IÉSEG SCHOOL OF MANAGEMENT

April 2021

WORKING PAPER SERIES

2021-ACF-02

What determines cross-country differences in fintech and bigtech credit markets?

Oskar Kowalewski
IESEG School of Management, Paris, France
LEM-CNRS 9221, Lille, France
Institute of Economics, Polish Academy of Sciences, Warsaw, Poland

Paweł Pisany
Institute of Economics, Polish Academy of Sciences, Warsaw, Poland

Emil Ślązak
Warsaw School of Economics, Warsaw, Poland

IÉSEG School of Management Lille Catholic University 3, rue de la Digue F-59000 Lille Tel: 33(0)3 20 54 58 92
www.ieseg.fr

What determines cross-country differences in fintech and bigtech credit markets? *

Oskar Kowalewski[a,b,c], Paweł Pisany[c,†], Emil Ślązak[d]

[a]*IESEG School of Management, Paris, France*

[b]*LEM-CNRS 9221, Lille, France*

[c]*Institute of Economics, Polish Academy of Sciences, Warsaw, Poland*

[d]*Warsaw School of Economics, Warsaw, Poland*

Abstract

This study is an investigation of the determinants of the development of technology-driven alternative credit markets, that is, fintech and bigtech credit. Using a data sample from 94 countries from 2013–2019, we confirmed the relevance of the availability of credit data, both the traditional and alternative types, with the latter being known as the so-called "digital footprint." Furthermore, we have provided evidence to confirm the positive role of strengthening Internet privacy protections in fostering the development of the fintech credit market, which may not necessarily be the case for the bigtech credit market. We have also shown that the growth of the fintech and bigtech credit market is preceded by a rising paytech services market. Furthermore, we have found that the development of fintech credit services is fostered by the strength of both principal institutions, like the rule of law, and credit-specific institutions, especially in terms of insolvency framework effectiveness, while, for the bigtech credit market, only the latter matters. Interestingly, we have also found that various national cultural profiles can boost the development of fintech and bigtech credit services. Lastly, we have shown that the fintech credit market develops faster in countries characterized by high levels of societal distrust toward banks and that the opposite seems to be the case with the bigtech credit market.

Keywords: alternative credit, fintech, bigtech, innovation, culture, trust, data access

JEL codes: G21, G23, L26, O30

* This work was supported by the National Science Center (NCN), Poland, under grant no. 2019/33/B/HS4/00369.

† Corresponding author.

E-mail addresses: ppisany@inepan.pl (P. Pisany), o.kowalewski@ieseg.fr (O. Kowalewski), eslaza@sgh.waw.pl (E. Ślązak)

1 Introduction

The development of financial technology (fintech) has changed the way financial services are provisioned across countries and, more importantly, it seems to be changing the way we think of banking and finance. Technology shapes banks' practices and can be used to boost their effectiveness, but it also creates opportunities for alternative financial business models to prevail. The availability of non-banking online personal loans, home equity loans and home equity lines of credit, peer-to-peer financing online platforms and marketplace platforms with various types of financial products, and business-dedicated financing models, such as merchant-cash advances, supply-chain financing, and digital invoice trading, has enriched the landscape of modern credit markets. Consequently, the position of banks and other traditional financial institutions, that are still leaders in credit markets, is being subjected to pressure nowadays and may be perceived as being undermined by small fintech and bigtech firms, with the latter being large technology companies entering financial markets. In the future, digital-first, technology-driven companies may even prevail in this competition, at least in some markets that have so far been dominated by traditional financial institutions.

The development of technology has also had a substantial impact on capital markets through the issuance of equity and debt-related financial instruments.[3] In this study, we focus solely on alternative debt financing that is classified into two categories, that is, fintech and bigtech credit services. This in-depth cross-country study on the development of the fintech and bigtech market was made possible thanks to the comprehensive global alternative financing database presented by the Bank for International Settlements and Cambridge Center for Alternative Finance (Cornelli et al., 2020).

Credit intermediation, especially in the realm of consumer credit, appears to be prone to transformation due to rapid technological advancements. On the one hand, it can be argued that the availability of information and communication technologies (ICT) supports decentralized, direct fintech-oriented peer-to-peer (P2P) credit models. Such platforms, however, have evolved and are already becoming marketplaces also for some traditional financial institutions, including banks. Therefore, this model is not limited to P2P services and still applies to companies whose core business remains finance.

On the other hand, we can observe the phenomenon of the bigtech credit market, in which companies with technological specialization attempt to enter the credit market and

---

[3] Ahmad et al. (2020) have discussed the impact of technology on equity, namely in terms of the Initial Coin Offering, in a comprehensive cross-country study.

monetize their information advantages. This is possible due to the development of artificial intelligence (AI) technologies, such as machine learning-based tools (ML), combined with the exponentially expanding availability of data from front-office services. First, new opportunities in risk management arise in such a context and are especially linked to creditworthiness assessments based on the vast amount of alternative data derived from direct online transactions with various clients. Second, technological specialization has been driving much faster progress aimed at streamlining credit models, that is, biometrics in fraud protection and "know your client" processes.

Moreover, due to fast digitalization, which has been further accelerated by the necessity of maintaining physical distance during the coronavirus 2019 (Covid-19) pandemic, remote distribution channels for financial products are gaining momentum. New entities, such as, for example, social media sites and e-commerce platforms, have appeared on the credit market and are striving to build their competitive advantage based on their unique, broad access to the data of potential borrowers.

We have defined "fintech" and "bigtech" following Cornelli et al. (2020); yet, it is worth highlighting that the essential difference between the two models lies in their core business. Fintech credit is perceived, in our study, as including lending activities, and it includes P2P and balance sheet lending by independent entrepreneurs and invoice trading, which are facilitated by online platforms. Moreover, fintech platforms extend their business models and they also act as brokers in sales of bank loans. This creates a sophisticated landscape, but the distinguishing features of fintech platforms remain the following: (i) the fact that their activity in the financial market is their core business; (ii) the fact that, compared to bigtech credit, fintech is a much less concentrated segment; and (iii) the fact that market regulators tend to focus on banks and bigtech, thus fintech activity is overlooked and under-regulated.

Bigtech credit business is a type of loan-based business operated by companies whose primary activities are of a technological nature. Bigtech credit activities include businesses formed in partnership with financial institutions, but also direct balance sheet lending by digital-first companies. Frost et al. (2019) argued that bigtech firms' business model is distinctive, as it is a combination of two key features, namely (i) network effects (generated by e-commerce platforms, messaging applications, search engines, etc.) and (ii) technology (e.g., artificial intelligence using big data). In other words, bigtech firms exploit their existing networks and access to a large amount of data to provide financial services. As such capabilities are limited to only few firms, the bigtech market is much more concentrated than the fintech one.

This has been explained to underscore the fact that fintech and bigtech credit are of substantial importance in modern finance. They create risks, such as, for example, credit risks linked to the quality of quickly expanding debt portfolios or the risk of engaging in so-called algorithmic discriminatory practices; at the same time, however, thanks to modern AI and ML algorithms and the availability of an unprecedented amount of data available for determining credit scores, they can be used as digital financial inclusion tools, especially in the case of "thin credit history" people. Fast digitalization of debt business models has both pros and cons, like two sides of the same coin.

Finally, fintech activities still take place in a relatively loose regulatory environment. Due to the lack of relevant regulatory experience, regulations tend to fail to keep pace with the developments and innovations in fintech activities. Moreover, regulators usually focus on preventing risks to "too big to fail" banks or implementing anti-monopoly policies in the bigtech field, thus overlooking the conceptually distinct risks associated with alternative, less-concentrated financial markets and sometimes also multi-faceted and multidimensional risks related to the bigtech credit market.

Against this background, one can clearly state that there is a crucial need to understand the essence of fintech as well as a newly defined category–bigtech credit. Understanding the determinants of such phenomena, not just from the technological perspective, but also from the economic, social, and cultural ones, will prepare us for upcoming challenges.

The fintech and bigtech credit phenomena are related to banks in many respects. Their relationship, as indicated by the extensive literature on the subject, can be considered partly competitive and partly cooperative. The changes, pace, and differentiation of the development of fintech and bigtech credit are also, in our opinion, largely conditioned by social and cultural factors. Hence, we are contributing to the scientific debate by applying these factors in studies on alternative technology-driven credit and providing empirical evidence of their core importance.

In this study, our aim is to provide a comprehensive view of the development of fintech and bigtech credit. We contribute to the existing literature by empirically confirming the links between alternative technology-driven fintech and bigtech credit services, not just with banking-sector conditions, but, more importantly, while controlling for data availability, privacy protection, paytech development level, institutional quality, various cultural dimensions as defined by Hofstede (2011), and the level of societal confidence in banks. Overall, for the first time (to best to our knowledge), this study presents a broad picture of the links between the development of the fintech and bigtech credit market and a set of "soft" determinants: institutional, social, psychological, and cultural factors; confirming the distinct natures of the two types of technology-driven credit.

The remainder of the paper is organized as follows. In Section 2, we review the existing literature and develop our hypotheses. In Section 3, we describe the empirical context of the study and present some anecdotical evidence. In Section 4, we present our data, variables, and methodology. In Section 5, we report our results and discuss our contributions as well as the study's limitations and some avenues for future research. We conclude the paper in Section 6.

2 Literature review and development of our hypotheses

Despite the relatively short history of the fintech sector, the economic research on it is substantial. Literature reviews by Allen et al. (2020), Branzoli and Supino (2020), Bömer and Maxin (2018), and Jagtiani and Lemieux (2018) have showed the scale and variety of studies undertaken in the field of fintech and digital finance. We summarize, in brief, those studies, and, based on them, we build our hypotheses, which is presented at the end of this section.

Financial innovation has primarily been analyzed from the perspective of relationships with the banking sector. Bömer and Maxin (2018) indicated fintech-banking sector connections as one of the four main strands of research on financial innovation in addition to definition problems, legal issues, and studies on the factors influencing the success of fintech services. In general, fintech is perceived as a competitive, disruptive market force (Lacasse et al., 2016) with an emphasis on enhancing the customer experience with new financial services and innovative functionalities (Gomber et al., 2018). The potential benefits coming from cooperation between banks and fintech firms have been underscored by Holotiuk et al. (2018). The existing studies emphasize the fact that fintech firms supply banks with technology solutions, providing innovative capabilities that are aligned with the digital area (Drash et al., 2018) and also tapping into a large customer base of banking customers, gaining customers' trust, and enhancing the credibility of their own onboarding processes (Klus et al., 2019). In their study focused on the formation of fintech startups, Kowalewski and Pisany (2020) described banking sector-fintech relationships as "coopetition" or a mix of cooperation and competition, but with predominant cooperation in developed economies and predominant competition in emerging ones. Moreover, Claessens et. al (2018) and Rau (2018) showed that the presence of little competition in the banking sector, proxied by high asset concentration in banks and a high Lerner index, is positively associated with the provision of debt financing by fintech firms. The results were confirmed by Cornelli et al. (2020), who used a larger sample of countries in their study. Overall, the topic of links between banks and the financial innovation sector seems to have been thoroughly analyzed in the economic literature.

In a recent, comprehensive study, Branzoli and Supino (2020) paid attention to empirical papers on the drivers of fintech credit use and distinguished between demand and supply factors. Among the demand-related drivers, one can identify general economic activity as measured by the GDP or labor market situation (Claessens et al., 2018; Rau, 2018). As far as supply-side factors are concerned, institutional quality and the level of development of legal systems, that is, contract enforcement effectiveness and lenders' rights in bankruptcy and insolvency procedures, have been shown to be significant factors affecting the entire fintech sector (Rau, 2018; Haddad and Hornuf, 2019; Cornelli at al., 2020). Among the supply-side factors, the Financial Stability Board (FSB, 2019) has mentioned technological advancements and regulatory issues in its conceptual analysis. Moreover, FSB has underscored the importance of demand transformation, that is, consumers' increasing preference for digital financial services.

Empirical studies have also been conducted while considering regulatory drivers. Claessens et al. (2018) showed that the GDP per capita and the Lerner index in the banking sector are significantly and positively associated with the volume of fintech credit, while a significant coefficient of the normalized regulation index has a negative sign. This finding led the authors to the conclusion that stringent financial regulations hamper the development of the fintech credit market. In line with this finding, Buchak et al. (2017) claimed that a lack of proper regulatory obligations, especially a lack of capital and regulatory requirements, can stimulate the growth of the financial innovation sector. Ziegler et al. (2019) showed, however, that countries with regulations assessed as adequate by fintech firms in surveys (neither excessive nor inadequate) had higher alternative finance volumes.

Technology-related factors are also often taken into consideration. Rau (2018) showed that the share of population using the Internet does not influence cross-country differences in marketplace lending volumes. Conversely, Kowalewski and Pisany (2020) confirmed the existence of a positive relationship between advancements in technology and the formation and functioning of fintech startups in their cross-country research. Similarly, Haddad and Hornuf (2019), in their comprehensive paper, found that a country's level of economic development, the availability of venture capital, the number of secure Internet servers and mobile telephone subscriptions, and the presence of an available labor force foster the formation of fintech firms.

The research by Kowalewski and Pisany (2020) and Haddad and Hornuf (2019) was, however, focused on the formation of fintech startups, not the alternative financing volumes provided by the financial technology sector. Thus, their conclusions are only indirectly related to the goals of our current research.

The use of alternative technology-driven financing services can be boosted by access to data, including alternative data from e-commerce and social media platforms. Jagtiani and Lemieux (2018) showed, in their comparative analysis focused on the US fintech credit market, that easy access to data, including alternative data (which may be used in determining credit scores) can affect the development of the fintech market. There are also studies, like those by Berg et al. (2018) for the German market, Frost et al. (2019) for the Argentinian market, and Gambacorta et al. (2019) for China, in which the effectiveness of determining credit scores based on a person's "digital footprint" and alternative data instead of traditional credit information from credit bureaus is examined. These studies' results showed that non-traditional data (e-commerce data/payment data/data from social media sites) are at least as useful as traditional credit-related information, and the accuracy of a model based on alternative data often exceeds that of models based on the traditional data. In line with this finding, but from a more rigorous methodological perspective, Albanesi and Vamosy (2019) proposed a deep learning credit-scoring model, which turned out to be significantly more effective than the traditional logit-based one. Based on a thorough analysis of the credit-scoring literature, Dastile et al. (2020) demonstrated that, despite their still-minimal application, deep-scoring models, such as convolutional neutral networks, yielded better results than statistical and classical ML models.

However, although new ways of assessing the creditworthiness of potential debtors based on AI and ML tools and alternative data may be effective, their use does not come without risks. Firstly, a fintech's debt portfolio may generate additional credit risks, as financing may be granted to segments of customers that banks are unwilling to serve (Tang, 2019; de Roure et al., 2018). Moreover, the risk of so-called "algorithmic discrimination" exists, and opaque, uncontrolled, unfair, and biased automated credit decisions can arise (Gikay, 2020; Desai and Kroll, 2017). The debate on the ethical aspects of using AI and ML in processing personal data and making automated credit decisions is currently gaining momentum in, for example, the European Union (EU) (see the EU Parliament Resolution - Framework of Ethical Aspects of

Artificial Intelligence, Robotics, and Related Technologies[4] and Proposal for a Regulation on a European approach for Artificial Intelligence by European Commission[5]).

Furthermore, a literature review reveals that links between culture and social factors, (for example trust in the banking system) and technology-driven alternative credit markets have not yet been the subject of empirical verification. As Branzoli and Supino (2020) claimed, none of the papers they were aware of touched upon this issue. We have thus strived to contribute to the discourse by including the impact of cultural dimensions and trust in banks in our study on the development of fintech and bigtech credit markets.

Lastly, it is worth mentioning that a substantial part of the existing empirical literature is focused on a single market, often the US. Jagtiani and Lemieux (2018) and Tang (2019) used data on the consumer credit market from the leading US P2P platform *LendingClub*, while Buchak et al. (2017) and Fuster et al. (2018) focused on the US mortgage lending market and its advancements through financial technology solutions. The aim of our study is, like that of the study by Cornelli et al. (2020), to shed some light on the drivers of fintech and bigtech credit use from a broad cross-country perspective while placing a special emphasis on "soft" factors, that is, cultural and institutional ones.

We have contributed to the existing knowledge by linking fintech and bigtech credit volumes with factors that, to the best of our knowledge, have not been considered in empirical, cross-country, comparative research, in particular: data and privacy issues, various cultural dimensions as defined by Hofstede (2011), and a lack of trust and confidence in the banking sector. Moreover, we have investigated the popularity of paytech and digital finance services instead of general technology advancement measures. This targeted approach has allowed us to capture technological improvements in basic financial services as determinants of the development of fintech and bigtech credit in specific markets. In addition, to the best of our knowledge, apart from the work of Cornelli et al. (2020), there have not been any available empirical cross-country studies focused on the bigtech credit market.

Based on a literature review that revealed the abovementioned research gaps, we have formulated five hypotheses that we verified using a newly published cross-country database on fintech and bigtech credit by Cornelli et al. (2020) and the broad dataset of explanatory variables that we will discuss in the next section.

[4] https://www.europarl.europa.eu/doceo/document/TA-9-2020-0275_EN.html
[5] https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-european-approach-artificial-intelligence

H1. Fintech and bigtech credit are significantly fostered by the easy availability of credit information, both traditional credit-related data and the so-called "alternative data" that come from e-commerce platforms.

H2. A high level of privacy protection on the Internet fosters the development of fintech and bigtech credit markets, as it increases confidence in using digital channels to provision financial services.

H3. The development of fintech and bigtech credit markets is preceded by the growth of the paytech services market and the development of remote access channels to basic transactional accounts, both bank and non-bank ones.

H4. High institutional quality, as measured by both general indicators—for example, the rule of law and political stability, and specific credit market indicators, that is, the effectiveness of the insolvency framework—fosters the growth of fintech and bigtech credit markets.

H5. The national culture and social attitude toward banks play an important role in the development of alternative technology-based credit services.

3 The various scales and structures of fintech and bigtech credit markets

The alternative technology-driven credit market is facing rapid-but-uneven growth nowadays. Moreover, the structure of the market is characterized by substantial cross-country differentiation. In the period covered by the study, the total global value of the fintech and bigtech credit market increased from USD 20.5 billion in 2013 to USD 795.5 billion in 2019 (Cornelli et al., 2020). The market has, therefore, experienced tremendous growth. Until 2017, the value of the annual fintech credit flow exceeded the value of the bigtech credit market. In 2018, the relationship reversed course, and bigtech credit services have prevailed since then. This took place due to a structural change in the largest alternative finance market in terms of total credit volumes, that is in China. Figure 1 presents the volume of the fintech and bigtech credit market across countries grouped based on their level of economic development. As the graphs show, in all the countries, the volume of the fintech and bigtech credit market has been growing over the last five years, especially in upper- and middle-income countries. This mainly occurred due to development of a bigtech credit market in China while, in high-income economies, the fintech credit market still had a significant advantage over the bigtech one. In 2019, the volume of fintech versus bigtech was equal to 70.2 bn USD versus 8.2 bn USD in the

US, 11.5 bn USD versus 0.1 bn USD in UK, and 12.2 bn USD versus 0.4 bn USD in the EU's 27 countries, respectively. In fact, the numbers show that there are significant differences across countries and reflect the underdevelopment of bigtech financial offer in some of the high income countries.

Furthermore, it is worth looking into relative measures, which we have employed as dependent variables in our regressions. In 2019, the amount of bigtech credit use per capita was the highest in China, Japan, and South Korea, and the same order was consequently reflected in absolute terms. The amount of fintech credit use per capita achieved the highest level in the US, UK, and Singapore. More importantly, the data reveal that the importance of bigtech credit is greater in middle- and low-income countries (seven of the top ten countries with the highest ratios of bigtech credit use per capita fell into this category), while fintech credit business models, which tend to be more decentralized, play a greater role in advanced economies. It is difficult to predict whether these relationships will persist and what the future development paths of both alternative credit forms will look like. In our opinion, the outcome will depend on, among other things, regulatory and supervisory approaches toward bigtech firms' entry into financial markets.

[Figure 1]

4 Data and methodology

4.1 Data

In our model, we have used the global alternative finance database published by Cornelli et al. (2020), with the amounts of fintech and bigtech credit per capita as our dependent variables. We then built a comprehensive database of potential explanatory variables that could be used to verify our five hypotheses. We combined this dataset with data retrieved from, among other sources, the World Bank, United Nations Conference of Trade and Development (UNCTAD), and Fraser Institute. All the variables used in this study, its definitions, and its sources are presented in Table A1 in the Appendix, while we present the descriptive statistics of the data used in the study in Table 1. The data reveal that there are large variations between countries in terms of the level of development and importance of the fintech and bigtech credit markets.

[Table 1]

Our final sample covers 94 countries, including high-, middle-, and low-income ones, from 2013-2019. The list of countries included in the study is shown in Table A2 in the Appendix.

4.2 Methodology

In choosing an empirical strategy, we follow Claessens et al. (2018), Rau (2018), and Cornelli et al. (2020) and used the ordinary least squares (OLS) as the main estimation method for our research on the fintech credit market. The dependent variable in estimations referring to the amount of fintech credit use is the natural logarithm of the amount of fintech credit use per capita. The amount of fintech credit use is, however, zero for some countries in some years and the logarithm cannot be defined for zero. Thus, we have added a constant to fintech credit. The explanatory variables have been lagged by one period to mitigate the potential problem of reverse causality (Dushnitsky et al., 2016) and to reflect the fact that interactions between variables take time to occur. When building subsequent estimations, we considered several number of variables separately due to the frequency of occurrences of multicollinearity.

As far as bigtech credit is concerned, we decided to conduct a logistic analysis on the binary variable in which a value of one was assigned if bigtech credit was available in a specific country in a specific year and zero was assigned otherwise. We did this to address the issue of abnormal distribution of the bigtech credit variable. As the authors of the database indicated, bigtech credit takes the value of zero in 47 countries (Cornelli et al., 2020). Thus, we have attempted to establish what the factors are that contribute to the presence of bigtech credit in specific country in a specific year and apply a logistic regression to identify the answer. In the logit estimations' results, we present the odd ratios, which means that a value of under one indicates a negative relationship between the factor and the likelihood of bigtech credit availability, while a value larger than one reveals a positive relationship. As a supplementary analysis, we conducted an OLS regression of the natural logarithm of bigtech credit use per capita for observations characterized by positive values for bigtech credit.

In the regressions, we controlled for GDP growth, which we assumed is positively associated with the volume of fintech and bigtech credit per capita. Moreover, we controlled for the average interest rates and the level of domestic credit granted to the private sector. Navaretti et al (2017) showed that the level of investment in fintech firms is higher when an economy has greater financial depth, as proxied by the ratios of credit and bank assets to the GDP. Hence, we controlled further for financial depth by including a variable that measures bigtech and fintech credit volume per capita in the regression where the dependent variable is fintech and bigtech credit volume per capita, respectively. Henceforth, we controlled for the depth of traditional and alternative financial information in our regressions. Lastly, we included a dummy variable that was a proxy for the global financial crisis (GFC) and equaled one for the year 2008 and zero otherwise.

We sought to verify our hypotheses in relation to both the fintech and bigtech credit markets according to the methodological framework described above. In general, our methodology has enabled us to explain variations in the fintech credit market to a greater extent than those in the bigtech one. Thus, we have decided to present the full results related to fintech credit and selected estimations of bigtech credit market determinants. Moreover, we have conducted robustness checks on subsamples of countries, that is, separate estimations for high-income economies and middle- plus low-income economies. Due to the high number of estimations performed, some of them have been omitted for brevity; however, all the estimations are available upon request.

5 Results

In Table 2 and 3, we present the results related to our first hypothesis (H1). We began the interpretation of the results by analyzing the control variables and found that fintech and bigtech credit are positively associated with lagged values of each other and with banking credit; however, the latter observation refers to middle- and low-income economies. We documented the fact that fintech credit remains much more of a complementary source of financing to other lending service types than a substitute for them, which is in line with the findings of Cornelli et al. (2020).

Moreover, we showed that fintech credit has developed in countries that experienced a systematic banking crisis during the financial crisis of 2008, but this finding applies to high-income countries, that is, the effect is not present in middle- and low-income countries. This shows that the development of the fintech credit market may be described as a kind of answer to the problems of the GFC and banking sector, but only in high-income economies. There is no convincing evidence of a relationship between the GFC experience and the emergence of bigtech credit.

As far as H1 was concerned, we introduced five proxies to measure the ease of access to and quantity of credit-related data. The proxies included the depth of credit information available in a country, the level of private bureau and public credit registry coverage, an index for e-commerce development that ranged from 0-100, and a composite privacy level indicator that also ranged from 0-100.

In Table 2, we can see that the coefficient of the variable for the depth of credit information is positive and highly significant, as in the variables *Private bureau* and *E-commerce*. This suggests convincingly that the development of the fintech credit market is significantly fostered by the quality and availability of credit-related information in terms of both traditional and alternative credit-related data that come from, for example, e-commerce platforms. The existence of such data increases the possibility of effective and innovative (AI and ML-based) credit-scoring. Spillovers between the e-commerce and fintech credit markets are multidimensional and include innovative distribution channels, such as, for example, the BNPL model (buy now, pay later), while e-commerce and fintech/bigtech credit may reinforce each other.

Furthermore, we documented the fact that improvements in the availability of alternative data foster the development of the fintech credit market in both emerging and developed markets. The availability of traditional credit-related data is relatively important for the fintech credit market in middle- and low-income countries where credit bureaus are still being established and developed.

The results of the logit model for bigtech credit use are shown in columns (1)-(2) of Table 3, which also confirm the great significance of and positive links between the depth of credit information and the binary dependent variable. Thus, the results confirm that bigtech creditors benefit from the existence of a well-established traditional credit-related data infrastructure that fosters all creditors' positions and from the availability of alternative data that enter their possession because of their core technology-driven business models. The results supplement those of Frost et al. (2019), who reported that bigtech lenders have an information advantage in credit-scoring relative to traditional credit bureaus. We found, however, that bigtech firms also benefit from the traditional infrastructure, which may give them a significant advantage over traditional lenders, as they have an additional information advantage, as reported by Frost et al. (2019).

Our results supplement those in the studies of Frost et al. (2019), Gambacorta et al. (2019), and, especially, Jagtiani and Lemieux (2018). While their studies were done using data from single countries, our study is based on aggregated cross-country data and, consequently, our conclusions are more universal. We have also shown that the drivers of fintech credit differ from those of bigtech credit, a difference that we further explored in the following regressions.

Next, we investigated our second hypothesis, in which we proxied the privacy protection variable using an independent expert composite indicator called the Internet Privacy Index[6] (variable *Privacy*), which includes information on (i) freedom of the press, (ii) the presence of data privacy laws, (iii) democracy-related statistics, (iv) freedom of opinion and expression, and (v) the presence of cybercrime legislation. The aim of using this broad indicator is to grasp the level of protection of information shared online in a specific country. The higher the value is, the stronger a country's privacy protection measures will be.

In Table 2, in which the results for fintech firms are presented, the coefficient of *Privacy* is positive and significant at the 1% level. This means that enhancing the protection of online privacy fosters the development of the fintech credit market. Conversely, an odd ratio for *Privacy* in the logit regression of binary variables (bigtech credit presence) in Table 3 is significant and under one, which would reveal the presence of a negative link between bigtech credit activity and the level of online privacy. We have given a lower priority to OLS results for positive observations of bigtech credit use per capita due to the relatively small number of observations. Still, it is worth noting that the coefficient of *Privacy* is positive in this case.

Our results confirm H2 in relation to fintech credit use. We claimed that fintech credit services, as they can be provided by many entities (by definition, it is a segment characterized by low concentration), are much more dependent on customers' sense of security. Increasing consumers' perception of safety will likely make them more eager to use Internet platforms, even small ones, to apply for a loan, which essentially requires sharing personal information with a fintech entity online.

On the other hand, bigtech credit is a highly concentrated market. Technology giants may be motivated to enter the financial market of a specific country if privacy protections are weak. This essentially means that there are fewer regulatory burdens and, consequently, fewer restrictions on which business models may be pursued. At the same time, the results of the OLS model with positive values for bigtech credit use per capita indicate that privacy protection fosters the growth of bigtech credit's volume, as it depends on demand. The demand for bigtech credit, in turn, seems to be linked to customers' perception of safety in applying for alternative credit through digital channels. In other words, poor Internet privacy protection may influence the decision of a bigtech company to enter the financial market in a specific country, but, in the following phase, it may become an obstacle to the business's development.

---

[6] The exact index scores and the details of the indicator and sources of the data in the sub-indexes are available at https://bestvpn.org/privacy-index/#tab-con-1.

[Table 2 and 3]

In Table 4 and 5, we present the results of our investigation in relation to H3. We proxied the paytech market and level of financial digitalization by using the lagged values of *Fin. digital*$_1$ and *Fin. digital*$_2$, which respectively refer to the percentage of adults using the Internet and mobile phones to access accounts with financial institutions and with a broader category of institutions, that is, transactional accounts.[7] Moreover, we used the lagged values of *Mobile transfer* and *Mobile pay,* variables that represented the degree of popularity of using mobile phones to send money and pay bills in a country.

In Table 4, in which we present the results for fintech credit use, we found a positive coefficient for *Fin. digital*$_1$, *Fin. digital*$_2$, and *Mobile pay*. The coefficients are significant at the 1% level at least. The results in columns (1)-(4) of Table 5, which pertain to bigtech companies, are similar, but only in relation to *Mobile pay* and *Mobile transfer* (highly significant odd ratios above one). In columns (5)-(10) of Table 5, in which we employed OLS as the estimation method, the coefficients of all four abovementioned independent variables are positive and significant. Consequently, we found that the results for fintech and bigtech credit use are similar, yet they are weaker for the latter.

Indeed, fintech and bigtech credit should be treated as the second step in the development of technology-based modern financial services. The initial condition is the development of online and mobile transactional services, which seems crucial for at least two reasons. Firstly, the development of such services prepares a sound infrastructure for conducting credit transactions, and, more importantly, it is a means of popularizing digital finance, shaping consumer attitudes, and, probably most vitally, it provides an opportunity to collect an initial set of payment/transaction data from potential future borrowers to be used in automated creditworthiness assessments.

The prior studies that have linked the general level of technological advancement of a country with growth in the financial innovation sector (Rau, 2018; Haddad and Hornuf, 2019) have yielded somewhat inconsistent results. They have not been focused on fintech credit use (but respectively, crowdfunding and fintech startups) and used the general measures of ICT advancement, like Mobile subscriptions. Thus, our results present a more detailed picture

[7] This is the indicator presented in the Findex database by Demirgüç-Kunt et al. (2017). It refers to the percentage of respondents who reported having an account (by themselves or with someone else) at a bank or some other type of financial institution or who reported personally using a mobile money service in the past 12 months.

confirming the positive relationship between the development of fintech/bigtech credit markets and the use of mobile devices for financial transactions.

[Table 4 and 5]

In our study, we have strived to present a comprehensive picture of the relationships between fintech and bigtech credit and institutions. We have applied a wide set of proxies for institutional quality to the data, which include, among other items, *Insolvency framework*, *Contract enforcement*, *Rule of law*, *Corruption control,* and *Political stability*. Due to the existence of high multicollinearity proxies, the measures of institutional quality are included in separate estimations. In Table 6, we present the results of the OLS regression for fintech credit use per capita. We have found that institutional quality is a vital factor influencing the growth of the fintech credit market. All the proxies are significant, both those related to institutions of principle importance, like *Rule of law,* and the credit market-specific ones, like *Insolvency framework*, *Insolvency years*, and *Contract enforcement*. The more effective insolvency/bankruptcy and debt-collection procedures are and the shorter the period required for debtor insolvency proceedings is, the more highly developed the fintech credit market of a country will be.

[Table 6]

In Table 7, we present some selected estimations of the bigtech credit market's measures on institutional explanatory variables, that is, we have shown the results of the regressions that yielded significant results. Interestingly, we have confirmed the existence of a highly significant positive relationship between the presence of bigtech credit and institutions, but only in terms of credit market-specific institutional quality, that is, the odd ratios for *Insolvency framework* and *Contract enforcement* are larger than one. Broad and principal institutions, as *Rule of law,* are, in the case of the bigtech credit market, insignificant.

Our results are in line with those in the vast body of existing literature linking financial innovation and regulatory/institutional quality (Cornelli at al., 2020; Haddad and Hornuf, 2019; Rau, 2018; Claessens et al., 2018; Buchak et al., 2017); however, we have underscored the role of both credit market-specific institutions and general, principal rules in addition to studying the differences between the fintech and bigtech credit markets in this context.

[Table 7]

We also claim that national culture is an important factor shaping the environment affecting the development of alternative debt financing options, that is, fintech and bigtech credit services (H5). To grasp the cultural differences between the countries included in this study, we used the six cultural dimensions outlined by Hofstede (2011).

In Table 8, we present the results for fintech credit use per capita and the additional control variables used as proxies for culture and social trust in banks. We found that the coefficients of *Power distance* (PDI), *Uncertainty avoidance* (UAI), and *Long-term orientation* (LTI) are negatively and highly significantly related to the prevalence of fintech lending. In contrast, we found that the coefficients of *Individualism* (IND) and *Indulgence* (INDG) are positively related to the prevalence of fintech lending.

The results reveal a seemingly coherent picture. We believe that, in the case of fintech credit use, the cultural dimensions of a country tend to affect the expected behaviors of both entrepreneurs and potential customers. The fintech market is much less concentrated than that of bigtech lenders. One can assume that the fintech credit market is much more decentralized and often provisioned through local platforms. Fintech sector entrepreneurs from low power distance countries with a low level of aversion to uncertainty are bound to challenge traditional, well-established, respected financial institutions, especially banks. However, we found that our results supplemented those of Ashraf et al. (2016), who showed that risk-taking by banks is more common in countries with a low level of uncertainty avoidance and low power distance cultural values.

The indulgent, individualistic attitudes of small entrepreneurs only intensify the willingness to question the current financial intermediation model. Boubakri and Saffar (2016) underscored the fact that individualism, masculinity, uncertainty avoidance, and power distance tend to affect firms' ability to overcome financial constraints, with individualism exhibiting a stronger, more robust impact than the other dimensions. Moreover, they indicated that firms' ability to overcome financial constraints was more affected by individualism when access to financing options was more restricted. Consequently, it is unsurprising that customers from countries with the abovementioned cultural features, especially indulgent, individualistic attitudes combined with a low power distance and a high level of uncertainty acceptance, are more eager to look for alternative financial services that are more "democratized" but less regulated and supervised than those offered by banks.

[Table 8]

In Tables 9A and 9B, we present the results for the bigtech credit market, which seem quite consistent; however, they are different from the ones obtained for the fintech market. The coefficients for *Power distance* (PDI) and *Long-term orientation* (LTI) are significantly and positively connected to the development of the bigtech credit market in a country (with an odd ratios greater than one), while *Individualism* (IND) and *Indulgence* (INDG) show a negative relationship (with odd ratios under one).

It seems reasonable to assume that cultural dimensions, in the case of bigtech credit use, describe the demand side of the market, that is, the expected customer behaviors. The bigtech market is relatively concentrated, and, often, especially in high-income countries, the services of e-commerce and social media platforms are provisioned across borders. Thus, we interpreted our results first from the perspective of customer behaviors. The research shows that customers with less-individualistic, less-indulgent attitudes characterized by high power distance and long-term orientation and are more likely to be willing to be serviced by large, well-established, powerful companies, like bigtech firms and joint ventures between such firms and banks.

[Tables 9A & 9B]

Lastly, we provide empirical evidence to support the existence of a relationship between societal distrust of banks and the development of digital alternative credit options. We aggregated the results of the World Value Survey by taking the average answer for each country. The higher our indicator *Distrust* was, the greater the distrust toward banks in a given country was.

In Table 8, we found that the coefficient of the variable *Distrust* was positively related to the development of the fintech credit market and was significant at the 1% level. The results show that decentralized fintech debt financing is gaining momentum in countries where banks are not trusted by consumers. Conversely, in Table 9A, which presents the results for bigtech firms, the odd ratio for *Distrust* is under one and is statistically significant at the 1% level. This essentially means that bigtech credit services do not tend to appear in countries characterized by a low level of trust in the banking sector. A high level of trust in banks fosters the development of the bigtech credit market. We believe that this occurs partially because bigtech credit firms embrace a business model in which a technology firm, such as, for example, an e-commerce platform, acts as a brokerage company and *de facto* facilitates the use of banking products via digital channels.

Moreover, the results, once again, confirm the existence of a substantial difference in the way that bigtech firms, fintech firms, and banks are perceived in most societies. We have assumed that banks and bigtech companies are viewed as well-established, rich companies that represent often multinational capital and are characterized by significant market power and "distance" from their customers. In contrast, small fintech credit businesses, especially P2P platforms, are perceived as an alternative to the big business world and are viewed as more "democratized" entities that are much closer to the people they serve.

The previous literature has not been focused on the links between culture and fintech (and bigtech) credit services, and little evidence supporting the relevance of the social aspects of the issue, like the general level of trust in a specific country, has been presented. Thanks to the availability of the new, broad, easily comparable cross-country data presented by Cornelli at al. (2020), we have conducted a comprehensive study in this field and discussed the sophisticated links between technology-driven alternative credit options on the one hand and the cultural dimensions by Hofstede (2011) and the level of distrust toward banks on the other.

6 Conclusions

We believe that the cross-country differentiation of technology-driven alternative credit services (both fintech and bigtech) is determined by several national characteristics. Some of them have not yet been discussed in the literature, and we have essentially integrated them in our five hypotheses. The relationships between banks and fintech firms are, in our opinion, well-described and have been thoroughly examined based on banking-sector data. We, however, have shown that the development of alternative credit options is connected to the availability of both traditional and alternative types of data, including "digital footprints." As with banks, the availability of credit-related data reduces the asymmetry of information, but, due to the proliferation of "digital footprints," fintech firms have successfully streamlined the credit-scoring process and can now focus on providing an enhanced customer experience. Moreover, the presence of effective protections for consumers' privacy hastens the development of the fintech credit market by reducing customers' fears of data breaches, possible negative consequences, and the potential risk to their reputations. Interestingly, this finding may not directly apply to bigtech firms, which might be willing to enter markets where personal information is not protected strongly, as the lack of regulation makes business easier for them in the short term, but such a context undermines customers' trust and confidence in the long term. We believe that data are the oil of the modern economy. The use of personal data by fintech platforms and by bigtech firms requires regulatory attention, as it creates the potential for digital financial inclusion; at the same time, however, the risk of abusive, discriminatory practices arises.

Furthermore, we have shown that the level of development of paytech technologies, that is, using mobile phones to access transactional accounts (both bank accounts and digital wallets) precedes the growth of the fintech/bigtech credit market. As a consequence, developing paytech technologies will be of utmost importance in expanding the learning curve of alternative financing customers and will thus pave the way for social acceptance of more advanced fintech and bigtech credit services. This confirms the fact that technology plays a role in the market's development, but positively shaping customer preferences regarding digital service channels in financing is a precondition of the development of the fintech and bigtech credit market. We have confirmed the role of institutions in the process; however, our results show that the bigtech credit market benefits from the existence of high-quality credit-related institutions (especially the insolvency framework), while the fintech credit market is also fostered by the strength of principal institutions, like the rule of law and credit-specific institutions.

Finally, we focused on cultural issues. We showed that, surprisingly, various national cultural profiles can encourage the development of the fintech and bigtech credit markets. We believe that fintech credit options are perceived as much more "democratic," decentralized, and entrepreneurial and are viewed as an alternative form of financing, while bigtech credit options are, from a cultural perspective, another reflection of the corporate big business model, like banks. This leads to differentiation in the cultural factors that support both technology-driven forms of debt financing. Last but not least, we showed that the fintech credit market develops faster in countries characterized by high levels of societal distrust toward banks. The opposite seems to be the case with the bigtech credit market.

Overall, this study presents a picture of the links between the fintech and bigtech credit markets and a set of institutional, social, psychological, and cultural factors. These factors enrich the way we understand the supporting environment for fintech and bigtech credit services, and, even more importantly, they enable us to confirm that these two types of technology-driven credit are distinct phenomena that may have different impacts on economies and societies. The bigtech and fintech credit markets should, therefore, elicit a balanced response from regulators and supervisors, who must consider the unique features of both alternative credit markets and their various potential for monopolies creation and the various levels and types of risks regarding the financial stability and the protection of consumer rights, privacy, transparency, and fairness.

References

Albanesi, S., Vamossy, D. F. (2019). Predicting consumer default: A deep learning approach. *NBER Working Paper* (26165).

Allen, F., Gu, X., Jagtiani, J. (2020). A Survey of Fintech Research and Policy Discussion, *Federal Reserve Bank of Philadelphia, Working Paper No 20-21*.

Berg, T., Burg, V., Gombovi´c, A. and Puri, M. (2018). On the rise of fintechs - Credit scoring using digital footprints. *NBER Working Paper* (24551).

Bömer, M., Maxin, H. (2018). Why fintechs cooperate with banks—evidence from Germany. *Zeitschrift für die gesamte Versicherungswissenschaft*, 107(4), 359-386.

Branzoli, N. and Supino, I. (2020). FinTech Credit: A Critical Review of Empirical Research Literature, *Bank of Italy Occasional Paper* No. 549.

Buchak, G., Matvos, G., Piskorski, T., Seru, A. (2017). Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks. *NBER Working Papers*, no 23288.

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

Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R., Ziegler, T. (2020). Fintech and Big Tech Credit: A New Database. *BIS Working Paper No. 887*,

Dastile, X., Celik, T., and Potsane, M. (2020). Statistical and machine learning models in credit scoring: A systematic literature survey. *Applied Soft Computing*, 91, 106263.

Drasch, B. J., Schweizer, A., and Urbach, N. (2018). Integrating the 'Troublemakers': A taxonomy for cooperation between banks and fintechs. *Journal of Economics and Business*, 100, 26-42.

Desai, D. R., Kroll, J. A. (2017). Trust But Verify: A Guide to Algorithms and the Law. *Harvard Journal of Law and Technology*, Available at SSRN: https://ssrn.com/abstract=2959472

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., Hess, J. (2017). The Global Findex Database. Measuring Financial Inclusion and Fintech Revolution. World Bank Group

Dushnitsky, G., Guerini, M., Piva, E. Rossi-Lamastra, C. (2016). Crowdfunding in Europe: Determinants of Platform Creation. *California Management Review 58*, 44-71.

Buchak, G., Matvos, G., Piskorski, T., Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics,* (130), 453–483.

Financial Stability Board. (2019). FinTech and market structure in financial services: Market developments and potential financial stability implications.

Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., and Zbinden, P. (2019). BigTech and the changing structure of financial intermediation. Economic Policy, 34(100), 761-799.

De Roure, C., Pellizon, L., Thakor, A. V. (2018). P2P lenders versus banks: Cream skimming or bottom fishing? *SSRN Working Paper*, (3174632).

Fuster, A., Plosser, M., Schnabl, P., Vickery, J. (2018). The Role of Technology in Mortgage Lending. *Federal Reserve Bank of New York Staff Reports, no. 836.*

Gambacorta, L. and Huang, Y. and Qiu, H. and Wang, J.(2019). How Do Machine Learning and Non-Traditional Data Affect Credit Scoring? New Evidence from a Chinese Fintech Firm. *BIS Working Paper No. 834.*

Gikay, Asress Adimi (2020), The American Way - Until Machine Learning Algorithm Beats the Law? Algorithmic Consumer Credit Scoring in the EU and US. *Case Western Reserve Journal of Law, Technology and the Internet*, Forthcoming, Available at SSRN: http://dx.doi.org/10.2139/ssrn.3671488

Gomber, P., Kauffman, R. J., Parker, C., and Weber, B. W. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220-265. Haddad, C., Hornuf, L. (2019). The emergence of the global fintech market: economic and technological determinants. *Small Business Economics*, 53(1), 81-105

Hofstede, G. (2011). Dimensionalizing Cultures: The Hofstede Model in Context. *Online Readings in Psychology and Culture,* 2(1), 2307-0919.

Holotiuk, F., Klus, M.F., Lohwasser, T.S., Moormann, J. (2018). Motives to Form Alliances for Digital Innovation: The Case of Banks and Fintechs. *BLED Proceedings, 22*.

Inglehart, R., Haerpfer, C., Moreno, A., Welzel, C., Kizilova, K., Diez-Medrano J., M. Lagos, P. Norris, E. Ponarin and B. Puranen et al. (eds.). (2020). World Values Survey: All Rounds – Country-Pooled Datafile. Madrid, Spain and Vienna, Austria: JD Systems Institute and WVSA Secretariat; http://www.worldvaluessurvey.org/; WVSDocumentationWVL.jsp.

Jagtiani, J., Lemieux, C. (2019). The Roles of Alternative Data and Machine Learning in Fintech Lending: evidence from the Lending Club Consumer Platform. Federal Reserve *Bank of Philadelphia Working Paper, no 18-15.*

Jagtiani, J., and Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, 100, 43-54.

Klus, M. F., Lohwasser, T. S., Holotiuk, F., Moormann, J. (2019). Strategic alliances between banks and fintechs for digital innovation: Motives to collaborate and types of interaction. *The Journal of Entrepreneurial Finance*, 21(1), 1

Kowalewski, O. and Pisany, P. (2020) The Rise of Fintech: A Cross-Country Perspective. *IESEG Working Paper Series 2020-ACF-07*.

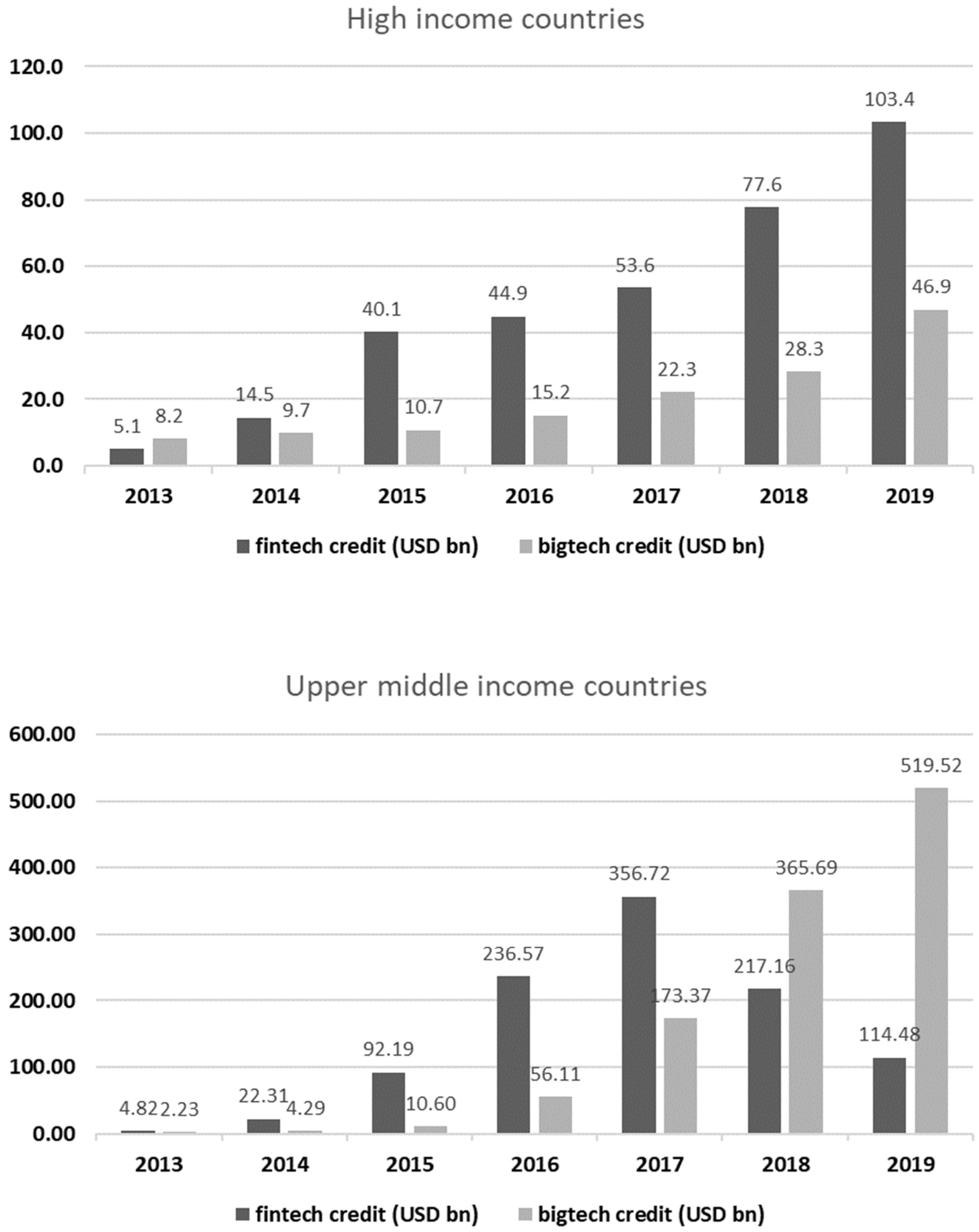
Lacasse, R. M., Lambert, B., Osmani, E., Couture, C., Roy, N., Sylvain, J., Nadeau, F. (2016). A Digital Tsunami: FinTech and Crowdfunding. *International Scientific Conference on Digital Intelligence*. Quebec City, Canada.

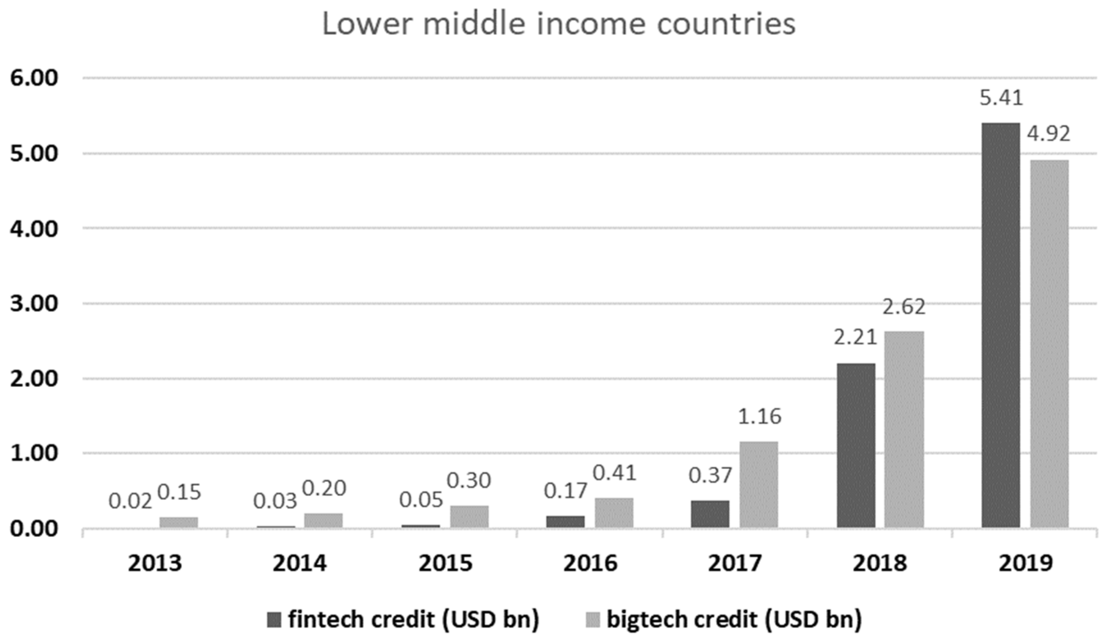
Rau, R. (2018). Law, trust, and the development of crowdfunding. *SSRN Working Paper,* (2989056).

Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? *The Review of Financial Studies,* 32 (5), 1938.

Ziegler, T., Shneor, R., Wenzlaff, K., Odorović, A., Johanson, D., Hao, R., Ryll, L. (2019). Shifting paradigms. The 4th European Alternative Finance Benchmarking Report, Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3772260

Figure 1 Volume of fintech and bigtech credit use in various countries from 2013-2019




Lower middle income countries
6.00
5.00
4.00
3.00
2.00
1.00
0.00
0.02
0.15
0.03
0.20
0.05
0.30
0.17
0.41
0.37
1.16
2.21
2.62
5.41
4.92
2013
2014
2015
2016
2017
2018
2019
fintech credit (USD bn)
bigtech credit (USD bn)

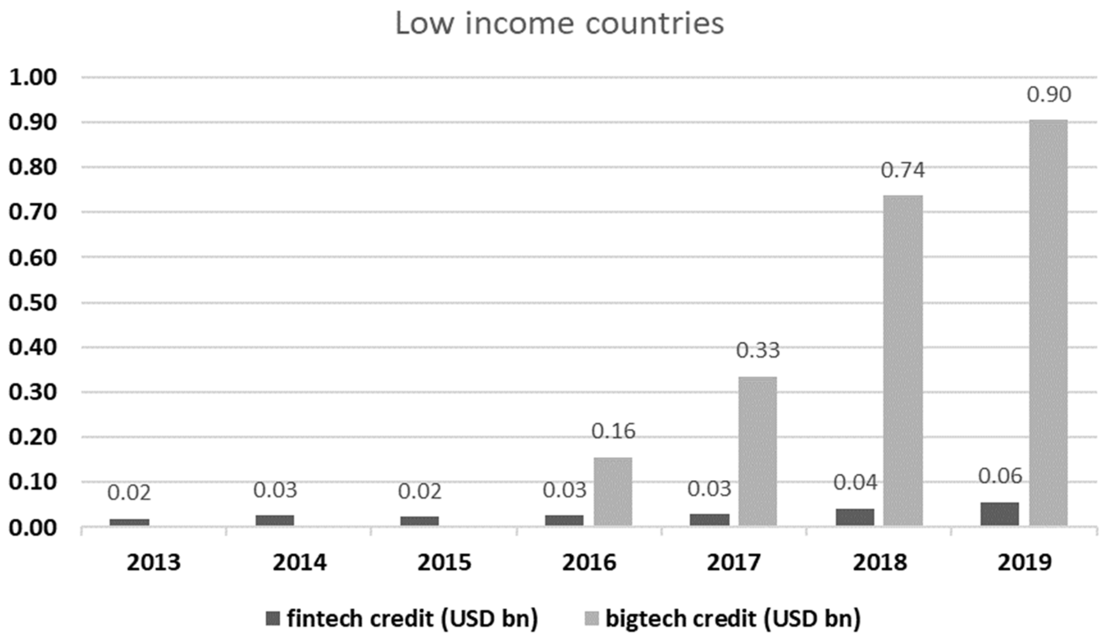

Low income countries
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.02
0.03
0.02
0.03
0.16
0.03
0.33
0.04
0.74
0.06
0.90
2013
2014
2015
2016
2017
2018
2019
fintech credit (USD bn)
bigtech credit (USD bn)

Table 1 Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Fintech credit	646	7.04	25.26	0.00	256.13
Bigtech credit	646	3.89	25.40	0.00	368.47
GDP growth	639	3.33	3.19	-27.99	25.16
Interest rates	394	7.22	8.69	-26.22	52.44
Bank credit	604	62.25	44.41	4.71	235.72
GFC 2008	646	0.20	0.40	0.00	1.00
Credit info.	639	5.78	2.73	0.00	8.00
Private bureau	639	41.78	39.64	0.00	100.00
Public registry	639	15.92	27.40	0.00	100.00
Social media	301	0.61	0.18	0.13	0.99
E-commerce	582	58.96	26.24	10.00	96.50
Privacy	523	48.63	21.31	13.10	90.10
Fin. digital$_1$	625	26.78	24.98	0.66	85.12
Fin. digital$_2$	632	31.69	23.15	1.10	85.12
Mobile pay	175	5.80	6.91	0.00	37.10
Mobile transfer	104	7.19	10.19	0.00	50.12
Insolvency$_y$	621	2.45	1.22	0.40	6.00
Insolvency$_f$	646	9.17	3.43	0.00	15.00
Enforcement	562	4.65	1.54	0.00	8.00
Credit reg.	557	8.23	1.46	2.50	10.00
Legal rights	639	5.46	2.91	0.00	12.00
Corruption	646	0.17	1.08	-1.66	2.40
Rule of law	646	0.22	1.03	-1.79	2.10
Judicial ind.	562	5.06	1.49	1.95	7.97
Impartial courts	562	4.95	1.31	2.63	7.58
Political stability	646	-0.09	0.93	-2.99	1.62
PDI	211	54.30	21.00	11.00	95.00
IND	211	49.28	24.05	11.00	91.00
MAS	211	48.24	19.58	5.00	95.00
UAI	211	71.69	18.82	29.00	95.00
LTI	268	43.20	23.46	3.53	100.00
INDG	261	47.75	21.85	0.00	97.32
Distrust	339	2.41	0.38	1.62	3.23

Table 2 Fintech credit in the context of data availability and privacy

This table presents the regression results of fintech credit use per capita on a set of country-wide variables denoting macro and banking sector as the control variables and the availability of credit-related data and privacy indexes. The dependent variable is the logarithm of fintech credit use per capita. The explanatory variables are lagged by one period. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
GDP growth	0.00933	0.0299*	0.00510	0.0291	0.0303*
	(0.0144)	(0.0156)	(0.0138)	(0.0177)	(0.0176)
Interest rates	-0.00662*	-0.00355	-0.00887**	-0.00342	-0.00225
	(0.00396)	(0.00356)	(0.00380)	(0.00365)	(0.00356)
Bigtech	0.0118***	0.0120***	0.0108***	0.00900**	0.0130***
	(0.00242)	(0.00276)	(0.00224)	(0.00369)	(0.00345)
Bank credit	0.00752***	0.00667***	0.00847***	0.00396	0.00732***
	(0.00208)	(0.00231)	(0.00199)	(0.00388)	(0.00237)
GFC 2008	0.802**	0.735**	0.886**	0.295	1.397***
	(0.384)	(0.362)	(0.397)	(0.358)	(0.474)
Credit info.	0.0631***				
	(0.0118)				
Private bureau		0.00695***			
		(0.00205)			
Public registry			0.00477		
			(0.00294)		
E-commerce				0.0218***	
				(0.00591)	
Privacy					0.0168***
					(0.00548)
Observations	334	334	334	299	289
R^2	0.282	0.296	0.270	0.340	0.357

Table 3. Bigtech credit in the context of data availability and privacy

This table presents the regression results of bigtech credit measures on a set of country-wide variables denoting macro and banking sector as the control variables and the availability of credit-related data and privacy indexes. In columns (1)-(2), the dependent variable is a binary variable taking a value of one if bigtech credit was present in a specific country in a specific year; in (3)-(4), it is the logarithm of bigtech credit use per capita, only in the cases when it is positive value. The explanatory variables are lagged by one period. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively. The full results for the bigtech credit market are available upon request.

	(1)	(2)	(3)	(4)
GDP growth	1.138**	1.031	-0.0519	-0.0230
	(0.0719)	(0.0464)	(0.0928)	(0.126)
Interest rates	0.979	0.983	-0.0182	-0.0229
	(0.0229)	(0.0204)	(0.0200)	(0.0201)
Fintech	1.018***	1.031***	0.0103***	0.0168***
	(0.00607)	(0.00847)	(0.00323)	(0.00252)
Bank credit	0.991***	0.998	0.00206	0.00897***
	(0.00338)	(0.00341)	(0.00581)	(0.00268)
GFC 2008	2.549**	1.503	-1.556**	-2.888***
	(1.152)	(0.807)	(0.690)	(0.637)
Credit info.	1.384***			
	(0.0997)			
E-commerce			0.0288**	
			(0.0139)	
Privacy		0.982*		0.0277*
		(0.00909)		(0.0163)
Observations	334	289	67	61
Pseudo R^2	0.142	0.0706		
R^2			0.430	0.559

Table 4 Fintech in the context of the previous level of financial digitalization of a country

This table presents the regression results of fintech credit use per capita on a set of country-wide variables denoting macro and banking sector as the control variables and the digitalization level indexes. The dependent variable is the logarithm of fintech credit use per capita. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)
GDP growth	0.0170	-0.00535	-0.0383	-0.0225
	(0.0147)	(0.0141)	(0.0428)	(0.0513)
Interest rates	-0.000988	-0.00495	-0.00554	-0.00133
	(0.00667)	(0.00424)	(0.00691)	(0.00663)
Bigtech credit	0.0102***	0.0108***	0.0100**	0.0253***
	(0.00251)	(0.00244)	(0.00469)	(0.00526)
Bank credit	-0.000396	0.00570***	0.00788**	0.0118**
	(0.00210)	(0.00197)	(0.00367)	(0.00499)
GFC 2008	0.178	0.544	0.596	-0.717**
	(0.314)	(0.339)	(0.548)	(0.310)
Fin. digital_1	0.0356***			
	(0.00526)			
Fin. digital_2		0.0193***		
		(0.00375)		
Mobile pay			0.0828***	
			(0.0285)	
Mobile transfer				-0.00496
				(0.00467)
Observations	321	327	108	81
R^2	0.407	0.329	0.414	0.383

Table 5 Bigtech credit in the context of the previous level of financial digitalization of a country

This table presents the regression results of bigtech credit measures on a set of country-wide variables denoting macro and banking sector as the control variables and the digitalization level indexes. In columns, (1)-(4), the dependent variable is a binary variable taking a value of one if bigtech credit was present in a specific country in a specific year; in (5)-(8), it is the logarithm of bigtech credit use per capita, only in the cases when it is positive value. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP growth	1.050	1.050	1.102	1.123	-0.157*	-0.227***	-0.322**	-0.0793
	(0.0507)	(0.0514)	(0.139)	(0.181)	(0.0801)	(0.0735)	(0.132)	(0.169)
Interest rates	0.995	0.979	0.965	0.900	-0.0126	-0.0235	-0.0299	0.0191
	(0.0266)	(0.0203)	(0.0551)	(0.0599)	(0.0207)	(0.0159)	(0.0310)	(0.0642)
Fintech credit	1.022***	1.021***	1.010	1.075	0.00595*	0.00739**	0.00584	0.0142***
	(0.00629)	(0.00593)	(0.00678)	(0.0581)	(0.00342)	(0.00320)	(0.00475)	(0.00159)
Bank credit	0.994	0.994*	0.994	1.009	0.00815**	0.0125***	0.0161***	0.0106**
	(0.00414)	(0.00360)	(0.00600)	(0.0117)	(0.00378)	(0.00320)	(0.00547)	(0.00355)
GFC 2008	2.407**	2.317**	3.172	11.60*	-1.988***	-1.753***	-1.684*	1.453*
	(1.067)	(0.993)	(2.370)	(15.78)	(0.696)	(0.645)	(0.952)	(0.688)
Fin. $digital_1$	1.003				0.0353***			
	(0.00905)				(0.0112)			
Fin. $digital_2$		1.008				0.0268***		
		(0.00778)				(0.00558)		
Mobile pay			1.079**				0.0524**	
			(0.0401)				(0.0194)	
Mobile transfer				1.092***				0.0348**
				(0.0364)				(0.0152)
Observations	321	327	108	81	70	70	28	18

R^2					0.510	0.551	0.547	0.829
Pseudo R^2	0.0555	0.0621	0.102	0.218				

Table 6 Fintech credit in the context institutional quality indexes

This table presents regression results of fintech credit use per capita on a set of country-wide variables denoting macro, banking sector as the control variables and institutional quality indexes, especially the insolvency framework. The dependent variable is the logarithm of fintech credit use per capita. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GDP growth	0.0185	0.0105	0.00621	-0.000555	0.00201	0.0172	0.0165	0.0159	0.00418	0.00868
	(0.0141)	(0.0139)	(0.0156)	(0.0154)	(0.0140)	(0.0141)	(0.0140)	(0.0136)	(0.0147)	(0.0140)
Interest rate	-0.000987	-0.00621*	-0.00706*	-0.00866**	-0.00224	-0.000410	-0.00122	-0.00702*	-0.00352	-0.00850**
	(0.00409)	(0.00346)	(0.00413)	(0.00389)	(0.00417)	(0.00366)	(0.00357)	(0.00382)	(0.00357)	(0.00424)
Bigtech credit	0.0107***	0.00998***	0.00940	0.0110**	0.0130***	0.0132***	0.0130***	0.00992	0.00935	0.0119***
	(0.00268)	(0.00251)	(0.00588)	(0.00530)	(0.00251)	(0.00314)	(0.00322)	(0.00639)	(0.00681)	(0.00267)
Bank credit	0.00706***	0.00823***	0.00491**	0.00869***	0.00808***	0.00180	0.000756	0.00671**	0.00353	0.00623***
	(0.00199)	(0.00192)	(0.00247)	(0.00257)	(0.00204)	(0.00263)	(0.00312)	(0.00269)	(0.00312)	(0.00217)
GFC 2008	0.811**	0.577	0.514	0.710*	0.837**	0.701**	0.659**	0.584	0.574*	0.736*
	(0.358)	(0.358)	(0.366)	(0.402)	(0.362)	(0.321)	(0.306)	(0.355)	(0.326)	(0.382)
$Insolvency_y$	-0.272***									
	(0.0501)									
$Insolvency_f$		0.0865***								
		(0.0175)								
Enforcement			0.278***							
			(0.0569)							
Credit reg.				0.0774*						
				(0.0441)						
Legal rights					0.0803***					
					(0.0199)					

Corruption						0.576***				
						(0.114)				
Rule of law							0.621***			
							(0.141)			
Judicial ind.								0.236***		
								(0.0808)		
Impartial courts									0.386***	
									(0.104)	
Political stability										0.272***
										(0.0751)
Observations	332	334	293	291	334	334	334	293	293	334
R^2	0.308	0.304	0.329	0.261	0.300	0.363	0.354	0.293	0.324	0.288

Table 7 Bigtech credit in the context institutional quality indexes

This table presents regression results of bigtech credit measures on a set of country-wide variables denoting macro, banking sector as the control variables and institutional quality indexes, especially the insolvency framework. In columns, (1)-(3), the dependent variable is a binary variable taking a value of one if bigtech credit was present in a specific country in a specific year; in (4)-(6), it is the logarithm of bigtech credit use per capita, only in the cases when it is positive value. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
GDP growth	1.084	1.084	1.036	-0.235**	-0.202**	-0.284***
	(0.0599)	(0.0563)	(0.0550)	(0.0935)	(0.0875)	(0.0895)
Interest rate	0.985	0.983	0.976	-0.0222	-0.0199	-0.0167
	(0.0198)	(0.0176)	(0.0271)	(0.0261)	(0.0245)	(0.0287)
Fintech credit	1.020***	1.020***	1.023***	0.0103***	0.00941***	0.00927**
	(0.00573)	(0.00640)	(0.00778)	(0.00297)	(0.00301)	(0.00375)
Bank credit	0.994*	0.995	0.987***	0.0139***	0.0131***	0.0115**
	(0.00350)	(0.00337)	(0.00467)	(0.00397)	(0.00416)	(0.00508)
GFC 2008	2.652**	1.943	2.433*	-1.264**	-1.329**	-2.067***
	(1.108)	(0.859)	(1.125)	(0.605)	(0.639)	(0.721)
$Insolvency_y$	0.777			0.0627		
	(0.127)			(0.140)		
$Insolvency_f$		1.138***			0.0437	
		(0.0521)			(0.0529)	
Enforcement			1.540***			0.334*
			(0.183)			(0.174)
Observations	332	334	293	70	70	49
Pseudo R^2	0.0691	0.0808	0.105			
R^2				0.437	0.440	0.545

Table 8 Fintech credit in the context of national cultural dimensions and distrust of banks

This table presents the regression results of fintech credit use per capita on a set of country-wide variables denoting macro and banking sector as the control variables and the national culture dimensions. The dependent variable is the logarithm of fintech credit use per capita. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP growth	0.0881**	0.0663	0.0509	-0.0687	0.0160	0.0625	0.128***
	(0.0421)	(0.0511)	(0.0466)	(0.0471)	(0.0320)	(0.0382)	(0.0399)
Interest rates	0.0137	0.00551	-0.00395	-0.0115	-0.00962	-0.0108	-0.00310
	(0.0105)	(0.00988)	(0.0113)	(0.0116)	(0.00989)	(0.00937)	(0.00989)
Bigtech credit	0.00855**	0.00764	0.00167	0.0106**	0.0110**	0.00776*	0.0118***
	(0.00402)	(0.00505)	(0.00629)	(0.00429)	(0.00451)	(0.00410)	(0.00243)
Bank credit	0.00574*	0.00725**	0.0126***	0.00680*	0.0161***	0.0100***	0.0112***
	(0.00331)	(0.00313)	(0.00369)	(0.00360)	(0.00343)	(0.00310)	(0.00227)
GFC 2008	1.432***	0.275	1.252**	0.869**	1.310***	1.230***	1.655***
	(0.393)	(0.387)	(0.483)	(0.362)	(0.441)	(0.389)	(0.631)
PDI	-0.0339***						
	(0.00656)						
IND		0.0308***					
		(0.00628)					
MAS			0.0126				
			(0.00949)				
UAI				-0.0347***			
				(0.00953)			
LTI					-0.0176***		
					(0.00603)		
INDG						0.0202***	

						(0.00452)	
Distrust							0.997***
							(0.270)
Observations	107	107	107	107	140	134	204
R^2	0.435	0.400	0.246	0.335	0.283	0.355	0.317

Table 9A Bigtech credit in the context of national cultural dimensions and distrust of banks

This table presents the regression results of bigtech credit measures on a set of country-wide variables denoting macro and banking sector as the control variables and the national culture dimensions. The dependent variable is a binary variable taking a value of one if bigtech credit was present in a specific country in a specific year. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP growth	0.981	0.995	1.043	0.982	0.973	0.944	0.807**
	(0.111)	(0.119)	(0.111)	(0.107)	(0.0849)	(0.0797)	(0.0807)
Interest rates	1.008	1.012	1.025	1.015	1.007	1.005	0.995
	(0.0290)	(0.0307)	(0.0277)	(0.0272)	(0.0261)	(0.0270)	(0.0423)
Fintech credit pc	1.020**	1.018*	1.009	1.008	1.021**	1.021**	1.030***
	(0.00951)	(0.0101)	(0.00757)	(0.00804)	(0.00961)	(0.00924)	(0.00918)
Bank credit	0.995	0.995	0.994	0.992	0.984**	0.995	0.991**
	(0.00693)	(0.00638)	(0.00659)	(0.00701)	(0.00747)	(0.00566)	(0.00369)
GFC 2008	3.634**	7.520***	4.606**	4.172**	1.477	1.889	47.93***
	(2.284)	(4.844)	(3.065)	(2.583)	(0.918)	(1.041)	(48.38)
PDI	1.021*						
	(0.0112)						
IND		0.981*					
		(0.0111)					
MAS			1.019				
			(0.0166)				
UAI				0.989			
				(0.0156)			
LTI					1.030***		
					(0.0109)		
INDG						0.984*	
						(0.00942)	
Distrust							0.0323***
							(0.0210)
Observations	107	107	107	107	140	134	204
Pseudo R^2	0.104	0.102	0.0971	0.0885	0.101	0.0664	0.231

Table 9B Bigtech credit in the context of national cultural dimensions and distrust of banks

This table presents the regression results of bigtech credit use per capita on a set of country-wide variables denoting macro and banking sector as the control variables and the national culture dimensions. The dependent variable is the logarithm of bigtech credit use per capita, only in the cases when it is positive value. The explanatory variables are lagged by one period when they are time-variant. All specifications include constants but not reported for brevity. Robust standard errors are presented in parentheses, and ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP growth	-0.358**	-0.511***	-0.530**	0.172	-0.0823	-0.352**	-0.301**
	(0.158)	(0.168)	(0.207)	(0.119)	(0.112)	(0.161)	(0.131)
Interest rates	-0.0658***	-0.0612***	-0.0702***	-0.0258**	-0.0161	-0.0224	-0.0371**
	(0.0186)	(0.0140)	(0.0213)	(0.0112)	(0.0150)	(0.0208)	(0.0155)
Fintech credit	0.0158**	0.0180***	0.00894	0.0222***	0.0164***	0.0112*	0.00798**
	(0.00669)	(0.00599)	(0.00747)	(0.00394)	(0.00391)	(0.00630)	(0.00304)
Bank credit	0.0216***	0.0215***	0.0176**	0.0275***	0.00642	0.0197***	0.0228***
	(0.00675)	(0.00658)	(0.00815)	(0.00386)	(0.00564)	(0.00637)	(0.00359)
GFC 2008	-1.728**	-0.561	-1.783*	-0.0878	-1.185***	-1.276*	-0.509
	(0.777)	(0.707)	(1.002)	(0.361)	(0.421)	(0.662)	(0.536)
PDI	0.0342**						
	(0.0160)						
IND		-0.0366***					
		(0.0123)					
MAS			-0.0135				
			(0.0169)				
UAI				0.0798***			
				(0.0120)			
LTI					0.0437***		
					(0.00670)		
INDG						-0.0196**	
						(0.00770)	
Distrust							-0.205
							(0.781)
Observations	35	35	35	35	41	41	52
R^2	0.612	0.642	0.551	0.877	0.735	0.543	0.680

Table A1 Variables definitions and sources

Variable	Definition	Source
Fintech credit	Financial technology-driven and loan-based business models, i.e.: peer-to-peer (P2P) or marketplace lending to consumers, businesses or for property; balance sheet lending to consumers, businesses or for property; invoice trading, debt-based securities (debentures and bonds) and mini-bonds; financing flow divided by country population (USD).	Cornelli et al. (2020)
Bigtech credit	Loan-based business models performed by large companies whose primarily business is technology ("big techs") have entered credit markets, lending either directly or in partnership with financial institutions; financing flow divided by country population (USD).	Cornelli et al. (2020)
Bigtech credit presence	The binary variable taking the value of 1, if bigtech credit was present in a given country, in a given year and 0 otherwise.	Cornelli et al. (2020)
GDP growth	Annual GDP growth (in %)	World Bank
Interest rates	Real interest rate (in %)	World Bank
Bank credit	Domestic credit to private sector by banks (% of GDP)	World Bank
GFC 2008	The binary variable that takes the value of 1, if the country had a systemic banking crisis in 2008, i.e. during the Global Financial Crisis	Laeven and Valencia (2012)
Credit information	Depth of credit information index (scale 0 - 8)	World Bank
Private bureau	Private credit bureau coverage (% of adults)	World Bank
Public registry	Public credit registry coverage (% of adults)	World Bank
Social media	The share of internet users in selected countries visiting social networking sites as of January 2020	Statista
E-commerce	The UNCTAD B2C E-Commerce Index, Index (0-100) as of 2016	UNCTAD
Privacy	A composite indicator (0 - 1-100)	BESTVPN; https://bestvpn.org/privacy-index/#tab-con-1
Fin. $Digit._1$	Used a mobile phone or the internet to access a financial institution account in the past year (% age 15+)	Findex 2017
Fin. $Digit._2$	Used a mobile phone or the internet to access an account (% age 15+)	Findex 2017
Mobile pay	Mobile phones used to pay bills (% age 15+)	Findex 2017
Mobile transfer	Mobile phones used to send money (% age 15+)	Findex 2017
$Insolvency_{ys}$	Time to resolve insolvency in years	World Bank

Insolvency$_f$	Strength of insolvency framework index (0-16)	World Bank
Enforcement	Index estimates the time and money required to collect a debt (0-10)	Fraser Institute
Credit reg.	Index containing information on bank deposits held in privately owned banks; private sector and interest rate controls.	Fraser Institute
Legal rights	Strength of legal rights index (0 - 12)	World Bank
Corruption	Control of corruption index (-2.5 - 2.5)	World Bank
Rule of law	Rule of law index (-2.5 - 2.5)	World Bank
Judicial ind.	Index containing information on perceived judicial independence (0 - 10)	Fraser Institute
Impartial courts	Index containing information on perceived courts impartiality (0 - 10)	Fraser Institute
Political stability	Political stability index (-2.5 - 2.5)	World Bank
PDI	Power Distance is the extent to which the less powerful members of organizations and institutions accept and expect that power is distributed unequally.	Hofstede 2011
IND	Individualism is the extent to which people feel independent, as opposed to being interdependent as members of larger wholes	Hofstede 2011
MAS	Masculinity is the extent to which the use of force in endorsed socially. In a feminine society, the genders are emotionally closer. Competing is not so openly endorsed, and there is sympathy for the underdog.	Hofstede 2011
UAI	Uncertainty avoidance deals with a society's tolerance for uncertainty and ambiguity.	Hofstede 2011
LTI	In a long-time-oriented culture, the basic notion about the world is that it is in flux, and preparing for the future is always needed.	Hofstede 2011
INDG	In an indulgent culture it is good to be free.	Hofstede 2011
Distrust	The average response for respondents to the question *I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: is it a great deal of confidence, quite a lot of confidence, not very much confidence or none at all? Banks* from a given country was taken into account. The answer range from 1 (a great deal) to 4 (none at all).	World Values Survey

Appendix A2 Countries included in the sample

1 Argentina
2 Australia
3 Austria
4 Bahrain
5 Bangladesh
6 Belgium
7 Bolivia
8 Brazil
9 Bulgaria
10 Burkina Faso
11 Burundi
12 Cambodia
13 Cameroon
14 Canada
15 Chile
16 China
17 Colombia
18 Costa Rica
19 Czech Republic
20 Côte d'Ivoire
21 Democratic Republic of the Congo
22 Denmark
23 Ecuador
24 Egypt
25 El Salvador
26 Estonia
27 Finland
28 France
29 Georgia
30 Germany
31 Ghana
32 Guatemala
33 Hong Kong
34 Iceland
35 India
36 Indonesia
37 Iraq
38 Ireland
39 Israel
40 Italy
41 Japan
42 Jordan
43 Kazakhstan
44 Kenya
45 Korea
46 Lao People's Democratic Republic
47 Latvia
48 Lebanon
49 Liberia
50 Lithuania
51 Luxembourg
52 Madagascar
53 Malawi
54 Malaysia
55 Mali
56 Mexico
57 Mongolia
58 Morocco
59 Myanmar
60 Netherlands
61 New Zealand
62 Nigeria
63 Norway
64 Pakistan
65 Panama
66 Paraguay
67 Peru
68 Philippines
69 Poland
70 Portugal
71 Russian Federation
72 Rwanda
73 Saudi Arabia
74 Senegal
75 Sierra Leone
76 Singapore
77 Slovakia
78 Slovenia
79 South Africa
80 Spain
81 Sweden
82 Switzerland
83 Tanzania, United Republic of
84 Thailand
85 Togo
86 Turkey
87 Uganda
88 United Arab Emirates
89 United Kingdom
90 United States of America
91 Uruguay
92 Viet Nam
93 Zambia
94 Zimbabwe