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A CROSS-COUNTRY ANALYSIS”

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Firma dello studente

Alla mia famiglia.

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INTRODUCTION

During the last few years, the development of *FinTech* and *BigTech* companies in the activity of providing financial services has been rapid, steady and growing. Since 2005 FinTech platforms have increasingly been accessed by people and firms in several economies, both advanced and emerging, for cloud computing, security, credit, payments and many other uses. The global volume of FinTech credit recorded in 2013 amounted to $11 billion and hit $284 billion in 2016 (Claessens et al., 2018). In 2017 the combined volume of new credit provided both by Fintech and BigTech companies exceeded $500 billion (de Guindos, 2019).

FinTechs and BigTechs are becoming more and more integrated in the financial world and in consumers' everyday lives, especially in Asia-Pacific and in Latin American countries. However, FinTechs and BigTechs - because of their very nature - operate in different ways: BigTechs are highly capitalized firms which provide financial services aside from a different core business; FinTechs are usually smaller non-bank platforms completely dedicated to financial activities. On the one hand, this structural divergence is reflected in different operational patterns and different ways to approach the financial markets: while FinTechs generally act as intermediaries between borrowers and potential investors, BigTechs are more likely to provide credit through their own balance sheet. On the other hand, FinTechs and BigTechs seem to talk to the same audience. In fact, they have a similar customer base, composed mainly by those individuals and small-medium enterprises which are more likely to be excluded from traditional credit lines.

The fast-paced development of FinTech and BigTech credit during the last few years attracted the attention of both regulators and academic literature. Frost et al. (2019) in Chapter 3 of *"BigTech and the changing structure of financial intermediation"* – the *Bank for International Settlements' (BIS) Working Paper No 779* – performed an early stage cross-country analysis of the elements driving BigTech and FinTech credit provision. Thanks to the cooperation with the BIS' Monetary and Economic Department (MED), I had the chance to work with the same data used by Frost et al. (2019) in said publication.

Therefore, in this document, similar to Frost et al. (2019), I address the following questions:

1. *What causes heterogeneity in FinTech and BigTech credit adoption among different countries?*
2. *Why are some countries more likely to host BigTech credit activities, rather than FinTech credit ones?*

Starting from the authors' findings, I expanded the scope of the analysis adding several elements to the picture. More specifically, I focused on the following areas of interest:

- *A country's human development and wealth inequality*. The overall economic environment, the distribution of wealth among individuals and the level of industrial development are idiosyncratic features defining a country's identity. Do these structural characteristics play a role in the evolution of FinTechs and BigTechs' credit activities?
- *Individuals' financial knowledge and ability in using digital tools*. Individuals' ability to understand and elaborate financial processes is a key element at the base of households' wealth management. At the same time, the growing expansion of financial activities taking place in the world wide web reflects a society globally shifting from analogic to digital. To what extent these elements could drive the development of alternative finance tools?
- *Financial institutions' accessibility*. Financial institutions are not always easy to access, especially in some jurisdictions. In particular, access to credit could be inhibited by geographical obstacles, income constraints, lack of relevant documentation or, in some cases, prejudicial discrimination. Could BigTechs and FinTechs' lending help to overcome these barriers and enhance financial inclusion?

To elaborate the answers, I organized the document according to the following structure.

- Chapter 1 first introduces the definitions of FinTech, going through the relevant literature, combining different descriptions and briefly analyzing the historical steps which finally led to FinTech as we know it today. Therefore, it analyzes from a broad perspective the operational sectors in which FinTech platforms operate, distinguishing them among financially related sectors and market innovations. It provides a detailed examination of FinTechs' key features, followed by a closeup on the Chinese market and its peculiarities. Then, the focus shifts on BigTechs, studying their structure and defining the major differences with respect to other FinTech activities. Finally, I report the most important threats and benefits that could arise from the growing activity of FinTechs and BigTechs in the financial sector.

- Chapter 2 focuses primarily on FinTechs and BigTechs' lending activity. It first provides recent evidences on the evolution of the phenomenon, distinguishing credit volumes by geographic areas. Then it describes the functioning of a generic FinTech lending platform, and it defines the different types of FinTechs operating in the credit provision we can encounter in financial markets. After a brief representation of lending volumes to SMEs and individuals, in this Chapter I change perspective by addressing the topic from regulators' standpoint. In fact, the Chapter shows a review of most important recently developed policy initiatives aiming to create a proper regulatory framework for FinTechs and BigTechs. At the very end of the Chapter, I briefly mention the most relevant academic publications covering FinTech and BigTech credit, and I summarize their main findings.

- Chapter 3 is dedicated to the representation of the models that will be used in the empirical analysis. In the first part, I lay down the econometric models starting from the Linear Probability Model (LPM) and its key features; therefore, I move to a brief representation of logit and probit models. In the second part of the Chapter, I summarize the elements comprised in the database, describing all the different variables and their sources. Concluding, I define the specifications that will be studied in the econometric analysis I conduct in the concluding Chapter.

- Chapter 4 focuses on the representation of the analysis' results. I first use OLS and LPM to estimate the effect of the variables on FinTech and BigTech lending volumes, making comparisons with analogous results from relevant academic literature. Then, I focus on BigTech credit provision, performing an estimation of logit and probit parameters to verify if a nonlinear relationship with the regressors better explains the data.

CHAPTER 1. DEFINITIONS, DIMENSION AND POSSIBLE SCENARIOS

1.1. FinTech: general overview and operational sectors.

In order to depict the phenomenon properly, I first lay down some building blocks which, put together, will set the groundwork for the following discussions. The very first step into the unfolding of the topic is trying to provide an unambiguous definition of FinTech, and it is itself a challenging task. Many different authors in literature and many different relevant institutions tried to define a proper label for FinTech and, even though they end up being quite similar, they still show a few minor differences. Hence, in the following paragraphs I report some of these classifications, in order to give an idea as complete as possible of its general meaning.

FinTech, in a broad sense, covers digital innovations and technology-enabled business model innovations in the financial sector (Philippon, 2020). These innovations had a groundbreaking effect in existing industry structures during the last few years, changing their shapes and boundaries and providing a new set of instruments that firms – and individuals – can use; in particular, the way services and products are facilitated, and the way firms connect and relate have been vastly revolutionized. These innovations also promoted financial inclusion, expanding the opportunities for small enterprises and individuals to obtain affordable access to credit.

A similar definition is given by the Financial Stability Board, which describes FinTech as technologically enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services[1].

Balz[2] (2019) defined Fintech players as fledgling start-ups offering innovative technology-enabled financial services. Another description of FinTech is provided by Ernst and Young (2019), which label FinTech as organizations combining innovative business models and technology to enable, enhance and disrupt financial services. In this context authors argue, in a slight contrast to Balz, that this definition refers to an industry that includes not only early-stage start-ups and new entrants, but also scale-ups, maturing firms and even non-financial services

[1] For further details: https://www.fsb.org/work-of-the-fsb/policy-development/additional-policy-areas/monitoring-of-fintech/.
[2] Member of Executive Board of the Deutsche Bundesbank.

firms. In fact, as it is stated also by Nicoletti (2017), one common misconception regarding FinTech is related to the fact that it is composed solely by start-ups or very young companies; on the contrary, even mature and maturing companies have started to transform their businesses with advanced financial technology solutions.

After this brief review it seems clear that there are a few common elements among all these classifications.

First, in this scenario digital technology seems to play a fundamental role. The exponential reduction in the cost of computer processing power, along with internet, made it possible instant sharing of large amounts of digitized information, and allowed the development of technologies - such as machine learning, big data management and robo-advisory[3] – widely used in FinTech, especially by BigTechs. The financial world is accustomed to the use of digital technologies. One example, in recent years, might be the increasing application of high-frequency technology in trading; just as well as FinTech, it proved to bring both unarguable benefits and potentially dramatic drawbacks; moreover, again just as well as FinTech, it evolved so fast that regulatory framework was hardly capable to keep the pace. However, two key aspects differentiate this digital tool with FinTech activities, and they represent with a good precision the heart of FinTech objective: the accessibility and the costs. While high-frequency trading is meant to be practiced by few specialized agents – and with huge investments upfront – FinTech aims to enhance accessibility to financial services to everyone, even to those who were refused by the conventional institutions on the first place.

Second, FinTech is considered to be dealing a disruptive and game-changing effect on the way the financial system works. It created newer and faster instruments, that can be accessed by many very easily. This of course may lead both to positive and negative consequences. On the one side we have financial inclusion enhancing, faster payments, efficient and personally tailored credit issuing; on the other side we have regulatory loopholes, privacy issues that could arise in managing big data, possible monopolistic risks, competitiveness with incumbent financial institutions – as we will see more in detail later on during this Chapter.

A final remark on this side is suggested by the Basel Committee on Banking Supervision (2018); there’s a clear distinction between asserting that these technologies have a “disrupting” effect and stating that they have an “innovative” effect: innovation entails FinTech platforms fitting in an existing regulatory framework, disruption entails the development of a new set of rules. FinTech operates in a sort of grey area in between disruption and innovation; however,

[3] It refers to a type of financial advisory providing financial advice or investment management online with moderate to minimal human intervention, based on mathematical rules or algorithms.

in order to set a specific approach for possible regulation, jurisdictions should try to identify which products and services are to be regulated by an existing framework and which ones need a brand new one.

FinTech, however, is not a new concept. The very first steps into the digitalization of financial services were undertaken through the introduction of the telegraph, in 1838, and the construction of the first transatlantic cable, in 1866 (Nicoletti, 2017). In fact, these innovations set the basis for financial globalization in the late 1800s, allowing faster communication. Another milestone considered as one of the fundamental steps of FinTech history was the installation of the first ATM in UK, on June 1967; the period going from 1866 and 1967 defined what Leong (2018) calls the *FinTech 1.0*, i.e. the very beginning of the development of Fintech as we know it. *FinTech 2.0* relates to technologies involving Internet and Internet of Things[4], which developed during the 1990s; these years were marked by the first experimentation of Internet banking from Wells Fargo in USA and ING in Europe. In addition to that, sharing of information and storage of data became even faster and more efficient. The end of *FinTech 2.0* is to be considered in 2008, year in which we could start talking about *FinTech 3.0*. Finally, *FinTech 4.0* is referred to events developing at time being; increased connection between physical and virtual machines, computerization of manufacturing, high interconnection between people through smartphones and other digital devices. In the context of this document, I will be focusing primarily on the latest developments of the phenomenon; therefore, from now on, I will be referring to what has been defined *FinTech 4.0* simply as "FinTech".

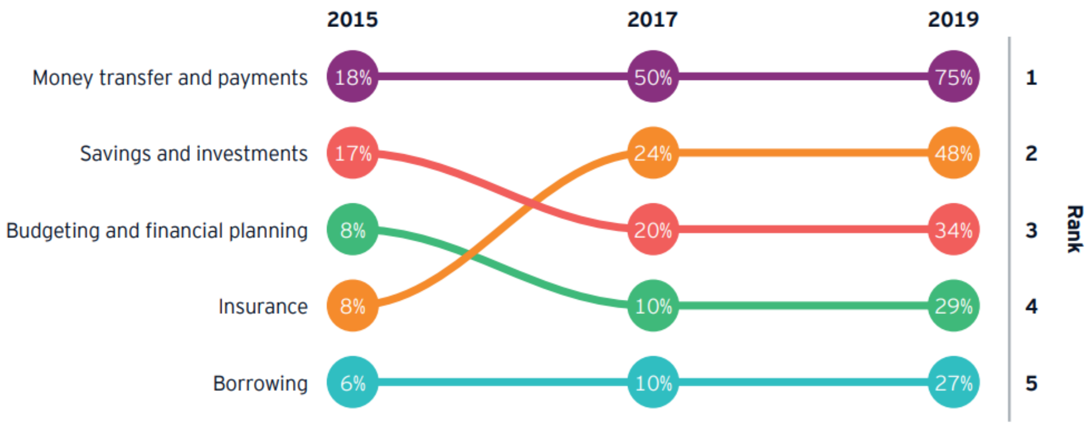
After defining FinTech, the next step of the analysis is trying to investigate what types of products and services these platforms are issuing, and in what sectors they are more active.

The scope of FinTech activities is wide, since they provide a vast variety of products and services to many different industries. *Figure 1*, as it is represented by Ernst and Young (2019), shows that in 2019 money transfer and payments played as the protagonist among categories of adoption, with an adoption rate[5] of 75%. In China, the adoption rate of FinTech payments touches the level of 95%. Then we have saving and investment (48%); budgeting and financial planning (34%), insurance (29%) and finally borrowing (27%).

[4] The Internet of things (IoT) is a system of interrelated computing devices, mechanical and digital machines provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction (https://en.wikipedia.org/wiki/Internet_of_things).

[5] FinTech users here are defined as people actively using two or more FinTech platforms in the previous six months in that category. Then, adoption rate is calculated as FinTech users as percentage of digitally active population (EY, 2019).

Figure 1: FinTech adoption rate by category.



Source: Ernst and Young (2019).

While payments have been undoubtedly the leading category during the last few years, insurance providing activities became more and more relevant making their way to second place in this specific leaderboard. According to the authors, nearly half the consumers globally use a premium comparison site, feeding information into an insurance-linked smart device, or buy products such as peer-to-peer insurance. In this context, FinTech adoption is characterized also by services such as equipping cars with "black boxes" to provide data for telematics insurance or providing apps on mobile phones that consumers can use to count steps and gain fitness discounts on their health insurance.

However, it is important to highlight that high levels of adoption rate do not necessarily mean high saturation of the market in that area of interest. In fact, it seems that in the categories of payments and insurance some demographic groups, such as women, rural areas citizens and consumers without university degree, show lower adoption rates and therefore a potential for FinTech expansion.

1.2. Key features of FinTech.

Even though FinTech activities significantly vary in shape and size, we can break down the core characteristics that identify them as technological innovations in the financial sector. Xie et al. (2018) investigated the key features of *internet finance*[6], and their main findings are hereafter displayed.

[6] The authors specify that they intend *internet finance* as a synonym to FinTech (Xie et al., 2018). Therefore, in the paragraph use both terms to identify the same concept.

1) Lower transaction costs

As a first and direct consequence of the digitalization on financial activities it comes lower transaction costs. The absence of physical branches allows FinTech platforms to reduce the costs by cutting out employees and all other costs incurring in maintaining physical activities. In addition to that, the network effect and the economy of scale that could arise in running FinTech activities on a vast context could also contribute in reducing transaction costs, leading, for example, to faster funding process or, in the case of third-party payment models, to net clearance of many transactions with third-party payment companies. The reduction of transaction costs will eventually translate into lower costs charged to customers.

2) Diminishing information asymmetry

Information asymmetry is one of the major issues of financial intermediation, as it has vastly been documented by academic literature. The development of cloud computing and search engines makes it possible to analyze big data with high efficiency. On the one hand, big data analysis allows to forecast and predict some specific values by training the machines with a given input dataset; on the other hand, it allows to explore hidden patterns among data, including correlations, trends, clustering and outliers' detection. The application of machine learning methods, for example, to risk management and credit worthiness may lead to more efficient assessments of credit scores (Frost et al., 2019) and to less discrimination of minorities (Philippon, 2020). BigTech companies, in particular, can retrieve massive amount of data through their existing platform and elaborate them to provide differentiated products and services among their customers. On the field of securities markets, big data analysis performed by FinTech companies could bring to a more complete disclosure of the behavior of investors, leading as a consequence to prices which more closely reflect market sentiment. In providing insurance, FinTechs could assign premiums that take into account the idiosyncratic differences among individuals, dynamically adjusting the actuarially fair price.

3) Expanding sets of feasible transactions

By arranging trades or investments between strangers, FinTech platforms extend the scope of feasible transactions. One example, among others, is crowdfunding: individuals could fund a project without geographic limitations, while generally – at least on small sized transactions - when arranging the same type of transaction offline usually individuals rely on friends, family and relatives. This feature entails some risks; the protection of financial customers online is put into danger when people served by internet finance lack financial knowledge, or when irrational behavior is amplified by the mass transactions happening online.

4) Financial disintermediation

Cutting off intermediaries is one of the main characteristics of non-traditional financial activities online. In the field of debt financing, for example, FinTech can give access to loans for consumption, investments and production to SMEs and individuals with reliable credit rating and lower costs. In the securities market some FinTech platforms allow bypassing the brokerage fees by granting a direct access to the stock exchange. Also the field of insurance products show signs of disintermediation due to FinTech technologies. As an example, some P2P platforms can allow individuals sharing similar risk profiles to pool resources to be used in case of realization of risk by one of the participants. This, in a way, is becoming more and more transparent thanks to big data analysis and could become a popular tool in future years.

5) Payments innovation

As previously mentioned, the system of payments is the branch of the financial world which most has been affected by the activity of FinTech. Internet finance and mobile payments are a widespread reality in China, as well as in other countries. As is suggested by Xie et al. (2018), one possible – but very extreme – future scenario would be the complete deletion of the financial intermediaries, by creating a direct account from the individuals to the central banks; this way, the effects of monetary policy would change drastically. In this context, also private digital currencies could play a relevant role; in modern society, the internationality and super sovereignty of potential Internet currencies could become relevant elements affecting the financial framework.

6) Blurred boundaries between financial sectors

In the framework of internet financial activities, FinTech platforms can operate – to some extent - as banks, insurance companies or even stock markets. All the products which are usually facilitated by these different institutions can be bought and exchanged by the same FinTech platform; therefore, the boundaries between financial sectors become thinner and harder to mark.

7) Integration of financial and nonfinancial factors

One last element to add to the analysis of the main characteristics of FinTech is the interconnection between nonfinancial infrastructures and financial instruments. Taking BigTechs as an example, the infrastructure providing the financial instruments is primarily intended to run nonfinancial activities, such as e-commerce or cloud computing. Sharing economy, to be considered as the exchange of activities conducted online, is playing a major role in connecting financial and nonfinancial elements. One example of sharing economy is Airbnb; internet improves efficiency of the allocation of resources – in the Airbnb example, rooms booking – on the one hand by enabling customers to find what they need faster and with lower transaction costs and on the other by allowing landlords to have higher frequency of reservations. In this context, e-commerce, the sharing economy and internet finance are closely related. E-commerce and sharing economy provide internet finance with data and a customer base; internet finance advances e-commerce and sharing economy.

Xie et al. (2018) conclude their analysis asserting that internet finance embodies the influences of the Internet and its characteristics. It focuses on openness, sharing, decentralization, equality, freedom of choice, inclusion, disintermediation; these features thus reflect the need of development in the financial activities operating online, and somehow it explains why these progresses take place with such a fast pace.

However, while these features are useful to understand the general behavior of FinTech platforms operating online, their narration tends to underline the bright and optimistic side of such activities. Analyzing the possible drawbacks of internet finance activities - as well as the benefits - is a fundamental step to make to fully understand how FinTech could affect the financial system in the years to come.

To give an idea, when operating in the financial sector, FinTech platforms are subject to the same market failures present in other areas of finance, including information asymmetries and adverse selection in lending, liquidity mismatches with deposits, systemic importance and moral hazard with large intermediaries (Frost, 2020). Later in this Chapter, I will discuss more in detail the potential threats and benefits deriving from FinTech operations.

1.3. Volumes and geographic distribution.

Defining the magnitude of FinTech on a cross-country base is a challenging task due to the patchiness of retrievable data. Available information shows a growing trend in the volumes of FinTech activities operated worldwide, both in advanced and emerging economies. However, when compared with an incumbent financial system with assets worth \$382 trillion globally in 2017, FinTech overall market value is quite small; in 2017 it accounted globally for \$545 billion, which corresponds to about 0.14% of the stock of global financial system assets. The relative impact of FinTech activities varies greatly over countries; while FinTech is a niche activity confined to certain business lines in some countries, in others it is moving into the mainstream of financial services (Frost, 2020); interestingly, this uneven behavior seems not to reflect either economic development or political boundaries. As stated by Chen (2016), it's not necessarily true that a good financial product or arrangement should be accepted universally – at least in the economically advanced countries; this statement holds also in the age of FinTech. In fact, different countries are experiencing different levels of engagement to FinTech activities.

Ernst and Young (2017, 2019) show some evidence of the adoption level by country from a global perspective. In 2017 the top five countries by adoption rate of FinTech technologies were China (69% of digitally active population), India (52%), United Kingdom (42%), Brazil (40%) and Australia (37%), with an average adoption of 33% worldwide. In 2019 the top five was quite different: China and India were tied at the first place with an adoption rate of 87%, followed by Russia (82%), South Africa (82%), Colombia (76%) and Peru (75%); the global average adoption was 64%. The global level of acknowledgement and usage of FinTech technologies increased sharply in the timespan 2017-2019, almost doubling the average adoption rate. The dynamic identity of FinTech is revealed by the fast change in the adoption rate by country; while China maintains its position as a leader in FinTech adoption and volumes, other countries are experiencing heterogeneous evolutions.

As documented by Frost (2020), many different drivers are affecting the heterogeneity of adoption. According to the author's analysis, in developing and emerging countries one important element driving FinTech adoption is financial inclusion; in such countries many don't have a bank account because it's too expensive, or because they lack the necessary documentation, and in these contexts FinTech has the opportunity to expand faster. In other jurisdictions the competition of the incumbent banking sector, the costs of financing and the banking sector mark-ups are relevant elements. The effect of younger cohorts is still to be investigated – even if there's evidence that, for some countries, a major presence of younger people could play a relevant role.

Some relevant drivers for the success of FinTech among individuals are the attractive fees and rates, the access to different and more innovative products and services with respect to the traditional financial institutions and the speed accounts can be set up with. SMEs have been increasingly adopting FinTech services during the last few years. As well as for individuals, also for SMEs the main drivers of FinTech usage are lower rates and fees, ease in setting up, configuring and using the service, and most importantly the range of functionality and features. Among SMEs, the average adoption rate[7] in 2019 hit 25%, with China playing as the main

[7] An SME is to be considered an adopter if it used services provided by FinTechs in all four categories (banking and payments, financial management, financing and insurance) over the previous six months (EY, 2019).

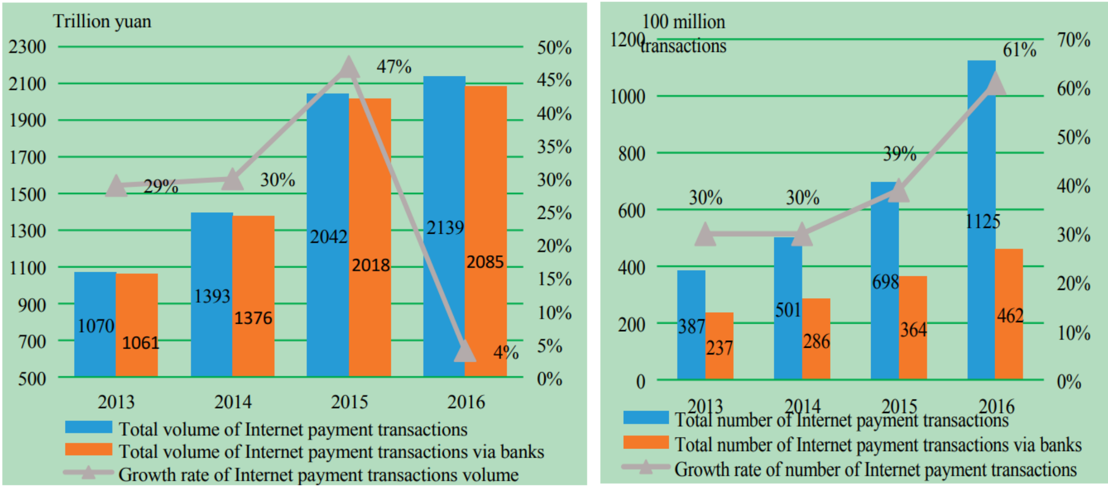
character (61%), followed by United States (23%), United Kingdom (18%), South Africa (16%) and Mexico (11%). Since China seems to follow a path which is very different from those of other FinTech-adopting countries, it's worth spending a few words to analyze more deeply how FinTech activities developed in that specific jurisdiction.

1.4. A focus on China.

China is by far the most dynamic country in terms of FinTech activities. Chen (2016) provides an analysis of the FinTech progress in China, sharing some information that are useful to understand its magnitude. If we consider the field of online payment, Alipay and WeChat Pay are the leading enterprises in the Chinese market; they cover almost all the online payments market with a split 54% - 40% for AliPay and WeChat Pay respectively. Alipay, the online payment platform founded in 2004 by Alibaba Group and Jack Ma, during 2019 had more than 520 million users[8] which, for sake of comparison, it is several times the number of active accounts of PayPal globally. WeChat Pay, the mobile payment section of the messaging app developed by Tencent in 2011, counted in the same year more than 800 million active WeChat mobile payment users. In the field of financing, Ant Financial Services Group, parent company of Alipay, issued more than 700 billion RMB (more than $100 billion) in loans to small-medium enterprises in the period from 2011 to 2016; it is the highest valued FinTech company in the world, with a valuation of $150 billion and 588 million users[9] – more than a third of China's total population. In the field of insurance, several insurance companies, including Zhong An Online P&C Insurance, sold 308 million policies of shipping-return reimbursement insurance[10] in one day in November 11th, 2015, becoming the largest number of policies sold in any single insurance category in history.

[8] For further details: https://en.wikipedia.org/wiki/WeChat#WeChat_Pay_digital_payment_services.
[9] For further details: https://en.wikipedia.org/wiki/Ant_Financial.
[10] This type of insurance gives the customer the possibility to return a purchased item without incurring in any extra shipping costs.

Figure 2: Internet payment transaction volume and number from 2013 to 2016.



Source: Xiao et al. (2017).

Xiao et al. (2017) depict in *Figure 2* the trend of internet payments in the period from 2013 to 2016 in China: internet payment maintained rapid growth, while the number of mobile payment transactions surpassed that of Internet payment via banks. In left panel we can see the evolution of volume of Internet payment transactions; commercial banks maintained their predominant position accounting for more than 97.5% of the total volume of internet payment transactions and, together with non-banking transactions, it was worth 2,139 trillion RMB. On right panel we have the evolution of the number of internet payment transactions; even though non-banking sector accounted for a very tiny fraction of total volume, when speaking of number of transactions, the non-banking sector takes the lead: it reflects the fact that it is mainly characterized by small and more frequent payments.

Chen (2016) provides a twofold explanation on why FinTech seems to feel particularly at home in China. First, the author states that China enjoyed the "late-mover advantage"; since FinTech – the way we know it today – first took place in United States and United Kingdom, Chinese enterprises could adopt the technologies already in the market by enhancing and fitting them to their own context. Second, and more importantly, the integrated growth of technology, finance and real-life need has been particularly significant during the last few years in China. The lack of accessibility to ordinary payment and credit institutions, the growth of technological standards, the patchiness of pre-existing banking system; all these factors, put together, played a major role in setting the foundations of FinTech evolution in China.

1.5. BigTech: investigating the phenomenon.

In the framework of FinTech platforms operating in the financial sector, BigTechs have recently made their way through obtaining a major role in contributing to the evolution of the phenomenon on FinTech.

BigTech[11], as it is described by the BCBS (2018), refers to large globally active technology firms with a relative advantage in digital technology; they usually provide web services (search engines, social networks, e-commerce or other online services) to end users over the internet and/or IT platforms, or they maintain infrastructure (data storage and processing capabilities) on which other enterprises can provide products or services. Frost et al. (2019) provide a similar definition: according to the authors, BigTech refers to large existing companies whose primary activity is in the provision of digital services, rather than financial services. Said differently, BigTechs do finance in parallel to non-financial activities, therefore not considering – in most cases – finance as the core activity.

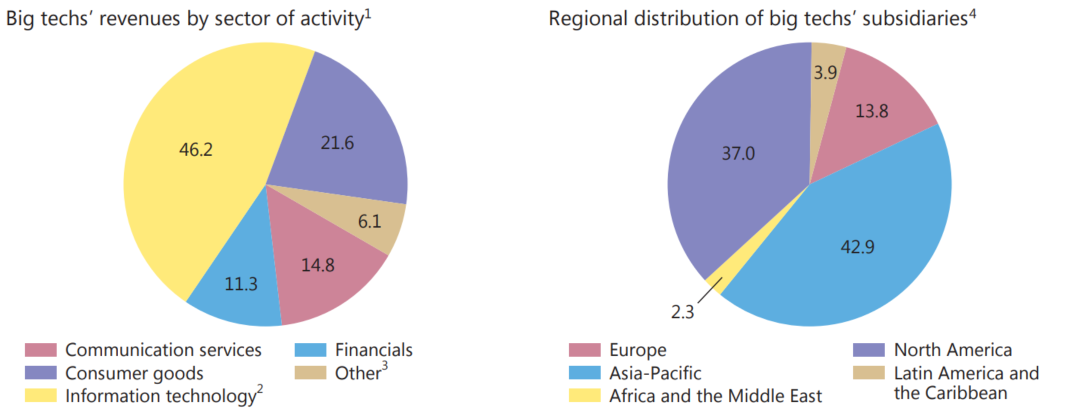
In *Figure 3* are shown some characteristics of BigTech companies. As we can see on the left-hand panel, financial activities account on aggregate only for the 11.3% of total revenues, while information technologies represent almost half the income (46.2%). Right-hand panel represents the geographic distribution of BigTech subsidiaries; while BigTech operate on a global perspective, their operations are mainly located in Asia-Pacific countries and North America.

Hence, BigTech is comprised under the umbrella of FinTech activities, since it represents technology-enabled innovations in the financial sector[12]. But interestingly, it seems to show different patterns and different characteristics with respect to other FinTech activities; to use the words of Balz (2019), "*BigTech firms are a different kettle of fish altogether*".

[11] Sometimes referred to, in literature, as "TechFins" (Frost et al., 2019).

[12] Most publications, to the current state of art, do not distinguish unambiguously between BigTech and FinTech; most commonly, BigTech volumes are not comprised in data referring to FinTech. Frost et al. (2019) contributed in combining together FinTech data and BigTech data to perform a comprehensive analysis of total FinTech volume.

Figure 3: BigTech activities and geographic distribution.



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

[1] Shares based on 2018 total revenues, where available, as provided by S&P Capital IQ; where not available, data for 2017. [2] Information technology can include some financial-related business. [3] Includes health care, real estate, utilities and industrials. [4] Shares are calculated on the number of subsidiaries as classified by S&P Capital IQ.

Source: BIS (2019).

Many different BigTech firms are now playing as main characters in several different countries: Apple, Amazon, Google and Facebook in the United States; Alibaba and Tencent in China; Vodafone M-Pesa in Africa and India; Mercado Libre in Latin America; Kakao Bank, KBank and Samsung Pay in Korea Republic; Line and NTT Docomo in Japan; Go-Jek and Grab in Southeast Asia; Orange in France. BigTechs are currently the largest companies in the world by market capitalization; if we pick the six largest BigTech companies and we compare them with some of the largest global systematically important financial institutions, we can easily conclude that the first ones surpass the latter by far, in terms of market capitalization.

BigTech companies have typically entered the financial activities only once they have established a solid customer base and a consistent brand recognition. These firms typically started their activity in the financial sector by providing payment services, and then moved into facilitating also insurance products or credit. Payments were the first financial service BigTechs offered, mainly to help overcome the lack of trust between buyers and sellers on e-commerce and other online platforms; buyers want the delivery of goods, but sellers are only wiling to deliver after being assured of payment (BIS, 2019). In payments, Chinese BigTech companies play a central role, following the same pattern already discussed with respect to other FinTech activities; in China, during 2017, payments for consumption facilitated by BigTech companies reached a volume equivalent to almost 16% of GDP (RMB 14.5 trillion). At a significant distance we find United States, India and Brazil, with BigTech mobile payments ranging from 0.3% to 0.6% of respective GDPs (Frost et al., 2019).

In this context, a key distinction must be made. There are two separate types of BigTech payment platforms: the BigTech activities relying on an existing infrastructure – i.e. credit cards and bank accounts already facilitated by incumbent banking system – and the BigTech activities which created a separate proprietary framework.

BigTechs tend to rely strongly on preexisting framework in countries where the banking sector is strongly and deeply ingrained, as for example United States, Europe and Korea. One example is the newly released Apple Card, which relies on Goldman Sachs infrastructure; it's a credit card highly integrated with the Apple world, which provides payment services with low fees and a Cash Back system based on monthly spending[13]. Other examples are Google Pay, Amazon Pay or Samsung Pay, which are also functioning thanks to the cooperation with incumbent banking system.

On the other side, we have companies such as AliPay by Ant Financial, WeChat Pay by Tencent, Mercado Pago by Mercado Libre and Vodafone M-Pesa, operating mainly in emerging and developing countries; they created proprietary infrastructures integrated to their own operating platform, and detached from incumbent banking system. As a matter of fact, the lower penetration of credit cards and banking accounts is one key element driving the fast-paced evolution of BigTech products and services in such jurisdictions.

The relationship between BigTechs and incumbent financial system is not one-sided; in fact, BigTech companies are not just depending on financial institutions because of their utilization of a preexisting framework, but they also provide third-party services to such financial institutions. For example, Amazon, the largest cloud services provider in the world, can count among its customers a huge number of said institutions which are using its non-financial services to run their ordinary activities.

After a first approach to the provision of financial activities through payments, BigTechs rapidly embraced also insurance products and credit issuance. Network effects allow BigTechs to bundle different products and services altogether, and to provide them to customers through their online platforms; hence, for example, one could incur on hand-tailored credit or insurance policy offerings while navigating on the platform for a different reason – e-commerce, chatting, social media. This ability BigTechs have in analyzing data, creating properly suited financial products and feeding them to customers is one of the main reasons BigTech evolution in the field of financial services was so fast and broadly expanded. As an example, Yu'ebao in China is a BigTech mobile money market fund, funded in 2013; it was initially intended to allow

[13] For further details: https://www.apple.com/apple-card/

AliPay customers to invest a small fraction (minimum investment of 1 RMB) of their money sitting on the online account. In a few years it reached a total of assets under management of RMB 1.7 trillion, equivalent to $266 billion, and thus became the largest mobile money market fund in the world. Again, Ant Financial and Tencent offer insurance products on their platforms, both third-party products and own dedicated ones. This network effect is much more tangible in the Chinese market; however, also in UK, United States and Europe BigTech companies are developing cross-platform and cross-sector financial products which can integrate some basic functions of the online platform to some additional financial services.

The Bank for International Settlements, in its *Annual Economic Report* in 2019, provide a description of what they define the "DNA" of BigTech firms or, said differently, the key features of BigTechs. "DNA", in their description, is used as an acronym that stands for ***D**ata analytics*, ***N**etwork externalities* and *interwoven **A**ctivities*; these three elements seem to reinforce each other and constitute the key elements of BigTechs' business models.

Network externalities, as already mentioned, relate mainly on the fact that a user's benefit from participating on one side of a platform – for example as a seller in an e-commerce platform – increases the number of users on the other side; they allow BigTech platforms to generate a high volume of data, which in turn makes platforms always enhancing their products to better fit customers' needs.

Data analytics greatly depends on the type of data recovered. Those BigTechs which operate mainly on e-commerce platforms are more likely to collect data on vendors – such as sales and revenues – and consumers habits; those with a core business in social media collect data on individuals and their preferences, as well as their connections; those who run search engines collect data on online searches of their customer base.

Interwoven activities are referring to the close connection between the activities run by FinTech companies, as well as the close relationship between the three key features. When collecting data from e-commerce transactions, BigTechs are enabled to use this data as input when performing credit scoring analyses; by collecting data from social media platforms or search engines, BigTechs can better understand users' preferences, both on their own and third-party's behalf.

As the authors conclude, combining their advanced technologies with richer data and a stronger customer focus, BigTechs have been adept at developing and marketing new products and services (BIS, 2019); and their size, relative to other firms in the financial market, allows them to highly influence the present and future of alternative finance.

1.6. Potential benefits and potential threats.

At the very center of the FinTech-related researches lies a question that comes as a natural consequence after analyzing the magnitude and the process of FinTech activities: are FinTechs and BigTechs a threat to financial stability, or could they enhance the quality of life of individuals by granting more accessible financial instruments? Of course, it is not possible to provide a unique solution to this question; what we can do instead is trying to understand what forces are pulling one way or the other and analyze what are the possible future scenarios depending on these elements.

The Financial Stability Board (2017) provided a comprehensive analysis of potential threats and potential benefits arising from alternative finance activities. The authors highlight the following elements as possible benefits.

1) Decentralization and diversification

Decentralization and diversification of FinTech activities could bring a milder effect on financial stability of financial shocks, in some circumstances. In fact, since FinTechs are generally smaller in terms of market capitalization with respect to traditional financial institutions, the failure of one of them is less likely to cause the shutdown of a market. This is not true, on the other hand, for BigTechs: as already mentioned, they are characterized by high market capitalization, and this may drive shocks the opposite way.

2) Efficiency

FinTech companies rely on strong efficiency in operations, which in turn translates into stable and growing business models. Since they support also the incumbent financial institutions, they contribute to overall efficiency gains in the financial system and the real economy.

3) Transparency

Transparency directly reduces information asymmetries among players in the financial markets. It enables to better manage risks, and therefore to assess more easily fair prices to be charged for such risks. In addition to that, transparency can help in the creation of financial instruments with exposure to specific risks, and hence in completing the markets and improving market participants' ability to manage risks.

4) Access to and convenience of financial services

As broadly discussed, lower transaction costs and higher frequency allows FinTechs to charge lower fees and interest rates to customers. This element is particularly relevant in understanding how FinTech enhanced financial inclusion, especially for households and SMEs. This is important for supporting sustainable economic growth and providing a diversification of exposure to investment risk.

All these elements should be taken into account by policymakers when assessing whether or not FinTech could be a useful resource to enhance quality of life and economic growth of a country. However, recent events pushed financial institutions and regulators to a prudential behavior, by strongly regulating the financial system and financial markets. The FSB (2019) documented a vast set of possible threats to financial stability. In order to provide a complete idea of all possible sources of potential threats, the FSB distinguishes Microfinancial risks from Macrofinancial risks; therefore, I will proceed analyzing them separately.

On the Micro side, the financial system could experience both financial related risks and operational related ones, depending both on the business structure of FinTech platforms and on the operational sector they work in.

A) Financial risk sources

1) Maturity mismatch

When financing contracts are settled with a given maturity date and, on the contrary, loans are extended after maturity, there's the possibility for rollover risk to arise. For example, maturity mismatches could become more evident through securitization, or when FinTechs start using their own balance sheet to provide credit. If the FinTechs provide critical products services in particular markets, systemic negative effects could arise.

2) Liquidity mismatch

The liquidity risk lies on imbalances in financial institutions' balance sheets between assets and liabilities liquidity characteristics. If the imbalance is evident and specific market conditions are met, this risk could become real and institutions could face bank runs. This would eventually translate in the need to liquidate relatively illiquid assets, causing negative effects on markets. Causes and consequences of such effect have been widely documented by academic literature with respect to traditional banking system (see for example Diamond and Dybvig, 1983). However, FinTechs are not proper banks, and they are generally not allowed either to provide deposit activities or to hold clients' money. Those who do, usually are required by regulations to invest the money they receive in liquid assets.

3) Leverage

High leverage could mean less equity available to absorb any losses arising from the realization of market, credit, or other risks. FinTechs seem not to be particularly vulnerable to this kind of risk at the time being; however, some types of platforms such as equity crowdfunding or consumers lending may borrow funds in order to finance temporary outstanding holdings, especially when these platforms operate using their own balance sheet to finance loans.

B) Operational risk sources

4) Governance and process control

When alternative finance institutions operate outside the financial regulatory framework, they may be subject to lower levels of control and therefore there could be lack of scrutiny of their businesses' operations. Many FinTechs operate on a grey area in between the institutional financial regulatory framework and some sets of rules hand-tailored to fit some specific activities. In certain jurisdictions, however, some operations are not subject to regulation at all.

5) Cyber risks

Technology growing at huge speed brings both positive and negative effects. On the one hand it enables faster communication, faster operations and interconnection between people and institutions; on the other, hacking issues could arise. These risks are more severe the higher the level of interconnection of the financial institutions among the internet. Big data stored online, private information, money accounts, e-wallets; they are all susceptible to cyber-attacks which could undermine the functioning of the financial system. The FinTech phenomenon, however, comes together with better awareness of such risk, and many FinTechs provide online security services. Cyber security and privacy protection are a key element to consider when analyzing potential threats to financial stability, since regulation on this topic is still patchy.

6) Third-party reliance

Some third-party activities, as for example the cloud computing or data providing, are highly concentrated among very few companies. Disruptions to these third-party companies could cause a negative impact on financial stability, especially if they are central in linking together multiple systematically important institutions or markets.

On the Macro side, the FSB specifies that there are some characteristics which could amplify over time shocks to the financial system, undermining financial stability. The extent to which these elements could translate into negative effects depends on the type of business and on the type of operations facilitated by FinTech platforms. Macro financial risks reported by the FSB can be summarized as follows.

1) Contagion

If FinTech activities are interacting directly with businesses and households, there's a risk that adverse shocks or significant losses in one specific platform could be interpreted negatively in the entire market. As they become more popular, FinTechs are subject to higher risks of contagion among customers, with cyber-security risks, interconnectedness and automated processes – implying lack of human supervision - playing a major role in pushing this effect even further.

2) Procyclicality

FinTech activities could exacerbate the level of impact of fluctuations in economic growth and market prices; they could therefore amplify upward swings as well as worsening the negative effects during bad times. Some examples come from the credit sector: increased access to cheap debt and equity financing may bring entrants to underprice risk while competing with incumbents; if entrants can actually bear such risk for a sustained period of time, incumbents could push prices even lower and increase risk-taking behavior.

3) Excess volatility

As they are constructed to be fast in nature, FinTechs could worsen the excess volatility in the markets. In more competitive environments, an increase in the speed and ease of switching between service providers could make the financial system more excessively sensitive to news.

4) Systemic importance

One last element to consider is the possibility that monopolistic or oligopolistic behavior could arise in the future. Especially in the BigTech context, these platforms being highly integrated and with huge dimensions, this risk is far from being fictional.

CHAPTER 2. INVESTIGATING FINTECH AND BIGTECH CREDIT

2.1. Magnitude of FinTech and BigTech credit.

So far, we explored FinTech and BigTech development with bird's-eye perspective, focusing on their core features and overall areas of activity. In this Chapter, I investigate more in detail FinTechs and BigTechs' lending activity; even though it represents just a small – yet steadily growing - fraction of the whole set of operational sectors covered by these platforms, it stands out for the possible implications it could arise, both from policy-makers perspective and from households-SMEs perspective.

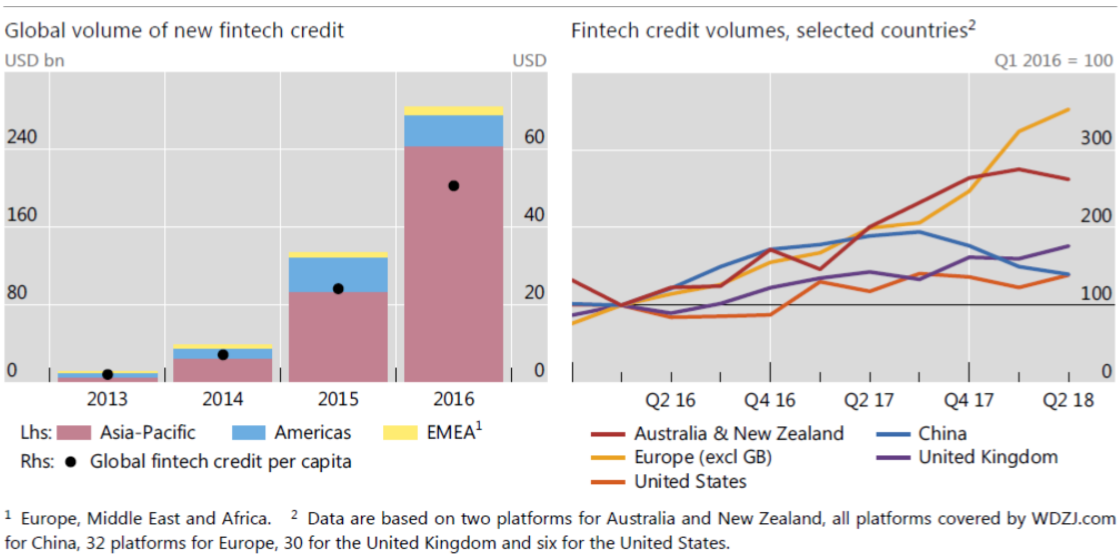
FinTech lending, as defined by Claessens et al. (2018), is a credit activity facilitated by electronic platforms that are not operated by commercial banks. This definition includes all credit activities facilitated by platforms that match borrowers with lenders. This general description entails several important divergences with respect to credit provision through conventional channels – which generally correspond to commercial banks.

First, FinTech platforms make use of digital technology to interact fully – or at least largely – with customers online and process large amount of digital information. Commercial banks, on the contrary, relate to customers on a limited amount via digital interactions, even though the provision of online services have been implemented vigorously by the banking sector in recent years. As online hubs granting access to a huge amount of financial services, FinTech platforms could operate faster than commercial banks and they could reach a high number of customers very easily. However, FinTech's complete digitalization of the interactions with customers leads to a few drawbacks: the absence of in-place branches is associated to lower possibilities to access exclusive customer data which is typically collected by commercial banks from their deposits and lending book. Nevertheless, FinTech platforms' vast capacity in terms of big data largely compensates for this absence – and this holds especially for BigTech companies.

Second, while banks can accept demand deposits, FinTech platforms cannot. Furthermore, FinTech platforms, since they figure as "alternative credit markets", are not always subject to the same prudential regulations that commercial banks need to follow. This last element leaves room for several considerations, especially from a policy making perspective; the never-ending regulating task operated by international institutions is severely put to the test when challenging such a fast-paced evolution of the phenomenon, and in current days regulators are called to action in deciding upon which measures to undertake.

We can easily appreciate the rapid growth of the overall volume of FinTech credit through a representation by Claessens et al. (2018) (left panel of *Figure 4*). It's clear that Pacific-Asian countries hold the most relevant share of the global volume, followed at a huge distance by Latin American countries. In fact, evidences state that the development of FinTech activities, and more in general of alternative finance, has been more substantial in the Asia Pacific countries (APAC), with China playing as the main protagonist: in 2017 it accounted for 99% of the volume of alternative finance registered in the APAC, with a market of $358 billion (Cambridge Centre for Alternative Finance, 2018). However, if we take a look at the right panel of *Figure 4* we can notice that trends have somewhat changed since the last quarter of 2017: China's FinTech credit volumes have been steadily decreasing, while UK and Europe (UK excluded) experienced and increase in FinTech credit provision.

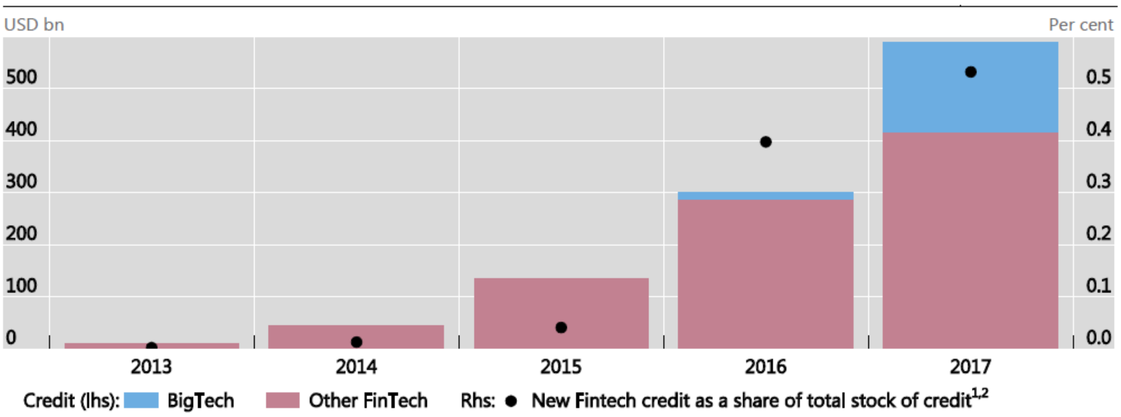
Figure 4: Dimensions of FinTech credit by region.



Source: Claessens et al. (2018).

Figure 5 highlights the evolution of FinTech credit, for the period 2013-2017, distinguishing between BigTech credit and other FinTech credit volumes. As we can derive from the picture, BigTech lending activity started to stand out in 2016 and exploded the subsequent year. In 2017, it accounted for almost a third of overall FinTech credit in terms of volume (almost $200 billion). Nonetheless, FinTech overall weight with respect to the total stock of credit is quite small; in 2017, FinTech newly issued credit was roughly 0.5% of total amount of credit.

Figure 5: Dimensions of FinTech vs. BigTech 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.

Source: Frost et al. (2019).

2.2. Operational structures.

To shed light more clearly on the evolution on FinTech credit among countries, we necessarily need to take a step further and dive deeper on FinTech platforms themselves, by analyzing their functioning.

Most commonly, FinTech platforms' operations in the credit activity are based on a peer-to-peer (P2P) system: they provide a low-cost standardized intermediation service between potential borrowers and potential investors (Claessens et al., 2018). Potential borrowers provide information about the projects they want to be financed and about their company's finance status; usually the online platform verifies this information, before proceeding. Then, potential investors kick in and decide to take the call of a potential borrower. When the matching between the counterparties is confirmed, a contract is automatically set up between them.

The online platform acts only as an intermediary in the process and therefore the investor takes on all potential risks and benefits of such contract. More often, investors cannot withdraw the money invested before a certain predetermined date, unless an outside buyer is found. Hence, some online platforms provide also a secondary market where investors can liquidate their investments to other potential buyers.

Online platforms, in this case, play the role of brokers for potential investors: they find out investment opportunities in return of ongoing fees. Platforms also keep the records, collect the repayments of the loans by the borrowers, distribute the cash-flow to investors and eventually manage the recovery of unmet obligations. Some of them, in order to smoothen the selection process of the investors, might also provide a ranking for the investment opportunities which helps to set interest rates properly.

Even though this is the most common type of FinTech platform, this is not the only way they can operate. These businesses vary greatly in structure, depending on the purpose and on the way transactions are managed. The Cambridge Centre for Alternative Finance (2019) provides a broad taxonomy of all the current profiles that alternative finance platforms adopt, as displayed in *Table 1*[14]. More particularly, it defines alternative finance models based on their basic functioning, their objective and the players who are involved.

Table 1: Alternative Finance platforms taxonomy.

P2P Consumer Lending	Individuals or institutional funders provide a loan to a consumer borrower.
Invoice Trading	Individuals or institutional funders purchase invoices or receivable notes from a business at a discount.
P2P Business Lending	Individuals or institutional funders provide a loan to a business borrower.
Real Estate Crowdfunding	Individuals or institutional funders provide equity or subordinated-debt financing for real estate.
Equity-based Crowdfunding	Individuals or institutional funders purchase equity issued by a company.
Reward-based Crowdfunding	Backers provide funding to individuals, projects or companies in exchange for nonmonetary rewards or products.
Balance Sheet Business Lending	The platform entity provides a loan directly to a business borrower.
Debt-based Securities	Individuals or institutional funders purchase debt-based securities, typically a bond or debenture at a fixed interest rate.

[14] This table is not intended to provide all the possible definitions for alternative finance platforms. Nonetheless, it gives a wide range of labels which can be easily applied to the vast majority of alternative finance activities operating at the current state of art.

P2P Property Lending	Individuals or institutional funders provide a loan secured against a property to a consumer or business borrower.
Donation-based Crowdfunding	Donors provide funding to individuals, projects or companies based on philanthropic or civic motivations with no expectation of monetary or material.
Minibonds	Individuals or institutions purchase securities from companies in the form of an unsecured retail bonds.
Profit Sharing	Individuals or institutions purchase securities from a company, such as shares or bonds, and share in the profits or royalties of the business.
Balance Sheet Consumer Lending	The platform entity provides a loan directly to a consumer borrower.

Source: Cambridge Centre for Alternative Finance (2019).

The popularity of these categories heavily depends on geographic areas. In Europe, during 2017, P2P Consumer Lending accounted for 41% of total European alternative finance volume, with a market of €1,392 million. Invoice Trading followed at a distance, accounting for 16% of total volume, which was worth €535 million. Following, we could find P2P Business Lending, with 14% of total volume – €466 million. The level of growth from 2016 to 2017 was substantial – but still heterogeneous - in all the three categories just mentioned: P2P Consumer Lending growth was 99.8%, Invoice Trading growth was 113% and P2P Business Lending growth was 33%.

If we take a closer look at Asian-Pacific countries, the analysis provides different results. In APAC countries – excluding China from the account - the most commonly diffused type of alternative finance platform in 2017 was again P2P Consumer Lending, accounting for 22.9% of total APAC alternative finance market, with a volume of $824 million. It was followed by Balance Sheet Business Lending, with a share of total market of 18.9% and a volume of $681 million. The third largest model was P2P Property Lending, with a share of 18.5% and a volume of $667 million.

Considering China alone, the most largely used type of platform in 2017 was, similarly to Europe and APAC, P2P Consumer Lending, with a share of 63% of total Chinese alternative finance market, and a volume worth $224 billion. The second largest model, P2P Business Lending, accounted for 27% of total market, with a volume of $97 billion. Finally, accounting for 4.4% of total market, we can find Balance Sheet Consumer Lending, which was worth $15 billion.

These evidences suggest that FinTech lending is mostly accessed by individuals, with SMEs playing a side role. This trend is also evident in EY (2019), which reports data regarding FinTech adoption rates (as defined in the previous Chapter) for consumers and for SMEs: while the adoption rate of consumers in 2019 was 64%, for SMEs it was 25%. However, SMEs are year by year increasingly joining FinTech ecosystems, attracted by the tailor-made instruments but more importantly by the relatively lower costs of financing with respect to traditional banking system.

Furthermore, as we can easily understand from *Table 1*, there's a significant distinction between P2P platforms and platforms operating directly through their own balance sheet. In the first case, FinTechs merely act as intermediaries connecting those who are looking for financing and those willing to invest; in the latter case, FinTechs operate lending on their own behalf, and therefore carry the credit risk themselves.

2.3. Credit to SMEs and individuals: evidences from APAC countries.

To better understand how FinTech credit is accessed and what is FinTech's credit relevance with respect to overall credit, I retrieved and elaborated data from the Cambridge Centre for Alternative Finance (CCAF) for the APAC region[15] during the period 2013-2017. Left panel of *Figure 6* depicts the ratio between the volume of FinTech loans to SMEs and the overall volume of credit[16] to SMEs – that is, the market share of FinTechs in the small businesses' credit sector; right panel represents the same ratio but referred to consumers. In both panels, yellow bars represent the fraction of credit provided by P2P FinTechs; red bars reflect the fraction of credit provided by FinTech platforms operating through their own balance sheet.

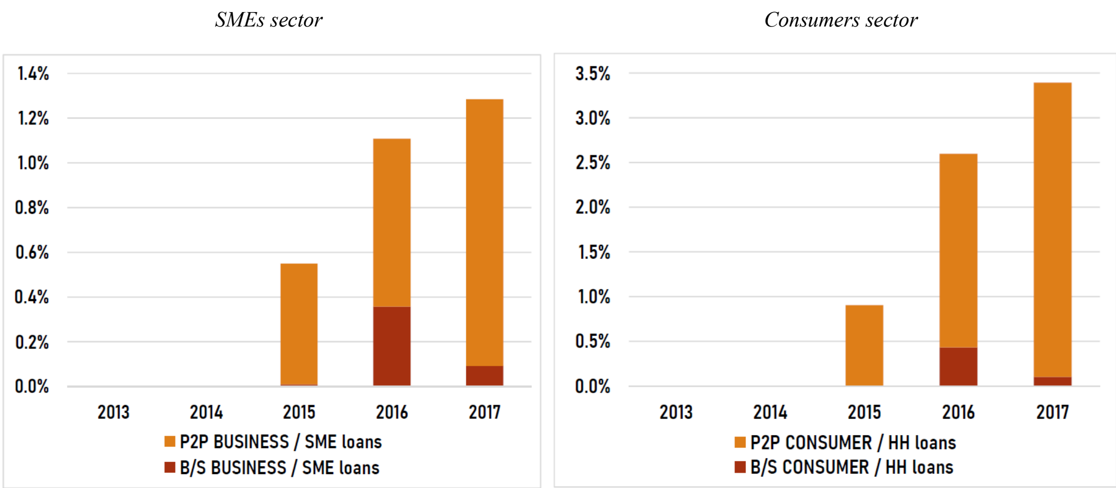
The first element we can notice is the quick growth of FinTech credit importance with respect to total credit since 2015; while during 2013 and 2014 the ratio is realized in a value so small to be very close to zero, in the timespan from 2015 to 2017 both sectors experienced sharply increasing FinTech lending. However, we can clearly see that the difference in shares

[15] Countries included in the calculations are Australia, China, Japan, India, Indonesia, Korea Republic, Malaysia, New Zealand.
[16] The overall credit volume, in both panels, is calculated as the sum of the numerator itself and loans provided by the banking system respectively to SMEs and consumers, as reported in IMF (2019).

between SMEs' credit and consumers' credit is quite substantial: in 2017 FinTechs accounted for almost 1.3% of all credit provided to SMEs in the APAC region, while, in the same year, they accounted for almost 3.5% of total consumers' lending.

Secondly, we can appreciate the huge distance in volumes between P2P systems and Balance Sheet ones. As I already mentioned early on in this paragraph, P2P platforms are by far the most widespread type of FinTech structure, and data on APAC region does nothing but stressing this point. In addition to that, we can see that from 2016 to 2017 the share of Balance Sheet platforms decreased dramatically, while the total share of FinTech credit, in both sectors, increased.

Figure 6: Market share of FinTech by lending sector (APAC countries).



Source: Cambridge Centre for Alternative Finance (2018), IMF (2019), my own calculations.

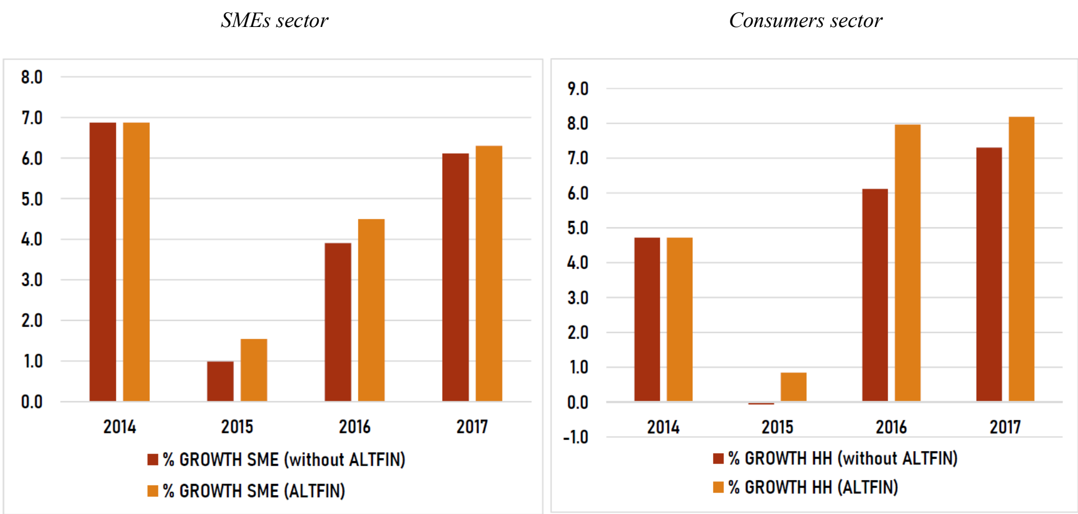
Figure 7 summarizes the growth rate of credit in the two sectors. Red bars represent the annual percentage change of credit volumes excluding alternative finance from the calculation; yellow bars, on the contrary, represent the annual percentage change of overall credit volumes, as a sum of banking loans and FinTech loans. Therefore, every year, the difference between the two represents the credit volume injected in the APAC economies by FinTech platforms. Once again, left panel refers to SMEs sector, while right panel refers to customers sector.

During 2014, in both panels we can notice no difference at all when considering credit volumes with and without taking into account FinTech credit; in fact, as we highlighted in *Figure 6*, FinTech lending volumes in years 2013 and 2014 were virtually zero, having almost an irrelevant impact in the economies' overall credit provision.

Nonetheless, the total lending volume was subject to a sharp growth during 2014; in the SMEs sector it increased by almost 7% and in the consumers sector by almost 5%.

During 2015, credit volumes' growth stopped dramatically; if we focus on households (the right panel) we can notice that the traditional banking system's credit provision didn't grow at all, but conversely it decreased. If we bring FinTech credit in the analysis, the growth of overall credit provision to consumers goes back to a positive value. This suggests how FinTech credit could represent a substitute to traditional lending in some economies, especially in circumstances where the supply side experiences negative shocks that result in lower loan provision. From *Figure 7* we can once again appreciate how, in general, FinTech credit impacts more substantially the households' sector. In 2016, the difference in growth of credit provision to consumers due to the presence of FinTechs is almost 2%; in 2017, it is roughly 1%.

Figure 7: Annual percentage growth of lending by sector (APAC countries).



Source: Cambridge Centre for Alternative Finance (2018), IMF (2019), my own calculations.

2.4. Policy issues.

In the context described so far, defining a regulatory environment for FinTech and BigTech activities is quite challenging. In fact, it is a key aspect of the current regulatory debate to understand how financial services regulation could facilitate an orderly adaptation of the industry's structure to a new environment characterized by new technologies, new players and new activities (Restroy, 2019). As I discussed in the previous Chapter, the growing activity of FinTechs and BigTechs in the financial sector entails both potential benefits and risks; policymakers might want to design a regulatory framework able to enhance the positive effects of alternative finance operations while minimizing the potential threats.

The challenges regulators face in regulating FinTech are two-folded. First, they need to identify those areas of the law dealing with each type of FinTech instrument or institution. Second, they need to establish whether regulation should be incrementally adapted to the various types of FinTech (Ferrarini, 2017).

To various extents, regulators are dealing with these challenges in different jurisdictions applying heterogeneous approaches. Nonetheless, when it comes to creating a regulatory environment for a complex subject such as FinTechs and BigTechs financial activities, one generalized and broadly well-recognized approach is "*same activity, same regulation*". In fact, regulators need to minimize the scope for regulatory arbitrage and loopholes; the "*same activity, same regulation*" pathway is often associated to sound policy to level a playing field and prevent regulatory arbitrage (Restroy, 2019).

The key thought is that all entities operating within a specific regulated activity should be subject to the same rules, regardless of their nature or legal status. When they are operating banking activity, for example, FinTechs and BigTechs should be rightfully subject to the same regulations that apply to banks. Accordingly, in most jurisdictions, regulators extended existing banking regulations to BigTechs, by including know-your-customer rules to prevent financial crimes (BIS, 2019), and to FinTechs, by applying liquidity coverage requirements such as 100% reserve for platforms operating in China and Brazil (Restroy, 2019).

However, the strict application of this approach could result in a poorly suited regulatory framework that doesn't take into account operations lying outside the scope of existing financial regulations. Focusing on BigTechs, for example, it's clear that their financial activities exist within a wider business portfolio which includes e-commerce, payment systems, lending and other activities. In this context, BigTechs could generate systemic risks, both due to their size and due to the interaction between operational risks generated by each activity.

The heterogeneity in FinTech and BigTech adoption and in regulatory purposes among countries consequently reflects, as already mentioned, in a heterogeneity of types of policy interventions that regulators have undertaken throughout last years. The Bank for International Settlements, in its *Annual Report* in 2019, usefully summarized recent policy interventions from different jurisdictions with a focus on BigTech activity, as portrayed in *Table 2*.

Types of regulators operating these interventions are categorized into three groups: financial regulators (blue dots), competition authorities (green dots) and data protection authorities (red dots).

To make a complete analysis on the BigTech regulatory framework and to better understand data hereafter described, the BIS (2019) provides the Table accompanied to a graphical representation – *Figure 8*.

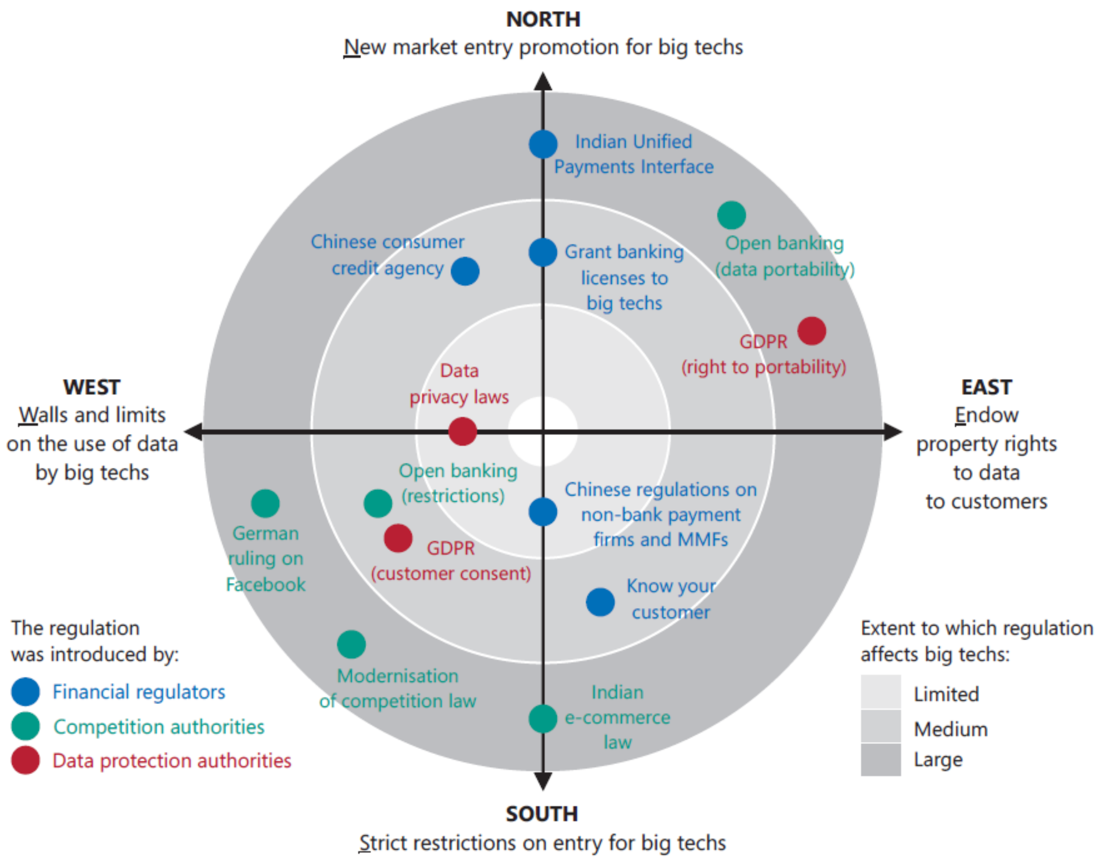
Table 2: Description of selected policy initiatives.

Type of policy intervention	*Countries/jurisdictions*	*Content*
• Unified Payments Interface (UPI)	India	The UPI was established by the Reserve Bank of India in April 2016. It is an instant real-time payment system that facilitates transfers of funds between two bank accounts on a mobile platform, to which all payment service providers have access.
• Granting banking licence to big techs	Hong Kong SAR, Korea, Luxembourg	Promotes competition across a wide range of (or all) banking services, while subjecting new entrants to strict regulations.
• Regulations on nonbank payment firms and MMFs	China	This set of regulations includes reserve requirements on customer balances in BigTechs' payment accounts ("float"), a requirement to channel payments through a state-owned clearing house (NetsUnion Clearing) and a cap on instant redemptions for all market mutual funds.
• Chinese consumer credit reporting agency (Baihang)	China	Baihang is a licensed consumer credit reporting platform which collects and stores personal credit information from its members and provides credit reports and ratings. It promotes competition by giving members access to relevant data, but also restricts the type and use of the collected data. It received its license from the People's Bank of China in January 2018.
• Know-your-customer (KYC) regulations	Various	Impose the same strict requirements on payment service providers as on banks. These include the collection of detailed information on customers regarding their identity and possible criminal intentions.
• Open banking	Australia (open banking), European Union (PSD2), United Kingdom (open banking), Mexico (fintech law)	The first open banking regulations came into force in 2018. This type of regulation requires financial firms to make their customers' financial transaction (or equivalent) data portable, i.e. directly transferable to third parties or competitors, typically through open APIs. The conditions under which data shall be shared are nonetheless restricted. Restrictions may be related to the type of data and participating institutions, customer consent or reciprocity.
• German ruling on Facebook	Germany	In February 2019, the German competition authority (Bundeskartellamt) prohibited Facebook from systematically combining user data from different sources (such as its other services WhatsApp and Instagram).
• Indian e-commerce law	India	In February 2019, a new e-commerce rule took effect that prohibits foreign e-commerce platforms from selling products supplied by affiliated companies on their Indian shopping sites.

• Modernisation of competition law	European Union, Germany, United Kingdom, United States	In March and April 2019, the German, EU and UK competition authorities received commissioned expert recommendations on how to sharpen their existing practices and methodologies for assessing anticompetitive conduct in digital markets. In the US, the Federal Trade Commission has recently been reported to examine potential anticompetitive conduct by BigTechs.
• Data privacy laws	Australia, California, China, European Union, India, Japan, Singapore, Switzerland	Data privacy laws (or adaptations thereof) typically require digital firms with access to personal data to inform their customers about the usage of their personal data. They started to be enacted in 2018.
• General Data Protection Regulation (GDPR)	European Union	The GDPR came into force in May 2018 and is one of the most comprehensive – and a precursor of – new data privacy laws being implemented. The regulation provides that customers have the right to receive their personal digital data in a structured and transferable way without hindrance. It also requires data holders to obtain their customers' active consent prior to using or sharing their personal data.

Source: BIS (2019).

Figure 8: A regulatory compass for BigTechs in finance.



Source: BIS (2019).

Figure 8 represents a compass which is composed by two axes. The North-South axis refers to the level of permissiveness of the financial regulatory initiatives regarding BigTechs: north indicates encouragement of new entry, while south reflects strict restrictions on entry.

On the contrary, the East-West axis focuses on data management regulations: the far east represents a decentralized approach that endows property rights over data to customers, while west indicates a restrictive approach placing walls and limits on BigTechs' use of such data.

Finally, the dots scattered through the compass represent the regulatory interventions that are displayed in *Table 2*, distinguishing among type of regulators.

Through the combination of *Table 2* and *Figure 8* we can draw some conclusion on the different approaches on the construction of a regulatory framework suitable for BigTechs, following BIS (2019) considerations.

The North-South axis of the compass represents the widely recognized partition in the two schools of thought on the entrance of BigTechs on financial activities. On the one hand, we have those who think that the entry of alternative finance platforms such as BigTechs is desirable for it improves competition and reduces market power of the incumbent banking sector. One example on this side is the development in India of the Unified Payments Interface giving mobile payment providers full access to the interbank payment system. On the other hand, we have those thinking that a less competitive banking sector is most wanted since it enhances financial stability. Yet, when talking about BigTechs, things are not that straightforward. In fact, when BigTech platforms enter a financial market, they are likely not to improve competition (as it would probably be the case for FinTechs); on the contrary, given their size, they could end up in reducing competitiveness and settle the ground for monopolistic behavior – especially if BigTechs' operations *outside* finance are intertwined with those of incumbent banking sector. The EU, India, United Kingdom and US, in this context, recently updated their rules for assessing anticompetitive behavior.

Contemporarily, in the East-West axis lies a relevant share of regulators' concern with respect to BigTechs' activity, that is data management issues. At the current state of art, data ownership is very rarely clearly assigned. In most cases, BigTechs and other online platforms managing customers' data are actually operating as the legitimate owners of such information, therefore freely being able to sell data to competitors. This uneven playing field with customers could partly be solved by assigning ownership fully to customers, which in turn decide whether or not to "sell" – or just hand – their information to a specific platform. However, this ideally perfectly competitive world where customers sell their information to the best bidder could backfire, resulting in the exact opposite of what it is intended to be. This could happen because

BigTechs value customers data *more* than the incumbent banking system does; therefore, they could use their size to impose themselves as best bidders, ending up in a less-competitive customers' data market. For this reason, a more suitable way to deal with this topic would be the introduction of proper limitations and additional rules to incentivize the creation of a level playing ground. In this context we can see the development of open banking regulations and of the General Data Protection Regulation from EU (in the compass, the correspondent dots on the eastside); both intend to facilitate greater market competitiveness, as they transfer data ownership from platforms to customers.

At the same time, regulators in some jurisdictions preferred to limit the scope of data sharing. In fact, not all customers' information is needed to provide effectively financial services, and not all types of providers should be granted full access to their customers' financial data. Both open banking regulations and the GDPR included these considerations among their set of rules (in the compass, the correspondent dots on the westside). On the far west we can find the German case, which constitutes the more extreme application of such limitations; Germany's competition authority prohibited Facebook from combining its user data with those collected from affiliated websites and applications.

To conclude, it's far too soon to be able to assess the effectiveness of recent interventions on BigTechs and FinTechs. The heterogeneity in the approaches reflects economics as well as society's preferences, especially in terms of privacy. However, a broadening of perspectives will be essential to make considered policy choices in this area (BIS, 2019).

2.5. Literature review.

Academic literature on FinTech and BigTech – and especially on their lending activity – is continuously expanding. FinTech and BigTech increasing activity in financial markets attracted the attention of regulators and academic literature during the last few years. In this paragraph I will briefly go through some of the most relevant publications, covering FinTech and BigTech credit, at the current state of art.

Claessens et al. (2018) studied the fundamentals of FinTech platforms, unfolding their structure and trying to understand the main forces driving FinTech adoption. In their cross-country analysis, the authors test a model which describes FinTech volume as a function of many different elements, such as GDP, the level of competitiveness of incumbent banking network and the stringency of regulatory system. They conclude that FinTech credit seems to be associated with countries having an overall developed economic system, where the regulatory environment is more permissive, and the incumbent banking system is less competitive.

FinTech credit adoption is, however, uneven among countries around the world. Frost (2020) brought to light some recent evidences on FinTech credit volumes for several economies, trying to explore more deeply what are the causes of such a different level of adoption. He found that there may be greater incentives for FinTech adoption where banking sectors are relatively uncompetitive and hence more profitable, and where regulation is less tight (as already highlighted by Claessens et al., 2018). In addition to that, he brought evidences on a wider FinTech adoption in jurisdiction composed by younger cohorts, where trust on technology is more evident: population ageing and changes in trust in technology and FinTech may have important effects, shaping not just the extent but the future direction of FinTech adoption.

Claessens et al. (2019) work has been further developed by Frost et al. (2019), which contributed significantly in the studies regarding FinTech credit by collecting information on BigTech credit volumes. They discovered that BigTech credit is driven by elements similar to those pointed out by Claessens et al. (2018), even though BigTech activities seem to be more sensitive than FinTech to changes in regulation and in the level of banks' branches density among countries.

In their focus on BigTech credit, they investigated also other key elements: the assessment of credit risk and the potential increase in firms' offered products due to the underwriting of a credit line. Through an analysis of data from Mercado Libre, Argentina's most popular e-commerce platform, and from the Chinese Ant Financial they came to very important conclusions. First, BigTech lenders have an information advantage in credit scoring, relative to traditional credit bureau, thanks to the application of machine-learning methods which allow more precise evaluation of insolvency risk. Second, BigTech credit can support firms' sales and supply of online products by opening a credit line with firms registered in e-commerce platforms.

The relationship between FinTech credit and SMEs' sales performance was analyzed, from another perspective, also by Chen et al. (2019). They recovered data on firms' sales from Ant Financial and studied how FinTech credit affects volatility in revenues. Their findings point out that FinTech credit access significantly reduces firms' sales volatility, improving stability in revenues. Furthermore, they conclude that the negative effect on firms' volatility in more concentrated in firms that are young, which operate in regions with lower economic growth, poorer legal environment, and in more competitive industries. In addition to that, the authors investigated the relationship between FinTech lending and firms' exit probability in the future, finding that FinTech credit significantly reduces firms' bankruptcy risk.

FinTechs and BigTechs promote inclusivity and a broader financial accessibility to individuals and SMEs. Barlett et al. (2019) study whether FinTech credit promotes or inhibits credit discrimination among individuals, too. Using a dataset including information at the loan level on income, race, ethnicity, loan-to-value and other related elements, they investigate discrimination in mortgage loan pricing, focusing primarily on the interest rates charged and on the probability of rejection in USA. In terms of pricing, they found that FinTech lenders discriminate roughly one third less than conventional lenders; the algorithmic credit scoring and the absence of direct, face-to-face interactions could help in improving a more equal environment in assessing loans' rates. In terms of accepting or rejecting the underwriting of a credit line, their findings suggest that FinTech platforms are operating no discrimination at all among individuals.

This topic is covered, from another standpoint, by Philippon (2020). In his research, the author first analyzes the changes in financial intermediation, finding that the unit cost of financial intermediation has been declining for the last ten years. Then he investigates access to finance and discrimination, focusing on two elements: the returns to scale brought by technology and the use of machine learning and big data. Through the development of a model of imperfect competition in asset management services, he pointed out that FinTechs, by lowering the fixed cost per relationship with consumers, allows more households to benefit from advisory services – in the FinTech context, robo-advisory. FinTech therefore effectively increases participation leading to potential benefits for minorities. However, it does not necessarily reduce inequality among all income levels, and it could create new regulatory issues.

Hau et al. (2019) come to similar conclusions analyzing FinTech lending to small firms in China. The authors created a model to analyze whether FinTech credit expands the extensive margin of credit borrowers of lower credit scores and if it faces a more intensive use of its credit lines from borrowers with lower credit scores. They therefore confronted the theoretical results of the model with evidences from Ant Financial. Through their analysis, they point out – once again – that FinTech credit generally contributes to a more inclusive financial system which creates credit access for borrowers excluded from traditional bank credit. In addition to that, the authors highlight that the benefit of FinTech credit might be largest in emerging markets – like China – with underdeveloped credit markets.

As I stressed in several occasions during the unfolding of the analysis, China is certainly the primary hub for alternative finance operations. It represents by far the most important player with respect to FinTech and BigTech volumes, payments, lending and insurance services. Therefore, it comes by no surprise that several authors, in the academic literature, decided to dive more deeply in the relationship between China and FinTech.

Chen (2016) explored this relationship starting from a broad analysis of FinTech development in China; the author portrayed the Chinese success of FinTech as a function of a technological environment highly integrated with individuals' everyday life and capable to answer to real-life needs.

Xie et al. (2016) discussed the theoretical pillars, core features and policy implications of internet finance, both from a general perspective and from the Chinese standpoint – as partly discussed in Chapter 1. They bring into light evidences showing how FinTech benefits from its activity in China by providing services at a lower price to a huge mass of customers, especially in rural and lower-tier cities; this operation enables FinTechs to access higher returns. In addition to that, they analyze the ecosystem of incumbent banking sector; their findings highlight how the low-efficiency and the distorted China's financial system created room for alternative finance, starting from excessive margins, low accessibility from rural areas and other structural elements; similar findings can be found also in Hau et al. (2019).

Finally, an important contribution to literature with respect to FinTech development is provided by the work from the Cambridge Centre for Alternative Finance[17] (CCAF). The CCAF is a research department of the University of Cambridge's Judge Business School, which studies the impact of financial innovation on regional economic development, asset pricing, corporate finance, trust, reputation, consumer behavior and many other aspects of a country's economy. The CCAF, among its many activities, tracks year by year evolution of FinTech on a regional level, collecting data on volumes, regulatory environment development, market dynamics and individuals' approach to alternative finance. It therefore constitutes an important foundation for FinTech-related studies as a cross-sectional data provider.

[17] For further information: https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/.

CHAPTER 3. MODELS AND SPECIFICATION

3.1. The econometric models.

This section briefly summarizes the main characteristics of the econometric models, other than OLS, that will be used to perform the analysis.

3.1.1. Logit and Probit models.

When we want to evaluate a regression for limited dependent variables, the first and simplest approach we could use is the Linear Probability Model (LPM). This type of regression implies the direct use of OLS to retrieve the values of the parameters of interest.

The main advantage of LPM is that it is easy to use, since it does not introduce any specific instrument to account for the binary nature of the dependent variable. Moreover, the analysis benefits from the fact that OLS parameters are unbiased and consistent.

However, by using LPM we incur in heteroskedasticity[18]. Therefore, to make computations we need to use robust standard errors; otherwise, we suffer the risk of underestimating the parameters.

On the one hand, the LPM is a quick and easy method to describe the data, but on the other hand it presents several limitations:

1. Fitted probability values could end up being less than zero and more than one; this makes no mathematical sense and could bring to misleading interpretations of results.

2. Partial effects of any explanatory variable appearing in level form is constant; however, nonlinearity could better represent data.

3. Errors are not normally distributed.

[18] In particular, if we assume $\mathbf{E}(e|\boldsymbol{x}) = 0$, we can demonstrate the presence of heteroskedasticity by computing the following: $var(e|\boldsymbol{x}) = \mathbf{E}(e^2|\boldsymbol{x}) = \mathbf{E}((y - \boldsymbol{x\beta})^2|\boldsymbol{x}) = (0 - \boldsymbol{x\beta})^2(1 - \boldsymbol{x\beta}) + (1 - \boldsymbol{x\beta})^2 = \boldsymbol{x\beta}(1 - \boldsymbol{x\beta})$.

In order to overcome such problems, we could introduce into our analysis binary response models. To describe the models I use to perform the analyses, I will largely refer to Woolridge (2013) and to Stock et al. (2016).

When we use binary response models, we're interested in the so-called *response probability*, defined as:

$$\mathrm{P}(y = 1|\boldsymbol{x}) = \mathrm{P}(y = 1|x_1, x_2, \dots, x_k) \ ,$$

where $\boldsymbol{x}$ represents the full set of explanatory variables in vector notation, P(.) represents probability and $x_1, x_2, \dots, x_k$ are the regressors used in the analysis.

Since $y|\boldsymbol{x}$ follows a Bernoulli distribution, we can write:

$$\begin{aligned} \mathbf{E}(y|\boldsymbol{x}) &= 1\ \mathrm{P}(y = 1|\boldsymbol{x}) + 0\ \mathrm{P}(y = 0|\boldsymbol{x}) \\ &= \mathrm{P}(y = 1|\boldsymbol{x}) \ . \end{aligned}$$

Hence, to study the conditional expectation of *y* given the set of regressors we need to analyze the response probability. We consider a class of binary response models of the form:

$$\mathrm{P}(y = 1|\boldsymbol{x}) = G(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k) = G(\beta_0 + \boldsymbol{x\beta}) \ ,$$

where *G* is a function taking on values: $0 < G(z) < 1$, and $\boldsymbol{\beta}$ represents the full set of parameters expressed in vector notation. To simplify the notation, we can incorporate the intercept β_0 into $\boldsymbol{x\beta}$.

Various nonlinear functions have been suggested for the function *G* to make sure probabilities are between zero and one. We will consider here the two most popular functions: the logistic function for *logit* models and standard normal cumulative distribution function (cdf) for *probit* models. In fact, when the function *G* takes the shape of a cdf we are sure that the predicted conditional probabilities lie in the interval between zero and one.

The two functions are described as follows:

1. Logit:

$$G(z) = \frac{e^z}{1+e^z} = \Lambda(z) \; ;$$

2. Probit:

$$G(z) = \mathbf{\Phi}(z) = \int_{-\infty}^{z} \Phi\,(v)dv \; .$$

where $\Phi(z) = \frac{1}{\sqrt{2\pi}} e^{\frac{-z}{2}}$ (the standard normal density).

In contrast to the LPM, with the logit and probit models it is not possible to interpret the estimated parameters as marginal effects. Still, it is our interest to evaluate such marginal effects, that represent the effect on the conditional probability $\mathrm{P}(y = 1|\boldsymbol{x})$ of a change in value of a particular regressor x_j, where $x_1, x_2, \ldots, x_j, \ldots, x_k$. For sake of simplicity, I will refer to $\mathrm{P}(y = 1|\boldsymbol{x})$ as p and to $\mathrm{P}(y = 0|\boldsymbol{x})$ as 1-p.

In the linear model, the marginal effect of a regressor x_j is simply provided by β_j. In binary response models, the computation of marginal effects is quite a bit more complicated, and has different structures depending on the nature of the regressor x_j.

When x_j is a continuous regressor, the marginal effect is the variation in p due to a unit increase in x_j keeping other regressors as fixed. We can represent it as follows:

$$\frac{\partial p}{\partial x_j} = \frac{\partial \mathrm{P}(y = 1|\boldsymbol{x})}{\partial x_j} = G'(\boldsymbol{x\beta})\beta_j \; ,$$

where G' denotes the first derivative of G with respect to x_j. Therefore, the marginal effect is not simply β_j, but it is the product of β_j with the first derivative of the nonlinear function.

When instead x_j is a binary variable, the marginal effect is given by:

$$\frac{\partial p}{\partial x_j} = \mathrm{P}(y = 1|x_1, x_2, \ldots, 1, \ldots, x_k) - \mathrm{P}(y = 1|x_1, x_2, \ldots, 0, \ldots, x_k)$$

$$= G(\beta_0 + \beta_1 x_1 + \ldots + \beta_j + \ldots + \beta_k x_k) - G(\beta_0 + \beta_1 x_1 + \ldots + 0 + \ldots + \beta_k x_k) \; ,$$

where x_j is equal to one in the first element on the right-hand side, and it is equal to zero in the second element.

Finally, we could compute the marginal effect when x_j is a discrete variable:

$$\frac{\partial p}{\partial x_j} = G(\beta_0 + \beta_1 x_1 + \ldots + \beta_j(c+1) + \ldots + \beta_k x_k) - G(\beta_0 + \beta_1 x_1 + \ldots + \beta_j c + \ldots + \beta_k x_k) \, ,$$

where c is a given discrete value attributed to x_j.

At this point, we can compute the marginal effect of x_j in the probit and logit models:

1. Logit:

$$\frac{\partial p}{\partial x_j} = \Lambda(\boldsymbol{x\beta})\big(1 - \Lambda(\boldsymbol{x\beta})\big)\beta_j$$

$$= \left(\frac{e^{\boldsymbol{x\beta}}}{1+e^{\boldsymbol{x\beta}}}\right)\left(1 - \frac{e^{\boldsymbol{x\beta}}}{1+e^{\boldsymbol{x\beta}}}\right)\beta_j \; ;$$

2. Probit:

$$\frac{\partial p}{\partial x_j} = \Phi(\boldsymbol{x\beta})\beta_j \; .$$

Given that both $\Lambda(\boldsymbol{x\beta})$ and $\Phi(\boldsymbol{x\beta})$ are positive, the sign of the partial effect is the sign of β_j; this implies that the sign of the coefficient is informative on the direction of the marginal effect. We cannot say the same about the magnitude of coefficients. In fact, logit and probit estimates are not directly comparable to OLS estimates. Some rules of thumb are commonly used in practice to make comparisons between probit, logit and OLS estimates[19].

The marginal effect depends on all the $\boldsymbol{x}$ regressors. This implies that the effect of a regressor on the dependent variable, all other things being equal, is not constant: a change in value of regressor x_j from $x_j - \epsilon$ to x_j has a different effect on p compared to a change in value from x_j to $x_j + \epsilon$.

3.1.2. Conditional Maximum Likelihood estimator.

The estimator to get the parameters of a binomial model such as probit and logit relies on specific assumptions on the full distribution of y given $\boldsymbol{x}$.

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[19] The following relationships are commonly used to compare estimates across different model specifications: $\hat{\beta}_{logit} \approx 4\hat{\beta}_{OLS}$; $\hat{\beta}_{probit} \approx 2.5\hat{\beta}_{OLS}$; $\hat{\beta}_{logit} \approx 1.6\hat{\beta}_{probit}$.

Suppose we do not know what the data generating process is. We define the unknown conditional density of the data generating process as $p_0(y|\boldsymbol{x})$. We want to find a function that describes the data generating process as closely as possible. A good candidate to this task is a model $f(y|\boldsymbol{x};\boldsymbol{\beta})$ satisfying the condition:

$$\int_{\gamma}^{+\infty} f(y|\boldsymbol{x};\boldsymbol{\beta})v(dy) = 1 \qquad \forall \boldsymbol{x} \in X \, ,$$

where γ and X are the supports of y and $\boldsymbol{x}$ respectively, $v(dy)$ is a measure that allows y to be continuous, discrete or a mixture of the two, and finally $\boldsymbol{\beta}$ represents the vector of parameters of interest. This expression essentially imposes that the function we are using is a density function. We should always keep in mind that the objective we are pursuing is finding the estimates for βs.

The model we use is therefore specified correctly if the following condition holds true at least for some β_j:

$$f(y|\boldsymbol{x};\beta_j) = p_0(y|\boldsymbol{x})$$

where β_j represents the true value of the j-th parameter.

The joint density of a sample, under i.i.d. observations for the i-th individual $(y_i, \boldsymbol{x}_i)$, is represented by:

$$f(y_1, y_2, \dots, y_n|\boldsymbol{x};\boldsymbol{\beta}) = \prod_{i=1}^{n} f(y_i|\boldsymbol{x}_i;\boldsymbol{\beta})$$

If we consider this last expression as a random function of the parameters $\boldsymbol{\beta}$ where y_i and $\boldsymbol{x}_i$ are the observed sample data, we define the *conditional likelihood function* and the *conditional log-likelihood function*:

3. Conditional likelihood function

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{n} f(y_i|\boldsymbol{x}_i;\boldsymbol{\beta})$$

4. Conditional log-likelihood function

$$l(\boldsymbol{\beta}) = \sum_{i=1}^{n} \log f(y_i|\boldsymbol{x}_i; \boldsymbol{\beta}) = \sum_{i=1}^{n} l_i(\boldsymbol{\beta})$$

where $l_i(\boldsymbol{\beta}) = \log f(y_i|\boldsymbol{x}_i; \boldsymbol{\beta})$.

After defining these measures, we can describe the *conditional maximum likelihood estimator* (CMLE) as the solution to the maximization problem:

$$\max_{\boldsymbol{\beta}} \frac{1}{n} l(\boldsymbol{\beta}) = \frac{1}{n}\sum_{i=1}^{n} l_i(\boldsymbol{\beta})$$

$$F.O.C.: \quad \frac{1}{n}\frac{\partial l(\boldsymbol{\beta})}{\boldsymbol{\beta}} = \mathbf{0}$$

In the case of probit and logit, the conditional density assumes the form[20]:

$$f(y_i|\boldsymbol{x}_i; \boldsymbol{\beta}) = G(\boldsymbol{x}_i\boldsymbol{\beta})^{y_i}(1 - G(\boldsymbol{x}_i\boldsymbol{\beta}))^{(1-y_i)}$$

where *G* describes the nonlinear functions above specified.
Therefore, the following specifications can be defined:

5. Conditional likelihood function

$$L(\boldsymbol{\beta}) = f(y_1, y_2, \dots, y_n|\boldsymbol{x}; \boldsymbol{\beta}) = \prod_{i=1}^{n} G(\boldsymbol{x}_i\boldsymbol{\beta})^{y_i}(1 - G(\boldsymbol{x}_i\boldsymbol{\beta}))^{(1-y_i)}$$

6. Conditional log-likelihood function

$$l(\boldsymbol{\beta}) = \sum_{i=1}^{n} (y_i) \log G(\boldsymbol{x}_i\boldsymbol{\beta}) \, (1 - y_i) \log(1 - G(\boldsymbol{x}_i\boldsymbol{\beta}))$$

The CLME estimator does not provide a closed-form solution for retrieving $\widehat{\boldsymbol{\beta}}$. However, thanks to modern softwares, we can easily apply iterative methods that allow to solve the maximization problem. In addition to that, the nonlinear nature of the models makes statistical theory for probit and logit much more difficult than OLS; nevertheless, under very general

[20] If y is distributed as a Bernoulli with probability P(y = 1|$\boldsymbol{x}$) = p_i, the conditional density is given by: ${p_i}^{y_i}(1 - p_i)^{(1-y_i)}$.

conditions, the general theory for CMLE for random samples implies that CMLE is consistent, asymptotically normal and asymptotically efficient.

3.2. Dataset and Variables.

As already highlighted in the Introduction, the main objective of the analysis is to understand:

7. What causes heterogeneity in FinTech and BigTech credit adoption among different countries?
8. Why are some countries more likely to host BigTech credit activities, rather than FinTech credit ones?

As a matter of fact, these questions are not new to financial literature. Claessens et al. (2018), for example, investigate the drivers of FinTech credit using data from the Cambridge Centre for Alternative Finance; however, the analysis considers FinTech credit not including BigTech in the calculations. Frost et al. (2019) expand the analysis of Claessens et al. (2018) adding information on BigTech credit.

Starting from these studies, I construct different specifications including in the analysis some added explanatory variables, with the intent of bringing new results and economic interpretations to light.

The database I built to perform the analysis is composed of data retrieved from different sources. The construction started from a groundwork built on data recovered thanks to the cooperation of the Bank for International Settlements. More precisely, I was able to work with the same data used in Chapter 3 of *"BigTech and the changing structure of financial intermediation"*, the *BIS Working Paper No 779* by Frost et al. (2019). From the starting point of this dataset I added several variables of interest, as it will be specified below.

The original BIS data is organized in a cross-sectional dataset which comprises information for 64 countries[21]; among them, 15 are currently known to host BigTech credit activities.

[21] In particular: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Burkina Faso, Burundi, Chile, China, Colombia, Denmark, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Germany, Ghana, Guatemala, India, Indonesia, Ireland, Israel, Italy, Jordan, Kenya, Korea Republic, Latvia, Lebanon, Lithuania, Madagascar, Malawi, Malaysia, Mali, Mexico, Mozambique, Netherlands, New Zealand, Nigeria, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Russian Federation, Senegal, Sierra Leone, Slovak Republic, Slovenia, South Africa, Spain, Switzerland, Tanzania, Thailand, Togo, Turkey, Uganda, United Arab Emirates, United Kingdom, United States, Uruguay.

Unfortunately, due to data accessibility constraints, in considering added variables I dropped some observations among those originally included in the BIS dataset. The total number of observations effectively used in the analysis is therefore 60[22].

The structure of the final dataset is very similar to the BIS dataset, since added variables are mostly observed for the same countries and for the same period of time (2013-2017). Dealing mostly with structural explanatory variables, hence not hugely affected by changes in value over years, when latest data was not available, I used most recent retrievable observations.

In this paragraph I proceed with a closeup description of the variables comprised in the complete dataset, distinguishing between those used as dependent variables and those used as explanatory variables. When not otherwise specified, the source is to be considered Frost et al. (2019).

3.2.1. Dependent variables.

- *FinTech and BigTech credit volumes*

This category comprises four different dependent variables: *FinTech credit per capita*, *BigTech credit per capita*, *FinTech&BigTech credit per capita*, and *BigTech credit share of total credit*. They all share similar characteristics: they are expressed in log-values and they are observed in 2017. With the exception of *BigTech credit share of total credit*, which is the log-value of a percentage, all other variables are log-values of US dollars.

As we already specified in Chapter 1, "FinTech" is a broad category which incorporates also BigTechs. However, in most publications, when authors refer to FinTech they are not including BigTech – mainly because of data availability issues. The additional step of including BigTech in the picture was taken by Frost et al. (2019).

FinTech&BigTech credit per capita represents the log of total FinTech credit volume per capita in given country *plus* the BigTech credit volume per capita.

BigTech credit per capita trivially represents the log of volume of FinTech credit per capita attributable exclusively to BigTech activities in given country. It follows that only if in given country BigTech credit is provided then we can observe level values different from zero. In particular, since this is the case only for 15 countries, for the rest of observations the level value

[22] Data regarding some of the added variables was unavailable for Burundi, Mozambique, Paraguay and Togo.

of BigTech credit per capita has to be equal to zero. However, data on this variable is reported in log-values. Since it would be mathematically impossible to apply a logarithm to zero, level values which should be zero are set to a predetermined positive value, very close to zero; then log-values are calculated[23].

FinTech credit per capita describes the log of volume of FinTech credit per capita *excluding* BigTech from calculations.

Finally, *BigTech credit share of total credit* expresses the log of BigTech credit per unit of total credit in given country. This last element is computed by Frost et al. (2019) as the sum of total FinTech credit and total credit to the non-financial sector in given country. In other words, it represents the credit market share of BigTechs.

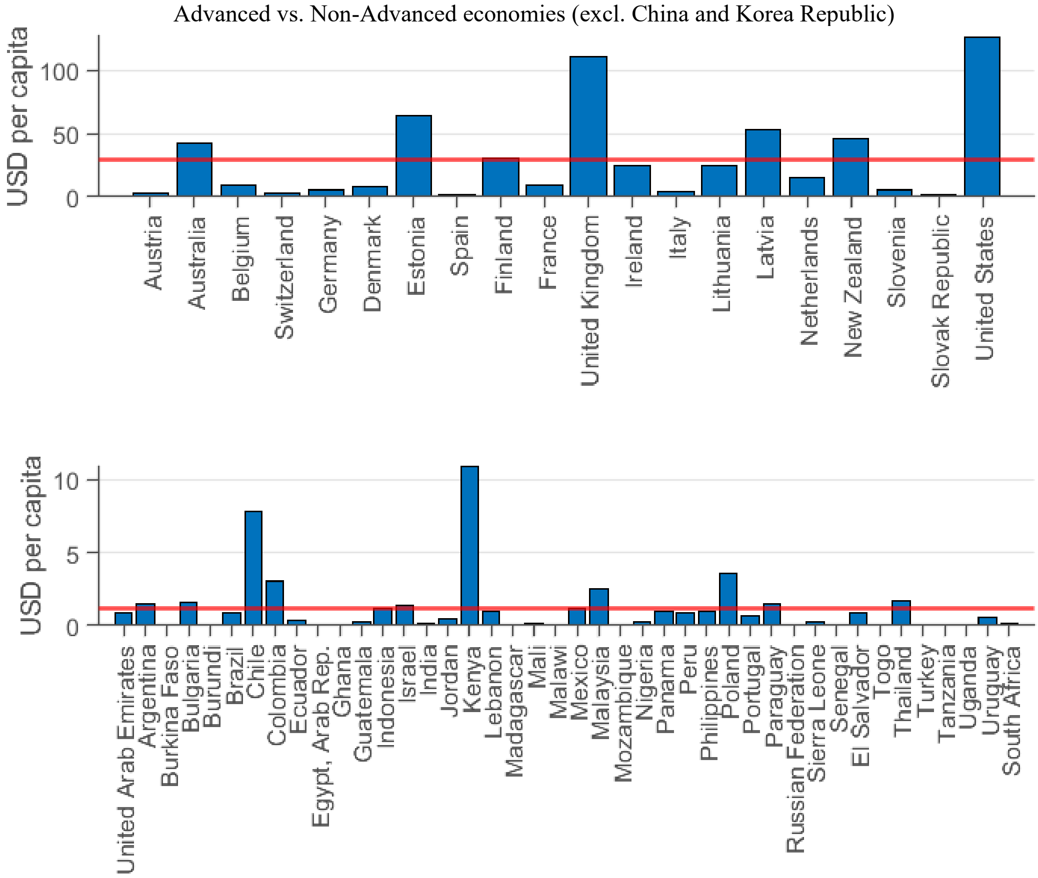
A preliminary analysis of FinTech credit volumes per capita allows to identify differences in adoption both between advanced and non-advanced countries and among geographic areas. In this early-stage step I will focus primarily on the variable representing the sum of all FinTech and BigTech credit activities. The upper panel in *Figure 9* represents the level of FinTech&BigTech credit per capita in the group of countries in the dataset considered as advanced economies; the lower panel, consequently, depicts values observed in non-advanced economies. The red horizontal line is set at correspondent mean value. For advanced economies the mean corresponds roughly to 13.5$ per capita; for non-advanced economies the same calculation leads to an average of less than half a dollar per capita.

However, non-advanced economies are characterized by much more heterogeneous levels of FinTech credit compared to advanced ones. Most countries' values lie below $2 per capita; on the contrary, a few countries stand out for higher levels of FinTech credit per capita: for example, Kenya with 10.98$ per capita and Chile with 7.79$ per capita.

Even if they are comprised in the non-advanced group, China and Korea Republic's data are not represented in the graph, since they surpass other non-advanced countries' volumes by far: China once again proves to be the leading country in terms of FinTech volume, with 372.28$ per capita, followed with a significant distance by Korea Republic with 115.56$ per capita.

[23] In the BIS dataset values are expressed as logarithm; the log-value for countries in which BigTech credit is not provided is equal to -7.18303. If we apply the inverse function, we can derive the level values: $e^{-7.18303} = 0.00076$. This means that in a country with absence of BigTech credit it would be attributed 0.00076$ of BigTech lending to each individual - which can be easily approximated to zero.

Figure 9: FinTech&BigTech credit per capita:
Advanced vs. Non-Advanced economies (excl. China and Korea Republic)



Source: BIS, my own calculations.

Grouping countries by geographic areas provides a different perspective; among continents, Oceania (including, in our case, only New Zealand and Australia) has by far the highest average level of FinTech credit per capita, with 43.82$ for each individual; it's followed by Europe with 7.78$ per capita, America with 1.59$ per capita, Asia with 1.22$ per capita and finally Africa with 0.09$ per capita.

- *BigTech dummy*

This is a dummy variable which takes value one if BigTech credit was extended in given country up to 2017, zero otherwise. In my analysis I both want to understand how several factors affect the probability that BigTech credit is provided and the effect of being in a country where BigTech credit is present on FinTech credit volumes. In the first case, I will consider *BigTech dummy* as a dependent variable – using models such as LPM, probit and logit to estimate the parameters – and in the second case I use this variable as a regressor among the explanatory variables.

3.2.2. Explanatory variables.

- *GDP per capita*

One of the most important macroeconomic measures of development and wealth in a country is undoubtedly given by gross domestic product. Therefore, it would be useful to understand the impact of such a relevant aspect of economic development in a country on the dependent variables above depicted, given a different set of explanatory variables with respect to Frost et al. (2019). Data on GDP is expressed as an average for the period 2013-2016 and it's measured in USD thousands. Values have also been double-checked by retrieving information on GDP from the World Economic Outlook (WEO) published by the International Monetary Fund (IMF) in 2019. In our dataset, the average value is \$21.14 thousands, and the standard deviation is \$16.46 thousands.

As suggested by both Frost et al. (2019) and Claessens et al. (2018), I will include in the analysis the square term of GDP per capita to account for possible nonlinearity.

- *Lerner Index*

Another key aspect to consider is competitiveness of the incumbent banking sector. The Lerner Index, in this case, captures the banking sector mark-up as an average of the period 2010-2015, and reflects the market power of incumbent financial institutions. In its general form, introduced by Lerner (1934), the Lerner Index can be described as:

$$LI = \frac{P - MC}{P}$$

where *P* is the market price set by a given firm and *MC* the marginal cost it has to cover. We can translate the ratio in banking sector terms by considering *P* as the interest rate charged by a given bank – or the average interest rate charged by a group of banks – on loans. The index generally ranges between zero and one. Zero corresponds to a perfect competition scenario in which $MC=P$ and therefore $L=0$; incumbent banks have no market power. One, on the contrary, corresponds to the very abstract scenario in which $MC=0$. Values in between reflect an oligopolistic or monopolistic scenario, in which $P>MC$ and $L>0$. In our case, the BIS dataset comprises also observations with negative values; this implies a situation in which $P<MC$, and

therefore banks are charging interest rates lower than the marginal costs. The mean value for this variable, in our dataset, is 0.267, with a standard deviation of 0.1308.

- *Incumbent Banking sector penetration*

The BIS dataset includes a variable that controls for another aspect of incumbent banking sector, that is the density of physical banks' branches; it represents the number of branches per 100,000 adults in a country as an average of period 2010-2015. The mean value in our dataset is 22.56 branches per 100,000 adults, with standard deviation of 23.37 branches. This variable would capture both the reach of the incumbent banking network in given country and its relative cost base.

- *Regulatory Stringency Index*

A measure of the stringency of regulatory framework concerning financial activities should be included in the picture. The Regulatory Stringency Index was introduced by Navaretti et al. (2017) as a measure of the sensitivity of the regulatory system to banks' risk-taking. For the construction of the index, the authors used 18 indicators from the World Bank's *Bank Regulation and Supervision Survey*, which periodically provides information on many aspects of regulation and supervision of the banking system. In the survey, most questions allow a yes-no answer; authors therefore collected information regarding the indicators of interest and then normalized the resulting measure so that the index ranges between zero and one. Zero represents a country whose banking system is characterized by very low stringency; one represents a country whose banking system is tightly regulated. In our dataset, the variable is characterized by a mean value of 0.74, with standard deviation 0.086.

- *Advanced Economies dummy*

As we already unfolded in describing dependent variables, there's a heterogeneity in the usage of FinTech credit among countries. Advanced economies seem to be more attractive for FinTech credit rather than non-advanced ones, while the opposite seems to hold true for BigTech credit. Therefore, it is important to include in the analysis a dummy variable which takes on value one if given country is an advanced economy, and zero otherwise. The composition of the two groups of countries is the same expressed in *Figure 9*, with China and Korea Republic included in the non-advanced group.

- *Mobile phones penetration*

The usage of FinTech and BigTech services is directly associated to the availability of internet connection and devices which enable to interact within online platforms. Currently, one of the most common tools to navigate online are smartphones. This variable reflects the number of mobile phones per 100 people in given country, with observations retrieved in 2016. In the dataset, the mean is 114.14 mobile phones per 100 population, with standard deviation of 32.83.

Explanatory variables described up to now are incorporated in the BIS dataset by Frost et al. (2019), as well as in the specification studied by Claessens et al. (2018). Therefore, by checking the results of these publications we can already guess what impact, in terms of sign and magnitude of correspondent parameters, we should expect these variables to have in the analysis. However, since I am bringing new information into play by adding new variables, I am interested in verifying whether or not the results highlighted by authors hold also with a different specification and, in the negative case, where the differences lie.

The newly added regressors are below specified.

- *Education Index*

Education is an important element which is correlated with households' level of income and choices in terms of financial assets management. In addition to that, it is also a major component used to measure economic development and quality of life. Hence, I want to study what correlation there is between a measure of the level of education within a country and the provision of FinTech and BigTech credit.

The variable that I use as an indicator of the level of education is the Education Index, as it is described in the UNDP's *Human Development Report 2019*. The Report aims to the construction of the Human Development Index, which combines information on income, education and life expectancy in several countries. The Education Index is calculated as follows:

$$EI = \frac{MYSI + EYSI}{2} \qquad MYSI = \frac{MYS}{15} \qquad EYSI = \frac{EYS}{12}$$

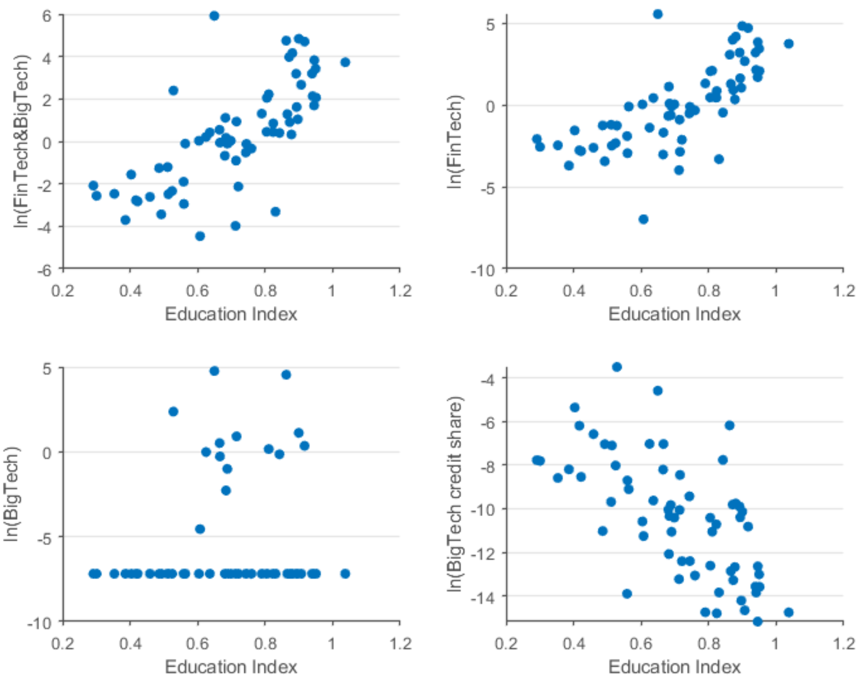
1. *MYSI* stands for *Mean Years of Schooling Index*, and it's the ratio between the average number of years of education received by people of age 25 and older (*MYS*)

– converted from education attainment levels using official duration for each level - and 15, which is the projected maximum level of this indicator for year 2025.

2. *EYSI* stands for *Expected Years of Schooling Index*, and it's the ratio between the expected number of years of schooling a child of school entrance is going to attend during her lifetime (EYS) and 18, which is the number of years employed to achieve a master's degree in most countries.

Data is observed in 2018. The average value in our dataset is 0.71, and standard deviation is 0.185. A preliminary analysis is performed by studying a simple bivariate correlation between the dependent variables – excluding *BigTech Dummy* - and Education Index; results are depicted in *Figure 10*. The figure is composed by four panels, each one representing a scatterplot having on the x-axis the Education Index and on the y-axis the *FinTech and BigTech credit volumes* dependent variables described above; on each panel, on y-axis values are expressed as logarithms. The plots suggest a positive correlation with both the logarithm of FinTech&BigTech credit per capita and the logarithm of FinTech per capita (the two top panels); correlation with the logarithm of the market share of BigTech seems to point on the opposite direction.

Figure 10: Scatterplots: Education Index.



Source: BIS, UNDP, my own calculations.

- *Gini Index*

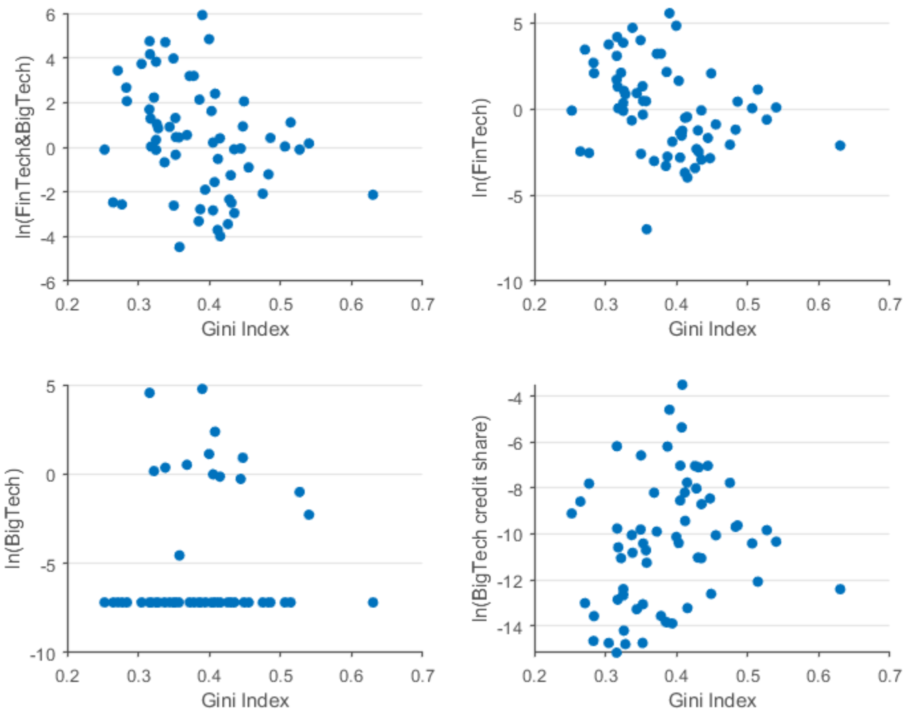
FinTech and BigTech platforms introduced sophisticated methods to calculate creditworthiness relying on machine learning and robo-advising. These methods, as it is suggested by Philippon (2020), are likely to reduce discrimination as long as algorithms do not suffer from any prejudice. Financial inclusion is a key concept in FinTech and BigTech lending, and inequality among individuals is likely to be associated to different levels of access to credit instruments.

The Gini Index measures the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. The Gini index measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. Thus, a Gini index of zero represents perfect equality (total wealth is perfectly distributed among individuals), while an index of one implies perfect inequality (total wealth is held uniquely by one individual). I retrieved data from the World Bank[24] and I calculated an average value for the period 2013-2017. Data on New Zealand was collected from World Economic Forum's *The Inclusive Development Index 2018*. In the dataset, the average value is 0.385, and the standard deviation is 0.0735.

Figure 11 describes the simple bivariate correlation between the Gini Index and the dependent variables concerning FinTech and BigTech credit volumes, as well as the BigTech credit market share. This early-stage analysis shows no clear patterns between the index and the dependent variables, neither linear nor nonlinear on the regressor; the points' dispersion might suggest non-significant parameters for the variable. However, the variable could have a significant effect on the probability of observing BigTech credit provision in given country; the correlation will be verified by regressing on *BigTech dummy*.

[24] For further information: https://data.worldbank.org/indicator/SI.POV.GINI.

Figure 11: Scatterplots: Gini Index.



Source: BIS, World Bank, World Economic Forum, my own calculations.

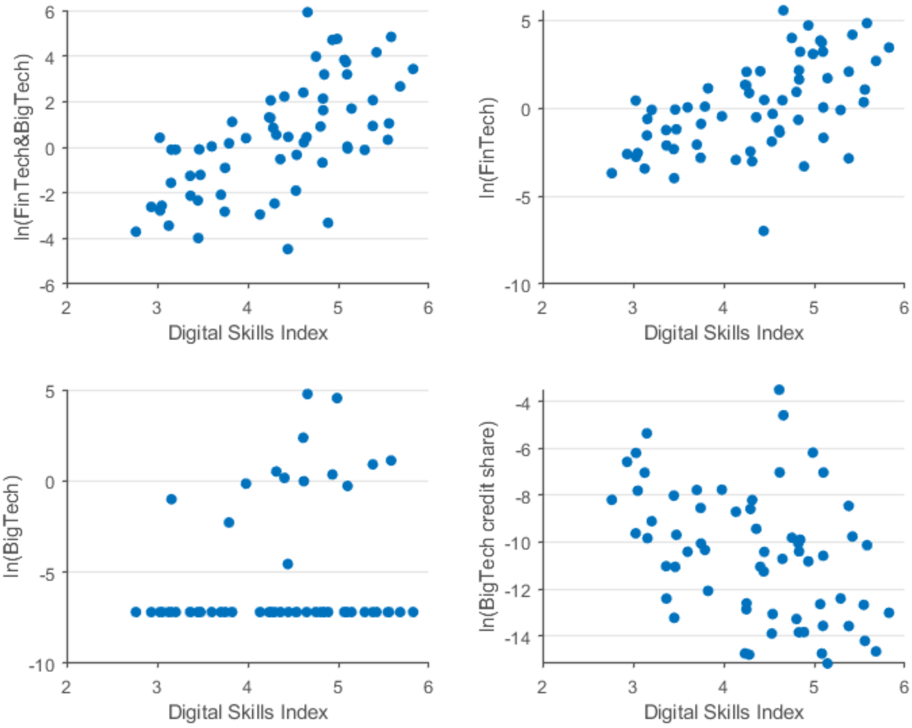
- *Digital Skills*

Through the variable *Mobiles* I take into consideration the penetration of one of the potentially most used devices for accessing the internet; with *Digital Skills* I want to bring in the analysis another measure related to internet usage: the average level of ability of a given country's citizens in using digital tools.

This variable is retrieved from World Economic Forum's *Global Competitiveness Report 2018*. It describes, in a value ranging between one and seven, to what extent in given country active population possess digital skills, defined as computer skills, basic coding, digital reading and other related abilities. One corresponds to a very limited level of skills, seven corresponds to high expertise. The mean value in our dataset is 4.34 and the standard deviation is 0.819.

Figure 12 shows the relationship between the variable and dependent variables. We can see a positive correlation with both *FinTech&BigTech credit per capita* (top-left panel) and *FinTech credit per capita* (top-right panel). The plots suggest also a negative correlation with the BigTech market share, although dispersion is quite relevant.

Figure 12: Scatterplots: Digital Skills.



Source: BIS, World Economic Forum, my own calculations.

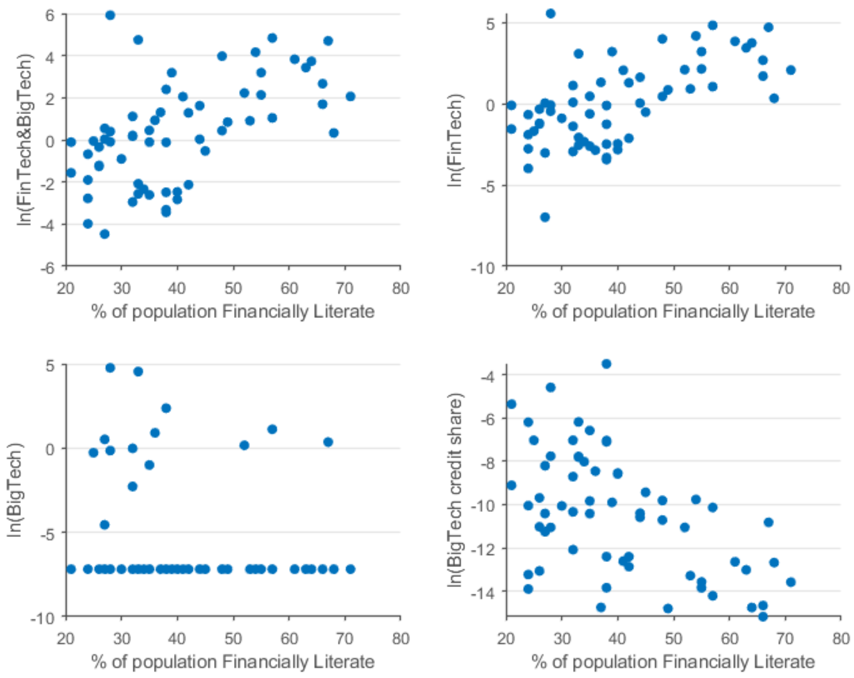
- *Financial Literacy*

Financial literacy could be defined as the ability to make informed financial choices regarding saving, investing, borrowing and other financially related operations (Klapper et al., 2016). As it is highlighted by many publications in literature, financial literacy plays a key role in defining individual choices in terms of financial assets management. Lusardi et al. (2015) discovered that more than 30% of wealth heterogeneity between households having different education levels, calculated around retirement age, can be attributable to financial literacy. Van Rooij et al. (2011) state that a high level of financial knowledge lowers the cost of gathering and processing information and reduces economic and psychological thresholds for stock market participation, allowing many individuals to benefit from the equity premium and from risk diversification. Bianchi (2017) shows that there is a significant positive correlation between financial literacy, education and wealth.

Given these assumptions, I find interesting to verify if financial literacy also has an impact on individuals' level of use of FinTech and BigTech credit. I retrieved data on financial literacy by country from the S&P's *Global FinLit Survey*; it investigates people's knowledge of risk diversification, inflation, numeracy and interest compounding of 150,000 people among over 140 countries. The observations are expressed as the percentage of adult population who are financially literate in 2014. In our dataset, the mean value is 40.26% and the standard deviation is 13.64%.

Figure 13 as usual, highlights the bivariate correlation between the variable and the dependent variables. Even in this case, the plots seem to represent a positive correlation with both *FinTech&BigTech credit per capita* (top-left panel) and *FinTech credit per capita* (top-right panel). Correlation with the BigTech market share points towards the other direction, although dispersion is quite relevant.

Figure 13: Scatterplots: Financial Literacy.



Source: BIS, S&P, my own calculations.

- *Bank account ownership*

One of the positive effects of FinTech and BigTech platforms in providing credit, as we have seen several times up to now, is higher accessibility to financial instruments; the targets are especially those who are currently excluded by incumbent banking system networks. Many reasons could induce – or force – individuals and firms to step back from the adoption of financial services and financial instruments provided by the banking system; among them, I decided to focus on the following.

First and foremost, they might find said services and instruments too expensive to afford, both in terms of interest rates charged and transaction costs. Secondly, they might find it difficult to reach the financial institutions due to geographical obstacles (distance, lack of branches, lack of transportation, etc.).

I account for these elements by controlling for two variables retrieved from the *2017 Global Findex*, a database constructed by the World Bank based on a cross-country survey.

1. *NAdistance*: it is an indicator expressing the percentage of individuals, among respondents, which reported distance from financial institutions as a reason for the absence of a bank account.

2. *NAcost*: it is an indicator expressing the percentage of individuals, among respondents, which reported excessive costs as a reason for the absence of a bank account.

A few remarks should be taken into consideration.

The survey was undertaken by individuals and report data on personal finance choices; therefore, we are capturing only individuals' behavior and we have no information on firms' behavior.

Answer reflect subjective information, not objective numbers; therefore, we should take into account that data mirror what could be interpreted as a general people's sentiment.

Finally, individuals were allowed to choose between multiple options; I decided to focus on distance and cost as they might fit well in the analysis I want to conduct.

Data is reported in percentage and was observed in 2017. The mean values, in our dataset, for *NAfiaway* and *NAtooexp* are respectively 15.37% and 23.98%. For any country, data which was observed below the level of 5% was automatically approximated to 0.

To conclude this part of the analysis, *Table 3* represents the summary of statistics of all the variables investigated so far.

Table 3: Summary of statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
FinTech&BigTech credit per capita *(USD per capita)*	64	17.52757	52.57622	0.011474	372.2814
FinTech credit per capita *(USD per capita)*	64	13.85327	38.57791	0.000925	254.8614
BigTech credit per capita *(USD per capita)*	64	3.674932	18.65164	0.000759	117.4227
BigTech share of total credit *(%)*	64	0.089785	0.394931	0.000026	2.99371
GDP per capita *(USD thousands per capita)*	64	21.13937	16.4602	0.73667	62.7902
GDP per capita squared *(USD thousands per capita)*	64	713.5771	899.794	0.542683	3942.61
Lerner Index	64	0.266262	0.130862	-0.26883	0.62094
Regulatory Stringency Index	64	0.740489	0.086946	0.521739	0.956522
Branches density *(n. per 100,000 adults)*	64	22.56403	23.36795	1.71061	145.995
Mobiles *(n. per 100 adults)*	64	114.1371	32.83298	32.1285	214.735
BigTech Dummy	64	0.234375	0.426956	0	1
Advanced Economies dummy	64	0.3125	0.467177	0	1
No Account cost *(%)*	63	15.37469	14.06183	0	51.1245
No Account cost *(%)*	63	23.98349	20.68241	0	59.4293
Education Index	64	0.708194	0.185502	0.291111	1.03722
Gini Index	64	0.385091	0.073505	0.2526	0.63
Financial Literacy	62	40.25806	13.6333	21	71
Digital skills	63	4.339555	0.819011	2.76498	5.82519

Source: BIS, my own calculations.

3.3. Models specification.

At this point, we have a picture of all the elements that are necessary to define the specifications that will be used in this document.

The first specification we will take in consideration is the following:

$$\begin{aligned} FinTBigT_i = {} & \beta_0 + \beta_1 y_i + \beta_2 {y_i}^2 + \beta_3 Lerner_i + \beta_4 RegStr_i + \beta_5 AEdummy_i + \beta_6 Edu_i + \\ & \beta_7 Branches_i + \beta_8 Gini_i + \beta_9 NAdistance_i + \beta_{10} NAcost_i + \beta_{11} DigitalSk_i + \\ & \beta_{12} FinLit_i + \beta_{13} BigTdummy_i + \beta_{14} Mob_i \;\; , \end{aligned}$$

where each element represents, for given country *i*:

$FinTBigT_i$:	Log of FinTech&BigTech credit per capita	$Gini_i$:	Gini Index
y_i:	GDP per capita	$NAdistance_i$:	No Account due to distance
${y_i}^2$:	GDP per capita squared	$NAcost_i$:	No Account due to costs
$Lerner_i$:	Lerner Index	$DigitalSk_i$:	Digital skills
$RegStr_i$:	Regulatory Stringency Index	$FinLit_i$:	Financial Literacy
$AEdummy_i$:	Advanced Economies dummy	$BigTdummy_i$:	BigTech dummy
Edu_i:	Education Index	Mob_i:	Mobiles
$Branches_i$:	Density of branches		

Then, I will test this very specification for other dependent variables, among those described in the previous paragraph. Using dependent variables different from Log of FinTech credit per capita, I will exclude from the list of regressors the BigTech dummy ($BigTdummy_i$).

Therefore, these specifications can be described as:

$$FinT_i = \beta_0 + \beta_1 y_i + \beta_2 {y_i}^2 + \beta_3 Lerner_i + \cdots + \beta_{13} Branches_i \;\; ;$$

$$BigT_i = \beta_0 + \beta_1 y_i + \beta_2 {y_i}^2 + \beta_3 Lerner_i + \cdots + \beta_{13} Branches_i \;\; ;$$

$$BigTshare_i = \beta_0 + \beta_1 y_i + \beta_2 {y_i}^2 + \beta_3 Lerner_i + \cdots + \beta_{13} Branches_i \;\; ;$$

$$BigTdummy_i = \beta_0 + \beta_1 y_i + \beta_2 {y_i}^2 + \beta_3 Lerner_i + \cdots + \beta_{13} Branches_i \;\; ;$$

where the dependent variables represent, for given country *i*:

$FinT_i$:	Log of FinTech credit per capita
$BigT_i$:	Log of BigTech credit per capita
$BigTshare_i$:	Log of BigTech share of total credit
$BigTdummy_i$:	BigTech dummy .

CHAPTER 4. ANALYSIS AND RESULTS

4.1. OLS and LPM estimation results.

Before analyzing the results (depicted in *Table 5)*, in *Table 4* I provide a snapshot of the effect I expect added regressors to have on the different specifications[25].

Table 4: Expected effect of added explanatory variables.

	(1) BigTech dummy	(2) BigTech credit per capita	(3) BigTech market share	(4) FinTech& BigTech credit per capita	(5) FinTech credit per capita
Education Index	No Effect	No Effect	No Effect	Positive	Positive
Gini Index	Positive	Positive	Positive	Positive	Positive
No Account distance	Positive	Positive	Positive	No Effect	No Effect
No Account cost	Positive	Positive	Positive	No Effect	No Effect
Digital Skills	Positive	Positive	Positive	Positive	Positive
Financial Literacy	Negative	Negative	Negative	Positive	Positive

The *Gini Index*, as an indicator of wealth inequality, is expected to positively affect all variables, as well as *Digital skills*. In the first case, as it is also suggested by Philippon (2020), both FinTechs and BigTechs are likely to diminish the exclusion of minorities from financial services, as they are less affected by prejudicial discrimination. In the second case, I trivially assume that the higher the ability of individuals in the use of digital tools, the higher the chances that they can efficiently access BigTech and FinTech credit.

For what concerns accessibility to financial institutions, I expect both the variables representing obstacles to access traditional financial services – either due to excessive costs or

[25] With respect to the explanatory variables already included in Frost et al. (2019), I expect their sign to remain the same specified by the authors. More specifically, I rely on the results summarized in Frost et al. (2019) in pg. 32.

due to excessive distance from financial institutions – to positively affect the BigTech-related dependent variables. Conversely, I don't see them having a relevant impact on FinTech-related ones. In fact, FinTech credit is more likely to be used to reimburse or refinance preexisting debt, and therefore to be accessed by individuals already owning a bank account – and most likely already having access to traditional credit. On the contrary, BigTechs seem to lend more actively to individuals and SMEs who do not have the possibility to access a credit line on the first place. Therefore, I assume that the higher the fraction of population excluded from traditional credit, the higher the BigTechs' credit volumes.

I expect *financial literacy* to positively impact BigTech-related dependent variables, and to negatively affect FinTech related-ones. I can reasonably assume that BigTech credit instruments are easier to be accessed by those individuals having lower levels of financial education, due to BigTechs' structure itself. In fact, BigTechs aim at maximum coverage, using their preexisting online platforms to convey their products to a vast number of consumers. On the contrary, FinTech platforms, operating exclusively financial activities, could require higher levels of financial education to be accessed.

Finally, with respect to *education*, I expect it to have a positive effect on FinTech-related dependent variables, and no relevant influence on BigTech-related ones. Highly educated people are more likely to have higher income, and higher possibilities to access credit from commercial banks. If they have already been provided loans from traditional sources, they might use FinTech lending to partly reimburse them. On the contrary, BigTech credit is widely accessed by individuals characterized by heterogeneous levels of education – and, consequently, of income. Therefore, I don't see any of the dependent variables referring to BigTech credit to be influenced significantly by different levels of education.

To elaborate the results, I first estimate the parameters through the application of OLS and LPM; all the econometric analyses are implemented using Stata. Results are summarized in *Table 5*. As recalled also in *Table 4*, I test the impact of the same explanatory variables on different indicators of FinTech and BigTech credit provision. This is reflected, in *Table 5*, by the presence of several columns, each one referring to a different dependent variable.

- In columns (1), (2), and (3) I investigate the effect of the variables of interest on BigTech-related indicators. More particularly: column (1) focuses on the probability of observing BigTech credit provision in a given country - the analysis is performed using LPM estimation; column (2) refers to overall BigTech volumes per capita; column (3) depicts the relationship between the independent variables and the market share of BigTech credit. In columns (2) and (3) the dependent variables are in log values.

- Column (4) focuses on a model using as dependent variable the sum of FinTech and BigTech total credit per capita, as it was introduced by Frost et al. (2019). Finally, column (5) refers to FinTechs' credit volume per capita alone. Again, the dependent variables are in log values. Apart from the analysis in column (1), all other estimates are retrieved using OLS.

GDP per capita has a positive and significant effect on the log of BigTech credit volume - column (2). However, differently from Frost et al. (2019), correlation with the other dependent variables is non-significant. GDP is a good proxy for the level of economic development of a country, and it represents a summary of many different factors. Added variables could capture more in detail the effect of some of those factors, ending up in eroding GDP's overall effect.

The positive and significant coefficient of GDP, in the specifications of column (2), is accompanied by equally significant and yet negative coefficients for the quadratic term: the positive effect of GDP becomes less and less important the higher its level.

The *Lerner Index* has a positive and highly significant impact on all dependent variables I used in the different specifications; this result is in line with Frost et al. (2019) findings. The positive effect clearly indicates that the higher the mark-ups of the banking sector (that is, the lower the competitiveness), the higher the credit activity of FinTech and BigTech platforms. As an example, a change in the value of the index from 0.1 to 0.2 implies an estimated increase in the probability of observing BigTech credit activity of 7.5% - a relatively high growth.

This effect represents one of the possible interpretations of the relationship between the incumbent banking sector of a country and FinTech-BigTech activities. The lower the competitiveness of incumbent banks, the higher the costs that are going to be charged to banks' customers. FinTechs and BigTechs, as new entrants, offer services and products at lower transaction costs and at lower interest rates, becoming a more attractive alternative to the existing banking system. To see the point from another perspective, BigTechs and FinTechs could find more interesting to be active in countries with lower competitiveness due to the higher margins they could obtain.

Table 5: FinTech and BigTech credit determinants.

	(1) BigTdummy	(2) BigT	(3) BigTshare	(4) FinTBigT	(5) FinT
GDP per capita	0.0414	0.400**	-0.0559	0.0623	0.0694
	(0.0252)	(0.195)	(0.121)	(0.0973)	(0.0976)
GDP per capita squared	-0.000553*	-0.00520**	-0.000315	-0.00107	-0.000960
	(0.000305)	(0.00251)	(0.00155)	(0.00125)	(0.00125)
Lerner Index	0.750*	7.909**	7.045***	4.945***	5.961***
	(0.392)	(3.560)	(2.203)	(1.771)	(1.777)
Regulatory Stringency Index	-0.305	-6.944	-5.297	-9.027***	-11.34***
	(0.597)	(5.451)	(3.373)	(2.642)	(2.722)
Advanced Economies dummy	-0.0237	-0.689	0.808	2.291***	2.668***
	(0.165)	(1.668)	(1.032)	(0.807)	(0.833)
Mobiles	-0.00395**	-0.0316*	-0.0148	-0.00588	-0.0118
	(0.00188)	(0.0174)	(0.0108)	(0.00868)	(0.00868)
Branches density	-0.00495**	-0.0384*	-0.0363***	-0.00591	-0.00978
	(0.00241)	(0.0207)	(0.0128)	(0.0104)	(0.0103)
Education Index	-0.335	-2.725	-1.857	4.048	3.980
	(0.738)	(6.832)	(4.228)	(3.310)	(3.411)
Gini Index	1.375*	9.364	2.625	2.010	4.365
	(0.742)	(7.576)	(4.688)	(3.742)	(3.782)
No Account distance	0.0127	0.128*	0.0179	-0.00909	-0.0458
	(0.00841)	(0.0672)	(0.0416)	(0.0333)	(0.0336)
No Account cost	-0.00599	-0.0678	-0.00480	0.00173	0.0163
	(0.00510)	(0.0424)	(0.0262)	(0.0208)	(0.0212)
Digital Skills	0.302***	2.037**	1.048*	0.559	0.203
	(0.111)	(0.883)	(0.546)	(0.458)	(0.441)
Financial Literacy Index	-0.0142*	-0.102*	-0.0447	-0.0166	-0.0171
	(0.00722)	(0.0574)	(0.0355)	(0.0289)	(0.0287)
BigTech dummy				1.205**	
				(0.552)	
_cons	-0.727	-9.208	-7.312*	-0.320	2.454
	(0.709)	(6.479)	(4.010)	(3.159)	(3.235)
N	60	60	60	60	60
adj. R^2	0.175	0.209	0.530	0.627	0.644

Standard errors in parentheses (Column 1 reports robust standard errors).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1): BigTech dummy; (2): Log of BigTech credit per capita; (3): Log of BigTech share of total credit; (4): Log of FinTech&BigTech credit per capita; (5): Log of FinTech credit per capita.

The *density of banks' branches* seems to play a quite relevant role in the analysis. It affects negatively and significantly the probability of observing BigTech activities, the log of BigTech credit volumes and the market share of BigTech credit - columns (1), (2) and (3). This suggests that the lower the number of banks' branches in a country, the higher the BigTech-related activities. In fact, parameters are significant only for the specifications studying exclusively BigTechs' behavior. This is a first evidence suggesting that low accessibility to incumbent banking sector's infrastructures – due to lower density – pushes individuals to find alternative sources of financing. Furthermore, it could also reflect higher costs for incumbent banks, which may find it more difficult to expand their reach. These elements establish a fertile ground for BigTechs to be more active in lending provision. On the contrary, as we already mentioned, FinTech credit is widely used to reimburse preexisting debt; therefore, the higher the banks' density, the more customers owning a preexisting credit line. This could explain the non-significance of parameters in the specifications for FinTech-related indicators.

Conversely, *regulation of the banking system* seems to be an important element to consider when analyzing FinTech-related specifications. In fact, the regulatory stringency index impacts negatively both FinTech&BigTech credit per capita - column (4) - and FinTech credit per capita alone - column (5); in both cases, the parameters are significant at a 1% level. A more stringent regulation is likely to be a deterrent for FinTech platforms to be actively lending within a given country. We can find the same negative relationship also when we consider all other specifications, but here coefficients are non-significant. The results regarding regulatory stringency are in line with Frost et al. (2019).

The coefficient of the *dummy variable for advanced economies* positively and significantly affects both FinTech&BigTech credit per capita - column (4) - and FinTech credit per capita - column (5) - at a 1% level, while it is non-significant for other specifications. This suggests another element of difference between FinTech and BigTech lending provision. In fact, while FinTechs are more widespread in highly industrialized countries, BigTech credit seems to be accessed by a more heterogeneous set of economies.

The *density of mobile phones* seems to be relevant on the BigTech side. In fact, coefficients appearing in the specifications in column (1) and column (2) are significant, in the first case at a 5% level and in the latter at a 10% level. The sign is, unexpectedly, negative in all considered cases. However, the magnitude of coefficients is quite small: one extra mobile phone – for a hundred people - decreases the probability of observing BigTech credit activity by 0.4% and decreases the volume of BigTech credit per capita by almost 1$ (corresponding to a decrease of the log-value of 0.0316).

Parameters on *education* are homogenously non-significant. Therefore, in the set of specifications we are analyzing education seems not to influence FinTech and BigTech credit activity at all. On the contrary, *financial literacy* seems to have a relevant effect on two BigTech-related dependent variables. In fact, *financial literacy* negatively affects the probability of observing BigTech lending activity - column (1) - and the overall BigTech credit volume per capita - column (2) - both with a 10% significance. These evidences suggest that BigTech credit is mostly provided in countries with poorer financial knowledge; this is in line with previous results, and it also suggests that BigTech lending is more likely to be accessed in developing countries. It is also in line with the characteristics of BigTech credit products themselves, as we earlier recalled. In fact, they are designed to be easy to use and to be accessed by a vast mass of people, even by those who are not hugely financially educated.

The *Gini index*, reflecting inequality among individuals, reports positive coefficients for all specifications; however, only for the specification for the BigTech dummy - column (1) - the parameter is significant. Overall, BigTech loans are likely to be more widespread in countries where wealth is concentrated among fewer people. In fact, these platforms could benefit from inefficiencies and from the high margins of the incumbent banking system, lending to high-risk individuals. This process ultimately brings the positive effect of an enhancement in financial inclusion. However, results highlight that there is a significant relationship only with the probability of observing BigTech credit; therefore, we cannot jump to the same conclusions for FinTech activities.

Results reported in *Table 5* highlight that BigTech volume per capita is positively correlated with a higher number of people reporting *distance from financial institutions* as one of the main reasons for the absence of a bank account - column (2). Together with the results for *Branches*, this suggests that higher geographical obstacles are related to higher BigTech credit volumes. On the one side, the low density of incumbent banking system attracts BigTechs, which could benefit from the opportunity of providing a service where there’s lower competitiveness on the field; on the other side, customers benefit from BigTechs credit as they find it more accessible.

Costs of financial instruments, on the contrary, seem not to be a relevant factor in the analysis. Coefficients for the variable reflecting the percentage of individuals reporting *excessive costs* as a deterrent to hold a bank account are generally non-significant.

As a footnote, in order to assess these parameters properly, it's important to recall that these two variables are not capturing objective information on actual geographical or financial obstacles for credit access, but they rather represent the summary of subjective perceptions.

Digital skills are a key element when studying the determinants of BigTech credit. The coefficient reported in column 1 shows that an increase by one step in the scale describing digital skills (going from 1 to 7) results in a 30% increase in probability of observing BigTech credit activity – quite an outstanding effect. Positive and significant coefficients are reported also in the specifications for BigTech credit volume and BigTech credit market share - columns (2) and (3). BigTech platforms largely rely on involving a huge mass of people through several digital tools. Therefore, it comes by no surprise that BigTech credit is more widespread in countries where, on average, people are more capable to deal with digital instruments. We cannot state the same for FinTech platforms: coefficients in columns (4) and (5) are reported to be non-significant.

Finally, *Table 5* reports the coefficient of the *dummy variable for the presence of BigTech credit activity* when it is used as a regressor on the specification for BigTech and FinTech credit - column (4). The parameter is positive and significant at 5% level, meaning that the presence of BigTech credit activity – ceteris paribus – implies higher overall FinTech and BigTech lending volumes. This result is in line with Frost et al. (2019) findings.

The effects we studied so far reflect some divergences in BigTech and FinTech drivers in credit activity. However, the positive effect of the presence of BigTech on overall FinTech volumes shows that, despite of these differences, the two types of platforms tend to compete for similar markets.

Outcomes are accompanied by the F-statistic and the correspondent p-value to test significance of all the regressors included in each specification represented in this paragraph (*Table 6*). For the specification (4) the test statistic distributes as a F(14, 45); in all other cases, the distribution is a F(13, 46)[26].

In all the considered cases we can reject the null hypothesis[27] and conclude that regressors in each model are not jointly statistically equal to zero. For the specification for BigTech credit per capita (2) we reject the null hypothesis at 5% level; for all other specifications, at 1% level.

[26] The difference in degrees of freedom is due to the presence of the BigTech dummy in the specification (4).

[27] The F-test aims in verifying the joint statistical significance of all the regressors included in the specification. The null hypothesis can be described as follows: $H_0 : \beta_1, \beta_2, \ldots, \beta_k = 0$, where $\beta_1, \beta_2, \ldots, \beta_k$ represent all the parameters of the regressors included in the model.

Table 6: F-test for joint statistical significance of entire model.

Specification	*F-statistic*	*p-value*
(1) BigTech dummy	4.54	0.0001
(2) BigTech credit per capita	2.20	0.0250
(3) BigTech share of total credit	6.12	0
(4) FinTech&BigTech credit per capita	8.09	0
(5) FinTech credit per capita	9.20	0

4.2. Accounting for heteroskedasticity.

Cross-sectional data are characterized by values with highly heterogeneous size, and our case makes no exception; hence data are more likely to show systematic changes in the spread of the residuals over the range of measured values. Heteroskedasticity may negatively affect the interpretation of the results. In fact, OLS estimation, in presence of heteroskedasticity, could evaluate p-values for coefficients' significance that underestimate the amount of variance in the dataset. Therefore, even though resulting coefficient estimates are not biased, hypothesis testing may suggest that parameters are significant even when it's not the case.

To detect heteroskedasticity, I conduct the Breusch-Pagan test[28]. The results are summarized in *Table 7*. Notice that I did not run the test for the specification using BigTech dummy as a dependent variable; in fact, since in LPM estimation we have heteroskedasticity by construction, I computed robust standard errors on the first place.

For the specifications (2) and (3) we reject the null hypothesis of homoskedasticity; conversely, for the specifications (4) and (5) we have not evidence to assess presence of heteroskedasticity.

[28] Also known as Cook-Weisberg test, it verifies the null hypothesis of homoskedasticity (*H_0 = constant variance*).

Table 7: Breusch-Pagan test.

Specification	*Test statistic*	*p-value*
(2) BigTech credit per capita	3.30	0.0693
(3) BigTech share of total credit	7.41	0.0065
(4) FinTech&BigTech credit per capita	0.37	0.5431
(5) FinTech credit per capita	0.72	0.3967

In order to deal with heteroskedasticity, I run the specifications considered so far using robust standard errors; results are displayed below, in *Table 8*.

No major differences can be detected when comparing these results with those retrieved in *Table 5*. Significance of parameters remains overall unchanged, and we do not find cases in which coefficients become non-significant due to the introduction of robust standard errors. The analysis on heteroskedasticity therefore points out estimates and t-statistics that are in line with the results obtained so far.

If we compare results on added variables with *Table 4*, we can see that the estimated effects tend to confirm the expectations. Generally, the signs are in line with the assumptions, even if significance is generally very low - especially on FinTech-related specifications. When we focus only on significant parameters, the corresponding effects perfectly match the expected signs.

With respect to those variables previously introduced by Frost et al. (2019), we could draw similar conclusions. Signs and significance of estimated parameters are generally coherent with Frost et al. (2019) results: the effects of the *Lerner Index*, of *Regulatory Stringency Index* and *banks' branches density* are robust to changes in the specification. Conversely, this is not true for the variable on GDP. As we could see, the effect of GDP is non-significant for most specifications, while in Frost et al. (2019) GDP has a strongly relevant impact on the analysis. The lower significance is likely to be attributable to the introduction of new variables (for example *Education*, *Financial Literacy*, or the *Gini Index*) capturing part of the effect of GDP in the various specifications.

Table 8: FinTech and BigTech credit determinants (robust errors).

	(1) BigTdummy	(2) BigT	(3) BigTshare	(4) FinTBigT	(5) FinT
GDP per capita	0.0414	0.400*	-0.0559	0.0623	0.0694
	(0.0252)	(0.205)	(0.122)	(0.0962)	(0.0850)
GDP per capita squared	-0.000553*	-0.00520**	-0.000315	-0.00107	-0.000960
	(0.000305)	(0.00251)	(0.00148)	(0.00122)	(0.00113)
Lerner Index	0.750*	7.909**	7.045***	4.945**	5.961**
	(0.392)	(3.118)	(2.281)	(2.281)	(2.289)
Regulatory Stringency Index	-0.305	-6.944	-5.297	-9.027***	-11.34***
	(0.597)	(5.965)	(3.404)	(3.097)	(3.552)
Advanced Economies dummy	-0.0237	-0.689	0.808	2.291***	2.668***
	(0.165)	(1.411)	(0.770)	(0.578)	(0.554)
Mobiles	-0.00395**	-0.0316*	-0.0148	-0.00588	-0.0118
	(0.00188)	(0.0165)	(0.0119)	(0.00797)	(0.00717)
Branches density	-0.00495**	-0.0384*	-0.0363***	-0.00591	-0.00978
	(0.00241)	(0.0198)	(0.0109)	(0.00861)	(0.00856)
Education Index	-0.335	-2.725	-1.857	4.048	3.980
	(0.738)	(5.312)	(3.046)	(2.634)	(2.757)
Gini Index	1.375*	9.364	2.625	2.010	4.365
	(0.742)	(5.960)	(3.858)	(2.841)	(2.924)
No Account distance	0.0127	0.128**	0.0179	-0.00909	-0.0458
	(0.00841)	(0.0584)	(0.0376)	(0.0335)	(0.0305)
No Account cost	-0.00599	-0.0678*	-0.00480	0.00173	0.0163
	(0.00510)	(0.0385)	(0.0235)	(0.0214)	(0.0196)
Digital Skills	0.302***	2.037**	1.048*	0.559	0.203
	(0.111)	(0.898)	(0.609)	(0.370)	(0.410)
Financial Literacy Index	-0.0142*	-0.102	-0.0447	-0.0166	-0.0171
	(0.00722)	(0.0623)	(0.0416)	(0.0260)	(0.0314)
BigTech dummy				1.205*	
				(0.667)	
_cons	-0.727	-9.208	-7.312*	-0.320	2.454
	(0.709)	(6.804)	(3.883)	(2.945)	(3.050)
N	60	60	60	60	60
adj. R^2	0.175	0.209	0.530	0.627	0.644

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1): BigTech dummy; (2): Log of BigTech credit per capita; (3): Log of BigTech share of total credit; (4): Log of FinTech&BigTech credit per capita; (5): Log of FinTech credit per capita.

4.3. A focus on BigTech: probit and logit estimation results.

Through the previous analysis we retrieved the parameters that describe a relationship between BigTech and FinTech credit activity and our independent variables. During this first step I calculated the coefficients with OLS and LPM estimation methods; however, as specified in Chapter 3, under some circumstances these methods could produce estimates that don't reflect properly the relationship between variables, which could lead to misinterpretation of results.

In this paragraph I will focus primarily on the study of BigTech determinants; to do so, I will take into account the specification for the *BigTech dummy*. This variable, trivially, is a binary dependent variable that can take on value zero and one; therefore, it would be useful to verify a nonlinear relationship with regressor, computing probit and logit estimates.

The results are depicted in *Table 9*. In all columns I use the *BigTech dummy* as a dependent variable. Column (1) reports parameters estimated through LPM, therefore being equal to those shown in *Table 5*, column (1); columns (2) and (3) report parameters estimated respectively using probit and logit models.

Before making comparisons between parameters, I should recall that the meaning of these coefficients is very different among models. While in the LPM case a parameter represents the marginal effect of an increase – or decrease – by one unit in the regressor value (ceteris paribus), in probit and logit they represent the value maximizing the CML estimator. The marginal effect of a regressor, in the case of probit and logit, depends on the nonlinear function considered and on all other regressors. However, we can compare estimates of OLS coefficients and probit/logit coefficients by looking at the sign and the significance.

Results on the importance of GDP changes significantly when we consider non-linearity in the regressors: the estimated coefficients become positive and significant both in logit and probit estimates. Evidences on the quadratic term are in line with previous results, highlighting a decreasing effect for higher levels of GDP.

Conversely, the competitiveness of the incumbent banking sector, reflected by the *Lerner index*, seems to lose significance when interpreting the results from the perspective of probit and logit models. This means that, when considering a nonlinear model, a lower level of competitiveness seems not to be accompanied by a higher probability of observing BigTech credit provision.

Table 9: Comparison between models.

	(1) BigTdummy (LPM)	(2) BigTdummy (Probit)	(3) BigTdummy (Logit)
GDP per capita	0.0414	0.241**	0.379*
	(0.0252)	(0.116)	(0.220)
GDP per capita squared	-0.000553*	-0.00316**	-0.00497*
	(0.000305)	(0.00145)	(0.00274)
Lerner Index	0.750*	3.116	5.003
	(0.392)	(2.284)	(4.416)
Regulatory Stringency Index	-0.305	-0.114	-0.151
	(0.597)	(2.574)	(4.605)
Advanced Economies dummy	-0.0237	-0.0632	-0.162
	(0.165)	(0.631)	(1.070)
Mobiles	-0.00395**	-0.0208**	-0.0345**
	(0.00188)	(0.00810)	(0.0142)
Branches density	-0.00495**	-0.0452***	-0.0782**
	(0.00241)	(0.0174)	(0.0349)
Education Index	-0.335	-2.030	-2.955
	(0.738)	(3.963)	(8.638)
Gini Index	1.375*	7.520*	13.41*
	(0.742)	(4.127)	(7.776)
No Account distance	0.0127	0.0504*	0.0852*
	(0.00841)	(0.0282)	(0.0502)
No Account cost	-0.00599	-0.0256	-0.0441
	(0.00510)	(0.0162)	(0.0286)
Digital Skills	0.302***	1.318**	2.465**
	(0.111)	(0.546)	(1.180)
Financial Literacy Index	-0.0142*	-0.0550*	-0.0983*
	(0.00722)	(0.0292)	(0.0574)
_cons	-0.727	-6.323	-11.80
	(0.709)	(3.904)	(7.884)
N	60	60	60
adj. R^2 / pseudo R^2	0.175	0.368	0.370

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Parameters on *regulatory stringency*, on the *dummy for advanced economies* and for *education* are non-significant, whatever the model considered.

On the contrary, *mobile phones density* and *branches density* are negatively and significantly correlated with the dependent variable even when estimating parameters with probit and logit.

The effect of inequality calculated through probit and logit is consistent with previous results. The parameters show a positive impact of the *Gini Index* on the BigTech dummy, with a 10% level of significance. This result seems to remark the conclusion that in countries where inequality is harsher it is more likely to observe provision of credit operated by BigTechs.

Conversely to the LPM case, probit and logit emphasize a positive and significant effect of the indicator reflecting the number of individuals who find *distance from financial institutions* as an obstacle to access to credit. The opposite holds for the variable explaining the number of individuals who point out *costs as a deterrent to hold a bank account*; in fact, probit and logit estimates, as well as LPM ones, are non-significant.

The effect of *digital skills* on the dependent variable is strikingly evident; whatever the model, coefficients are positive and highly significant. Therefore, we can conclude that the higher the understanding of individuals of the digital tools, the higher the probability to observe credit provision facilitated by BigTech.

Finally, the effect of *financial literacy* is consistent among models, too. Indeed, estimates are negative and significant at a 10% level for all models considered. This is in line with the results highlighted in the previous paragraph.

To better compare the probit and logit results with LPM, we could calculate the marginal effects of independent variables on BigTech probability. In *Table 10* I report respectively the marginal effects at mean for the regressors in probit and logit models. To do so, I plug in the models the mean of observed values for each explanatory variable, and then I calculate the marginal effect of every regressor keeping all other variables fixed at their means. Values reported in the following tables just represent one simple way to compare the effects of the regressors among nonlinear models and the LPM; however, it is important to recall that marginal effects in probit and logit models are *not* constant.

The marginal effects are consistent with the analysis we conducted so far. They are generally similar, in both probit and logit, to the parameters retrieved through LPM estimation - column (1) of *Table 9*. However, they slightly deviate from LPM results for those variables which change in significance when estimated through logit and probit.

Table 10: Marginal effects at mean: probit and logit models.

	(1) Marginal Effects (Probit)	(2) Marginal Effects (Logit)
GDP per capita	0.0593*	0.0482
	(0.0316)	(0.0309)
GDP per capita squared	-0.000777*	-0.000632
	(0.000415)	(0.000402)
Lerner Index	0.766	0.637
	(0.683)	(0.658)
Regulatory Stringency Index	-0.0281	-0.0192
	(0.780)	(0.703)
Advanced Economies dummy	-0.0154	-0.0202
	(0.216)	(0.186)
Mobiles	-0.00512*	-0.00439*
	(0.00284)	(0.00264)
Branches density	-0.0111**	-0.00995**
	(0.00550)	(0.00506)
Education Index	-0.499	-0.376
	(1.081)	(1.055)
Gini Index	1.849	1.707
	(1.274)	(1.167)
No Account distance	0.0124	0.0108
	(0.00981)	(0.00889)
No Account cost	-0.00629	-0.00561
	(0.00575)	(0.00514)
Digital Skills	0.324**	0.314**
	(0.156)	(0.151)
Financial Literacy	-0.0135*	-0.0125
	(0.00820)	(0.00784)
N	60	60

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Marginal effect of a variable is calculated keeping all other variables at their mean value.

CONCLUSIONS

In this document we analyzed in detail the determinants, the characteristics and the structure of FinTech and BigTech platforms, focusing primarily on the lending activity. We started from some preexisting evidences provided by the relevant literature; in particular, I could work with the same data used by Frost et al. (2019) in *BIS Working Paper No 779*, and I used such data as a backbone for the construction of my dataset.

In general, the analysis confirms Frost et al. (2019) results. On the FinTech side, a tighter banking regulatory system is associated with lower FinTech credit activity. We could imagine several explications: on the one hand, FinTechs could find it more attractive to operate in more liberal jurisdictions; on the other, the prudential behavior of some countries could make it harder for FinTech platforms to launch new activities.

The conclusions on the Lerner Index are also consistent with previous literature, suggesting that both FinTechs and BigTechs benefit from the high margins deriving from low competitiveness of incumbent banking system.

Finally, evidences suggest that FinTechs are more active in advanced countries. This could be due to the relationship FinTechs establish with incumbent banking systems. Advanced countries are usually characterized by more solid and developed financial infrastructures, and often FinTechs benefit from cooperation with incumbent financial institutions as they can use such infrastructures to convey their products. On the contrary, we cannot state the same for BigTechs. In fact, they tend to compete with rather then cooperate with the preexisting banking system, using their own network to reach customers. This ambiguity in the relationship between FinTechs-BigTechs and preexisting financial institutions is a crucial element to be further investigated through future research.

All variables we added to the picture seem to have – to some extent – a relevant impact on BigTech credit. We discovered that BigTechs are more likely to actively provide credit in countries with higher inefficiencies, such as higher wealth inequality or geographical obstacles in reaching financial institutions. We also showed that financial literacy plays a role when studying the probability of observing BigTech credit activities; the lower the share of financially literate population, the higher the odds to find BigTech lending. On the contrary, education has no significant effect on FinTechs and BigTechs' credit provision. Finally, we stressed out the strong and positive effect of digital knowledge on both the BigTech dummy and BigTechs' credit volumes; as we could expect, these technologies are accessed more easily in countries where population is more capable to deal with digital instruments.

FinTechs and BigTechs represent an ever-changing set of technological innovations; therefore, the ways they operate are quite a novelty to the financial sector. The study developed in this document, together with Frost et al. (2019), represents an early-stage investigation on the dynamics at the base of BigTechs and FinTechs activities; as such, it relies on a constrained amount of information, due to limited data availability. As new data are collected every year by several institutions (i.e. BIS, CCAF, EY etc.), future works may address this topic with the help of larger amount of information, leading to a clearer image of the factors driving FinTechs and BigTechs evolution.

In addition to that, no publication in literature could observe FinTechs and BigTechs during a full economic and financial cycle. Therefore, it is yet to be tested how the results highlighted by academic works (and by this very document) could change during economic stress situations. If we look at recent events, the outbreak of Covid-19 forced several economies to stop significant portions of economic activity for a substantial period of time. This will most likely bring to significant negative consequences on a global scale. How will FinTechs and BigTechs operate in a framework of uncertainty and adverse expectations?

If we focus only on BigTechs, we could outline some other issues which are yet to be investigated. For example, their huge size, in terms of market capitalization, could open up the possibility for monopolistic behavior, which could negatively affect financial stability.

Furthermore, as they manage an incredibly large amount of information, customers' privacy is put into danger. Big data stored online, private information, money accounts, e-wallets; all of these elements could be subject to cyber-attacks (FSB, 2017). How could a major leak of relevant data affect the financial system? How should the sale of customers' information from BigTechs to third parties be regulated to guarantee customers' protection?

To conclude, even if it represents only a small fraction of overall credit volume, FinTechs and BigTechs' lending activity is becoming more and more important in several jurisdictions, such as APAC and Latin American countries. In this context, regulators need to operate a proper intervention, in the form of adequate and proportionate regulation and supervision (Frost, 2020), in order to enhance the possible benefits that could arise from alternative finance and minimize all potential negative consequences.

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