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FinTech Megatrends: What Welfare Implications Can We Draw for Financial Consumers?

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A B S T R A C T

This study aims to assess the welfare implications of the FinTech service providers on financial consumers, by focusing on one particular subsector - the online capital-raising activities (CRA) including P2P lending and crowdfunding. To that end, the key arguments advanced by the recent studies are synthesized as follows: Thanks to the rapid deployment of online platforms and digital data in recent years, the CRA service providers have greatly enhanced intermediation efficiency, which results in lower transaction cost and heightened convenience for financial consumers, and have also extended financial inclusion for marginal borrowers in both developed and developing countries; These alternative service providers tend to narrow the credit gap caused by information asymmetry between borrowers and lenders by utilizing soft data for ex ante credit evaluation; However, some concerns are raised as to the likelihood of over-leverage by certain segments of P2P platform borrowers as well as the heightened risk of cyber-crimes such as identity theft and voice phishing. Based on these findings, policy implications as to designing effective measures of financial consumer protection, both from demand-side and supply-side of the CRA service sectors, are discussed.

Keywords: FinTech, Online Capital-Raising Activities, Financial Consumers, Information Asymmetry

Ⅰ. Introduction

The traditional branch-based banking is under attack, as non-banking firms of various kind have been expanding their financial services backed by digital technologies and 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) 2020) 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 reached 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 technologies (generally referred to as FinTech) 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

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operation, technology and infrastructure development, and data processing and analysis. 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.[1] 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 in countries like the United Kingdom (U.K.), 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 welfare implications of one particular FinTech sector on financial consumers - the online capital-raising services (P2P lending and crowdfunding of various types) by synthesizing the arguments advanced by recent studies.[2]

In a broad sense, the FinTech sector represents the financial market version of digital transformation, for which the recent literature documents three broad categories of expected welfare gains (as elaborated in Section 3): (1) the platform effect that reduces transaction costs in service delivery and, at the same time, accumulates digital data through internet or mobile platforms; (2) the prediction power effect that lowers the error in selecting an optimal production technology or business model; and, (3) the new analytics effect that expands the scope of empirical analyses to various alternative (or non-conventional) data enabled by the AI-driven new analytical methods.

In the case of the FinTech CRA service providers, four particular welfare implications have emerged in the literature: first, those online service providers deliver services to financial consumers with a much cheaper, faster, and more convenient intermediation process 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); second, they are shown to be reducing the information asymmetry by collecting and utilizing various types of soft data for ex ante credit evaluation (e.g., social or friend network, digital footprint, location of borrower, and indicators of trustworthiness), which helps grasp a fuller and more real-time picture of borrowers' creditworthiness (Lin et al. 2013, Iyer et al. 2016, Puri et al. 2017, Hildebrand et al. 2017, Freedman and Jin 2017,Berg et al. 2020); third, the CRA service providers are shown to be "bottom-fishing" in the scale of creditworthiness, i.e., serving those borrower segments or geographical areas that are left out by existing financial institutions due to low credit scores or no or insufficient credit history (so-called "thin filers") (Jagtiani and Lemieux 2018, De Roure et al. 2018); and, finally, the rise of the FinTech sector in general also increases the incidences of illegal or fraudulent financial transactions, such as cyber-thefts, voice phishing (i.e., fishing private information for the purpose of demanding money transfer through mobile phone or other means), ponzi schemes for fake private equity funds, and "darknets" (platforms for illegal online transactions based on crypto-currencies) (Wellicz 2016, Foley et al. 2019).

As to the financial consumer protection (FCP), three policy implications are elaborated given the survey. First, the FCP measures should be designed to tame specific behavioral patterns that are frequently observed from the financial markets, e.g., pro-cyclical lending, misrepresentation or incomplete sales, overleverage by liquidity-constrained financial consumers, and herd behavior or uninformed investment by liquidity-surplus financial consumers. Second, as to the information provision to financial consumers (on product or service details), doing so in a timely and understandable (to financial consumers) fashion should be an important principle to stick to, as emphasized by recent studies. Third, on the supply-side, strengthening financial supervision of CRA service providers, both for their ex-ante (before point-of-sale) activities and for ex-post regulatory requirements to incentivize them to treat consumers fairly and ethically, is very much warranted.

The rest of the paper consists of the following five sections: the underlying trends of relevancy (Section II), the implications of digital transformation (Section III), four welfare implications for financial consumers (Section IV), policy implications as to the measures of financial consumer protection (Section V) and concluding remarks (Section VI).

[1] 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 U.K., 49% in Latin America, 41% in Europe (ex. U.K.), 36% in Asia Pacific (ex. China), and 19% in Africa) (CCAF 2020).

[2] To the extent relevant, the issues relevant to the mobile payment sector will also be covered.

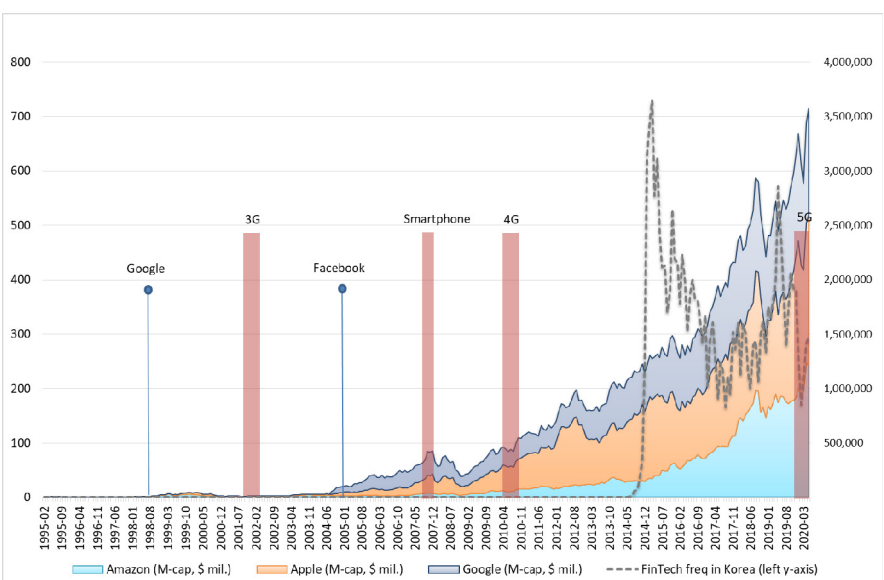
Ⅱ. Underlying Trends of Relevancy

A. The Advancement of the Digital Technologies

Innovations in the financial service sector date back to the 13th century when the paper check was first introduced, a disruptive technology that fundamentally changed the ways of financial and non-financial transactions being settled. Since then, a series of other innovations occurred over time, including double-entry book keeping (1400s), telegraph (1800s), credit card (1950s), Automated Teller Machine (ATM) (1970s). During the last three decades, however, the intensity of innovations in the sector driven by the digital data and technologies, often termed as digital transformation, finds no match with any historical period. In particular, they start 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 these recent innovations, the market capitalizations of the leading web-based global corporations (e.g., Amazon, Google, and Apple) have been steeply rising during the last two decades (see Figure 1).

While the recent innovations in the financial service sector propelled by the digital transformation appear to have started from 1990s in the U.S. and other advanced economies, most emerging market countries tend to lag in riding on the innovation cycle. Taking Korea as an example, the internet subscription rate was fairly low throughout the 1990s (only 5.7 percent among the adult population in 1998), which has steeply increased in the subsequent years (about 80 percent in 2008). And the media coverage of the term FinTech rose sharply around 2015, the same time as the introduction of the first mobile payment service (KakaoPay) in the country (Figure 1).

In contrast, the U.S. financial service industry implemented various online B2B and B2C systems from the mid-1990s, which have evolved into the current FinTech lending platforms. One such example was the Automated Underwriting System (AUS) used by the residential mortgage finance industry in the U.S. from the mid-1990s, an online document validation and credit evaluation system that delivered a substantial efficiency gain for both consumers and financial intermediaries but, at the same time, worked as a mass production mechanism of the high-risk



Source: Author

Figure 1. Evolution of Technologies, IT Firms, and the Emergence of FinTech (in Korea)

subprime mortgage contracts prior to the financial crisis.[3] As an enhanced version of AUS, the FinTech mortgage lending platforms are expanding their business volumes in recent years, which are shown to be faster in processing loan applications with comparable outcomes in credit evaluation (assessed by the ex-post delinquency rates) with the conventional offline lending channels (Fuster et al. 2018). The phase of innovation in this FinTech sector has recently been accelerating thanks to the introduction of other digital technologies (e.g., AI, IoT, Cloud, Big Data, Block Chain), with the early examples of the service providers including Prosper (established in 2005 in the U.S.), ZOPA - Zone of Possible Agreement (in 2005 in U.K.), and Lending Club (in 2006 in the U.S.).

On the other hand, the FinTech lenders in the emerging market countries began their operations in more recent years. For example, the leading Chinese lending platforms started around 2014, e.g., iZhongchou (from 2014 and affiliated to Alibaba), and QQ Gongyi (from 2014 and affiliated to Tencent); In the Korean case, it was around 2017 when a number of the P2P and crowdfunding platforms were established, and there are also three "internet-only" (with no branch network) banks that are in operation as of today - K-Bank (from 2017 and affiliated to the mobile phone servicer Korea Telecom), Kakao Bank (from 2017 and to the chatting app and e-commerce company, Kakao), and Toss Bank (from 2021 and affiliated to the first FinTech unicorn[4] from the country).

B. The Global Trend of Online Capital Raising Activities (CRA)

The concept of FinTech is still evolving, as indicated by the varying definitions introduced in the literature.[5] To our end, FinTech is simply defined 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 2, the FinTech services utilize a diverse 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.[6] This study focuses on the online capital raising services (P2P lending and crowdfunding of various types), and, to the extent relevant, the mobile platform-based payment and settlement services.

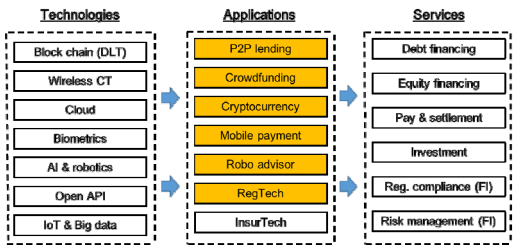


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Figure 2. Technologies and FinTech Services

The online capital-raising activities have been proliferating in 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 (2020) 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).[7]

[3] 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.

[4] A non-listed SME whose asset exceeds one billion USD.

[5] FinTech is alternatively defined as: an application of technology within the financial industry (Barberis 2014); a new financial industry that applies technology to improve financial activities (Schueffel 2016); and, a cross-disciplinary subject that combines finance, technology management, and innovation management (Leong and Sung 2018).

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

[7] There are also two other types of service providers that can be included in the FinTech industry - the internet-only banks (Rakuten Bank, Go Bank, WeBank, KakaoBank, K-Bank), and the mobile-only banks (Monese 2015, Revolut 2015, Starling Bank 2017).

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%), U.K. (3.4%), Europe excluding U.K. (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 U.K., 7% in Asia-Pacific ex. China, and 12% in the U.S.), indicating a steady growth of the sector globally except in China.

The P2P MPL Lending to Consumers represents the largest subsector in most areas (except U.K.), 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 - make up almost the whole 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 U.K., with relatively high shares of P2P MPL Property (17%), Invoice Trading (8%), and equity and real estate Crowdfunding (8%). The U.K. 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.

The mobile-phone based payment 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

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.U.K.)	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
U.K.	173%	63%	27%	31%	28%	29%	2%	13.84
Europe (ex. U.K.)	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 (2020)

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

	China	USA	U.K.	Eur. (ex.U.K.)	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)

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 of GDP amounts to a 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 U.K.) (Frost et al. 2019).

Ⅲ. Implications of the On-going Digital Transformation

As to the implications of digital transformation to an economic system as a whole, there has been an increasing volume of academic studies on the topic during the last several years. The key focuses of their inquiries include the role of the new breed of digital technologies that enable collecting·sharing·analyzing digital data through internet or mobile platforms (e.g., ICBM - IoT, Cloud, BigData, AI and Machine Learning, and other online platform related technologies), and the expected benefits (or welfare gains) and costs (or risks) involved with the advancement of these technologies. In particular, three anticipated social effects of the on-going trend of digital transformation (DT) are documented.

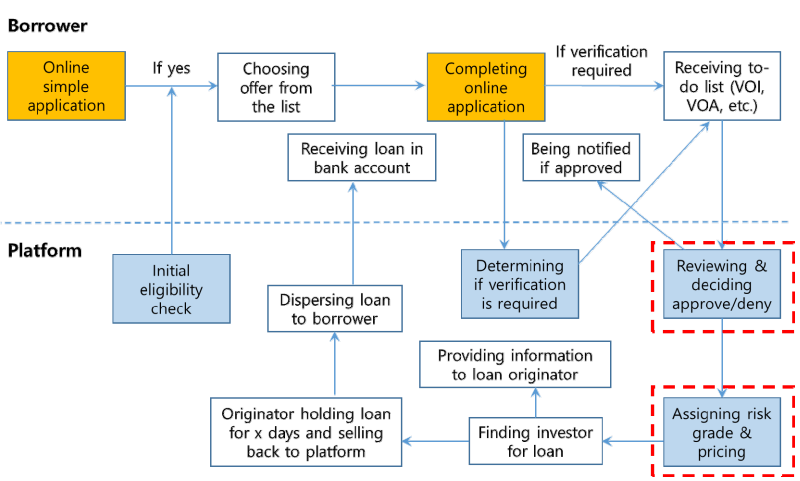
First, the platform effect of DT can substantially reduce the transaction costs in service provision (compared to the traditional offline services), which can enhance the welfare of consumers in general. At the same time, the platform operator can accumulate various digital data on consumer behavior, which can be utilized for product development and risk management. In the financial service sector, the platform effect can result in a diminishing role of the existing service channels (along with a reduction in workforce), which is termed as disintermediation in the sector (Philippon 2015, 2016, Park et al. 2021). Another anticipated outcome of the platform effect, as documented in the literature, is an increased cyber-risk (e.g., voice-phishing and other cyber-crimes).

Second, on the viewpoint of individual firms, the prediction power effect of DT (i.e., reducing prediction error in selecting an optimal technology or business model thanks to increased quantity of data accumulated) can result in an increase in production productivity and the quality-adjusted output (Farboodi and Veldkamp 2021). The study further argues that this prediction power effect tends to be larger (or increasing returns to scale) for smaller firms (e.g., start-ups) or when the level of data accumulation is low. In a related vein, other studies demonstrate that accumulating more data tends to: increase the accuracy in predicting business cycles (Ordonez 2013, Fajgelbaum et al. 2017); raise the predictive power in assessing the credit risk in the lending sector and, hence,

reduce the cost of capital for business borrowers (Begenau et al. 2018); and, lower the importance of collateral for household borrowers due to the heightened accuracy in evaluating the credit risk (Gambacorta et al. 2020).

Third, the new analytics effect of DT implies that the AI-driven analytical methods (e.g., ML and DL - Machine Learning and Deep Learning) allow use of both conventional and non-conventional data for scientific inference. For example, there are empirical studies that utilize satellite pictures to forecast economic activities in certain geographical areas, use tax reports (10K Reports for business entities) to categorize, and assess performance of, firms, or use external aesthetic views of buildings in property valuation.[8] There are also AI-based new analytical methods (e.g., regression trees, LASSO, random forests, ensemble) as well as software packages that facilitate their uses (R, Python). These new analytics, as argued by Mullainathan and Spiess (2017), influence the way that empirical analyses are performed in economics and other academic disciplines. That is, while the typical empirical investigation via an econometric model is in general deductive (i.e., a top-down approach that starts from a theory and proves/disproves a hypothesis derived with regression coefficient estimated $\hat{\beta}$, by assuming a particular model specification), the process of inquiry with the AI-based analytical methods tends to be inductive (i.e., a bottom-up approach that automatically tests a large number of permutations among explanatory variables and searches a model that minimizes the error term, $\hat{\epsilon}$).

In the context of the online CRA services, the above three effects of DT boil down to an enhanced risk assessment performed by the platform service providers. As illustrated in Figure 3, the FinTech lending process starts with an online loan application by a prospective borrower. 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, an approval-denial (underwriting) 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, an appropriate risk premium based on which the investors can bid (i.e., pricing decision). 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, which will be elaborated in the next section.



Source: Frost et al. (2019), p. 12; Revised and re-produced based on the original source

Figure 3. A Typical Online Intermediation Process

[8] See Mullainathan and Spiess (2017) for a survey of those studies.

Ⅳ. Welfare Implications for Financial Consumers

A. Enhanced Intermediation Efficiency

For the purpose of defining the concept of intermediation efficiency, suppose that a profit-maximizing service provider in the financial market has the following objective function:

$$(1)\quad EY_t = r_t^l - r_t^f - \delta_t - E_t\left[Loss_{t+k}\right]$$

where EY_t is a short-term excess yield (from its per-period operation), 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), and δ_t is a per-period operational cost expressed as a percent to each dollar lent. The last term in the right-hand side, $E_t\left[Loss_{t+k}\right]$, represents an expected credit loss that can happen in future (time t+k) and is evaluated today (time t).

EY_t represents an indicator of the efficiency in financial intermediation, and, ceteris paribus, the lower EY for a given financial service sector (or for an individual service provider), the more efficient (the more welfare-enhancing for financial consumers) its intermediation is. In the case of the U.S. Philippon (2015) demonstrates that EY_t for the financial service sector as a whole has been consistently and unjustifiably high since the early 1980s, for which he refers to the increased market power of the large financial institutions (FIs) through the active mergers-and-acquisitions from the early 1990s as a possible reason. In a follow-up study, he also claims that those existing FIs did not properly reflect the reduction in the operational cost, δ_t, caused by the automation and other data·ICT-driven innovations related to the intermediation process, and that the FinTech service providers potentially enhance the intermediation efficiency in the whole financial service sector by posing a heightened levels of competition and contestability, which is often labeled a “catfish effect” (Philippon 2016).

In fact, a number of studies document that the FinTech lenders 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). As an empirical evidence based on the household-level micro data, Fuster et al. (2018) report that the FinTech mortgage lenders in the U.S., 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 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.

B. Reduced Information Asymmetry

1. On the Type A and Type B information asymmetries

Information asymmetry, and credit rationing as a consequence thereof, have long been a topic of investigation in the finance literature (Stiglitz and Weiss 1981, de Meza and Webb 1987, 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 the risk premium (a proxy for $E_t\left[Loss_{t+k}\right]$) goes up to reflect a higher expected credit loss if and when the borrower defaults, low-risk borrowers self-select out of the credit market, causing an adverse selection problem for the lender. Knowing that an increase in the lending rate, r_t^l, to reflect a hgher risk premium will cause a faster drop out by low-risk borrowers than by high-risk ones, at a certain level of expected credit loss, the lender either reduces or even stops credit supply, which results in a credit gap (or excess demand) in the lending market.

A solution to the above type of information asymmetry, to be labeled as “Type A Info-asymmetry,” is a separate, rather than a pooled, equilibrium: that is, if a service provider is capable of measuring segment-specific risk levels (for high-risk vs. low-risk consumers) and of reflecting them in underwriting and pricing decisions, then the

above-mentioned possibility of adverse selection and credit rationing can disappear. The implication of this risk-based consumer segmentation and pricing goes beyond the efficiency in risk assessment in that such supply-side behavior can expand financial service to marginal consumer segments (e.g., borrowing-constrained households in lending market, and those excluded from a particular type of insurance contract). In fact, more accurate risk assessment and charging actuarially-fair risk premiums can actually enhance the welfare of marginal borrowers in that they are more likely to be included in formal financial service sector and are less likely to be steered to a more costly, or even informal, service sectors (i.e., 2nd- or 3rd-tier FIs for which consumers must pay much higher interest rates).

However, the asymmetry can go the other way when financial consumers are disadvantaged in understanding arcane financial products in terms of their risk-return profiles. In fact, it is well-documented that financial consumers in general tend to be myopic, present-time biased, and lacking even basic understandings of financial products (Miles 2004, Campbell 2006, Campbell et al. 2011). Hence, they are vulnerable if a profit-driven service provider sells a product by charging an excessive amount of risk premium or by misrepresenting embedded product risk (i.e., under-stating the expected credit risk or over-charging for underlying risks. The general solution to this problem, to be labeled as "Type B Info-asymmetry," is to make a leveled playing field between service providers and financial consumers, through appropriate (or effective) financial education programs on the demand-side and various legal and regulatory requirements on the supply-side, which is the focus of discussion in Section 5.

2. On the use of soft data by FinTech service providers

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[9] (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. 2020).

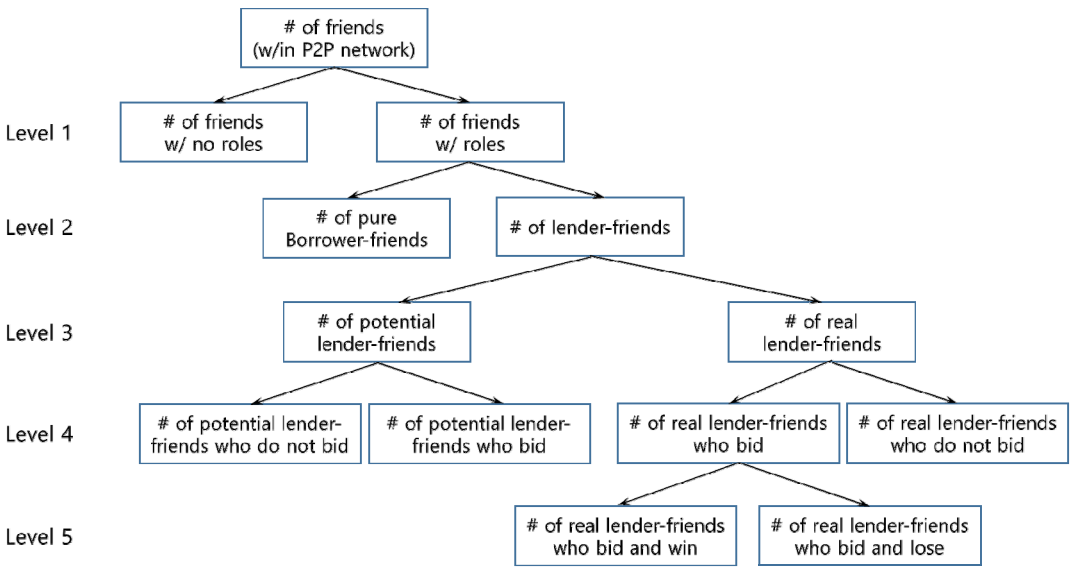
The main outcome documented empirically in the literature is that including soft data improves the model fit by reducing the omitted variable bias and does enhance the accuracy of the incidence model. There are several specific types of soft data whose effects are documented in the literature. First, 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 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. The study also shows an empirical implementation of defining friend types in a hierachical fashion (as shown in Figure 4).[10]

Second, a series of "digital footprint" variables is also shown to be a part of soft data.[11] For example,Berg et al. (2020) 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

[9] See Gorton and Winton (2003) for a review.

[10] At the top level in Figure 5 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.

[11] Our dataset 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.



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

Figure 4. Friends Hierarchy (revised and recreated from Lin et al. (2013))

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. A number of studies recently documents a gain in accuracy for credit risk assessment with the use of different types of soft data (e.g., Freedman and Jin 2018, Puri et al. 2017, Berg et al. 2017, Hildebrand et al. 2017, Herzberg et al. 2016, Iyer et al. 2016).

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, Jagtiani and Lemieux 2018). Previous studies have found 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; 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 soft data. (Duarte et al. 2012; Ravina 2008; Pope and Sydnor 2011; Duarte, Siegel, Gonzalez and Loureiro 2012; Young 2012). 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.

C. Extended Financial Inclusion

Do FinTech lenders make the financial service sector more complete by serving "the underserved"?[12] The recent studies indicate that the answer 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 empirical evidence, the P2P lenders in the U.S. are shown to be bottom-fishing borrowers with low credit scores, e.g., those with FICO scores less than 640 who are generally rated as a 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 3, 13.6 percent in the U.S., representing the case of Lending Club, and 10~25 percent in U.K.) and the average lending rates are high (14.2 percent in the U.S. and 10.86 percent in U.K.).

There is one particular consumer segment whose welfare appears to be clearly improved by the FinTech lenders, i.e., those with no or scanty credit history ("thin filers"), for whom the FinTech lenders show a potential to fill this gap and to expand financial inclusion for them (Berg et al. 2018). As another 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. Also documented is that as the number of banks and banking offices continue to decline, the presence of FinTech lenders tends to supplement the availability of unsecured consumer credit (Jagtiani and Lemieux 2018, De Roure et al. 2018), Buchak et al. 2017).

In a dynamic sense, however, whether FinTech lenders deliver a similar welfare gain on a longer-term basis is less clear. As empirical evidence to that end, using a large credit bureau dataset 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 point 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 rises by 35% (33%) 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 sub-

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)

[12] 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 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.

sequently (with the subprime MPL borrowers 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 funds, 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.

From the perspective of the developing countries, a large segment of financial consumers tends to be excluded from formal financial services, and the FinTech service sector is playing an important role in filling the gap through mobile platforms. In fact, a number of studies document that the mobile payment systems are serving as a powerful mechanism of financial inclusion by leap-frogging the development of the conventional financial service mediums (e.g., checking and savings accounts, insurance contracts, investments, and credit cards) (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).

D. Increased Cyber-Crimes

The more connected the financial service sector through the online platforms is, the higher the chance of illegal financial transactions becomes, as documented in the literature. As a case in point, IMF (2016) reports that the number of exposed identities has been rising steeply by jumping 23 percent in 2015 with the total 429 million cases, resulting in global damages estimated to be more than $500 billion per year. In the FinTech service sector, the number of cases for a pseudo (or fraudulent) intermediation by illegal transaction counterparties is also increasing, such as stealing private data through hacking, threatening financial consumers through "voice phishing" (fishing private information for the purpose of demanding money transfer through mobile phone or other means), and spreading a ponzi scheme to recruit investors for a fake investment product (e.g., fake private equity funds, stock listings, derivative contracts, and cryptocurrency trades). In this vein, the "darknets"[13] in which transactions are enabled by the cryptocurrencies are known for various illegal trades (e.g., drugs, hacks and thefts, illegal pornography, and, even, murder-for-hire) in an anonymous and efficient fashion, whose economic value is estimated to be around $76 billion in 2017 (Foley et al. 2019).

As one incident to note as to the consumer protection problem in the online CRA sector, there were a large number of P2P platforms (over 3,000 out of about 5,000) that were either closed or ceased operations between 2014 and 2017 when the regulatory authority in the country strengthened the supervision on the sector (Citi GPS (2018). Such cases indicates that the sector should be properly supervised, not only in terms of financial safety and soundness of their online operations (via a regime of risk-based capital requirements and other regulatory measures to contain the liquidity and operational risks), but also protecting financial consumers with a set of effective measures in both demand-side and supply-side of the CRA service sector.

One particular issue to be discussed in this vein is MyData,[14] a new data consultancy service based on consumers' own private data. This service area appears to be potentially promising in that it clearly assigns the property right on private (or personal) financial data to financial consumers and, at the same time, allows the use of personal data in a welfare-enhancing fashion. For example, in Korea where MyData was introduced in early 2020, the service encompasses a fairly broad scope of operations for the service providers (e.g., credit evaluation, training, lending, among others, in addition to the consultation). Furthermore, it is also designed to cover not only financial data but also other consumer data (for medical service, education, and government services of certain types). Though it remains to be seen whether this new service area actually enhances consumer welfare-enhancing in any meaningful fashion, it can serve as a stimulator to utilize private data to innovate financial services for consumers.

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[13] The study estimates that there are about 30,000 darknet domains in operation, with the famous case of "Silk Road," in which a very elaborate drug transaction system via Bitcoin and other cryptocurrency-based escrow accounts is established (descriptions of many different types of drug, insurance and refund policies, and postage methods and locations of delivery).

[14] As a new financial service business, MyData generally refers to 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.

Ⅴ. FinTech and Financial Consumer Protection

What implications can we draw from the above discussions on the workings of the online CRA service providers as to the financial consumer protection (FCP)? The key policy objective for FCP, as the recent literature argues, boils down to ensuring two behavioral principles in the financial markets - informed and sound (i.e., financially-savvy) decisions by consumers in choosing financial products and services and, at the same time, fair and ethical treatment of the consumers by financial institutions (FIs) and their employees despite the fact that their primary incentive is in maximizing profit.[15] As such, the FCP policy instruments should target to tame specific behavioral patterns that are frequently observed from the financial markets, such as:

- Pro-cyclical lending, or excessive pursuance of short-term profits by financial institutions and their employees at long-term costs;
- Credit rationing caused by "Type-A" information asymmetry, i.e., the service providers' being disadvantaged as to financial consumers' creditworthiness, and excess demand created in the lending sector;
- Misrepresentation or incomplete sale caused by "Type-B" information asymmetry, i.e., financial consumers being disadvantaged in understanding arcane financial products;
- Pseudo or fraudulent intermediations by illegal service providers, e.g., theft of private data, voice phishing, and a ponzi investment scheme;
- Overleverage by liquidity-constrained financial consumers (as borrowers in the lending sector);
- Herd behavior or uninformed investment by liquidity-surplus financial consumers (as investors in the lending sector); and,
- Myopic and uninformed decisions by consumers caused by a lack of fundamental knowledge and information on financial products and services.

As to the specific FCP measures on the demand-side, the traditional education programs are generally viewed as having a limited effectiveness at least for adults (those for school-age children on basic financial concepts may be more useful). In the literature, it is emphasized that a timely provision of information to financial consumers (via training, counseling, and product summary) such that they can make more sound and informed decisions should be the way in designing education or counseling programs (Mandell 2006, Lynch et al. 2013, Lusardi and Mitchell 2015, Cude 2020). In addition, providing product information to financial consumers in an understandable fashion is also stressed as an underlying principle, for which various experiments on consumer behavior to explore the best practice is also warranted.[16] In terms of the empirical methodology, the randomized controlled trial (RCT), which is being popularized as a sound research design in different academic disciplines, appears to be a promising way to test if the demand-side FCP measures in fact influence consumer behavior and wellbeing.[17]

On the supply-side, various FCP measures have been instituted since the 2008 financial crisis, which can be categorized into two groups: that is, those ex ante (i.e., before point-of-sale) measures of voluntary or regulatory requirements, including information provision, code of business conduct, training on business ethics, and so on; and, those ex-post measures for conflict resolution (before a lawsuit), ombudsman, and FCP-related KPIs used in performance evaluation. While it is generally the case that the conventional service providers (e.g., banks, insurance companies, security dealers) tend to employ these measures during the last decade or so, the FinTech service sector tends to lag in instituting similar measures. In a sense, those FCP measures are more warranted for this online platform-based service providers given its vulnerability to cyber-crimes, which should be the task for financial supervisors in coming years.

Ⅵ. Concluding Remarks

This study attempts to document the main implications of the online CRA sector on financial consumers, examin-

[15] See Cho and Part (2021) for a literature survey along with the institutional arrangements of the demand- and supply-side FCP measures.

[16] See Knoll (2021) as an example.

[17] See Kaiser et al. (2020) for the meta-analyses on those studies that utilize the RCT method for testing the effects of financial education.

ing specific areas of welfare gain or loss for consumers - enhanced intermediation efficiency, reduced information asymmetry, expanded financial inclusion, and increased risk of cyber-crimes. Overall, the sector is greatly changing the ways to deliver financial services by utilizing digital technologies and data, making it possible to combine financial and non-financial transactions as a one-stop shopping for financial consumers. In addition, through a more accurate measurement of credit risk, the sector also extends financial inclusion for those marginal consumer segments who are excluded from the conventional financial service sectors. As a wrap-up, three points are elaborated below to suggest the role to be played by the global research community in making the sector even more welfare- enhancing going forward.

First, there should be a heightened level of empirical investigation on whether those FCP measures discussed actually have an impact on behavioral outcomes and, further, on types of nudges to induce such behavioral changes. Financial education represents one particular area that will benefit from such research endeavor in future. Nonetheless, some of the supply-side FCP policy elements should also be the topics of similar empirical investigation. For example, effects of different training programs for business ethics, specific rules and regulations to reflect the usual principles of business conduct, and alternative dispute resolution mechanisms can be the targets of such empirical endeavor. In addition, the inter-play between the FCP measures and other public policy goals (e.g., the safety and soundness regulations) should also be a topic of future theoretical and empirical research.

Second, the human dimension of the FCP policy regime should also be investigated. That is, even if a country has the best possible FCP institutions in both demand- and supply-side, they will not be effective and will not deliver intended outcomes unless a group of professional, capable, and committed personnel carries out those tasks. Hence, there should be a conscientious effort and strategy to develop and place such people in key positions, whether they are educators, counselors, or regulators. In the end, it is more likely to be those who run it rather than the system itself that can make the system fail and cause a large-scale systemic problem. Hence, the statement, "it is singer not the song," should also apply to designing a FCP policy regime. In that sense, it is important to deploy those who are technically capable of carrying out the FCP policy measures in the era of digital transformation, with skills in AI-based analytics and the non-conventional data that are increasingly important.

Finally, there should be a long-term and international research collaboration on the various topics that warrant sound and careful research in the future. Given the diverse topics for future research in this space, the nature of the research should also be interdisciplinary among financial economists, legal scholars, education experts, and others in related fields. In addition, lessons learnt by one country, whether they are positive or not, can be useful to other countries, which represents another argument for the international research collaboration. To that end, it is also important to work with those existing organizations, e.g., the international academic and policy-coordination bodies such as IAFICO (the International Academy of Financial Consumers), CI (the Consumer International), FinCoNet, among others, which can serve as sustainable forums to share research findings and policy practices among interested scholars.

References

Barberis, J. (2014). The rise of Fintech: Getting Hong Kong to lead the digital financial transition in APAC. *Fintech Report. Fintech HK*, *13*(4).

Berg, T., V. Burg, A. Gombović, & Puri, M. (2020). On the Rise of FinTechs - Credit Scoring using Digital Footprints. *The Review of Financial Studies*, *33*(7), 2845-2897.

Bertsch, C., Hull, I., & Zhang, X. (2021). Monetary Normalizations and Consumer Credit: Evidence from Fed Liftoff and Online Lending. *International Journal of Central Banking, 18(5), 279-325.*

Bricker, J., Dettling, L. J., & Henriques, A., Hsu, J. W., Jacobs, L., Moore, K. B., Pack, S., Sabelhaus, J., Thompson, J., & Windle, R.A. (2017). Changes in U.S. Family Finances from 2013 to 2016: Evidence from the Survey of Consumer Finance. *Federal Reserve Bulletin*, 103(3):1-42.

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks. *Journal of Financial Economics, 130(3) 453-483.*

Campbell, J. Y. (2006). Household Finance. *Journal of*

Finance, 61, 1553~1604.

Campbell, J., Jackson, H., Madrian, B., & Tufano, P. (2011). Consumer Financial Protection. *Journal of Economic Perspectives, 25(1), 91-114*.

Cambridge Center for Alternative Finance (CCAF). (2020). The Global Alternative Finance Market Benchmarking Report. *CCAF, April 2020*.

Carroll, P., & Rehmani, S. (2017). Alternative Data and the Unbanked. *Oliver Wyman Insights*, http://www.oliverwyman.com/our-expertise/insights/2017/may/alternative-data-and-theunbanked.html

CCAF. (2020). Transforming Paradigms A Global AI in Financial Services Survey. *CCAF, January 2020*.

Chava, S., & Paradkar, N. (2018). Winners and Losers of Marketplace Lending: Evidence from Borrower Credit Dynamics. *Georgia Tech Working Paper 18-16, SSRN*: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3178322.

Chen, B. S., Hanson, S. G., & Stein, J. C. (2017). The Decline of Big Bank Lending to Small Banks: Dynamic Impacts on Local Credit and Labor Markets. *NBER Working Paper 23843*.

Cho, M. (2009). Managing Mortgage Credit Risk: What Went Wrong with the Subprime and Alt-A Mortgage Markets? *International Real Estate Review, 12(3), 295-324*.

Cho, M. (2007). 180 Years' Evolution of the U.S. Mortgage Banking system: Lessons for Emerging Mortgage Markets. *International Real Estate Review, 10(1), 171-212*.

Citi GPS. (2018). BANK OF THE FUTURE: The ABCs of Digital Disruption in Finance. *Citi GPS: Global Perspectives & Solutions, March 2018*.

Crowe, C., & Ramcharan, R. (2013). House Prices and Household Credit Access: Evidence from Prosper. Com. *Journal of Money, Credit and Banking, 45(6), 1085-1115*.

Cude, B. J. (2020). Financial Education in the United States. *The International Review of Financial Consumers, 5, 25-31*.

de Meza, D. and Webb, D.C. (1987). Too Much Investment: A Problem of Asymmetric Information. *Quarterly Journal of Economics, 102(2), 281-292*.

De Roure, Pelizzon, L., & Thakor, A. (2018). P2P Lenders versus Banks: Cream Skimming or Bottom Fishing? *SAFE Working Paper 206*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3174632

DiMaggio, M., & Yao, V. (2021). Fintech Borrowers: Lax-Screening or Cream Skimming? *The Review of Financial Studies, 34(10), 4565-4618.*

Duarte, J., Siegel, S., & Young, L. (2012). Trust and Credit: The Role of Appearance in Peer-to-Peer Lending. *The Review of Financial Studies, 25(8), 2455-2484*.

Fajgelbaum, P. D., Schaal, E., & Taschereau-Dumouchel, M. Uncertainty Traps. *The Quarterly Journal of Economics, 132(4), 1641-1692*.

Fama, E. (1985). What's different about banks? *Journal of Monetary Economics, 15(1), 29-39*.

Farboodi, M., & Veldkamp, L. (2021). A Growth Model of the Data Economy. *NBER Working Paper 28427*.

Foley, S., Karlsen, J., & Putnin, T. (2019). Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies? *The Review of Financial Studies. 32(5), 1798~1853*.

Freedman, S., & Jin, G. (2017). The Information Value of Online Social Networks: Lessons from Peer-to-Peer Lending. *International Journal of Industrial Organization, 51, 185-222*.

Frost, J., Gambacorta, L., Huang, Y., Shin, H.S., & Zbinden, P. (2019). BigTech and the Changing Structure of Financial Intermediation. *Economic Policy, 34(100), 761-799.*

Fuster, A., Plosser, M., Schnabl, P. & Vickery, J. (2019) The Role of Technology in Mortgage Lending. *The Review of Financial Studies, 32(5), 1854-1899.*

Gambacorta, L., Huang, Y., Li, H., Qiu, H., & Chen, S. (2020). Data vs collateral. *BIS Working Papers No 881*.

Gao, Q., Lin, M., & Sias, R. (2014). Word Matters: The Role of Texts in Online Credit Markets. *Journal of Financial and Quantitative Analysis, forthcoming.*

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology, 91(3), 481-510*.

Hamermesh, D. S., Biddle, J. E. (1994). Beauty and the Labor Market. American Economic Review, 84(5), 1174-1194.

Havrylchyk, O., Mariotto, C., Rahim, T., & Verdier, M. (2018). What Has Driven the Expansion of the Peer-to-Peer Lending? *Universite Paris, Boston University, and the European Commission Working Paper.*

International Monetary Fund (IMF). (2017). Fintech and

Financial Services: Initial Considerations. *IMF Staff Discussion Note, SDN/17/05*.

Iyer, R., Khwaja, A., Luttmer, E., & Shue, K. (2016). Screening Peers Softly: Inferring the Quality of Small Borrowers. *Management Science, 62(6), 1554-1577*.

Jack, W., Ray, A., & Suri, T. (2013). Transaction networks: Evidence from mobile money in Kenya. *American Economic Review, 103(3), 356-61*.

Jagtiani, J., & Lemieux, C. (2019). The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform. *Financial Management, 48(4), 1009-1029.*

Jagtiani, J., and Lemieux, C. (2018). Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks? *Journal of Economics and Business, 100, 43-54*.

Kaiser, T., Lusardi, A., Menkhoff, L., & Urban, C. (2021). Financial Education Affects Financial Knowledge and Downstream Behaviors. *Journal of Financial Economics.*

Knoll, M. (2021). Disclosure Research at the CFPB. *Presented at the 2021 IAFICO seminar, June 18, 2021*.

Leong, K., & Sung, A. (2018). FinTech (Financial Technology): What Is It and How to Use Technologies to Create Business Value in FinTech Way? *International Journal of Innovation, Management and Technology, 9(2)*.

Lin, M., Prabhala, N. & Viswanathan, S. (2013) Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. *Management Science, 59(1), 17-35*.

Mbiti, I., & Weil, D. (2011). Mobile banking: The impact of M-Pesa in Kenya. *African Successes, 3, 247-294.*

Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives, 31(2), 87-106*.

Ordonez, G. (2013). The Asymmetric Effects of Financial Frictions. *Journal of Political Economy, 121(5), 84*.

Organization of Economic Cooperation and Development (OECD). (2019). The Digital Innovation Policy Landscape in 2019. *OECD SCIENCE, TECHNOLOGY AND INNOVATION POLICY PAPERS, No. 71.*

Park, S., Kesuma, P. E., & Cho, M., (2021). Did Financial Consumers Benefit from the Digital Transformation? An Empirical Investigation. *International Journal of Financial Studies, 9(57)*.

Petersen, M., & Rajan, R. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. *Journal of Finance, 49(1), 3-37*.

Petersen, M.A., & Rajan, R. (2002). Does Distance still Matter? The Information Revolution in Small Business Lending. *Journal of Finance 57(6), 2533-2570*.

Philippon, T. (2016). The FinTech Opportunity. *NBER Working Paper 22476*.

Philippon, T. (2015). Has the US finance industry become less efficient? on the theory and measurement of financial intermediation. *The American Economic Review, 105(4), 1408-38*.

Pope D, S. J. (2011). What's in a picture? Evidence of discrimination from Prosper.com. *Journal of Human Resources, 46(1):53-92.*

Puri, M., Rocholl, J., & Steffen, S. (2017). What do a million observations have to say about loan defaults? Opening the black box of relationships. *Journal of Financial Intermediation 31, 1-15*.

Rajan, R. & Zingales, L. (1998). Financial Dependence and Growth. *American Economic Review, 88, 559-586*.

Ravina, E. (2019). Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets. *Northwestern University, working paper.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1107307

Schueffel, P. (2016). Taming the Beast: A Scientific Definition of Fintech. *Journal of Innovation Management, 4, 32-54*.

Stiglitz, J E., & Weiss, A. (1981). Rationing in Markets with Imperfect Information. *American Economic Review, 71(3), 393-410.*

The World Bank. (2012). Good Practices for Financial Consumer Protection. *The World Bank, Financial Inclusion Practice, 70157*.

The World Development Report (WDR). (2015). Mind, Society, and Behavior. *The World Bank Group Flagship Report*.

Uzzi, B. (1999). Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing. *American Sociology Review, 64(4), 81-505*.

Waller, C., & Lewarne, S. (1994). An Expository Model

of Credit Rationing. *Journal of Macroeconomics, 16 (3), 539-545*.
Wellisz, C. (2016, September). The Dark Side of Technology. *Finance and Development, 53(3), 14-17*.

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