October 2021

WORKING PAPER SERIES

2021-ACF-07

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Oskar Kowalewski
IESEG School of Management, UMR 9221 - LEM - Lille Economie Management, Lille, France
Univ. Lille, UMR 9221 - LEM - Lille Economie Management, Lille, France
CNRS, UMR 9221 - LEM - Lille Economie Management, Lille, France
Institute of Economics, Polish Academy of Sciences, Warsaw, Poland
o.kowalewski@ieseg.fr (O. Kowalewski; ORCID 0000-0001-5520-3559)

Paweł Pisany
Institute of Economics, Polish Academy of Sciences, Warsaw, Poland
ppisany@inepan.pl (P. Pisany; ORCID 0000-0001-9665-8840)

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

Banks' consumer lending reaction to fintech and bigtech credit emergence in the context of *soft* versus *hard credit information* processing[*]

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

[a]*IESEG School of Management, UMR 9221 - LEM - Lille Économie Management, Lille, France*

[b]*Univ. Lille, UMR 9221 - LEM - Lille Économie Management, Lille, France*

[c]*CNRS, UMR 9221 - LEM - Lille Économie Management, Lille, France*

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

Abstract

We analyze competition in the consumer lending segment between banks and financial technology (or "fintech") companies (or "fintechs") as well as giant technology (or "bigtech") companies (or "bigtechs") providing alternative credit. We use a database combining bank-level characteristics and country-level proxies for 72 countries during 2013–2018. We find that in developed markets, the relations between fintech/bigtech credit providers and banks are similar and competitive in nature. However, banks' consumer lending grows simultaneously with fintech credit market development in emerging economies but decreases in the aftermath of bigtech credit emergence. Fintech credit seems to penetrate market segments not serviced by banks; thus, it plays a complementary role, but only in emerging economies. Bigtechs compete even more with banks and push some banking offers out of the market, both in emerging and developed economies. Furthermore, we show that domestic and privately owned banks are more negatively affected by competition from technology-based lending, particularly bigtech, compared to foreign banks. Thus, bigtech lending may be treated as a serious competition for banks' relationship lending, based on soft credit information processing, provisioned traditionally by local banks.

Keywords: alternative credit, fintech, bigtech, financial inclusion, local banks, competition, relationship lending, soft credit information

JEL codes: G21, G23, O33

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[*] Funding: This work was supported by the National Science Center (NCN), Poland, under grant **OPUS 15 no. 2018/29/B/HS4/00594.**

[†] Corresponding author.

E-mail addresses: *E-mail addresses*: o.kowalewski@ieseg.fr (O. Kowalewski; ORCID 0000-0001-5520-3559), ppisany@inepan.pl (P. Pisany; ORCID 0000-0001-9665-8840)

Introduction

Technology has always set the conditions of running a business; in particular, the current fast development of information and communication technologies (ICT) and data availability influence the perspectives of financial markets. Financial technology ("fintech") is currently a buzzword in the business world. Meanwhile, there is a growing discussion about the potentially disruptive impact of giant technology ("bigtech") companies ("bigtechs"), such as e-commerce platforms entering the financial markets. While there have been some empirical studies on fintech, most focus only on a particular provider. New reliable cross-country data have only recently emerged that allow for in-depth empirical studies of the nature of competition between fintech companies ("fintechs") and banks. Moreover, we know even less about experiences related to the emergence of bigtech credit. This study offers some empirical insights in this field using bank-level data and country-level proxies for fintech and, even more importantly, bigtech credit. We use the term "*alternative tech-based lending providers*" in the paper to cover fintech and bigtech creditors together to emphasize that we focus on those specific fintech/bigtech business models that provide alternative financing to retail customers. However, we investigate these phenomena separately and highlight the main differences.

The term *fintech* sometimes refers to the technologies used by banks to transform and modernize their business models. This is an important aspect of this topic. However, technological innovation opens up the possibility of provisioning financial services by new categories of non-banking entities. Thus, a new type of competitors for banks emerge who are potentially very strong but, more importantly, poorly regulated and supervised. We consider this area to be of crucial importance today. How does such competition affect banks? Which banks are particularly exposed to the new competition? Do fintech and bigtech credit, as alternative tech-based lending, affect banks in the same way or do they have different potential impacts on the banking sector? Here, we try to shed new light on the above-mentioned issues from an empirical perspective using recently available data on technology-based (or "tech-based") lending for a large number of countries.

We also analyze the relationships between banks and tech-based lending (fintech and bigtech credit) in the context of competitive advantages in *soft* and *hard credit data* processing. We try to indicate the nature of financial business models developed by tech-based lending, particularly bigtechs, and which banks may be subject to significant competitive pressure. We show that fintech credit can indeed play a complementary role to bank credit, especially in emerging markets, while in high-income countries, fintech credit is rather a competition. Importantly, we provide evidence that bigtech credit providers can be important competitors for banks in both emerging and developed economies, and the first symptoms are already visible in the consumer credit market.

We also show that local, domestic banks are most exposed to the new type of competition, especially from bigtechs. In our opinion, the results document that bigtechs' unprecedented informational and technological advantage over other market participants probably allows them to develop such an effective distribution and, more importantly, credit scoring tools; these can act as the equivalent of market feeling and environmental knowledge by local banks.

To the best of our knowledge, this is the first empirical bank-level study based on banks operating in many different countries which addresses the problem of competition between fintech/bigtech lenders and banks on consumer lending markets; also taking into account the ownership types of banks.

We have chosen consumer lending because this segment seems to be the most exposed to fintechs' and, primarily, bigtechs' financial services offer due technology companies' position in e-commerce/social media and well-established relations with clients. According to Odinet (2018), the rise of tech-based lending is a consequence of the 2008 financial crisis when lenders pulled back from lending, particularly to consumers. Then, technology companies stepped into the void and have since expanded globally. Interlinkages between core business models of technology companies and the consumer lending market are multithreaded, and include enhancing the effectiveness of digital distribution channels as well as broad and deep information on the customer base.

Consequently, innovative forms of services arise, such as buy now, pay later (BNPL) developed often by bigtechs, where e-commerce platforms offer consumer credit just in the moment of purchase. It is often balance sheet lending, that is, granted from the e-commerce platform's own funds; therefore, the margin goes to the platform. In addition, combining product sales and financing for consumers is a way to increase turnover on the platform, as these two reinforce each other.

As the lending of nonbanks is not funded by depositors (hence, they are often called shadow banks), they are not subject to traditional regulations. However, shadow banks should be monitored because their balance sheet lending may be financed by both institutional investors, including venture capital, as individual investors, for example through corporate bonds market. Moreover, they compete with banks in the same markets on services and prices, and consequently, are now an important part of the country's financial system. Therefore, Seru

(2019) argues that regulators should simultaneously assess banks and shadow banks in their policy analysis. It seems that nowadays technology development leads to emergence of new-type lending providers that act like shadow banks.

Mortgage and corporate lending still require more bureaucratic procedures, and it is harder to organize through digital channels, at least in most jurisdictions. Thus, we do not expect those two segments to be penetrated by fintech and bigtech credit providers in current market conditions and the current regulatory environment, especially on a global scale, when we assess the situation in many markets.

In addition, we conduct our analysis considering banks' ownership types; thus, we are able to show which banks are most exposed to new tech-based competition. We interpret this in the context of *soft* versus *hard credit information* processing and claim that our research sheds some light on the essence of the market advantage of tech-based credit providers, particularly bigtechs. We believe that our results may be of interest to financial regulators, supervisors, and policymakers, as well as the banks themselves.

The remainder of this study is organized as follows. Section 2 presents a short review of the literature and develops the hypotheses. Section 3 describes the data and introduces the econometric methodology. Section 4 presents the results. Finally, section 5 presents the conclusions of this study.

Literature review and hypotheses development

Our study corresponds with two strands of finance research. The first strand refers to relatively new, but dynamically rising, literature on fintech and its relations with traditional financial intermediaries, particularly banks. In the second strand, we are inspired by studies investigating banks' behavior depending on their comparative advantage in processing the *soft* or *hard credit data*, which are often associated with banks' business models, scale of operations, and ownership type. In our research, we strive to verify whether banks' lending reactions to fintech and bigtech credit emergence, and whether domestic, local banks (characterized by high competences in *soft credit data* processing) or foreign banks (that rely more on *hard credit data*) are more affected by tech-based competition.

Literature on bank – fintech / bigtech relations

Several recent studies have provided comprehensive and up-to-date literature reviews focused on fintech research (see, for example, Thakor (2020), Agarwal and Zhang (2020), Allen et al.

(2020), Branzoli and Supino (2020), OECD (2020), Bömer and Maxin (2018), and Jagtiani and Lemieux (2018)). Thus, we review only the most relevant studies, in our opinion, which are related to our study.

Relations between fintech and banking credit supply have been the subject of empirical verification but only in selected countries and markets. Several studies have focused on *peer-to-peer* (P2P) lending, that is, narrower and more specific segments of fintech credit. de Roure et al. (2019) investigate whether P2P lending platforms–one of the fintech credit segments classified by Cornelli et al. (2020), which we also employ in our study, constitute competition for the banking sector or fulfill a complementary role by serving clients to whom banks do not address their offer. Using data on consumer credit in Germany provided by banks and the largest P2P platform, the authors document that P2P lending and bank consumer credit are indeed negatively correlated. Moreover, they report that the P2P market has taken away risky and less profitable clients from banks. Thus, alternative P2P lending competes with banks but only to some extent, that is, only in particular segments of clients. Similarly, Tang (2019) determines to what extent banks and P2P lending platforms are substitutable and complementary, that is, whether they serve different customer segments. The author focuses on the US market and uses a regulatory reform in 2010, which forced banks in the US to tighten lending conditions, as an example of a negative bank credit supply shock. Using data from Lending Club, a leading American P2P platform, the author shows that P2P lending has developed in market segments exposed to negative bank credit shocks. Moreover, low-quality bank clients have migrated to P2P first; thus, the overall quality of the P2P loan portfolio has deteriorated after the expansion. Simultaneously, in terms of small-scale loans, P2P and banks seem to complement each other more.

Buchak et al. (2018) analyze mortgage lending and claim that the decline in mortgage lending by traditional banks in the US may be explained by increasing regulatory burdens and substantially improvements in lending technologies that allow shadow banks to offer cheaper products in a more convenient way. Supplementing Buchak et al. (2018), Fuster et al. (2019) provide evidence that fintech presence in the US mortgage lending market has helped reduce inefficiencies, such as lengthy loan processing. Moreover, Jagtiani et al. (2019) show that fintech lenders' market share is larger in areas characterized by higher credit denial rates and lower consumer credit scores. In the very recent country-level study Hodula (2021) investigates banking sectors reactions to fintech credit and shows quite mixed results depending among others on banking sector concentration. We present, however, a more granular approach and wider scope, i.e. bank-level study, and we focus on the banks' reaction to fintech and bigtech credit separately. Finally, our research allows for a complex analysis and indication, which banks are particularly vulnerable to tech-based competition.

One of the basic innovative features of tech-based finance is the *alternative data* that can be used both for increasing marketing and distribution effectiveness, as well as for assessing the creditworthiness of potential borrowers. Alternative credit data sources are e-commerce and the Internet, particularly social media activities. Alternative data are sometimes figuratively called *digital footprint* (Berg et al., 2020). Thus, bigtechs have significant information advantage in this area that they use to build net effects and finally penetrate new markets. Berg et al. (2018) for the German market, Frost et al. (2019) for the Argentinian market, Gambacorta et al. (2019) for China, and Iyer et al. (2016) and Jagtiani and Lemieux (2019) for the US show that non-traditional alternative data (e-commerce data/payment data/data from social media) are at least as good as traditional credit information in credit scoring. Combining both types of credit data is expected to yield the best results. In addition, Berg et al. (2020) present alternative data usage as a factor that is boosting financial inclusion worldwide. Regarding the above-cited research on fintech/bigtech lending, studies underlining potential increases in credit risk should be mentioned once again (Freedman and Jin, 2016; Tang, 2019; de Roure et al., 2018) as well as papers on the topic of algorithmic discrimination, and unfair and biased automated credit decisions (Gikay, 2020; Desai and Kroll, 2017; Fu et al., 2018; Acemoglu, 2021).

However, compared to fintech, bigtech credit is an even younger trend and its presence in financial markets has been a subject of research nowadays. Frost et al. (2019) explore the informational advantage of e-commerce platforms with respect to credit scoring and show the mechanism of bigtech's entrance into financial markets. Large technology platforms usually start from payment services (Kowalewski et al., 2021) and then expand to other financial market segments, in particular lending, either balance-sheet lending or brokerage, and marketplace creation for other financial intermediaries. Stulz (2019) explores the technology and scale advantages of bigtech compared to both banks and fintechs. Padilla and De la Mano (2018) provide a comprehensive conceptual analysis of the bigtechs' entrance into credit markets, especially in the context of retail offers. The authors hypothesize that bigtechs may succeed in monopolizing origination and distribution of lending to consumers as well as small and medium enterprises (SME), and reduce the role of banks to "low cost manufacturers" which only fund some of the loans distributed by bigtechs. We are still far from this scenario materializing today; however, in our empirical study, we strive to check whether some signs of the trend forecasted by Padilla and De la Mano (2018) are already visible in financial markets. Cornelli et al. (2020) construct a cross-country database on fintech and bigtech credit annual volumes for the period 2013 – 2019. They underline that bigtech credit exceeded fintech credit volumes worldwide in 2018 and 2019, and show the set of banking sector-related drivers of bigtech credit. Kowalewski et al. (2021) extend the list of drivers of fintech and bigtech credit with factors related to trust in banks in a given society and dimensions of national culture. Furthermore, we should underline that bank-bigtech relations do not refer only to potential competition in the lending business. Bigtechs are often third-party service providers for banks, primarily in terms of cloud computing solutions.

Carstens et al. (2021) underline the potential sources of bigtechs' advantage thanks to vast amounts of data from core business lines in e-commerce and social media. The authors also focus on shortages of existing regulatory frameworks and claim that with bigtechs' entrance into financial markets; new challenges arise, particularly related to market power concentration and data governance. Moreover, issues such as consumer protection and operational resilience have become increasingly important. Bigtech's informational advantage seems to be even enhanced in the current regulatory framework; for example, in the European Union, banks are obliged to share customer data (after customer consent) with other supervised financial entities under the Payment Services Directive regime, while bigtechs are not. Finally, Carstens et al. (2021) emphasize the need for a balanced regulatory framework that considers both activity- and entity-based provisions. In current conditions, this practically means the extension of entity-based regulations towards bigtechs.

Overall, studies indicate that bigtechs have market power due to their scale of operations as well as technological and information advantage; this allows them to create more severe and more significant competition for banks than the one generated by the fintech sector. Understanding the main directions of this competition seems to be of principal importance for future regulations. Thus, we strive to contribute to our research by empirically verifying the following hypothesis:

H1. ***Consumer lending by banks grows simultaneously with fintech credit market development but decreases in the aftermath of bigtech credit emergence.***

Soft and hard credit information used by different types of banks and tech-based credit providers

The second principal strand of the literature we build on is research related to bank ownership and access to credit. Here, we examine whether foreign- or domestic-owned banks are differently affected by competition from fintechs and bigtechs.

Research on ties between ownership structure and bank behavior is extensive, multi-threaded, and has a long history. Cull et al. (2018) present a comprehensive survey of the literature on bank ownership. The authors note that one of the vital assumptions in studies on foreign versus domestic bank lending (for example Detragiache et al., 2008) is that domestic banks have a significant informational advantage over foreign banks in lending to local and more opaque borrowers. Further, domestic banks have a better understanding of local borrowers, local specific features, and better knowledge of the business and social environments. Thus, they are able to use *soft credit information*. Cull et al. (2018) define soft information as the mean knowledge of borrowers' intangible traits, such as character, competence, and work ethics. In contrast, foreign banks are expected to rely more on *hard credit information,* for example, from credit history, balance sheets, and income statements in the case of companies as well as collateral audited valuations.

The abovementioned theoretical conjecture–foreign-owned banks may be more eager to lend to large and more transparent companies–has been supported by empirical research for Argentina (Berger et al., 2001), Mexico (Beck & Martinez Peria, 2010), India (Gormley, 2010), and Central and Eastern Europe (Beck & Brown, 2015). Supplementing these findings, De Haas et al. (2010) and Giannetti and Ongena (2012) show that although foreign bank activity was not connected with decrease in financing availability for SMEs in Eastern Europe, foreign banks, compared to domestic banks, indeed tended to lend more to larger, less opaque entities. The significance of relationship lending to SMEs, based on soft credit information, has been questioned in the literature, in particular by Berger and Udell (2006). Beck et al. (2011) empirically show that foreign banks use hard credit information and arms-length technologies in lending more often; furthermore, there are no significant links between lending technologies, on the one hand, and the extent, type, and pricing of lending to SMEs, on the other hand. Furthermore, Hasan et al. (2021) have confirmed the role of domestic banks in financing small local businesses; however, the local banks' advantage in soft credit information processing turned to be quite difficult to establish empirically.

In their extensive literature survey, Thakor (2020) underlines that the discussion on financial services in the context of the type of information on borrowers and the relationship with these borrowers had already been going on before 2000 (e.g., Boot and Thakor (1997, 2000), and Song and Thakor (2010)). It was then a reflection of the comparative research on bank financing versus capital markets financing; the main conclusion was that the borrowers seeking for relationship loans (associated with soft credit information processing) went to banks, while those seeking for transaction loans (associated with hard credit information) went to debt capital markets.

Against this background, we strive to empirically find which types of banks are most exposed to competition, and the potentially disruptive impact of fintech and bigtech lending. If tech-based credit providers have an advantage in hard credit information processing, then foreign bank lending may be most vulnerable. In contrast, if alternative data analysis with advanced machine learning algorithms (conducted mostly by bigtechs) can be treated as equivalent to soft credit information processing, then local banks' lending may be most exposed to new competition types.

We are aware of one comprehensive research that has similar goals but quite different approaches and scopes from Balyuk et al. (2020). Using data on a leading US fintech platform (online marketplace) that coordinates alternative small business lending, the authors show that fintechs were most successful in penetrating market segments previously dominated by large commercial, often multinational, banks that use hard credit information, such as financial statements and collateral values, to determine credit scores. Contrary to Balyuk et al. (2020), we analyze a large sample of banks acting in different markets, both in emerging and developed economies, and we try to identify their reaction to the emergence of tech-based competition in lending for consumers.

Thus, our hypothesis differs from that of Balyuk et al. (2020). We assume that using large amounts of alternative data (digital footprint) and modern numeric methods (mostly machine learning) allow alternative credit providers to capture the undefinable information on potential debtors (consumers), which is close to soft information/soft credit data, previously obtained by local banks because of direct relationships with borrowers. This is actually the goal of digital footprint bigdata analysis, that is, to catch the mechanisms and interlinkages that correctly reflect reality and allow for forecasts, even if these connections are difficult to express verbally.

We hypothesize that modern informational advancement in finance may represent a kind of equivalent and, consequently, competition for old-fashioned relationship lending. Thus, we propose the second hypothesis:
H2. ***Domestic banks are more negatively affected by competition from tech-based lending than foreign banks. Thus, tech-based lending may be treated as a competition for relationship lending by local banks, based mostly on soft credit data processing.***

Finally, we investigate the potential differences between emerging and developed economies regarding banks' reaction to tech-based lending. We hypothesize that in high-income countries, which are well penetrated by financial services, fintech and bigtech credit providers need to compete directly with banks to gain customers. In contrast, in emerging economies, banks and smaller fintechs may coexist. Banks in emerging economies, which are probably less technologically advanced, service clients in more traditional channels, while fintechs play a role in developing digital, remote channels for customer lending. Thus, fintechs' and banks' offers are complementary to some extent.
We base our assumptions on our previous research (Kowalewski and Pisany, 2020) on the role of all-type fintech startups (measured by their total number in the economy) for the banking sector. In the said study, we show that in developed economies, there is a large space for cooperation between fintechs and banks as the former often provide banks with technological solutions, for example, in the field of artificial intelligence and machine learning applications or distributed ledger technology use. However, thanks to the new database presented by Bank for International Settlements (BIS) (Cornelli et al., 2020), we can grasp the specific role of fintech credit, that is, the fintech segment that, to a large extent, aspires to provide alternative financing. Therefore, we assume that the relationships between fintech credit versus banks, and bigtech credit versus banks will be competitive in developed economies. However, this is the next empirical question that cannot be solved theoretically. Hence, we present the following thesis, which we verify here.
H3. ***In high-income countries, both fintech and bigtech credit compete with banks in the consumer lending segment. Meanwhile, in emerging economies, only bigtech credit providers are competitors for banks and push some bank lending out of the market.***

We contribute to the literature on bank-fintech relations by presenting a comprehensive bank-level study using a cross-country research sample. As the literature review notes, empirical studies touch upon the topic in a single market, mostly the US (Jagtiani and Lemieux, 2018; Tang, 2019; Buchak et al., 2018; Fuster et al., 2019) and Germany (de Roure et al., 2019). Here, we combine bank-level lending data and country-level alternative credit data. Thanks to cross-country fintech and bigtech credit data by Cornelli et al. (2020), we are able to study banks' lending reactions to alternative tech-based credit development in a particular country in a specific year.

In our analysis, we consider different ownership types of a bank (domestic versus foreign-owned) and different income levels of the host country. Importantly, we investigate banks' reactions to fintech and bigtech credit separately; thus, we introduce the phenomenon of bigtech credit to empirical cross-country financial studies.

Finally, based on the ownership dimension, we use the estimation results and discuss whether alternative tech-based credit compete with hard-information lending provisioned by international banks or relationship/soft-information lending provisioned by local banks.

Data and methodology

We retrieved bank-level data for commercial, saving, and cooperative banks from Bureau van Dijk's BankScope and BankFocus database. We supplement them with country-level alternative tech-based credit data by Cornelli et al. (2020).

Our dependent variable is the natural logarithm of net consumer loans in USD (*Loan*) of bank *i* in country *c* in year *t*. In our regressions, in line with the relevant literature on banks' lending behaviors (de Haas and van Lelyveld, 2014; Bonin and Louie, 2017; Allen et al., 2017; Meriläinen, 2016; Chen et al., 2016), we first control for bank characteristics, that is, liquid assets to total assets (*Liquidity*), loans to deposits (*LtD*), return on assets (*ROA*), equity to assets (*Equity*), and total bank assets to the gross domestic product (GDP) of a given country (*Size*). We winsorize at the 1% level for all bank-level explanatory variables and lag them by one period while introducing them into the estimations.

We follow Allen et al. (2017) and employ country-level control variables, i.e., GDP growth (*GDPgrowth*) and inflation rate (*CPI*) that show, in the most basic way, the attractiveness of a given country as a place for running a financial business. We assume that bank loans are positively (negatively) associated with GDP (high inflation).

We conduct our analysis for the sub-samples of banks according to ownership type (foreign-*versus* domestic-owned) as well as income level in the host country (high income *versus* emerging economies). We also perform additional estimations as robustness checks, for example, without China (which is quite specific due to the substantial role of the state in financial and technology sectors) or an estimation for domestic private banks only. While referring to the results, we do not present all tables in the paper for brevity.[3]

Regarding definitions, in line with the literature (Allen et al., 2017), we treat a bank as foreign-owned when at least 50% of its capital is owned by foreign shareholders. Otherwise, the bank is classified as domestically owned. We conduct robustness for domestic private banks, excluding government-owned banks. Following La Porta et al. (2002), we treat a bank as state-owned if the government controls (directly or indirectly) at least 20% of the bank; otherwise, it is a private bank. Thus, we analyze domestic private banks if more than 50% of a bank's shares are in the hands of private domestic residents.

Moreover, we create two subsamples consisting of high- (developed markets), and low- and middle-income economies (emerging markets) by dividing the countries based on the World Bank's classification. We use these subsamples to conduct separate estimations for developed and emerging markets.

In our model, we proxy fintech and bigtech credit development by introducing the following six variables: *Fintech credit pc (per capita)*, *Fintech credit/GDP*, *Fintech credit, Bigtech credit pc (per capita)*, *Bigtech credit/GDP*, and *Bigtech credit*. As our study focuses on consumer lending by banks, we consider fintech/bigtech proxies relative to the population as the most accurate measure. We treat the results for *Fintech credit per capita* and *Bigtech credit per capita* as primarily important. We also introduce the natural logarithm of the alternative credit proxies to the model. A list of all variables (dependent and explanatory) is presented in Appendix A1.

While we consider our sample to be quite substantial, it is restricted by fintech/bigtech credit data availability; specifically, this is due to the short history of those market segments. As tech-based lending is a relatively new phenomenon and gathering the data seems to be a challenge, we can effectively use data from six years in our study from 2013 to 2018. Our sample covers banks from 72 countries, including high-, middle-, and low-income countries. Overall, we are able to perform our estimations on 14,186 bank-year observations. For the time being, one still cannot investigate the phenomenon of tech-based alternative credit in cross-country studies throughout the entire financial cycle, which is confirmed by the BIS database coverage. Nevertheless, we think that a database of over 14,000 bank-year observations from both developed and emerging economies allows for interesting insights.

[3] All our results, including the codes, are available upon request.

We have used the new and unique country-level alternative finance database by Cornelli et al. (2020), which has data on the absolute annual fintech and bigtech credit inflows as well as fintech and bigtech credit per capita. We follow these authors' definitions of fintech and bigtech credit. Fintech credit is thus associated with technology-driven and loan-based business models, that is, 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 (in mn USD). For fintech credit per capita (in USD), financing flow is divided by the country's population. Meanwhile, bigtech credit is associated with loan-based business models performed by large companies, whose primary business is technology (bigtechs), and have entered credit markets and lend either directly or in partnership with financial institutions. Again, for bigtech credit per capita (in USD), financing flow is divided by country population.

Furthermore, the bigtech market is much more concentrated than fintech. One can assume that fintech credit is provided by smaller, often local platforms, while bigtech services, including alternative new-type lending, are provisioned by over a dozen and up to several dozen global entities. In our estimations, we use the natural logarithm of tech-based lending proxies. Table 1 presents the descriptive statistics of the variables used in this study.

[Table 1]

We employ Equation (1) to verify our theses on bank lending – alternative tech-based lending interlinkages:

$$\boldsymbol{Loan}_{\boldsymbol{i,t,c}} = \boldsymbol{\beta_1} + \boldsymbol{Bank}_{\boldsymbol{i,t-1,c}}\,\boldsymbol{\beta_2} + \boldsymbol{M}_{\boldsymbol{c,t}}\,\boldsymbol{\beta_3} + \boldsymbol{X}_{\boldsymbol{c,t}}\boldsymbol{\beta_4} + \boldsymbol{\alpha_t} + \boldsymbol{\varepsilon_{i,t}} \tag{1}$$

where $Loan_{i,t,c}$ represents the natural logarithm of net consumer loans in USD of bank *i* in year *t* in country *c;* $Bank_{i,t-1,c}$ is a vector of bank-level control variables for bank *i* in year *t -1* (one period lagged); $M_{c,t}$ represent country macro-level control variables for country *c* in year *t*; $X_{c,t}$ represent control variables for fintech or bigtech credit development in country *c* in year *t.* All regressions include a constant, year fixed effect (α_t), and an error term ($\varepsilon_{i,t}$).

In choosing the empirical method, we follow Claessens and van Horen (2014), Beck et al. (2011), Chen et al. (2016), and Bonin and Louie (2017), and estimate Equation (1) using pooled ordinary least squares. We also include year fixed effects and constant. We weigh the observations, with weights equal to the number of banks in the host country to prevent any bias due to differences in market size. The bank-level explanatory variables have been lagged by one period to mitigate the potential problem of reverse causality (Dushnitsky et al., 2016). In our estimations, we consider several variables separately due to the multicollinearity of independent variables.

Results and theses verification

Table 2 presents the baseline results for the estimations with bank- and country-level control variables as well as fintech/bigtech credit market proxies for all bank-ownership types and all countries. Hypothesis H1 is supported as the coefficients of the explanatory variables *Fintech credit pc* and *Fintech credit* are positive and statistically significant at the 1% level. Furthermore, in line with our thesis, the coefficients of all three variables related to bigtech credit are negative and statistically significant: in the case of *Bigtech credit/GDP* and *Bigtech credit* at the 1 % level, while *Bigtech credit pc* at the 10% level.

Regarding control variables, in line with the literature (e.g., Allen et al. (2017)), we find that bank profitability is positively correlated with credit growth. The coefficient for *ROA* is positive and significant in almost all regressions at the 1% level. Moreover, we find that the coefficient for *Size* is positive and significant, that is, larger banks are more engaged in consumer lending. The negative signs of the coefficients of variables *Liquidity* and *Equity* are coherent with the fact that consumer lending is developed by banks looking for higher levels of risk. As the coefficients for bank control variables do not change signs and remain stable across specifications, we do not discuss them further here.

Regarding macroeconomic controls, the coefficient of inflation (*CPI*) is negative and mostly significant, as expected. However, the coefficients of *GDPgrowth* differ between the estimations; in estimation for all countries and all bank-types, they are negative in most cases. In our opinion, this is related to the different responses in developed and emerging economies, as confirmed in Table 5A and Table 5B. In emerging economies, the growth in GDP fostered consumption and consumer debt as financial markets are still underdeveloped, while in developed economies, rising GDP probably supported non-leveraged consumption of households and shifted consumer credit demand for mortgage loans.

While the above explanation seems reasonable, we need to be cautious in interpretations from our sample because the BIS database coverage effectively includes six years, which is even less than one financial cycle. In our opinion, the length of the time series available is one of the major shortcomings of our study. However, thanks to the novel and quite unique database by Cornelli et al. (2020), only now has it become possible to grasp and explore the relationship between bank credit and alternative tech-based credit. Earlier cross-country studies (e.g., Haddad and Hornuf (2019)) were based on the number of fintech formations; this measure was less approximate to the competition in lending towards banks' offer.

[Table 2]

However, we have confirmed our initial assumptions in the estimation performed on all bank types and all country samples (Table 2). We claim that the ownership type of a bank and the income level of a host country may differentiate the behaviors of alternative tech-based credit providers and banks' reactions. Thus, we perform the following estimations on the subsamples. In Table 3, we present the regression results for the subsample of domestically owned banks. The coefficients of the fintech credit proxies are all positive and highly significant. Thus, the results once again confirm that banks' consumer lending grows simultaneously with an increase in fintech credit; this relationship is even stronger for domestic banks. Furthermore, we observe that bank consumer lending decreases simultaneously with bigtech credit growth. The coefficients of the bigtech credit proxies are all negative and significant, at least at the 5% level. We also perform an analogous set of estimations for domestic- and privately-owned banks. Our results remain qualitatively similar.

[Table 3]

The results presented in Table 3 need to be compared with estimations from Table 4, where we present reactions of foreign-owned banks on the emergence of fintech and bigtech competition in the host markets. Table 4 shows mixed results. The coefficient of *Fintech credit/GDP* is negative, while the coefficients of the two remaining fintech credit proxies are positive. The coefficients of bigtech credit proxies are negative; however, *Bigtech credit per capita*, which we consider to be primarily important, shows statistically insignificant results.

Thus, we show that domestically owned banks are more affected by alternative tech-based lending compared to foreign-owned banks. Specifically, bigtech credit is the force that pushes some local banks' offers out of the market. Thus, hypothesis H2 is supported. We find empirical evidence that bigtech lending may be treated as a competition for relationship lending by local banks. We associate this with alternative data usage by bigtechs, which is unprecedently large and accurate set of information on potential borrowers that may replace relationships, while making borrowing extremely comfortable in digital channels.

In contrast to domestic banks, foreign banks are looking for a different set of borrowers. We claim that foreign banks are focused on less opaque potential clients, while bigtech credit providers are looking for smaller individual loans which are considered to be more opaque. This claim holds as the coefficient of *Bigtech credit pc* is negative and significant in estimation (4) in Table 3, while it is insignificant in Table 4. Thus, bigtechs compete with local banks to a greater extent than with international banking groups. However, in the long run, bigtech credit providers will probably be interested in all lending market segments. This result partly contradicts Balyuk et al. (2020); however, we present a different approach, wider geographical scope of markets, and, most importantly, separately include the phenomenon of bigtech credit in our research.

[Table 4]

We present our analysis performed on the sub-samples of banks from high income (Table 5A) and emerging economies (Table 5B) separately. We find significant differences regarding the behaviors of tech-based alternative credit providers. For high-income countries, the coefficients of all tech-based credit proxies are negative and highly significant; in particular, the coefficients of our main explanatory variables, *Fintech credit per capita* and *Bigtech credit per capita*, are significant at the 1% level. This confirms that both fintech and bigtech credit may be treated as competitors for banks in the consumer lending market in developed economies.

However, in the case of emerging markets, we find a positive relationship between fintech credit and consumer lending by banks. The coefficients of all three fintech credit proxies in estimations (7), (8), and (9) in Table 5B are positive and significant at the 1% level.

Thus, hypothesis H3 is partially supported. First, we show that relations between banks, on the one hand, and bigtech as well as fintech credit, on the other, are competitive in developed markets. Moreover, we provide evidence that fintech credit providers and banks can co-exist in consumer lending markets in emerging economies as they probably service customers in different channels: banks through traditional channels and fintech through digital channels.

[Table 5A]

[Table 5B]

Table 5B, however, shows only weak evidence that bigtech credit and consumer lending by banks are linked to each other in emerging markets. Table 5C presents one of our robustness checks, that is, the estimations performed on banks acting in emerging economies, excluding China, which is a large and quite specific market, characterized by significant links between technology as well as payment and banking, on the one hand, and the state, on the other hand. Moreover, this market is currently in the middle of substantial regulatory and structural reforms in the area of bigtech and paytech. In columns (4)–(6) of Table 5C, we find that after excluding China from the sample, the coefficients of all three bigtech credit proxies are negative and highly significant. Meanwhile, in columns (1)–(3) of Table 5C, we find that the fintech credit relations with consumer lending by banks are almost insignificant. This is a big shift in the results for emerging economies; however, we claim that excluding China seems reasonable, and negative interlinkages between bigtech credit and banks' lending in other emerging markets are worth mentioning. Thus, hypothesis H3 is almost fully supported.

[Table 5C]

Discussion and conclusions

Our empirical study on a wide sample of banks operating in countries with different income levels confirms our three theses. For hypothesis H1, we provide evidence that banks' consumer lending grows simultaneously with the fintech credit market but decreases in the aftermath of bigtech credit's emergence. Thus, we interpret that the fintech credit offer is probably aimed at market segments that are relatively skipped by banks; however, this applies mostly to emerging markets. In this sense, fintech credit and banking offers in emerging economies may be complementary. These results are consistent with previous research with a similar purpose, but a different approach, focused on the analysis of debt transactions in the fintech credit market of one country (Tang, 2019; de Roure et al., 2019). We supplement these studies by indicating potential significant cross-country differences. In the case of developed countries, we observe competitive relations between banks and tech-based lending for both fintech and bigtech credit. Regarding hypothesis H2, we provide evidence that domestic and privately-owned banks are negatively affected by bigtech credit competition to a greater extent than foreign banks. We claim that new tech-based lending business models compete with local private banks in the first place. We interpret that tech-based lending, particularly bigtech credit, may be treated as a competition for relationship lending by local banks, based mostly on soft credit data processing. Wide access to alternative data provides unprecedented informational advantage to bigtechs over other lenders. This probably allows bigtech credit providers to develop effective credit scoring tools based mostly on machine learning algorithms, which can act as equivalent to local banks' market feeling. Thus, bigtechs may question the positions of small local banks. In other words, bigtechs compete with local, small, private banks effectively as these banks no longer have a competitive advantage in soft credit information processing and relationship lending. Banks have lost this advantage to technology companies, mainly e-commerce platforms, that have huge sets of alternative data on both individuals seeking products and companies selling products. In addition, bigtechs probably have the highest analytical competences in the global economy, including the use of machine learning algorithms and more broadly, artificial intelligence. Bigtechs can use their information advantage and monetize it through effective, targeted distribution of debt products to consumers as well as by enhancing the assessment of borrowers' credit risk. This makes them potentially key players in the future loan market. To the best of our knowledge, our study is the first to focus on empirical bank-level evidence on competition between banks, on one hand, and fintech and bigtech credit providers, on the other hand.

The technology-driven transformation of financial markets, and the emergence of new categories such as fintech and bigtech credit are vital opportunities for development, among others, in terms of customer service standards. However, these trends are also very important business challenges for banks and regulatory issues for economic policy. Note that bigtech credit is a potentially useful tool for enhancing financial inclusion. However, this finding is poorly supported in our research. Bigtechs compete with banks in both emerging and developed markets; however, it may turn out that they actually push some banking offer out of the market, rather than servicing customer segments ignored by banks. In contrast, it seems that in the years we investigated, fintech credit providers (smaller ventures) enhanced financial inclusion in emerging economies. As our research show, and in line with the arguments and postulates presented by Carstens et al. (2021), regulating bigtech should be at the center of the economic debate today, especially with respect to financial markets. We think that all potential advantages of technology improvement, including innovations offered by giant technology companies, may be achieved and serve sustainable development if this progress occurs in a properly regulated environment. Moreover, the role of appropriate data gathering in monitoring the market, both in the case of fintechs and bigtechs, is vital. This is a challenge in reference to global players; however, local technology companies, such as e-commerce country leaders, may sometimes pursue similar business models, and consequently, generate similar risks. It is likely that the category of bigtechs should be enlarged to better capture the potential future risks.

In the potential scenario of flourishing growth of tech-based lending, fintech, and bigtech credit, which rather compete primarily with local banks, the question of stability of this new type of lending should be asked. After all, bigtech is a highly concentrated market. Next, attention should be paid to the challenges related to market competition and consumer protection as well as transparency and fairness in personal data use. Finally, we need to re-assess the role of bigtechs in financial inclusion, as their positive impact may be an illusion.

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Table 1 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Liquidity	0.1331786	0.1273068	0.0194805	0.5793413
LtD	0.7927731	0.2362283	0.2238132	1.337017
ROA	0.0117602	0.0081909	-0.011976	0.0326795
Equity	0.1158676	0.0447467	0.0409213	0.3076923
Size	0.0016846	0.0054235	5.79E-07	0.0237109
GDPgrowth	0.0240716	0.0141205	-0.0354587	0.2516253
CPI	0.0240825	0.0252772	-0.0374915	0.2950661
Fintech credit pc (USD)	91.67932	62.67188	0	256.13
Fintech credit / GDP	0.00000169	0.00000198	0	0.0000293
Fintech credit (USDmn)	30911.56	28359.42	0	356039.3
Bigtech credit pc (USD)	3.705167	13.03446	0	260.1
Bigtech credit / GDP	0.00000021	0.00000136	0	0.0000267
Bigtech credit (USDmn)	1898.56	17145.22	0	362936

Table 2 Consumer lending by banks in the context of competition from fintech and bigtech credit

This table reports the coefficients of the linear regression model using weighted least squares for banks in 72 countries over the period 2013-2018. The dependent variable is the natural logarithm of net consumer lending, and the independent variables are defined in Appendix Table A1. The bank control variables are lagged by one period. All specifications include country control variables, year fixed effects and constant 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)
Liquidity	-3.752***	-3.685***	-3.676***	-3.604***	-1.585	-3.644***
	(0.575)	(0.667)	(0.579)	(0.574)	(0.982)	(0.573)
LtD	0.529**	0.628**	0.454*	0.583**	0.669	0.529**
	(0.250)	(0.279)	(0.247)	(0.244)	(0.412)	(0.245)
ROA	19.71***	19.29***	20.45***	18.10***	-0.102	18.06***
	(6.541)	(7.463)	(6.589)	(6.662)	(10.93)	(6.572)
Equity	-17.45***	-19.07***	-16.71***	-17.87***	-16.84***	-17.80***
	(1.266)	(1.416)	(1.248)	(1.210)	(1.988)	(1.208)
Size	180.5***	172.4***	188.0***	178.4***	223.5***	174.8***
	(6.725)	(7.512)	(6.904)	(6.630)	(19.37)	(6.835)
Fintech credit pc	0.210***					
	(0.0542)					
Fintech credit/GDP		-0.00479				
		(0.0305)				
Fintech credit			0.168***			
			(0.0208)			
Bigtech credit pc				-0.102*		
				(0.0600)		
Bigtech credit/GDP					-0.245***	
					(0.0451)	
Bigtech credit						-0.0758***
						(0.0226)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,186	13,842	14,186	14,186	12,404	14,186
R^2	0.546	0.530	0.552	0.541	0.546	0.543
Adj. R^2	0.546	0.530	0.552	0.541	0.545	0.543

Table 3 Consumer lending by domestic-owned banks in the context of competition from fintech and bigtech credit

This table reports the coefficients of the linear regression model using weighted least squares for domestic-owned banks in 72 countries over the period 2013 - 2018. The dependent variable is the natural logarithm of net consumer lending, and the independent variables are defined in Appendix Table A1. The bank control variables are lagged by one period. All specifications include country control variables, year fixed effects and constant 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)
Liquidity	-2.317***	-1.620**	-2.227***	-2.362***	-1.336	-2.456***
	(0.659)	(0.760)	(0.660)	(0.665)	(0.907)	(0.661)
LtD	1.333***	1.743***	1.185***	1.336***	1.402**	1.283***
	(0.302)	(0.334)	(0.299)	(0.300)	(0.562)	(0.300)
ROA	16.84*	9.963	17.63*	17.36*	14.34	17.72*
	(9.338)	(9.983)	(9.111)	(9.233)	(10.69)	(9.192)
Equity	-16.81***	-17.48***	-15.97***	-17.61***	-18.00***	-17.61***
	(1.799)	(1.774)	(1.762)	(1.749)	(1.840)	(1.735)
Size	213.3***	213.2***	219.9***	211.3***	260.7***	207.2***
	(7.551)	(8.415)	(7.857)	(7.515)	(14.02)	(7.687)
Fintech credit pc	0.197***					
	(0.0511)					
Fintech credit/GDP		0.0758**				
		(0.0361)				
Fintech credit			0.145***			
			(0.0235)			
Bigtech credit pc				-0.112**		
				(0.0555)		
Bigtech credit/GDP					-0.165***	
					(0.0413)	
Bigtech credit						-0.0766***
						(0.0216)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,758	12,580	12,758	12,758	11,837	12,758
R^2	0.623	0.629	0.628	0.619	0.690	0.621
Adj. R^2	0.623	0.629	0.627	0.619	0.690	0.621

Table 4 Consumer lending by foreign-owned banks in the context of competition from fintech and bigtech credit

This table reports the coefficients of the linear regression model using weighted least squares for foreign-owned banks in 72 countries over the period 2013 - 2018. The dependent variable is the natural logarithm of net consumer lending, and the independent variables are defined in Appendix Table A1. The bank control variables are lagged by one period. All specifications include country control variables, year fixed effects and constant 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)
Liquidity	-4.250***	-4.791***	-4.234***	-3.997***	-1.470	-3.980***
	(0.851)	(0.908)	(0.839)	(0.817)	(1.408)	(0.814)
LtD	0.270	0.0337	0.278	0.341	-0.415	0.284
	(0.362)	(0.399)	(0.367)	(0.361)	(0.531)	(0.362)
ROA	24.04***	28.22***	24.42***	22.01***	-3.677	21.76***
	(8.045)	(9.322)	(8.316)	(8.398)	(12.55)	(8.267)
Equity	-13.90***	-14.85***	-13.74***	-14.03***	-13.83***	-13.92***
	(1.764)	(2.041)	(1.750)	(1.710)	(2.782)	(1.707)
Size	149.9***	134.3***	155.4***	148.1***	146.2***	144.7***
	(10.19)	(11.28)	(10.55)	(10.20)	(32.11)	(10.61)
Fintech credit pc	0.154*					
	(0.0855)					
Fintech credit/GDP		-0.0895**				
		(0.0427)				
Fintech credit			0.125***			
			(0.0362)			
Bigtech credit pc				-0.112		
				(0.118)		
Bigtech credit/GDP					-0.218***	
					(0.0672)	
Bigtech credit						-0.0811*
						(0.0436)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,428	1,262	1,428	1,428	567	1,428
R^2	0.474	0.459	0.477	0.472	0.362	0.473
Adj. R^2	0.470	0.454	0.472	0.467	0.348	0.469

Table 5A Consumer lending by banks in the context of competition from fintech and bigtech credit in developed economies

This table reports the coefficients of the linear regression model using weighted least squares for foreign-owned banks in developed economies over the period 2013 - 2018. The dependent variable is the natural logarithm of net consumer lending, and the independent variables are defined in Appendix Table A1. The bank control variables are lagged by one period. All specifications include country control variables, year fixed effects and constant 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)
Liquidity	-2.825***	-2.573***	-3.122***	-3.224***	-2.240**	-3.238***
	(0.653)	(0.749)	(0.670)	(0.672)	(1.014)	(0.671)
LtD	0.765*	0.900**	0.820*	0.752*	0.173	0.720*
	(0.400)	(0.451)	(0.424)	(0.429)	(0.475)	(0.429)
ROA	87.41***	85.89***	88.49***	87.79***	32.58**	88.29***
	(10.19)	(11.36)	(10.89)	(10.95)	(16.54)	(10.95)
Equity	-19.21***	-20.28***	-18.03***	-16.96***	1.815	-16.92***
	(2.513)	(3.290)	(2.590)	(2.429)	(2.852)	(2.426)
Size	142.5***	143.0***	145.4***	150.0***	274.9***	146.2***
	(10.18)	(11.40)	(10.90)	(9.605)	(15.45)	(9.947)
GDP growth	-15.23***	-14.75***	-16.86***	-17.16***	-100.7***	-17.68***
	(4.254)	(4.963)	(3.947)	(3.958)	(26.02)	(3.848)
CPI	-9.445	-8.537	-9.402	-9.323	-32.99	-9.358
	(7.008)	(8.459)	(7.097)	(7.130)	(21.18)	(7.141)
Fintech credit pc	-0.387***					
	(0.0798)					
Fintech credit/GDP		-0.254***				
		(0.0659)				
Fintech credit			-0.0674**			
			(0.0287)			
Bigtech credit pc				-0.204***		
				(0.0756)		
Bigtech credit/GDP					-0.260***	
					(0.0778)	
Bigtech credit						-0.113***
						(0.0268)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,959	11,905	11,959	11,959	11,166	11,959
R^2	0.515	0.505	0.489	0.489	0.703	0.491
Adj. R^2	0.515	0.504	0.488	0.488	0.703	0.491

Table 5B Consumer lending by banks in the context of competition from fintech and bigtech credit in emerging economies.

This table reports the coefficients of the linear regression model using weighted least squares for foreign-owned banks in emerging economies over the period 2013 - 2018. The dependent variable is the natural logarithm of net consumer lending, and the independent variables are defined in Appendix Table A1. The bank control variables are lagged by one period. All specifications include country control variables, year fixed effects and constant 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)
Liquidity	-3.859***	-3.791***	-3.823***	-3.729***	-1.827	-3.675***
	(0.760)	(0.921)	(0.774)	(0.775)	(1.142)	(0.773)
LtD	0.0801	-0.164	0.102	0.172	1.048**	0.138
	(0.273)	(0.313)	(0.273)	(0.272)	(0.489)	(0.273)
ROA	-2.098	3.630	0.0326	-0.0292	2.183	-0.572
	(6.872)	(7.886)	(6.921)	(6.996)	(9.368)	(6.891)
Equity	-16.41***	-15.83***	-16.04***	-16.48***	-17.11***	-16.32***
	(1.409)	(1.645)	(1.417)	(1.413)	(2.215)	(1.406)
Size	198.3***	195.8***	205.0***	197.3***	177.9***	194.7***
	(8.348)	(9.764)	(8.473)	(8.609)	(27.27)	(8.747)
GDP growth	8.481**	9.771**	9.165***	8.738**	40.20***	9.239***
	(3.502)	(4.406)	(3.480)	(3.464)	(6.309)	(3.431)
CPI	2.560	4.968***	2.810*	1.050	1.189	0.827
	(1.679)	(1.808)	(1.683)	(1.616)	(2.105)	(1.606)
Fintech credit pc	0.413***					
	(0.0608)					
Fintech credit/GDP		0.0658**				
		(0.0310)				
Fintech credit			0.190***			
			(0.0254)			
Bigtech credit pc				0.0811		
				(0.0769)		
Bigtech credit/GDP					-0.119**	
					(0.0487)	
Bigtech credit						-0.0164
						(0.0276)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,227	1,937	2,227	2,227	1,238	2,227
R^2	0.528	0.506	0.529	0.517	0.501	0.517
Adj. R^2	0.525	0.503	0.526	0.514	0.496	0.514

Table 5C Consumer lending by banks in emerging economies excluding China in the context of competition from fintech and bigtech credit

This table reports the coefficients of the linear regression model using weighted least squares for foreign-owned banks in emerging economies excluding China over the period 2013 - 2018. The dependent variable is the natural logarithm of net consumer lending, and the independent variables are defined in Appendix Table A1. The bank control variables are lagged by one period. All specifications include country control variables, year fixed effects and constant 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)
Liquidity	-3.747***	-3.852***	-3.739***	-3.545***	-2.126*	-3.805***
	(0.783)	(0.920)	(0.787)	(0.757)	(1.136)	(0.758)
LtD	0.218	-0.0681	0.212	0.183	0.994**	0.0310
	(0.275)	(0.312)	(0.273)	(0.273)	(0.503)	(0.274)
ROA	-0.996	4.985	-0.521	-2.342	4.735	-1.405
	(7.014)	(7.688)	(6.843)	(6.757)	(8.812)	(6.651)
Equity	-15.65***	-13.82***	-15.57***	-14.52***	-13.80***	-14.58***
	(1.429)	(1.672)	(1.422)	(1.422)	(2.161)	(1.426)
Size	199.9***	204.3***	202.2***	193.7***	159.6***	187.1***
	(8.469)	(9.765)	(8.617)	(8.629)	(27.93)	(8.786)
Fintech credit pc	0.0938					
	(0.0882)					
Fintech credit/GDP		-0.0640*				
		(0.0385)				
Fintech credit			0.0642			
			(0.0476)			
Bigtech credit pc				-0.540***		
				(0.116)		
Bigtech credit/GDP					-0.194***	
					(0.0548)	
Bigtech credit						-0.197***
						(0.0376)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,115	1,825	2,115	2,115	1,126	2,115
R^2	0.523	0.515	0.523	0.531	0.500	0.534
Adj. R^2	0.520	0.512	0.521	0.528	0.494	0.532

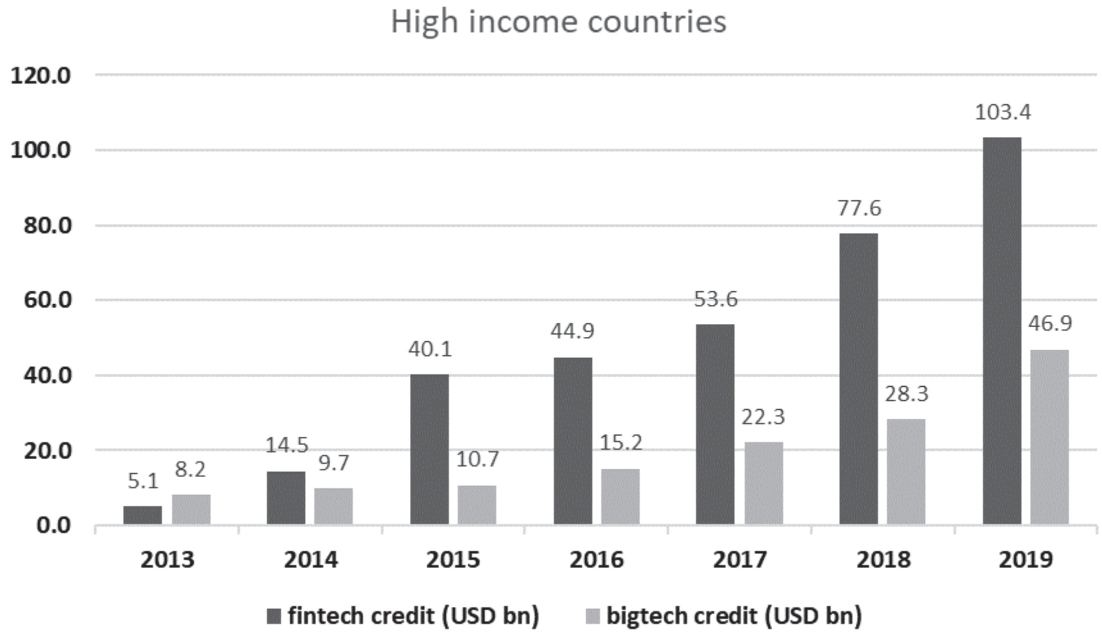
Table 1A List of variables used in the research

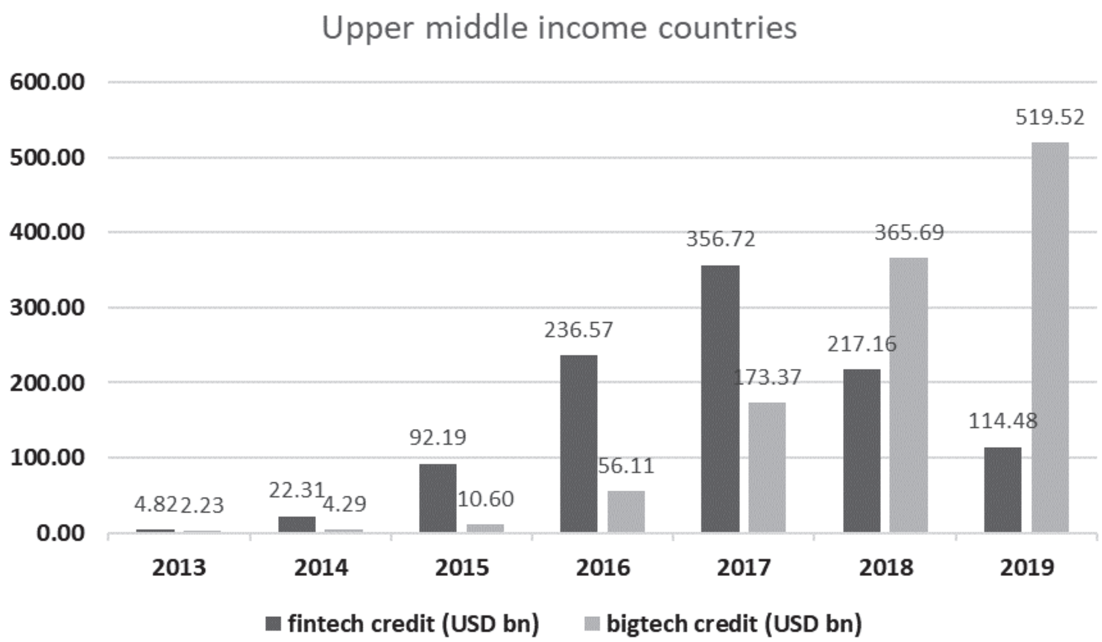
Variable	**Description**
Bank level variables	
Consumer loans	Ln of net value of consumer loans in a bank in USD
Liquidity	Liquid assets over total assets
LtD	Ratio of total loans to total deposits
ROA	Ratio of gross profit to total assets
Equity	Ratio of equity capital to total assets
Size	Ratio of bank's total assets to countries GDP
Country level variables	
GDPgrowth	Real rate of growth of GDP
CPI	Consumer price inflation
Fintech credit pc (per capita)	Ln of 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)
Fintech credit / GDP	Ln of ratio of fintech credit to GDP
Fintech credit	Ln of fintech credit in absolute terms
Bigtech credit pc (per capita)	Ln of lending either directly by bigtechs or in partnership with financial institutions by country population (Cornelli et al., 2020)
Bigtech credit / GDP	Ln of ratio of bigtech credit to GDP
Bigtech credit	Ln of bigtech credit in absolute terms in USD

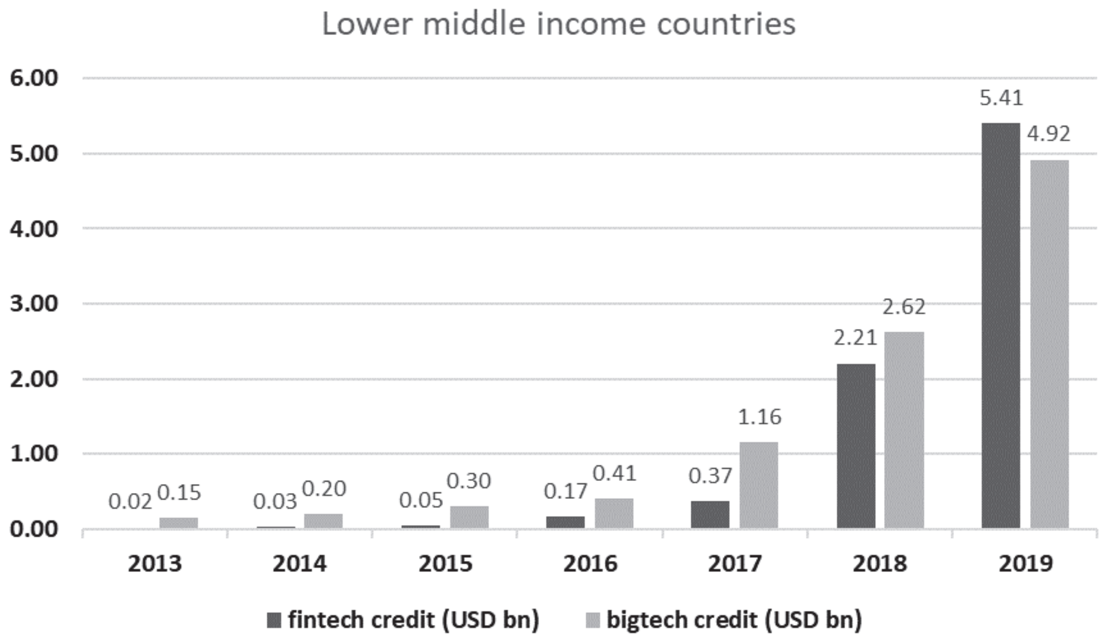
Table 2A List of markets including in the research

AUSTRALIA	GUATEMALA	PANAMA
AUSTRIA	HONG KONG	PERU
BAHRAIN	INDIA	PHILIPPINES
BANGLADESH	INDONESIA	POLAND
BELGIUM	IRELAND	PORTUGAL
BOLIVIA	ISRAEL	REPUBLIC OF KOREA
BRAZIL	ITALY	RUSSIAN FEDERATION
BULGARIA	JAPAN	SAUDI ARABIA
BURKINA FASO	JORDAN	SENEGAL
CAMBODIA	KAZAKHSTAN	SINGAPORE
CANADA	KENYA	SLOVAKIA
CHILE	LATVIA	SLOVENIA
CHINA	LEBANON	SOUTH AFRICA
COLOMBIA	LITHUANIA	SPAIN
COSTA RICA	LUXEMBOURG	THAILAND
COTE D'IVOIRE	MALAYSIA	TURKEY
CZECH REPUBLIC	MALI	UGANDA
DENMARK	MEXICO	UNITED ARAB EMIRATES
ECUADOR	MOROCCO	UNITED KINGDOM
EGYPT	NETHERLANDS	UNITED REPUBLIC OF TANZANIA
ESTONIA	NEW ZEALAND	UNITED STATES OF AMERICA
FRANCE	NIGERIA	URUGUAY
GEORGIA	NORWAY	VIETNAM
GERMANY	PAKISTAN	ZAMBIA

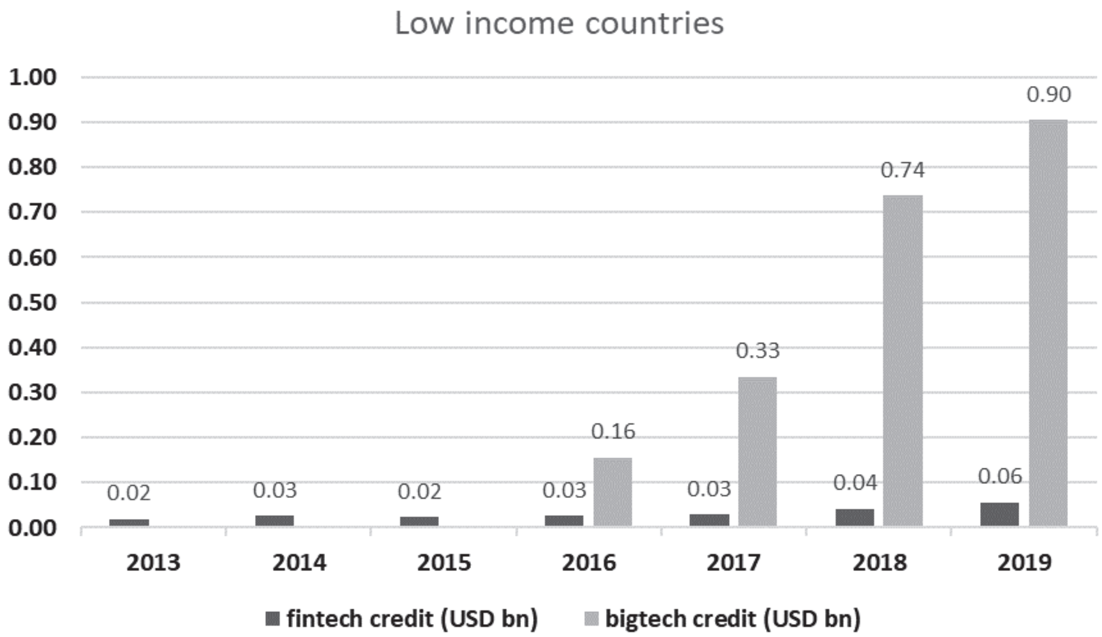
Figure 1A Volume of fintech and bigtech credit use in various countries from 2013-2019







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)