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Firma dello Studente

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Abstract

L'avvento delle grandi compagnie tecnologiche, anche note come BigTechs, nel mondo della finanza, pone le basi per un cambiamento radicale nelle dinamiche relative al sistema finanziario su scala internazionale. L'obiettivo del presente lavoro è quindi quello di analizzare le potenzialità e le implicazioni di tale fenomeno alla luce delle numerose opportunità che caratterizzano in particolare l'offerta di credito da parte delle BigTechs. Al fine di raggiungere tale intento, viene proposta una panoramica generale atta ad inquadrare le attività, le peculiarità dei modelli di business, la compresenza di particolari fattori che ne determinano il grado di adozione e la regolamentazione quale aspetto critico del fenomeno. L'enfasi viene poi posta sui cambiamenti apportati dalle BigTechs nell'attività dell'offerta di credito. La nuova dinamica di intermediazione varia in relazione ai possibili modelli di piattaforma tramite i quali può essere realizzata; le attività ex-ante di valutazione del rischio ed ex-post di controllo ed applicazione ma anche di determinazione del prezzo adottate delle grandi compagnie tecnologiche vengono messe in relazione con le tradizionali modalità afferenti alle istituzioni finanziarie. Le opportunità che iniziano ad emergere vengono poi consolidate in relazione ai potenziali benefici futuri per il sistema finanziario in termini di inclusione finanziaria, efficienza e crescita, da controbilanciare anche con potenziali ripercussioni dovute a scenari competitivi alternativi. La conclusione dell'analisi verte infine su un conciso studio delle quattro maggiori compagnie tecnologiche, Google, Amazon, Facebook ed Apple atto a valutarne le prestazioni congiuntamente alle limitazioni ad alcune considerazioni finali che ne scaturiscono.

Introduction

Big technology firms, also known as BigTechs, have experienced unprecedented growth over the last few years, gradually becoming a standing point for the entire market given their ceaseless expansion into new industries. What is particularly noteworthy is the entrance of these companies in the financial system. Although it could be argued that their presence in finance is still limited, they have what it takes to establish themselves turning the current tide of the international landscape.

The importance of this phenomenon is concretely perceptible by the reflection that it has to the vast majority of the worldwide population in everyday life. Just think about searching on Google a new book to read, maybe asking friends for advice through a Facebook social media. Then buying the chosen one on Amazon marketplace via Apple Card or just comparing prices and buying it in the nearest bookshop by paying with Google or Apple Pay. What if, beyond the payment facilities, BigTech companies would offer credit to individual and small and medium enterprises as it already happens with some tech companies? What would be the future implications and opportunities these firms have to offer? This work, trying to address the aforementioned questions, is going to examine the BigTechs in general first, focusing then more specifically on credit provision, with the objective to understand the phenomenon in terms of future opportunities and consequences for the financial system.

Overall, the document is divided into three sections primarily based on recent Bank for International Settlements and Financial Stability Board reports and publications, and empirical studies mainly by Frost and Gambacorta *et al.*. More in detail, the first chapter will provide an overview of the BigTechs expansionary strategy in finance. It shall introduce the topic by presenting activities, business models peculiarities, economic drivers and international regulatory environment that characterise these companies. Moving from general to specific, the second section will focus on the innovative dynamics of the tech firms' credit provision. There will be described, in detail, the different models of the lending platform and the alternative cutting-edge credit risk assessment's features and accuracy in comparison with traditional methods adopted by financial institutions. Along with the ex-ante elements of financial intermediation, monitoring, enforcement and pricing strategies shall be discussed. The last chapter, foremost, will define the potential advantages that these firms could bring regarding financial inclusion, efficiency and growth, together with alternative competition development scenarios. Lastly, to have a more complete overview, it is suggested a brief analysis of the performances of Google, Amazon, Facebook and Apple together with the limitations and other considerations that emerge alongside.

1.BigTechs in Finance: Overview of the Phenomenon

1.1 BigTechs' Activities

BigTechs, defined as "large, globally active technology firms with a relative advantage in digital technology" (Bank for International Settlements, 2018), have faced a fast growth over the years up to representing the world's largest companies for market capitalisation (Frost *et al*., 2019). The Western leader tech firms are primarily Google, Amazon, Facebook, and Apple, which are often mentioned in the literature as GAFA. Likewise, the most prominent companies for the Asian market operating in the industry are the Chinese Baidu, Alibaba and Tencent, conventionally referred to as BAT (Tanda and Schena, 2019).

According to the Bank for International Settlements (2019), the activities of the BigTechs in the financial field represent peculiar cases of *FinTech* innovations. These are recognised as technology-enabled innovations which could result in new business models, products or processes with an effect on financial market or institutions, as well as in financial services provision (Financial Stability Board, 2017). BigTechs, as the other FinTech firms, have highly automated operations and buoyant software development process. Nonetheless, their original core business is not constituted by financial services. Their primary activities lie indeed on web services provision as search engines, social networks and e-commerce to final users or IT infrastructures like data storage and processing capabilities (Tanda and Schena, 2019). The relatively low weight of financial activities over the entire business is shown by Figure 1.1., which illustrates the proportion of representative[1] BigTechs' activities in percentage of their revenues[2]. The pie chart is divided into information technology, which accounts for the most substantial part (about 46% of the total revenues), consumer goods, communication services, financials and other marginal activities as health care, real estate, utilities and industrials, all clustered under the heading "Other". Financial activities account for a share of just approximately 11%, which include payment services, credit provision, money market funds and insurance products (Bank for International Settlements, 2019).

[1] The companies included are Alibaba, Alphabet, Amazon, Apple, Baidu, Facebook, Grab, Kakao, Mercado Libre, Rakuten, Samsung and Tencent.

[2] The revenues considered refer to 2018 data if available, to 2017 revenues otherwise.

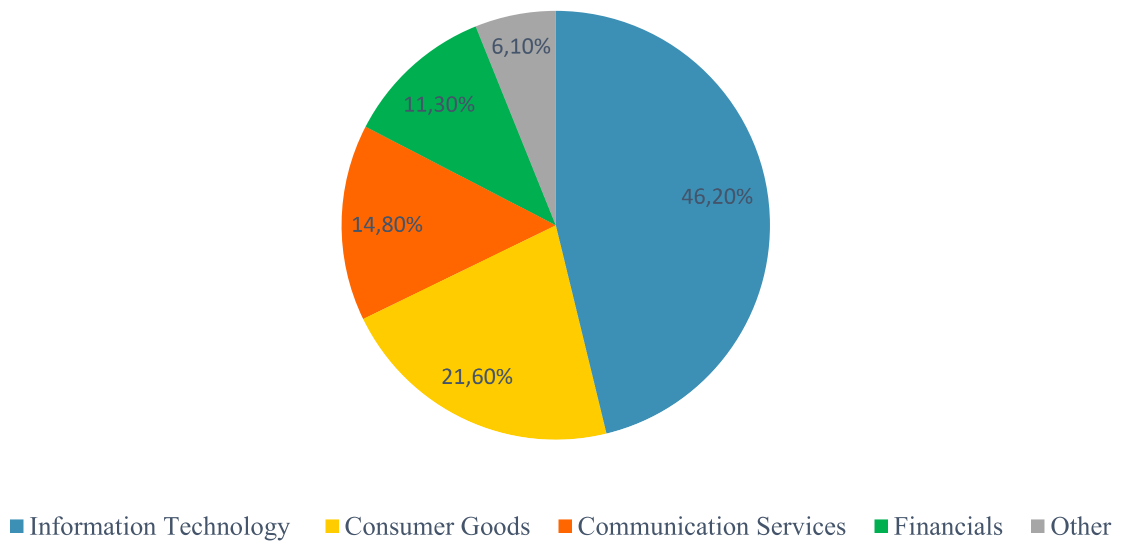

Figure 1.1 BigTechs' revenues by sector of activity: financial services are only a minor part of the business (Bank For International Settlements, 2019).

Looking at the types of activities, BigTech companies usually enter into financial services offering payment facilities and then expanding their activities to the supply of credit. Furthermore, the most advanced ones are active in insurance, savings and investments related financial services (Frost *et al.*, 2019). The evidence of this process can be clearly seen in the case of Amazon. Said company started offering a payment product first, "Amazon Pay", to manage the transactions taking place on its platform, to ending up with credit supply. Indeed, in 2011 Amazon launched a lending service to micro, small and medium enterprises operating in its marketplace (Bilotta and Romano, 2019). More recently[3], it has further expanded inaugurating several "Amazon Credit Cards" (Amazon, 2020a) and "Amazon Cash", a depository for cash that enables customers to deposit money to a digital account (Amazon, 2020b). To understand the BigTechs' aggressive expansionary strategies, it is necessary to analyse both the distinctive aspects from which the market dominance derives and the economic drivers able to explain differences in financial technology adoption rate.

[3] Amazon Cash was launched in 2017, while Amazon Pay in 2007 (CBInsights, 2019).

1.2 Business Models Idiosyncrasies

Despite the differences in terms of products and services provided, what is common among the tech giants are the source of their competitive advantage which made them *winner-take-all*. Typically, BigTechs do not compete in a traditional fashion through cost leadership or quality improvement, rather by focusing upon building an ecosystem based on digitisation and network theory (Iansiti and Lakhani, 2017). Foremost, BigTechs have considerable incentives in broadening the range of their activities by reason of the extreme economies of scale they benefit. The "non-rivalrous" characteristic of digital products allows simultaneous utilisation by a limitless number of people without loss of content, generating, *de facto,* low-to-zero marginal costs (Barwise and Watkins, 2018). Among other activities, the entrance in financial services, notwithstanding the lower profitability of the sector compared to their core business, appears to be valuable in a broader sense. Their venturing derives from the desire to diversify their revenue streams, complement and reinforce the principal commercial activities by increasing loyalty and customers base, and access new sources of data (Financial Stability Board, 2019b). The willingness of users' data base enlargement should be explored in the light of the peculiar features of their business models capable of generating an advantageous self-reinforcing mechanism. These idiosyncratic characteristics are represented by the DNA acronym: Data analytics, Network externalities and interlacing Activities. According to the network externalities, cornerstones of BigTechs' competitive advantage, users' benefits from participating to one side of a techs' platform surge as the number of users on the other side increases[4]. Network externalities, which originate from the multi-sided platforms' nature lying on multilateral exchanges rather than traditional bilateral relationships, not only generate more users but also cause, indirectly, additional data. Thus, more users automatically mean more disposable data to analyse (Bank for International Settlements, 2019). The analysis of the resulting extensive amount of granular and real-time data sets, namely *big data*, through automated data analytics techniques, called *machine learning*, can further reinforce the network effects (Barwise and Watkins, 2018) allowing the enlargement of the business offer once the critical mass of customers is reached. Lastly, supplementary, and improved services for

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[4] It is possible to differentiate said direct network effects, with indirect network externalities, a situation whereby the value for the participants in each market is related to the number of participants in another complementary market. The latter is crucial in the digital market since techs' platform create value by matching consumers with complementary needs, e.g. users and advertisers (Barwise and Watkins, 2018).

customers, enable attracting further users on the platform, completing the feedback loop cycle as exhibited by Figure 1.2.

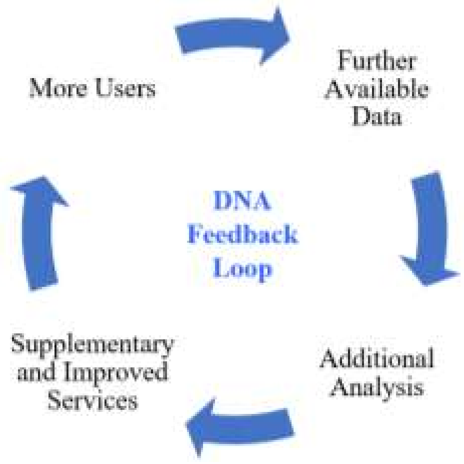


Figure 1.2 DNA feedback loop: the self-reinforcing mechanism which could explain the expansion of BigTechs activities (Bank for International Settlements, 2019).

Financial services provision particularly benefit from the resulting DNA feedback loop. An example of this synergy is provided by the marketplaces. Network externalities, which arise from the fact that benefits for the e-commerce sellers increase as the number of buyers expands, generate more users and information inputs for data analytics. The platform can then exploit the analysis, based on payment transactions, financial and consumers habits as well as considering other information collected via social media, in order to customise existing services such as targeted advertising and to propose other financial services, e.g. credit assessment (Bank for International Settlements, 2019).

1.3 Economic Drivers

Financial technologies have emerged in both developed and developing markets up to reach a percentage of average global adoption[5] of 33% in 2017 (EY, 2017). Nonetheless, they are not homogeneously important in each country. Evidence of this is represented by Figure 1.3 that provides an outline of cross-country FinTech credit volume in 2017 divided into BigTechs' credit and other FinTech credit provision. It can be seen that in China, United States, Republic of Korea, and Kenya, tech giants' credit platforms are particularly economically relevant in absolute term. However, the percentage of FinTech credit as a share of the total stock of credit results still limited, in the vast majority far less than 1% of the outstanding banking and other lenders credit. The only exceptions are China and Kenya, where the weight of tech firms' credit is relatively high even if still small in aggregate terms compared with the overall credit market (Frost, 2020).

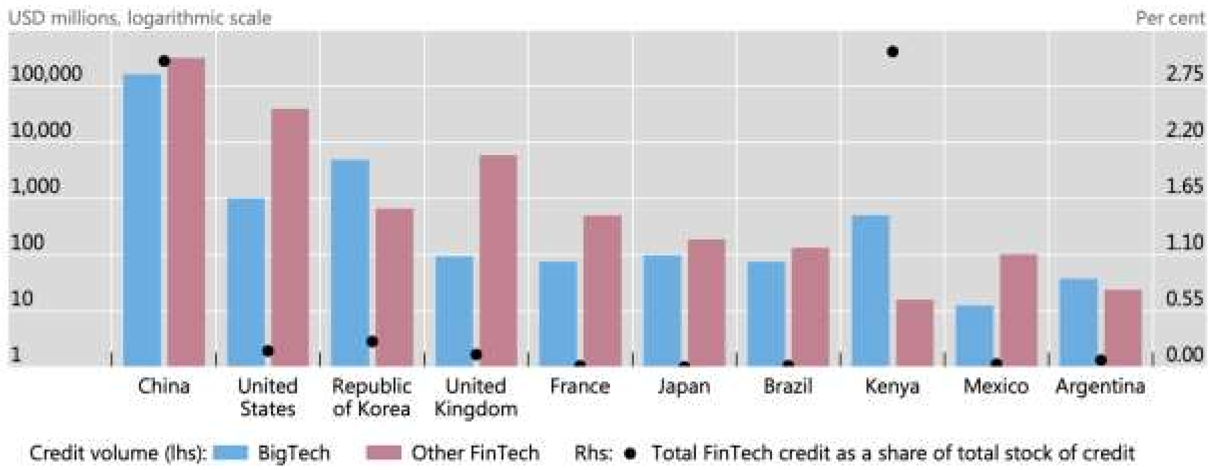


Figure 1.3 Total FinTech credit volume in 2017: it shows the differences in cross-country importance of BigTechs' financial activities as concern the credit provision (Frost, 2020).

Notwithstanding the increased level of investment from tech firms in Europe represents one-third of the global investment level, in Italy, investments in financial innovation are still modest (Banca d'Italia, 2019). Lastly, even within countries, relevant differences could arise. In some cities, it is recorded an unexpectedly high rate of financial innovation adoption (e.g. Hangzhou, Seattle and Tel Aviv), while in other traditional financial centres this datum is less relevant than expected (e.g. Tokyo and Milan) (Frost, 2020).

The afore-explained features that characterise the large technological firms' business models do not explicate the differences in terms of development thereof. Frost *et al*. (2019) analyse the reasons underlying the cross-country differences in the rate of FinTech adoption of BigTechs activities looking at what drives these companies into the financial sector. The drivers of

[5] "Average percentage of digitally active consumers using FinTech services" (EY, 2017).

BigTech activities in finance come from both the demand and the supply viewpoints. From the demand point of view, the factors to consider are unmet customers demand and customers preferences. First, as will be explored in the third chapter, a considerable opportunity for tech firms derives from the demand for financial services from the faction of the population which results unserved by traditional institutions (Bank for International Settlements, 2019). The second key driver includes consumers and businesses preferences. Both of them are more likely to use BigTechs' financial services when they are comfortable with new technologies. The discriminative factors for final users are demographic elements comprising age. The higher percentage of final users who prefer to use digital channels and technologies are indeed consumers from twenty-five to thirty-four years old (EY, 2017). Whereas, one of the main reasons for small and medium enterprises (SME) FinTech's implementation is the range of functionality and features offered by the companies (EY, 2019). Moreover, a 2019 consumer survey found that 65% of the respondents trust Amazon for financial needs, and 58% of them are confident for the same reason in Google, accentuating an apparent growing trust towards BigTechs (McKinsey&Company, 2019).

From the supply side perspective, besides access to data and technological advantage which enable BigTechs to obtain and process better and superior information, it is noteworthy the importance of lack of competition, funding availability and discrepancies in regulation. BigTech firms result especially attractive in the case of the high cost of finance and high mark-ups adopted by the banking sector. The funding access driver varies according to the platform type adopted by the company, which can rely either on proprietary funds or bank partnerships (Frost *et al.*, 2019). The regulatory environment, instead, does not seem a main driver on an aggregate level. Vice versa at a specific activity level, certain FinTech activities could be driven by regulatory arbitrage which can involve geographical dissimilarities (Frost, 2020). Adequate regulation, intended as neither excessive nor insufficient level of legislation, seems to be associated with higher FinTech volume adoption (Cambridge Centre for Alternative Finance, 2019). It is fundamental to distinctly explore the current frameworks of innovative financial regulation on an international level, not simply as an economic driver, but as a critical point of the phenomenon.

1.4 Public Policy and Regulation

The entrance of BigTech companies in finance raises several issues for policymakers due to the inadequacy of ordinary rules and tools reserved to traditional financial institutions in front of a such complex phenomenon. As conveyed by the Bank for International Settlements (2019), a first approach to the regulatory problem relies on the so-called "same activity, same regulation" principle. Based on this principle, regulators have extended the existing regulation and instruments on banking undertakings to BigTechs engaging in substantially identical activities carried out by banks, e.g. consumer protection regulation. Nevertheless, when BigTechs activities fall out of the scope of the current financial prudential regulation or supervision, this safeguard may not be sufficient. The same European Union, through the 2018 "FinTech Action Plan", acknowledges that some financial innovation activities might be excluded from the supervision dedicated to the traditional activities (Bianchini, 2020). Moreover, the Basel Committee on Banking Supervision highlights the additional problems concerning these FinTech firms operating in multiple jurisdictions with cross-border operations, claiming for the further need of global coordination and cooperation (Bank for International Settlements, 2018). The Bank for International Settlements (2019) proposes the "risk-based" principle as a guideline together with a proportionate adaptation of the regulatory toolkit emphasising the need for a holistic approach, able to go beyond the mere financial legislation. In a perspective of *de iure condendo,* it is necessary a comprehensive approach able to encompass competition, financial stability, and data protection issues, but also capable of managing the potential trade-off between the different regulatory objectives. The overlapping among these regulatory fields as well as the heterogeneity of policy tools among jurisdictions are evident by looking at the regulatory compass, which frames the current normative for BigTechs in finance across several countries. As can be seen in Figure 1.4, this tool displays, on the north-south axis, the level of promotion (north) or restrictions (south) towards the entry of BigTechs within the financial field. Whereas, the west-east axis shows the different approach to data protection, from restrictive methods based on limits on the use of data (west) to decentralised ones lying on property right assignment to customers (east). It is also exposed the extent to which normative affects BigTechs (the further it is moving outward the more impact), together with the associated authorities which have introduced the regulation.

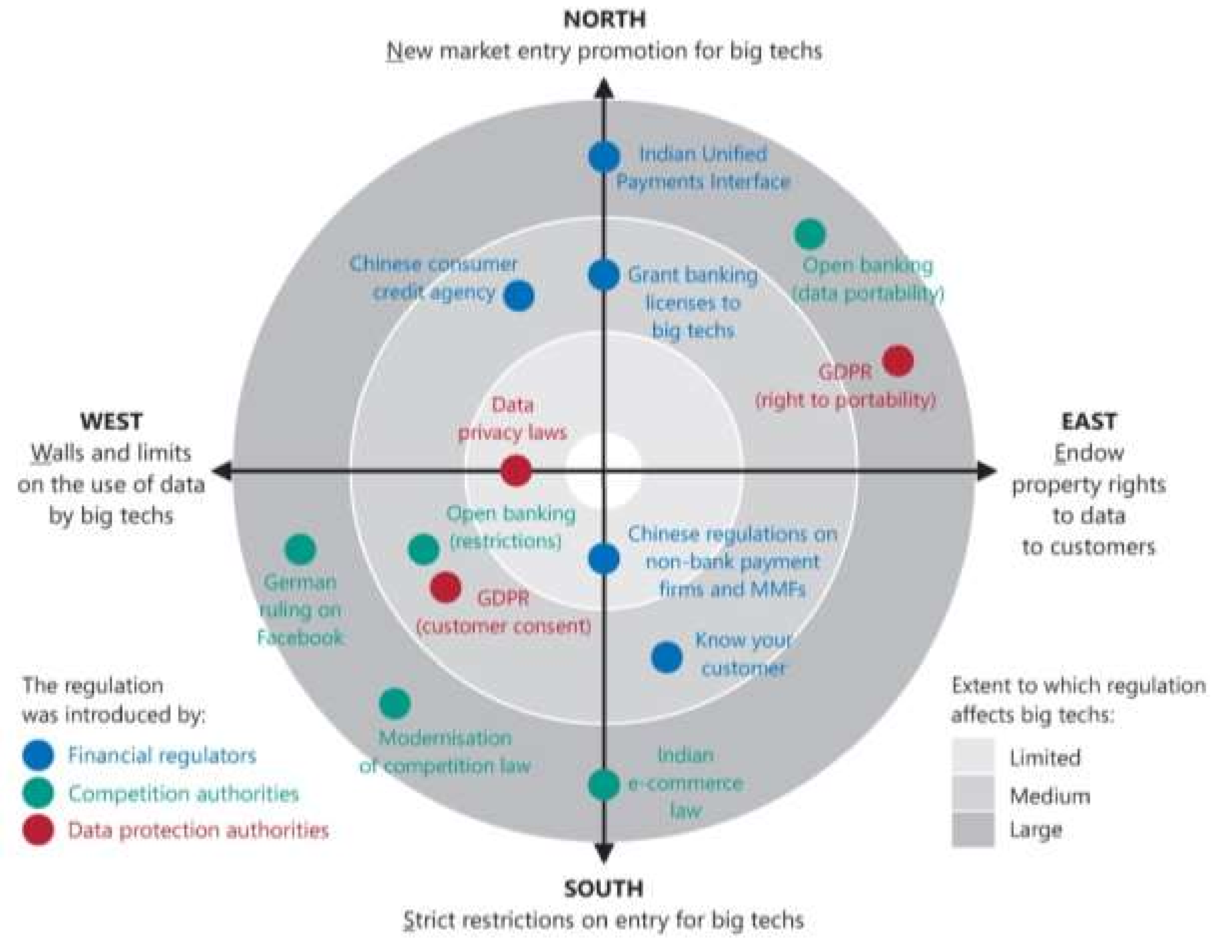


Figure 1.4 Regulatory compass: public policies in different countries, affecting, to some extent, BigTechs' activities in finance (Bank for International Settlements, 2019).

Looking at the European Union, on a financial regulation perspective, it is remarkable the adoption of the know-your-customer (KYC) rule which imposes to BigTechs the same banking requirements on payment services in order to prevent financial crimes, and that results in a medium impact for BigTechs. The competition authorities intervene to the open banking regulation with the Payment Services Directive (PSD2)[6] which obligates banks to provide access to customers data to authorised third-party providers (TPPs) allowing *de facto* digital players to compete with banks in offering payment services (De La Mano and Padilla, 2019). In addition to this, in 2019, to assess anticompetitive conduct in the digital market, the EU competition authorities received recommendations on how to adapt the current practices. This "modernisation of competition law" results in a high impact for BigTechs involving strict restriction on the entry for these companies, as also exhibited by the current examination of potentially anticompetitive conduct of some BigTech companies by the US Federal Trade

[6] Directive (EU) 2015/2366 (EUR-Lex, 2020).

Commission. Lastly, the EU General Data Protection Regulation (GDPR)[7], marks a new era for data privacy. The GDPR provides, besides an active consent requirement from consumers for data sharing, the "right to portability". According to the latter, customers are entitled to receive their personal digital data in a structured and transferable manner without any obstruction. Even if this measure is far from establishing a "Coasian"[8] solution, it is certainly a decentralised approach, placed to the eastern part of the regulatory compass. A peculiar law within the European Union is the "German ruling on Facebook" based on which the German competition authority prohibits Facebook from combining its user data with others collected from its affiliated companies, i.e. WhatsApp and Instagram (Bank for International Settlements, 2019). Moreover, looking at the Italian scenario, in 2019, it was established a FinTech Committee, and it was officially introduced into the national regulatory body a regulatory sandbox[9]. This tool expressly allows for FinTech experimentation of financial services and products based on new technology (Consob, 2019).

On an international landscape, the Chinese and Indian regulations applied to large technology firms stand out. The first one has a unique regulatory scheme for these firms engaging in financial activities since BigTechs' money market funds (MMFs) play an important role in interbank funding. The "Regulation on non-bank payment firms and MMFs" involves "a cap on instant redemptions" for the MMFs, a mandatory reserve requirement of customers balances in a reserve account of the People's Bank of China, and the specific requirement to clear payments on a common and public clearinghouse. India, from the one hand, promotes the entrance of BigTechs in finance through the "Unified Payments Interface" measure. It facilitates banks' transfer of funds on a mobile platform to which every payment service provider can access. On the other hand, with the "Indian e-commerce law", the country severely hinders these companies by prohibiting foreign e-commerce platforms from selling on their Indian marketplace products supplied by its affiliated companies (Bank for International Settlements, 2019). To conclude the global overview, in the United States, despite FinTech firms undergo to specific Federal regulations, they are subjected to the same consumer protection rules applying for banks and other credit intermediaries (Reiners, 2020).

[7] Regulation (EU) 2016/679 (EUR-Lex, 2020).

[8] Approach to solve inefficiencies based on the provision of property rights for data and the consequent formation of a competitive market where consumers can directly choose to which sell or share data (Bank for International Settlements, 2019).

[9] L. 28 June 2019, n.58; Dl. 30 April n.34 (Consob, 2019).

Nevertheless, in every country, specific legislation varies depending on the type of activity undertaken by these companies.

2. Credit Provision: Innovative Financial Intermediation Dynamics

2.1 Lending Platform Models

BigTechs credit provision, representing one of the most promising activities of these firms in finance, is considered as a sub-group of FinTech credit. Credit provided by FinTech firms is recognised by the Bank for International Settlements and Financial Stability Board (2017) as "credit activity facilitated by electronic platforms" with the further condition of not being engaged by banks (Frost *et al.*, 2019).

The tech giants can operate through various lending platform models. The types with the highest growth[1] in Europe in 2017 for FinTech in general are the traditional P2P lending and invoice trading models (Cambridge Centre for Alternative Finance, 2019). While for BigTechs, mainly relying on equity as a primary source of funding (Frost *et al.*, 2019), the balance sheet model could be considered more suitable. Other types are the guaranteed return and the notary models. The traditional P2P lending model (Figure 2.1.1) is a peer-based platform which allows lenders and borrowers to trade with each other directly. A prospective borrower can apply for a loan after having provided credit information verified and approved by the platform, while potential creditors can decide to fund loans available contracting straight with the borrowers rather than with the platform. The platform benefits take the form of fees imposed on the transacting parties for account setup, loan origination and repayment.

Figure 2.1.1 P2P lending model (Bank for International Settlements and Financial Stability Board, 2017).

In the invoice trading model, the platform offers invoice financing services, also called factoring. The client companies may sell invoices and receivables in order to obtain instant[2] liquidity at a discount provided by a third party. The default risk with regard to the invoices

[1] Measured as alternative finance volume in euros.

[2] Before the invoices or receivables maturity.

sold remains to the original creditor in the case of a recourse factoring model. In contrast, with a non-recourse model, the risk translates to the receivable purchaser. The balance sheet model (Figure 2.1.2) goes beyond the matching function, counting on an own balance sheet to originate and retain loans. The resulting capital sources are debt, equity and securitisation[3] to fund origination. The investors involved can be both retail investors, which receive claims in exchange of funds, and institutional investors, which are entitled to securitise the loan sold by the lending platform. However, in this structure, it is the platform with its balance sheet that keeps the loans and that undertakes the responsibility of the credit risk analysis, providing funds and expecting repayments directly from borrowers.

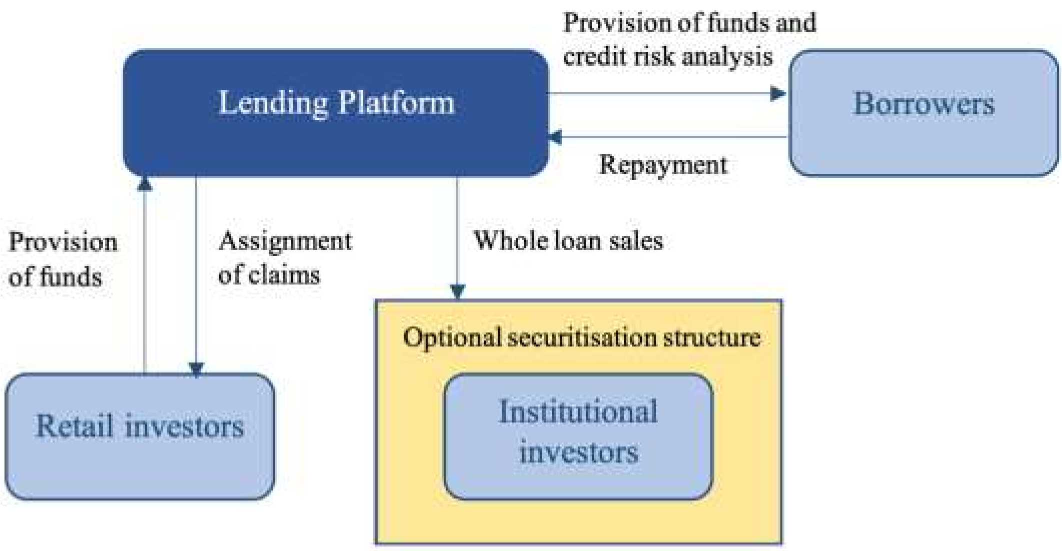


Figure 2.1.2 Balance sheet lending model (Bank for International Settlements and Financial Stability Board, 2017).

Similarly to the P2P lending model, in the guaranteed return model, the company operates as an intermediary platform between borrowers and lenders providing credit risk analysis to borrowers and investments information to lenders. The peculiarity is that the platform guarantees for creditors the principal and the interest on loans, or one of these two only, in return for guarantee fees. Lastly, the notary model (Figure 2.1.3) is based on the cooperation between two players: a lending platform and a fronting bank[4]. Both actors may tackle the credit risk analysis, but the lending platform act only as an intermediary. Loans origination and assignment of these to creditors are indeed undertaken by the partnering bank. As a

[3] The optional securitisation structure treats investments as shares in a "pooled loan scheme" by generating a large number of contracts and maintaining each relationship separately.

[4] Partnering bank that issues and retains loans.

consequence, the lending platform is the mean through which the borrowers may apply, but it does not directly originate loans (Bank for International Settlements and Financial Stability Board, 2017).

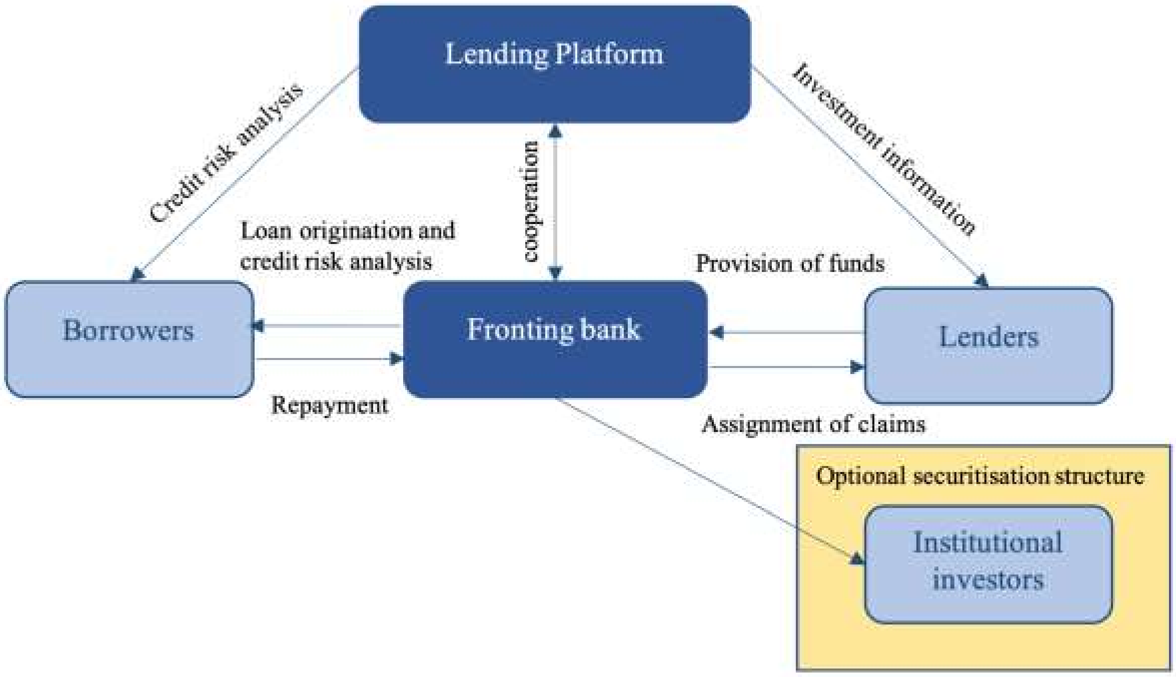


Figure 2.1.3 Notary lending model (Bank for International Settlements and Financial Stability Board, 2017).

2.2 Ex-Ante Evaluation: Credit Scoring Models

Independently from the lending model adopted, platforms characteristically can provide the credit risk analysis of potential borrowers. The risk assessment delivered by technology firms differs from the models used by traditional financial institutions since new credit scoring models involve machine learning and alternative data sources, going beyond conventional information.

Traditional data used to evaluate the creditworthiness are that information incorporated in the credit bureau assessment based on credit records from banks, sociodemographic and payment behaviour data (Berg *et al*., 2018). In detail, the sub-elements that compose the credit records are evident in the FICO score[5] computation which includes payment history, total amount owed, credit history length and a mix of credit cards, credit accounts, instalment and mortgage loans (myFICO, 2020). Moreover, financial intermediaries with a network of branch distribution, having the possibility for human loan officers to interact with borrowers directly, are able to gather "soft" information in addition to traditional credit data.

On the contrary, what is not typically encompassed by traditional lending players drawing up credit ratings or credit approval criteria, are alternative types of material collected, analysed and processed through big data, machine learning technology and other artificial intelligence algorithms. Alternative data analysis embraces transactions evidence which includes sales volumes and average selling prices, reputation status as it appears from the claim ratio, complaints management, and industry-specific characteristics, including eventual seasonality of sales, trends, and macroeconomic responsiveness. Furthermore, most tech giants can collect and combine supplementary information through social media (Frost *et al.*, 2019). The so-called digital footprint[6] can be used as a proxy of potential borrowers' economic status for predicting consumers default. The variables that seem to have the highest economic significance on loan default rate are errors in the first trial of inserting emails address, purchases via mobile device type instead of desktop or tablet, use of Android system, and purchases during the night as check-out time. Digital footprints information appears to be a successful predictor of default rates, however, since the small correlation[7] between the scores based on digital footprints variables and the credit bureau scores, online footprints may better act as complements of traditional data instead of substitutes (Berg *et al*., 2018).

[5] Used by 90% of the US lending institutions for credit risk assessment (myFICO, 2020)

[6] Digital "trace of simple, easily accessible information" e.g. operating system, tracking device settings allowances, email service provider and emails address (Berg *et al*., 2018).

[7] The Cramér's V between these two sources is economically small, ranging between 0.01 and 0.07.

But, the point is to what extent the new models built on machine learning techniques and alternative data outperform the classical credit scoring models. First, Khandani, Kim and Lo (2010) analyse a forecast model scores for customers focuses on machine learning algorithms. They find that this model is effective in capturing consumers credit default and that this accuracy is useful in predicting credit events from three to twelve months beforehand. Nevertheless, the mentioned study is restricted to a stationary external environment.

Gambacorta *et al*. (2019) overcome this limit studying a Chinese FinTech company[8] data set engaging in lending activities before and after an exogenous regulatory shock. The estimated models are represented by three different equations to foresee borrowers' losses. In the first one (1) the independent variable used is the FinTech credit score based on machine learning technology and information given by consumers such as credit card transactions, e-commerce platform and digital application data. In detail, $L_{i,t}$ stands for the loss rate as a percentage of the origination volume for a particular borrower i at time t and it represents the dependent variable for all models; α is the coefficient of the regression variable $CS_{i,t}$ which refers to the FinTech credit score for the i-borrower at time t. Lastly, as in each model, it is included province fixed effects μ_ρ, time fixed effects μ_T, and error term $\varepsilon_{i,t}$.

$$L_{i,t} = \alpha CS_{i,t} + \mu_\rho + \mu_T + \varepsilon_{i,t} \tag{1}$$

The second credit loss model (2) uses as independent variables only information from traditional bank-type data. The structure of this regression model is similar of that of the first equation, however, β stands for the coefficient of the $X_{i,t}$ variable which represents a vector of variables collected through credit cards, namely information commonly available to traditional financial institutions.

$$L_{i,t} = \beta X_{i,t} + \mu_\rho + \mu_T + \varepsilon_{i,t} \tag{2}$$

The last model (3) accounts for independent variables on both traditional and non-traditional set of information. In fact, in addition to the classical variables taken into account by banks introduced in (2), it is included the term $\delta Y_{i,t}$, where δ is the coefficient of the $Y_{i,t}$, vector of non-traditional variables available to the FinTech firm.

$$L_{i,t} = \beta X_{i,t} + \delta Y_{i,t} + \mu_\rho + \mu_T + \varepsilon_{i,t} \tag{3}$$

[8] Said firm decided to remain anonymous.

The regression output reported by Figure 2.2.1, built through a Tobit regression model estimation[9], suggests that the FinTech score equation (1) is an extremely significant loss rate predictor and that the mixed model with traditional and non-traditional information, equation (3), is useful too. Looking at the pseudo R^2 of the first model (0.0367) results to be almost double that of the third model (0.0217) and both of them are higher than the second model (whose pseudo R^2 is 0.0169).

	Loss rate		
	I	II	III
Variables	Fintech credit score	Traditional information only	All information
Fintech credit score	−0.00845*** (8.30e−05)		
Traditional information			
Number of bank accounts (12 months)		−0.00198** (0.00100)	−0.00195* (0.00100)
Frequency of usage (12 months)		−2.14e−05 (0.000150)	−0.000119 (0.000150)
Frequency of usage (3 months)		−0.000756 (0.000476)	−0.000671 (0.000474)
Large payment count		−0.00126*** (5.87e−05)	−0.00100*** (5.80e−05)
Credit line		−2.97e−07*** (6.78e−08)	−1.52e−07** (6.69e−08)
Defaults (12 months)		0.0121*** (0.00197)	0.0159*** (0.00196)
Defaults (3 month)		0.00978 (0.00674)	0.0117* (0.00669)
Repayments (12 months)		−3.60e−07 (7.71e−07)	−4.32e−07 (7.96e−07)
Number of bank accounts (3 months)		0.0140*** (0.00347)	0.0155*** (0.00351)
Credit history		−0.00624*** (0.000149)	−0.00600*** (0.000150)
Salary in debit card		−4.55e−06*** (5.13e−07)	−4.64e−06*** (5.21e−07)
Non-traditional information[1]			
Max call duration			−3.55e−10*** (1.16e−10)
Call times to family			2.97e−06 (4.70e−06)
Frequency of calls (daily)			−0.0191*** (0.000978)
Taobao payments (daily)			−1.69e−05*** (1.64e−06)
Observations	310,919	310,919	310,919
Pseudo R^2	0.0367	0.0169	0.0217

Figure 2.2.1 Regression output of the loss rate for the three models specifying variables included and results for the three equations presented (Gambacorta et al., 2019).

[9] The Tobit regression model is an example of a censored regression model used in the case of censored data nature (Stock and Watson, 2016).

As a result, the model related to the FinTech credit scoring (1) appears to outperform in predicting credit losses, while the traditional and non-traditional data credit scoring model (3) can be considered a second-best, and lastly, the model based on traditional bank-type information only (2), perform worst. However, it should be mentioned that the machine learning model (1) use more data compared to the others, and this may be a reason for better performances. The predictive power of the three models is further tested following a regulatory shock which caused an increase of 3% on loans default rate supplied by the firm in approximately one month. Figure 2.2.2 shows the performances of the models before and after the change in regulation signalled by the vertical line.

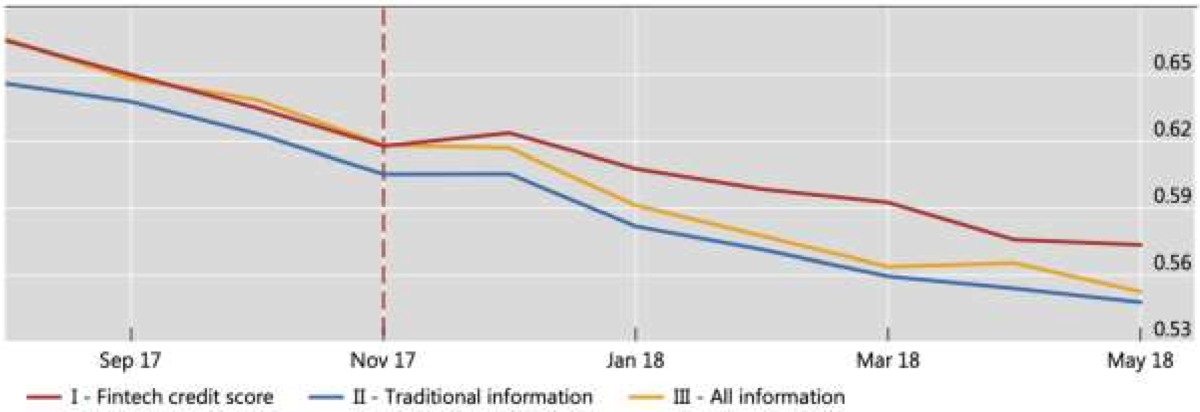


Figure 2.2.2 Discriminatory power of the different credit scoring models before and after the regulatory shock. The vertical axis represents the AUROC, the area under the ROC curve (receiver operating characteristics), metric ranging from 50% (purely random prediction) to 100% (perfect prediction) (Gambacorta et al., 2019).

The findings illustrate that despite the three models perform worse after the structural shock, model (1), achieves relatively better results than the others, even though the difference between models (1) and (3) is not statistically significant especially before the stock. A possible explanation might be that non-traditional information are the primary reasons for the predominance of the model (1) before the shock, while during periods of stress results more relevant the capacity of machine learning in capturing dynamic[10] relationship between variables. Additionally, all models perform better in the case of a longer relationship with customers, although the comparative advantage of the two leading models tends to fall as the relationship length increases. Overall, credit scoring models based on machine learning encompassing traditional and non-traditional data, appear to be better predictors of losses and default compared to the traditional models (Gambacorta *et al*., 2019).

[10] This is due to the non-linearity of the machine learning models.

2.3 Ex-Post Actions: Monitoring and Enforcement

Both BigTechs and traditional financial institutions, once a loan has been approved following the credit risk assessment, implement *ex-post* strategies in order to supervise and incentivise borrowers to repay it. Banks commonly leverage loans reimbursement on customers monitoring through direct supervising. This allows reducing the risk that borrowers' actions fall outside the projects' scope initially agreed at the loan underwriting. Moreover, the measure enables financial institutions to develop mutual trust through a long-term relationship, limiting the deliberate borrowers' default attractiveness. Traditional enforcement typically requires pledging tangible assets from borrowers as collateral to offset potential losses in the event of default.

The *ex-post* strategies implemented by BigTech companies focus on their ecosystem and network externalities exploitation rather than direct supervision and collateral. BigTechs may enforce loan repayments by leveraging on the value of their ecosystem both directly and indirectly. Tech giants are able to obtain loans repayments directly deducting borrowers' revenues that transit on its e-commerce payment account (Bank for International Settlements, 2019). Amazon, for example, states that loan payments are deducted from the seller account disbursement subsequent the loan payment due date, and, if it is not sufficient, the platform will deduct the residual balance from the following disbursement until the full loan repayment is achieved (Amazon, 2020c). At the same time, an indirect effect comes from the threat of the platform to downgrade or even exclude from its ecosystem borrowers which refuse or are unable to repay the credit obtained (Bank for International Settlements, 2019). This is undoubtedly a significant threat to future affairs for those sellers who mostly rely on the platform network effects exploitation. In this case, suspending the borrowers' account might be a significant "counter-moral-hazard strategy" (Bilotta and Romano, 2019). If monitoring and threats are not sufficient to avoid borrowers' default, platforms usually collaborate with debt collection agencies in order to recover loans. Other firms provide investors with insurance contracts, provision funds or dedicated guarantees (Bank for International Settlements and Financial Stability Board, 2017).

2.4 Pricing Strategies

The *ex-ante* risk evaluation and the *ex-post* monitoring and enforcement strategies are strictly related to the cost of lending (Bank for International Settlements, 2019). To understand how loans are priced, Davis and Murphy (2016), highlight three different approaches to set interest rates on loans. The first pricing strategy is based on allowing borrowers to set a maximum rate according to their willingness to borrow, which must be above a risk-related minimum rate decided by the platform, and letting investors bid for loans in an auction process. If the bids received are able to fund the loan at a closing date entirely, the resulting interest rate is that of the highest successful bid in case of uniform rate auction. Otherwise, in case of mixed rate auction, the interest rate derives from a weighted average[11] of the successful bids. In the second approach, borrowers set a maximum acceptable interest rate after having received from the platform an indicative estimate of potential interest rate receivable in the market according to risk level and loan maturity. Investors are allowed to see the indicative market rate of the available investment possibilities and set a minimum rate which they are willing to invest. Lastly, the platform combines compatible interest rates from borrowers and investors. The third method lies instead on imposing a specific interest rate according to the grade of risk assigned to the loan.

The resulting cost of lending that BigTech firms can propose to borrowers is potentially lower than traditional financial intermediaries. This is due to reduced operating cost, having no need for physical branch networks, process automation advantages thanks digital technologies, and less regulatory costs (Bank for International Settlements and Financial Stability Board, 2017). Lack of information about BigTechs lending[12] and credit risk differences between potential borrowers make it difficult to compare interest rates between those offered by techs giants and those applied by traditional institutions. Nevertheless, it is possible to see that in some countries the cost of bank lending is extremely high. Table 2.4, constructed on The World Bank (2019) data, outlines the top twenty countries for the uppermost lending interest rate in 2018[13]. The interest rate average for these countries is 24.47%, and even considering the first one,

[11] In this case, the interest paid from the borrowers and that received from investors differ. Borrowers are required to pay a weighted average of the interest rate offered, while investors are entitled to receive the rate bidden during the auction process.

[12] E.g. Amazon Lending proposes loans to customers through invitation directly to the seller account and releasing no interest rate information publicly (Amazon, 2020c).

[13] The interest rates considered refer to representative rates provided by banks to the private sector, particularly to resident customers, for short-term and medium-term financing needs (The World Bank, 2019).

Madagascar, as an outlier, having a 55.4% of interest rate, the remaining countries have still an average rate of 22.84%.

	Country	Lending Interest rate
1	Madagascar	55.40%
2	Brazil	39.10%
3	Argentina	37.40%
4	Malawi	32.30%
5	Gambia	28.00%
6	Tajikistan	27.20%
7	Congo	24.70%
8	Mozambique	23.00%
9	Angola	20.70%
10	Sao Tome and Principe	19.90%
11	Uganda	19.80%
12	Kyrgyz Republic	19.50%
13	Ukraine	19.00%
14	Egypt	18.30%
15	Sierra Leone	17.90%
16	Honduras	17.80%
17	Mongolia	17.70%
18	Azerbaijan	17.40%
19	Tanzania	17.40%
20	Nigeria	16.90%

Table 2.4 Lending interest rate in percentage: the top twenty countries for the highest lending interest rate in decreasing order for the country with available 2018 data (The World Bank, 2019).

By way of illustration, as a term of comparison can be considered Ant Financial, an affiliate of the Chinese tech giants Alibaba. According to sources reported by Bloomberg (2018), it underwrites loans with an interest rate typically below 15%, percentage far below the average of the twenty countries for the highest interest rates. This example suggests the potential benefits that BigTechs could bring in terms of lower loans pricing, at least towards those countries facing a high cost of lending.

3. Future Scenarios: a New Era for the Financial System

3.1 Financial Inclusion and Efficiency Gains

As already emerged by the previous chapters, BigTechs establishment as a player in the financial system[1] have an enormous potential. The tech giants have the scale, technical know-how, and cutting-edge systems that FinTechs would need to leap forward, they are not affected by organisational issues that banks face, and, simultaneously, they have access to an extremely valuable amount of data (Stulz, 2019). Thus, even if to date the credit offer from BigTechs is still limited, a future expansion of the same might have significant effects, heralding the arrival of a new era. Therefore, it is necessary to explore the consequences that might derive from this phenomenon in terms of financial inclusion promotion, efficiency and competition.

Firstly, these firms may promote financial inclusion lowering barriers for those households and firms excluded or at risk of exclusion from the financial system (Bank for International Settlements, 2019). The World Bank Group (2018) estimated that, in 2017, 31% of the global population does not have an account at a financial institution or a mobile money provider correspondent to 1.7 billion of adults unbanked, among them women are overrepresented, especially in developing economies. The reasons at the basis of this financial inclusion imbalance that are, apart from low incomes, distance, lack of documentation, cost issues and distrust in the financial system, can be potentially solved by BigTechs. As mentioned, the technological advantages they benefit from may determine more convenient and accessible financial services provision (Financial Stability Board, 2019b). Notwithstanding the low-income problem, approximately two-thirds of the unbanked population has a mobile phone. Through this, tech firms are able to easily reach customers in geographically remote areas offering the so-called *electronic wallets*, such as Apple Pay and Google Pay that makes services accessible directly through smartphone *super apps*[2] (Bank for International Settlements, 2020). Moreover, as a consequence of credit assessments including alternative data, both households and SMEs may be able to access to credit overcoming the lack of minimum requirements for traditional banking loans application, such as the absence of audited financial statements (Bank for International Settlements, 2019). Some borrowers classified as subprime by traditional scoring models may also obtain better grades and lower price credit (Jagtiani and Lemieux, 2019). Likewise, risk algorithmic models enable a reduction in human decisional biases,

[1] "A set of markets for financial instruments, and the individuals and institutions who trade in those markets, together with the regulators and supervisors of the system" (Howells and Bain, 2008, pp. 4).

[2] Super apps offer end-users "a one-stop shop" for a wide range of services, from core business activities (e.g. e-commerce) to payment, loans and insurance for businesses and consumers.

particularly in pricing discrimination against minorities. From a study by Bartlett *et al*. (2019) emerges that FinTech lenders discriminate about one-third less compared to face-to-face lenders in terms of pricing.

Secondly, BigTechs can lead to efficiency improvements to the entire system pushing the traditional sector to adaptation. Data shows that incumbents already have accelerated technology spending and industry digitalisation, offering relevant efficiency enhancement outlooks (Moody's, 2018). Moreover, machine learning application can increase efficiency in financial services, enabling faster risk assessment and underwriting processes (Frost *et al.*, 2019). A study by Fuster *et al.* (2018) tests the origination loans time as an efficiency measure of technology in US mortgage lending. Technology-based lenders seem to reduce the processing time[3] by 20% of the average traditional lenders time without resulting in risk increases, supporting the hypothesis of tech-based financial services efficiency improvements. At the same time, looking at the whole society, cutting-edge technologies, i.e. artificial intelligence, can increase transparency helping to prevent and detect irregularities and fraudulent activities as money-laundering through transaction monitoring (Swiss Finance Council, 2020).

Thirdly, from a broader perspective, BigTechs may foster a higher rate of competition and diversity, strengthening the financial system. However, the debate about competition is not clear, such as to justify a more in-depth investigation.

[3] Measured as total days from loan application submission until the closing.

3.2 Alternative Competition Outlooks

As just emerged, it is still unclear whether this phenomenon will increase competition or not and what are the likely consequences for the financial system in each scenario. At the current state of affairs, the relationship between BigTechs and incumbents embraces both cooperation and competition flowing into a "coopetition" approach in which both sides have incentives to cooperate each other albeit in competition (McKinsey&Company, 2016). Currently, unlike Alibaba and Tencent, Amazon, Google, and Apple are mostly recurring to partnerships with banks to engage in financial activities (Bank for International Settlements, 2019). However, since the existing predominance of cooperation over competition is based on a win-win situation driven by BigTechs-Banks complementarities[4], what it will happen once the BigTechs have fulfilled all the necessary competencies and capabilities to compete directly?

According to a first view, from an increase in competition, it could result in a more efficient and resilient financial system (Financial Stability Board, 2019a). From the economic theory, if in a market operates a higher number of vendors, the possibility of strategic behaviours adoption is lower (Katz, 2015). The further a system is strayed from a perfect competition situation, the greater the potential welfare loss. If borrowers can only find few lenders, and after costly and intensive searching, the demand for funds would be lower together with the supply, compared to the case with a greater number of lenders. As shown by Figure 3.2, these financial system movements can impact the aggregate demand composition affecting the real economy[5]. With a higher level of funds supply (S'), the lower cost of borrowing (i') would encourage real investments expenditure pushing the economy to reach a higher rate of growth (Howells and Bain, 2008).

[4] Mainly, banks benefit from technological capabilities of these firms to improve their services, while BigTechs advantage on the banks' availability of funding and existing infrastructures (Financial Stability Board, 2019b).

[5] Part of the economy that produces real goods and services as opposed to the financial part of the economy (Howells and Bain, 2008).

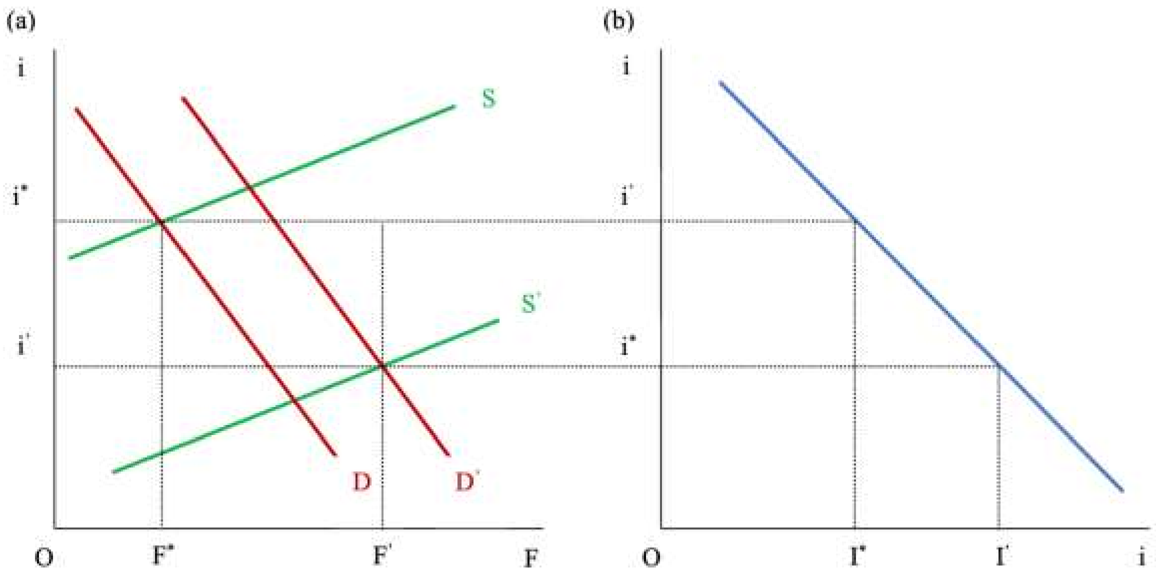


Figure 3.2 The financial system and the real economy: the effects of funds supply on the interest rate (a) and on the investments spending (b). The x-axis corresponds to the flow of funds for (a) and investment spending for (b), while the y-axis is represented by the rate of interest for both graphs (Howells and Bain, 2008).

Several studies in the literature empirically examine the relationship between competition and economic growth. Cetorelli and Gambera (2001) find evidence that bank concentration has a negative effect on growth in aggregate terms, proving the theoretical prediction of a higher amount of credit available in the economy with lower bank concentration. However, they also notice that banking competition does not automatically dominate monopoly.

An opposite stance on competition argues that a less competitive banking sector is instead desirable, emphasising the side effects arising from trade-offs between competition, financial stability, and data protection. First, from a financial stability perspective, less competition leads to more profitable incumbents, that are able to accumulate stronger equity base and act, as a consequence, more prudently (Bank for International Settlements, 2019). According to a McKinsy&Company (2017) study, the global banking industry return on equity (ROE) could decrease by 3.4 percentage points[6] by 2025 as a consequence of customers reduction and absence of mitigating actions to prevent from BigTechs. This could lead to an excessive risk-taking from incumbents to protect against this adverse scenario. Furthermore, BigTechs partnerships with banks might create new dependencies, operational and financial interconnections, accentuating the risk of contagion in the event of a financial shock or operational failure. Moreover, as an effect of the relatively sizable pool of funds managed outside the banking system, such as through electronic wallets instead of banks deposits, the transparency of the linkages within the financial system may decrease (Financial Stability

[6] From 8.6% in 2016 to 5.2% by 2025 (McKinsy&Company, 2017).

Board, 2019b). It is ambiguous whether the transmission mechanism of the monetary policy may be affected by the money flowing in the economy through new channels and competition induced by tech firms. Doubtful are the consequences on the monetary policy of a potential reduced impact of banks in the financial system due to a less concentrated environment, and the likely shrink of the demand for central banks balances[7] (Lagarde, 2018).

It should also be considered the possibility that BigTechs could reduce the competition rather than increase it since the possibility of rapidly establish a dominant position. The problem is that once a captive ecosystem is in place, the market power and the DNA feedback loop could lead to "digital monopolies". The main threat is that these "data-opolies" might be exploited not only to improve their services but also to put in place anticompetitive practices with subsequent potential negative economic and welfare consequences (Bank for International Settlements, 2019). Again, this draws the attention to the need for a comprehensive regulatory approach, as claimed in the first chapter.

[7] Since central banks primarily affect asset prices through open-market operations providing liquidity at fixed prices to banks.

3.3 GAFA's Analysis

To conclude the analysis on this phenomenon, the last question is whether these companies, facing a negative business cycle phase, will be able to sustain future financial services provision. In fact, the results mentioned above are subjected to the limitation of not being tested over the entire business and financial cycles[8] yet (Bank for International Settlements, 2019). The existing literature on BigTechs is still limited, compared to FinTech in general, and mostly referring to said issue without addressing the specific question. Tring to fill this gap, the remaining parts of this chapter are going to analyse the BigTechs' performances to make some projections on the possible reaction to a negative business cycle.

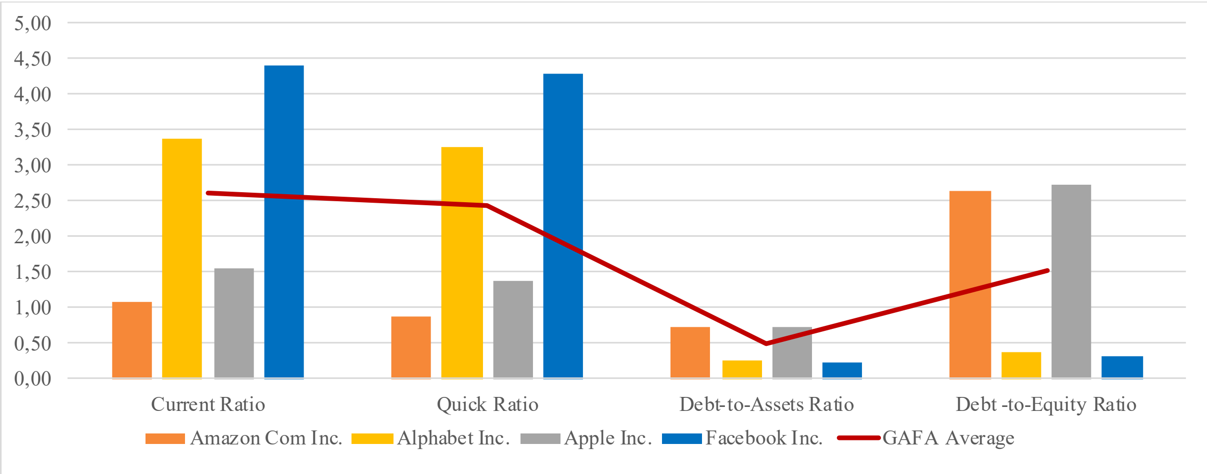
Before trying to draw any conclusion on the BigTechs firms' response to an economic contraction, it is suggested a brief assessment and comparison of BigTechs' performances. The following analysis shall be focused on the GAFA (Google, Amazon, Facebook, Apple) although the credit provision from these companies is limited so far compared to Chinese tech firms, i.e. Alibaba[9]. The reason lies in the assumption that these firms could be the ones with the greatest potential future development in the financial field since the large mass of consumers which hold. The subsequent graphs illustrate the outcomes of selected ratios analysis, whose equations and tables are enclosed in the appendix section, built on 2019 financial statements information from the "10-K" files available at the US Securities and Exchange Commission (2020). Graph 3.3.1 shows some liquidity and solvency ratios to evaluate the ability to meet, respectively, short-term, and long-term obligations. It is evident that Facebook and Google[10] outperform the other two companies in terms of a higher level of liquidity, standing well above the average value of the GAFA. This comparative plus persists even considering the quick ratio, which is more conservative than the current ratio, given that it takes into account the more liquid current assets only. The quick ratio average for these companies is 2.44 signalling that the relative amount of cash, short-term marketable investments and receivables is more than double their current liabilities.

[8] A business cycle comprises an expansion phase followed by recession and recovery which flows into another expansion stage of the subsequent cycle, and it can be measured using the real gross domestic product (GDP) *per capita* (Kose and Terrones, 2015). Whereas, the financial cycle, is characterised by the term "upturn" for the recovery phase and "downturn" for the contraction one with credit, house, and equity prices as main measures (Claessens, Kose and Terrones, 2011).

[9] Which already seems to demonstrate its strength notwithstanding the slowdown. It recently announced its willingness to contribute to offset the adverse phase by enabling short-term loans with preferential rates of interest to their merchants (Alibaba Group, 2020).

[10] Represented by the parent company Alphabet Inc.

In the same perspective, the debt-to-equity ratio is significantly higher for Amazon and Apple, reflecting weaker long-term solvency compared to the other two firms. The debt-to-asset ratio instead, even confirming the healthier position of Google and Facebook, in term of lower financial risk deriving from a lower percentage of assets financed with debt, seems to be quite concentrated around the GAFA average (0.49) with a less-than-one standard deviation.

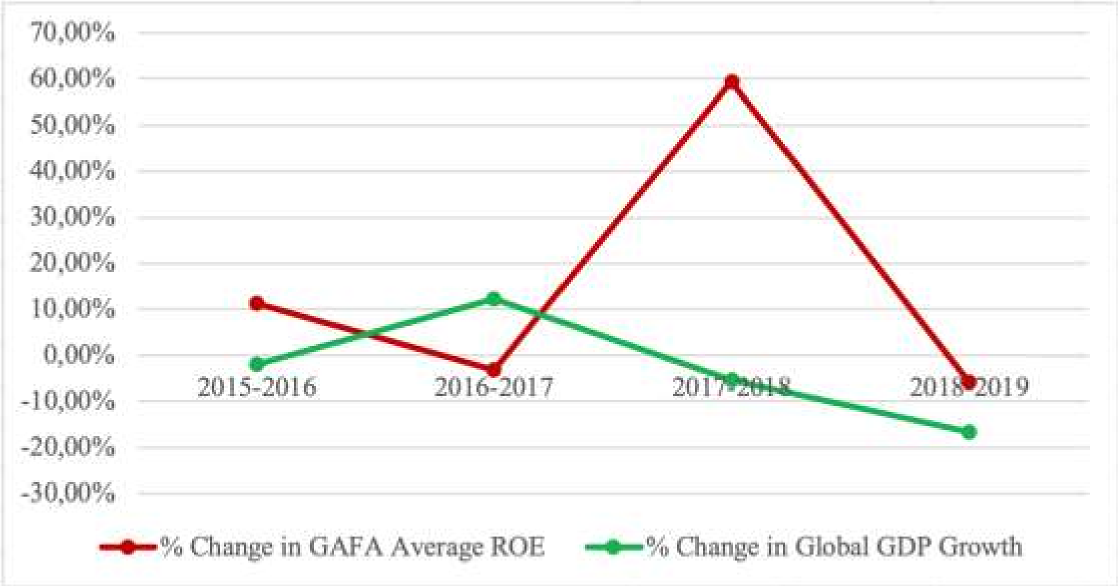


Graph 3.3.1. Liquidity and solvency ratios: current and quick ratios have been selected to represent the short-term liquidity situation, while debt-to-assets and debt-to-equity ratios to characterise the longer-term solvency position (data from US Securities and Exchange Commission (2020)).

The profitability measure designated to determine the ability to generate profits from the capital invested as a key indicator of the companies' overall value is the return on equity (ROE) calculated for the period from 2015 to 2019. Apple, independently from the year considered, generates a higher return on its equity, averagely of 46.61%. Even not considering this extreme value, the average ROE of Alphabet and Facebook from 2015 to 2019 is 16.19% which is consistent with the average return on equity for the entire technology sector. Conversely, Amazon's ROE is seven percentage points smaller than the average ROE of the retail sector, albeit still greater than the same ratio for the S&P500 computing for the same timeframe[11]. It could also be helpful to supplement the findings with multiple years analysis and other historical economic data. Graphs 3.3.2 exhibits the aggregate annual percentage change in GAFA's average return on equity from 2015 to 2019 and the annual percentage change in global gross domestic product. From the line chart emerges large fluctuations in average profitability in terms of return on equity annual percentual change for the GAFA with a more than 50% increase from 2017 to 2018. Furthermore, looking at the relative GDP growth annual change,

[11] The ROE for the technology sector is approximately 17.43%, for the retail sector is about 20.91%, while for the S&P500 is 11.17% (computed from CSIMarket (2020) data). For further information see section III.b) of the appendix.

an opposite trend between these two measures seems to emerge from 2015 to 2018[12]. When the change in GDP is positive, the change in GAFA's return on equity is negative and vice versa. What if this suggests that GAFA's performances, *ceteris paribus*, would not automatically be subject to a weakening in the event of an adverse business cycle characterised by a decline in GDP growth?



Graph 3.3.2 Annual percentage change in GAFA average ROE and global GDP growth from 2015 to 2019 (data from US Securities and Exchange Commission (2020) and Statista (2020a)).

As a result of the reported comparison assessment on liquidity and solvency points of view, Google and Facebook seem to perform better. Whereas, on a profitability perspective, Apple pulls the GAFA, though all the companies considered appear in a solid position. These could be a positive premise in the event of a negative business cycle under the assumption that a healthier company might react better to a period of stress. Considering that from 2019 the economy started to appear analogous to the previous global downturns (Kose, Sugawara and Terrones, 2020), it is possible to obtain a short-term feedback merely regarding the market reaction. Notwithstanding the downward pressures, further worsened by the latest economic impact of the Covid-19 pandemic[13], the GAFA's stock market valuations appear indeed extremely positive[14], at least in this early stage.

[12] The parallelism is considered as a term of comparison only without venturing any sort of causal relation.

[13] As proven by a 3% decrease in annual percentage change in global GDP in 2020 (International Monetary Fund, 2020).

[14] The annual percentual change of the common stocks' valuation from 2019 to 2020 is significantly high for the GAFA with an average increase of approximately 50%. Additional information in section IV of the appendix.

3.4 Limitations and Considerations

The previous outcomes are subjected to several limitations that it is necessary to point out. Firstly, the suggested analysis, referring to past situations, might be a useful starting point, but it is not enough to foresee future trends. Likewise, the stock market valuations are proposed only to assess the initial market reaction to the adverse phase towards these companies. However, said market response might be only temporary not to mention merely deriving from the peculiarities of the current slowdown, e.g. increased use of social media and search engines as well as switching purchases from offline to online (Statista, 2020b). Secondly, it could be interesting changing perspective. As mentioned in the first chapter, financial services represent just a small part of BigTechs revenues compared to their core businesses. Thus, it is not clear to what extent these firms have incentives to expand their financial services offer risking to engage in strict capital and liquidity requirements.

Most importantly, good performances do not necessarily mean more credit provision from BigTechs companies. Therefore, the study highlighting a solid situation for these firms could be read only as a necessary, but not sufficient, condition for the future enlargement and sustainability of credit activities. Since the current credit offer from the GAFA is limited, additional analysis scrutinising other companies beyond Google, Amazon Facebook and Apple, would be required to understand whether BigTechs' credit offer would remain at the same level as in growing times even in a downturn. Moreover, it is not easy to generalise since the potential impact on credit provision also depends on the type of lending model adopted. Firms' hardiness likely matters predominantly in the balance sheet and the guaranteed return models where the platform itself issues the loan or guarantees the promised return respectively, as explained in the second chapter. Whereas, the other types are less dependent on the platform strength. In the case of a notary model, companies could hypothetically ensure credit provision as in normal times with the only condition that the partnering bank is able to originate loans. Criticalities arise from traditional P2P lending models, exposed to the challenge of a reduction in the willingness to invest from lenders, which will likely result in a lowered credit offer. Additionally, the transaction-based affiliation, typically pursued by these firms, may not be a mitigating factor of crises as the relationship banking appears to be with doubtful consequences in the event of a worsened evolution of the negative business cycle (Bolton et al., 2016). From these summary considerations, the need for further investigations emerges. Understanding whether techs giants would be able to sustain credit activity even in a long-term perspective, remains ambiguous. Nevertheless, it is undoubtful that the foregoing potential opportunities that BigTechs could offer to the financial system and the entire economy are extremely relevant.

Conclusion

Overall, the purpose of this work is represented by the analysis of the potential of the BigTechs in finance, in terms of future opportunities and implications for the financial system. At the current state of affairs, although BigTechs' credit footprint results still limited compared to the outstanding credit, tech credit platforms appear economically relevant in absolute terms, notably in China, Korea and the United States.

As far as concern future opportunities, these companies are distinguished by thriving development prospective mainly due to their technological advantages. BigTechs have a unique mix of scale, cutting-edge systems, and access to an extremely valuable amount of data that neither FinTechs nor banks have. In addition to technology, at the basis of these firms' opportunities, there are other economic drivers, either from the demand and the supply side. Distinctly, BigTechs can benefit from unmet customers demand from the traditional sector to positively complement banks by increasing financial inclusion. They can overcome situations of high cost of finance, evident in some developing countries, by offering more convenient and accessible financial services. Credit scoring models reliant on machine learning and alternative information, including digital footprints, seem to bring consistent improvements in terms of better loss prediction and human biases reduction. These large tech companies also promote efficiency enhancements about financial system digitalisation and transparency. A further advancement concerns the impact on the real economy. The possible expansion in the amount of credit available would indeed encourage real investment spending, fostering a higher rate of growth in the economy.

These positive scenarios should, however, be balanced with opposite stances on competition relating to financial stability drawbacks, since a more concentrated financial sector could restrain from an excessive risk-taking. Other doubts arise from the potential affection of the monetary policy transmission mechanism due to the likely upsurge of funds managed outside the banking system and the accentuated risk of contagion. The possible negative exploitation of data-opolies power to put in place anticompetitive practices complete the adverse implications picture drawings the attention to the regulation as a critical point of the phenomenon. The main difficulty concerns precisely the overlapping among competition, financial stability and data protection issues. Not to mention, the venturing of BigTechs in finance raises further concerns for policymakers regarding inadequacy of ordinary rules and tools and heterogeneity among different jurisdictions. Lastly, the sustainability over the full business cycle of the BigTechs activities within the financial environment results still unproven. From the analysis of the GAFA emerges a healthier liquidity and solvency position for Google and Facebook. The profitability condition exhibits a general solid position, though exceptionally positive for Apple. The point is that virtuous performance does not automatically mean financial activities sustainability, even considering that the current level of credit provision from the companies studied is still limited. These limitations, as well as the other considerations and criticalities pointed out, would require further specific investigations to draw complete long-term conclusions. In the light of the previous chapters and the objective of this work, the presented phenomenon should be wisely kept an eye on how to limit its negative implications. Nonetheless, as a concluding remark, it must be recognised that it has, at the same time, significant present and future opportunities within and beyond the financial system.

Appendix

I. Equations

Debt-to-Equity Ratio	$\frac{Total\ Debt}{Total\ Equity}$
Debt-to-Assets Ratio	$\frac{Total\ Debt}{Total\ Assets}$
Current Ratio	$\frac{Current\ Assets}{Current\ Liabilities}$
Quick Ratio	$\frac{Cash + Short - term\ Marketable\ Investments + Receivables}{Current\ Liabilities}$
ROE	$\frac{Net\ Income}{Total\ Equity}$

Table I. Equations used in paragraph 3.3 (Henry, Robinson and Van Greuning, 2015).

II. Liquidity and Solvency Ratios

	Debt -to-Equity Ratio	Debt-to-Assets Ratio	Current Ratio	Quick Ratio
Amazon Com Inc.	2.63	0.72	1.1	0.86
Alphabet Inc.	0.37	0.27	3.37	3.25
Apple Inc.	2.74	0.73	1.54	1.38
Facebook Inc.	0.32	0.24	4.4	4.28
GAFA Average	1.52	0.49	2.6	2.44

Table II. Liquidity and solvency ratios related to Graph 3.3.1 (US Securities and Exchange Commission, 2020).

III. Return on Equity Ratio

a) GAFA

ROE	2019	2018	2017	2016	2015
Amazon Com Inc.	18.67%	23.13%	10.95%	12.29%	4.45%
Alphabet Inc.	17.05%	17.30%	8.30%	14.01%	13.59%
Apple Inc.	61.06%	55.56%	36.07%	35.62%	44.74%
Facebook Inc.	18.29%	26.28%	21.43%	17.26%	8.34%
GAFA Average	28.77%	30.57%	19.19%	19.80%	17.78%
Trimmed Mean 50%	18.48%	24.71%	16.19%	15.63%	10.96%

Table III. a) GAFA's ROE from 2015 to 2019 associated with Graph 3.3.2 (US Securities and Exchange Commission, 2020).

b) Technology, Retail sectors and S&P500

	Technology Sector (ROE)	Retail Sector (ROE)	S&P 500 (ROE)
1Q 2015	19.07%	18.84%	11.38%
2Q 2015	18.81%	19.07%	10.65%
3Q 2015	14.54%	15.70%	9.81%
4Q 2015	11.75%	15.98%	8.10%
1Q 2016	15.26%	19.26%	9.39%
2Q 2016	16.84%	18.97%	9.09%
3Q 2016	16.96%	21.39%	10.66%
4Q 2016	17.73%	20.06%	11.07%
1Q 2017	17.50%	23.94%	11.45%
2Q 2017	19.68%	21.22%	11.94%
3Q 2017	18.82%	21.45%	11.50%
4Q 2017	14.76%	25.96%	11.81%
1Q 2018	16.30%	21.85%	12.33%
2Q 2018	18.14%	20.86%	12.86%
3Q 2018	19.04%	26.28%	13.58%
4Q 2018	23.73%	23.80%	13.17%
Average (5Y)	17.43%	20.91%	11.17%

Table III. b) ROE for the technology and retail sectors and S&P500 mentioned in paragraph 3.3 (CSIMarket, 2020).

c) ROE and GDP Annual Percentage Change

	2015-2016	2016-2017	2017-2018	2018-2019
Annual % Change in GAFA Average ROE	11.35%	-3.08%	59.32%	-5.89%
Annual % Change in Global GDP Growth	-2.02%	12.39%	-5.25%	-16.62%

Table III. c) Annual percentage change for GAFA's ROE and global GDP growth from 2015 to 2019 used to build graph 3.3.2 (US Securities and Exchange Commission, 2020; Statista, 2020a).

IV. Common Stock Valuation Annual Percentage Change

	Δ% Common Stock
Amazon (AMZN)	+44.29%
Google (GOOGL)	+38.01%
Apple (AAPL)	+83.46%
Facebook (FB)	+37.12%
JPMorgan Chase (JPM)	-8.59%
Bank of America (BAC)	-9.60%
Wells Fargo (WFC)	-40.54%
Citigroup (C)	-23.48%
GAFA Average	50.72%
Banks Average	-20.55%

Table IV. Annual percentage change in common stock from 3/06/2019 to 29/05/2020 associated with paragraph 3.3 (NASDAQ, 2020). The four banks considered as a term of comparison are the four US biggest commercial banks according to the Federal Reserve Statistical Release (2019).

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