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Public Policy Drivers of Fintech

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Abstract

Fintech startups utilize technology to deliver improved financial services to users. Innovative business models created by them are increasingly important, because innovations have potential to reinvent the financial industry, but they also might bring additional risks. Around the world, agencies face the challenge of regulating these new entities, addressing potential risks without stifling innovation. In this paper, two empirical models are developed to examine the drivers of the fintech market in different countries from a public policy perspective. There is robust evidence of regulatory arbitrage as an important driver. The introduction of regulatory sandbox is found to be successful in promoting fintech funding, but only in pioneer countries in this approach and jurisdictions that adopt Common Law. Monetary policy has less robust direct association with fintech funding. However, exchange rate volatility and very high gross capital flows decrease fintech market attractiveness. Macroeconomic policies that reduce these sources of financial instability and promote financial market development have the most impact in the fintech markets. There is also evidence that less competitive financial sectors attract more fintech funding and that banking concentration is unrelated to competitiveness.

Keywords: fintech, public policy, regulation, monetary policy, sandbox

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1. Introduction

The idea that fintech is reshaping the financial services industry is widespread in financial expert analyses, in entrepreneur speeches and also in international organization reports. (IMF, 2019) It is almost certain that machines will play a larger role in the next generation of financial services. Even central banks and other policymakers will likely change how they execute their activities. The extent to which machines will dominate these activities is not clear, given that it depends on how they can cope with the immense uncertainty about the economy. (Lagarde, 2018)

"Financial technology", or "fintech" refers to the employment of technology to deliver financial solutions. Rather than a new phenomenon, the interlinkage of finance and technology has a long history. The introduction of the telegraph in 1838 and, more recently, of the Automatic Teller Machine (ATM) in 1967 are examples of innovations that enabled financial globalization and improved the convenience of financial services. Indeed, the financial services industry are the larger purchaser of information technology (IT) products and services globally since the decade of 1990. The traditional banks were the unquestionable leaders of fintech for a long period that ended in 2008, in an already digital and globalized financial industry. (Arner et al, 2015)

The great financial crisis represented a turning point and has catalyzed the growth of a new fintech era. With the crisis, the public perception of banks deteriorated due to, for example, predatory lending. The large economic impact of the crisis led to distrust in the traditional banking system. Another fundamental factor was that a newer generation of highly educated, fresh graduates was facing a tough labor market and possessed tools and skills to be applied in a new financial segment of startup companies. They were complemented by under-utilized educated workforce that had once worked in the traditional banks. On top of these changes, post-crisis regulation increased the compliance obligations of banks, particularly on capital requirements, provoking a reshape of the traditional bank structure. (Arner et al, 2015)

The new fintech era that started after 2008 was marked by the financial services provision not solely by regulated entities. In the previous period, the internet-based banking was seen as similar to traditional service, in terms of risks. These new players in the financial industry changed this perception among regulators and posed additional issues because of the blurred geographical borders in some segments. An important factor to accelerate the transformations was that, while the banks' image was shaken, the technology companies enjoyed growing confidence by users. (Arner et al, 2015) The new technology-enabled financial services were designed to be used on the internet and on mobile devices, combining other recent technologies, such as cloud computing, distributed ledger or blockchain technology, or artificial intelligence (AI). (European Commission, 2019)

Fintech firms currently represent a small share of overall revenue of the financial services industry, however their growth and contribution to innovation are apparent. The fintech share of patenting activity in the financial sector is twice their revenue share. (IMF, 2019) In 2019, the fintech users adopt these innovative services mainly because of the lower rates of fees (27% of the consumers) and range of functionalities and features (66% of the small and medium enterprises), according to a global fintech adoption survey. Apart from these most chosen reasons, the full availability at any time and the simplicity in installing, configuring and using the service also ranked high among adopters. The same research showed, however, a recovering of trust in the incumbent providers, among the fintech non-adopters, as these institutions begin to offer their own fintech services. (EY, 2019)

Retail payments is one of the most benefited areas of financial services with this new era's innovation. Real-time retail payment systems are enabling the development of new solutions for peer-to-peer and consumer-to-merchant payments, while digital wallets and NFC technologies are making card-based payments possible to go mobile. Moreover, other innovative solutions are arising from the application of distributed ledger technologies (DLTs) to cross-border payments. There are efficiency benefits to providers and customers, as well as possible increasing risks. (González-Páramo, 2017)

Credit provision is the other segment that the rise of fintech is most apparent. Credit risk models accuracy can be greatly improved by the combination of increased availability of data, greater data processing capabilities and new analytical techniques, which is usually referred to as "big data". Also, the use of new sources of data can extend credit access to segments that were previously excluded due to the inability to assess their creditworthiness. New players in this market, lending or crowdfunding marketplaces connect savers and borrowers and facilitate them to directly reach credit agreements, without participating as financial intermediaries. They potentially improve the efficiency of credit markets, through increasing competition in some segments and credit provision extension to under-served consumers. (González-Páramo, 2017)

Other important segment to fintech is investments. Automated trading strategies, such are high-frequency trading (HFT), benefit from quickly processing of information on market conditions and from the ability to react instantaneously to such information, through the use of algorithms. It also increases efficiency of markets, but it has complex implications for financial stability and investor protection. (González-Páramo, 2017) The wealth management activity is also being transformed, with the introduction of automated investment services, or "robo advisors", that compete with traditional firms, which are being forced to become more digital. (Sironi, 2016)

Moreover, the insurance consolidated business model is being challenged by innovators, that employ technologies such as big data, AI and cloud computing. This industry is data-driven, what makes it especially suitable for disruption. (VanderLinden, et al., 2018)

Fintech startups are providing most of the innovations to final users in these and other areas, generally targeting more niche markets and offering more personalized services than traditional financial firms. They are driving the phenomenon of unbundling financial services, the use of one provider for each service, instead of relying in one financial institution for all the financial needs. (Lee and Shin, 2018)

The incumbents try to adequate their services to higher standards demanded by the customers, but the success of novel technologies is hindered by heavy and rigid legacy infrastructures. Companies are trying to overcome this problem with the employment of other technological solutions to evolve towards "smart" infrastructures, like cloud computing, which are flexible, agile and efficient. (González-Páramo, 2017) Furthermore, some of the new fintech companies provide services like payments and digital advice which focus on cooperation among them and banks, a growing segment commonly referred to as business-to-business (B2B). (Puschmann, 2017)

The importance of the fintech phenomenon to the financial services industry is clear, but its causes are still being studied, given how recent it is. In this paper, the drivers of fintech development will be investigated from a public policy perspective. *Does financial regulation affect this market's growth? What role does monetary policy play in it?* Furthermore, we will test if innovative approaches to regulation adopted since 2016 are successful in stimulating this new market, while helping regulators to understand the financial risk effects of the new solutions. The remainder of the paper is organized as follows. Section 2 reviews the literature related to the most important concepts for this research. Section 3 introduces the statistics object of study in the model, analyses the data and the methodology. Section 4 elaborates on the design of the first model and its results, while section 5 examines the outcome of an additional model that will complement the first findings. Section 6 will be dedicated to robustness tests on assumptions of the models. Finally, a conclusion of the learnings from these exercises will be presented in section 7.

2. Literature Review

This section will present some fundamental concepts and findings from the literature about the new fintech market and economic public policies. First, we will go through the drivers of the market and follow the benefits and drawbacks associated with it. We will understand what the literature identifies as the traditional regulation responses and also the most used innovative approaches to deal with these new solutions. Finally, we will examine the relationship between monetary policy and fintech development.

2.1.Drivers of Fintech

Given the hefty grow of the fintech industry and the transformations it has potential to provoke in the financial industry, some research was made around its drivers and why some markets have developed differently than others.

While some papers' analyses are theorical, others created empirical models to test the factors that influences the growth of the sector. Between these later ones, two researches that offer important insights can be highlighted. Claessens et al. (2018) investigated solely the credit fintech platforms and conduct a multivariate cross-country regression analysis with data from 2016. Haddad and Hornuf (2019) researched more comprehensively the determinants of all fintech segments using a panel dataset with data between 2005 and 2014, with focus in economic and technological factors.

Both papers found that GDP per capita is positively associated with fintech development. To Claessens et al. (2018), this measure likely captures other aspects of a country's stage of development. The authors' model presented negative coefficient estimate on squared GDP per capita in their model, what suggests that such effects on credit platforms become less important at higher levels of development.

Investigating the effects of banking markets competition, Claessens et al. (2018) found a positive relationship between the credit activity and the Lerner index, an indicator of market power. This result is consistent with the idea that the fintech market has more opportunities for development in less competitive markets, but the economic relevance of this relationship was not large. Haddad and Hornuf (2019) tested the effect of the soundness of the financial sectors on the fintech markets and found a negative coefficient. They concluded that more fragile financial sectors tend to attract more fintech innovation.

The effect of financial regulatory stringency was tested by Claessens et al. (2018). The results point to a negative effect of the stringency on credit activity. The authors reason that jurisdictions with more liberal banking regulations might also be more liberal regarding fintech licensing and prudential rules, what could result in simpler processes to launch lending fintech solutions. This is evidence against the existence of regulatory arbitrage in that setting. This point will be more explored in the present study. Proponents of the existence of regulatory arbitrage sustain that traditional sector lenders face higher capital and liquidity requirements on loans than lending through FinTech credit platforms outside the prudential regulatory perimeter. These factors would represent cost advantages for new online lending platforms, that perform similar activities than the traditional players and benefit from regulatory arbitrage. (BIS, 2017A)

Technology is indisputably an important part of the fintech business models. Haddad and Hornuf (2019) results indicate that countries witness more fintech startup formations when latest technology is readily available, and people possess more mobile telephone subscriptions. The authors ponder that technological changes enable new practices and business models to emerge. Moreover, mobile telephone diffusion increases the supply and demand of fintech startups, as individuals who are seeking entrepreneurial activity based on these technologies have more opportunities to succeed. Haddad and Hornuf (2019) found that the development of capital markets and the availability of labor force are additional significant factors that drive fintech innovation.

Among the theoretical papers that explore the drivers of fintech, some offer useful insights about the forces driving the transformations. BIS (2017A) states that, in the case of credit markets, traditional lenders have left room for new entrants, because they withdrew from some market segments in the post-crisis period. Furthermore, banks often “underservice” certain market segments, such as micro business loans. On the demand side, internet-connected devices have given rise to higher customer expectations with regard to convenience, speed and cost of financial services. In addition, demographic factors, such as rising acceptance of new technologies and the growing financial influence of younger “digital native” generation drive demand for new solutions.

Dapp et al. (2014) place this phenomenon in the broader context of the digitization of many traditional industries like media and music. The authors identify three important elements that allowed this process: increasing storage and usage of intangible (digital) information goods, for a fraction of the costs of a few years earlier; viral and exponential global growth of data within virtual networks (network effect); and expanding reach of the World Wide Web (penetration effect). Supplementary economic drivers of the digitization are economies of scale and the network effects, since the utility of a digital good or a digital service depends on how many other individuals or actors use them. This digital change opens possibilities for innovative business models, which are altering the structure of existing business sectors, as traditional market structures are disintegrating, sector boundaries are shifting, and new market entrants are appearing.

2.2. Benefits and drawbacks of fintech

Financial technology opened a big avenue of opportunities to improve some aspects of the financial systems, while also potentially bringing additional risks to financial stability and integrity. There is evidence that, although there are important regional and national differences, countries are broadly embracing these opportunities to boost economic growth and inclusion while balancing the risks. (IMF, 2019)

Novel technologies, including artificial intelligence (AI), cloud computing and blockchain are enabling new solutions that can have positive effects on the efficiency, accessibility and security of financial services provision. The results for the users are better tailored, less costly and faster services. For example, payments services are an activity that is essential for our daily lives, and the traditional options were, in many cases, marked by being slow, costly, hard to track and not always secure. Mobile payments and peer-to-peer (P2P) applications, have arisen seeking to fill the gaps. (IMF, 2019)

One additional important opportunity associated with the rise of fintech is improving financial inclusion. The reach of financial services has increased significantly, since digital finance has improved the access to them by under-served groups. Technology can reach remote locations and the prevalence of mobile devices in the world today is much larger than of bank accounts. (BIS, 2017B)

Other positive effects might be noticed on the competition in the financial sector since the entrance of new players could eventually fragment the banking services market and reduce the systemic risk associated with players of systemic size. Also, the use of innovative technologies can help financial institutions comply with regulatory requirements and pursue regulatory objectives. The new fintech segment conventionally called Regtech can improve the efficiency of compliance, risk management as well as of supervisory activity. (BIS, 2017B)

Despite the major positive impact that the innovations can bring to both demand and the supply side, there is a probability that the new solutions bring additional risks to the system. New credit solutions may reverse a positive trend of diminishing operational risks and improving capital adequacy of the financial system. Credit provided by fintech companies might present materially higher risk than when provided by traditional banks because of greater credit risk appetite, untested credit risk models and the potential for misaligned incentives. Related to these issues, there are worries that the new credit available in platforms might increase procyclical credit provision. Additionally, the emergence of large players that concentrate the fintech credit market activity is already perceived in many jurisdictions. The availability of substitute forms of credit, either other platforms or traditional players, is one key aspect to mitigate systemic risk. (BIS, 2017A)

There are other concerns about the credit fintech operations and its implications to systemic risks. Their operations are highly sensitive to liquidity shocks, some of their activities may lead to huge leverage, and the maturity mismatch between assets and liabilities may be substantial as well. Traditional banks, as a response to lower market prices due to heightened competition, may pursue a riskier business policy to offset revenue shortfalls, which may also affect the level of systemic risk. Big data-based credit analysis might also be misleading when the data quality deteriorates, leading to higher operational risks. (MNB, 2017)

If we consider the effects of fintech on customers, it is possible that trust issues appear, since innovative technological solutions and business models require some kind of initial trust of the clients. Especially in sectors outside the regulatory perimeter, some players can abuse of this, encouraging excessive risk-taking or inappropriately managing personal data. (MNB, 2017)

Cyber-risk is likely to rise in the future, if controls do not keep pace with change of technologies and new services. The increased interconnectivity between market players, while create benefits for financial companies and consumers, amplify security risks, potentially making the banking system more vulnerable to cyber-threats, and exposing large volumes of sensitive data to potential breaches. The effective management and control of cyber-risk should be a priority to companies and regulators. (BIS, 2017B)

2.3.Regulation responses

In order to promote innovation in the financial services industry and simultaneously maintain high standards for safety, soundness and consumer protection required to the banking industry, the jurisdictions seek to adequate the regulatory framework to the new business solutions.

The objective of financial regulation is to address vulnerabilities and imperfections in financial markets that weaken financial stability, undermine market efficiency, and expose consumers to risks. The main focus of financial regulation should be, consequently, in providing incentives for institutions to take into account systemic risk; protecting consumers where information is hard or costly to obtain; and supporting competition and preventing oligopolistic behavior. In light of these objectives, the boundary for regulation should be flexible and enable regulatory arbitrage between the unregulated and regulated perimeter to be monitored and adjusted to ensure that systemic risks are contained, and the goals of regulation are sustained. (He et al, 2017)

As market structure is changing, regulation may need to complement its focus on entities. Traditionally, financial regulation is based on entities or activities. The tendency of "unbundling" and migration of services from intermediaries to networks may require regulator to shift from entity-based regulation to a more activity-based approach. Anti-money laundering and countering financing of terrorism (AML/CFT) requirements for use of virtual coins is already one sign of this strategy shift. (He et al, 2017) Regulators should also remain technology-neutral, since technology often needs time to find its final use and applicability and regulation's influence in market innovation or technological standards might be prejudicial. (Arner et al, 2015)

To Philippon (2016), a defining feature of the regulation frameworks enacted since the 2008 Great Financial Crises is that they focus almost exclusively on incumbents. The author claims that this characteristic makes it difficult to implement deep structural changes because of it has heightening effects in leverage, size and interconnectedness. These distortions are, then, embedded in the current financial system to such an extent that the political and coordination costs of removing them have become prohibitive.

There are some regulatory dilemmas associated with the rapid fintech growth. The main one is how to strike a balance between a laissez-faire approach and a fully prohibitive regulatory stance. The most permissive strategy has the benefit of improving awareness and accelerating the deployment of new solutions, but it entails the risks of exposing consumers and investors to immature solutions that, ultimately, will cause unexpected losses. Moreover, this approach creates unfair competitive advantage to this segment compared to heavy regulated traditional banks. On the other side of the spectrum, a complete ban on fintech applications might curb willingness to innovate, and preserve ossified, classic functioning of the traditional players. All the benefits of increased competition and efficiency are lost. (MNB, 2017)

Zetzsche et al. (2017A) identify four approaches that emerged as regulators deal with this challenge. The first one is to continue to rely on the traditional regulatory responses: doing nothing, which can result on either one of the most extreme stances; or developing specific regulatory frameworks for the new sectors. Doing nothing can lead to the lasses-faire approach, what China have initially adopted to boost innovation and was successful at first. However, it caused lack of visibility and regulatory market comprehension, as some players like the Alibaba group grew intensely in a short period of time. Chinese regulators push back to pursue a comprehensive new regulatory framework, stricter than before but still more innovation encouraging than others. But changing nothing in regulation can also mean that the regulator requires fintech to comply with all requirements as any player of the traditional sector, with the cost of stifling innovation. The other traditional response, implementing specific rules to the new segments, can be similarly as strict if the licensing and some prudential rules are not adapted to the new solutions. Many jurisdictions have already developed new frameworks in the segments of credit (such as equity crowdfunding and P2P lending) and payment.

The second approach is classified by the Zetzsche et al. (2017A) as the cautiously permissive approach based on forbearance. Regulators allow certain amounts of flexibility on a case-by-case basis, granting no-action letters, restricted licenses, special charters or partial exemptions for innovative firms, or established intermediaries testing new technologies. These regulators usually have a mandate associated to financial development, growth or innovation. Although this method has merits of providing a useful tool for regulators to acquire market knowledge, it fails to provide long-term legal certainty for business development and it is not an international standardization tool, due to its case-by-case nature. The remaining two approaches are innovative forms of regulating financial services to be discussed in the following section.

2.4.Innovative approaches to regulation

Some jurisdictions implemented in the last years novel approaches to regulation, seeking to balance open frameworks that enable innovation with systemic wellbeing. They understood there is a need for clear, enabling regulation, but the solution remains a challenge. (di Castri and Plaitakis, 2018)

Uncertainty about the legal and regulatory environments is a factor that may hinder some investments, especially in developing countries. It is often not clear to new entrants how much they can do before they need to comply with onerous requirements that range from banking, payments to data protection rules. While these ambiguities can be a source of competitive advantage, due to a regulatory arbitrage, most companies and investors would rather operate under a clear regulatory and supervisory framework. Examples from other industries shows that the speed of innovation, revenues and valuations of startups are negatively impacted by regulatory uncertainty. Furthermore, existing regulation originated in a time with less technological possibilities can become a barrier to innovation, once the rules do not contemplate the new services that may be safer than the incumbent. (di Castri and Plaitakis, 2018)

Regulatory sandbox is a concept that derives from the world of software development and, in that environment, permits a new code to be tested in a ring-fenced setting, without affecting the operations and safety of the wider system. (Ofgem, 2018) It was adapted to financial regulation initially by Financial Conduct Authority (FCA) in the United Kingdom and proved to be popular among international regulators. More than 50 countries have followed around the globe. (Buckely et al, 2019) In financial context, regulatory sandboxes enable innovators, both start-ups and established incumbents, to test solutions in a controlled environment for a set duration (typically 6 months) without immediately incurring all the usual regulatory costs or having to tweak their products to fit in a predefined category. Regulators still impose a range of security and customer safeguards including enhanced disclosures. (di Castri and Plaitakis, 2018)

The general objective of this approach is to support innovation in financial technologies. Some common stated specific goals are to stimulate competition and innovation (e.g. the United Kingdom), to ensure the regulatory framework is fit-for-purpose (e.g. Singapore), to identify gaps in the availability of necessary market products (e.g. Malaysia) and to promote financial inclusion (e.g. Bahrain and Indonesia). (IMF, 2019)

Regulatory sandboxes are the third approach to financial regulation to fintech identified by Zetzsche et al. (2017A), apart from the two more traditional ones. It has the advantage of enhanced communication between innovators and regulators, which learns from the experiences and concerns discussed during the process. Additionally, there is a benefit of signaling to the players and external observers that the regulator has a propensity to support innovation. In this line, this approach may help the regulatory agencies to achieve an optimal level of openness for innovation, while managing the risks. An effective regulation process pair the sandbox with a strong, fact-based, research-driven dispensation and licensing practice that can further innovation while minimizing risks, enjoying the benefits of the learning.

One of the drawbacks of the implementation of sandboxes is the lack of transparency, since many jurisdictions do not clearly disclose the details of sandbox relief, causing problems of unlevel playing field between regulated and unregulated entities. Other problem is a negative signal it sends to the market, especially to potential customers, considering that the sandboxed activities are not fully regulated. These services also lack the standardization associated with regulation, what makes the sandboxed activity unfit for cross-border provision of services and, furthermore, makes economies of scale more difficult. (Zetzsche et al, 2017A)

Considering all the benefits and limitations of sandboxes, IMF (2019) understands that sandboxes are providing valuable insights to policymakers but cannot be relied upon to be a comprehensive solution for harnessing innovation and regulating fintech. Their research found a growing consensus that it is too early to determine their success. The document also advises that the underlying market conditions and the compatibility with the existing legal and regulatory framework are important factors to determine the success of sandboxes. There is a concern about cost and complexity of setting up and running a sandbox. In addition, IMF (2019) suggests that the coordination of several regulatory authorities within the jurisdictions is essential.

Zetzsche et al. (2017A) lists a fourth alternative to regulate. They reason that the evolution of fintech companies in the last decade improved the regulators' sophistication in understanding the business models and adapting their frameworks, however the tools discussed so far lacks the ambition of developing a new regulatory paradigm. The authors propose a new regulation standard that they name "smart regulation". Its main elements are the focus on risk fundamentals, instead of on technology or activities, lower barriers to entry, in order to increase competition, and, finally, the regulation in four stages. First, there should be a testing and piloting environment; then a regulatory sandbox, which widens the scope of testing and piloting; the third phase would be restricted licensing or special charter scheme; finally, when size and income permits, the move to operating under a full license.

There is one other innovative approach to regulation already adopted in many jurisdictions, associated or not with regulatory sandboxes. An innovation hub is a portal, a means by which innovators can readily access regulators to discuss their proposed fintech solutions, gain some guidance on navigating regulatory requirements, and potentially seek dispensations or adjustments in the specific regulations to which they will be subject. (Buckely et al, 2019)

Buckely et al. (2019) argue that a large part of the benefits regulatory sandboxes promise is delivered by innovation hubs. They include the informal advisory activity of regulators to guide innovators on regulatory compliance and waivers or modification of any "unduly burdensome rule" for the purpose of the test. Additionally, the learning opportunity created by sandboxes are better enjoyed if it is coupled with innovation hubs. The authors reason that in settings with limited resources, like emerging economies, regulators should focus on innovation hubs rather than sandboxes, since they share similar benefits but not the downsides of the sandbox approach. However, in many cases a combination between both strategies should lead to best results.

Di Castri and Plaitakis (2018) recommendations for emerging markets follow the same line of thought. To the authors, sandboxes alone will not generate the desired innovation, since investor consider other factors when deciding to enter a market and segment. Important points should be, besides initiatives like innovation hubs, adoption of fintech solutions by governments, as well as improving the digital and financial infrastructure of the country and the increasing the transparency and effectiveness of the legal framework.

Besides the other weaknesses of sandboxes, the legal system of the country can impose additional difficulties. Most pioneer countries are under Common Law system (e.g. United Kingdom and Singapore). Although challenging due to the legal nature of the Civil Law system, it is possible to deploy it in these jurisdictions with some meticulously deliberated adjustments. (Kasiyanto, 2017) Common Law systems are marked by more extensive freedom of contract, while Civil Law systems are generally more prescriptive and require specific legislation for a sector. (World Bank, 2016B)

The Financial Stability Board (FSB) and the International Monetary Fund (IMF) study how to prepare the financial system for future crises, while capturing benefits from innovation. The organizations proposed four key pillars that any solution should consider: well-defined policies on the control and management of new technological risks to be adopted by private sector; knowledge centers and innovation hubs; regulatory sandboxes; and increasing knowledge and capacity of the authorities' staff in relation to digital innovation, as well as develop a collaborative mindset. (González-Páramo, 2017)

2.5.Monetary policy and fintech

Monetary policy, similar to regulation, is affected by the growth of fintech. The policymakers should, therefore, closely follow the developments of this segment, analyze the implications and adapt both policies. (Bernoth et al, 2017) At the same time, the inverse is true as fintech companies are impacted by monetary policy decisions.

Promoting macro-economic stability, especially in terms of prices, is the central goal of the monetary policy, but it depends on transmission channels to cause the desired effects on the economy. Changes in interest rates affect aggregate lending via balance sheet of financial intermediaries, a mechanism that is known as bank lending channel. Credit fintech companies can also act as intermediary in this context. Increases in the short-term rates via monetary policy raise funding costs (liabilities) but leave long-term loan return rates (assets) relatively unchanged. This causes an effect in the net worth of the intermediary that is proportional to its leverage, which is defined as total debt compared to equity or net worth, and its maturity mismatch. It is important to notice that banks' leverage is limited by prudential regulation, while non-banks like fintech companies might not be subject to these rules and present higher leverage. The overall effect of nonbanks on the bank lending channel is hard to assess a priori since it depends on factors like firm size, access to (international) capital markets, and diversification of funding portfolios, dimensions that vary substantially across countries. (Bernoth et al, 2017)

The risk-taking channel is another monetary policy transmission channel that affects the activities of financial intermediaries. Generally, monetary policy expansions lead to increased risk-bearing capacities of financial intermediaries and, ultimately, increased lending activity. Differences in the business structure of banks and nonbank intermediaries, like fintech companies, affect risk taking in response to monetary policy changes. Entities with more leverage are more benefited by the bank lending channel and have their risk-bearing capacity increased. Furthermore, decreases in short-term interest rates via monetary policy can encourage search-for-yield behavior, especially for entities with a large portion of fixed nominal yield liabilities. (Bernoth et al, 2017)

Notice that, while provoking effects in the monetary supply, the policy decisions alter the profitability of the credit suppliers and might make the credit fintech activity more or less attractive to potential investors in these companies. But this last effect depends on how the investors evaluate the longer-term interest rates expectations and how the loan rates will be affected by them.

In the aftermath of the global economic crisis of 2008, the interest rates have decreased to historically low levels in the most developed economies. About the consequence of this new environment to innovators, Bellavitis (2016) indicates that, on one hand, lower interest rates increase the supply of venture capital, one important source of funding to startups. On the other hand, low interest rates discourage venture capital funds to invest in riskier startups such as younger ventures, ventures located in different countries, ventures operating in less popular industries, and in startups new to the venture capital industry. These results suggest that, when investing their capital, the venture capital funds compare the returns with the returns available to their investors elsewhere.

The effects of the low rates in the broad financial sector are investigated by Brei et al. (2020). They found that institutions adjusted their business toward a less risky credit profile, combined with higher capitalization, which strengthened their resilience and lending capacity. But the lenders presented lower profitability, which might make them more vulnerable in the longer term. How fintech companies that are native in this environment are affected by the changes remains to be studied.

There are other important aspects related to the supply of funding capital to innovative companies to be considered. Many countries open their capital markets to foreign investments and, especially in smaller economies, the entrepreneurs rely on the attractiveness of the business prospects, that are influenced by the fundamentals of the overall economy, to entice foreign investment. For example, between 1992 and 2018, countries like Iceland, Ireland and Sweden raised more than USD 600 per capita in venture capital and between 16 and 35% of these investments had United States investors. (Woodward, 2019) It is interesting to comprehend how other macroeconomic variables interact with monetary policy decisions, since they might impact international investments.

For many decades, international macroeconomics has postulated the existence of a "trilemma", that meant that with free capital mobility, independent monetary policies are feasible if and only if exchange rates are floating. In a relevant addition to the literature, Rey (2015) reveals the existence of a global financial cycle in capital flows, asset prices and in credit growth. Whenever capital is freely mobile, this global financial cycle constrains national monetary policies regardless of the exchange rate regime. There is, accordingly, a "dilemma": independent monetary policies are possible if and only if the capital account is managed.

The global financial cycle causes a co-movement of gross capital flows, asset prices, leverage and credit creation, which are all closely linked to fluctuations in risk aversion and uncertainty, measured by the VIX (Chicago Board Options Exchange Market Volatility Index). Tracking gross flows, it is possible to monitor currency and maturity mismatch of financial intermediaries and households of a given country. Both of these mismatches are well known contributors to financial instability. (Rey, 2015)

The exchange rate regime does not influence the independency of the monetary policy, but the volatility of this price might have an adverse impact in the capital inflows of an economy. It increases the uncertainty of the investment decision and dampens capital inflows, especially the more irreversible types, according to Jehan and Hamid (2017). However, this negative effect of exchange rate volatility diminishes if the role of financial development is incorporated. The financial sector development would help to provide a conducive environment for business, that has potential to offset the impact of exchange rates. It is possible to argue, then, that investments in fintech might be negatively impacted by exchange rate volatility, but the same fintech market can help to diminish this effect, if it improves the financial sector effectiveness.

3. Data and Methodology

In this section, the indicators of fintech market size are discussed, while we examine the implications of using them in the model to capture the volume of the industry. Next, the fintech market data is analyzed, including considerations about the countries, technologies and segments. The section is concluded with an explanation of the methodology of the empirical model.

3.1.Market size indicators

To estimate the size of Fintech market in each country is not straightforward. It is composed basically by startups, which are private entities. If we consider that the size of the market is the aggregated market value of the companies of the sector, as it is usually done for industries mostly composed by public companies, we would have to estimate the value of each startup. The value is a function of their growth potential, which depends on a number of factors. There is no academically accepted methodology to estimate them.

Classens et al. (2018) limited the scope of the analysis to the P2P credit platforms and considered the amount of credit exchanged through these platforms as a measure of the volume of the credit fintech market. This measure has the merit of being based on granular transactions that captures the use of that service and tend to be sensible to the incentives and drivers. However, this approach disregards all the other fintech markets and this metric cannot be considered a good proxy of the whole fintech segment. Take the case of China, one of the major fintech markets in the world, for example. After years of substantial growth, there was a sharp decline of the lending volumes in the second semester of 2017 and 2018 in that country. The explanation was a series of events. Risks have increased significantly due to inappropriate market practices and frauds, including Ponzi schemes. The response of regulation was strict, and the new rules have imposed restrictions on fund raising and other activities. These incidents were mostly restricted to that segment of fintech. (Claessens, et al., 2018)

Another possibility to estimate the market size is to consider the investment in startups and other players of the segment. The information is tracked by companies like Crunchbase, which developed a platform with investments and funding data, among other information like founding members and individuals in leadership positions, of more than 100 thousand public and private companies. Crunchbase sources its data in four ways (the venture program, machine learning, an in-house data team, and its community) and their main clients are entrepreneurs, investors, researchers and other analysts.

The advantage of using Crunchbase data is that it captures the attractiveness of the sector to investors at each point in time and place. This piece of information is closely related to the value of the companies and, if the markets are efficient, should reflect the growth prospect of the companies. The numbers are also very reliable because they are constantly checked by users of the platform, that include large technology firms and investors.

Haddad and Honuff (2019) opt to use Crunchbase data and consider in their main model the number of fintech startup formations as dependent variable. In this study, the approach is slightly different, and the dependent variables will be the number of funding rounds of fintech companies in a given year and country. As opposed to their measure, the same company can appear various times in this model, if it continues to grow and attract more rounds of investment. Although their choice may capture better the innovation in the sector, the intention, with the approach used in this paper, is to measure the attractiveness of the fintech sector, with the progress of the businesses.

There is another variable tracked by Crunchbase that could be used to measure the market. It is the aggregated amount raised in fintech funding rounds. The advantage would be that for individual companies in the given funding round date, the amount invested is the best estimate of the market value, once both the founders and the investors agreed on that amount. Also, companies would be weighted in the model according to an estimative of their importance in the market. However, there are some problems with this approach. First, 2.5 thousand transactions (26% of the total rounds) has no disclosed value in the platform. It is possible that the investment was non-monetary (like office space or mentorship). Most importantly, in our dataset, there is a majority of data points with less than 10 deals per country and year and the white noise would increase if we decided to use this variable. That is because this data is associated with investors' and invested companies' idiosyncratic characteristics that makes it very dispersed and reflect poorly the whole industry, in case the number of transactions is low.

3.2.Market Data

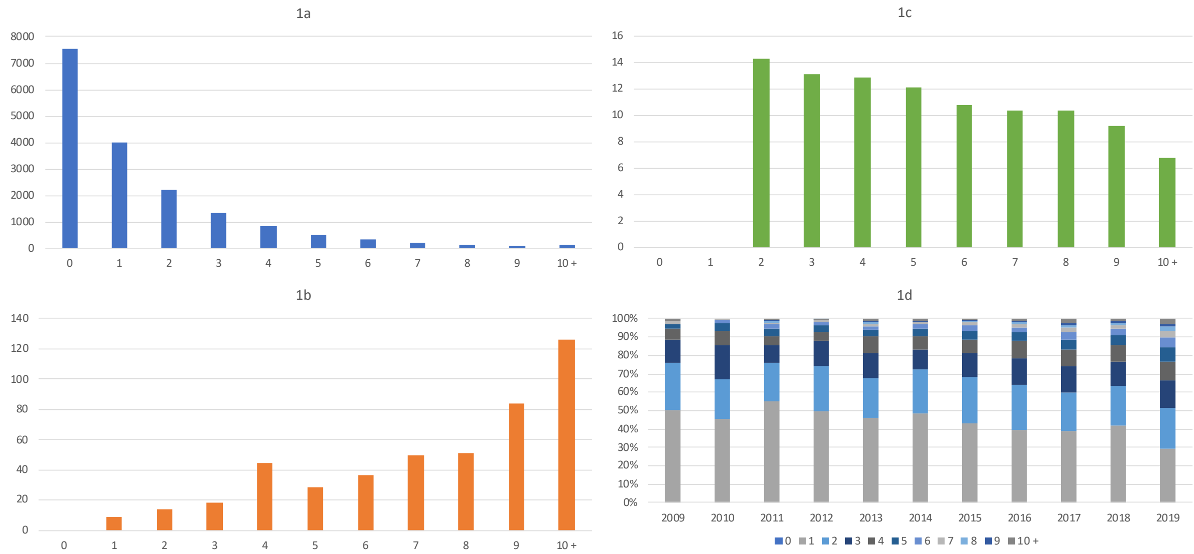
The analyzed period was from 2009 to 2019, the 11 years following the financial crisis that marked the beginning of a new era for the fintech market. In this period, there were 9.7 thousand funding rounds for fintech companies worldwide. Of these rounds, 8.6 thousand invested in companies founded after 2008, probably because investors prioritized new enterprises potentially with innovative services. On the other hand, there were 7.5 thousand fintech firms founded in the same period, and, among them, 3.5 thousand did not receive any known funding from Venture Capital firms, Private Equity, seed money, IPO or other forms, according to Crunchbase. These startups either failed to attract investors or grew with only internally generated resources, which is a competitive disadvantage, and are not covered in this model.

The invested companies receive 2.5 rounds of financing, on average. Only 12.5% of the first round invested companies reach 5 rounds of financing, although this number might increase with the future growth of the market. See Figure 1 for details of the average funding numbers in the fintech sector. The money raised in each round increase as the company gets larger. The first round raises 8 M USD on average, while the companies that reach ten or more rounds receive 127 M USD per round. The average time distance between rounds decreases as the company progresses and it revolves around 9 to 14 months. In the later years of the analyzed period, more investors are being attracted by more mature companies that already passed the first rounds of investment, which might indicate that this market is more established.

The growth of the number of fintech funding deals worldwide can be divided in three phases. It was very steep between 2009 and 2014, rising from 95 to 875 yearly in this period, when the sector was still nascent. The pace of evolution slowed from 2015 to 2018, but it still exceeded 15% yearly. In 2019, nonetheless, we observed for the first time decline in the number of deals.

The evolution of the total capital invested in these events had a different growth trajectory. The strongest growth happened between 2013 and 2018, when the yearly growth exceeded 65% every year, except for 2016. In the end of this period, the amount invested reached USD 44.6 billions in 2018. The year of 2019 also marked a decline in terms of money invested. In total, USD 147.9 bi were invested in fintech in 11 years. See Appendix 1 for the evolution of fintech funding and also the distribution in countries and regions.

Figure 1: Fintech financing (2009-2019). Number of funding rounds at each stage (0 refers to companies that did not receive any funding round) (1a), average amount raised in each round, USD millions (1b), average number of months passed since the last round (1c) and the evolution of the funding rounds per year (1d). Source: Author's calculation based on Crunchbase data.



During the analyzed period, the United States was a leader in the development of the fintech companies. The invested company's headquarters was in that country in 39.9% of the deals. United Kingdom (13.0%) also present relevant activity being the second largest, followed by India (4.6%), China (4.0%) and Germany (3.1%). If the money raised in the deals is considered, China was the second largest market, raising 28.3% of the total amount. The Asian country was the leader in that metric between 2016 and 2018 and presented an exceptionally high average amount of money raised per funding round. The United States were also the leaders in the total amount raised.

The number of deals data was collapsed into a panel dataset that consists of 451 observations covering 41 countries, being 24 advanced and 16 emerging economies, according to the IMF, and 11 years. The countries were selected because of their relevance in the segment (they had at least 20 funding deals in the whole period) and the consistency of the attractiveness of their companies (they had deals in at least 6 years). Appendix B, Table B1 contains the list of countries in the model.

The total number of deals in the analyzed period was 9.4 thousand and the total number of invested fintech companies was 4.0 thousand, covering a wide range of categories inside the financial services industry. As expected, the main categories were the payment and lending companies (including credit platforms), responding for 16.1% and 9.6% of the total, respectively. The insurance category comprised 5.6% and wealth management 2.8% of the companies. The last category raised a significant amount of capital (USD 27.3 bi, 18.4% of the total).

The mobile technology was the most commonly used by the companies according to Crunchbase classifications. The prevalence of smartphones on the population makes it a useful channel for companies to provide convenient services for their customers. Other more inventive technologies are gaining space in the fintech sphere, blockchain being the most relevant of them. Interestingly, these more pioneering companies that employed this technology or artificial intelligence and big data attracted relatively less money from investors in the period. It is possible that these companies were still in experimental phase and these technologies not mature for commercial use during this period. Appendix B, Table B2 displays some of the main categories, technologies and segments covered by the companies analyzed.

The investors that provided funding for the events considered in the analysis varied from angel investors to debt financers after the IPO of the company, and even innovative forms of raising money, like ICOs. The most common type of funding for fintech in the 11 years studied was Venture Capital (36.6% of the rounds), followed by seed rounds (33.9%), which are provided generally while the company is young and working to gain traction before the first rounds of venture capital. (Crunchbase, 2020) The capital invested in the Venture Capital rounds responded for 62.2% of the total rounds considered, making it the most important source of capital for these companies. Debt financing was also important for the industry development, providing 20,0% of the money raised. Appendix B, Table B3 presents the distribution of the funding rounds according to their type.

3.3.Methodology

The variable studied in this model is a case of count data, that is, it is a series of nonnegative integers. Classical linear regressions may not be appropriate for models with this type of data due to the restriction on its range. Generalized linear models were developed as a natural generalization of classical linear models that accommodate several special cases like the non-continuity of count data. They share with each other a number of proprieties such as linearity and assume the error distribution to be non-Normal, as opposed to the classical linear models. (McCullagh and Nelder, 1989) Generalized linear models that use Poisson or negative binomial distributions are conventionally utilized for modeling count data.

Another specificity of the dependent variable in this model (number of fintech funding rounds) is that it is overdispersed, which means that its variance exceeds its mean. That is a common case of a wide range of applications in different fields, like other social sciences and ecology. In Poisson distribution, conversely, the variance is equal to the mean, what makes it unfit for this type of data. Given the prevalence of count datasets with overdispersion, several models have been developed to solve this issue. Among them, the most commonly used are the quasi-Poisson and the negative binomial models, mainly because they are widely available in software and they generalize easily to the regression case. (Ver Hoef and Boveng, 2007)

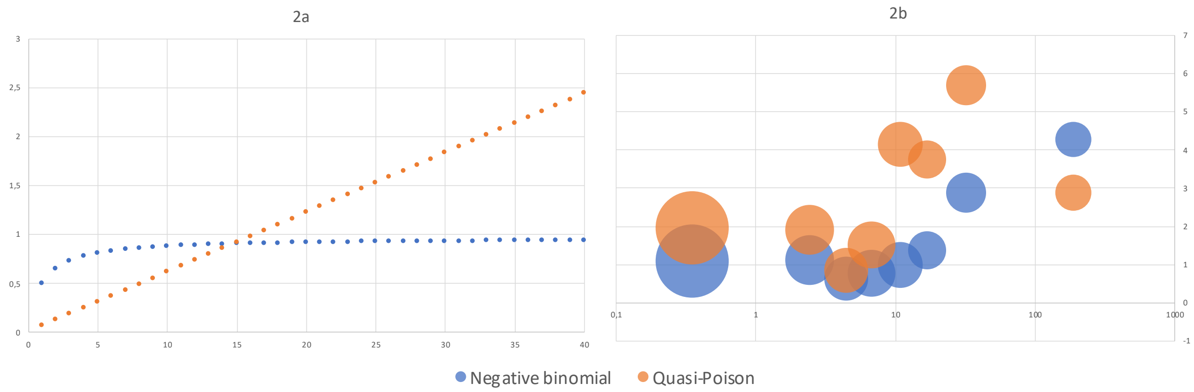
The main difference between quasi-Poisson and the negative binomial models is how they adjust the variance for overdispension. Being Y a random variable, the expected value would be E (Y) = μ , where μ is the mean of the distribution. In quasi-Poisson distribution, the parametrization of the variance would be $var(Y) = \nu_{Poi}(\mu) = \theta\mu$, where $\theta > 0$ is the overdispersion parameter. When the negative binomial distribution is utilized, the expected value parameter is the same, but the variance is $var(Y) = \nu_{NB}(\mu) = \mu + \kappa\mu^2$. In this case, overdispersion (the amount in excess of μ) is the multiplicative factor 1 + $\kappa\mu$, which depends on μ. (Ver Hoef and Boveng, 2007)

The fitting of the coefficients of the regression is affected by the choice of the distribution because both models uses weighted least squares to fit the coefficients to the data and these weights are inversely proportional to the variance. Thus, each distribution will weight observations differently. While quasi-Poisson model weights are directly proportional to the mean, negative binomial model weights have a concave relationship to the mean. That is, very small mean values get very little weight in negative binomial model, but as the mean increases, weights quickly level off to 1/ κ, as demonstrated in Figure 2a, that reflects the real parameters of this model. In our application, negative binomial regression gives more weight for the smaller number of funding deals, compared to quasi-Poisson that prioritizes the fit for larger observations, whose difference from the mean and median is very substantial like the United States and the United Kingdom datapoints. (Ver Hoef and Boveng, 2007)

Therefore, the choice of the model should depend on how the overdispension is related to the mean of the data: linearly or quadratic. There is no formal test to classify the fit of the distribution, since information theoretic approaches such as Akaike information criteria (AIC) or Bayesian information criteria (BIC) should not be used to compare quasi models and distributional models like the negative binomial. Ver Hoef and Boveng (2007) suggest plotting of the squared residuals against the mean to compare the models. In Figure 2b, it is possible to compare both regressions' average squared residuals, calculated for pools of observations with close "y" values (number of deals). The size of the circles represents the quantity of observations in each pool and, the X axis indicates the average "y" variable of these categories, in logarithmic scale for better visualization. It is possible to notice that the quasi-Poisson regression make systematic larger errors in the fit of all smaller categories of observations to be able to accommodate the very large ones, due to the large weight of these last numbers. The negative binomial, on the other hand, have a better fit in the majority of the data points, as the weight is distributed more equally.

Considering these evidences and that the importance of the larger observations to explain the drivers of the fintech industry must not be directly proportional to their sizes, we understand that the negative binomial regression is the better option to our model. The robustness section will return to this comparison between different distribution models to investigate how this decision affect the model results.

Figure 2: Graphs comparing two regression models for overdispersed count data. Weights to value of observations (2a) and squared residuals to the mean – logarithmic scale (2b).



The negative binomial regression models the log of the expected count as a function of the predictor variables. Therefore, its coefficient can be interpreted as follows: for a one-unit change in the predictor variable, the difference in the logs of expected counts of the response variable is expected to change by the respective regression coefficient, given the other predictor variables in the model are held constant. (Statistical Consulting)

The model coefficient can also be interpreted as an incidence rate ratio, if adapted, because count variables are technically rates. In this particular case, the number of fintech funding rounds in one year is the rate of fintech deals per year. From the model results, it is possible to know how the response variable would change in relative terms, in case a specific predictor variable increase by one unit and the other predictor variables are unchanged. See Appendix 3 for the relationship between the coefficient and the incidence rate ratio. (Statistical Consulting)

4. Full Model and Results

To better understand the driving forces and the effect of public policies on the development of the fintech markets, regressions are conducted in two panel datasets. The first one is more comprehensive in length, covering the whole period since the 2008 Great Financial Crisis and is called the Full Model. The second is more concentrated in the recent years.

4.1.Full Model

The Full Model comprise data of 41 countries in all of the 11 years in the study (2009-2019) and its primary objective is to investigate the effect of regulations and monetary policy. The regressions on this model are centered on the following the baseline specification:

$$
\begin{aligned}
\Pr(y_1, y_2 \dots y_T) \\
&= F(Population_{i,t-1} + Population\ under\ 26_{i,t-1} \\
&+ Bank\ Concentration_{i,t-1} + Lastest\ Technology_{i,t-1} \\
&+ Mobile\ Subscription_{i,t-1} + Internet\ use_{i,t-1} \\
&+ Regulation\ Stringency_{i,t-1} + Exch.Rate\ CV_{i,t-1} \\
&+ Gross\ Capital\ Flow_{i,t-1} + Nominal\ Interest\ Rate_{i,t-1} \\
&+ Slope\ of\ Nominal\ Interest\ Rate_{i,t-1} + US\ dummy_{i,t-1} \\
&+ China\ dummy_{i,t-1})
\end{aligned}
$$

Where y is the number of fintech funding deals in country i and year t. F(.) represents a negative binomial distribution function.

The summary statistics of all variables in the model can be seen in the Table 1, that also present the mean value of developed economies and emerging markets. Some of the independent variables seek to control for demographic, economic and technological factors. Population of a country is a variable that leads to a lot of positive consequences for its fintech markets. With the size of the population, the demand for financial services increases, as well as, potentially, the sources of labor and funding. The population varies widely between the countries in the model and the emerging economies are in general more populated, because only larger developing countries attracted relevant fintech investments in the period.

Population under 26 years old is included as a share of the total population. This factor can be a source of advantage of a country, since the younger generations tend to adopt more easily innovative technologies. The average is 20 per cent of total population and the advanced economies present smaller share.

GDP per capita is an economic indicator that reflects the level of development of an economy. The variation among countries is also very substantial. Bank concentration refers to the share of assets held by the three largest commercial banks in comparison to the total assets of the system and revolves around 60 per cent in the model.

Table 1: Summary statistics of the Full Model variables

Variable	Total					Adv. Econ.	Emerg. Mkt.
	Mean	Median	Std. Dev.	Min.	Max.	Mean	Mean
Number of Deals	19.88	5.00	64.48	0.00	643.00	27.84	8.66
Population (millions)	122.34	44.49	280.23	1.31	1.392.73	40.62	238.87
GDP per capita (USD)	30,392	29,462	23,265	902	102,913	46,549	7,537
% of population under 26	20.91	18.24	7.34	12.21	44.22	16.93	26.55
Bank Asset Concentration (top 3)	62.29	62.04	19.25	23.44	100.00	71.23	49.71
Latest technology availability	5.57	5.75	0.80	3.33	6.87	6.10	4.80
Mobile subscriptions per 100 hab.	112.52	114.89	26.99	21.02	174.91	118.68	103.69
% of population using internet	64.42	72.50	25.17	4.17	97.21	81.05	40.73
Regulation Stringency index	0.68	0.68	0.11	0.45	0.91	0.62	0.76
General regulatory quality	0.92	1.16	0.84	-1.07	2.26	1.51	0.07
Exchange rate coef. of variation (%)	4.31	3.40	3.05	0.10	26.18	3.95	4.82
Gross capital flow (% of GDP)	28.85	17.38	37.02	0.00	341.89	39.88	13.29
Nominal interest rate	3.55	1.75	4.66	-0.75	45.42	1.03	7.12
Slope of nominal interest rate	-0.18	-0.04	1.81	-7.15	19.00	-0.33	0.03
Number of observations			451			264	187

The technology related variables reflect important factors for the development of fintech companies both in the demand and in the supply sides, since technology is used in the elaboration and deployment of the financial services. Haddad and Honuff (2019) tests technology statistics in a similar context, providing some guidance of which ones are important. They find that the availability of the latest technology in the country is a significant driver of fintech innovation. This indicator is measured based on answers to the Executive Opinion Survey question about to what extent the latest technologies are available in the country. The values range from 1 and 7. In Table 1, it is possible to see a great discrepancy between developed and emerging economies. Mobile subscriptions per 100 inhabitants is another important factor for business models that rely on mobile channels and was found significant by Haddad and Honuff (2019). In the majority of countries, there is more than 1 mobile subscription per person, but some countries are still laggard in the period. The share of individuals using internet is included in this model given the importance of internet for this segment, despite not being significant in Haddad and Honuff (2019) study. This indicator presents high standard deviation among countries and a particularly large difference between advanced and emerging economies.

Table 2: Correlation Matrix of Full Model variables

Number of Deals	A	1,00															
Population	B	0,18	1,00														
GDP per capita	C	0,17	-0,33	1,00													
% of population under 26	D	-0,07	0,15	-0,57	1,00												
Bank Asset Concentration (top 3)	E	-0,21	-0,37	0,57	-0,32	1,00											
Latest technology availability	F	0,18	-0,33	0,78	-0,47	0,56	1,00										
Mobile subscriptions per hab.	G	0,00	-0,41	0,27	-0,55	0,24	0,22	1,00									
% of population using internet	H	0,14	-0,40	0,77	-0,73	0,53	0,73	0,51	1,00								
Regulation Stringency	I	0,05	0,06	-0,61	0,50	-0,54	-0,55	-0,19	-0,62	1,00							
General Regulatory Quality	J	0,12	-0,43	0,81	-0,66	0,61	0,84	0,33	0,81	-0,63	1,00						
Exchange rate coefficient of variation	K	-0,12	-0,11	-0,11	0,11	-0,02	-0,23	-0,10	-0,11	0,12	-0,12	1,00					
Gross capital flow (% of GDP)	L	-0,06	-0,18	0,43	-0,22	0,36	0,32	0,13	0,29	-0,33	0,42	-0,05	1,00				
Nominal interest rate	M	-0,12	0,19	-0,53	0,54	-0,39	-0,66	-0,20	-0,52	0,47	-0,70	0,45	-0,26	1,00			
Slope of nominal interest rate	N	0,04	0,00	-0,05	0,07	-0,10	-0,10	0,07	0,01	0,06	-0,13	0,19	-0,04	0,43	1,00		
Dummy US	O	0,79	0,11	0,16	-0,03	-0,23	0,17	-0,06	0,07	0,09	0,10	-0,06	-0,07	-0,10	-0,01	1,00	
Dummy CN	P	0,03	0,70	-0,16	-0,06	-0,08	-0,24	-0,22	-0,15	-0,15	-0,22	-0,15	-0,07	0,07	0,00	-0,02	1,00
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P

The state of regulation is tested in the model through the financial regulation stringency index. It is a measure developed by Navaretti et al. (2017) to measure the sensitivity of the regulatory system to financial institution risk-taking, based on 18 answers for the World Bank's Bank Regulation and Supervision Survey. It takes into account capital requirements, what risks are covered by prudential regulation, supervisory agencies' enforcement power and asset classification, among other aspects. The answers are normalized to range from 0 (low stringency) to 1 (high stringency). The average value and the median in the model are 0.68, while some variation was observed. Emerging markets present, on average, more strict regulation in the period.

One other statistic studied to be part of the model is the general regulatory quality, that is part of the Worldwide Governance Indicators. It is constructed to capture perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. The sources focus on aspects of efficiency of competition, financial freedom, excessive bureaucracy, among others, and do not include the financial sector specific regulations. It was dropped from the model because of its high correlation with three other variables, namely GDP per capita, latest technology availability and share of population using internet. The higher than 0.8 correlations indicate that the quality of overall regulation is associated with development of economy and access to advanced technologies. This indicator will, nonetheless, be tested in the robustness section.

The other group of variables in the model is macroeconomic related and aims at understanding the effect of the monetary policy decisions and the macroeconomic environment on the development of fintech markets. The main policy decision is the short-term interest rates, normally decided by the Central Bank or other public committee. The implications of the rates can be seen in the supply of venture capital, for example, that might fuel the growth of innovative companies. (Bellavitis, 2016) The period is marked by low rates in many of the analyzed countries, as demonstrated by the median of 1.75% per year. However, emerging economies like Argentina raised the rates as high as 45% during these years. The effect of the short-term movements of the rates is also tested in Full Model. The slope of the nominal rate is the difference of the average rate in the year and the rate one year earlier. The average movement was negative, but some increases were hefty in the period.

Given the existence of the "dilemma" proposed by Rey (2015) between open capital flows accounts and independent monetary policy, the gross capital flows as a share of the GDP are in the model to control for the effect of restrictions of capital movements. Additionally, these gross flows can indicate financial fragility and problems in the overall credit conditions. This is because surges in cross-border capital flows, especially in credit flows, are reflections of a buildup of the global financial cycle and are associated with increases in leverage worldwide. Monetary conditions in the center country (United States) are transmitted worldwide through cross-border gross credit flows. Countries with high gross flows tend to be more sensible to the global cycle and therefore, these flows should be monitored. The net flows, on the other hand, are connected to current account imbalances and long-run sustainability. The gross measure included in the analysis is calculated based on balance of payments accounts. Some of the smaller countries in the model present gross capital flows that exceed 100% of the GDP (eg. Ireland and Singapore), which can be a source of financial fragility, but the median value of all economies is much lower at 17.4 per cent.

The volatility of the exchange rate might also negatively affect the investment inflows in the economy, especially the more irreversible types like seed and venture capital. (Jehan and Hamid, 2017) The coefficient of variation of the daily exchange rates of the currencies relative to the United States dollar is in the model to capture the volatility of the rates. Coefficient of variation is defined as the ratio of the standard deviation to the mean and, being a standardized measure of dispersion, is not affected by the level of the variable. This metric is then comparable among currencies with different nominal values. The average coefficient of variation of the currencies in the model indicates that the daily standard deviation is 4.3% of the mean currency value, in an annual basis. This metric is strongly influenced by the euro variation, since 10 (24% of the total) countries adopt this currency. Furthermore, the different exchange rate regimes are reflected in the numbers. Some central banks, especially in emerging economies, decide to manage the rates to pursue price stability goals while others opt not to intervene in the market prices of the currency. (Montiel, 2003) Indeed, both the lowest and the highest variations are found in emerging markets during the period.

Dummy variables are included in the model to isolate idiosyncratic factors that affect only central economies, following Claessens, et al. (2018) approach. United States has the world's most developed venture capital market and the many of the most prestigious and innovative Universities, among other advantages in the fintech markets. China, the second largest economy in terms of GDP, has innovation-friendly regulation for some fintech sectors and a fast-growing economy.

4.2.Results of Full Model

The results of the regressions indicate that both the size of the population and the percentage of younger individuals are associated with more developed fintech markets. See Table 3 for the detailed results of the models. Interestingly, in this setting, the GDP per capita, which is a proxy of the level of development of the economy, was not significant, in contrast to other fintech studies. Only if the dummy variables for United States and China are removed (column F1), this indicator gains significance possibly because the United States has high GDP per capita and large number of fintech events. One hypothesis for weak significance is that the effect of economic development is better captured in technology-related variables, once these factors are more important for the expansion of fintech activity.

The technology control variables are found relevant to explain the fintech market attractiveness. Both mobile subscriptions per habitant and percentage of individuals using the internet are highly significant in all versions of the model, with a positive coefficient. The availability of the latest technology was not significant in this case. These outcomes combined suggest that a large potential customer base with access to internet and mobile devices is more important in the demand side than the availability of state-of-the-art technologies in the supply side of the market in the period.

Table 3: Full Model regressions of fintech startup funding rounds on regulation, monetary policy and macroeconomic environment variables with demographic, technology and economic control variables

Dependent variables	F1 2009-2019	F2 2009-2019	F3 2009-2016
(Intercept)	-10.53***	-8.08***	-9.46***
Population	3.85E-09***	3.89E-09***	3.97E-09***
GDP per capita	9.30E-06*	1.09E-06	-3.72E-06
% of population under 26	0.11***	0.09***	0.06**
Bank Asset Concentration (top 3)	-0.02***	-0.02***	-0.02***
Bank Competition Lerner Index			1.1*
Latest technology availability	0.26	0.08	0.45*
Mobile subscriptions per hab.	0.02***	0.01***	0.02***
% of population using internet	0.07***	0.07***	0.06***
Regulation Stringency	5.43***	3.98***	3.74***
Exchange rate coefficient of variation	-0.07**	-0.08***	-0.07
Gross capital flow (% of GDP)	-4.13E-04	4.64E-04	-7.84E-03*
Nominal interest rate	-0.04*	-0.03	-0.03
Slope of nominal interest rate	0.07*	0.08*	0.08
Dummy US		1.48***	1.4**
Dummy CN		-1.26*	-0.82
Number of observations	451	451	295
AIC	2840.2	2823.4	1549
2 x Log-likelihood	-2812.196	-2791.386	-1515.002
Distribution	neg. binomial	neg. binomial	neg. binomial

Significance levels: * < 5%, ** < 1% and *** < 0.1%.

Concentration and competition in the banking industry presents complex relationship with the fintech market growth in the period. The coefficient for the asset concentration in the three largest banks is negative and highly significant. Hence, more concentrated banking sector is related to less growth for the fintech segment. People usually associate concentration to less competition. If that is the case, this result is unexpected, since less competitive markets should be less efficient and more innovation inducive. However, concentration measures are generally not good predictors of competition. The accuracy of concentration measures on predicting banking competition is challenged by the concept of market contestability, which is associated with threat of entry and exit. Banks are pressured to behave competitively in an industry with low entry restrictions on new participants and easy exit conditions for unprofitable institutions, even if the market is concentrated. (World Bank, 2016A)

The recent literature on banking competition focused on direct measures of bank pricing behavior or market power. The Lerner index is defined as the difference between output prices and marginal costs (relative to prices) and indicates market power in the banking markets. (World Bank, 2016A) The correlation between the Lerner index and the concentration measure in this dataset is -0,04, confirming that these indicators behave very differently in practice. In Table 3 column F3, it is possible to observe that the Lerner index (which indicates less banking competition) presented positive significant effects on the fintech development from 2009 to 2016. This outcome confirms the initial banking competition hypothesis that less competitive banking markets are associated with more fintech activity. The indicator was not included in all models because it is not available since 2015.

Regarding the effects of financial regulation stringency, very significant positive coefficients are found, providing evidence of regulatory arbitrage in this market. Stringent regulation is related to larger fintech opportunities possibly due to the advantage of complying to lighter or no requirements while competing with very strictly regulated traditional players. Associated with this effect, there might be higher demand for fintech solutions in jurisdictions where the regulated financial institutions are more constrained by regulation. This result is the opposite of Claessens, et al. (2018) finding for the credit platform segment with 2016 data.

The macroeconomic variables present one very significant result and one coefficient whose significance is weaker in the model. The exchange rates volatility is associated with less fintech funding events. An increase of one per cent in daily standard deviation relative to the mean of the exchange rate in one year is related with 7.9% decrease in the number of funding events in the following year. This is evidence that the uncertainty associated with currency volatility hinder fintech investments. Economic literature indicates that the effect of uncertainty in capital inflows is especially strong for more irreversible and more information intensive investments. The discount rates in more uncertain environments are higher and investors have higher incentive to wait for better times. More developed financial markets, however, can offset this negative volatility effect, according to Jehan and Hamid (2017), what might suggest that underdeveloped financial industries are the main responsible for this outcome in the model.

The other macroeconomic significant result was a positive coefficient of the slope of the short-term interest rate. Increases in the interest rates by the financial authority are associated with more attractive fintech sector. One interpretation is that the monetary policy might be successful in its financial stability goals in the period. When policymakers adopt contractionary movements to pursue price and financial stability, they also induce innovation investments in the following year, but this effect is partially offset by the negative coefficient of the level of nominal interest rates, considering all other variables unchanged. The number of fintech funding deals increases 8.4% for each one per cent increase in the interest rates, due to the slope effect, but it also decreases 3.1% due to the level effect of the rates, considering both variable incidence rate ratios and that other variables are constant. The final impact of the nominal interest rate movement is unknown because it depends on the joint relationship between level and slope variables and the number of fintech deals. Moreover, the monetary policy decisions have effects in the currency markets and can influence exchange rate volatility and cross border capital flows, adding complexity to these effects. It is worth also noting that the significance of the slope result is not very robust, while the level of the nominal rates is not significant at 5% threshold.

In the model F1, that do not isolate the central economies, the negative coefficient for nominal interest rates gains significance. This is one evidence that the low interest rate environment in developed economies after the 2008 global economic crisis had positive impact for the provision of funding to fintech innovative companies and fueled the relevance of the new markets.

Country dummy variables included in the model, as seen in columns F2 and F3, indicate that the United States has significantly more fintech activity than the model would predict. China, notwithstanding, does not present significantly higher activity. The Akaike information criteria (AIC) indicates that the inclusion of these variables improves the quality of the model for this dataset.

5. New Model and results

The second set of regressions is called New Model and sheds light in other questions related to regulation that were not explored in the first panel. There is evidence that regulation has impact in the fintech markets, but *what are the results of the innovative forms of regulations, namely the sandbox approach*?

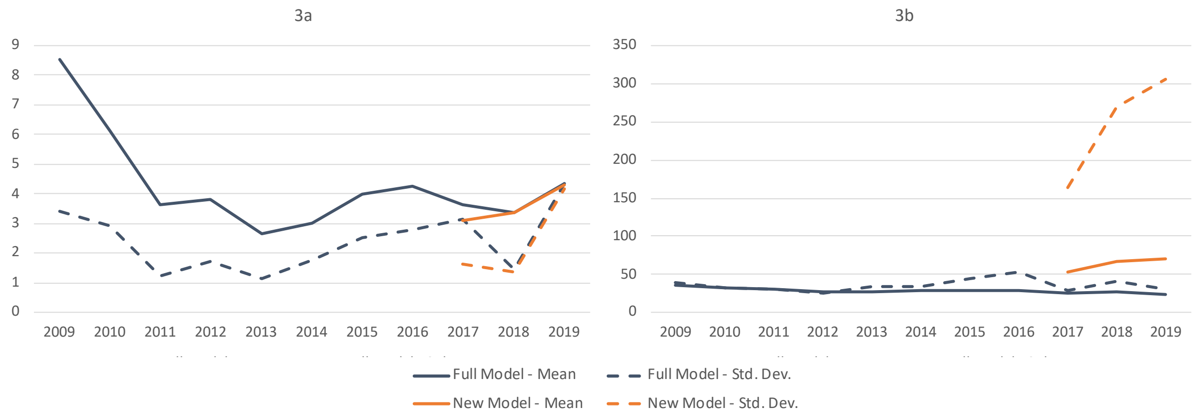
5.1.New Model

The name of this model is "new" because it focusses on the most recent years of the period (2017-2019). Furthermore, six additional countries are included in this panel dataset, since they lately presented more fintech activity. One country present in the Full Model is out because of lack of data. The specification of the model is the following:

$$
\begin{aligned}
\Pr(y_1, y_2 \ldots y_T) \\
&= F(Population_{i,t-1} + Population\ under\ 26_{i,t-1} \\
&+ Bank\ Concentration_{i,t-1} + Lastest\ Technology_{i,t-1} \\
&+ R\&D\ Expenditure_{i,t-1} + Mobile\ Subscription_{i,t-1} + Internet\ Use_{i,t-1} \\
&+ Digital\ Skills_{i,t-1} + Regulation\ Stringency_{i,t-1} + Exch.Rate\ CV_{i,t-1} \\
&+ Gross\ Capital\ Flow_{i,t-1} + Nominal\ Interest\ Rate_{i,t-1} \\
&+ Slope\ of\ Nominal\ Interest\ Rate_{i,t-1} + Sandbox\ dummy_{i,t-1} \\
&+ US\ dummy_{i,t-1} + China\ dummy_{i,t-1})
\end{aligned}
$$

Where y is the number of fintech funding deals in country i and year t. F(.) represents a negative binomial distribution function.

Figure 4: The evolution of the exchange rate coefficient of variation (%) (3a) and of the Gross Capital Flow (% of GDP) (3b). Both metrics for the Full Model and New Model sample. The difference of countries in sample explain the difference in curves.



All the variables of the Full Model remain in this model to allow comparison between the years, but these comparisons must account that the countries are not exactly the same. Additionally, new indicators that are available only more recently were contemplated. See Table 4 for summary statistics of the variables in this model. The number of fintech funding rounds per country and year is substantially higher than in the last model, a reflection of the growth in the period. The technology variables indicate an evolution of internet access, particularly in emerging economies. The numbers for latest technology availability are very similar to Full Model statistics. This fact indicates that as the technologies develop, the most advanced country continues to have privileged access to them and the discrepancy between countries is unchanged in the period.

The macroeconomic variables indicate, on average, a lower exchange rate volatility in the period. This reduced uncertainty is beneficial for the fintech markets. The Figure 3a shows that the inclusion of different countries did not impact these numbers. The gross capital flow divided by the GDP median is in line with the Full Model. However, the mean and standard deviation of this metric are substantially higher in this sample. See Figure 3b for this difference. The inclusion of Luxemburg, whose economy is highly dependent of inflows and outflows of capital, was the most important factor. This European country has values as high as 2000% for this metric.

Table 4: Summary statistics of New Model variables

Variable	Total					Adv. Econ.	Emerg. Mkt.
	Mean	Median	Std. Dev.	Min.	Max.	Mean	Mean
Number of Deals	33.77	10.50	87.25	1.00	643.00	47.06	33.77
Population (millions)	112.99	37.51	276.26	0.46	1392.73	38.33	112.99
GDP per capita (USD)	31,164	27,446	24,933	1,402	116,640	48,470	31,164
% of population under 26	19.42	17.57	5.94	12.21	40.90	16.58	19.42
Bank Asset Concentration (top 3)	60.54	59.94	18.33	26.45	95.55	68.18	60.54
Digital skills among active population	4.76	4.81	0.75	3.16	5.97	5.20	4.76
Latest technology availability	5.52	5.64	0.76	3.73	6.61	6.07	5.52
R&D expenditures	1.63	1.37	1.07	0.08	4.29	2.30	1.63
Mobile subscriptions per hab.	119.89	120.63	23.55	63.73	161.92	122.63	119.89
% of population using internet	74.05	80.07	20.56	15.00	97.75	86.93	74.05
Regulation Stringency	0.66	0.68	0.10	0.44	0.84	0.606	0.66
General regulatory quality	0.96	1.16	0.82	-0.83	2.18	1.56	0.18
Legal framework's digital adaptability	4.28	4.24	0.71	3.01	5.84	4.60	4.28
Exchange rate coefficient of variation	3.58	3.09	2.74	0.66	26.18	3.19	3.58
Gross capital flow (% of GDP)	66.27	17.36	252.54	0.00	2087.40	105.43	66.27
Nominal interest rate	2.97	1.01	5.79	-0.75	45.42	0.30	2.97
Slope of nominal interest rate	0.10	-0.01	1.95	-4.25	19.00	0.01	0.10
Dummy Sandbox	0.25	0.00	0.43	0.00	1.00	0.24	0.25
Dummy Common law wout sandbox	0.07	0.00	0.26	0.00	1.00	0.10	0.07
Dummy Sandbox wout common law	0.17	0.00	0.37	0.00	1.00	0.12	0.17
Dummy Sandbox and common law	0.08	0.00	0.27	0.00	1.00	0.13	0.08
Dummy New sandbox	0.19	0.00	0.39	0.00	1.00	0.17	0.19
Dummy Old sandbox	0.06	0.00	0.23	0.00	1.00	0.08	0.06
Number of observations			138			78	60

The Global Competitiveness Report, by the World Economic Forum, tracks many statistics in a country level that are relevant for the innovation environment. Three of them were included in the model. The first indicator is the digital skills among active population. This factor is the result of Executive Opinion Survey answers about to what extent the active population possess sufficient digital skills, including computer skills, basic coding, digital reading. This variable is related to technology education and serves as a compliment to other control variables. The advanced economies' population have higher digital skills, according to the survey, but the difference is smaller than the perceptions about the latest technology availability.

Table 5: Correlation Matrix of New Model variables

Number of Deals	A	1,00																								
Population	B	0,26	1,00																							
GDP per capita	C	0,18	-0,29	1,00																						
% of population under 26	D	-0,04	0,18	-0,47	1,00																					
Bank Asset Concentration (top 3)	E	-0,23	-0,40	0,36	-0,42	1,00																				
Digital skills among active population	F	0,23	-0,12	0,64	-0,32	0,44	1,00																			
Latest technology availability	G	0,23	-0,38	0,78	-0,44	0,49	0,72	1,00																		
R&D expenditures	H	0,18	-0,09	0,57	-0,43	0,31	0,58	0,70	1,00																	
Mobile subscriptions per hab.	I	-0,17	-0,42	0,20	-0,46	0,40	0,19	0,18	0,12	1,00																
% of population using internet	J	0,09	-0,44	0,71	-0,70	0,53	0,55	0,75	0,60	0,43	1,00															
Regulation Stringency	K	0,11	0,32	-0,54	0,38	-0,62	-0,45	-0,66	-0,48	-0,19	-0,59	1,00														
General Regulatory Quality	L	0,15	-0,41	0,80	-0,60	0,56	0,73	0,90	0,59	0,27	0,83	-0,67	1,00													
Legal framework's digital adaptability	M	0,38	0,03	0,59	-0,20	0,24	0,79	0,67	0,47	0,10	0,45	-0,35	0,64	1,00												
Exchange rate coefficient of variation	N	-0,04	-0,07	-0,12	0,03	-0,03	-0,27	-0,17	-0,13	0,16	0,10	0,08	-0,16	-0,18	1,00											
Gross capital flow (% of GDP)	O	-0,06	-0,09	0,51	-0,12	-0,10	0,09	0,17	-0,04	0,16	0,20	-0,13	0,19	0,29	-0,01	1,00										
Nominal interest rate	P	-0,07	0,14	-0,43	0,47	-0,34	-0,44	-0,60	-0,39	-0,03	-0,37	0,46	-0,60	-0,33	0,61	-0,11	1,00									
Slope of nominal interest rate	Q	0,01	-0,05	-0,03	0,08	-0,07	-0,09	-0,06	-0,05	0,00	0,03	0,04	-0,06	-0,03	0,74	-0,01	0,55	1,00								
Dummy Sandbox	R	0,13	-0,03	0,09	-0,01	0,04	0,15	0,10	-0,04	0,03	0,05	0,02	0,11	0,12	-0,09	-0,08	-0,08	-0,02	1,00							
Dummy Common law without sandbox	S	0,34	0,22	0,16	0,11	-0,15	0,17	0,07	-0,03	-0,25	-0,01	-0,14	0,14	0,19	-0,08	0,00	-0,05	-0,04	-0,16	1,00						
Dummy Sandbox without common law	T	-0,11	-0,08	-0,04	0,05	0,01	0,04	-0,03	-0,11	0,03	-0,04	0,07	-0,07	-0,08	-0,07	-0,07	-0,05	-0,02	0,78	-0,13	1,00					
Dummy Sandbox and common law	U	0,36	0,07	0,20	-0,10	0,05	0,19	0,19	0,09	0,01	0,13	-0,05	0,27	0,29	-0,04	-0,03	-0,07	0,00	0,51	-0,08	-0,13	1,00				
Dummy New sandbox	V	0,12	0,01	0,03	0,02	0,01	0,08	0,04	-0,05	0,03	0,00	0,02	0,04	0,08	-0,03	-0,07	-0,05	-0,03	0,84	-0,13	0,68	0,41	1,00			
Dummy Old sandbox	W	0,05	-0,06	0,12	-0,06	0,06	0,16	0,11	0,01	0,00	0,09	0,01	0,14	0,08	-0,11	-0,02	-0,08	0,01	0,43	-0,07	0,31	0,27	-0,12	1,00		
Dummy US	X	0,90	0,11	0,17	-0,01	-0,21	0,23	0,19	0,16	-0,11	0,08	0,10	0,11	0,32	-0,04	-0,03	-0,05	0,04	0,03	0,34	-0,07	0,14	0,06	-0,04	1,00	
Dummy CN	Y	0,08	0,69	-0,13	-0,04	-0,19	-0,02	-0,22	0,06	-0,21	-0,15	0,18	-0,21	0,06	-0,05	-0,03	0,04	-0,02	-0,09	-0,04	-0,07	-0,04	-0,07	-0,04	-0,02	1,00
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y

The second indicator is the research and development expenditure measured as a percentage of GDP. It focuses on both public and private research on creative work undertaken systematically to increase knowledge and its use on new applications. This variable likely captures the resources applied on innovative projects. The standard deviation reveal substantial variability among countries and the range in the period is from 0.08% to 4.29%.

The third new variable taken from the Global Competitiveness Report is the legal framework's adaptability to digital business models, which is another indicator based on Executive Opinion Survey responses. The question is about the velocity of the legal framework adaption to digital business models in each jurisdiction. The example of business models provided in the question are e-commerce, sharing economy and also fintech. It reflects the perception among business executives of the legal framework adaptability, which might also depend on the respondents' expectations. In general, this indicator has lower grades than the other survey questions (latest technology and digital skills), but the variability between countries was similar.

Finally, there is a group of variables included in the model to test the introduction of regulatory sandboxes. One of the objectives of this regulatory approach is to incentivize the development of innovative companies in the country, and the inclusion of these dummy variables aims at gathering evidence about the effectiveness of the approach in this goal. The data about the existence of sandboxes in each country and year is taken from research performed by Buckley et al. (2019). Among 45 countries in this panel, 22 presented at least one form of sandbox in this period. The rate of adoption in emerging and advanced countries was similar. Additional dummy variables are included in other derivative models to investigate how the sandbox variable interact with aspects of the law system and also if the effects are enduring.

5.2.Results of New Model

In the more recent period and with a slightly different set countries, some results observed in the Full Model were maintained, while other changed their significance. See Table 6 for the regressions results. The analysis of the factors unrelated to the sandbox is mainly focused on the model in column N2, because it has better fit for the data, according to AIC method.

The size of population is still positively associated with the number of fintech funding events in a country, but not the share of younger individuals. This altered result comparing to the Full Model might be due to a new phase of fintech development, with more mature markets and wider reach to different segments of the population.

The GDP per capita gains significance in contrast with the Full Model results, indicating positive association between economic and fintech development in later years. The banking asset concentration, contrarily, did not present significant coefficient, confirming the proposition that this indicator is not capturing the bank competition.

The technology variable results indicate a change of drivers in the recent years. Mobile subscriptions and percentage of individuals using the internet ceased to be associated with the development of fintech markets. A large majority of people in advanced economies have access to internet and mobile devices and the growth in both metrics is gradual. In emerging markets, the growth of adoption of internet was slower than in the earlier years, when a large portion of the population was excluded. See Appendix E for the evolution of these statistics. The availability of the latest technology, that did not influence fintech growth in the Full Model, was significant in the recent years. These outcomes suggest that the accessibility of latest technology (e.g. artificial intelligence, blockchain) is increasingly important as competitive advantages of countries in the fintech markets. The wide access to more primary technologies (e.g. internet), on the other hand, is not representing advantage anymore. Interestingly, digital skills among active population had negative significant results. Possible explanations are that the executives' perception does not reflect the true skills of the workforce in an international comparison or that the markets with less trained people present also more fintech opportunities. Research and development expenditures did not present significant results relative to the development of fintech.

The regulation stringency index presents again a positive significant coefficient in explaining the attractiveness of the fintech sector. This result suggests the regulation arbitrage persists in the market. The adaptability of legal framework to digital business models was not significantly associated with the fintech evolution in N2, but the results were positive and significant in N1 and N3. This might indicate that the adaptation of the legal framework does impact financial innovation environment, but this effect depends more on the law system of the country.

In contrast with the regulation results, the evidences of macroeconomic environment relationship with the fintech markets are very different than in the previous model. In this case, the exchange rate volatility is not significant, whereas the gross capital flow presents negative association to the fintech market attractivity. The countries that rely relatively more in internal capital had advantage compared with more open economies, controlling for the other factors in the model. This finding is in line with Rey (2015) reasoning that large gross flows disrupt asset markets and financial intermediation. That is, they represent substantial costs for the economy because they make it vulnerable to the global financial cycle, increasing financial instability. Luxemburg, Ireland and Singapore are the most affected countries by this problem in this sample, since gross flows represented more than 100% of the GDP in at least one year.

The sandbox variable result provide evidence in favor of the approach as incentive to development of innovative companies. In the model in Table 6, column N1, the coefficient is significant and positive. The introduction of the sandbox is associated with a 46% increase in the number of fintech funding rounds. Although the number of companies directly benefited by the sandbox flexibilization is typically very small, a positive message to the industry that the regulator is approachable and open to deal with innovation topics might make the sandbox successful. (Buckley et al, 2019)

Table 6: New Model regressions of fintech startup funding rounds on regulation, monetary policy and macroeconomic environment variables with demographic, technology and economic control variables. The difference between the three versions presented in the columns are due to the dummy variables related to the introduction of regulatory sandbox.

Dependent variables	N1 2017-2019	N2 2017-2019	N3 2017-2019
(Intercept)	-4.02**	-3.84**	-3.89**
Population	2.63E-09***	2.16E-09***	2.62E-09***
GDP per capita	2.26E-05***	1.22E-05*	2.24E-05***
% of population under 26	0.01	0.01	0.01
Bank Asset Concentration (top 3)	4.35E-03	9.33E-03	4.26E-03
Digital skills among active population	-0.93***	-0.61***	-0.92***
Latest technology availability	0.78**	0.76***	0.76**
R&D expenditures	-0.12	-8.57E-03	-0.11
Mobile subscriptions per hab.	-2.92E-03	-6.02E-03	-3.00E-03
% of population using internet	0.01	0.01	0.01
Regulation Stringency	3.41***	3.93***	3.31***
Legal framework's digital adaptability	0.58**	0.23	0.58**
Exchange rate coefficient of variation	0.03	0.03	0.04
Gross capital flow (% of GDP)	-2.15E-03***	-1.35E-03**	-2.14E-03***
Nominal interest rate	0.02	0.01	0.02
Slope of nominal interest rate	-0.1	-0.08	-0.1
Dummy Sandbox	0.39**		
Dummy Common law without sandbox		0.34	
Dummy Sandbox without common law		-0.06	
Dummy Sandbox and common law		1.37***	
Dummy New sandbox			0.32*
Dummy Old sandbox			0.64*
Dummy US	1.62***	1.8***	1.66***
Dummy CN	-0.73	-0.28	-0.72
Number of observations	138	138	138
AIC	1042.5	1015.3	1043.1
Log-likelihood	-1002.534	-971.337	-1001.088
Distribution	neg. binomial	neg. binomial	neg. binomial

Significance levels: * < 5%, ** < 1% and *** < 0.1%.

The legal system of the country can be a problem in the introduction of the sandbox because it involves dispensation and flexibilization of requirements, in an impermanent condition. (Kasiyanto, 2017) Column N2 presents a version of the model that separates the effect of the sandbox by the legal system of the country. In this case, the baseline situation is a country with a different law system than common law and no sandbox proposed or implemented. The outcome indicates that the positive association between sandbox and fintech ecosystem is completely due to countries with common law system, namely United Kingdom, Australia, Singapore and, to a lesser extent because of later adoption, the United States. Countries that adopt civil law, mixed or other law systems does not enjoy significant association between introduction of sandbox and fintech market. Important to notice that common law countries with no sandbox in effect also does not present significant results, hence the law system per se does not provoke the association. The coefficient indicates that a country with a given level in all other factors in the model, that adopts common law system and introduced the regulatory sandbox approach have 288% more fintech funding events per year than if it does not have these two characteristics. In the case of United Kingdom, the pioneer in this approach, this number represent 162 less rounds for fintech companies and 2,2 bi USD loss in investments (considering the average money raised in the country and the number of rounds in 2019).

The explanation of the significant result only for common law countries in this model can be an indifference to sandboxes among the business communities in other jurisdictions, since they are aware of the more prescriptive and rigid requirements, and that modifications via sandbox would be problematic. An alternative explanation, that is not directly related to the law system, is that the strength of the positive message may be time specific, as noted by Buckley et al. (2019). That is, the first jurisdictions that adopted sandboxes might have sent a much stronger pro-innovation signal than the followers. These pioneer countries adopt the common law system. It is noteworthy, however, that the positive impact of the adaptability of the legal framework to digital business models is significantly positive in other models that do not control for the law system, suggesting that the law system of the country is related to how they adapt their legal environment to digital business. Sandboxes may assist policymakers in this adaptation.

The motivation for the model in column N3 is to examine how enduring is the positive impact of the sandbox introduction to fintech market growth. The findings of the model suggest that the strength of the message that regulatory sandboxes send to the market does not fade with time. After more than one year of introduction the coefficient is still significantly positive.

6. Robustness checks

The models constructed so far, as all statistical models, are simplifications of reality and are based on assumptions. In this section, some robustness checks will be performed to reduce model uncertainty, that can be understood as the probability that the assumptions or data are flawed. (Neumayer and Plümper, 2017)

6.1.Jackknife Robustness Test

The first technique to be used is called jackknife robustness test and consists in a structured permutation test. It systematically excludes one or more observations from the estimation at a time until all observations have been excluded once. (Neumayer and Plümper, 2017) In this case, one country is excluded at a time, and the model is calculated with the remaining countries.

Table 7: Jackknife Robustness Test for the Full Model (F2) regressions of fintech startup funding rounds on regulation, monetary policy and macroeconomic environment variables with demographic, technology and economic control variables. Results of 41 regressions in which one country was excluded at a time. The number of models whose coefficients are positive, negative and their significance is expressed.

Dependent Variables	Positive				Negative			
	***	**	*	NS	NS	*	**	***
(Intercept)	0	0	0	0	0	0	0	**41**
Population	**41**	0	0	0	0	0	0	0
GDP per capita	0	0	0	**32**	9	0	0	0
% of population under 26	**41**	0	0	0	0	0	0	0
Bank Asset Concentration (top 3)	0	0	0	0	1	1	3	**36**
Latest technology availability	0	0	0	**38**	3	0	0	0
Mobile subscriptions per hab.	**41**	0	0	0	0	0	0	0
% of population using internet	**41**	0	0	0	0	0	0	0
Regulation Stringency	**41**	0	0	0	0	0	0	0
Exchange rate coefficient of variation	0	0	0	0	0	0	3	**38**
Gross capital flow (% of GDP)	0	0	0	**36**	5	0	0	0
Nominal interest rate	0	0	0	1	**38**	1	1	0
Slope of nominal interest rate	2	1	**35**	3	0	0	0	0
Dummy US	**38**	1	0	0	1	0	0	0
Dummy CN	0	0	0	0	1	**31**	6	2

Significance levels: * < 5%, ** < 1% and *** < 0,1%. NS is "not significant at 5% p.value". The bold number highlights the models that present the same significance as the baseline model.

The first model to be tested is the Full Model with US and China dummy variables (F2). The Table 7 presents the results for the 41 models generated in this test. The sign and significance of many coefficients are the same in the baseline model and in all of the models in this test, an indication that none of the countries are strongly driving the results. Six of the fourteen variables in the model present this characteristic. The ones related to public policy issues and macroeconomic environment are the regulation stringency index and exchange rate coefficient. This outcome reveals that the robustness of the regulatory arbitrage and negative association between currency volatility and fintech development is notable.

The other macroeconomic variables do not present the same degree of robustness. Interestingly, the nominal interest rate coefficient is significant and negative in two models. If Brazil or India is excluded from the sample of countries, this rate presents negative coefficient in the model. These countries presented higher fintech activity than peers with similar high interest rates in the period and had influence in the baseline model result. The negative association between short-term rates and fintech development is expected, since lower interest rates create an environment that drives investments to more risky ventures.

In a 'group-wise jackknife' robustness test, it is possible to drop a set of countries that share some characteristics and test how robust the result is in a subset of countries. This technique permits to test the model in a completely different set of countries. (Neumayer and Plümper, 2017) In this case, the test verifies if there are differences in the model results for advanced economies and emerging markets. Besides clear differences in stage of economic development, the technology, demography and financial regulation of the countries vary widely between the two groups of countries.

See Table 8 for the results of the regressions in both set of countries. The regulation stringency coefficient was again robust in this test. Nevertheless, the exchange rate coefficient of variation and the interest rate slope presented different results in the emerging and advanced countries models. In both cases, the advanced economies are mainly responsible for the significant coefficient in the baseline model. Although the gross capital flow per GDP is not significant in the baseline model, it presented significantly positive coefficient for advanced economies and significantly negative for emerging markets. Rey (2015) argues that this measure signalizes currency and maturity mismatch, what have proved many times to contribute to financial instability. This complex result might be evidence that, in certain settings, openness to foreign capital flows can be a source of economic advantage, in line with economic intuitions that it improves allocative efficiency and risk-sharing in the economy. Rey

(2015) adds, nevertheless, that many studies attempted to measure these gains using different methodologies and this literature found no relevant welfare gains from the capital account openness until that point.

Table 8: Results of the group-wise Jackknife Robustness Test for the Full Model (F2). The same model is applied to advanced economies and emerging markets.

Dependent variables	F2 2009-2019	F2 - Advanced 2009-2019	F2 - Emerging 2009-2019
(Intercept)	-8.08***	-9.7***	-7.52***
Population	3.89E-09***	1.97E-08***	3.65E-09***
GDP per capita	1.09E-06	1.54E-05**	-1.63E-05
% of population under 26	0.09***	0.1***	0.07**
Bank Asset Concentration (top 3)	-0.02***	-0.01	0.02**
Latest technology availability	0.08	-0.35	0.24
Mobile subscriptions per hab.	0.01***	0.01**	0.02***
% of population using internet	0.07***	0.09***	0.05***
Regulation Stringency	3.98***	5.79***	1.96*
Exchange rate coefficient of variation	-0.08***	-0.12**	-0.01
Gross capital flow (% of GDP)	4.64E-04	3.27E-03*	-0.05***
Nominal interest rate	-0.03	-0.24***	-3.27E-03
Slope of nominal interest rate	0.08*	0.23*	6.71E-03
Dummy US	1.48***	-2.92***	N/A
Dummy CN	-1.26*	N/A	-1.28**
Number of observations	451	264	187
AIC	2823.4	1761.2	965.31
2x Log-likelihood	-2791.386	-1731.206	-935.306
Distribution	neg. binomial	neg. binomial	neg. binomial

Significance levels: * < 5%, ** < 1% and *** < 0.1%.

The jackknife robustness test is similarly applied to the New Model, as shown in Table 9. The model that considers the law system (N2) was chosen because it presented higher AIC, a measure of fitness of the model to the data. The lower number of observations in each model in this exercise (135) compared to the Full Model (440) might contribute for the lower robustness of the coefficients and also for the smaller number of strong significant coefficients.

Table 9: Jackknife Robustness Test for the New Model (N2) regressions of fintech startup funding rounds on regulation, monetary policy and macroeconomic environment variables with demographic, technology and economic control variables. Results of 46 regressions in which one country was excluded at a time. The number of models whose coefficients are positive, negative and their significance is expressed.

Dependent Variables	Positive				Negative			
	***	**	*	NS	NS	*	**	***
(Intercept)	0	0	0	0	2	9	**30**	5
Population	**46**	0	0	0	0	0	0	0
GDP per capita	0	3	**32**	11	0	0	0	0
% of population under 26	0	0	0	**45**	1	0	0	0
Bank Asset Concentration (top 3)	1	2	13	**30**	0	0	0	0
Digital skills among active population	0	0	0	0	0	0	3	**43**
Latest technology availability	**22**	22	2	0	0	0	0	0
R&D expenditures	0	0	0	17	**29**	0	0	0
Mobile subscriptions per hab.	0	0	0	0	**32**	13	1	0
% of population using internet	0	3	3	**40**	0	0	0	0
Regulation Stringency	**46**	0	0	0	0	0	0	0
Legal framework's digital adaptability	0	0	4	**42**	0	0	0	0
Exchange rate coefficient of variation	0	0	0	**45**	1	0	0	0
Gross capital flow (% of GDP)	0	0	0	1	0	3	**37**	5
Nominal interest rate	0	0	0	**44**	2	0	0	0
Slope of nominal interest rate	0	0	0	0	**44**	2	0	0
Dummy Common law without sandbox	1	0	1	**43**	1	0	0	0
Dummy Sandbox without common law	0	0	0	0	**46**	0	0	0
Dummy Sandbox and common law	**45**	1	0	0	0	0	0	0
Dummy US	**43**	1	0	1	0	0	0	0
Dummy CN	0	0	0	1	**42**	1	0	1

Significance levels: * < 5%, ** < 1% and *** < 0,1%. NS is "not significant at 5% p.value". The bold number highlights the models that present the same significance as the baseline model.

The regulation stringency index is again significant in all of the models, one of the most robust variables, after the population and some dummy variables. The outcome indicates further evidence of regulatory arbitrage. One less robust outcome was the gross capital flows, that had negative significant coefficient in all models, except for one. If Luxemburg is excluded from the sample, the coefficient is positive and not significant. This fact indicates high influence of the country in the baseline result. The dummy variable for countries with sandbox and common law system is significant in all of the models. None of the countries solely drives the association between them and higher fintech development.

The interpretation of the 'group-wise jackknife' robustness test for the subset for advanced economies and emerging markets is undermined by the low number of observations in each model. The advanced economies model has more observation points and also presents more significant results. The sandbox dummy variable was significantly associated with fintech in these countries, what drives the baseline model result. Similarly, the legal framework's adaptability to digital business models and regulation stringency index have significant result in the baseline model and it is highly associated to advanced economies performance, but do not present significant coefficient for emerging markets.

Table 10: Results of the group-wise Jackknife Robustness Test for the Full Model (F2). The same model is applied to advanced economies and emerging markets.

Dependent variables	N1 2017-2019	N1 - Advanced 2009-2019	N1 - Emerging 2009-2019
(Intercept)	-4.05**	1.88	-0.88
Population	2.64E-09***	8.40E-09*	2.49E-09***
GDP per capita	2.33E-05***	1.63E-05**	-3.81E-05
% of population under 26	0.01	0.05	0.02
Bank Asset Concentration (top 3)	4.16E-03	-8.52E-03	0.02*
Digital skills among active population	-0.96***	-0.63*	-0.47*
Latest technology availability	0.77**	-0.3	0.37
R&D expenditures	-0.12	-0.17	7.53E-03
Mobile subscriptions per hab.	-2.68E-03	-9.77E-03	-9.92E-04
% of population using internet	0.01	-0.01	0.01
Regulation Stringency	3.47***	3.33***	1.17
Legal framework's digital adaptability	0.6***	1.19***	0.04
Exchange rate coefficient of variation	0.02	0.12	0.02
Gross capital flow (% of GDP)	-2.21E-03***	-2.15E-03***	-8.91E-03
Nominal interest rate	0.02	-0.36**	0.03
Slope of nominal interest rate	-0.09	0.44	-0.08
Dummy Sandbox	0.38**	0.83***	-0.05
Dummy US	1.6***	-1.21	N/A
Dummy CN	-0.73	N/A	-0.22
Number of observations	135	78	60
AIC	1028.6	614.29	389.14
2x Log-likelihood	-988.58	-576.288	-351.14
Distribution	neg. binomial	neg. binomial	neg. binomial

Significance levels: * < 5%, ** < 1% and *** < 0.1%.

6.2.Non-significant variables

Both models presented in earlier sections include variables that are not statistically different than zero, in some instances called irrelevant variables. The decision of removing them or not is controversial. In models that aims at studying what drives one economic phenomenon, like this research, it is common to include the important variables even if they are irrelevant according to the regression, to explicitly demonstrate the observed coefficient. In ordinary least squares (OLS) models, for example, the inclusion of these predictors in the model does not affect the unbiasedness of the estimators but increase their variances. (Wooldridge, 2006) Statisticians, consequently, normally exclude these variables in order to improve the overall quality of the model in all linear models, by reducing variance and complexity of the model. In the process, some coefficients of important variables might change significance or even the sign. In this robustness test, the most irrelevant variable, considering their z value, will be removed one at a time, until we reach a reduced final model with all explanatory variables statistically different than zero. This model should have better quality than the original and this test will evaluate if the earlier results are robust to this approach.

The cases of the two models developed in this study are very different, because the Full Model presents few irrelevant variables. See Table 11 for the results of the tests. Regulatory quality, an explanatory variable earlier excluded from the models because it is excessively correlated to many control variables, is incorporated here, since many of these variables are removed during the exercise. The final reduced version has lower AIC than the original, indicating better quality, as expected. Important to notice that the indicator penalizes model complexity. All conclusions drawn from Full Model results remain valid using this method. The only substantial addition is that the Regulatory Quality indicator, that in the initial model was irrelevant, gains significance, with positive coefficient. The outcome suggests that regulations that promote efficiency, competition, financial freedom on non-financial sectors are also associated with development of financial innovation.

Table 11: Results for the Full Model (F2) and New Model (N2) in the beginning and in the end of the exercise of removing irrelevant variables step by step. The final model has only significant coefficients.

Dependent variables	F2 - Start 2009-2019	F2 - Final 2009-2019	N2 - Start 2017-2019	N2 - Final 2017-2019
(Intercept)	-7.83***	-7.72***	-3.47*	-4.47***
Population	3.99E-09***	3.95E-09***	2.22E-09***	2.11E-09***
GDP per capita	-6.02E-07		1.20E-05*	
% of population under 26	0.09***	0.09***	0.01	
Bank Asset Concentration (top 3)	-0.02***	-0.02***	8.85E-03	
Digital skills among active population			-0.65***	-0.45***
Latest technology availability	-0.02		0.7**	1***
R&D expenditures			-3.69E-03	
Mobile subscriptions per hab.	0.01***	0.01***	-5.63E-03	
% of population using internet	0.07***	0.07***	9.88E-03	0.01**
General Regulatory Quality	0.27	0.31*	0.14	
Regulation Stringency	4.01***	3.86***	3.89***	3.89***
Legal framework's digital adaptability			0.23	
Exchange rate coefficient of variation	-0.08***	-0.09***	0.03	
Gross capital flow (% of GDP)	-3.09E-05		-1.36E-03**	-9.78E-04***
Nominal interest rate	-0.02		0.02	
Slope of nominal interest rate	0.08*	0.07*	-0.08	
Dummy Common law without sandbox			0.28	0.66**
Dummy Sandbox without common law			-0.06	
Dummy Sandbox and common law			1.32***	1.45***
Dummy US	1.49***	1.5***	1.87***	1.6***
Dummy CN	-1.26*	-1.27*	-0.28	
Number of observations	451	451	135	135
AIC	2823.7	2816.9	1004	997.63
2x Log-likelihood	-2789.68	-2790.892	-957.986	-975.633
Distribution	neg. binomial	neg. binomial	neg. binomial	neg. binomial

Significance levels: * < 5%, ** < 1% and *** < 0.1%.

The baseline New Model has many irrelevant variables, so this exercise is potentially transformative for it. The final result interpretation is, nevertheless, not very different than the one observed in the earlier sections. The first of the three main changes are in the GDP per capita coefficient that is not significant, in line with the Full Model. Moreover, the share of population using the internet is significant and positively associated with fintech activity. Finally, the dummy for Common Law countries with no sandbox gains significance. This result is evidence that the legal system might partially explain why only countries with this law system observed positive association between sandbox and fintech development. But the difference in the coefficients for Common Law countries with and without sandbox suggests that this regulatory approach is still important in this setting. According to the reduced New Model, countries with no sandbox like New Zealand, Ireland, India and United States (the last two before introduction of sandboxes) are associated with 93% higher fintech activity than the countries that adopts different law systems and also do not have sandbox. On the other hand, this number is 326% for Common Law countries with sandbox compared to countries that does not have any of these characteristics.

6.3.Distribution test

All models so far relied on the assumption that the distribution of the number of fintech funding events follows a negative binomial distribution. As demonstrated in the methodology section, this assumption can be disputed since other types of distribution are also utilized to model count data. Poisson is the most popular, but not adequate in this case because it does not cope with overdispersion. Quasi-Poisson, on the other hand, adjusts the variance to the higher dispersion observed in the data.

In Table 12, the two models present results for the Full Model regressions that have the same variables in both sides, changing only the distribution from negative binomial to quasi-Poisson. It is possible to evaluate the effect of the distribution choice in the coefficients and their significance. Each regression fits the data to a different distribution, what results in changes on the level of the coefficients. Their sign and significance nevertheless are not heavily affected by this process. None of the 14 variables change its significance result using 0.05 threshold. Three of them (Mobile subscriptions, Exchange rate volatility and China dummy) change result if 0.001 threshold is considered. The main conclusions of the negative binomial model are still valid if the quasi-Poisson regression is used. This is an indication that the model is robust in respect to the distribution.

Throughout this section, the robustness of the sample of countries, irrelevant variables approach, and the distribution assumption was tested. This exercise provided new insights about the results and how they can be interpreted to better understand the fintech phenomenon between 2009 and 2019.

Table 12: Results for Full Model (F2) using negative binomial and quasi-Poisson distributions.

Dependent variables	F2-NB 2009-2019	F2-QP 2009-2019
(Intercept)	-8.08***	-6.31***
Population	3.89E-09***	3.42E-09***
GDP per capita	1.09E-06	3.04E-06
% of population under 26	0.09***	0.06***
Bank Asset Concentration (top 3)	-0.02***	-0.02***
Latest technology availability	0.08	0.23
Mobile subscriptions per hab.	0.01***	6.33E-03*
% of population using internet	0.07***	0.06***
Regulation Stringency	3.98***	3.54***
Exchange rate coefficient of variation	-0.08***	-0.1**
Gross capital flow (% of GDP)	4.64E-04	2.04E-03
Nominal interest rate	-0.03	-0.05
Slope of nominal interest rate	0.08*	0.11*
Dummy US	1.48***	1.13***
Dummy CN	-1.26*	-1.36***
Number of observations	451	451
AIC	2823.4	NA
2 x Log-likelihood	-2791.386	NA
Distribution	neg. binomial	quasi-poisson

Significance levels: * < 5%, ** < 1% and *** < 0.1%.

7. Discussion and Conclusion

Financial technology is key to the development and future of financial markets. Although the fintech startups are still small compared to traditional banks in terms of market share, they are relevant in technological innovation and present solid growth. Increased efficiency and wider reach are the main benefits of the introduction of technological innovations in the financial services industries, but it might also increase systemic risk, as well as credit, operational and cyber risks. In this study, two empirical models examine the drivers of fintech startup funding growth and the results of new regulatory approaches.

The method utilized in the models has the advantage of indicating which aspects of the countries are more associated with the attractiveness of fintech from a public policy perspective. Policymakers can derive from these results some important learnings about how their decisions might impact the innovation incentive in the financial sector. Ultimately, this research might help to understand how policies can have positive or negative effect on financial innovation, with consequences on the effectiveness of the financial services, intermediation and the whole economy.

The results presented robust evidence that regulatory arbitrage is a relevant factor for the development of the fintech markets. More strict financial regulation is associated with higher funding amount to innovative companies in financial services, controlling for other effects. It is possible that in these environments, fintech companies have additional advantage of complying to fewer burdensome regulations. The unlevel playing field between regulated and unregulated activities also creates competition problems and can lead to increasing risks. Many regulatory agencies are adopting sandbox to promote innovation, while learning about novel business models and controlling the risks. The results indicate that the approach is associated with increasing attractiveness of fintech markets, possibly due to the innovation-friendly signal it represents. The positive result, however, is concentrated in developed countries that were pioneer in sandboxes and adopts common law. Other jurisdictions do not present significant evidence of effectiveness of sandbox in this goal.

The monetary policy decisions are found to have little significance in the development of this novel market. However, if only the developed economies are considered, the low policy-related interest rates that market the period after the 2008 financial crisis are related to fintech development. The macroeconomic environment of lower currency volatility, what is translated in reduced uncertainty, also have positive results for the attractiveness of fintech ventures. The development of financial markets, however, can offset the negative volatility effect, according to Jehan and Hamid (2017). In more recent years, the countries with very high gross capital flows are associated with less attractive fintech markets, possibly because the reliance on external inflows and outflows disrupt intermediation and leads to financial fragility. (Rey, 2015) The monetary policy can, therefore, have stronger impact in the evolution of financial innovation if it can improve currency stability, support financial system development or decrease vulnerability to global financial cycles.

Less competitive banking industries provide a more inducive environment to innovative fintech companies, according to the model. These financial markets might be less efficient and fintech is attracted by demand for better and more cost-effective services. Introduction of fintech startups is especially beneficial in these settings because of their potential to improve efficiency. Competition is not commonly translated into banking concentration. Banking asset concentration is associated with less fintech funding rounds in the whole post-financial crisis period, but this result vanished more recently.

About the hypothesis that younger generations of consumers tend to prefer modern solutions, the results of the model confirm that the countries with younger population are associated with more fintech activity, controlling for economic and technological factors. The availability of the most advanced technologies is increasingly important for countries to attract fintech ventures.

However, the study has some important limitations, that can be addressed in future research. First, the development of the fintech sector might make other indicators related to its size and importance available, different than the number of funding rounds. The service revenues, amount of money intermediated and the number of active users are examples that would provide supplementary insights.

Moreover, the emergence of the "TechFins" is a new trend in the fintech environment that is not covered in this methodology. These companies are generally already successful in technology and e-commerce sectors and are slowly entering the financial services market. Their quantity, variety and how they seek to leverage data gathered in their primary business can have profound effect in the financial sector. They typically start in the financial business with large pre-existing non-financial services customer bases, access to consumers and a data-based view of their customers' preferences and behaviors. These are substantial advantages if compared with fintech startups. (Zetzsche, et al., 2017B)

Finally, a more technical limitation of the methodology refers to the interpretation of the models. The regressions should be interpreted predictively, as associations, and allow comparisons between predictors and the explained variable. However, they do not imply causation between these variables, even though there is a one-year lag between them. If causal inference was possible, we could predict what would have happened to the number of fintech rounds as a result of a hypothesized "treatment" or intervention. For that, stricter assumptions are need. In the case of panel data, the literature often uses fixed effects regression to adjust for unobserved unit-specific and time-specific confounders at the same time or separately. Unfortunately, the use of these models also relies on modelling assumptions. (Imai and Kim, 2020) Most importantly, the ability of fixed effects regression models to adjust for unobserved time-invariant confounders comes at the expense of dynamic causal relationships, that are not incorporated in this model. (Imai and Kim, 2016) That is especially problematic in a model that predicts countries' behavior, since they are constantly changing their policies and other important factors. Testing the consequence of the introduction of a regulatory sandbox, for example, with a robust methodology that allows causal inference is a challenge for future studies.

8. References

Arner, Douglas W. and Barberis, Janos Nathan and Buckley, Ross P. (2015). The Evolution of Fintech: A New Post-Crisis Paradigm?, University of Hong Kong Faculty of Law Research Paper No. 2015/047; UNSW Law Research Paper No. 2016-62.

Bellavitis, Cristiano (2016). Do Interest Rates Affect Venture Capital Investments?, Academy of Management Proceedings. Vol. 2016. No. 1.

Bernoth, Kerstin, et al. (2017). Monetary Policy Implications of Financial Innovation, DIW Berlin: Politikberatung kompakt 120.

BIS (2017A). FinTech credit: Market structure, business models and financial stability implications, May 22, https://www.bis.org/publ/cgfs_fsb1.pdf.

BIS (2017B). Sound Practices: Implications of fintech developments for banks and bank supervisors, 31 October, https://www.bis.org/bcbs/publ/d415.pdf.

Brei, Michael, et al. (2020). Bank intermediation when interest rates are very low for long, https://voxeu.org/article/bank-intermediation-when-interest-rates-are-very-low-long.

Buckley, Ross P., et al. (2019). "Building FinTech Ecosystems: Regulatory Sandboxes, Innovation Hubs and Beyond." UNSW Law Research Paper 19-72.

Claessens, Stijn, et al (2018). Fintech credit markets around the world: size, drivers and policy issues, BIS Quarterly Review September.

Crunchbase (2020). Glossary of Funding Types, https://support.crunchbase.com/hc/en-us/articles/115010458467-Glossary-of-Funding-Types.

Dapp, Thomas, et al (2014). Fintech—The digital (r) evolution in the financial sector, Deutsche Bank Research, Frankfurt am Main.

di Castri, Simone, and Plaitakis, Ariadne (2018). Going beyond regulatory sandboxes to enable FinTech innovation in emerging markets." Available at SSRN 3059309.

European Commission (2019). 30 Recommendations on Regulation, Innovation and Finance - Final Report to the European Commission, December, https://ec.europa.eu/info/sites/info/files/business_economy_euro/banking_and_finance/documents/191113-report-expert-group-regulatory-obstacles- financial-innovation_en.pdf.

González-Páramo, José Manuel (2017). Financial innovation in the digital age: Challenges for regulation and supervision, Revista de estabilidad financiera 32.9.

Haddad, Christian and Hornuf, Lars (2019). The emergence of the global fintech market: Economic and technological determinants, Small Business Economics 53.1 (2019): 81-105.

He et al (2017). Fintech and Financial Services: Initial Considerations. IMF Discussion Note, SDN/17/05

IMF (2019). FinTech: The Experience so Far, June 27, Policy Paper No. 19/024.

Imai, Kosuke, and In Song Kim (2020). On the use of two-way fixed effects regression models for causal inference with panel data. Harvard University IQSS Working Paper). Cambridge, MA. Retrieved from https://imai. fas. harvard. edu/research/twoway. html

Imai, Kosuke, and In Song Kim (2016). When should we use unit fixed effects regression models for causal inference with longitudinal data? American Journal of Political Science 63.2 (2019): 467-490.

Jehan, Zainab and Hamid, Azooba (2017). Exchange rate volatility and capital inflows: role of financial development, Portuguese Economic Journal 16.3: pp. 189-203.

Kasiyanto (2017). Implementing a Regulatory Sandbox under Civil Law System: A Breakthrough or Disaster?, https://essl.leeds.ac.uk/law/events/event/202/implementing-a-regulatory-sandbox-under-civil-law-system-a-breakthrough-or-disaster.

Lagarde, Christine (2018). "Central banking and fintech: A brave new world." Innovations: Technology, Governance, Globalization12.1-2: 4-8

Lee, In, and Yong Jae Shin. (2018). Fintech: Ecosystem, business models, investment decisions, and challenges, Business Horizons

McCullagh, P. and Nelder, J. A. (1989). An outline of generalized linear models, Generalized Linear Models, Springer US, pp. 21–47.

MNB (2017). Innovation and Stability Overview of Fintech in Hungary, December, https://www.mnb.hu/letoltes/consultation-document.pdf.

Montiel, Peter J (2003). Macroeconomics in Emerging Markets, Cambridge University Press, p. 360.

Navaretti, Giorgio Barba, et al (2018). "Fintech and Banking. Friends or Foes?." Friends or Foes.

Neumayer, E., and Plümper, T (2017). Robustness tests for quantitative research. Cambridge University Press.

Ofgem (2018). What is a regulatory sandbox?, September 7th, https://www.ofgem.gov.uk/publications-and-updates/what-regulatory-sandbox.

Philippon, Thomas (2016). The fintech opportunity. No. w22476. National Bureau of Economic Research.

Puschmann, T. (2017). Fintech. Bus Inf Syst Eng 59, https://doi.org/10.1007/s12599-017-0464-6.

Rey, Hélène. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence., No. w21162. National Bureau of Economic Research.

Sironi, Paolo. (2016). FinTech innovation: from robo-advisors to goal based investing and gamification., John Wiley & Sons.

Statistical Consulting, Institute for Digital Research & Education, The University of California, Los Angeles, Negative Binomial Regression | Stata Annotated Output, https://stats.idre.ucla.edu/stata/output/negative-binomial-regression/.

VanderLinden, Sabine LB, et al (2018). The Insurtech Book: The Insurance Technology Handbook for Investors, Entrepreneurs and FinTech Visionaries. John Wiley & Sons.

Ver Hoef, Jay M., and Peter L. Boveng (2007). Quasi-Poisson vs. negative binomial regression: how should we model overdispersed count data?, Ecology.

Woodward, Susan E. (2019). The American Role in European Venture Capital. Available at SSRN 3320838.

Wooldridge, Jeffrey (2006). Introductory Econometrics: A Modern Approach.

World Bank (2016A). Key Terms Explained: Banking competition https://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/banking-competition.

World Bank (2016B). Key Features of Common Law or Civil Law Systems, https://ppp.worldbank.org/public-private-partnership/legislation-regulation/framework-assessment/legal-systems/common-vs-civil-law.

World Economic Forum (2019). The Global Competitiveness Report, http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf.

Zetzsche, Dirk A., et al. (2017A). Regulating a revolution: From regulatory sandboxes to smart regulation. Fordham J. Corp. & Fin. L.

Zetzsche, Dirk A., et al. (2017B). From FinTech to TechFin: The regulatory challenges of data-driven finance." NYUJL & Bus.14: 393.

Appendix

A: Fintech funding events and distribution in countries and regions

Figure A1: Evolution of the number of funding deals per country/region

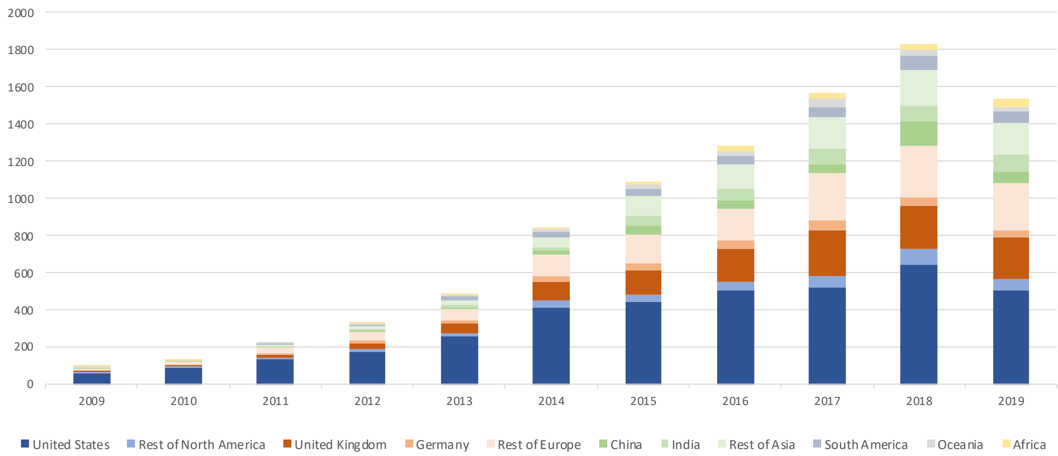


Figure A2: Evolution of the total money raised in funding events (USD millions) per country/region

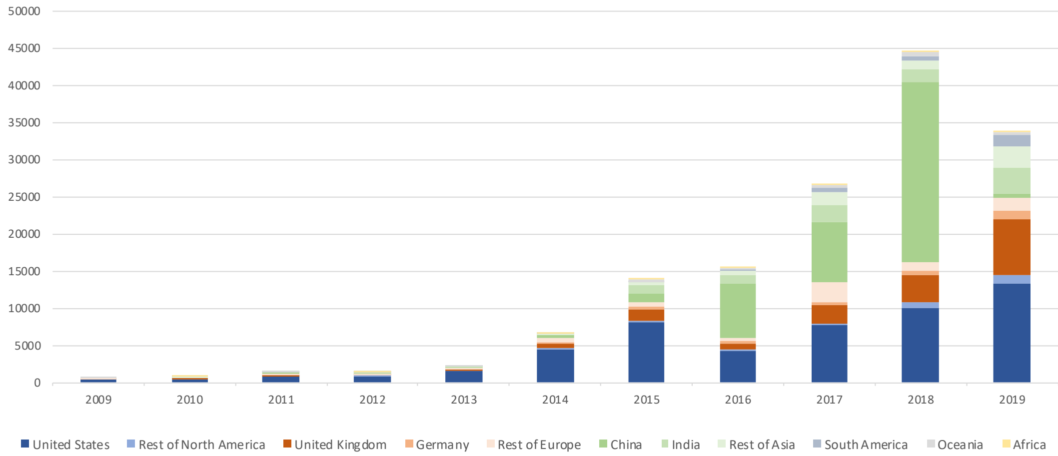
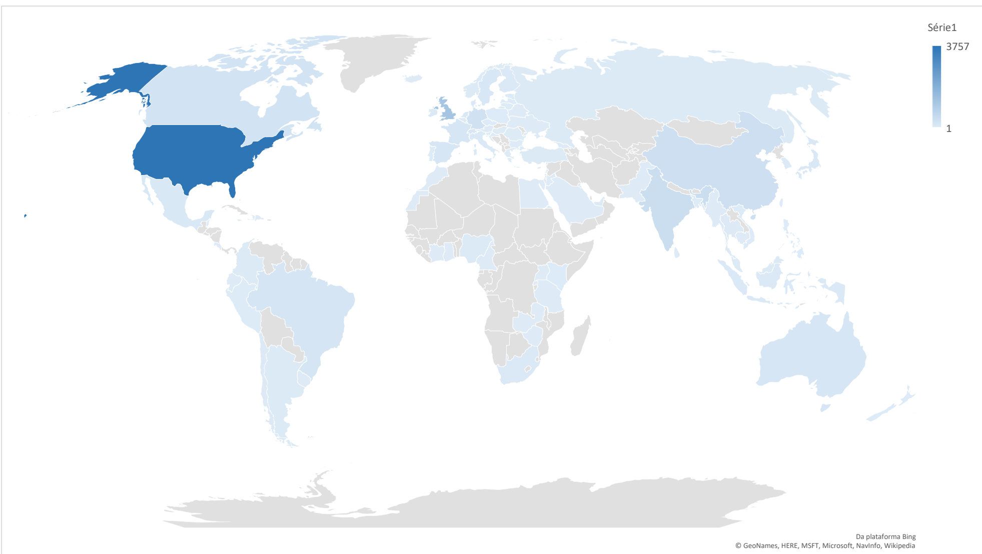


Figure A3: Distribution of fintech funding deals in the world (2009-2019)



Source: Crunchbase

B: Data on fintech funding events and fintech companies between 2009 and 2019. Source: Crunchbase

Table B1: Countries in the model by number of funding rounds

Country	*Deals 2009-19*	*%*	*Years w/ deals*	*Country*	*Deals 2009-19*	*%*	*Years w/ deals*
United States	3757	39.9%	11	Colombia	47	0.5%	9
United Kingdom	1224	13.0%	11	Turkey	45	0.5%	10
India	430	4.6%	11	United Arab Emirates*	44	0.5%	6
China	374	4.0%	11	Nigeria***	43	0.5%	8
Germany	290	3.1%	9	Argentina	42	0.4%	8
Singapore	269	2.9%	11	Estonia	42	0.4%	6
Canada	258	2.7%	11	Norway	42	0.4%	7
Brazil	197	2.1%	10	Russian Federation	41	0.4%	9
Spain	174	1.8%	11	Malaysia	35	0.4%	7
France	157	1.7%	11	Belgium	32	0.3%	8
Australia	156	1.7%	10	Austria	32	0.3%	8
Sweden	143	1.5%	11	Chile	31	0.3%	10
Switzerland	141	1.5%	11	Thailand	30	0.3%	6
Hong Kong*	111	1.2%	9	New Zealand	27	0.3%	9
Mexico	110	1.2%	11	Poland	24	0.3%	6
Israel	101	1.1%	9	Czech Republic	24	0.3%	7
Japan	82	0.9%	8	Philippines	23	0.2%	6
Netherlands	82	0.9%	10	Kenya	21	0.2%	7
Ireland	77	0.8%	8	Lithuania**	13	0.1%	4
Italy	72	0.8%	10	Romania**	13	0.1%	5
South Africa	67	0.7%	7	Hungary**	13	0.1%	3
Finland	58	0.6%	10	Malta**	12	0.1%	5
Denmark	57	0.6%	8	Bangladesh**	12	0.1%	4
Indonesia	55	0.6%	6	Luxembourg**	11	0.1%	4
South Korea	54	0.6%	8	Others	225	2.4%	-
				Total	**9420**	**100%**	

* Countries excluded due to lack of macroeconomic data
** Countries included only in New Model
*** Country included in the Full Model, but excluded from the New Model because of lack of data

Table B2: Fintech categories, technologies and segments between 2009 and 2019.

	Number of Companies	***%***	***Number of Deals***	***%***	***Money raised (USD M)***	***%***
Category						
Payments	654	16.2%	1783	18.8%	47.714	32.3%
Credit	389	9.6%	1276	13.5%	32.721	22.1%
Insurance	230	5.7%	546	5.8%	7.587	5.1%
Wealth Management	161	4.0%	367	3.9%	27.267	18.4%
Crowdfunding	145	3.6%	365	3.9%	2.633	1.8%
Accounting	78	1.9%	222	2.3%	1.787	1.2%
Risk Management	77	1.9%	212	2.2%	2.496	1.7%
Technology						
Mobile	485	12.0%	1315	13.9%	16.795	11.4%
Blockchain	348	8.6%	708	7.5%	5.171	3.5%
Cryptocurrency	256	6.3%	510	5.4%	5.481	3.7%
Artificial Intelligence	185	4.6%	400	4.2%	2.959	2.0%
Big Data	147	3.6%	398	4.2%	3.396	2.3%
Machine Learning	98	2.4%	222	2.3%	1.848	1.2%
Segment						
Personal Finance	235	5.8%	659	7.0%	13.965	9.4%
E-Commerce	206	5.1%	531	5.6%	28.430	19.2%
Consumer	141	3.5%	467	4.9%	8.482	5.7%
Small and Medium Businesses	96	2.4%	291	3.1%	3.131	2.1%

Table B3: Fintech funding rounds by type (2009-19)

Funding Type	*Number of Deals*	*%*	*Money raised (USD M)*	*%*
Angel	457	4.8%	353	0.2%
Pre-Seed	474	5.0%	141	0.1%
Seed	3207	33.9%	2975	2.0%
Venture - Earlier stages	1803	19.0%	1803	22.2%
Venture - Later stages	494	5.2%	494	31.4%
Venture - Series Unknown	1165	12.3%	12634	8.5%
Equity Crowdfunding	190	2.0%	300	0.2%
Product Crowdfunding	11	0.1%	10	0.0%
Private Equity	144	1.5%	7569	5.1%
Convertible Note	242	2.6%	198	0.1%
Debt Financing	442	4.7%	29582	20.0%
Secondary Market	45	0.5%	1591	1.1%
Grant	214	2.3%	299	0.2%
Corporate Round	76	0.8%	1353	0.9%
Initial Coin Offering	87	0.9%	3096	2.1%
Post-IPO Equity	64	0.7%	3838	2.6%
Post-IPO Debt	19	0.2%	2773	1.9%
Non-equity Assistance	167	1.8%	13	0.0%
Funding Round	170	1.8%	1884	1.3%

C: Interpreting negative binomial regression coefficient as incidence rate ratio

A rate is defined as the number of events per time (or space). Count variables are technically rates, in most cases.

Furthermore, negative binomial regression coefficients are interpreted as the difference between the log of expected counts. Formally, this relation can be written:

$$\beta = \ln\left(\mu_{x_0+1}\right) - \ln\left(\mu_{x_0}\right)$$

Where β is the coefficient of the regression, μ_{x_0} is the response count variable, μ_{x_0+1} is the response variable in case the predictor variable changes by one unit.

From this definition, it is possible to calculate:

$$\beta = \ln\left(\frac{\mu_{x_0+1}}{\mu_{x_0}}\right)$$

$$IRR = e^{\beta} = e^{\ln\left(\frac{\mu_{x_0+1}}{\mu_{x_0}}\right)} = \frac{\mu_{x_0+1}}{\mu_{x_0}}$$

Where IRR is the Incidence Rate Ratio.

Therefore, the model coefficient (with one adaptation) can be interpreted as the incidence rate ratio. This number indicates the expected response variable relative change in case the respective predictor variable increases by one unit and the other predictor variables are unchanged. (Statistical Consulting)

D: Details and sources of the models' variables.

Panel A	
Population	Population of the country. Source: Global Financial Development database
GDP per capita	GDP per capita. Source: Global Financial Development database
% of population under 26	Percentage of population that is under 26 years old. Source: Calculated based on data from Global Financial Development database
Bank Asset Concentration (top 3)	Assets of three largest commercial banks as a share of total commercial banking assets. Source: Global Financial Development database
Bank Competition Lerner Index	A measure of market power in the banking market. It is defined as the difference between output prices and marginal costs (relative to prices). Prices are calculated as total bank revenue over assets, whereas marginal costs are obtained from an estimated translog cost function with respect to output. Higher values of the Lerner index indicate less bank competition. A 2-year average was used. Source: Global Financial Development database
Latest technology availability	Constructed from responses to the survey question from the Global Competitiveness Report Executive Opinion Survey: "In your country, to what extent are the latest technologies available?" (1 = not available at all, 7 = widely available). Source: WEF - Global Information Technology Report dataset
Mobile subscriptions per hab.	Number of mobile cellular subscriptions per individual. A 5-year average was used. Source: International Telecommunication Union, World Telecommunication/ICT Development Report and database
% of population using internet	Percentage of the individuals in the country using the Internet. Source: International Telecommunication Union, World Telecommunication/ICT Development Report and database
Regulation Stringency	Regulatory stringency is an index based on the World Bank's Bank Regulation and Supervision Survey. The index is normalized between 0 (least stringent) and 1 (most stringent) based on 18 questions about bank capital requirements, the legal powers of supervisory agencies, etc. (Claessens et al, 2018) Constructed originally by Navaretti et al. (2017).

General regulatory quality	Regulatory Quality is part of the Worldwide Governance Indicators (WGI) project and captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. The aggregate indicators combine the views of a large number of enterprises, citizen and expert survey respondents in industrial and developing countries. The sources focus on aspects of efficiency of competition, financial freedom, excessive bureaucracy and do not include the financial sector specific regulations. Source: Worldwide Governance Indicators
Exchange rate coefficient of variation	Coefficient of variation of the daily exchange rate of the currency against the USD throughout one year. For the United States, the USD variation agaoinst the USDX was used. USDX is US Dollar Index, measure of the value of the dollar against a basket of six world currencies. The six currencies are the euro, Swiss Franc, Japanese Yen, Canadian dollar, British pound, and Swedish Krona. Sources: BIS (Bank of International Settlements). For USDX, Nigeria, Kenya and Bangladesh, Yahoo Finance.
Gross capital flow (% of GDP)	A gross measure that sums both assets and liabilities of the countries' balance of payments calculated based on Rey (2015). Accounts considered were the entire Capital Account, Financial Derivatives (Other Than Reserves) and Employee Stock Options, Portfolio Investment, Reserve Assets, Direct Investment and Other Investment. Nominal values were divided by the GDP. Source of Balance of Payments: IMF
Nominal interest rate	Annual average of the monetary policy related interest rate (percent per year) Sources: BIS and IMF
Slope of nominal interest rate	Difference between the average nominal interest rates in one year and one year earlier. Sources: BIS and IMF
Dummies US and China	Country dummy variables. Based on Claessens et al., 2018
Panel B	
Digital skills among active population	Response to the survey question "In your country, to what extent does the active population possess sufficient digital skills (e.g. computer skills, basic coding, digital reading)?" [1 = not all; 7 = to a great extent] Source: World Economic Forum, Executive Opinion Survey (various editions).

R&D expenditures	Expenditures for research and development are current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge—including knowledge of humanity, culture and society—and the use of knowledge for new applications. R&D covers basic research, applied research and experimental development. Expressed as a percentage of GDP. Source: World Bank, World Development Indicators database
Legal framework's digital adaptability	Response to the survey question “In your country, how fast is the legal framework of your country adapting to digital business models (e.g. e-commerce, sharing economy, fintech, etc.)?” [1 = not fast at all; 7 = very fast] Source: World Economic Forum, Executive Opinion Survey
Dummy Sandbox	Dummy variable that indicates if the country has implemented or proposed the introduction of a regulatory sandbox by the beginning of the year. Source: Buckley et al. (2019)
Dummy Common law without sandbox	Dummy variable that indicates if the country adopts a common law system and didn't implemented or proposed the introduction of a regulatory sandbox by the beginning of the year. Source: Buckley et al. (2019) and CIA
Dummy Sandbox without common law	Dummy variable that indicates if the country adopts a different law system and has implemented or proposed the introduction of a regulatory sandbox by the beginning of the year. Source: Buckley et al. (2019) and CIA
Dummy Sandbox and common law	Dummy variable that indicates if the country adopts a common law system and has implemented or proposed the introduction of a regulatory sandbox by the beginning of the year. Source: Buckley et al. (2019) and CIA
Dummy New sandbox	Dummy variable that indicates if the country has first implemented or proposed the introduction of a regulatory sandbox less than two years previously. Source: Buckley et al. (2019)
Dummy Old sandbox	Dummy variable that indicates if the country has first implemented or proposed the introduction of a regulatory sandbox more than two years previously. Source: Buckley et al. (2019)

E: Evolution of technology variables

Figure E1: Evolution of number of individuals using the internet and mobile subscriptions for a group of 1000 people in advanced economies and emerging markets