Fintech and big tech credit: a new database[1]

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Abstract

Fintech and big tech platforms have expanded lending around the world. We estimate that the flow of these new forms of credit reached USD 223 billion and USD 572 billion in 2019, respectively. China, the US and the UK are the largest markets for fintech credit. Big tech credit is growing fast in China, Japan, Korea, Southeast Asia and some countries in Africa and Latin America. Cross-country panel regressions show that such lending is more developed in countries with higher GDP per capita (at a declining rate); where banking sector mark-ups are higher and where banking regulation is less stringent. Fintech credit is larger where there are fewer bank branches per capita. We also find that fintech and big tech credit are higher where the ease of doing business is higher, investor protection disclosure and the efficiency of the judicial system are higher, the bank credit to deposit ratio is lower and where bond and equity markets are more developed. Overall, alternative credit seems to complement other forms of credit, not to substitute for them.

Keywords: fintech, big tech, credit, data, technology, digital innovation.

JEL classification: E51, G23, O31.

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1. Introduction

Credit markets around the world are undergoing a transformation. While banks, credit unions and other traditional lenders remain the chief source of finance for companies and households in most economies (with capital markets playing an important role in some cases), new intermediaries have recently emerged. In particular, digital lending models such as peer-to-peer (P2P) / marketplace lending and invoice trading have grown in many economies in the past decade. These types of credit, facilitated by online platforms rather than traditional banks or lending companies, are referred to as "debt-based alternative finance" (Wardrop et al., 2015) or "fintech credit" (Claessens et al., 2018). Moreover, in the past few years, many large companies whose primarily business is technology ("big techs") have entered credit markets, lending either directly or in partnership with financial institutions (BIS, 2019; Stulz, 2019).

While these digital markets and business models often use new sources of data for credit scoring, an irony is that data on their overall size are notably scarce. There are well-developed systems for official reporting of bank lending volumes (flow) and credit outstanding (stock). Recently, there have been efforts to improve the data on non-bank credit to the private sector (Dembiermont et al., 2013; FSB, 2020) and on fintech (Serena, 2019; IFC, 2020). Central banks and public sector authorities use such data to monitor economic and financial conditions, to guide monetary policy decisions and to set macroprudential policies, such as the countercyclical capital buffer.[2] Yet for fintech and big tech credit, authorities often rely on non-official sources. Some individual fintech credit platforms voluntarily publish detailed data on their loan portfolios, but these are generally not comparable across platforms and reporting is not standardised across jurisdictions. The most comparable data on fintech credit volumes come from the Cambridge Centre for Alternative Finance (CCAF), e.g. Rau (2020) and Ziegler et al. (2020). These data, based on surveys of platforms around the world, provide annual flows of new lending. Claessens et al. (2018) use CCAF, Brismo and WDZJ data. Data on big tech credit volumes are patchy. Frost et al. (2019) have assembled estimates of big tech credit for 2017, and sought to explain volumes in a cross-country setting. We are not aware of any other comparable cross-country data sources on big tech credit.

The lack of data on these new forms of credit is at odds with the macroeconomic relevance of credit markets. By allocating resources to allow for productive investment and consumption smoothing, credit contributes to economic growth and welfare (Levine, 2005). Yet when credit in an economy expands too rapidly (a credit boom), this can be a harbinger of a financial crisis and severe recession (see Drehmann et al., 2010; Schularick and Taylor, 2012; Kindleberger and Aliber, 2015). In order to detect credit booms in real time, authorities need adequate information on lending. As fintech and big tech credit become more economically relevant, it will become ever more important to have sound data on flow and stock of loans and other credit characteristics (interest rates, defaults, margins, etc.).

In this paper, we assemble and update available data on fintech and big tech credit volumes for a large number of countries around the world. The database is then used to answer the questions: how large are fintech and big tech credit markets, in absolute

[2] The countercyclical capital buffer sets bank capital requirements that are higher in periods of high credit growth, when financial vulnerabilities may build up, and can be released during a downturn. The buffer is set by authorities based on the credit-to-GDP gap (a measure of credit market conditions) and supervisory judgment. See Drehmann and Tsatsaronis (2014).

terms and relative to overall credit markets? What economic and institutional factors are driving their growth and adoption? How large and important could they become in the future?

There are key differences between the two types of credit. Fintech credit models were originally built around decentralised platforms where individual lenders choose borrowers or projects to lend to in a market framework. Platforms help to solve problems of asymmetric information both through their screening practices, and by providing investors with information on the risk of a loan and other borrower features. Over time, some platforms have moved to fund loans from institutional investors rather than only individuals, and many use increasingly sophisticated credit models (see e.g. Jagtiani and Lemieux, 2019). Yet the core business of fintech credit platforms remains financial services.

Big tech firms, by contrast, have a range of business lines, of which lending forms represent only one (often small) part, while their core business activity is typically of a non-financial nature. These firms have an existing base of users, which facilitates the process of on-boarding borrowers. They can use large-scale micro-level data on users, often obtained from non-financial activities, to mitigate asymmetric information problems. While these large volumes of information allow big tech firms to effectively measure loan quality and potentially reduce loan defaults, it is also plausible that these models could raise problems of price discrimination (Morse and Pence, 2020; Philippon, 2019), and concomitant issues for competition and data privacy (Carstens, 2018; BIS, 2019; Petralia et al., 2019; Boissay et al., 2020).[3] Policy makers will need to weigh the efficient loan supply potential in their economies against issues of discrimination, competition and privacy when deciding which types of credit to encourage.

For both fintech and big tech credit, understanding the size and growth of these markets is of fundamental importance for policy makers, who monitor markets and set monetary and macroprudential policies based on credit aggregates. Such data are also essential for research on credit and digital innovation. A key contribution of this paper is thus to assemble estimates on the size of these markets and make these available for policymakers and researchers as a public good.

Our main findings are as follows. First, we estimate that in 2019, fintech and big tech credit (together "total alternative credit") reached USD 795 bn globally. Big tech (USD 572 bn) has shown particularly rapid growth in Asia (China, Japan, Korea and Southeast Asia), and some countries in Africa and Latin America. Global fintech credit volumes (USD 223 bn) have actually declined in 2018-19 due to market and regulatory developments in China. Outside China, fintech credit is still growing. We also show that returns to investors in fintech credit have declined over time, and that big tech firms show much higher profit margins in their overall business. This, together with their large volumes of platform, may be one factor in big techs' overall growth.

To understand drivers of this growth, we run cross-country panel regressions of fintech and big tech credit for 79 countries over 2013-2018. We distinguish between supply and demand drivers, and hypothesise that fintech and big tech credit should be higher where it is more attractive for new intermediaries to offer credit, and where there is an un(der)met credit demand. We find that such alternative forms of credit are more developed in countries with higher GDP per capita (at a declining rate), where banking sector mark-ups are higher and where banking regulation is less stringent. Regulation

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[3] As a further illustration of the issues for competition, Kamepalli et al. (2020) show how high-priced acquisitions by incumbents (e.g. digital platforms) may actually deter the funding of new entrants.

and banking sector mark-ups are relatively more important for fintech credit. Fintech credit is also more developed where there are fewer bank branches per capita. We find that fintech and big tech credit are more developed where ease of doing business is higher, investor protection disclosure and the efficiency of the judicial system are higher, the bank credit to deposit ratio is lower, and where bond and equity markets are more developed. Based on our results, we look ahead at how large these markets may become in the future. Overall, alternative credit seems to complement other forms of credit, not to substitute for them. These alternative forms of credit contracts seem to help complete the market and are mostly demand-driven. We discuss how rapid credit growth may raise risks to financial stability. We argue that the Covid-19 pandemic may accelerate the growth of big tech credit in particular.

The rest of the paper is organised as follows. Section 2 discusses the construction of our database and explores trends in fintech and big tech credit markets. Section 3 illustrates an empirical analysis on the drivers of fintech and big tech credit volumes over time. Section 4 concludes with policy implications and avenues for future research. Several methodological notes on data construction are given in Annex A. Annex B reports the results of several robustness checks.

2. Database construction and credit market trends

This section discusses the data collection for our study, and analyses trends in fintech and big tech credit markets. In particular, it describes the sources used and necessary choices on data aggregation and estimation. It discusses the growth in global volumes and in credit across different regions and countries, including the economic importance of such markets relative to the stock of total credit. It then reviews the pricing of fintech and big tech credit, and the performance to date in terms of credit defaults and profit margins.

Data collection

The data on fintech credit come from the Global Alternative Finance Database (2013-2018) held at the Cambridge Centre for Alternative Finance (CCAF). Data are collected from an annual industry survey and web-scraping by CCAF and academic partners (Wardrop et al., 2015; Ziegler et al., 2018; Ziegler et al., 2020). Firms are asked in an online questionnaire to report annual alternative finance volumes, with 11 time-series required questions that serve to pinpoint exact transaction values, the number of stakeholders, etc. All loan-based business models are counted as fintech credit. This includes peer-to-peer (P2P) or marketplace lending to consumers, businesses or for property; balance sheet lending to consumers, businesses or for property; invoice trading, debt-based securities (debentures and bonds) and mini-bonds. Equity-based, donation-based and reward-based crowdfunding are not included in fintech credit. This excludes profit-sharing crowdfunding, community shares, pension-led funding and real estate crowdfunding, which are counted in the broader category of alternative finance.

CCAF survey responses for 2019 are currently being collected and are hence not yet available. As such, fintech credit volumes for 2019 have been estimated based on 2018 volumes and more recent data from Brismo, the People's Bank of China, Reserve Bank of India, Bank Indonesia and the Korea P2P Lending Association. Annex A gives further details.

The data on big tech credit have been collected from contacts at central banks and big tech firms, and from a variety of publicly available sources. The former were collected under agreements to keep company-specific figures confidential. Because most big tech firms do not report their lending flows by country and year, and many do not even file annual reports, we have had to rely on partial information and assumptions in some cases. These include the following:

- Where only end-year stocks of outstanding credit are available, we have estimated the credit flow as the difference between these stocks, plus those loans assumed to have matured over the year based on estimates of the average loan maturity (see Annex A for the methodology used). Available numbers for firms with both stock and flow data suggest that this is a very reasonable assumption. Additionally, we have cross-checked these aggregate estimates with central banks directly.
- Where a firm only reports its total lending over several countries, we have distributed this lending volume proportional to its revenue in those countries or, where this is not available, proportional to the GDP of these countries. Where data were available, we checked that the growth in revenues was aligned with the growth in the number of unique users. In several cases, we have cross-checked these estimates with the central bank or a regulator in the country in question.
- Where 2019 lending volumes were not yet available, we have assumed that growth is proportional to the number of overall users. Where this is not available, we have extrapolated 2019 volumes with the growth rate over 2017/2018. From those platforms with data for 2017, 2018 and 2019, we can confirm that this is a reasonable assumption.

Big tech firms in our sample have credit activities in 31 countries as of 2019 and include Airtel, Amazon, Alibaba / Ant Group, Apple, Au Jibun Bank, Baidu / Du Xiaoman, BKash Facebook, Fuse, Go-Jek, Google, Grab, JD.com, Jumia, Kakao Bank, K-bank, LINE, Mercado Libre, Microsoft, MTN, MTS bank, Mynt, Ola Cabs, Orange, Ovo, Ozon, Rakuten, Samsung, STC, Tencent / WeBank, Telenor, Tigo, Tokopedia, Toss, Uber, Vodacom / Vodafone (M-Pesa) and Yandex. Not all of these companies have lending activities.

Because of the patchy nature of disclosure by big tech firms, and the assumptions needed to estimate fintech and big tech credit volumes, there will necessarily be some measurement error. In particular, it is possible that some big tech firms or some of their activities are not captured in our sample. Moreover, in those cases where lending flows have been estimated, it may be that actual lending flows differ from estimates based on end-year stocks, and that the distribution of firms' activities across countries or their 2019 growth differs from our estimation. Overall, these factors may mean that our database tends to underestimate actual alternative credit volumes. Based on the uncertainty around the 2019 estimates and the unavailability of some of our independent variables, we conduct our regressions only for the period 2013-2018. We have higher confidence around the lending flow estimates than around the stocks, but we make both available as part of our database.

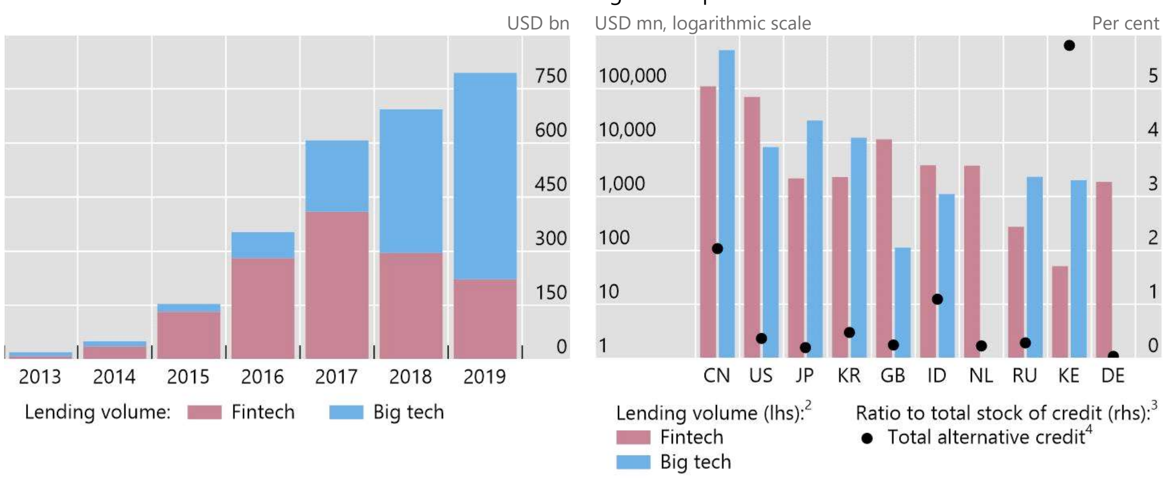
Growth in global volumes

Available data and estimates show that fintech credit volumes reached USD 297 billion (bn) in 2018, while big tech credit volumes surged to USD 397 bn.[4] This represents a dramatic increase since 2013, when volumes were only USD 9.9 bn and 10.6 bn, respectively. Combined lending by fintech credit platforms and big tech companies thus reached USD 694 bn in 2018. While still small overall, fintech and big tech lending flows are much larger relative to the stock of lending in certain economies, notably China and Kenya (see next sub-section). We estimate (subject to somewhat greater uncertainty) that the stock of fintech and big tech credit reached USD 303 bn at the end of 2018, or about 0.3% of the stock of overall credit to the private sector in markets around the world.

Global big tech credit is booming, overtaking fintech credit | Graph 1

Big tech credit is overtaking fintech credit[1]

These alternative forms of lending are becoming a significant portion of total credit in a few economies



Figures include estimates. CN = China, US = United States, JP = Japan, KR = Korea, GB = Great Britain, ID = Indonesia, NL = Netherlands, RU = Russia, KE = Kenya, DE = Germany.

[1] 2019 fintech lending volume figures are estimated on AU, CN, EU, GB, NZ and US. [2] Data for 2019. [3] Domestic credit provided by the financial sector. Data for 2018. [4] Total alternative credit is defined as the sum of fintech and big tech credit. Data for 2019.

Sources: IMF *World Economic Outlook*; World Bank; Brismo.com; Cambridge Centre for Alternative Finance and research partners; WDZJ.com; companies' reports; authors' calculations.

Based on the estimates for 2019, big tech credit volumes may have been as large as USD 572 bn in 2019. While definitive fintech credit volumes are not yet available, estimates based on higher-frequency sources yield a global volume of USD 223 bn. This means that big tech credit was at least twice as large as fintech credit in 2019 (Graph 1,

[4] Throughout the paper, fintech and big tech credit volumes refer to the flow of new lending over a calendar year. This differs from the standard methods for reporting bank credit, which are end-year stocks of loans outstanding. A quirk of the fintech and big tech lending market is that firms are more likely to report the accumulative loan flow over a year or since the inception of their business, rather than a current outstanding loan book. This also because contract maturities tend to be quite short. For more details, see Annex A.

left panel). There is substantial variation across countries, with the sum of fintech and big tech credit flows ("total alternative credit") equivalent to 5.8% of the stock of total credit in Kenya, 2.0% in China and 1.1% in Indonesia.[5] In other major markets like the United States, Japan, Korea and the UK, fintech and big tech lending flows are less than 1% of the stock of total credit.

Growth in volumes by geography

The largest market for both fintech credit and big tech credit is China. Big tech companies like Alibaba's Ant Group, Tencent's WeBank, Baidu's Du Xiaoman and e-commerce platform JD.com lent USD 363 bn in 2018 and 516 bn in 2019, according to data provided by the People's Bank of China. This covered a wide range of borrower types, from small businesses on Alibaba's Taobao platform (Ant Group) to smartphone-based consumer loans (WeBank) to rural student loans (Du Xiaoman). Ant Group and WeBank, in particular, were able to make use of the extensive payments data from their mobile payment services to price credit (see Frost et al., 2019). Fintech credit (P2P) platforms, which had been numerous and fast-growing in the period through 2017, actually contracted their lending in 2018 and 2019, as a series of defaults and platform failures took their toll on the sector. From a peak of 3,600 fintech credit platforms in November 2015, only 343 were still in operation in December 2019, with steady exits but no new platform entries since September 2018 (Graph 2, left panel). New lending was only at 17% of its peak (July 2017) level, while the stock of loans was at 46% of its (May 2018) peak (Graph 2, right panel). Of the lending that has still happened, loan tenors have steadily risen, reaching 15.7 months, at an average interest rate of 9.5%. It is expected that P2P lending in China will continue to decline over 2020. Because of the (previously) large size of the Chinese fintech credit market, this has a large impact on global fintech credit volumes. Based on our method for converting flows to stocks, the stock of fintech and big tech credit may have been as large as USD 173.1 bn at end-2019. Notably, due to the short tenors of many big tech loans relative to fintech (P2P) loans, the stock of fintech credit may still have been larger than the stock of big tech credit.

The US is the second largest market for fintech credit, but big tech credit volumes are relatively small – certainly compared to the economy's deep credit markets. Fintech credit reached USD 70.2 bn in the US in 2019 (up from USD 57.7 bn in 2018). This was made up primarily of P2P / marketplace consumer lending, with investment coming predominantly from institutional investors rather than individual lenders. It came in large part from platforms like Lending Club, SoFi, Prosper and OnDeck. These platforms often partner with financial institutions, originating loans that are sold on to banks and other institutional investors.[6] While the US is home to many of the largest big tech companies in the world, only Amazon engaged in any significant lending in 2018, to the tune of roughly USD 1 bn, according to public reporting.

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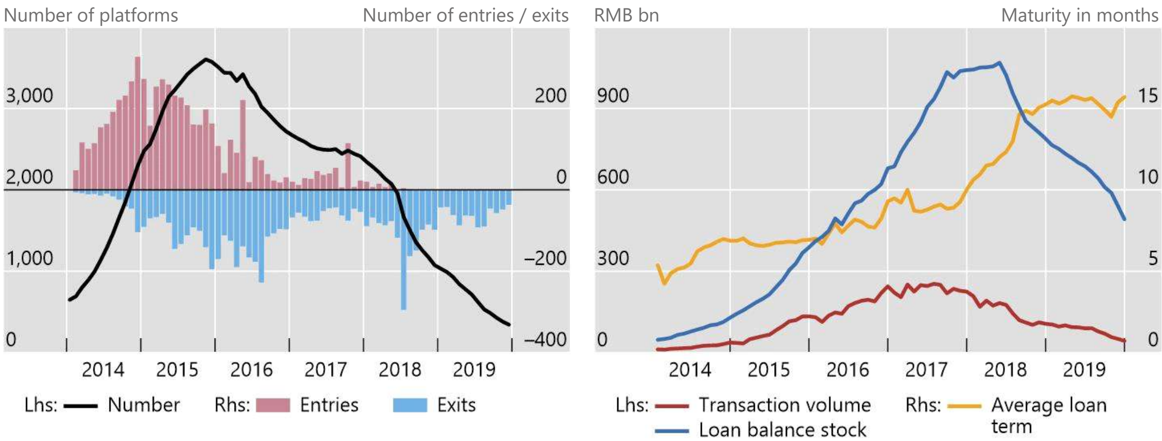
5 In Indonesia, big tech credit activities are performed in partnership with financial institutions. Big tech firms are prohibited by law from direct lending.

6 Another large group of lenders, not captured in our fintech credit data, are fintech mortgage lenders such as Quicken Loans, Amerisave, Cashcall, Guaranteed Rate, Homeward Residential and Move Mortgage, which often originate loans for the government-sponsored enterprises (GSEs) like Fannie Mae and Freddie Mac. See Buchak et al. (2018) and Fuster et al. (2018).

Fintech credit platforms continue to exit in China, as stock and flow of loans fall — Graph 2

Number of fintech credit platforms in China

Stock and flow of loans is falling as average tenors rise



Data based on all platforms covered by WDZJ.com for China.

Sources: WDZJ.com; authors' calculations.

As of 2019, Apple launched its Apple Card in cooperation with Goldman Sachs, which had outstanding balances of USD 7 bn by year-end.[7] Plans by Google to offer a checking account product, in conjunction with Citi, Stanford Federal Credit Union and several other banks, and a cooperation between Amazon and Goldman Sachs on small business lending may be relevant in the future, but were not yet in operation. Uber Money began to offer payment and wallet products to its drivers, but executives noted that lending was not yet on the roadmap (Shevlin, 2019). The stock of fintech and big tech credit together reached an estimated USD 54.1 bn at end-2019.

The second-largest market for big tech credit is Japan (USD 23.5 bn of lending in 2019). In Japan, Rakuten has offered a suite of financial products since 2013, including payments, transaction lending, credit card issuing and acquiring, mortgages and insurance. Meanwhile, social media company LINE offers consumer lending (through a joint venture with Mizuho Bank and a credit card company), telecommunication firm NTT DoCoMo provides customer credit scoring services (upon contractual agreement with banks and customers) and Amazon lends through its seller lending programme. The second-largest telecommunications provider, KDDI, has a joint venture with MUFG Bank called Au Jibun Bank.[8] Fintech credit (estimated at USD 2.2 bn in 2019) in Japan is primarily through P2P / marketplace business and property lending.[9]

In Korea, big tech credit (lending flow of USD 12.4 bn in 2019) is provided by two major virtual banks – KakaoBank and KBank, which launched in 2017 by messaging platform Kakao and telecommunication company KT, respectively. These firms offer loans with a relatively short maturity (roughly one year on average) to users of their respective networks. Information on their lending is provided publicly by the Financial

7 The stock of fintech and big tech credit together reached an estimated USD 54.1 bn at end-2019.

8 This bank is counted in our sample starting on 1 April 2019, when it became a consolidated subsidiary of KDDI. The announcement emphasized that the bank would be able to benefit from the big data and user network of KDDI – consistent with the characteristics of a number of other big tech lenders.

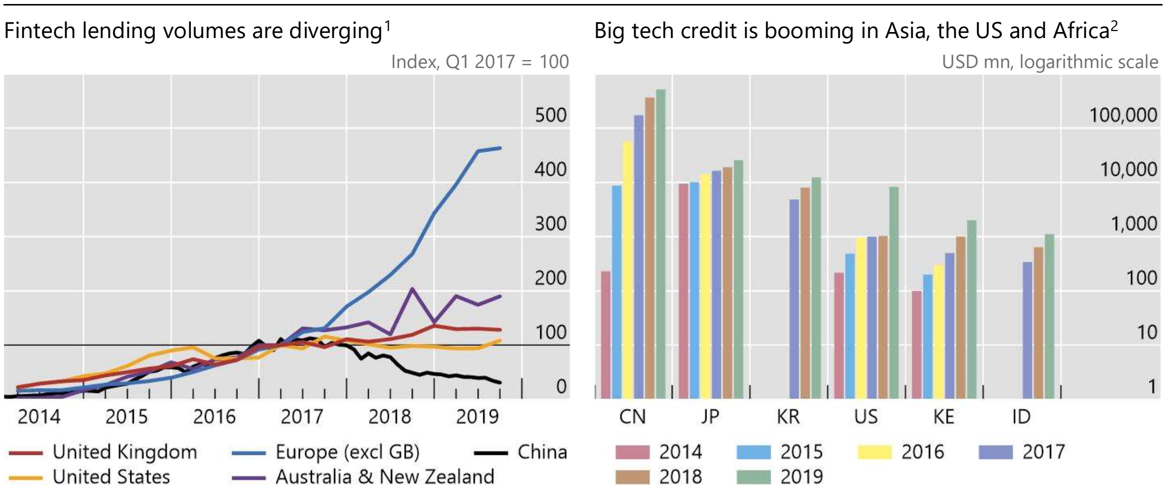
9 The stock of fintech and big tech credit is estimated to have reached USD 34.3 bn at the end of 2019.

Supervisory Service and Bank of Korea. Fintech credit volumes reached about USD 2.3 bn in 2019, and the market is dominated by P2P / marketplace property lending.[10]

The UK, meanwhile, had estimated fintech credit volumes of USD 11.5 bn in 2019 (up from USD 9.3 bn in 2018), made up of a vibrant mix of P2P / marketplace business, consumer and property lending, and smaller volumes of balance sheet lending and invoice trading. After rapid growth in 2013-2016, fintech lending volumes have been relatively steady in the UK in the past 3 years, perhaps reflecting greater maturity and saturation in the relevant market segments. For instance, Ziegler et al. (2020) estimate that fintech credit platforms accounted for up to 27.7% of equivalent bank credit to small and medium enterprises with annual turnover below GBP 2 million (mn) in 2018. This may have been encouraged by public policy; for instance, the government-owned British Business Bank invested over GBP 165 mn over 2014-18 for lending through Funding Circle, a UK credit platform, and announced a commitment for a further GBP 150 mn to support small business lending (British Business Bank, 2018). Big tech credit volumes are estimated to be much smaller, at an estimated USD 100 mn in 2017 and 2018, primarily through Amazon's Seller Lending programme.[11]

Looking beyond the largest fintech and big tech credit markets, higher-frequency data from Brismo and WDZJ show that fintech credit volumes have continued to grow rapidly in the European Union, Australia and New Zealand, even as they have plateaued in the US and UK and declined in China (Graph 3, left panel). In many emerging market and developing countries (not shown), fintech lenders are becoming economically relevant lenders for specific segments, such as small and medium-sized enterprises (SMEs) (Cornelli et al., 2019; World Bank, 2020). Some fulfil so-called "agency banking" functions, by which they function as agents to expand the reach of banks, especially in Latin America and parts of Asia and Africa.

Fintech credit is growing in Europe, big tech credit is booming in Asia — Graph 3



CN = China, JP = Japan, KR = Korea, US = United States, KE = Kenya, ID = Indonesia.

[1] Data are based on five platforms for Australia and New Zealand, all platforms covered by WDZJ.com for China, 49 platforms for Europe, 34 for the United Kingdom and five for the United States. Volumes are reported in local currency. [2] Figures include estimates.

Source: Brismo.com; WDZJ.com; companies' reports; authors' calculations.

[10] The stock of fintech and big tech credit is estimated at USD 15.2 bn as of end-2019.

[11] The stock of fintech and big tech credit may have reached USD 7.7 bn at end-2019.

Big tech credit is achieving economically relevant scale in China, Japan, Korea, parts of Southeast Asia, East Africa and (to a lesser extent) some countries in Latin America (Graph 3, right panel). This is driven by the lending activities of e-commerce platforms like Mercado Libre, ride-hailing companies like Grab and Go-Jek, and telecommunication and mobile money providers like M-Pesa. In many cases, these lenders initially target a specific group of users (e.g. sellers on the e-commerce platform, or drivers) but then expand such credit offerings to more users over time.

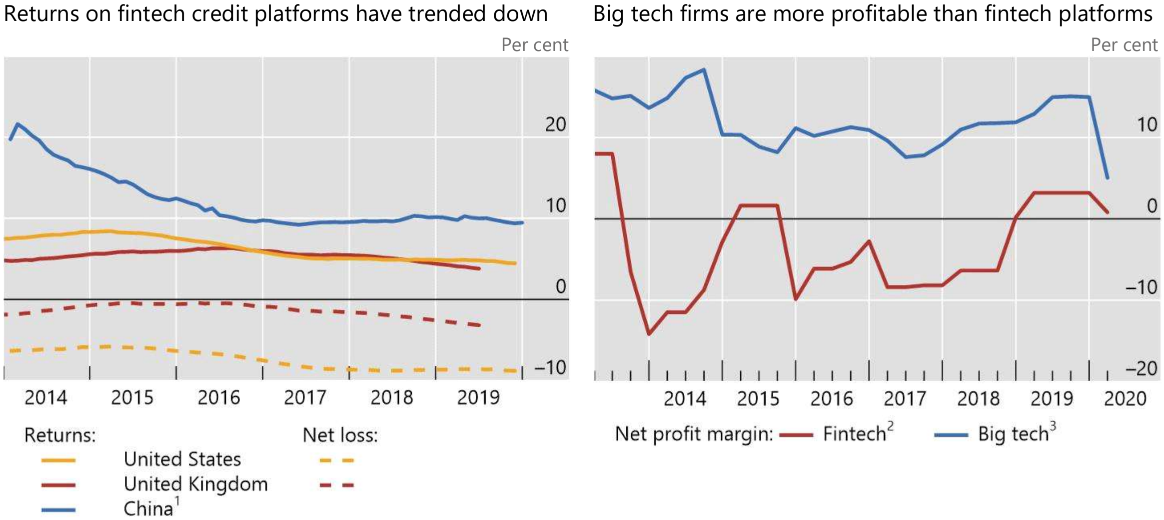
Interest rates, defaults and margins

Information on interest rates, defaults and profit margins is not available for all countries in the sample, but available data can give some useful insights.

The interest rates charged on fintech credit appear to be roughly in line with comparable bank loans. For borrowers, as of the latest readings by CCAF, typical interest rates charged on the major US fintech credit platforms range between 9 and 28%. In the UK, interest rates are between 6.5 and 24%. In China, interest rates have been more volatile in past years given the changes in the market and regulation (Gambacorta et al., 2019). Data on the interest rates charged by big tech companies are not available. Looking across the largest fintech credit markets, it is apparent that the returns paid to investors in fintech credit platforms have been relatively high in the past 5 years, but are trending downward globally (Graph 4, left panel). For big tech companies, the return on loans could also include the benefit obtained from supporting companies' core business lines (e-commerce, social media, advertising, etc.), user loyalty to the platform's overall services, and user data.

Big tech firms are highly profitable, while fintech platforms have often struggled — Graph 4

Returns on fintech credit platforms have trended down | Big tech firms are more profitable than fintech platforms



[1] Average interest rate. [2] Simple average of Black Knight Financial Services, Elevate, Enova International, Fellow Finance, Funding Circle, LendingClub, Lendingtree, Nelnet, OnDeck and Synchrony. [3] Simple average of Alibaba, Amazon, Apple, Baidu / Du Xiaoman, Facebook, Google, JD.com, Kakao, LINE, Microsoft, MTS bank, Orange, Rakuten, Samsung, Tencent, Uber, Vodacom, Vodafone and Yandex.

Source: Brismo.com; Refinitiv Eikon; WDZJ.com; authors' calculations.

Defaults at fintech credit platforms have picked up in the past few years. More granular default data show that certain loans segments like US consumer lending have seen a worsening of credit quality in the past 3 years; high-frequency data on the impact of the Covid-19 pandemic on credit quality are not yet available. At the same time, available empirical evidence suggests that some fintech and big tech lenders, through the use of alternative data and machine learning, have been able to achieve lower default rates than with traditional data and models, and even to achieve superior performance after a downturn in the credit cycle (Gambacorta et al., 2019). It is an open question how credit models will perform in the current downturn.

For fintech and big tech platforms to continue to grow, intermediation needs to be profitable for the providers (a separate consideration than the return provided to investors). In this light, the profit margins of big tech firms (that benefit, however, of a more diversified bundle of activities) are relatively high. Margins are particularly high when compared to those of fintech credit platforms, which have often struggled to achieve profitability (Graph 4, right panel) and have relied on new investor funding for expansion. For big tech firms, this often relates to the high profit margins in core businesses lines. In some cases, there are questions about whether big tech platforms wish to engage directly in lending at all, since it is less profitable than these other activities (FSB, 2019). This, as well as regulations, may be a factor behind the use of partnership models, where the big tech distributes financial products but a financial institution retains such lending on its balance sheet.

3. Drivers of credit volumes across economies: a panel analysis

In this section, we seek to explain fintech and big tech volumes in different economies over time. This is a novelty with respect to earlier studies (Claessens et al., 2018; Frost et al., 2019) that analyse such volumes in the cross section. Leveraging on the new database and following Rau (2020), we extend the analysis using a panel approach. We look at the drivers of fintech and big tech separately, and then take a deeper look at a range of specific country characteristics that are most salient in the cross-section dimension, for their sum (total alternative credit).

We hypothesise that fintech and big tech credit per capita can be broadly related to **demand-side** and **supply-side** drivers. On the demand side, we expect that more developed economies (with higher GDP per capita) will have a higher demand for credit from firms and households, but that this relationship may show a decreasing trend for very high levels of development (see Claessens et al., 2018; Frost et al., 2019; Bazarbash and Beaton, 2020). Similarly, we expect that fintech and big tech credit will be higher when incumbent banking services are more expensive (higher banking sector mark-ups), for instance because of less competition, and where there is a larger un(der)met demand for financial services, as proxied by lower bank branches per capita. On the supply side we expect that more stringent banking regulation (a proxy for the overall stance of financial regulation) will create barriers to the entry for fintech and big tech firms. A number of additional institutional characteristics, such as the ease of doing business, investor protection and disclosure, the judicial system and characteristics of the incumbent banking system will be discussed later. We will try also to answer the open question of whether fintech and big tech credit complement or substitute for bank credit and other forms of finance.[12]

Our baseline regression takes the form:

$$\ln(Credit_{it}) = \alpha + \beta_1 y_{i,t-1} + \beta_2 y_{i,t-1}^2 + \gamma LI_{i,t-1} + \delta RS_{i,t-1} + \mu BN_{i,t-1} + \sigma X_{i,t-1} + \vartheta D_k + \varepsilon_i \quad (1)$$

where $Credit_{it}$ is the volume of fintech or big tech credit per capita in economy i at time t, or total alternative credit. Thus, we consider three credit aggregates as left-hand side variables, each with the same regressors.[13]

The right hand side includes a number of regressors that are lagged by one year to mitigate endogeneity issues. $y_{i,t-1}$ is the GDP per capita in economy i at year t-1, and the variable $y_{i,t-1}^2$ is its quadratic term, to address the non-linear relationship between credit development and income levels. $LI_{i,t-1}$ is the Lerner index[14] of banking sector mark-ups in economy i, reflecting market power by incumbent banks; a higher value may reflect a less competitive banking sector. $RS_{i,t-1}$ is an index of regulatory stringency for the banking sector of economy i, as constructed by Barba Navaretti et al. (2017) from World Bank data.[15] $BN_{i,t}$ is the density of the bank branch network in country i compared to the adult population (which may capture both the reach of the banking sector and its relative cost base). $X_{i,t}$ is a vector of control variables that includes: growth in GDP and total credit; a real short-term interest rate; a dummy for whether a country had suffered a financial crisis since 2006, as defined by Laeven and Valencia (2018); mobile phone subscriptions (given the mobile-based nature of many platforms); and a dummy for advanced economies. Bank branches and mobile subscriptions are measured relative to the adult population.[16] D_k is a vector of geographical area fixed effects and $\varepsilon_{i,t}$ is an error term.[17]

Table 1 reports descriptive statistics for our sample of 79 countries over the period 2013-2018. Given the lower coverage of many variables for 2019, we have excluded this year from regressions. Data come from a variety of sources, including the IMF's World Economic Outlook and the World Bank's Global Financial Development Database (GFDD) and Findex.

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12 For Germany, De Roure et al. (2016) find that P2P lending substitutes the banking sector for high-risk consumer loans. De Roure et al. (2018) present a theoretical model and further evidence in favour of such "bottom fishing". For the United States, Tang (2019) finds that P2P lending is a substitute for bank lending in terms of serving infra-marginal bank borrowers, but that it complements bank lending with respect to small loans.

13 Frost et al. (2019) refer to the sum of fintech and big tech credit as "total fintech credit". Here, to prevent confusion, we refer to the sum of fintech and big tech credit as "total alternative credit". We also regress bank credit per capita using the same specification to check for significant differences.

14 The Lerner Index of banking sector mark-ups, has been updated over the period 2015-2017 using information the alternative cyclical measure devolped by Igan et al. (2020). See Annex A. A higher value indicates higher margins and profitability among traditional banks, and thus less competition.

15 The regulatory stringency variable is constructed as an index (normalised between 0 and 1) based on the World Bank's Bank Regulation and Supervision Survey. The index takes a value between 0 (least stringent) and 1 (most stringent) based on 22 questions (2011 survey) or 23 questions (2019 survey) about bank capital requirements, disclosure, the legal powers of supervisory agencies, etc.

16 When observation for bank branches, mobiles and credit growth were not yet available we extrapolated the figures using the cross-country average growth rate or the cross-country average change.

17 The inclusion of some (barely) time invariant country specific regressors (see next section) prevents us from using a complete set of country dummies.

Descriptive statistics

Table 1

Variable	Observations	Mean	Standard deviation	Min	Max
GDP per capita (in thousands of USD)	453	21.53	18.21	0.67	87.76
Lerner index[1]	453	0.30	0.15	-0.05	1.00
Bank branches per 100,000 adults	453	17.65	14.03	1.43	83.75
Normalised index of bank regulatory stringency[2]	453	0.72	0.10	0.38	0.96
Score-Starting a business (overall)	425	82.55	11.46	23.04	99.96
Score-Time (days)	425	81.96	17.33	0.00	100.00
Score-Paid-in Minimum capital (% of income per capita)	425	94.85	15.45	0.00	100.00
Score-Cost (% of income per capita)	425	84.92	26.95	0.00	100.00
Extent of disclosure index (0-10)	425	64.44	23.80	0.00	100.00
Trial and judgment (days)	425	407.85	203.51	90.00	1095.00
Enforcement of judgment (days)	425	177.98	110.59	26.00	597.00
Enforcement fees (% of claim)	425	5.37	5.23	0.00	23.30
Bank credit to bank deposits (%)	212	105.39	80.48	27.73	702.09
Bank regulatory capital to risk-weighted assets (%)	197	17.20	3.81	10.59	35.65
Provisions to non-performing loans (%)	187	64.29	37.26	0.00	232.06
Loans from non-resident banks to GDP (%)	194	27.53	28.33	1.24	158.53
Proportion of firms with a transactions account (%)	276	85.48	15.18	18	100
Corporate bond average maturity (years)	135	10.26	5.75	3.54	34.09
Corporate bond issuance volume to GDP (%)	137	2.14	1.81	0.05	13.83
Total factoring volume to GDP (%)	145	5.16	4.90	0.07	16.29
Global leasing volume to GDP (%)	78	1.32	0.95	0.01	4.81
Stock market total value traded to GDP (%)	167	50.64	89.08	0.00	562.92
Stock market turnover ratio (%)	161	53.61	67.37	0.84	556.91
Ln(Total alternative credit per capita (in USD)[3])	453	0.93	1.43	-1.97	5.11
Ln(Big tech credit per capita (in USD))	453	0.09	0.99	-3.57	4.55
Ln(Fintech credit per capita (in USD))	453	-1.14	2.76	-7.20	4.81

Ln = natural logarithm. The dependent variables have been winsorised at the 1% and 99% level.

[1] The Lerner index of banking sector mark-ups in economy i reflects market power by incumbent banks. World Bank data. For 2015-2017 data are estimated based on Igan et el (2020). [2] The index is normalised between 0 (no regulation) and 1 (max regulation). The index is calculated from a survey conducted by the World Bank in given years, and therefore data are not available over the whole sample period, but proceed in steps. See https://datacatalog.worldbank.org/. [3] Defined as the sum of big tech and fintech credit.

Sources: IMF, *World Economic Outlook*, World Bank; Cambridge Centre for Alternative Finance and research partners; company statements; authors' estimates.

Empirical results on fintech and big tech credit

Table 2 reports our panel regression results. It starts with estimations for total alternative credit (big tech plus fintech credit; column 1), and then big tech credit (column 2) and fintech credit (column 3). A formal test for differences between the coefficients for big tech credit and fintech credit is also reported (column 4).

As in Claessens et al. (2018) and Frost et al. (2019), we find that total alternative credit activity, as well as its two component parts (big tech and fintech credit), is positively associated with GDP per capita, but at a declining rate. Since GDP per capita is likely to be a proxy for many aspects of a country's stage of development, this result confirms a positive relationship between a country's overall economic and institutional development and these new credit activities. The negative coefficient estimate on GDP per capita squared suggests that the link becomes less important and even slightly negative at higher levels of development. Interestingly, the relationship between fintech credit per capita and GDP per capita remains positive up to a level of GDP per capita of around USD 52,000. A total of 73 out of the 79 countries in our database have a level of GDP per capita below this threshold. This means that for the vast majority of countries, there is still a positive relationship between fintech credit and GDP per capita. On the other hand, big tech credit per capita peaks at a level of USD 37,600 per capita; 20 of the 79 countries are above this threshold. This may relate to the high values of big tech in countries toward the middle of the income distribution, such as China, Korea and several Southeast Asian economies, and the (so far) very low big tech credit volumes in high-income countries like most of continental Europe, Singapore and Hong Kong. The difference between the estimated coefficient for fintech and big tech credit for GDP per capita is statistically significant. As we will show later, these differences are also detected in the cross-sectional analysis.[18]

Meanwhile, the positive correlation with the Lerner index of banking sector mark-ups suggests that these two alternative forms of credit, other things being equal, are more developed in those jurisdictions with a less competitive banking sector. This result could be explained by demand-side factors, e.g. the notion that these forms of credit are more flexible than bank credit, and that the ease and speed of receiving the loan decision is higher – an element that could be particularly important for underbanked clients. Moreover, the repayment obligations tend to be more flexible than with a bank (e.g. no penalty for early repayment, etc.). It may also be that, on the supply side, high margins make entry more attractive for the fintech and big tech firms, themselves. Bank mark-ups explain around 5% of the variability of total alternative credit per capita (the overall R^2 is 46.9%). The elasticity of big tech credit to the Lerner index is lower than for fintech credit, and this difference is significant at the 95% level.

The density of the bank branch network is negatively correlated with the development of fintech credit, but not of big tech credit. The difference between the

18 These differences are not due to a different average size of fintech and big tech loans. Both forms of credit are typically granted to households and small enterprises and are of modest average loan size. See Gambacorta et al. (2020) for the case of China.

two coefficients is statistically significant. This is consistent with the view that fintech credit serves clients in underbanked areas and that it is therefore complementary to traditional bank credit. This is also consistent with the use of agency banking. Big tech credit, while also relying on digital distribution channels rather than physical branches, does not appear to be correlated with the number of bank branches relative to the adult population, all else equal. This result could depend upon the global nature of big techs business models that could reduce the link with domestic bank distribution conditions.

Drivers of fintech and big tech credit volumes

All variables are expressed in current USD, except where indicated — Table 2

	Ln(total alternative credit per capita)	Ln(big tech credit per capita[5])	Ln(fintech credit per capita[6])	Difference │b-a│
		(a)	(b)	H_0: │b-a│ <0
GDP per capita[1]	0.123***	0.069***	0.171***	0.102***
	(0.022)	(0.020)	(0.038)	(0.043)
GDP per capita^2	-0.002***	-0.001***	-0.002***	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Lerner index[2]	1.438***	0.867**	2.436***	1.569**
	(0.401)	(0.365)	(0.732)	(0.818)
Bank branches per 100,000	-0.017***	0.005	-0.028***	0.033***
adult population	(0.005)	(0.005)	(0.009)	(0.010)
Normalised regulation index[3]	-4.665***	-1.735***	-8.427***	6.692***
	(0.560)	(0.544)	(1.068)	(1.199)
Other controls[4]	Yes	Yes	Yes	
Geographic area fixed effects[7]	Yes	Yes	Yes	
No. of observations	453	453	453	
Estimation method	OLS	OLS	OLS	
R^2	0.469	0.112	0.516	

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variables have been winsorised at the 1% and 99% level.

[1] GDP per capita (in USD thousands). [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; a dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] Big tech credit is zero in 47 countries. To allow the computation of the log of the ratio (not defined for zero), big tech credit has been rescaled summing an arbitrary constant (the minimum value). [6] Fintech credit is defined as credit activity facilitated by electronic platforms that are not operated by commercial banks or big tech firms. [7] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF; IMF, *World Economic Outlook*; World Bank; authors' calculations.

The coefficient of the stringency of banking regulation is negative for both forms of credit: more stringent banking regulation is significantly linked to less big tech and fintech credit activity. Banking regulation explains around 10% of the variability of total alternative credit per capita in the baseline model, and contributes to more than one-fifth of the R^2. This result, similar to that found by Barba Navaretti et al. (2017), Claessens et al. (2018) and Frost et al. (2019), could have several possible explanations. This could suggest that regulation of alternative forms of credit in general 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. The elasticity of big tech credit to the regulatory index is significantly lower than for fintech credit. The quantitative effects of regulation are also economically relevant. Specifically, a country with an index that is one-standard deviation lower in the cross section (looser regulation) has a ratio of total alternative credit per capita that is 0.5 percentage points higher.[19]

The additional controls are generally not significant and are not reported in the table. Overall, our estimations are able to explain 51.6% of the variation of fintech credit but only 11.2% of the variation of big tech credit. This may relate to the smaller number of countries and years in which big tech credit is present, and the fact that big tech firms operate in different countries. This could reduce the capacity of domestic controls to capture the global nature of big tech business models.

Results are qualitatively very similar when looking at a simple cross section, obtained by averaging all values over 2013-2018 (Table B1 in Annex B). This robustness check is particularly relevant to mitigate endogeneity concerns. Overall, the results can be broadly confirmed. The results are also robust to the inclusion of a complete set of time dummies that, however, tend to capture the common global trend in the evolution of these forms of credit (see Table B2 in Annex B).

Table B3 in Annex B reports the results when the log of the stock of bank credit to the private sector is considered as a dependent variable. The relationship between bank credit per capita and GDP per capita remains positive up to a level of GDP per capita of around USD 48,700. A total of 71 out of the 79 countries in our database have a level of GDP per capita below this threshold. This means that for the vast majority of countries, there is still a positive relationship between bank credit and GDP per capita. The negative correlation with the Lerner index of banking sector mark-ups suggests that, other things being equal, bank credit is more developed in those jurisdictions with a more competitive banking sector. As expected, the density of the bank branch network is positively correlated with the development of bank credit. Finally, more stringent banking regulation is significantly associated with lower bank credit activity.

As a final check we consider the impact of explicit fintech regulation. Following Rau (2020), we include in model (1) a dummy variable that takes a value of 1 if an explicit regulation of fintech credit ("crowdfunding debt models") was in place in a given country and year, and 0 elsewhere. During our sample period, 21 countries introduced explicit regulation for fintech credit. The results in Table B4 in Annex B indicate a positive correlation between explicit regulation and fintech credit. Due to potential endogeneity issues, we do not claim a clear causal relationship from the introduction of a fintech regulation to greater fintech credit volumes; indeed, regulatory initiatives could take place as a specific reaction to the development of fintech credit markets. Rau (2020) assesses this in more depth and uses a matching and instrumental variable approach to

[19] We have also investigated the effects of regulation that is specific to fintech and big tech credit, but at the moment, information is scarce. Surveys from Rowan et al. (2019) and Ehrentraud et al. (2020) provide relevant insights on regulatory frameworks in 2019. However, this is later than the sample period for our regressions, which ends in 2018 and the surveys do not report systematically when these regulations were introduced. Regulations that were only enacted shortly before the survey would not be expected to influence fintech and big tech credit volumes over 2013-2018. Rau (2020) estimates the year that dedicated frameworks for debt and equity crowdfunding were enacted and does find a significantly positive link with actual volumes one year later. This remains an important area for further investigation.

establish at least partial causality. To our end, what is important is that the main results of the study remain unaffected when controlling for explicit regulation of fintech credit.

Controlling for country institutional characteristics

In this section, we include additional country characteristics in baseline model (1). This represents a novelty with respect to the literature so far, which focuses primarily on cross-sectional analysis and a very limited number of explanatory variables. While we continue to use the full range of country-year observations, we zoom in on the impact of specific indicators that could be highly correlated with one another. To avoid multicollinearity problems, we therefore include these relevant country-specific characteristic one at a time. In particular, we consider:

- Barriers to entry, as expressed by the ease of doing business variables (World Bank, 2019);
- Investor disclosure and efficiency of the judicial system;
- More specific characteristics of the banking sector; and
- Bond and equity market development.

Descriptive statistics for these variables are included in Table 1.[20]

First, we evaluate whether potential barriers to entry, such as restrictions to start a new business, could affect the development of total alternative credit. These barriers to entry can be seen as both demand-side and supply-side drivers. In particular, easier procedures to start a business may allow new firms – such as those that sell products on e-commerce platforms and use fintech or big tech credit – to enter the market, thus increasing the demand for credit. Easier procedures may also allow fintech and big tech intermediaries to emerge, or foreign firms to enter these markets, thus increasing the fintech and big tech credit supply.

In Table 3, we add to the baseline specification a number of indicators that measure how easy is to open a new business. Each indicator ranges from 0 (difficult to open a business) to 10 (maximum ease). In particular, we consider one at a time (to avoid collinearity problems) the following measures: (i) the overall score for the ease to start business; (ii) a specific score based on the median duration to complete the procedure for creation of a firm; (iii) a specific score based on the minimum capital required for an entrepreneur to start up and formally operate a business; and (iv) a specific score based on overall costs officially required for an entrepreneur to start up and formally operate an industrial or commercial business. In 2013 and 2014, these indicators are available only for 65 of the 79 countries in the sample and therefore the number of observations drops from 453 to 425.

The results indicate that total alternative credit is positively correlated with all the indicators that measure the ease to start new business. To get an indication of the quantitative effect, we can observe countries in different quartiles of the overall score distribution. For example, the difference in total alternative credit per capita between those countries in the first quartile of the distribution (where it is relatively difficult to

[20] Beyond the focus of this paper, institutional factors and social arrangements may influence not only the volume of alternative credit, but also the form that such credit takes. See Wardrop (2020).

create a new business) and countries in the last quartile (where it is relatively easier to create a new business) is between 1 and 16%, depending on the specification.

Drivers of total alternative credit – ease of doing business indicators

All variables are expressed in current USD, except where indicated — Table 3

	Ln(total alternative credit per capita)			
GDP per capita[1]	0.108***	0.112***	0.124***	0.112***
	(0.023)	(0.023)	(0.023)	(0.024)
GDP per capita^2	-0.001***	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Lerner index	1.475***	1.520***	1.639***	1.518***
	(0.418)	(0.421)	(0.416)	(0.418)
Bank branches per 100,000	-0.019***	-0.020***	-0.019***	-0.019***
adult population	(0.005)	(0.005)	(0.005)	(0.005)
Normalised regulation index[3]	-4.570***	-4.604***	-4.816***	-4.684***
	(0.605)	(0.607)	(0.599)	(0.600)
Score starting a business (overall)	0.010**			
	(0.005)			
Score-Time (days)		0.006**		
		(0.003)		
Score-Paid-in Minimum capital (% of income per capita)			0.004**	
			(0.002)	
Score-Cost (% of income per capita)				0.005*
				(0.003)
Other controls[4]	Yes	Yes	Yes	Yes
Geographic area fixed effects[5]	Yes	Yes	Yes	Yes
No. of observations[6]	425	425	425	425
Estimation method	OLS	OLS	OLS	OLS
R^2	0.459	0.459	0.466	0.457

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variable has been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; a dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF; IMF, *World Economic Outlook*; World Bank; authors' calculations.

In Table 4, we analyse how the development of total alternative credit per capita depends on investor protection disclosure and efficiency of the judicial system. Higher investor protection may make it easier to set up a new lending platform and to find investors. Superior contract enforcement frameworks may limit credit risk and thus make lending more attractive. Both are, thus, supply-side factors. Again, to avoid multicollinearity problems, we add one indicator at a time. The first column includes an indicator for the business extent of disclosure (the extent to which investors are protected through disclosure of ownership and financial information). The index ranges from 0 to 10, with higher values indicating more disclosure. The other indicators take into account the efficiency of the judicial system and the strength of insolvency resolution. All indicators are taken from the World Bank Ease of Doing Business database.

Drivers of total alternative credit – investor protection and judicial system

All variables are expressed in current USD, except where indicated — Table 4

	Ln(total alternative credit per capita)			
GDP per capita[1]	0.109***	0.108***	0.110***	0.113***
	(0.024)	(0.023)	(0.025)	(0.023)
GDP per capita^2	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Lerner index	1.428***	1.391***	1.647***	1.525***
	(0.418)	(0.410)	(0.413)	(0.423)
Bank branches per 100,000	-0.019***	-0.017***	-0.017***	-0.020***
adult population	(0.005)	(0.005)	(0.005)	(0.005)
Normalised regulation index[3]	-4.541***	-4.495***	-4.678***	-4.544***
	(0.605)	(0.603)	(0.610)	(0.607)
Extent of disclosure index (0-10)	0.004*			
	(0.002)			
Trial and judgment (days)		-0.001***		
		(0.000)		
Enforcement of judgment (days)			-0.001**	
			(0.001)	
Enforcement fees (% of claim)				-0.018*
				(0.010)
Other controls[4]	Yes	Yes	Yes	Yes
Geographic area fixed effects[5]	Yes	Yes	Yes	Yes
No. of observations	425	425	425	425
Estimation method	OLS	OLS	OLS	OLS
R^2	0.460	0.466	0.462	0.459

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variable has been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; a dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.
Sources: CCAF; IMF, *World Economic Outlook*; World Bank; authors' calculations.

Countries with more disclosure and stronger judicial systems have more developed alternative forms of credit. The latter is higher where investors are protected through laws that allow for higher disclosure of ownership and financial information. The sum of fintech and big tech credit per capita is also larger in countries with: a lower average number of days to complete a trial/judgement; a lower number of days to enforce the law; and lower judicial enforcement fees.

Table 5 considers the development of total alternative credit in relation to country characteristics of the banking system.[21] We find that total alternative credit is less developed in countries where the banking system supplies a larger amount of credit relative to their deposit capacity (loan-to-deposit ratio). The correlation between total alternative credit per capita and the overall bank loan-to-deposit ratio is negative and significant. From a quantitative point of view, the difference in total alternative credit per capita between those countries in the first quartile of the distribution (where bank loans to deposits are low) and countries in the last quartile (where bank loans to deposits are high) is around 4%.

By contrast, total alternative credit is more developed where banks have a higher level of capital. The second column shows a positive and significant correlation between the average level of the bank regulatory capital to risk-weighted assets ratio and the amount of total fintech credit per capita. This correlation is interesting because the relationship between bank capital and bank risk aversion is uncertain *a priori* (Gambacorta and Mistrulli, 2004). If a higher level of bank capital reflects a higher level of risk aversion (Flannery, 1989; Dewatripont and Tirole, 1994), a larger volume of fintech credit may reflect lending to risky, potentially unbanked borrowers. If well-capitalised banks are more risk-averse, they could select a pool of borrowers *ex ante* who are on average less financially fragile, thus containing banks' exposure to default risk when an economic downturn occurs. Interestingly, alternative credit is also higher in countries with a higher level of bank provision to non-performing loans. This could indicate a role for fintech and big tech credit in economies where the banking system is more cautious or is more constrained by recent credit losses.

The fourth column includes an additional indicator for the presence of foreign banks: outstanding loans from non-resident banks to GDP in each country. The result indicates that total alternative credit is more developed when the level of foreign presence is low. This result could indicate larger fintech and big tech credit volumes in those countries with lower competition in the credit market, and thus corroborates the finding obtained using the Lerner index of banking sector mark-ups.

In a last regression we include an indicator for the share of firms with access to transaction accounts. This indicator is very important for developing economies and tends to reduce the significance of the GDP per capita indicator. It shows a strong positive correlation, implying more credit where a larger share of firms uses a formal bank account or other formal transaction account services. This underscores that fintech and big tech credit may complement bank credit to firms, as such alternative credit is higher in those economies where firms are likely to have access to banking services.

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[21] The lower number of observations compared to Table 2 is due to the lack of data for the additional independent variables used. Data are available for 65 countries out of 68 and only for 2015–2017.

Drivers of total alternative credit – banking sector characteristics

All variables are expressed in current USD, except where indicated — Table 5

	Ln(total alternative credit per capita)				
GDP per capita[1]	0.112***	0.156***	0.130***	0.146***	0.086*
	(0.027)	(0.033)	(0.029)	(0.032)	(0.045)
GDP per capita^2	-0.001***	-0.002***	-0.002***	-0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Lerner index	1.491***	1.349**	1.162**	1.631***	2.600***
	(0.520)	(0.615)	(0.561)	(0.598)	(0.474)
Bank branches per 100,000 adult population	-0.015**	-0.006	-0.015*	-0.016**	-0.044***
	(0.006)	(0.007)	(0.008)	(0.007)	(0.010)
Normalised regulation index[3]	-4.916***	-6.211***	-5.740***	-6.498***	-3.772***
	(0.820)	(0.946)	(0.834)	(0.954)	(0.669)
Bank credit to bank deposits (%)	-0.001**				
	(0.000)				
Bank regulatory capital to risk-weighted assets (%)		0.077***			
		(0.020)			
Provisions to non-performing loans (%)			0.007***		
			(0.003)		
Loans from non-resident banks to GDP (%)				-0.009**	
				(0.004)	
Proportion of firms with a transactions account (%)					0.013***
					(0.004)
Other controls[4]	Yes	Yes	Yes	Yes	Yes
Geographic area fixed effects[5]	Yes	Yes	Yes	Yes	Yes
No. of observations	212	197	187	194	276
Estimation method	OLS	OLS	OLS	OLS	OLS
R^2	0.642	0.605	0.585	0.592	0.529

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variable has been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; 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; Mobile phones per 100 persons; a dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF; IMF, *World Economic Outlook*; World Bank; authors' calculations.

Drivers of total alternative credit – financial market development

All variables are expressed in current USD, except where indicated | Table 6

	Ln(total alternative credit per capita)					
GDP per capita[1]	0.177***	0.149***	0.139***	0.101	0.131***	0.152***
	(0.044)	(0.045)	(0.050)	(0.074)	(0.035)	(0.037)
GDP per capita^2	-0.002***	-0.002***	-0.002***	-0.002**	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Lerner index	2.175***	1.464*	2.344**	-0.942	0.948	0.639
	(0.802)	(0.810)	(0.910)	(1.330)	(0.853)	(0.861)
Bank branches per 100,000	-0.018**	-0.015*	-0.015*	0.003	-0.004	0.005
adult population	(0.008)	(0.009)	(0.008)	(0.008)	(0.010)	(0.009)
Normalised regulation index[3]	-7.766***	-7.527***	-7.127***	-8.213***	-4.410***	-5.692***
	(0.998)	(1.002)	(1.083)	(1.410)	(0.910)	(0.865)
Corporate bond average maturity (years)	0.032**					
	(0.015)					
Corporate bond issuance volume to GDP (%)		0.114**				
		(0.057)				
Total factoring volume to GDP (%)			0.028			
			(0.025)			
Global leasing volume to GDP (%)				0.730***		
				(0.175)		
Stock market total value traded to GDP (%)					0.011***	
					(0.002)	
Stock market turnover ratio (%)						0.004**
						(0.002)
Other controls[4]	Yes	Yes	Yes	Yes	Yes	Yes
Geographic area fixed effects[5]	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	132	137	145	78	163	161
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS
R^2	0.686	0.622	0.534	0.706	0.614	0.634

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variable has been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; a dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF; IMF, *World Economic Outlook*; World Bank; authors' calculations.

Finally, in Table 6, we show that total alternative credit is positively correlated with indicators of development of the bond and equity market, and with other forms of non-bank credit: factoring and leasing. Our hypothesis is that that alternative credit tends to emerge alongside stock and bond markets, factoring and leasing, i.e. that they are broadly complements. In this case data are available for a lower number of countries (42 to 49 depending on the specification) and for 2015-18 only. Despite the more limited sample, overall, total alternative credit shows a statistically significant correlation with corporate bond maturity and issuance volumes, total factoring and leasing volumes and stock market value and turnover.

While fintech and big tech credit often serve smaller (e.g. SME) corporate borrowers, and individuals, volumes do correlate with market financing for larger firms. Further tests (not reported) show that total alternative credit shows a strong positive association with venture capital, private equity and merger and acquisition activity and the number of such deals, from PitchBook Data. Thus, alternative credit seems to complement these other forms of finance, not to substitute for them. This is consistent with other work on how alternative finance and capital market financing can reach underserved borrowers, particularly SMEs (World Bank, 2020).

4. Conclusion

This paper has documented the growth in the past years of fintech credit, provided by non-bank online platforms, and big tech credit, provided by large companies whose primary business is technology, sometimes in partnership with traditional financial institutions. Based on data collected from the CCAF surveys, public sources and contacts with firms and central banks, we have shown that both forms of credit have risen dramatically since 2013, but that since 2018, big tech credit has overtaken fintech credit in total size. Based on preliminary data, the shift to big tech credit was likely even more pronounced in 2019.

We have assessed the economic and institutional factors driving growth and adoption of fintech and big tech credit. We find that fintech and big tech credit are higher with higher GDP per capita, but at a declining rate. We also find that these alternative forms of credit are larger where banking mark-ups are higher and where banking regulation is less stringent. Regulation and to a lesser extent mark-ups are particularly important for fintech credit. Fintech credit is also more prevalent where there are fewer bank branches per capita. We also find that fintech and big tech credit are more developed where ease of doing business is higher, investor protection disclosure and the efficiency of the judicial system are higher, the bank credit to deposit ratio is lower, and where bond and equity markets are more developed. Overall, these alternative forms of credit seems to complement more traditional credit markets, not to substitute for them.

It is of course difficult to foresee how large fintech and big tech credit will become in the future. Given accommodative supply-side and demand-side drivers in some economies, fintech and big tech credit are growing to sizes that could be relevant to financial stability. In specific markets, for instance small businesses lending in the UK and China and consumer lending in Kenya, fintech and big tech lending have a relevant market share. Some big tech players (particularly in China) have likely reached a level of systemic importance. Moreover, as credit has grown rapidly, there is the potential for over-indebtedness by individual borrowers, and – as in past periods of rapid credit growth – even for risks to financial stability. Whether this growth represents the natural diffusion of a promising new type of intermediation or a credit bubble remains an open question; it may only be possible to assess this after the economy has undergone stressed conditions.

In this light, the current economic shock from the Covid-19 pandemic represents a test to fintech and big tech credit – and could have a large impact on both types of lending going forward. First, on a very basic level, the reduced physical mobility and social distancing in the pandemic have encouraged online communication channels. Thus, the use of online interfaces to originate and service loans could make both fintech and big tech lending more attractive relative to brick-and-mortar financial institutions. Second, the pandemic has benefitted e-commerce and online economic activities, while hurting activities that rely on physical location. This may accelerate certain more general trends toward digitalisation, and may even give big tech firms greater margins in their core businesses (e-commerce, social media, advertising, gaming, telecommunication, etc.). Finally, the shock marks the first economic downturn that many fintech and big tech lenders have undergone, and it is thus a test of the resilience of their credit scoring models under stress. Evidence from a 2017 regulatory shock in China (Gambacorta et al., 2019) suggests that models with alternative data and machine learning may outperform traditional data in predicting distress after a shock. Yet it is also plausible that machine learning models that use short periods of historical data may perform worse, or that this may differ across different markets. Big tech firms, which have a more diversified range of business lines and fund loans either through their own balance sheet or financial institution partners, may have greater capacity to absorb credit losses and continue lending than fintech credit platforms, who are focused solely on financial services and must continue appealing to investors. Big tech credit may also be less correlated with collateral values (Gambacorta et al., 2020).

Regardless of the impact of the current shock, there is a need to ensure that authorities and researchers have the proper data to monitor and study fintech and big tech credit platforms going forward. Authorities with a mandate for guaranteeing financial stability should not have to "fly blind" or rely exclusively on non-official data sources; they should have access to timely and accurate information about fintech and big tech credit in their own economy and economies around the world. We hope with this paper to make a small contribution toward this goal. Complementary efforts to bring fintech and big tech lenders into the fold of official regulatory reporting should continue apace.

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Annex A: Methodological notes on database construction

This annex gives a brief overview of methodological choices in the construction of the database.

- **Fintech credit in 2019:** CCAF survey data for 2019 are not yet available. As such, 2019 volumes have been estimated based on the 2018 CCAF survey and more recent data. For instance, the 2019 estimate for fintech credit in China is based on information from the People's Bank of China, while the estimate for Indonesia comes from Bank Indonesia. For these countries, it is assumed that the ratio between the 2018 CCAF survey data and the 2018 estimates for these countries remains constant in 2019, to arrive at a projected 2019 CCAF survey estimate. For India, we use input from a sample study by Reserve Bank of India for total lending on digital platforms in 2019. For the US, UK, European Union, Australia and New Zealand, estimates have used platform-level information from Brismo where available, and the median growth rate for remaining platforms. For Korea, we have used data from the Korea P2P Lending Association, kindly translated by Bank of Korea. Together, these countries made up 98.5% of global fintech credit volumes in 2018. Data for other markets (i.e. the remaining 1.5% of volumes) were extrapolated based on the median growth rate in 2017-2018.
- **Converting stocks to flows (and vice versa):** In most cases, fintech credit platforms and big tech firms report their cumulative lending flow over a calendar year or since the inception of their business (if they report at all). A smaller number report the stock of loans outstanding at the end of a year. In the latter case, it is necessary to convert the credit stock to a lending flow. To do this, we take the difference between end-year stocks (e.g. at end-2017 and end-2018), and add to this the volume of loans that are assumed to have matured over the calendar year. This can be estimated by the stock of loans at the start of the year divided by the average maturity. To estimate the stock of fintech credit, we do the reverse procedure, adding the lending flow minus matured loans to the stock of lending from the end of the previous year, assuming an average maturity of 9 months. To estimate the stock of big tech credit, we take the ratio of credit stocks (where available, and excluding China) to flows, and apply the same ratio to other countries. For China, where loan maturities are shorter, we apply the same estimation technique, but the ratio is calculated only on Chinese big tech firms. For African countries, where loan maturities are generally much shorter, we assume an average maturity of one month (based on input from company contacts).
- **Lerner Index:** The World Bank Lerner Index of banking sector mark-ups is available only through 2014. To fill in the values for 2015-2017, we perform a simple OLS regression of the World Bank data for 2011-2014 against the the alternative cyclical measure devolped by Igan et al. (2020). We then use the predicted (fitted) values for 2015-2017. Outliers (Greece and Guatemala) were winsorised at the 99% level.

The big tech and fintech credit dataset is available along with the paper.

Annex B: Robustness checks

Drivers of fintech and big tech credit volumes: cross-section analysis

All variables are expressed in current USD, except where indicated — Table B1

	Ln(total alternative credit)	Ln(big tech credit[5])	Ln(fintech credit[6])	Difference │b-a│
		(a)	(b)	H_0: │b-a│ <0
GDP per capita[1]	0.139***	0.054*	0.215***	0.161**
	(0.032)	(0.030)	(0.076)	(0.082)
GDP per capita^2	-0.002***	-0.001**	-0.002**	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Lerner index[2]	1.223	0.831	2.214	1.383
	(0.777)	(0.827)	(1.365)	(1.596)
Bank branches per 100,000	-0.014	0.005	-0.020	0.025*
adult population	(0.010)	(0.009)	(0.016)	(0.018)
Normalised regulation index[3]	-4.428***	-1.879	-8.783***	6.904***
	(1.491)	(1.294)	(2.662)	(2.960)
Other controls[4]	Yes	Yes	Yes	
Geographic area fixed effects[7]	Yes	Yes	Yes	
No. of observations	79	79	79	
Estimation method	OLS	OLS	OLS	
R^2	0.578	0.183	0.626	

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variables have been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; and country specific real interest rates. [5] Big tech credit is zero in 47 countries. To allow the computation of the log of the ratio (not defined for zero), big tech credit has been rescaled summing an arbitrary constant (the minimum value). [6] Fintech credit is defined as credit activity facilitated by electronic platforms that are not operated by commercial banks or big tech firms. [7] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF, authors' calculations.

Drivers of fintech and big tech credit volumes (Region and year fixed effects)

All variables are expressed in current USD, except where indicated — Table B2

	Ln(total alternative credit)	Ln(big tech credit[5]) (a)	Ln(fintech credit[6]) (b)	Difference │b-a│ H$_0$: │b-a│ <0
GDP per capita[1]	0.122***	0.070***	0.169***	0.099***
	(0.020)	(0.020)	(0.034)	(0.039)
GDP per capita^2	-0.002***	-0.001***	-0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Lerner index[2]	1.282***	0.894**	2.041***	1.147*
	(0.380)	(0.362)	(0.651)	(0.745)
Bank branches per 100,000	-0.014***	0.005	-0.020**	0.025***
adult population	(0.005)	(0.005)	(0.008)	(0.009)
Normalised regulation index[3]	-3.901***	-1.850***	-6.556***	4.706***
	(0.632)	(0.681)	(1.144)	(1.331)
Other controls[4]	Yes	Yes	Yes	
Geographic area fixed effects[7]	Yes	Yes	Yes	
Year fixed effects	Yes	Yes	Yes	
No. of observations	453	453	453	
Estimation method	OLS	OLS	OLS	
R^2	0.520	0.117	0.612	

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variables have been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; and country specific real interest rates. [5] Big tech credit is zero in 47 countries. To allow the computation of the log of the ratio (not defined for zero), big tech credit has been rescaled summing an arbitrary constant (the minimum value). [6] Fintech credit is defined as credit activity facilitated by electronic platforms that are not operated by commercial banks or big tech firms. [7] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF, authors' calculations.

Drivers of bank credit volumes

All variables are expressed in current USD, except where indicated — Table B3

	Ln(bank credit) Baseline	Ln(bank credit) Cross section
Ln(GDP per capita)[1]	0.187***	0.196***
	(0.008)	(0.024)
Ln(GDP per capita)^2	-0.002***	-0.002***
	(0.000)	(0.000)
Lerner index[2]	-0.399**	-0.962
	(0.193)	(0.784)
Bank branches per 100,000 adult population	0.015***	0.022**
	(0.002)	(0.008)
Normalised regulation index[3]	-1.455***	-2.257***
	(0.271)	(0.726)
Other controls[4]	Yes	Yes
Geographic area fixed effects[5]	Yes	Yes
No. of observations	453	79
Estimation method	OLS	OLS
R^2	0.946	0.921

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variable has been winsorised at the 1% and 99% level.

[1] GDP per capita, in USD thousands. [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere;; Mobile phones per 100 persons; dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: CCAF, authors' calculations.

Drivers of fintech and big tech credit volumes

All variables are expressed in current USD, except where indicated — Table B4

	Ln(total alternative credit per capita)	Ln(big tech credit per capita[5]) (a)	Ln(fintech credit per capita[6]) (b)	Difference │b-a│ H_0: │b-a│ <0
GDP per capita[1]	0.113***	0.067***	0.151***	0.084**
	(0.021)	(0.020)	(0.038)	(0.043)
GDP per capita^2	-0.002***	-0.001***	-0.002***	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Lerner index[2]	1.480***	0.875**	2.523***	1.648**
	(0.404)	(0.365)	(0.737)	(0.822)
Bank branches per 100,000	-0.016***	0.006	-0.025***	0.031***
adult population	(0.005)	(0.004)	(0.009)	(0.010)
Normalised (banking) regulation index[3]	-4.853***	-1.770***	-8.814***	7.044***
	(0.545)	(0.533)	(1.054)	(1.181)
Explicit fintech credit regulation dummy	0.497***	0.092	1.025***	0.933***
	(0.182)	(0.166)	(0.288)	(0.332)
Other controls[4]	Yes	Yes	Yes	
Geographic area fixed effects[7]	Yes	Yes	Yes	
No. of observations	453	453	453	
Estimation method	OLS	OLS	OLS	
R^2	0.484	0.113	0.533	

Estimation period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significant at the 1/5/10% level. Ln = natural logarithm. The dependent variables have been winsorised at the 1% and 99% level.

[1] GDP per capita (in USD thousands). [2] Lerner index of banking sector mark-ups in economy i, reflecting market power by incumbent banks. [3] The index is normalised between 0 (no regulation) and 1 (max regulation). [4] Other controls include: GDP growth; a crisis dummy that takes the value of 1 if the country was hit by the GFC and 0 elsewhere; total banking credit growth to the private non–financial sector; Mobile phones per 100 persons; a dummy that takes the value of 1 for advanced economies and 0 elsewhere; and country specific real interest rates. [5] Big tech credit is zero in 47 countries. To allow the computation of the log of the ratio (not defined for zero), big tech credit has been rescaled summing an arbitrary constant (the minimum value). [6] Fintech credit is defined as credit activity facilitated by electronic platforms that are not operated by commercial banks or big tech firms. [7] The sample has been divided into 5 geographical areas: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

Sources: Rau (2020); CCAF; IMF, *World Economic Outlook*; World Bank; authors' calculations.