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FinTech Megatrends: An Assessment of Their Industrial and Welfare Implications

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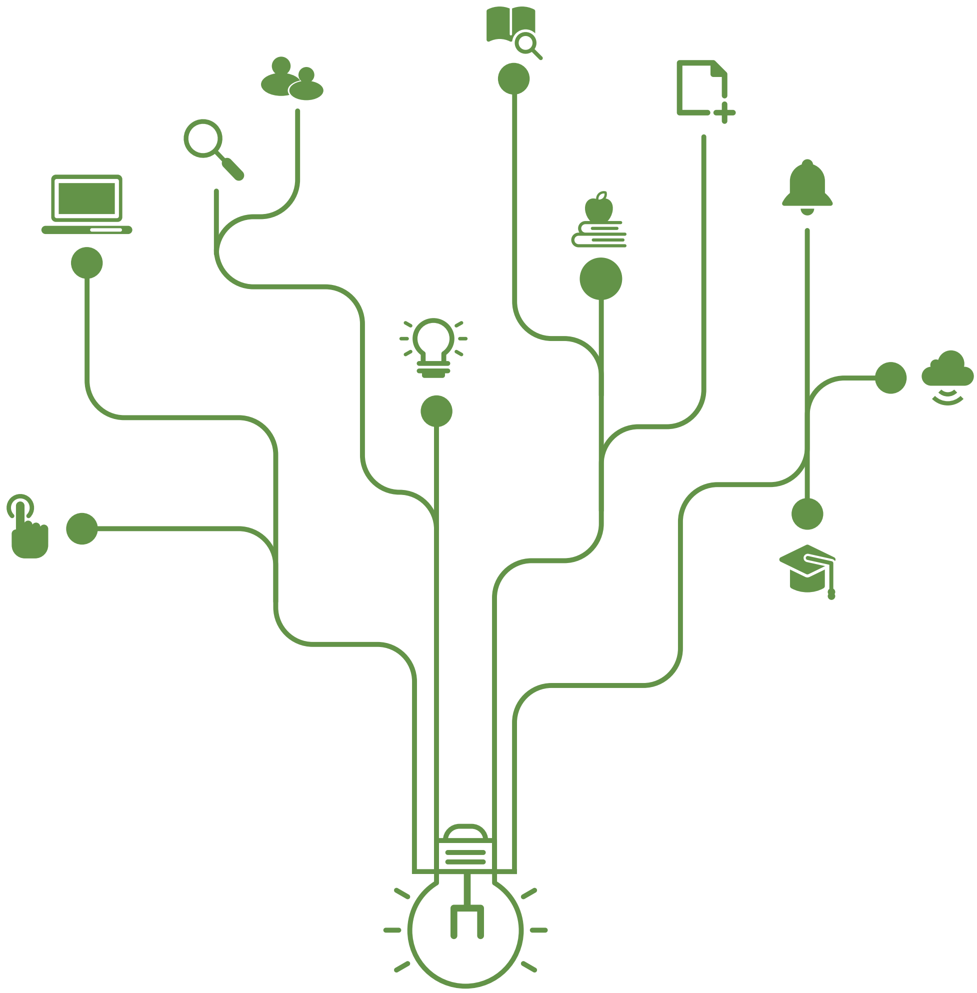

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FinTech Megatrends:

An Assessment of Their Industrial and Welfare Implications

Abstract

This study aims to assess the industrial and welfare implications of FinTech as documented in the literature, by focusing on its four subsectors - online capital-raising platforms, alternative payment systems, AI and robot based investment consultancy, and alternative regulatory compliance service. Key findings obtained include: thanks to the advancement in the technologies of relevancy since the 1990s, the FinTech service providers have greatly enhanced both efficiency of financial intermediation and extent of financial inclusion in the developed as well as developing countries; these alternative financial service providers tend to narrow credit gap caused by information asymmetry between borrower and lender by collecting and utilizing soft data for ex ante credit evaluation; however, some concerns are also raised as to the likelihood of over-leverage by certain segments of P2P platform borrowers, the lack of appropriate skin-in-the-game arrangement in sharing ex post credit losses, and the inadequate consumer protection measures in the face of the heightened cyber-security risk. Based on these findings, an assessment is made as to whether or not the sector is capable of instituting a full-blown risk-based, or marginal-cost, pricing for embedded credit risk. In addition, one particular segment of the FinTech service providers, those affiliated with BigTech companies, is examined in terms of its potential contribution to social welfare not only through posing a heightened competition and contestability to existing financial institutions but also through innovation- and information-sharing among firms within their ecosystems. Included as the main contents in the study are trends and institutional characteristics of the four FinTech sub-sectors, financial theories of relevancy, the FinTech's welfare implications, and the regulatory issues to be considered for the sector.

Keywords: Financial innovation, FinTech (Financial Technology), BigTech, Market Place Lending, crowdfunding, AI and robo-advisor, RegTech

1 Introduction

The traditional branch-based banking is under attack, as non-banking firms of various kind have been expanding their financial services backed by innovative technologies and digital data in the recent years. As cases in point, the size of the online capital-raising services in the world, i.e., P2P lending and crowdfunding, increased from \$11.7 billion in 2013 to \$301.7 billion in 2018, a 25-fold growth within five years. (Cambridge Center for Alternative Finance, CCAF (2020a)) In addition, the alternative payment and settlement mechanisms (alternative to fiat money) such as mobile payment platforms and cryptocurrencies are rapidly spreading across the globe, as evidenced by the fact that the mobile payment volume in China reaches to 16 percent of GDP in 2018. (Frost et al. (2019)) And similar phases of rapid expansion in other alternative financial services are also observed in the investment consultancy (via robo-advisors) and the regulatory compliance (via RegTech). The growth of these innovative, and also disruptive, financial services enabled by Information and Communication Technologies (ICTs) and alternative data, generally referred to as FinTech (Financial Technology), is expected to continue in coming years given the on-going advancement in underlying technologies and data analytics.

The sector is highly diverse and evolving. To illustrate, the supply-side of FinTech includes firms in varying types and sizes, e.g., start-ups, SMEs, and BigTechs, that involve with the related businesses of internet and mobile platform operation, technology and infrastructure development, and data processing and analyses. The funding sources, or investors, include both individuals (or households) and institutions (e.g., banks, pension funds, mutual funds, and family offices), the shares of which also vary widely across countries and geographical areas: for example, while the share of the institutions in the total P2P lending and crowdfunding in the U.S. amounts to 88%, it is much lower in others (50% in UK, 49% in Latin America, 41% in Europe (ex. UK), 36% in Asia Pacific (ex. China), and 19% in Africa). (CCAF (2020a)) In terms of the use of funding, the non-collateralized lending to consumers and small businesses takes a majority share in most countries, but more diverse uses are observed and expanding in the countries like UK, e.g., debt- and equity-financing for property acquisition, mini-bond issuance, pension-led funding, invoice trading, microfinance, and community project funding. Given this backdrop, this study aims to assess the industrial and welfare implications of FinTech as documented by the literature to date, by focusing on four particular subsectors: (1) online capital-raising services (P2P lending and crowdfunding of various types); (2) alternative payment services (mobile platform based payment systems and cryptocurrencies); (3) alternative financial advisory services (via robo-advisor); and, (4) alternative regulatory compliance services (via RegTech).

The current study documents several key findings. First, thanks to the internet and mobile technologies developed during the last three decades, the FinTech service providers have greatly enhanced both efficiency of financial intermediation and extent of financial inclusion in the developed as well as developing countries. Examples of this type of welfare gain are shown in the P2P lending and crowdfunding of various types, the mobile-app based payment services, as well as the AI-robot based investment advisory services. The main mechanism of the efficiency gain by the sector is through a reduction in transaction cost for their service delivery vis-à-vis the traditional branch-based financial institutions, with a much cheaper, faster, and more convenient intermediation based on an internet or mobile platform. (IMF (2017), Buchak et al. (2017), Fuster et al. (2018), Frost et al. (2019), Jagtiani and Lemieux (2019), OECD (2019), FSB (2019)). However, for some borrowers, the FinTech platform lending is shown to lead to over-leverage: that is, while consumers use the borrowed funds to consolidate their credit card debts, which reduces the card balances and improves their credit scores right after the funding; but, after several quarters, the platform-based borrowers tend to receive additional credit from their existing bank or credit card relationships, resulting in a higher aggregate indebtedness and a significant increase in ex post credit card defaults. (Green and Sharfstein (2013), Chava and Paradkar (2018), and DiMaggio and Yao (2018)) In an aggregate level, it is also shown that the sector can work as a destabilizer in the financial market with a pronounced credit cycle, as evidenced by the P2P lending crisis in China: namely, close to 3,000 platforms were closed or inoperable (out of about 5,000) since 2014; and, consequently, the total funding volume to the sector dropped by about 40% between 2017 and 2018. (CCAF (2020a))

As to the financial inclusion, the FinTech service providers are shown to "bottom-fish" in the scale of creditworthiness: that is, serving those borrower segments or geographical areas that are left out by existing financial institutions due to low credit scores or no/insufficient credit history (so-called "thin filers"). As an empirical evidence, ceteris paribus, the P2P lenders in the U.S. tend to serve those borrowers with low credit scores or thin filers more, and their lending activities penetrate those areas with fewer bank branches per capita, as well as those where the local economy is not performing well. (Jagtiani and Lemieux (2018) and De Roure et al. (2108)) And, in a viewpoint of developing countries, the FinTech industry tends to fill the gap left out by the formal financial service sectors in those countries, by leap-frogging the conventional financial service mediums (e.g., checking and savings account, insurance contract, investment account, and credit card) and by offering the payment and other services to a large number of consumers who were underserved due to the non-existing, or minimal, financial intermediation by the formal sector. (Aker and Mbiti (2010), Mbiti and Weil (2011), Jack and Suri (2013), CitiGroup (2018), Gathoto (2018))

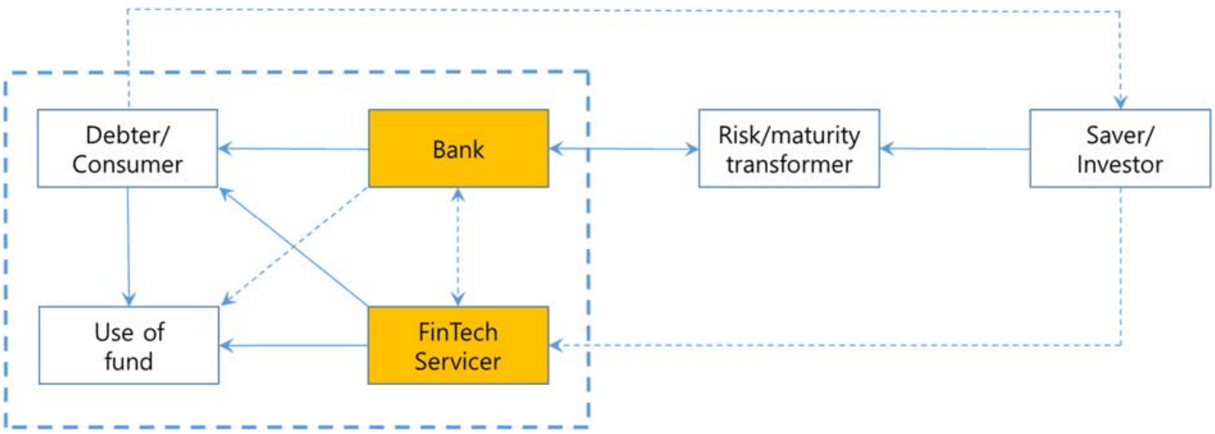
As to information asymmetry between borrower and lender, the finance literature has long been arguing that using "soft data" about credit quality of borrowers, those that go beyond conventional credit scores and standard ratios, is critical in reducing the credit gap caused by the asymmetry and in deriving successful lending outcomes. (Fama (1985), Granovetter (1985), Petersen and Rajan (1994), Uzzi (1999), Agarwal and Hauswald (2007), Petersen and Rajan (2002)) The FinTech service providers are shown to be doing that, by collecting and utilizing various types of soft data for ex ante credit evaluation for financial consumers, such as social or friend network (within a particular peer/customer network), digital footprint (online shopping and other consumer behavior data), location of borrower, and indicators of trustworthiness. And, as it turns out, doing so helps grasp a fuller and more real-time picture about consumers' financial lives and their creditworthiness and, accordingly, significantly enhances the accuracy of the default incidence (or probability of default) model. (Lin et al. (2013), Iyer et al. (2016), Puri et al. (2017), Hildebrand et al. (2017), and Freedman and Jin (2017), Berg et al. (2018)) As another trend to note, the FinTech service providers are increasingly transitioning from platform servicers to credit intermediaries (i.e., those to whom the function of credit evaluation is being delegated) and, in that juncture, a question is raised in this study as to whether or not they are properly suited for a full-blown credit risk management, not just for a risk-based rank-ordering (or segmentation) of financial consumers but also for a risk-based (or marginal-cost) pricing as well. Furthermore, it is unclear whether they have enough stake, or skin-in-the-game, in sharing ex post credit losses borne by their intermediation activities.

Those FinTech service providers affiliated with BigTech firms take a special position in the sector. BigTechs represent the large technology-enabled online companies whose primary businesses are not finance, e.g., various internet and mobile service providers (Google, Amazon, Microsoft, and Baidu), e-commerce service providers (Alibaba), mobile phone manufacturers and service providers (Apple, Samsung, Vodafone, KT – Korea Telecomm, and Mercado Libre), and SNS service providers (Facebook, Tencent, and Kakao). The BigTech-affiliated financial services are spreading rapidly across the globe, which blurs the traditional divisions among different industries, in particular, between banking and commerce. One common characteristic of these BigTech-driven ecosystems is the fact that they offer a mobile payment service and use that as an inlet for collecting diverse data on consumer behavior, which are subsequently used for consumer profiling, product differentiation, as well as risk management. (Citi GPS (2018)) In so doing, innovations introduced by one company within the group can be shared with others in the ecosystem, which makes it possible to provide upgraded financial and non-financial services to consumers, often in a non-rivalrous fashion with zero marginal cost. As a supporting evidence, Frost et al. (2019) shows that the credit scoring systems developed by two BigTech-affiliated firms, Mercado Libre in Brazil and Ant Financial in China, are assessed to be superior to those developed by the traditional credit bureaus, and that those credit risk indicators are widely used for various online as well as offline businesses by the firms within their groups.

In a broader sense, those BigTech-affiliated financial service providers can contribute to macroeconomy in two main ways: first, by imposing competition and contestability to existing financial institutions, and by increasing factor productivities of the firms within a BigTech-driven innovation ecosystem. To the former point, Philippon (2015) demonstrates empirically that the financial service sector in the U.S. has been "too expensive," i.e., having enjoyed the excessive yields that consistently and unjustifiably exceeded its long term equilibrium level since the early 1980s, due in large part to the increased market power of, and the resulting rent enjoyed by, the existing large financial institutions. And the author also argues that their entrenched interests and subsidies, both implicit and explicit, can be reduced by a bottom-up reform derived from more innovative and efficient services from the FinTech sector. As to the productivity gain, the BigTechs' entry to the financial service sector disrupts the existing division between finance and commerce, and those firms within a BigTech ecosystem can share information and innovation for product development and service delivery through their collective customer networks. These emerging BigTech effects make it necessary for policy makers to re-think the traditional man-made divisions across different industries, for the purpose of maximizing their positive external effects on sustainable consumption and production growth.

As to its societal role, Shiller (2012) defines finance as a functional science of goal architecture, i.e., enabling households, firms, and governments to achieve their intended goals and, in so doing, managing embedded financial risks and delivering actuarially-fair risk-adjusted returns to investors. While many would agree with this general definition, the actual form of financial intermediation has evolved over time. For example, for a long while, a narrow banking used to be the typical mode of financial intermediation in the U.S., in which intermediaries invested in assets that had little or low credit and interest rate risk (usually with short maturities) by issuing demandable liabilities. (Pennachi (2012)) During the last several decades, however, various maturity and risk transformation facilities have been introduced, e.g., asset securitization, options and futures, and other derivative products (as illustrated in Figure 1), which often worked as a destabilizer in the financial markets as demonstrated by the recent financial crisis. However, at the same time, this extended banking model yields a positive outcome as well in that it helps make financial services more accessible and affordable for marginal borrowers who were either un-served or under-served before. Given this backdrop, several welfare implications of the FinTech industry are discussed in the following.

Figure 1. Traditional & FinTech-based Financial Intermediation



First, as it appears, FinTech is revolutionizing the delivery of financial services to demanders, thanks to two critical ingredients – technology and digital data. As depicted in Figure 1, this new breed of financial service providers essentially combine financial services with various on- and off-line transactions, making one-stop shopping for financial consumers possible (the phenomenon often termed as “a bank in your pocket”). In the supply-side, the FinTech service providers can collect various alternative data on consumer behavior through their platforms, and can utilize those data in developing and delivering more tailor-made, and possibly more welfare-enhancing, financial products. One can view this phenomenon as a continued innovation from the internet revolution from the 1990s when numerous B2B and B2C platforms were developed and used as data collection channels. In the new millennium, however, that trend has been accelerating with the introduction of smartphone and other related technologies (e.g., AI, IoT, Cloud, Big Data, Block Chain). In an analytical sense, the growing volume of literature on the multi-sided platform based industries (e.g., Rochet and Tirole (2003) and (2006), Schmalensee (2005) and (2011), and Evans and Schmalensee (2018)) is likely to serve as a base for future research on examining various micro aspects of, and optimal business strategy for, this technology and data driven financial service sector.

Second, one can pose a question as to whether or not the FinTech service providers, the online capital-raising platforms in particular, are properly suited to perform the delegated credit risk management function. The short answer is both yes and no. For one aspect, the industry has demonstrated that it can enhance the risk-based segmentation of financial consumers by utilizing soft data. Nevertheless, it is far uncertain if the FinTech service providers are better positioned than other market participants for implementing a full-blown credit risk management, i.e., not only doing a segmentation specific risk-based rank-ordering but also instituting a risk-based pricing via computing and charging actuarially-fair risk premia for those defined risk buckets. In a sense, the sector is has not yet been tested with a real stress event and, hence, it is uncertain how sustainable this new breed of financial intermediaries would be if and when such event arrives (maybe the on-going COVID19 crisis poses such an event). Here again, there appears to be a series of research issues that should be pursued by research community going forward, e.g., on the role of soft data in a broad context of risk management, on sound measurement framework to combine product- or consumer-driven (idiosyncratic) risk factors with market-driven (systematic) risk drivers in implementing a full-blown risk-based pricing system, and on efficient risk-sharing arrangements between the industry along with public and private market participants.

Third, how to ensure a leveled playing field between the FinTech industry and the existing FIs represents an important public policy issue to ponder in coming years. In a broad sense, the industry should be properly supervised to make sure financial safety and soundness of the intermediaries involved as well as fair and ethical treatment of financial consumers by their employees, while, at the same time, external effects of innovations from the industry along with the efficiency gain in their intermediation should also be promoted and maximized. Although designing a policy regime in this vein will have to reflect various country-specific market and institutional conditions, one can consider several ground rules, such as: targeting those high-risk FinTech sub-sectors first (e.g., equity-crowdfunding) in instituting similar measures of financial supervision to those applied to existing FIs; nurturing innovations and entrepreneurship to maximize their spillover effects via such enabling mechanisms as regulatory sandbox, and other support instruments for start-ups and SMEs; and, fostering the BigTech-driven agglomeration effects by re-considering the conventional and man-made divisions of industries involved. To this end, a national FinTech policy would be warranted, for which the one employed by UK since 2015 can serve as a benchmark.[1]

The rest of this manuscript consists of the following five sections: scoping the FinTech industry by

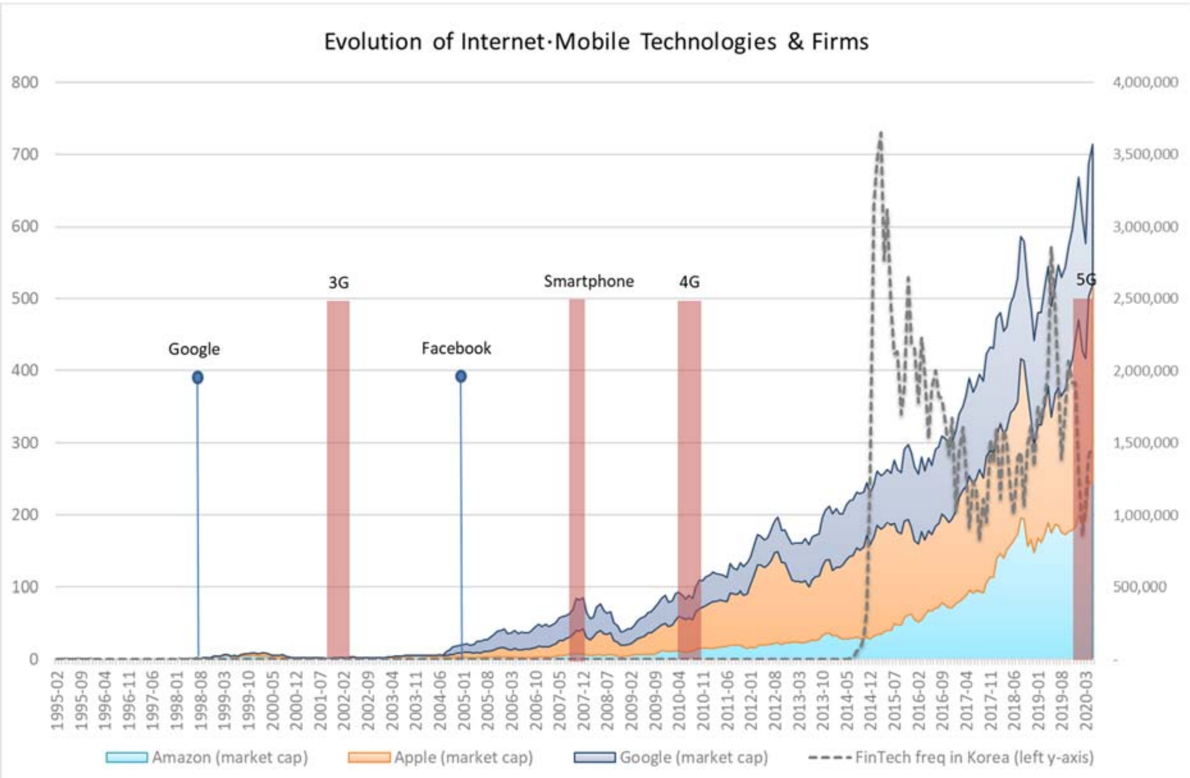
[1] The UK FinTech policy was formulated by the ten recommendations made by the UK Government Science Office (2015), and includes an industry-academia-government cooperative mechanism, manpower planning (in the end innovation is done by innovator), research and educational programs in leading universities, periodic benefits-cost analyses on social effects of FinTech, enabling regulatory framework (i.e., regulatory sandbox), and frontier reporting and analysis systems (e.g., RegTech).

discussing the four subsectors in terms of current state, key trends, and players of each (Section 2); theoretical underpinning by surveying financial theories of relevancy (Section 3); assessment of industrial and welfare implications with four specific topics – intermediation efficiency, financial inclusion, information asymmetry and risk management, and BigTech effects (Section 4); regulatory issues to be considered (Section 5); and, concluding remarks (Section 6).

2 Scoping FinTech

Innovations in the financial service sector date back to the 13th century when the paper check was first introduced, a disruptive technology by then that fundamentally changed the ways of financial and non-financial transactions being settled. Since then, a series of other innovations occurred over time, including the double-entry book keeping (1400s), telegraph (1800s), credit card (1950s), Automated Teller Machine (1970s). During the last three decades, however, the intensity of innovations in the enabling technologies for the sector finds no match with any historical period, starting from World Wide Web (www) invented by the English scientist Berners-Lee in 1989, followed by the wireless communication technologies (1G in the 1980s, to 3G in 2002 and to 5G right now) and, more recently, iPhone and other brands of smartphone from 2007. Thanks to the combined effects of these recent innovations, the market capitalizations of the leading web-based companies (Amazon, Google, and Apple) are experiencing a steep growth during the last two decades (Figure 2) and, at the same time, the landscape of the financial service sector globally appears to be going through a fundamental change.

Figure 2. Evolution of technologies, internet firms, and the FinTech terminology



During the 1990s, various B2B platforms enabled by the internet and ICT were developed and utilized in the financial markets of the advanced economies. One such example was the Automated

Underwriting System (AUS) used by the residential mortgage finance industry in the U.S., an online document validation and credit evaluation system that delivered a huge efficiency gain for both consumers and financial intermediaries but, at the same time, worked as a mass production mechanism of the mortgage contracts prior to the subprime mortgage crisis.[2] Given the trend observed from the 1990s, one can infer that the current FinTech phenomenon in the U.S. and other developed economies is a continuation of financial innovation from that decade, the phase of which, however, is accelerating in the new millennium with the introduction of smartphone and other related technologies (e.g., AI, IoT, Cloud, Big Data, Block Chain). Some of the early and well-known lending platforms in those countries, e.g., Prosper (established in 2005 in the U.S.), ZOPA – Zone of Possible Agreement (in 2005 in UK), and Lending Club (in 2006 in the U.S.), provide an indirect evidence for such inference.

On the other hand, FinTech represents more recent, and in a sense more abrupt, phenomena in most emerging market countries. As one evidence, the leading Chinese lending platforms started around 2014, e.g., iZhongchou (in 2014 and affiliated to Alibaba), and QQ Gongyi (in 2014 and affiliated to Tencent), and the frequency of the terminology FinTech used in the Korean popular press also jumps from the mid-2014 (Figure 2). In the Korean case, what ignited the attention to FinTech around that time period was the licensing of the first mobile payment system, KakaoPay, owned by the chatting app company Kakao, with over a 30 million customer base right now (out of 52 million total population in the country).[3] Since then, the FinTech firms of various sort have been emerging in the country, such as the internet-only banks, P2P lending platforms, and robo-advisors; And the government has also put forth a series of policy initiatives to nurture and promote the sector.

The concept of FinTech is still evolving, as indicated by the varying definitions introduced in the literature: to name a few, an application of technology within the financial industry (Barberis (2014)); a new financial industry that applies technology to improve financial activities (Schueffel (2016)); an economic industry composed of companies that use technology to make financial services more efficient (Cizinska et al. (2016); and, a cross-disciplinary subject that combines finance, technology management, and innovation management (Leong and Sung (2018)). To our end, we define FinTech as those financial services enabled by innovative technologies and digital data that potentially supplement or replace human-based services in the financial service sector. As shown in Figure 3, the FinTech services utilize a diver set of technologies, cover pretty much all major categories of financial service to consumers and business entities, and are also applied to the back-office functions such as regulatory compliance and risk management. This study focuses on four particular subsectors of FinTech, each of which will be surveyed in this section in terms of its current state, notable trends, and key players: (1) online capital raising services (P2P lending and crowdfunding of various types); (2) alternative payment services (cryptocurrency- or mobile platform-based payment and settlement services); (3) financial

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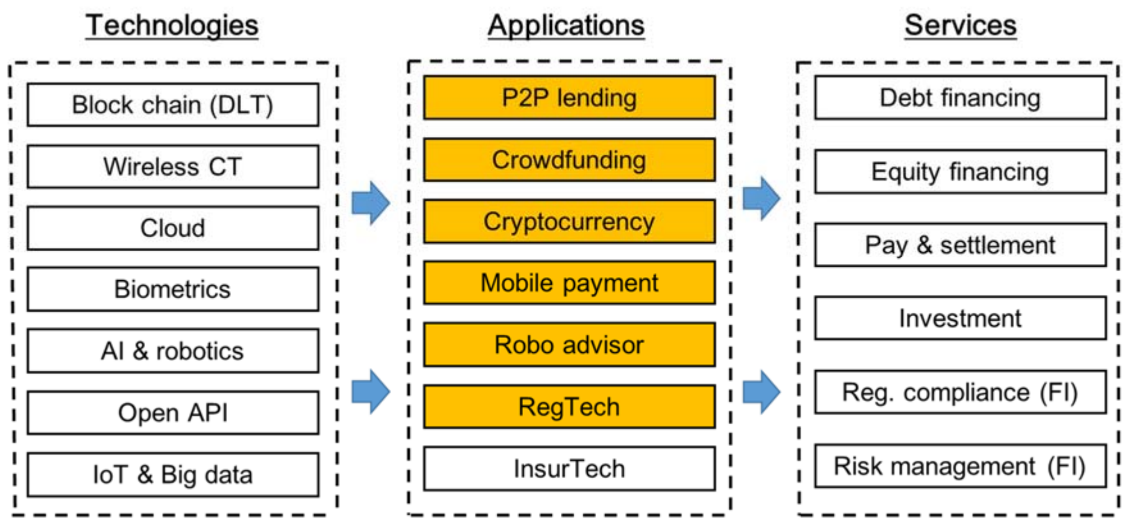
[2] AUS in the U.S. greatly reduced time and cost for mortgage borrowers but, later on, also worked as a mass production mechanism for the subprime and Alt-A mortgage loans. See Cho (2007) and (2009) for further discussion on AUS and its role in the subprime mortgage debacle.

[3] Maeil Business News Korea (2014.9.12)

advisory services (or robo-advisors); and, (4) regulatory compliance services (RegTech).[4] In so doing, the role of three distinct categories of the FinTech service providers will also be discussed to the extent relevant: (1) FinTech startups and SMEs; (2) BigTech companies (usually non-financial firms that offer financial services through their established platforms and customer networks); and, (3) existing financial institutions that employ the technologies and digital data to improve their services.

Figure 3. Technologies and FinTech services



2.1 Online capital-raising service

The online capital-raising activities have been proliferating in the recent years, which can be differentiated by platform characteristics (Market Place Lending, MPL, vs. Balance Sheet Lending), funding type (equity-financing, debt-financing, and reward or donation), borrower type (consumer vs. business entity), capital-raising purposes, and so on. As to the taxonomy, CCAF (2020a) classifies those online platforms as: (1) P2P MPL Lending (to both consumers and SMEs without its own capital); (2) P2P Balance Sheet Lending; (3) Investment-based Crowdfunding (e.g., equity-based, real estate collateral based, and profit-sharing based capital raising with or without the platform's own capital); (4) Non-investment-based Crowdfunding (e.g., reward-based, and donation-based); and, (5) various other services (e.g., invoice trading, mini bonds, debt-based securities, community shares, pension-led funding, and crowd-led microfinance).[5] The CCAF study compiled a sample of 2,322 firm-(or platform)

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[4] This list is far from being exhaustive in that it omits certain sectors that should be rearded as parts of the FinTech industry, e.g., InsurTech, SupTech, and PropTech, along with various infrastructure service providers.

[5] There are also two other types of service providers that can be included in the FinTeh industry - the internet-only banks (Rakuten Bank, Go Bank, WeBank, KakaoBank, K-Bank), and the mobile-only banks (Monese

and country-level observations that is enhanced by a web-scraping of 192 additional firm-level entries. The discussion below will utilize the report as one of the main data sources.

As shown in Table 1, the sector exhibits an explosive growth in the recent years, from $11.7 billion (USD) outstanding funding volume globally in 2013 to $301.7 billion in 2018. However, the volume declines by 27.6% from its 2017 level of $417 billion. In terms of the geographical breakdown, China leads the sector with 71.4% market share, followed by the U.S. (20%), UK (3.4%), Europe excluding UK (2.6%), Asia-Pacific excluding China (2%), Middle East (0.3%), and Africa (0.1%). The drop in the volume in 2018 was solely caused by China, which experienced a 40% decline for the year; But other parts of the world show a strong and sustained growth in 2018 with some of them recording a three-digit annual growth rate. As expected, the standard deviation of the annual growth rates is highest in China with 89%, whereas those for other areas are much lower (e.g., 2% in UK, 7% in Asia-Pacific ex. China, and 12% in the U.S.), indicating a steady growth of the sector globally except China.

Table 1. Total online alternative finance volume for capital-raising activities

(a) Outstanding volume (million USD)

	2013	2014	2015	2016	2017	2018
China	5,600	24,300	102,200	243,300	358,300	215,400
USA	4,400	11,560	28,400	34,530	42,810	61,140
Europe(ex.UK)	400	800	1,100	2,300	3,800	7,700
Asia-Pacific (ex.China)	100	300	1,100	2,000	3,600	6,100
Middle East	36	91	159	177	347	801
Africa	44	61	83	182	104	209
Global	11,680	40,112	137,942	288,689	417,061	301,750

(b)Annual growth rate (%)

	2014	2015	2016	2017	2018	μ(16~18)	Σ(16~18)	CV
China	334%	321%	138%	47%	-40%	48%	89%	0.54
USA	163%	146%	22%	24%	43%	29%	12%	2.53
UK	173%	63%	27%	31%	28%	29%	2%	13.84
Europe (ex. UK)	100%	38%	109%	65%	103%	92%	24%	3.90
Asia-Pacific (ex. China)	200%	267%	82%	80%	69%	77%	7%	11.54
Middle-East	153%	75%	11%	96%	131%	79%	61%	1.29
Africa	39%	36%	119%	-43%	101%	59%	89%	0.67
Global	243%	244%	109%	44%	-28%	59%	40%	4.90

Source: CCAF (2020a)

(2015), Revolut (2015), Starling Bank (2017)).

P2P MPL Lending to Consumers represents the largest subsector in most areas (except UK), having a 64% share in the global outstanding funding volume in 2018. However, as shown in Table 2, a wide variation is observed across the countries/regions as to the composition of the sector: that is, two particular subsectors in China – P2P MPL to Consumers and that to Businesses – pretty much take almost all market in the country (96% in total); in the U.S., on the other hand, the total Balance Sheet Lending (48%) is comparable to the total MPL (46%); and, a more evenly-distributed composition is observed from UK, with relatively high shares of P2P MPL Property (17%), Invoice Trading (8%), and equity and real estate Crowdfunding (8%). The UK result indicates that this online capital-raising service has penetrated to more diverse segments of the financial market, compared to other regions/countries. The divergence in the composition observed seemingly represents consequences of differing financing needs and financial sector characteristics in those geographical areas.

Table 2. Share of different alternative finance services within each country/region (%; As of 2018)

	China	USA	UK	Eur.(ex. UK)	AP(ex.CH)	Middle East	Africa	LAC	Global
P2P MPL, consumers	76%	42%	20%	38%	16%	12%	54%	27%	64%
P2P MPL, business	20%	3%	24%	13%	29%	6%	9%	8%	16%
P2P MPL, property	1%	1%	17%	2%	11%	69%	0%	3%	2%
Balance Sheet, consumers	0%	12%	6%	1%	14%	0%	0%	9%	3%
Balance Sheet, business	3%	20%	8%	1%	15%	1%	22%	16%	7%
Balance Sheet, property	0%	16%	1%	18%	0%	0%	0%	1%	4%
Invoice Trading	0%	0%	8%	10%	2%	6%	0%	34%	1%
Crowdfunding, equity	0%	1%	5%	4%	3%	4%	1%	1%	0%
Crowdfunding, real estate	0%	3%	3%	8%	4%	0%	2%	2%	1%
Others	0%	2%	8%	6%	6%	1%	12%	0%	1%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source: CCAF (2020a)

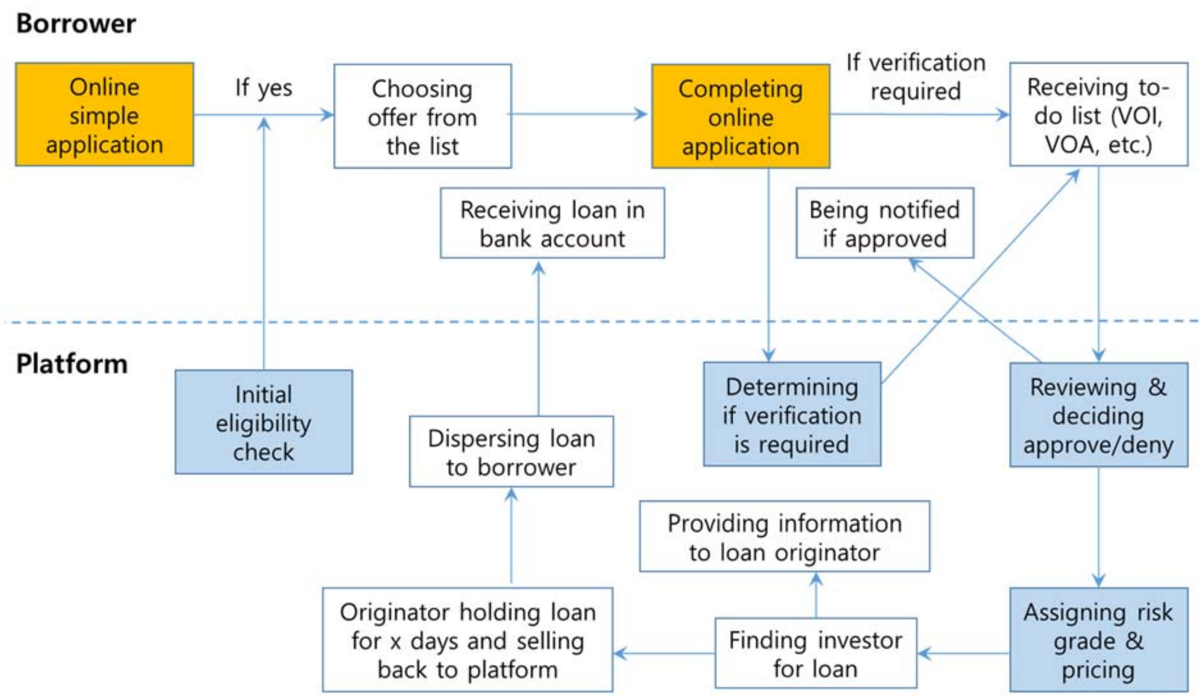
The fund suppliers include both individuals (or households) and institutions (e.g., banks, pension funds, mutual funds, and family offices), and the latter takes about a half of the total funding worldwide ($162 billion in 2018). The share of the institutions, however, varies widely across the regions/countries, with 88% in the U.S., 50% in UK, 49% in Latin America, 41% in Europe (ex. UK), 36% in APAC (ex. China), and 19% in Africa.[6] Another on-going trend to note is the rising volume of cross-border transactions, e.g., Africa having 83% inflows (i.e., funds from investors who come from abroad) and 90% outflows (i.e., funds that go to fundraisers abroad) but the U.S. showing only 16% inflows and 10% outflows.

The online intermediation process typically involves with several key players – the platform itself, loan applicant, investors (or those who bid for funding), and loan disbursement entity. As the name ZOPA – Zone Of Possible Agreement – implies, the platform's main function is to mediate the applicant and the investor for finding successful bidders and, in so doing, to perform various tasks involved with

[6] Data for China is not available.

loan underwriting (e.g., document validation, credit evaluation, and risk spread computation). As shown in Figure 2, the process starts with an online loan application by a prospective borrower after registering on the platform. Upon the completion of the application, the platform makes a soft credit check into the borrower's credit history and pulls the borrower's credit score, debt, credit utilization ratios, the number of accounts under the borrower's name, and the outstanding balances on these accounts. Using both the self-reported data and the credit report, the platform makes two main decisions: first, making an approval-denial decision based on the documents and data compiled for credit risk assessment (on loan amount, loan purpose, income, wealth, credit history, various ratios, and so on); second, coming up with appropriate risk premium based on which the investors can bid. In performing these functions, the platforms increasingly use soft data, i.e., various types of nonconventional data that are traditionally not used by financial intermediaries.

Figure 4. A typical online intermediation process



Source: Frost et al. (2019) (Revised and re-produced based on the figure in p. 12 of the paper.)

2.2 Alternative payment service

The second FinTech service to be surveyed is the alternative payment channels. The first such mechanism is the mobile-phone based payment, which turns out to be a powerful substitute to the existing means of exchange (e.g., fiat money and credit card) in both developed and developing countries. This alternative payment channel is offered by a number of global ICT or e-commerce companies, such as Google Pay, Amazon Pay, and Apple Pay (obviously by Google, Amazon, and Apple, respectively), Messenger Pay by Facebook, Alipay by Alibaba (via its affiliate Ant Financial), TenPay by Tencent, Baidu Wallet by Baidu, Samsung Pay by Samsung, M-Pesa by Vodafone (used in Kenya and other African countries), and Mercado Page by Mercado (used by Argentina and other Latin American countries). As of 2018, the yearly mobile payment volume as a percent to GDP amounts to staggering 16% in China, far higher than other countries (0.6% in the U.S. and in India, 0.3% in Brazil, and 0.1% in UK). (Frost et al. (2019))

As the expression, "a bank in your pocket," implies, the mobile payment system delivers a huge convenience and efficiency gain in the demand-side, in that consumers can use this system for all kinds of online and offline transactions. In the supply-side, the system essentially works as a similar data collection instrument to IoT (Internet of Things) in that the service provider can compile and utilize various consumer behavior data such as location and movement, shopping pattern, peer network, among others. Subsequently, the collected data can be used for consumer profiling, product differentiation, as well as credit evaluation.

Another alternative payment channel is the cryptocurrency,[7] which was conceptualized by Nakamoto (2008), believed to be pseudonymized, and has been proliferating with numerous different types in the recent years (e.g., Bitcoin, Etherium, Ripple, DASH, Litecoin, and so on). Crytocurrency represents a non-physical (unlike coin or paper money) and pure-electronic mean of payment and settlement, secured and validated by Distributed Ledger Technology (DLT, a subset of which designed for cryptocurrency trade is called as Blockchain). As such, it has a potential of becoming a highly efficient mechanism for certain financial transactions (e.g., inter-country money transfer), and some central banks even developed their own versions recently, Central Bank Digital Currency (CBDC), to enable digital transmissions of transfer payment among other uses.

However, there are several issues for cryptocurrency to become a safe and stable mean of exchange. First, its value turns out to be highly volatile, as evidenced by the extreme price boom-bust in the recent years: namely, the total global market value of this subsector as of January 2017 was $18 billion, which had an explosive growth to $660 billion in January 2018, a over 3,500% growth rate within one year, but declined to $430 billion in March 2018 (a 35% decline within 3 months); and, a similar price dynamics is observed for Bitcoin, as shown in Figure 5. The incidence shows that this channel appears to be lacking one critical attribute as a currency, i.e., a stable mean of value storage over time. Second, contrary to its original intention of creating a low-cost and decentralized mean of exchange, the infrastructure that enables its storage and exchange appears to be high-cost and convoluted with a number of intermediaries of its own (e.g., Exchanges, Digital Wallets, Miners, and Payment Companies).[8] Third, use of cryptocurrency for illegal purposes seems to be prevalent, and the funding

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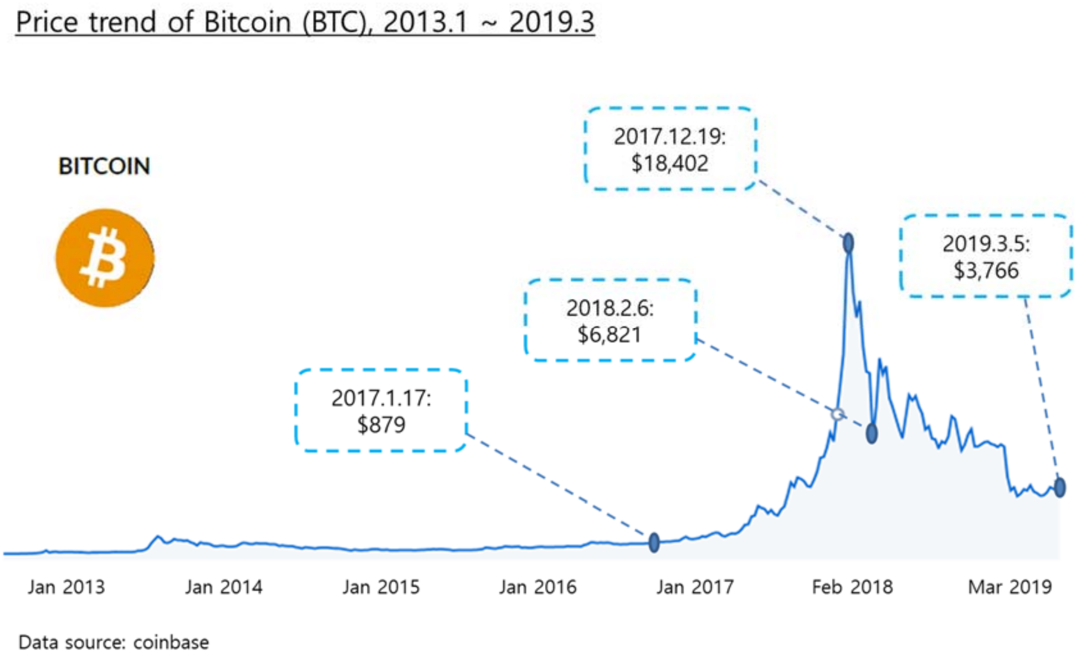
[7] Its name varies widely, with different prefixes to asset (digital-, crypto-, virtual, or even DLT-) and with the same set thereof to currency. According one survey (CCAF (2019d)), the naming convention, and the underlying perception about its very nature, are fairly evenly divided between "asset" and "currency."

[8] As a case in point, the total electricity consumption used by the miners in 2016 exceeded that of Argentina.

mechanism for those entities involved, ICO (Initial Coin Offering), is also shown to be a source of fraudulent financial transactions. That is, while ICO is supposed to be an enabling mechanism to mobilize capital for related start-ups (e.g., infrastructure and app developers, network operators), many ICO cases involve with a ponzi scheme with fraudulent deposit taking, money laundering, and tax evasion; According to one study, 81% of ICOs being initiated turn out to be illegal. (Citi GPS (2018))

Figure 5.



Nonetheless, its underlying technology, DLT or Blockchain, goes beyond cryptocurrency, and is being applied to various other financial and non-financial transactions, such as domestic and international money transfer (e.g., SoftBank, and BitPesa by European Visa), trades of non-listed stocks (by those exchanges in the U.S., Australia, Japan, & Germany), international trades and logistics management (e.g., Bank of America), and real estate transaction and registration (e.g., the State of Vermont in the U.S., and Swedish Real Estate Registry). Going forward, it is expected that more diverse DLT structures will be developed and utilized to serve various different purposes.[9]

(Citi GPS (2018))

[9] CCAF (2018) reports that there are three typical layers in the DLT governance structure, for each of which a wide variation is observed in the DLT systems surveyed: (1) Protocol Layer (working like a constitution in a nation by defining all governance rules), (2) Network Layer (as the degree of openness to general public), and (3) Data (or Ledger) Layer (how the electronic transaction data, i.e., are stored, accessed, and used).

2.3 Alternative investment advisory service

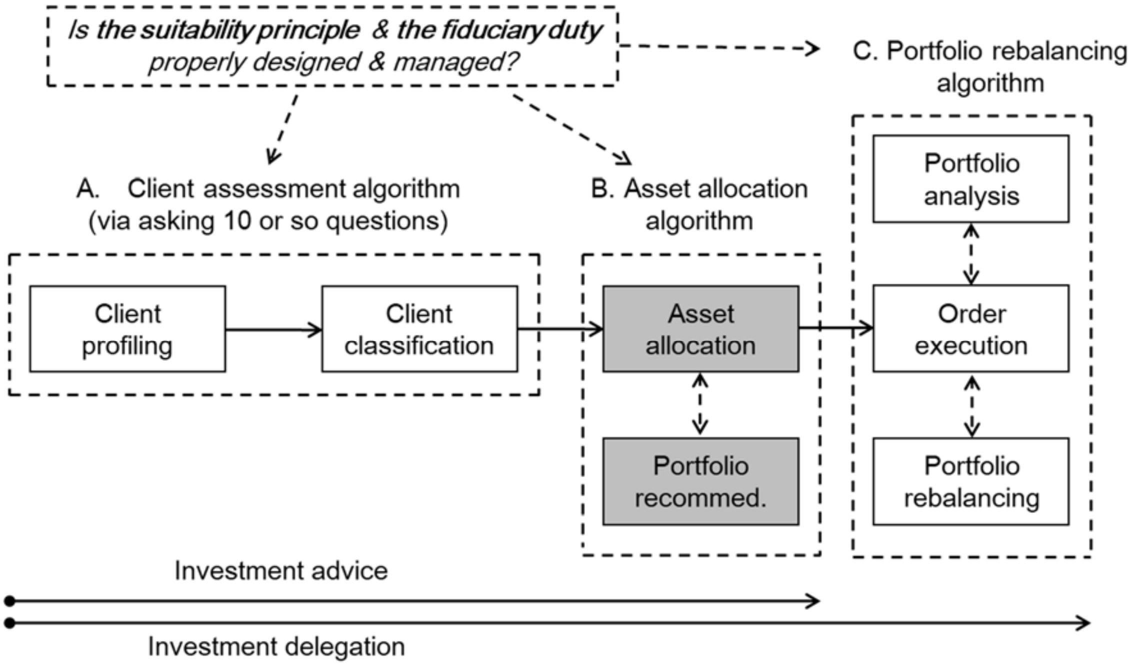
The third FinTech service to be surveyed is the alternative investment advisory service enabled by AI and robot (conveniently referred to as robo-advisor), which is also in a rapidly-growing path in the recent years.[10] As one evidence for its growth, the total funding for AI-related ventures globally increased from $1.7 billion in 2013 to $15.2 billion in 2017, with ‘Banking and Securities’ having the largest funding amount; and, the number of the AI-related patent publications also quite dramatically increased, e.g., “Deep Learning” related patents from China being only 3 in 2013 but having risen to 652 in 2017. (Citi GPS (2018)) Before the robo-advisor, the online wealth management services have been around since 1990s, e.g., mPower in 1995 (the first on-line investment advisor), Financial Engines in 1996 (specialized in retirement saving & pensions), and iRebal in 2005 (an automated portfolio rebalancing tool). However, the new breed of machine-based investment consultation systems is rapidly replacing the conventional human-based services in the advanced countries, with the leading examples such as Betterment (the first robo-advisor developed in 2007, with $7.2 billion Asset Under Management (AUM) as of 2017), Wealthfront (developed in 2008, with $5 billion AUM), Vanguard Personal Advisor (the largest robo-advisor with $47 billion AUM), and Schwab Intelligent Portfolio (with $10.2 billion AUM).

At the core of robo-advisor is a rule-based computer algorithm that is capable of independent thinking and self-improvement through Machine Learning (ML). The underlying algorithm for robo-advisor generally reflects the common finance theories, e.g., Modern Portfolio Theory (MPT) and Capital Asset Pricing Model (CAPM), but decisions out of the system are empirically improved over time with constant learning from updated data of various sort, both conventional and non-conventional data such as market statistics including stock price data, annual and quarterly reports of companies in consideration, popular press articles, and so on. As such, there are several key enabling technologies for the system’s self-learning besides AI, e.g., Big Data, Cloud, and IoT. In terms of the service process, a typical robo-advisor system performs five sequential steps as depicted in Figure 6.[11]

[10] AI represents a suite of technologies, exhibiting some degree of autonomous learning and enabling: (1) Pattern detection by recognizing regularities in data; (2) Foresight by extrapolating learned patterns in the presence of uncertainty; (3) Customisation by generating rules from specific profiles and applying general data to optimise outcomes; (4) Decision-making by generating rules from general data and apply specific profiles against those rules; (5) Interaction by communicating with humans through digital or analogue mediums. Quality of and access to data and access to talent are considered to be major obstacles to implementing AI, while the aspects like the cost of hardware/software, market uncertainty, and technological maturity represent lesser hindrances. (CCAF (2020))

[11] Those steps include: (1) assessing risk appetite of client; (2) categorizing investable assets (or an opportunity set); (3) determining matching portfolio(s); (4) executing orders; and, (5) rebalancing existing portfolio; And, in so doing, financial supervisors are increasingly require the conventional principles applied to the investment consulting service, e.g., suitability principle, fiduciary duty, and avoidance of incomplete sale.

Figure 6. Typical steps of consultation in robo-advisor



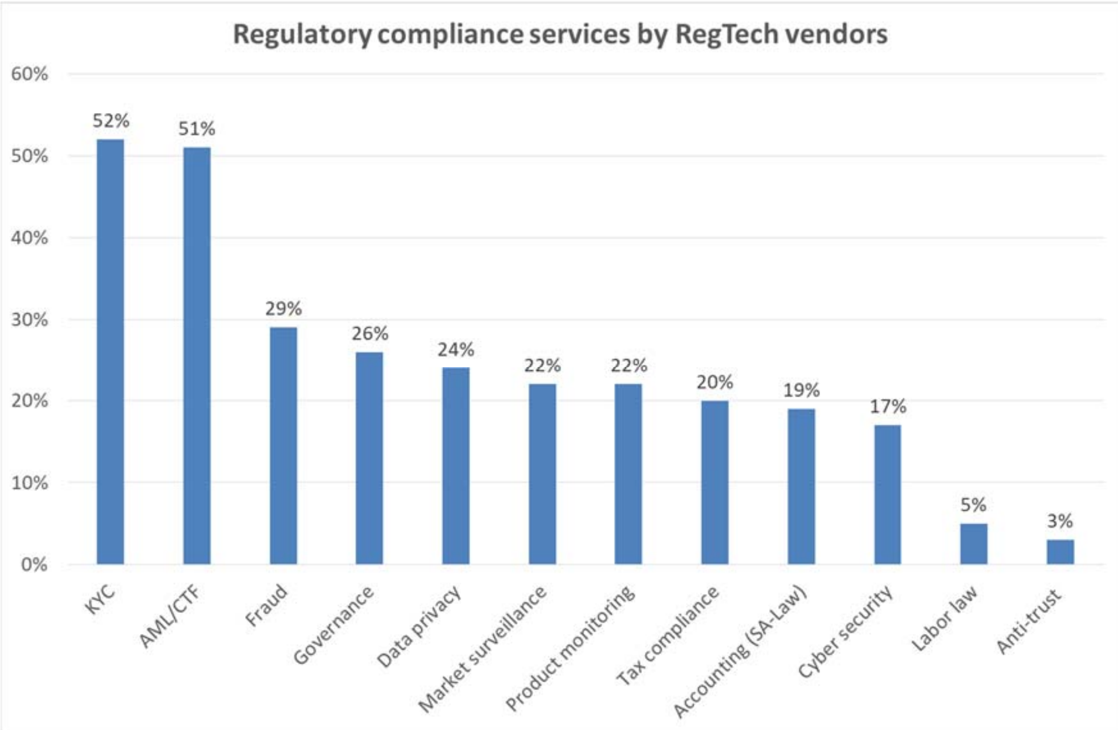
Source: The author

2.4 Alternative regulatory-compliance service

The last FinTech service to be surveyed is RegTech, a technology driven analytical and reporting system used for regulatory compliance along with other back-office functions of financial intermediaries. Typically, the system is capable of matching structured and unstructured data to generate information taxonomies or decision rules, which are subsequently used for automating regulatory compliance or internal oversight processes. As a background, there have been the new financial regulations over the last two decades, particularly for those large financial institutions with global operations, such as Know-Your-Customer (KYC), Anti-Money Laundering (AML), fraud detection, and compliance to the privacy laws; And there have been well-publicized cases of punishment with large fines or criminal sanctions for non-compliance, e.g., $8.9 billion fine to BNP Paribas in 2014, $1.9 billion to HSBC in 2012, and $662 million to Standard & Chartered in 2012. In response, the market for RegTech has been surging in between 2014 and 2018, with some of the early entrants including Ayasdi (2008, US), RedOwl Analytics (2011, US), Elliptic (2013, UK), Compliance Advantage (2014, UK), and Saude (2014, UK).

According to CCAF (2019a), RegTech has now established itself as a legitimate sub-sector of FinTech, and its use goes beyond the readily quantifiable areas of regulatory compliance to the predictive analytics such as Enterprise-wide Risk Management (ERM) and other business decision making processes. As shown in Figure 7, the most frequent applications of RegTech (based on the survey responses by RegTech firms) include KYC (52%) and AML/CTF (51%), followed by fraud detection (29%), governance or management accountability and conflict of interest checks (26%), personal data protection and privacy laws (24%), along with a series of other internal functions (e.g., trade and market surveillance, product governance and quality, tax accountability, cyber-security, labor laws, and anti-trust law). Diverse technologies are utilized in a RegTech system, for which Institute of International Finance, IIF (2016) identifies six major ones, including AI and robotics, cryptography, biometrics, blockchain, API (Application Programming Interfaces), shared utility functions and cloud applications .[12]

Figure 7. RegTech's frequent applications (a survey result documented by CCAF (2019a))



Data source: CCAF (2019a)

[12] They include: (1) AI and robotics (for data mining with large sets of structured and unstructured data, modeling and forecasting as needed for stress testing, and interpreting and reflecting new regulations); (2) cryptography (for a secure, faster and more efficient data sharing in and between financial institutions, and with clients and supervisors); (3) biometrics (for efficiency and security improvements by automating client identification); (4) blockchain (for the development of more efficient trading platforms, payments systems, and information sharing mechanisms in and between financial institutions); (5) Application Programming Interfaces (APIs) (for interoperability to make sure that different software programs can communicate with each other); and, (6) shared utility functions and cloud applications (for allow financial institutions to pool some of their compliance functions on a single platform, allowing for efficiency gains).

3 Theoretical Underpinning

What do finance theories say about social impact of FinTech? This section aims to shed light on that question by summarizing those theories of relevancy. In a social welfare point of view, finance is a mean to an end in that it is supposed to allocate financial resources efficiently to economic agents – households, firms, and government entities – so that they can achieve their welfare-enhancing objectives and, also to manage underlying financial risks involved in performing that resource allocation role. In so doing, the financial service sector is expected to achieve two primary policy goals - stability of financial markets and (easy and wide) access to services by financial consumers. As discussed below, GFC brought about a widespread doubt as to whether the existing service providers, particularly those large ones with global operations (e.g., G-SIBs or Global Systemically Important Banks) - have been properly meeting those goals expected from the sector.

To use the concept of intermediation efficiency as a starting point of discussion, suppose a portfolio lender whose per-period profit function is expressed as the following excess yield, EY_t:

$$(1) \quad EY_t = r_t^l - r_t^f - \delta_t - RP_t$$

where r_t^l is a lending rate (an average across all loans issued during a given time period t), r_t^f is a funding rate (or an average risk-free rate for comparable maturities for the loans made), δ_t is a per-period cost (including both fixed and variable costs) expressed as a percent to each dollar lent, and RP_t is a risk premium that represents an expected loss evaluated today that can be caused by a future (hence, uncertain) risk event, i.e., $RP_t = E_t[Loss_{t+k}]$.[13] Ceteris paribus, the lower EY for a given financial service sector, the more efficient its service provision is.

The first welfare implication expected from the FinTech industry as elaborated in the literature is the efficiency gain by posing a heightened competition to existing financial institutions. (Philippon (2015) and (2016), Cochrane (2014), Pennachi (2012), and Chamley et al. (2012)) In particular, to his self-posed question, "has finance been too expensive," Philippon (2015) demonstrates that EY in the U.S. financial service sector has been consistently and unjustifiably higher than its long-term equilibrium level since the early 1980s, and he refers a monopoly or oligopoly rent resulted from the increased market power through active merge-and-acquisitions as a possible reason.[14] In a related vein,

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[13] In a conceptual sense, RP_t should reflect different types of financial risk – in particular, credit risk, interest rate risk, and liquidity risk, but the discussion in this section mostly deals with the first one.

[14] Lack of entry and competition, however, has been an endemic problem in finance in recent decades. Berger et al. (1999) review the evidence on consolidation during the 1990s. The number of US banks and banking organizations fell by almost 30% between 1988 and 1997, and the share of total nationwide assets held by the largest eight banking organizations rose from 22.3% to 35.5%. Several hundred M&As occurred each year,

a narrow or limited-purpose banking has been proposed as a more efficient, and possibly more welfare-enhancing, alternative in the post-GFC era, for which FinTech is deemed as a potential candidate. (Philippon (2016))

Traditionally, a narrow banking was the typical mode of financial intermediation in the U.S., in which intermediaries invest in assets that have little or low credit and interest rate risks (usually with short maturities) by issuing demandable liabilities.[15] (Pennachi (2012)) During the last several decades, however, various maturity and risk transformation facilities have been introduced, e.g., asset securitization, options and futures, and other derivative products. And the large global banks widely and frequently used those facilities to develop and trade the long-maturity and high-risk financial products, contributing to the growth of the shadow banking sector in the global financial system. As an alternative banking model after the global financial crisis, a financial service provider with a limited and specialized function is recommended as an alternative business model. (Chamley et al. (2012), Cochrane (2014)) Nonetheless, it is fair to say that the current extended banking model has a benefit of making access to financial services for marginal borrowers easier, which should be weighed in as a consideration for setting a banking policy going forward.

Information asymmetry, and the credit rationing as a consequence thereof (one type of market failure), have long been a topic of investigation in the finance literature. (Stiglitz and Weiss (1981), de Meza and Webb (1987), and Waller and Lewarne (1994)) The theory goes that, like in a used car market, a borrower knows more about his own credit quality (i.e., likelihood of repaying principal and interest as contracted) than a lender; And, as RP_t (hence, r_t^l) goes up to reflect a higher expected credit loss if and when the borrower defaults, low-risk borrowers self-select out of credit market, causing an adverse selection problem for the lender. Knowing that an increase in r_t^l (due to a higher RP_t) will cause a faster drop out by low-risk borrowers than by high-risk ones, at a certain level of expected credit loss, $E_t[Loss_{t+k}]$, the lender either reduces or even stops credit supply, creating a backward-bending supply curve that results in a credit gap (or excess demand) in the lending market.

However, the extent of credit rationing as argued in the above can be reduced if the lender is capable of implementing a risk-based (or marginal cost) pricing: that is, if the lender has sufficient data (and experience) in measuring and managing embedded credit risk, then a segment-specific and actuarially-fair RP_t can be computed and charged for a given borrower segment that is commensurate with anticipated level of credit loss, i.e., a possibility of separate equilibria that can eliminate the adverse selection and credit rationing from happening. A question to pose is whether or not the FinTech service providers contribute to making this this possibility as reality. To that issue, it is fair to say that there has

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including megamergers between institutions with assets over $1 billion.

[15] "Loans often were bills of exchange which financed trade and were collateralized by the goods in transit. Promissory notes were another common loan backed by a borrower's and any cosigners' or guarantors' personal wealth. Both types of loans had short maturities, typically averaging between 65 and 80 days; Data from the Survey of Terms of Business lending indicates that the weighted-average maturity for commercial and industrial loans was 241 days in 1997, rising to 537 days in 2011" (Pennachi (2012)).

been a general trend of improvement toward the risk-based pricing during the last three decades, in terms of both theoretical constructs[16] and heuristic indicators (e.g., corporate bond ratings, and consumer credit scores). At the same time, however, there are still loose ends in measuring borrower- and product-driven (or idiosyncratic) credit risk, not to mention in reflecting market-driven (or systematic) risk factors in computing RP_t. Furthermore, the current risk assessment process tends to leave out a large number of borrowers who have no or scanty credit history, i.e., "thin filers," and, hence, limiting their access to financial services. As documented in the literature, the FinTech service providers do demonstrate a potential to fill this gap, at least partially, in the ex ante risk assessment of financial consumers, but whether or not they are better positioned over other market participants in implementing a full-blown risk-based pricing remains to be seen.

In a viewpoint of developing countries, the FinTech industry is shown to be greatly enhancing financial inclusion, i.e., making the financial service sectors in those countries more complete and more accessible to marginal borrowers. As elaborated in the literature, the financial sector development in general tends to have an endogenous, or mutually-reinforcing, relationship with economic growth, as evidenced by a positive association between the size of private credit and the GDP growth rate.[17] (King and Levin (1993), Rajan and Zingales (1998), Manning (2003), Levin (2005), Pagano and Pica (2012), and Hwang (2020)) And, in the process of economic growth, it is often the case that scarce financial resources are allocated based on a policy priority, e.g., the directed credit policies toward the export-generating sectors in the East Asian countries since the 1970s. Hence, due to a combination of a less-developed financial service sector and a directed credit policy, a large segment of financial consumers in the developing world is likely to be excluded from formal financial services, and serving them in those countries via technology and digital data will be one important form of financial inclusion. As will be discussed subsequently, the FinTech service providers are filling that gap through internet and mobile platforms.

What linkage can one establish between FinTech and financial market stability? In general, it is premature to make any evidence-based judgement on this issue given that the FinTech industry is still very much young and evolving. Nonetheless, one can differentiate the FinTech service providers into two groups - those who offer financial services with their own funding (e.g., the balance sheet P2P lenders) vs. those who are pure platform servicers (e.g., the P2P MPL lenders), and can consider each one's anticipated behavior under a financial market boom-bust. For the former, there is no reason to believe that their behavior will be different from the conventional financial institutions who have repeatedly shown a pro-cyclical lending behavior, i.e., relaxing lending standards during an ebullient

[16] Examples include the structural corporate default model based on the Mertonian distance-to-default theory, and the reduced-form default model based on observed credit spreads and risk-neutrality argument.

[17] In addition, an inverse U-shaped relationship between economic growth and the ratio of private credit to GDP is also documented, implying that the financial market deepening can have a detrimental effect on the growth after a certain threshold (e.g., the 100% of the ratio of private credit to GDP as reported), possibly due to an overinvestment in non-trading (or less productive) sector of economy (Cecchetti and Kharroubi (2012), Arcand et al. (2012), and Cournède and Denk (2015)).

time that causes an excessive credit supply but abruptly constraining them during a downturn that often results in an amplified credit cycle and a liquidity trap (DeLong et al. (1990), Welch (2000), Fostel and Geanakoplos (2008), Brunnermeier et al. (2009), Geanakoplos (2010), among others).[18]

How prone the portfolio FinTech lenders are to such pro-cyclical lending behavior will depend on their portfolio composition. As illustrated below, if they are properly capitalized (measured by A/E or by any variant capital ratio) and follow a safe banking practice (i.e., holding short-maturity and low-risk asset, A1, financed by comparable maturity liability such as L1), then their operation will be relatively more immune to the market dynamics. However, if they hold a large share of illiquid, high-risk, and long-maturity asset (A2), then they will be more incentivized to get into the business of interest rate arbitrage, i.e., "a borrow-short-lend-long" business practice. That was prevalent during the several years prior to GFC (2002 to 2005 to be exact) when the long-short spread, $r_t^l - r_t^f$, was consistently high and delivered a hefty margin of two to three percentage points to the arbitrageurs, which later on became one of the main sources of destabilization in the whole global financial system.

A	**L/E**
A1 (liquid, no/low risk)	L1 (demand deposit)
A2 (illiquid, high risk)	L2 (debts - bonds/loans)
	E (equity)

On the other hand, the pure platform-service providers (e.g., P2P MPL lenders) would be less prone to the above term structure driven cyclical behavior. In fact, their revenue largely relies on fees, for origination and servicing, which will be dependent upon demand- and supply-side market conditions. However, those platform service providers are now becoming a credit risk assessor and, as such, how efficient they are in their ex ante assessment of credit losses from different borrower segments, $E_t[Loss_{t+k}]$, and how actuarially-fair those assessments are with ex post (or realized) loss amounts should be the determinants of their profitability and long-term sustainability. In addition, whether or not the platforms have enough "skin-in-the-game" in sharing expected and unexpected credit losses with other market participants (e.g., investors, and insurers) should also be a part of a regulatory design governing the FinTech service providers. Yet, another group of FinTech servicers, those who are affiliated with BigTechs, should be assessed in a different angle as there are added dimensions of welfare implication involved with their business models.

Finally, the linkage between FinTech and financial consumer protection should be elaborated. In the recent years, how to ensure a proper protection of financial consumers from the arcane financial products as well as financial frauds receives a heightened attention from academia and policy circles. As argued in the literature, financial consumers generally lack even basic financial knowledge and tend

[18] See Cho (2017) for a survey of the literature in this vein.

to make myopic and systematically-biased decisions.[19] (Kahneman (2003), Miles (2004), Campbell (2006), Evans (2008), Campbell et al. (2011), and the World Development Report, WDR (2015)). As such, it is warranted to strengthen financial literacy and capability of consumers through education and counseling (as emphasized in several studies, "just-in-time" education) in the demand-side. (Houston (2010), CFPB (2015) and (2017), Nicolini (2019), Cude (2020)) In addition, proper product sales behavior (e.g., providing appropriate information, ensuring a cooling-off period, checking affordability, and so on) as well as dispute resolution mechanisms (e.g., ombudsman, conflict resolution commission, appropriate foreclosure practice) in the supply-side should also be instituted.

[19] One such example is the consumers' choice of the backloaded mortgage products (IO-ARM, Option ARM) as one of the key causes of the subprime mortgage debacle (Cho (2009), Foàet al. (2015), Agarwal et al. (2019), Seay (2020)) Misconduct being concentrated in firms with retail customers with low education and elderly populations (Egan et al. (2016))

4 Assessing the FinTech Implications

4.1 On the efficiency gain

As elaborated by a number of studies, FinTech service providers tend to enhance the intermediation efficiency by lowering transaction costs in delivering their services vis-à-vis the traditional branch-based financial institutions, mainly through much cheaper, faster, and more convenient internet or mobile platforms. (IMF (2017), Buchak et al. (2017), Fuster et al. (2018), Frost et al. (2019), Jagtiani and Lemieux (2019), OECD (2019), FSB (2019)) Examples of this type of welfare gain are shown in the online capital raising activities (the P2P lending and crowdfunding of various types), the mobile-app based payment services, as well as the AI-robot based investment advisory services. As another form of efficiency gain, the FinTech service providers also tend to pose a heightened competition to existing financial institutions (i.e., "catfish effect"). As a case in point, when facing the entry of two internet-only banks in Korea – KakaoBank and K-Bank (owned by one chatting app company, Kakao, and by one mobile phone service provider, Korea Telecomm, respectively) – in August 2018, four major commercial banks in the country lowered their lending rates but raised their deposit rates right after their market entry. (Kang (2018))

Although empirical backing with real data in support of the efficiency gain discussed above is rare, there are some exceptions that document such evidences. For example, using the household-level micro data from the U.S., Fuster et al. (2018) report that the FinTech mortgage lenders, those who provide an end-to-end online service from data entry to pre-approval (e.g., QuickenMortgage, LoanDepot.com, and Guaranteed Rate), process the loan applications about 20% (or 10 days) faster than non-FinTech lenders with fairly comparable ex post default rates. They also document that those online lenders are more elastic in responding to exogenous mortgage demand shocks than their counterparts, deliver a bigger efficiency gain for refinancing mortgage applications (14.6 days faster on the average) than purchase loan applications (9.2 days faster), and work as a more efficient transmission mechanism of monetary policy compared to the conventional mortgage lenders.

As discussed in Section 2, the P2P lending and Crowdfunding platforms today can be viewed as a next-generation online underwriting systems proliferated in the 1990s. However, the today's platforms represent an enhanced version with more advanced technologies and data analytics with which one can efficiently collect various borrower-, collateral-, and market-related data, and can automatically check them against external sources (e.g., employment databases, property records, credit history records, bank account deposit records, even marriage and divorce records) to detect missing or inconsistent data fields or to identify fraudulent loan applications. Over time, these next-generation online platforms are expected to penetrate to a wide range of credit markets, e.g., small business lending, personal unsecured lending, and commercial real estate lending. (Goldman Sachs Research, 2015) In that juncture, it is difficult to over-emphasize the importance of proper documentation and its validation as a part of credit evaluation: that is, as shown in the case of the subprime mortgage crisis, the Alt-A mortgages (those mortgage contracts with no or low documentation that are known with various acronyms, e.g., NINA for No Income (documentation) No Asset, SISA for Stated Income and Stated Asset, and NINJA for No Income No Job and Asset) worked as the major source of credit losses in the U.S. mortgage finance industry. (Cho (2009))

In a dynamic sense, however, whether the FinTech lenders deliver a similar welfare gain in a longer-term basis is less clear. As an empirical evidence to that end, using a large credit bureau data set including about one million borrowers who used an MPL platform, Chava and Paradkar (2018) shows that the borrowers use the funds from the platforms mainly to consolidate their credit card debts, due to which the card balances decline by 47% on the average right after the funding relative to the previous quarter and their credit card utilization ratios also decrease accordingly. As a result, the credit scores for the MPL borrowers improved, a 19 points increase on the average, in the quarter right after loan origination, and the transition probability of subprime (near-prime) borrowers to the near-prime (prime) category rise by 35% (33%) more compared to non-MPL borrowers in the same location (ZIP+4 geographical area). However, the study also reports that the MPL-borrowers tend to receive additional credit from their existing bank relationships, resulting in a higher aggregate indebtedness three quarters after the funding and a significant increase in credit card defaults subsequently (with the subprime MPL borrowers experiencing up to 1.5 times more likely to default than their non-MPL counterparts). DiMaggio and Yao (2018) report a similar result in that, while the FinTech borrowers' credit outcomes improve right after receiving the fund, they are significantly more likely to be delinquent and exhibit higher indebtedness after several months. They also report that the FinTech borrowers are more likely to be present-time biased and tend to carry a significant credit card balance.

Do the FinTech lenders deliver a similar efficiency gain to the investors? To this question, Kraussl et al. (2018) points out that the LendingClub's portfolio generates a positive abnormal returns, and Morse (2015) also elaborates that the investors seem to capture some rents associated with the removal of the intermediation cost and, because of that, the platforms can attract capital more easily. In this juncture, the MPL platforms have evolved from trading venues into credit intermediaries in that they assess the applicants' creditworthiness and offer suggested risk premia that reflect anticipated risk levels. (Balyuk and Davydenko (2018), and Morse (2015)) Whether FinTech service providers perform this new role in an efficient and stable fashion, and whether they can contribute to the stability of financial markets are seemingly important public policy issues that should be addressed in coming years. In fact, there is one case of failure in the risk management by the sector that has an detrimental impact on a large number of financial consumers, that is, the closure or in-operation of about 3,000 P2P platforms in China since 2014 (out of about 5,000 platforms) when the regulatory authority in the country starts strengthening the supervision on the sector from that year. (Citi GPS (2018))

4.2 On the financial inclusion

Do FinTech service providers make the financial service sector more complete by serving "the underserved"?[20] The recent studies indicate that the answer to the question is generally yes, in that this new breed of service providers tends to extend financial inclusion by serving those borrower segments or geographical areas that are left out by existing financial institutions. As an empirical evidence, the P2P lenders in the U.S. are shown to be bottom-fishing those borrowers with low credit scores, e.g., those with FICO scores less than 640 who are generally rated as non-prime segment, as well as those with thin or no filers, i.e., those consumers who have either no or insufficient credit history. Reflecting this, the average approval rates by the platforms are generally low (as shown in Table 2, 13.6 percent in the U.S., representing the case of Lending Club, and 10~25 percent in UK) and the average lending rates are high (14.2 percent in the U.S. and 10.86 percent in UK).

As a more direct empirical evidence, using account-level data from a major P2P lender in the U.S., Jagtiania and Lemieux (2018) reports that, ceteris paribus, the platform's consumer lending activities penetrate those areas that may be underserved by traditional banks, such as in highly concentrated markets and areas that have fewer bank branches per capita, as well as those areas where the local economy is not performing well. And also documented is that, as the number of banks and banking offices continue to decline, the presence of FinTech lenders tend to supplement the availability of unsecured consumer credit. (Jagtiani and Lemieux (2018), De Roure et al. (2108), and Buchak et al. (2017)).

Table 3. Comparison of P2P lending sector across the selected countries

		US[1]	UK[2]	China[3]	Korea[3]
Lending	Approval rate	13.6%	10~25%	na	5~10%
	Maturity	3.5(yrs)	1~5	9.3 months	6 m~3 yrs
	Average lending rate	14.21% (6.9~29.3%)	10.86% (3.2~34.9%)	10.45% (na)	12.4% (4.4~19.9%)
Investment	Average yield[4]	5.54% (-0.7%~10.8%)	6.67% (2.9~6.1%)	na	10%

1.Based on the lending Club rates (those loans issued in 2016)

2.Based on the Zopa lending rates (& the average yield)

3.Representing industry averages collected from various sources (for China and Korea)

4.Before tax yield after subtracting fees

(Sources: Lee(2017).p.38)

[20] The size of the credit-constrained consumers is quite substantial even in the developed economies: as an illustration, Bricker et al. (2017) reports that, based on the 2016 Survey of Consumer Finance, 20.8 percent of families feel as credit-constrained; and, Carroll and Rehmani (2017) estimates that as many as 60 million people in the U.S. may have been unable to access credit because of their thin credit files or lack of credit history.

In the developing countries, the mobile payment systems are a powerful mechanism of financial inclusion, as it is filling the service gap by leap-frogging development of the conventional financial service mediums (e.g., checking and savings account, insurance contract, investment account, and credit card), and is offering the payment and other services to a large number of consumers who were underserved due to the non-existing, or minimal, financial intermediation by formal financial service sector. (Aker and Mbiti (2010), Mbiti and Weil (2011), Jack and Suri (2014), CitiGroup (2018), Gathoto (2018)) Good examples are the mobile payment systems that are widely used in China (AliPay and TenPay) and in African countries (M-Pesa, MTN MobileMoney, and OrangeMoney). One interesting aspect of the mobile payment systems in Africa is the existence of a large number of "Agents" (e.g., over 400,000 for M-Pesa and over 500,000 for MTN MoMo, as shown in Table 4). Their function is literally a human ATM that makes the payment and other financial services involved completed, implying that the development of underlying technologies in the region (the wireless communication and related technologies) is such that the mobile phone based payment and settlement services are not yet entirely online and electronic, leaving a room for further efficiency gain in the region going forward.

Table 4. Characteristics of the leading mobile payment system in Africa

	M-Pesa	Orange Money	MTN MoMo	Airtel Money
Release year	2007	2008	2009	2010
Revenue ($, million)	810	459	534	70
Customer base (million)	37	45	35	14
# of countries covered	7	17	16	15
"Agents"	400,000	220,000	517,000	240,000

Source: Mbazi and Abdulkadir (2020)

Another form of financial inclusion to be discussed is the expansion of the investment consultancy enabled by robo-advisors, which lowers the cost of such service and, hence, includes more consumers to that particular service sector, the phenomenon often termed as "democratization of investment consulting service." As one key attribute of the robo-advisor is that, while it takes a high initial development cost, its marginal cost in serving one more customer is virtually zero. As such, unlike the traditional human-based service usually targeting a small number of high net-worth individuals, the new service can cover a large number of high- as well as low- and moderate-net worth households. One indicator for this type of financial inclusion is the minimum account balance required, which is zero for a number of the robo-advisor systems (e.g., Betterment, WiseBanyan, Acorns, and Wealthsimple); And the advisory fee is also generally lower for robo-advisors than the human-based systems (15 to 50 bps for the former vs. 50 to 200 bps for the latter). (Lee (2018))

4.3 On the information asymmetry

On the risk-based rank-ordering of financial consumers

The finance literature has long been arguing that gathering "soft" information about credit quality of borrowers beyond credit scores and standard ratios are critical to reduce the credit gap caused by information asymmetry and to derive successful lending outcomes.[21] (Fama (1985), Granovetter (1985), Petersen and Rajan (1994), Uzzi (1999), Agarwal and Hauswald (2007), Petersen and Rajan (2002)) A growing number of studies documents that the FinTech service providers are capable of doing that, i.e., collecting and utilizing "soft data" to grasp a fuller and more real-time picture about consumers' financial lives and their creditworthiness. (Iyer et al. (2009), Lin et al. (2013), Puri et al. (2017), Hildebrand et al. (2017), and Freedman and Jin (2018), Berg et al. (2018)) As one indirect evidence, LendingClub, the largest P2P lender in the U.S., develops and utilizes its own consumer credit ratings (the letter grades from A to G) based on both hard data (HD) and soft data (SD), and the correlation between them and the FICO scores, the widely-used consumer credit scores in the country, has declined over time from about 80 percent for the loan cohorts originated in 2007 to only about 35 percent for the more recent vintages originated in 2014–2015. Given the fact that the FICO scores mostly rely on HD, the reduced correlation indicates a rising importance of the nontraditional alternative data (i.e., SD) for the FinTech lender's operation.[22] (Jagtiani and Lemieux (2019))

In a statistical sense, ex ante (or pre-origination) assessment of credit worthiness of loan applicant requires to fit a credit incidence model of the following form to estimate probability of credit event (or default) to happen during a certain time span after origination:

$$(2)\ Prob_i(Event_i = 1; \mathrm{t} < \tau) = \mathrm{f}(HD_i,\ SD_i;\ \beta) + e_i\ ,$$

where $Prob_i$ is the probability of credit event to happen (i.e., default or delinquency of a certain duration) by borrower i at a given post-origination time t ($t < \tau$ with the latter being a pre-determined post-origination time limit such as two years after origination), HD_i is a set of variables for those conventional risk indicators such as consumer credit score and its underlying determinants - income, wealth, employment status - along with usual ratios - debt-to-income ratio, loan-to-value ratio, and so on, SD_i is a group of variables representing soft data (i.e., those non-conventional risk drivers as collected through various online means), and [β, e] are parameters to estimate. The purpose of fitting the model of this type is to obtain the best unbiased estimator (or BUE), and the usual estimators for fitting the incidence model of the above type include a logit model, a probit model, or a proportional

[21] See Gorton and Winton 2003 for a review

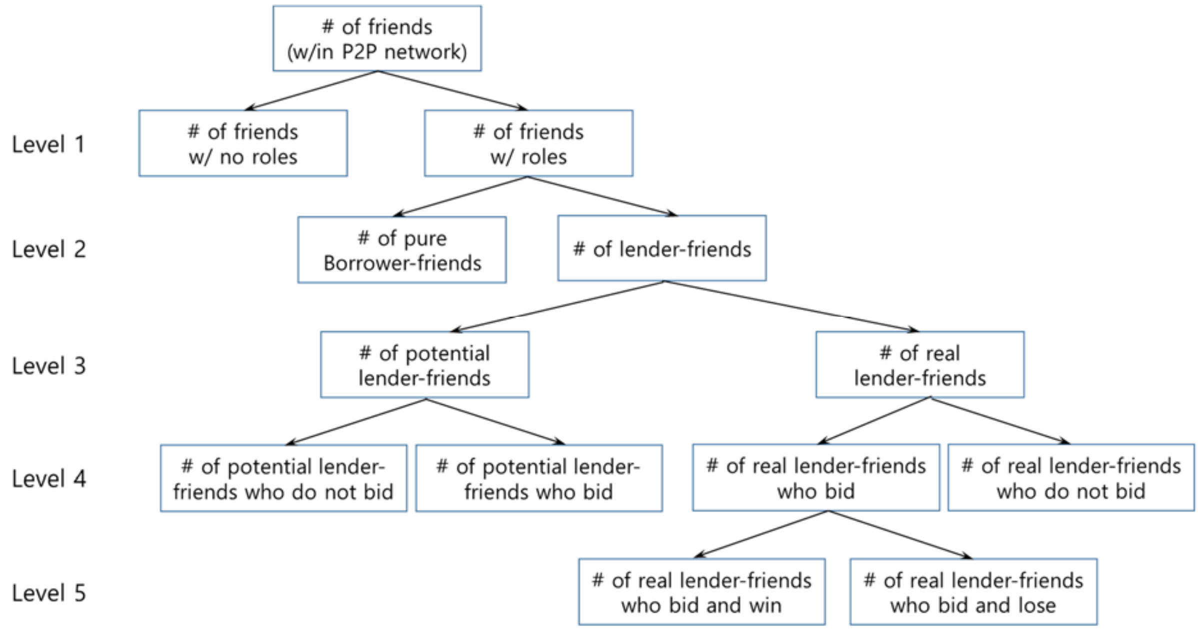
[22] In the American Banker article, Ron Suber, former president of Prosper Marketplace, states that "Prosper gets 500 pieces of data on each borrower; the FICO score is just one data point." The company uses FICO scores to screen borrower candidates; a score of at least 640 is needed to be considered for a loan. Prosper analyzes additional data to determine its ultimate credit decision. These data sources were not normally used by traditional lenders.

hazard model, often with unobserved heterogeneity in the residual variance allowed. Once the model is estimated, then it is generally used to rank-order consumers from the highest risk to the lowest one based on the predicted probability, $\widehat{Prob_\iota}$, to segment them into different risk buckets (e.g., high-, medium-, and low-risk groups). The discretization of this kind is important in a viewpoint of making risk management decisions (e.g., underwriting, pricing, and hedging) because it is generally cumbersome to directly use the continuous variable like $\widehat{Prob_\iota}$ to that end.

The main outcome documented empirically in the literature is that including SD improves the model fit by reducing the omitted variable bias and do enhance the accuracy of the incidence model. There are several specific types of SD whose effects are documented in the literature. First, social or friend network matters in fitting the incidence model. In particular, Freedman and Jin (2017) demonstrates that the value of friends of loan applicant is a statistically significant predictor for probability of default, and that this signal is more pronounced in lower credit grades; Everett (2010) finds that loans funded by the investors in a given peer network who are personally connected to borrowers tend to perform better; Likewise, Lin et al. (2013) finds that the credit quality of a borrower's friends is related to the higher probabilities of funding, lower interest rates, and lower default rates.

How can one define friends? As an answer to this question, Lin et al. (2013) shows an empirical implementation of defining friend types: At the top level in Figure 8 are friends who play a least role in a peer network and for whom loan applicant can register only simple identifier such as email address; As the friendship hierarchy goes up (from Level 1 to Level 5 as shown in Figure 8), they play a more significant role as general investors or as those who are actually willing to fund loan application in question, and loan applicants can identify more detailed (and personal) information on those friends such as social security number, bank accounts, and driver's license, and so on. Consistent with the signaling hypothesis, Lin et al. (2013) shows that friendships with those who play more active roles increase the probability of a successful funding but lower the lending interest rate.

Figure 8. Friends Hierarchy (revised and recreated from Lin et al. (2013))



Source: Lin et al. (2013) (Re-produced based on Figure 1, p. 19)

Second, a series of "digital footprint" variables is also shown to be a part of SD.[23] For example, Berg et al. (2018) uses various variables of this category: (1) the operating system of mobile phone (iOS or Android), (2) the channel through which a customer comes to an e-commerce company's website, (3) email service provider, (4) existence of first and/or last name in email address, (5) typing error. Through a regression analysis, the study reports that the probability of credit incidence is lower: if customers use iOS (Apple) (instead of Android), with the difference in default rates between customers using iOS (Apple) and Android being equivalent to the difference in default rates between a median credit score and the 80th percentile of the credit score; if customers come from a price comparison website (i.e., an indicator of non-compulsive purchaser); and, if they use their name in e-mail address.

As related findings, Bertrand and Kamenica (2017) documents that owning an iOS device is one of the best predictors for being in the top quartile of the income distribution. As to the text data, Yencha et al. (2018) reports that text descriptions of small businesses can predict whether a small business loan will be funded, and that this information may be more useful for borrowers with low FICO scores; and, Gao and Lin (2012) shows that more complex narratives are correlated with higher default rates. As to

[23] Our data set contains a set of ten digital footprint variables: the device type (for example, tablet or mobile), the operating system (for example, iOS or Android), the channel through which a customer comes to the website (for example, search engine or price comparison site), a do not track dummy equal to one if a customer uses settings that do not allow tracking device, operating system and channel information, the time of day of the purchase (for example, morning, afternoon, evening, or night), the email service provider (for example, gmail or yahoo), two pieces of information about the email address chosen by the user (includes first and/or last name and includes a number), a lower case dummy if a user consistently uses lower case when writing, and a dummy for a typing error when entering the email address.

using the names, Belenzon, Chatterji, and Daley (2017) and Guzman and Stern (2016) have documented an eponymous-entrepreneurs-effect, that is, whether a firm is named after their founders matters for its performance.

Third, location of loan applicant (e.g., a high-crime area, an area where factories are being shut down or relocated) is shown to be determinant of the incidence. (Buchak et al. (2017), Havrylchyk et al. (2018), Chen et al. (2017), Alyakoob et al. (2017), and Jagtiani and Lemieux (2018)) Previous studies have found the evidence that local economic information could serve as a relevant source of nontraditional information by FinTech lenders; And some fintech lenders can identify whether the loan applications are submitted from a high-crime area or in an area where factories are being shut down or relocated. (Crowe and Ramcharan (2013); Bertsch et al. (2016); Buchak et al. (2017); Havrylchyk et al. (2018); Chen et al. (2017); Alyakoob et al. (2017); and Jagtiani and Lemieux (2018)

Fourth, trustworthiness assessed by photo and other information (e.g., an index in that vein) is sometimes used as a part of SD. (Duarte et al. (2012)); Ravina (2008); Pope and Sydnor (2011); Duarte, Siegel, Gonzalez and Loureiro (2012); and Young (2012)) In particular, Duarte et al. finds that borrowers who appear more trustworthy have higher probabilities of having their loans funded, and they indeed have better credit scores and default less often. This finding suggests that appearance-based impressions affect individuals' decisions not only in labor markets and politics (e.g., Hamermesh and Biddle 1994; Todorov et al. 2005) but also in financial transactions. However, the results imply that the platform lending can be biased toward seemingly attractive or trustworthy faces but away from those lacking such attributes, which potentially carries a risk of disparate treatment and fair lending violation. A central issue to the value of this line of research is that, once borrowers understand that lenders are using such information, they could choose to alter the way they submit text or photo information.

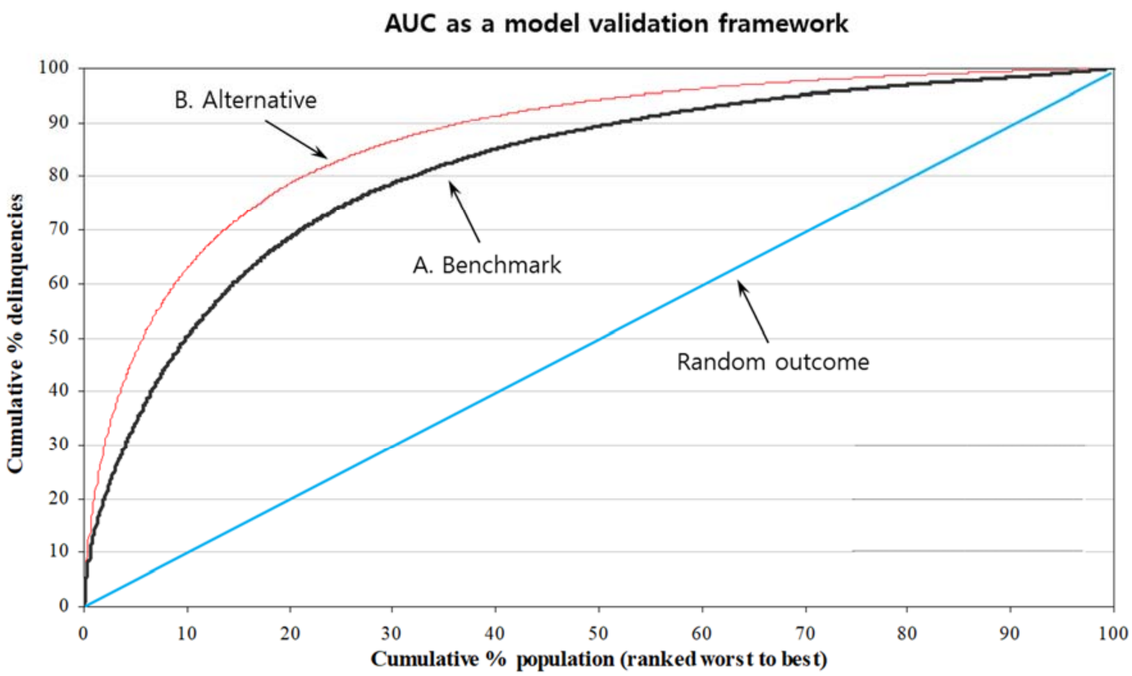
As to the accuracy of the incidence model, the usual analytical framework employed is Area Under Curve (AUC), a sample-based performance testing tool for alternative incidence models fitted. As illustrated in Figure 9, the testing starts with a loan performance sample that encompasses a certain proportion of actual credit events occurred (e.g., a sample of 10,000 originated loans with 100 actual delinquent cases), based on which one estimates multiple incidence models, Model A and Model B in the figure. The loans in the sample are then rank-ordered from high-risk to low-risk according to the predicted probability of incidence ($\widehat{Prob_i}$), and each model's performance is assessed based on how many actual delinquent cases are captured (y-axis) by a certain proportion of high-risk segment (x-axis). The closer the fitted line to northwest corner, the more accurate the model prediction is (hence, Model B out-performs Model A in Figure 9).[24]

As a recent evidence, Berg et al. (2018) reports the improvement in AUC with the digital footprint variables: that is, the AUC using the credit bureau score alone is 68.3%, the model using the digital footprint variables only shows AUC of 69.6%, and the one including both groups of variables has AUC of 73.6%, a 5.3 percentage points gain compared to the model using only the credit bureau score, a

[24] See Hanley and McNeil (1982) for more details.

substantial improvement in accuracy in this type of analysis. The results also show that the digital footprint variables help enhance financial inclusion for the unscorable customers who have no or insufficient credit history data. Similar results for the accuracy gain in the cases of different types of SD are reported by a number of empirical studies in the recent years (e.g., Freedman and Jin (2018), Puri et al. (2017), Berg et al. (2017), Hildebrand et al. (2017), Herzberg et al. (2016), and Iyer et al. (2016)).

Figure 9.



Source: The author

On the risk-based (marginal-cost rather than average-cost) pricing

The incidence model discussed in the above is a necessary, but not sufficient, input for sound credit risk management. That is, in order to implement a full-blown risk-based pricing system, one should have an additional inputs that enable computation of actuarially-fair risk premia for different borrower segments (e.g., $\widehat{RP_{j,t}}$ for segment j at time t), which generally requires not only the incidence model but also the severity model to gauge amounts of credit losses if and when default happens. Furthermore, a full-blown measurement scheme should also reflect market-driven risk factors, or systematic risk drivers, e.g., forward-looking interest rates, unemployment rates, or expected collateral price movements, along with risk-neutrality and other assumptions.

Specifically, a full-blown risk premium term (or RP_t) can be expressed in the following lending rate equation:

$$(3)\ r_{j,t}^{l} = \ r_t^{f} + OC_{j,t} + E_t\big[Loss_{j,t+k}\big(\widehat{Prob}_{j,t+k}\big)\big];\ \ \delta_t) + v_{j,t}$$

where $r_{j,t}^{l}$ is a lending rate for consumer segment j (at time t), r_t^{f} is a risk-free rate (of comparable maturity), $OC_{j,t}$ is operating cost on the part of lender for servicing segment j, $E_t\big[Loss_{j,t+k}\big(\widehat{Prob}_{j,t+k}\big)\big]$ represents an expected amount of credit loss from segment j that is assessed today, time t, but should reflect forward-looking scenarios of state variables for a future time period (i.e., t through t+k), and [δ v] are parameters to estimate. Estimation of $E_t[\cdot]$ generally requires a simulation procedure that covers a large number of economic scenarios (or, alternatively, is also done through a stress test) along with the fitted performance (i.e., the incidence and severity) models.[25]

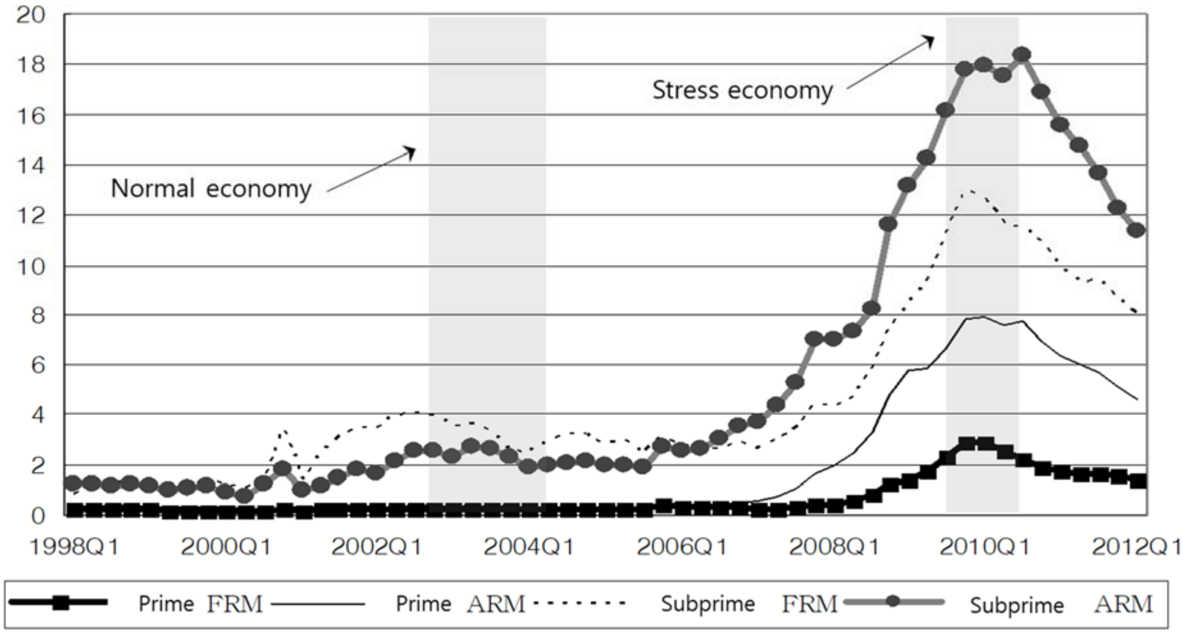
In this vein, the empirical evidences we have so far on the role of SD as a determinant of $E_t[\cdot]$ are fairly limited in the context of equation (3). As such evidences, Lin et al. (2013) reports that borrowers with friends, especially of the sort that are more likely to be credible signals of credit quality and play more pronounced roles in a peer network, tend to be charged with lower interest rates on funded loans (i.e., the Level 3 to 5 friends in Figure 8); And Freedman and Jin (2018) documents that borrowers with social ties are consistently more likely to have their loans funded and are charged with lower interest rates. However, it should be further validated going forward whether or not those and other elements of SD are the ones that should be reflected as a significant element in estimating RP as elaborated in the above.

As another question to be posed, who would be best equipped with the resource required in measuring and managing the underlying credit risk among the market participants, not only in terms of risk-based segmentation but also in terms of risk-based pricing? The task is not trivial in terms of data requirement as well as analytical capability and experience, and should reflect the expected credit losses from a particular segment, $\widehat{RP_{j,t}} = E_t\big[Loss_{j,t+k}\big(\widehat{Prob}_{j,t+k}\big)\big]$, from both normal economies as well as stress ones (i.e., tail events). As a case in point, as shown in Figure 10, while the spread in the historical delinquency rates between the subprime adjustable-rate mortgage vs. the prime fixed-rate mortgage in the U.S. was around 2.5 percentage point during the normal economic condition (2002 to 2005), the gap spiked to over 15 percentage points in 2010, the stress time period caused by the subprime mortgage crisis. The case illustrates that, even though the FinTech service providers are shown to improve the accuracy of the incidence model by adding SD to the model specification, that should not be a proof that they are capable of implementing a full-blown credit risk management or have an advantage over other market participants in doing so. This issue is seemingly an important public policy issue to

[25] In terms of measuring the probability of default (PD), Saunders and Allen (2010) discusses three main analytical frameworks: namely, the Mertonian distance-to-default (or structural PD) model; the decision-tree based (or reduced-form) PD model; and, the scorecard-based heuristic PD model.

comptemplate going forward.

Figure 10. 90+ Days Mortgage Delinquency Rates in the U.S. (By Loan Product)



Source: Cho (2017)

4.4 On the BigTech effect

Can the FinTech industry contribute to economic growth? Given that the sector is still fairly young and evolving, empirical evidence to that end has not yet been firmly established in the academic literature. However, in the case of the BigTech-affiliated service providers, there exist some indirect evidences indicating a positive linkage between their operation and macroeconomic outcomes. As mentioned in Chapter 2, the BigTech-affiliated financial service providers tend to operate within a business ecosystem that encompasses diverse financial and non-financial companies, in which innovation introduced by one firm can be shared across multiple businesses and, in that way, can lead to a productivity gain for them as well as for a whole economic system. (Citi GPS (2018), Frost et al. (2019))

As shown in Table 4, BigTechs represent those large ICT companies whose primary businesses are not finance,[26] and usually enjoy two main advantages: 1) network effects (generated by their online

[26] They include various internet and mobile service providers (Google, Amazon, Microsoft, and Baidu)), e-commerce platform service providers (Alibaba), mobile phone manufacturers and service providers (Apple, Samsung, Mercado Libre, KT – Korea Telecom, Vodafone), and SNS and related service providers (Facebook,

platforms with large customer bases); and 2) technological innovations (in those areas related to FinTech, e.g., AI, BigData, Cloud System, API, among others). (Frost et al. (2019)) One common characteristic of these BigTech firms is the fact that they provide a mobile payment service, which works as an inlet for collecting diverse data of large quantity on consumer behavior, which are subsequently used for different business purposes, e.g., credit provision, investment advisory, and other online and offline transactions. As an example of efficiency gain by utilizing those data, Frost et al. (2019) shows that the credit scoring systems developed by two BigTech-affiliated firms, Mercado Libre in Brazil and Ant Financial in China, are assessed to be superior to those developed by the traditional credit bureaus, and that those credit risk indicators are widely used for various online as well as offline businesses by the firms within their groups.

One well-quoted example of the BigTech-affiliated financial service provider is Ant Financial, a technology and financial service arm of Alibaba (Figure 11). As of February 2020, the total market capitalization of Alibaba Group amounts to $554 billion, and it has Ant Financial along with other e-commerce and technology companies as its affiliates. Ant Financial, which itself is a business group, sets its strategic vision as "leveraging the power of the internet and big data" and "providing inclusive financial services to both consumers and SMEs" (Citi GPS (2018)), and includes the affiliated companies such as: AliPay, a mobile payment service provider; Yu'ebao and Ant Fortune, the wealth management service providers; Ant Insurance Service, an insurance service provider; Zhima (Sesame) Credit, a credit scoring service provider; and, Ant Credit Pay and Ant Cash Now, the lending service providers. The company also employs an aggressive business alliances internationally by partnering with local payment systems in about 30 countries to provide a global payment and other financial services. Ant Financial, along with other BigTech-affiliated financial service providers (e.g., the Tencent's subsidiary WeBank), provide the payment, lending, insurance, and other services to hundreds of millions of consumers and small-medium sized firms in China, and, as such, they greatly enhance the financial inclusion in the country. The business model introduced by Ant Financial is also new and disruptive in that it is essentially breaking down the conventional wall between finance and commerce. (Citi GPS (2018))

This BigTech model of providing financial services is less pronounced in other countries than in China, perhaps due to the presence of a strongly-established incumbent financial service sector along with its own regulatory regime. However, the BigTech companies from other countries,[27] as listed in

Tencent, Kakao).

[27] Examples of BigTechs in other countries (ex. China) include: In Korea, following the introduction of virtual banking licenses, the messaging company Kakao established Kakao Bank, which attracted 820,000 customers in its first four days of operation, and granted KRW 5.2 trillion (USD 4.5 billion) of loans over 2017; In the United States, Amazon granted over $1 billion in small business loans to more than 20,000 Amazon customers lenders in 2017.4 Amazon has also begun a partnership with Bank of America on small business lending, and is reportedly in talks with banks about a checking account product; In Latin America, Mercado Libre had outstanding credit of over $127 million in Brazil, Argentina, and Mexico as of late 2017, and is making tentative entries into asset management and insurance products.

Appendix 1, appear to have a similar potential to combine financial and non-financial services and, by doing that, to contribute to macroeconomic outcome in two main ways: first, by imposing a real and formidable competition and contestability to existing financial institutions, and by increasing factor productivities of the firms within a BigTech-driven ecosystem. An important question to pose is how to maximize societal benefits of financial innovations introduced by BigTechs, via economy of scale and economy of scope with other policy objectives such as ensuring fair trades between big and small firms. These and other public policy issues are the topics of the next section.

Figure 11. The linked business ecosystem by Alibaba Group and Ant Financial

Alibaba group Alibaba.com

Affiliated companies	Description & key business area
Alibaba.com	The leading wholesale marketplace for global trade
1688.com	The leading integrated domestic wholesale market place in China
Alibaba Cloud	A cloud computing service provider
AliExpress	A global retail e-commerce platform
Alimama	A marketing technology platform
Taobao.com	The China's largest mobile commerce platform
TMALL.com	The China's largest B2C platform
Cai Niao	A logistics data platform operator
Ant Finanial	A technology company offering inclusive financial services

Ant Financial Group 蚂蚁金服 ANT FINANCIAL

Affiliated companies	Description & key business area
AliPay	A mobile payment platform with 520m+ users, and business partners across over 15 countries
Yu'e Bao	The largest money market fund in the world, managing $221b
Ant Fortune	MPL for Ant Financial and third-party financial products, with 180m users.
Ant Insurance Service	An insurance service firm with 400m users, offering its own and 80+ insurance companies' products.
Zhima (Sesame) Credit	A credit scoring company, using social networks and payments history with about 260m users.
Ant Cash Now	A credit company for quick funding for AliPay users,

	based on user risk profiles.
Ant Credit Pay	A consumer lending company with 100m active users, having lent $95b to consumers through Q1’17.

5 Regulating FinTech

Despite its rapid growth, the FinTech industry as a whole is still small relative to the whole global financial system and, as such, a FinTech-driven systemic risk is seemingly a remote possibility at this point. However, the industry shares a number of similarities with the conventional financial service sector and, because of that, the regulators should ensure safe and sound operation of, and appropriate consumer protection measures by, the FinTech service providers. At the same time, the sector has its own peculiarities such that the regulators are supposed to employ a modified regulatory approach to balance between instituting conventional financial supervision measures with promoting technology- and data-driven innovations from the sector. In addition, as another spillover effect from the FinTech industry, Pilippon (2016) and Darolles (2016) claim that there are regions of the financial system where incumbents are entrenched with their optimized use of implicit and explicit public subsidies with barriers to entry, and that a more effective way to enhance efficiency in the whole financial service sector is a bottom-up approach by regulating and fostering the new entrants, the FinTech service providers, to undo the existing distortions.

The first policy area to be considered for the FinTech service providers is the prudential regulation, to help prevent a platform run from happening by ensuring financial safety and soundness in their operation. As to the global trends of regulating FinTech, CCAF (2019a) reports that: while the sector is typically unregulated, “bespoke” (i.e., sector-specific or tailor-made) regulation is catching on and, more importantly, a high-risk FinTech sector is generally more heavily regulated (e.g., only 22% of the jurisdictions surveyed by the report formally regulating P2P lending vs. 39% for equity-crowdfunding). Some of the specific prudential policy measures that are already adopted by different countries include: the licensing and approval requirements by financial supervisor (in UK and other countries); the minimum capital requirement for the platforms, e.g., a stepwise required capital amount based on business volume as in UK; the investment caps for small (or household) investors, those in accordance with the income level, as in Korea; and, requirement of periodic and special reporting to ensure sound risk management practice (underwriting, servicing, loss mitigation practices). In addition, given the fact that the platforms tend to hold a fairly significant amount of reserve owned by financial consumers, the regulators may also consider instituting a deposit insurance mechanism that is customized to the sector. And, by fostering a partnership among public and private institutions, a fair and efficient risk-sharing arrangement would be another useful instrument to be considered, which can ensure a sufficient skin-in-the-game on the part of the FinTech platform operators.

The second area of regulatory concern is the business conducts of the FinTech service providers, in particular, those related to financial consumer protection (FCP). Traditionally, FCP measures are instituted both in demand-side and in supply-side of financial markets: that is, in the demand-side, enhancing financial literacy and financial capability of consumers is a major policy initiative, to assist financial consumers with various education and counseling programs so that they can make informed and rational decisions; and, in the supply-side, those instruments to make sure fair and ethical treatment of financial consumers by financial institutions and their employees are the main policy focus, which is generally achieved through ex ante (i.e., before contract signing) information provision, code of business conduct employed by FIs, ethics training programs for their employees, and ex post conflict resolution mechanism.[28] While it is generally the case that the conventional consumer finance sectors (e.g., lending, insurance, and investment) already employ the measures as listed in the above, it is fair to say that the FinTech sector generally lags behind in instituting similar FCP instruments, which should be the task for financial supervisors in coming years. In a sense, such FCP measures are more warranted for the FinTech sector given its vulnerability in cyber-theft and other online crimes as well as the use of digitalized customer data.

The third public policy area is what to do for data privacy, i.e., how to ensure proper protection of personal data and, at the same time, how to make them available to the FinTech service providers in a safe and stable fashion. This has already become a critical policy issue in many countries (e.g., the EU GDPR, General Data Privacy Regulation), and fostering a data economy - an ecosystem that generates economic and social values by exchanging or trading digital data – will become a more important public policy issue toward the FinTech industry as well in the era of digital transformation. At the core of such data-driven efficiency gain is in sharing and trading personal data on financial transactions, for which such new business areas such as MyData is already arising (i.e., a consultation service provided by a third party on personal financial planning with consent by financial consumers on use of his or her private financial data). Over time, this may become another FinTech subsector in which service providers combine both digital data and related technologies (e.g., robo-advisors) to offer innovative financial services.

The fourth area of regulatory concern is about how to maximize external benefits of BigTech-driven innovations, both in technology and in data analytics. The BigTechs' entry to the financial service sector can disrupt the existing industrial division between finance and commerce, as shown in the case of Ant Financial, and can lead to both efficiency gain in the financial service sector as well as to productivity growth in various online and offline businesses in a given economy. While an inquiry about right industrial policy given these possibilities is beyond the scope of this study, it appears to be

[28] Financial educations are generally regarded as ineffective in changing consumers' behavior. However, "just-in-time education" (i.e., providing right education or counseling in right timing when needed) is often the best way to help make the consumers sound financial decisions. (Cude (2020)) IFA can also be an effective mean, but it can suffer a bias of various sorts. For example, Mullainathan et al. (2012) documents that advisers fail to de-bias their clients and often reinforce biases that are in their interests, and advisers encourage returns-chasing behavior and push for actively managed funds that have higher fees. Foàet al. (2015) find that banks are able to affect customers' mortgage choices not only by pricing but also through an advice channel.

warranted to have a comprehensive FinTech policy as a part of national technology and innovation strategy; And such policy should encompass a set of necessary ingredients to foster and nurture the BigTech industries. Using the UK case as a benchmark,[29] those ingredients include, among others, manpower planning to promote innovations (in the end, innovation is done by innovator), a cooperative mechanism among FinTech industry, government, and academia, research and educational programs on FinTech and related innovations in premier universities, periodic assessment of social benefits-costs (BC) of FinTech, enabling regulatory framework for startups and SMEs (e.g., the regulatory sandbox), and frontier reporting and analysis systems for financial statistics and compliance (via RegTech and other means).

6 Concluding remarks

FinTech represents a new, innovative, and disruptive mean of financial intermediation, which is expected to further grow in coming years thanks to the ongoing megatrends of the fourth industrial revolution and the digital transformation. Accepting that as a fact, this study attempts to document the welfare implications of the FinTech industry by surveying the findings so far as documented in the literature, which can be summarized as: the FinTech service providers tend to enhance both efficiency of financial intermediation and extent of financial inclusion in the developed as well as developing countries; they seemingly narrow credit gap caused by information asymmetry between borrower and lender by collecting and utilizing soft data; some concerns are also raised as to the welfare implications, such as the likelihood of overleverage by certain segments of P2P platform borrowers, the lack of appropriate skin-in-the-game arrangement in sharing ex post credit losses, and the inadequate regulatory and consumer protection measures. Furthermore, the BigTech-affiliated financial service providers are examined as a special segment of the industry because they introduce a new and disruptive business model, for which regulators in different countries should carefully design a policy framework by balancing the key policy issues involved.

In a sense, the FinTech service sector is revolutionizing the delivery of financial services by utilizing two critical ingredients – technologies and digital data, essentially making financial services with other on- and off-line transactions as one-stop shopping for financial consumers. In the supply-side, the sector also allows the collection of various data on consumer behavior through internet and mobile platforms, which are further utilized for credit evaluation, product differentiation, and automation of back-office functions such as regulatory compliance and internal controls. As to the credit risk management, this study raises an issue as to the FinTech sector is ready to take on the task of instituting a full-blown risk-based pricing, or has any comparative edge over other market participants

[29] The Royal Scientific Advisors of UK (2014)

in so doing. Given the general trend of delegating the credit risk management role toward the sector, this appears to be an important public policy issue, for which thorough research on a series of involved issues is also called for, including the role of soft data in a broad context of risk management, sound measurement framework to combine product- or consumer-driven (idiosyncratic) risk factors with market-driven (systematic) risk drivers in implementing a full-blown risk-based pricing system, and efficient risk-sharing arrangements between the industry along with public and private market participants.

As a final note, the broader issues of what should be a right banking model in this era of the 4th industrial revolution and the digital transformation (i.e., narrow banking vs. extended banking vs. BigTech vs. anything in between) and of what industrial policies of relevancy the regulators will have to design also warrant careful interdisciplinary research on various topics involved. The core policy issue in this vein appears to lie in balancing two regulatory objectives – ensuring financial safety and soundness of the FinTech service providers vs. nurturing innovations and entrepreneurship to maximize spillover effects by BigTech and other players in the sector. To name a few interdisciplinary research topics of relevancy, value capture mechanisms from innovations, pricing structure in multi-sided platform businesses, entrepreneurial process and commercialization, financial risk management, and other diverse research issues in economics or other disciplines are seemingly important; And, as the author hopes and expects, volume of in-depth interdisciplinary research for these and other topics should go up in coming years.

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Appendix 1. BigTechs from Different Countries

A list of selected BigTechs

	Alphabet (Google)	Amazon	Apple	Facebook	Microsoft	Alibaba	Tencent	Baidu
Market cap ($, billion)	1,080	1,657	2,152	773	1,617	5,816	5,222	42
Anchor business	Advertising, Clould Service	Clould Web Service, E-Commerce	Smartphone, App store	Advertising	Software service	E-Commerce	Game Online Service, SNS Service	Advertising
Payment	Google Pay	Amazon Pay	Apple Pay	Messenger Pay	Microsoft pay	AliPay (via Ant Financial)	TenPay (& WeChat)	Baidu Wallet
Lending	Collaborating w/ Lending Club	na	na	na	na	MYBank (SMEs and online clients)	WeBank	Baixin Bank
Current account	na	Adyen	ACH transfer	na	Host Card Emulation (HCE)	MYBank	WeBank	Baixin Bank
Asset management	na	na	na	na	na	Yu'eBao (the largest MMF)	na	na
Insurance	na	na	na	na	na	Stakes in Cathay Ins. & Zhong An	na	na

Data sources: Google Search Engine (August 25, 2020); Frist et al. (2019)

A list of selected BigTechs (cont'd)

	Vodafone Group (UK)	Mercado Libre(Argentina)	MTN Group(South Africa)	Samsung	Kakao	KT
Market cap ($, billion)	41	60	126	377	33	5
Anchor business	Tele-communication	E-commerce, online auction	Tele-communication, Clould Service	Electronics, SmartPhone	SNS service	Mobile service
Payment	M-Pesa	Mercado Pago	MTN MoMo	SamsungPay	KakaoPay	ISP/Paybook
Lending	Safaricom	Mercado Credito	ubank(mobile only)	na	KakaoBank (internet-only b.)	K-Bank (internet-only bank)
Current account	G4S, ASB Bank, First Rate	na	ubank	na	KakaoBank	K-Bank
Asset management	na	na	Ericsson	Samsung Security	na	VP
Insurance	Carole Nash	na	na	Samsung Life Insurance	na	na

Data sources: The Economist (February 1, 2020); Frist et al. (2019)