and challenges in online marketplace lending", May.

Van Liebergen, B (2017): "Machine learning: a revolution in risk management and compliance?", *The Capco Institute Journal of Financial Transformation*, 45, 60-67.

Xie, P, C Zou, and H Liu (2018): "The fundamentals of internet finance and its policy implications in China", *China Economic Journal*, 9(3), 240–252.

Zetzsche, D, R Buckley, D Arner, and J Barberis, (2017): "From FinTech to TechFin: The Regulatory Challenges of Data-Driven Finance", *New York University Journal of Law and Business*.

ANNEX: 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 (WeBank, 2018; Ant Financial, 2018). Kakao Bank has communicated its overall lending over the period July 2017-January 2018 (Kakao, 2018). Amazon communicated that it lent "over $1 billion" in 2017 (Amazon, 2018). Amazon Lending is available in the UK 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. The total assets as of March 2018of KBank (launched in 2017) are taken as a proxy for lending over 2017 (KT, 2018). 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 (WEO). Data on the Lerner Index of banking sector mark-ups and bank branches relative to the adult population come from the World Bank Global Financial Development Database (GFDD) and World Development Indicators (WDI), respectively. The index of regulatory stringency is from the World Bank's Bank Regulation and Supervision Survey. Data on mobiles per adult comes from the International Telecommunication Union (ITU).

Previous volumes in this series

All volumes are available on our website www.bis.org.