

## Fintech and the Future of Financial Service: A Literature Review and Research Agenda \*

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### Abstract

The rise of fintech in the past decade has received growing scholarly attention. This paper surveys fintech-related articles published in the leading finance, accounting, and management journals from 2010 to 2019. It aims to generate a taxonomy of fintech and accumulate knowledge in the fields of text analytics, algorithmic trading, fintech lending, crowdfunding, blockchain, cryptocurrencies, and the use of artificial intelligence in financial services. Critical reflections are also presented, and future research agendas in fintech are suggested.

**Keywords:** Fintech, Text Analytics, Algorithmic Trading, Blockchain, Cryptocurrencies, Artificial Intelligence, Big Data

**JEL:** D41, D82, G11, G12, G14, G21, G23, G24, G31, G32, G34, O31, O32, O33

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## I. Introduction

Technological innovations in financial services (fintech) are increasingly transforming the provision of financial services. The enabling technologies of such innovation involve artificial intelligence (AI), blockchain, cloud computing, data analytics, and the Internet of Things (IoT) (ABCD-i). Fintech activities take various forms and encompass different sectors of the financial industry.

Technology can improve financial services through its influence on cost reduction, improved decision making or execution, and broadened access. For example, substantial reductions in the cost of computing, storage, and devices will facilitate the affordable analysis of massive volume of data and thus improve the accessibility of financial services. The interaction between technology and financial services can take two paths. Firstly, the *evolution* path of fintech involves financial services and products adopting technology for improved service delivery. Examples of this include the traditional bricks-and-mortar banks using technology to enhance their services through automated teller machines (ATMs); electronic, internet, and mobile banking; and AI-based banking. In contrast, the *revolution* path involves technology firms whose primary business is providing digital services but who also offer financial products as a subsector of their business. Known as BigTech (Frost *et al.*, 2020), technology giants like Google, Apple, Facebook, Amazon, Tencent, and Alibaba are reinventing the business model of finance through disrupting the design and delivery of financial services. They offer various forms of payment, lending, or other financial services, and are taking market share from large financial institutions.

Scholarly attention to fintech has gone hand-in-hand with these evolutions and revolutions since the 2010s. This paper surveys fintech-related articles published in the leading finance, accounting, and management journals from 2010 to 2019 using a structured literature review (SLR) methodology. SLR is “a method for studying a body of scholarly research to develop insights, critical reflections, future research paths and research questions” (Massaro *et al.*, 2016, 767). The objectives of SLR resemble the three outcomes of critical management research identified by Alvesson and Deetz (2000), namely insight, critique, and transformative redefinition, and thus are appropriate to explore nascent and multidimensional concepts such as fintech. In particular, our literature review attempts to achieve the following three objectives:

1. to provide a taxonomy of the fintech phenomenon;
2. to gather “what we know” in the primary fields of fintech from an economic perspective; and
3. to provide reflections on “what we do not know” and “why we do not know” and suggest a future research agenda.

In short, this paper offers a “bird’s-eye view” of the developments in fintech research. It will be of value to scholars who are interested in fintech research but are unfamiliar with the

literature. Also, researchers who focus on particular topics can get a full picture of the fintech research from the survey.

To our knowledge, three other review articles on fintech are available. The *Review of Financial Studies* published a special issue on fintech following a registered reports editorial protocol. The leading article by Goldstein *et al.* (2019) reviews the emerging fintech research and introduces the 10 articles included in the special issue. *Financial Management* has also published a special issue on fintech, in which Das (2019) discusses the promises and pitfalls in the 10 primary fields of fintech from the perspective of practitioners. More recently, Allen *et al.* (2020) have provided a comprehensive survey of the literature based on different market segments. This paper is distinct from these three publications because we survey fintech-related articles published in eight leading finance, accounting, and management journals. Notably, our target readers are scholars in the fields of economics and finance. Our analysis focuses on the incremental contribution of each article, the key research questions, research design, primary findings, data, and identification strategies.

The remainder of this paper is organised as follows. Section II introduces the survey criteria, scope, and summary statistics. Section III critically reviews the literature within seven primary fields, namely algorithmic trading (AT), automated textual analysis, blockchain and cryptocurrencies, crowdfunding, fintech lenders, peer-to-peer (P2P) lending, and big data/AI in financial services. Section IV presents the conclusions.

## II. Survey Criteria, Scope, and Results

Chen *et al.* (2019) argue that fintech consists of a set of recently developed digital computing technologies that have been applied or will likely be applied in the future to financial services. They formulate a broad typology of fintech comprising seven categories, namely cybersecurity, mobile transactions, data analytics, blockchain, P2P, robo-advising, and the IoT (Chen *et al.*, 2019). Building upon these technological classes, we employed a combination of keyword search and human verification of article titles and abstracts to search for fintech-related articles. The keywords employed included “Fintech,” “Big data”, “Artificial Intelligence/AI”, “Blockchain(s)”, “P2P/marketplace lending”, “Crowdfund(ing)”, “Text(ual) analysis”, “Algorithmic trad(ing)”, and “Robo-advis(ing)” among others. When this gave rise to uncertainty, we read the abstract to determine whether the article fell within the broad conceptualisation of fintech.

To ensure that the scope of our review remained manageable, we confined our search to eight leading journals in finance, accounting, management, and information systems research. In particular, we included three journals in the finance sector; *The Journal of Finance*, *Journal of Financial Economics*, and *The Review of Financial Studies* and three journals in accounting; *The Accounting Review*, *Journal of Accounting and Economics*, and *Journal of Accounting Research*. We also included two management journals, namely, *Management Science* and

*Information Systems Research*. We confined the search to articles published between 2010 and 2019. This timeframe is reasonable because the fintech phenomenon emerged in the late 2000s, and a time gap was evident between practice and publication in these leading journals due to data availability and the editorial process.

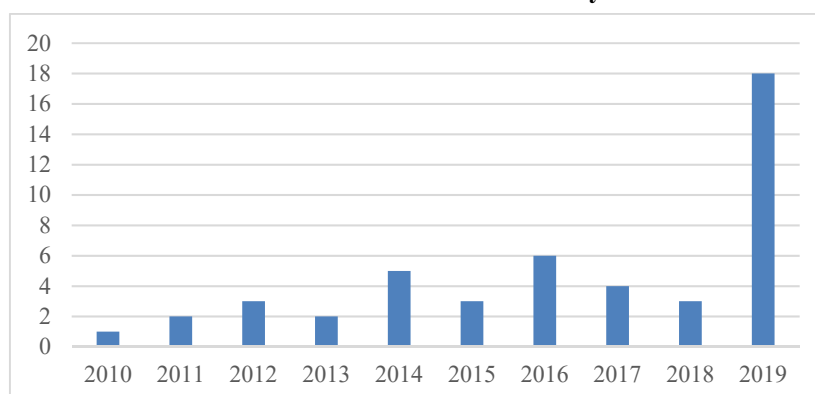
This methodology generated 47 fintech-related articles for review. Panel A of Table 1 lists the journals that published the most work on fintech. *The Review of Financial Studies* stands out as a major candidate, having published 18 fintech-related articles over the past decade. This productivity may be partially attributed to a special issue entitled “To Fintech and Beyond,” which included 11 fintech articles. Following suit is *Management Science*, which has published 15 articles on the topic.

**Table 1 Panel A: Fintech Articles by Journal**

Journal	Total articles
The Review of Financial Studies	18
Management Science	15
The Journal of Finance	4
Journal of Financial Economics	4
Information Systems Research	3
The Accounting Review	1
Journal of Accounting and Economics	1
Journal of Accounting Research	1

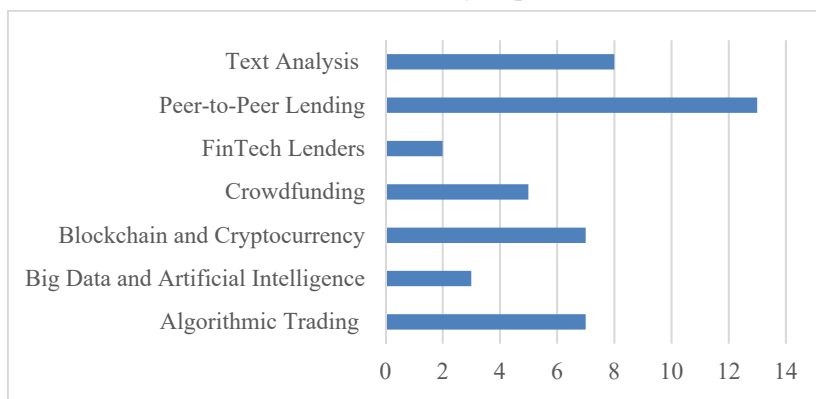
Panel B illustrates the number of fintech articles published each year. It can be seen that fintech-related articles occupied little space in these journals during the first half of the 2010s (one to five articles per year). However, during the second half of the decade, the number of articles rose considerably, from six in 2016 to 18 in 2019, suggesting a rising scholarly interest in fintech.

**Table 1 Panel B: Fintech Articles by Year**



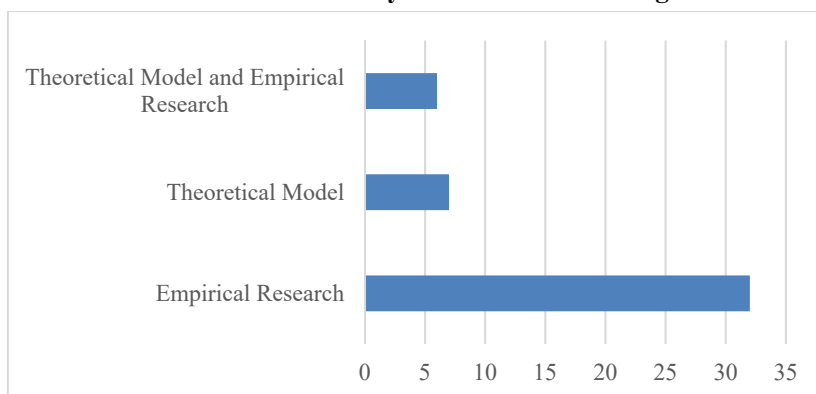
Panel C classifies the articles based on their key topics of interest. Apart from the two survey articles (“To fintech and beyond” [Goldstein *et al.*, 2019] and “Textual analysis in accounting and finance: A survey” [Loughran and McDonald, 2016]), the most popular topic was “P2P lending” (or marketplace lending) with 13 articles. This may be largely attributed to data availability. The next most popular topic was “text analysis” with eight articles. In addition, a total of seven articles on AT, seven articles on blockchain and cryptocurrencies, five articles on crowdfunding, three articles on big data and AI, and two articles on fintech lenders were identified.

**Table 1 Panel C: Articles by Topics of Interest**



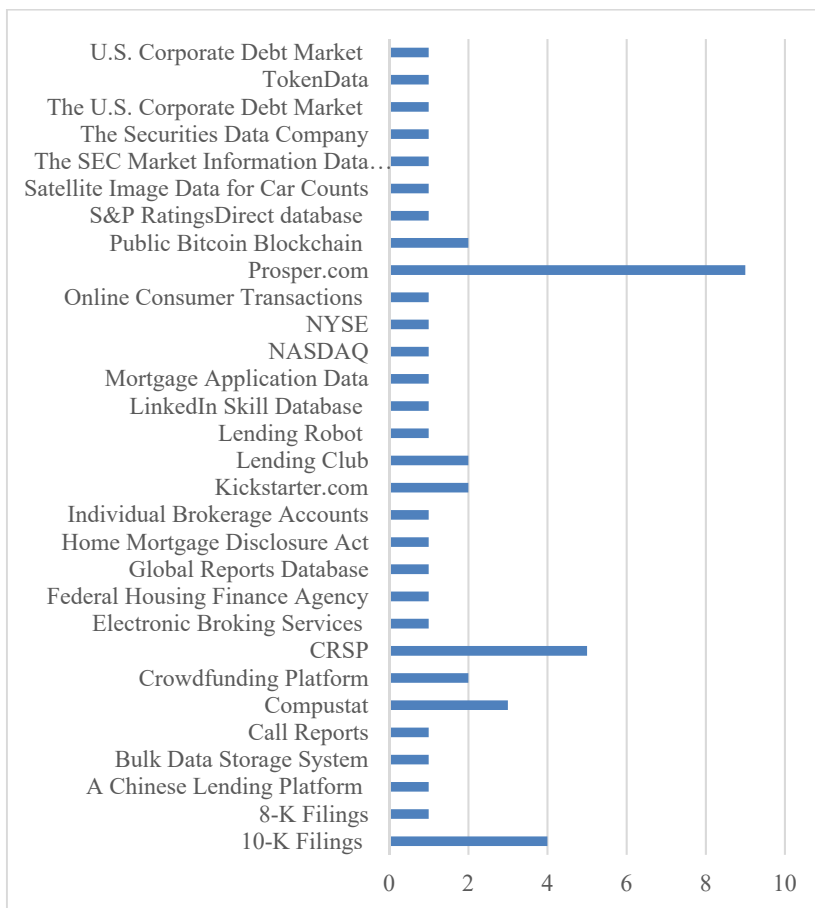
In terms of the type of scholarly work undertaken, survey, empirical, and theoretical papers are all found in the fintech research. Panel D of Table 1 demonstrates that apart from the two survey articles, there were 32 empirical papers, seven pure theoretical papers, and six papers that employed both theoretical and empirical approaches. Within the empirical literature, a quasi-experimental design, including event study, using a difference-in-differences approach was the most popular strategy. Moreover, the phenomenon of both theoretical and empirical methods appearing in the same article is also prevalent.

**Table 1 Panel D: Articles by Research Methodologies Used**

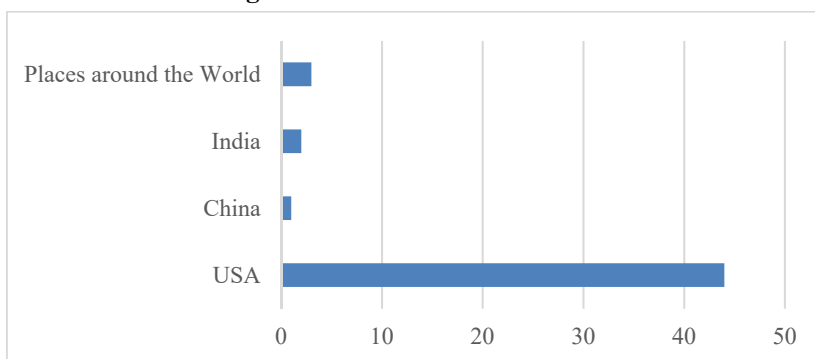


Panel E of Table 1 illustrates the various data sources used in the fintech empirical papers. Nine papers on P2P lending employed data from Prosper.com. Five papers using textual analysis drew on financial data from Crispr Therapeutics Ag (CRSP). Other popular data sources included the public Bitcoin blockchain, TokenData, and the crowdfunding website Kickstarter.com. The rise of alternative datasets including online consumer transactions, satellite images, and LinkedIn skills database is also evident.

**Table 1 Panel E: Articles by Data Source**



**Table 1 Panel F: Regional/National Distribution of the Data Sources**



Panel F of Table 1 sets out the regional/national distribution of the data sources. About 88% came from the United States with two from India and one from China. This distribution, however, is not consistent with the development of actual fintech markets across the world. According to the Cambridge Center for Alternative Finance (2020), China makes up more than 70% of total market share, followed by the US which contributes around 20% of the total value.

China's leadership in fintech is not surprising. Chinese financial services were not well developed. This opened up an opportunity for tech companies such as Alibaba and Tencent to offer financial services to a large and digitally savvy population. Also, the regulatory environment in China is less constraining towards fintech companies compared to the West. However, among the 47 fintech-related papers we surveyed, only one used data from China (a Chinese lending platform). This imbalance translates into ample research opportunities outside the US, especially in areas where China and India are taking the lead. For example, China has a very significant worldwide lead in mobile payments (about 50 times the US). In areas like biometric digital ID, India is the global leader.

### III. Review of Fintech Research by Topic

This section discusses the papers categorised by topic in Table 2. Published papers from other journals or working papers will be referenced to support our review where necessary.

**Table 2** Surveyed Articles by Category

AT	Hendershott, Jones, and Menkveld (2011) Brogaard, Hendershott, and Riordan (2014) Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) Hoffmann (2014) Biais, Foucault, and Moinas (2015) Foucault, Hombert, and Roşu (2016) Weller (2018)
Automated Textual Analysis	Hoberg and Phillips (2010) Loughran and McDonald (2011) Bao and Datta (2014) Hoberg and Maksimovic (2015) Lang and Stice-Lawrence (2015) Agarwal, Chen, and Zhang (2016) Loughran and McDonald (2016) Buehlmaier and Whited (2018) Chen, Wu and Yang (2019)
Blockchain and Cryptocurrency	Biais, Bisiere, Bouvard, and Casamatta (2019) Cheng, De Franco, Jiang, and Lin (2019) Chiu and Koepl (2019) Cong and He (2019) Easley, O'Hara, and Basu (2019) Foley, Karlsen, and Putnins (2019) Howell, Niessner, and Yermack (2020)

Crowdfunding	Burtch, Ghose, and Wattal (2013) Burtch, Ghose, and Wattal (2016) Chemla and Tinn (2020) Cornelius and Gokpinar (2019) Kim and Hann (2019)
Fintech Lenders	Buchak, Matvos, Piskorski, and Seru (2018) Fuster, Plosser, Schnabl, and Vickery (2019)
P2P Lending	Duarte, Siegel, and Young (2012). Michels (2012) Zhang and Liu (2012) Lin, Prabhala, and Viswanathan (2013) Iyer, Khwaja, Luttmer, and Shue (2016) Lin and Viswanathan (2016) Butler, Cornaggia, and Gurun (2017) Hildebrand, Puri, and Rocholl (2017) Paravisini, Rappoport, and Ravina (2017) Wei and Lin (2017) Du, Li, Lu, and Lu (2019) Tang (2019) Vallee and Zeng (2019)
Big data and AI in Finance	D'Acunto, Prabhala, and Rossi (2019) Zhu (2019) Tambe (2014)

### 3.1 AT

AT is commonly defined as the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission. Compared with human beings, algorithmic investment strategies have the ability to produce superior returns owing to their informational advantage and trading speed. Their informational advantage comes from the fact that algorithms have a larger capacity than humans to receive and process information. Their speed advantage, often through high-frequency trading (HFT), enables the algorithm to harvest the most favorable deals in the market ahead of human investors.

An increasing number of studies have investigated the effect of introducing AT on market efficiency. On the one hand, AT fastens price discovery, enhances price informativeness, and improves market quality (Hendershott *et al.*, 2011; Du and Zhu, 2014; Hasbrouck and Saar, 2013; Brogaard *et al.*, 2014; Foucault *et al.*, 2016). On the other hand, AT introduces adverse selection costs to slow traders (Hendershott and Moulton, 2011; Chaboud *et al.*, 2014; Biais *et al.*, 2015). Hoffman (2014), Budish *et al.* (2015) and Pagnotta and Philippon (2018) have all showed that private profits from AT lead to a socially wasteful arms race on HFT investment.

Weller (2018) investigates the effect of AT strategies on the acquisition of new information. He argues that AT contributes to market efficiency with respect to public information, given that such information is revealed by other sources, although this may occur



at the expense of discouraging the acquisition of new information. Weller (2018) uses the price jump ratio to measure relative information acquisition and finds that a single standard deviation of algorithmic activity decreases the amount of information in prices by nine percent, to 13%. Thus, AT might reduce price informativeness despite its importance in translating available information into prices. The overall impact of AT on market quality remains an open question.

### 3.2 Automated Textual Analysis

Text analysis is found across many disciplines under various aliases. By parsing text, users can extract machine-readable facts and create structured data. Loughran and McDonald (2016) survey and describe the nuances of the methods of textual analysis and highlight several tripwires in their implementation from an accounting and finance perspective. This section reviews the results of our survey of how value-relevant information can be extracted from the text-based disclosures of firms using various textual analysis methods, which can then be employed to formulate trading strategies.

Loughran and McDonald (2011) develop negative word lists (Fin-Neg) and create a term-weighting scheme to capture the *tone* of 10-K documents. They find that the Fin-Neg incrementally reflects the excess return during a 10-K filing period. That is, if everything else is held equal, the high amount of negative tones reduces the excess return. Moreover, the tone of the 10-Ks also predicts trading volume, volatility, and fraud. Agarwal *et al.* (2016) use textual analysis to extract negative and positive tone from Standard & Poor's (S&P) credit rating action reports. They show that the net tone (negative minus positive tone) is significantly and negatively related to abnormal stock returns and could predict future rating changes.

Lang and Stice-Lawrence (2015) conduct an international study of annual report texts in 42 countries and find that textual attributes such as length, presence of boilerplate, comparability, and complexity are associated with regulation and incentives for transparent disclosure. These attributes are also correlated with economic outcomes such as liquidity, institutional ownership, analyst following, and mutual fund ownership.

Hoberg and Phillips (2010) employ text-based analysis of the *product descriptions* in 10-K to predict mergers and acquisitions. Using a novel textual analysis method (e.g., basic, local, and broad cosine similarity), they note that firms are more likely to enter restructuring transactions when the language describing their assets is similar to that of all other firms, which is consistent with their assets being redeployable. They also find that the targets earn decreased announcement returns when there are similar alternative target firms in existence.

Bao and Datta (2014) employ unsupervised learning (as opposed to dictionary- or supervised learning-based text analysis) to analyze 30 risk types from the *corporate risk disclosures* of firms (section 1A of the 10-K). They find that nearly two-thirds of risk types have no ability to inform. Furthermore, the remaining informative risk types do not

necessarily increase the risk perception of investors. The disclosure of the three types of systematic and liquidity-related risks (i.e., macroeconomic, funding, and credit risks) increases the risk perception of investors. However, the five types of unsystematic risks (i.e., human resources, shareholders' interests, environment, information security, and disruption risks) are negatively associated with investors' postdisclosure risk perception.

Two studies employ text-based methods to redefine the financial constraints of firms. Hoberg and Maksimovic (2015) construct constraint variables from 10-Ks and find that the most constrained firms are high-growth firms seeking external equity financing. An increasing number of constraint firms are likely to curtail R&D, capital expenditure, and equity and debt issues following negative shocks. Buehlmaier and Whited (2018) also use textual analysis to show that constrained firms earn a high risk-adjusted return. Their portfolio indicates that long financially constrained and short financially unconstrained firms earn an annualised risk-adjusted excess return of 6.5%, thereby suggesting that financial constraints can be priced.

Chen *et al.* (2019) use textual analysis and machine learning to investigate the patent filings of firms, classify them into different fintech categories, and assess the value of fintech innovation. They reveal that the IoT, robo-advising, and blockchain are the most valuable fintech innovation types for the financial sector in general. In addition, they document a disruption effect in which fintech innovations negatively affect industries when they involve disruptive technologies originating from nonfinancial startups.

The above research mainly focuses on the analysis of language and words in company filings. With the development of technology, the latest research uses more advanced techniques such as machine learning to conduct image and video analysis. Fang *et al.* (2020) use image analysis to construct a novel measure of noise trading (an indicator of whether the firm placed advertisement(s) in the *Wall Street Journal* seven calendar days earlier) and find that this ad-based measure is positively associated with informed trading and stock price volatility but negatively associated with adverse selection. More recently, Hu and Ma (2020) use machine learning algorithms with video as the data input. They quantify human interactions in three-V dimensions (visual, vocal and verbal) using videos of startups pitching investors for funding, and document investors' interaction-induced biases.

In summary, our review suggests textual analysis is an emerging area in accounting and finance. With increasing computational power and the explosion of digital text including SEC filings, news articles, earnings conference calls, and text from social media, this area provides ample fodder for applying machine learning and other advanced technologies. However, as Loughran and McDonald (2016) point out, relative to the quantitative methods traditionally used in accounting and finance, textual analysis is substantially less precise. The devil is in the detail; many of the text-based empirical constructs have inherent limitations and potentially add more noise than signal. Researchers introducing new techniques to the literature must bear the burden of carefully explaining the method, considering its power in

terms of their specific application, and providing transparent results. Last but not least, the literature focus on textual analysis in the English language, but other languages present their own advantages and challenges. For example, Zhao and Lin (2014) demonstrate how textual analysis can be employed to study Chinese modified auditor's opinions. These knowable but still unknown fields invite more research attention.

### 3.3 Blockchain and Cryptocurrencies

Blockchain is a specific type of distributed ledger technology (DLT). DLT is a term widely used to describe various record-keeping technologies, such as decentralised data architecture and cryptography, which allow the keeping and sharing of records in a synchronised way while ensuring their integrity through the use of consensus-based validation protocols. Blockchain contains blocks of records that are linked using cryptography. Each block contains a cryptographic hash of the previous block, a timestamp, and the transaction data. Blockchain is designed to be an open and distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way.

The potential use of blockchain as a new way to create, exchange, and track ownership of financial assets has attracted an explosion of interest from the industry since 2015. Blockchain technology has also facilitated the creation of smart contracts; computerised protocols comprising terms contingent on a decentralised consensus that are tamperproof and self-enforcing via automated execution. This section reviews articles on blockchain that cover a heterogeneous range of research interests. Studies have focused on the equilibrium strategy of rational, strategic miners (Biais *et al.*, 2019), blockchain-based smart contracts (Cong and He, 2019), gains from blockchain-based settlements (Chiu and Koepl, 2019), blockchain-based disclosures of public firms (Cheng *et al.*, 2019), and blockchain-based bitcoin ecology (Foley *et al.*, 2019; Easley *et al.*, 2019; Griffin and Shams, 2020).

Biais *et al.* (2019) adopt a game theory approach to analyzing the strategies of miners. Although mining the longest chain, without forking, is regarded as the Markov perfect equilibrium, blockchain protocol is a coordination game where multiple equilibria with forks exist.

Chiu and Koepl (2019) discuss the systemic design and feasibility of a permissionless blockchain for securities settlements. In the presence of proof-of-work, the blockchain must restrict settlement speed to generate fees from investors through controlling the block size and time, thereby providing miners with a great incentive to deter forking. When the blockchain model is calibrated to the corporate debt market of the US, they find that the net gains from blockchain settlement range from one to four bps.

Easley *et al.* (2019) explore the role of bitcoin transaction fees on the evolution of the bitcoin blockchain from a mining-based structure to a market-based ecology. They develop a game theory model to explain the emergence of transaction fees. In their model, factors such as waiting times and bitcoin price are the main responses to the emergence of bitcoin

transaction fees. Moreover, the authors use transaction data from the bitcoin blockchain to test this model and provide empirical evidence of its predictive ability.

Cong and He (2019) focus on blockchain as a decentralised consensus and investigate the level of intelligence of blockchain-based smart contracts. They build a model incorporating decentralised consensus and information distribution and highlight that decentralisation increases the efficacy of the consensus of increased information distribution. Furthermore, increased information distribution can mitigate information asymmetry but may induce increased collusion. Thus, a trade-off exists between decentralised consensus and information distribution on the blockchain.

Enthusiasm for blockchain and cryptocurrencies also encourages public firms to speculatively disclose their public files by stating a commitment to blockchain-related business in their public filings. Cheng *et al.* (2019) consider the relationship between the initial 8-K disclosures of public firms that mention blockchain and investors' response to these disclosures. They classify these companies as speculative (existing) companies if their initial blockchain-related 8-K filings reveal that the company lacks (has) a significant commitment to, or a track record in, blockchain technology. Subsequently, the authors analyze the short-window buy-and-hold abnormal returns (BHAR), centering on the filing date of the first blockchain-related 8-K filings, and find that investors actively react to the blockchain-related 8-K filings of speculative firms during the initial seven-day event window but this reaction is likely to reverse over the 30 following days. Furthermore, this reaction become stronger as bitcoin returns increase.

Cryptocurrency can also have real consequences for enterprises. Howell *et al.* (2020) state that initial coin offerings (ICOs) have emerged as a new mechanism for entrepreneurial finance, with more than 1,500 ICOs collectively raising a total of \$12.9 billion. They also find that an ICO token exchange listing is associated with higher future employment by the issuers.

As well as this, the rapid growth of cryptocurrencies and their anonymity pose considerable challenge to surveillance methods. Foley *et al.* (2019) estimate that 46% of bitcoin transactions (worth \$76 billion per year) are associated with illicit activities based on *ex post* law enforcement, but that illegal bitcoin activity declines over time with mainstream interest in bitcoin and the growing emergence of opaque cryptocurrencies. The study also reveals that illegal users tend to increase their transactions in smaller increments, often transact with a given counterparty repeatedly, and hold a low amount of bitcoin.

In summary, we know the blockchain, as a form of DLT, has the potential to transform well-established financial institutions and result in lower costs, faster execution of transactions, improved transparency, auditability of operations, and other benefits. Moreover, the blockchain-based smart contract can eliminate some contracting frictions like the need for costly verification or enforcement, in an automated and conflict-free way (Cong and He, 2019; Harvey, 2016). Moreover, blockchain has become a buzzword partly because it is the main

technology underlying bitcoin and many other cryptocurrency transactions. Proponents of cryptocurrencies highlight their role as a new form of financing innovation in the digital age. Critics note that cryptocurrencies facilitate illicit financial activities and create rampant speculation and financial instability (Foley *et al.*, 2019; Fernández-Villaverde and Sanches, 2019). What is less well understood, however, is what determines the fundamental value of cryptocurrencies. Sockin and Xiong (2018), Cong *et al.* (2020), Pagnotta and Buraschi (2018), and Schilling and Uhlig (2019) propose several pricing models.

### 3.4 Crowdfunding

Crowdfunding is a form of alternative finance which allows the entrepreneur to raise capital from a large number of people, typically through an internet-based platform. Donation-based crowdfunding first gained popularity among the arts and music communities as a means of helping to fund artists to produce public goods. In reward-based crowdfunding, entrepreneurs presell a product or service in order to launch a business concept without incurring debt or sacrificing equity. Equity-based crowdfunding involves the backer receiving shares of a company, usually one in its early stages, in exchange for the money pledged. Studies on equity or reward-based crowdfunding have centered on several key questions such as (1) the determinants of success; (2) the behaviors of crowdfunders; (3) firms' learning through crowdfunding; and (4) the relationship between crowdfunding and other sources of finance. We discuss debt-based crowdfunding (also known as P2P lending) separately in section 3.6.

Burtch *et al.* (2013) examine social influence in a crowd-funded marketplace for online journalism projects (a public good). They show a partial crowding-out effect, where crowdfunders become inclined to reduce their contribution after observing prior crowdfunders who have contributed frequently. Furthermore, long funding durations apparently improve the success of crowdfunding, suggesting that the funding process has implications for project outcomes.

Burtch *et al.* (2016) find that the preference of campaign contributors to conceal their usernames or contribution amount from public display has a negative influence on the likelihood of conversion of subsequent visitors, as well as their average contributions. They emphasise the importance of crowdfunding platform design for encouraging contributions and reducing moral hazard.

Chemla and Tinn (2020) focus on the learning behavior of firms through crowdfunding. They develop a reward-based crowdfunding model and claim that learning from crowdfunders creates a valuable option for firms with highly uncertain demands. This is because they can learn more about demand for their product from these crowdfunders early in the production cycle and make further decisions on whether or not to invest. In addition, learning can also enable firms to overcome the moral hazard problem. Firms that raise a large amount of funds have low incentive to divert these funds to purposes other than those stated on the

crowdfunding platform, provided that the third-party crowdfunding platforms limit the length of the campaign.

Cornelius and Gokpinar (2019) investigate the effect of customer investor input on crowdfunding success. They use the comments left by customers on a project page as a substitute for customer investor input and find that it has a positive effect on crowdfunding success, particularly for individual project creators. Therefore, customer input could reduce the principal-agent cost in reward-based crowdfunding. Moreover, project revisions based on both customers' description of projects and input from customers with distant funding experience (measured by funding experience under different product categories) also increase the likelihood of funding success.

Kim and Hann (2019) examine the relationship between the difficulty of obtaining bank loans and crowdfunding use by entrepreneurs. Using local housing prices as a proxy for the collateral-based credit availability for entrepreneurs, they find that an increased decline in housing prices considerably increases the creation of crowdfunding projects, thereby suggesting that crowdfunding can serve as a feasible supplement to traditional sources of revenue raising. However, crowdfunding cannot fully benefit disadvantaged people in areas with low socioeconomic status.

In short, crowdfunding as a new source of entrepreneurial finance facilitated by technology has drawn considerable scholarly attention. Moritz and Block (2016) review 127 articles on crowdfunding and identify heterogeneous motives for capital providers to participate. Despite the large information asymmetry, studies show that both hard and soft information about the entrepreneur determines funding success, and that platform design matters in terms of encouraging contributions and reducing moral hazard. On the other hand, several important questions remain unanswered. While startups have traditionally relied on venture capital to raise funds and grow, crowdfunding provides an alternative by raising financial resources from a large number of capital providers. However, the types of ventures for which crowdfunding is the most suitable financing alternative remains unclear. Also, to what extent does (technology-enabled) crowdfunding help to close the early-stage financing gap? Moreover, what are the conditions for the wisdom of the crowd to hold in equity- and reward-based crowdfunding?

### 3.5 Fintech Lenders

The concept of fintech lenders describes how conventional lending institutions adopt technology to overcome their inherent limitations or to access underserved markets. Research comparing financial institutions' traditional default prediction models with more advanced techniques using alternative data and AI or machine learning appear to suggest that the latter helps to improve predictive ability, especially for borrowers with limited credit history and the unbanked population (Jagtiani and Lemieux, 2019; Goldstein *et al.*, 2019; Croux *et al.*, 2020). While lenders are adopting new technologies to varying degrees, it is clear that some

are at the forefront of using technology to fundamentally streamline and automate the lending process.

Fuster *et al.* (2019) define fintech lenders as those whose business model features an end-to-end online loan application and centralised underwriting and processing augmented by automation. They find that fintech lenders increased their market share of US mortgage lending from two to eight percent over the period 2010 to 2016. Furthermore, fintech lenders process loan applications 20% faster than other lenders and fail to target borrowers with low access to traditional finance. Thus, they are primarily competing with traditional mortgage lenders rather than broadening access.

Buchak *et al.* (2018) find that the regulatory burden on traditional banks and technology development contributes to the growth of shadow banks in the US. In this context, shadow banks include fintech and nonfintech lenders. A lender is classified as a fintech lender if it has a strong online presence and if nearly all of the debt application process takes place online with no human involvement from the lender. Furthermore, only banks or shadow banks qualify as fintech lenders. They show that fintech lenders serve creditworthy borrowers, charge a premium of 14-16 basis points, and provide convenience rather than cost savings to borrowers. A quantitative model that decomposes the effects of regulation and technology indicates that each of these factors accounts for about 60% and 30% of shadow bank growth, respectively.

This section focuses on how traditional lenders (banks and other lending institutions) employ technology to enhance credit provision and services. Our review suggests the efficiency gain may come from improved credit scoring using alternative data and AI or machine learning, which reduces the time and human effort required for loan processing. However, the evidence appears to suggest that convenience comes at a cost to end users (Buchak *et al.*, 2018). Moreover, there is no solid evidence to show the investment in IT of traditional banks pays off in terms of, for example, helping to improve loan performance or access to new markets. This is not surprising, because financial institutions face serious competition from technology firms expanding into the credit market. As discussed below, the latter are quickly grabbing a share of the credit market due to their unique advantages in data and technical knowhow, and they are lightly regulated at present.

### 3.6 P2P Lending

Distinct from fintech lender activity, P2P or marketplace lending is a revolutionary fintech innovation that enables individuals to borrow directly from other individuals, cutting out the financial institution as the middleman (Tang, 2019). This activity falls under the category of debt-crowdfunding. In P2P lending, the platform (typically a technology company) acts as an information intermediary, an online meeting place between lenders and borrowers, and a matchmaker. Our literature review identifies 13 articles in three broad categories; (1) the behavior of lenders; (2) the design of incentives and mechanisms in P2P platforms; and

(3) the interrelationship between P2P lending and bank finance.

### 3.6.1 Behavior of lenders in P2P lending

In P2P lending, lenders bid for noncollateralised loan listings from anonymous borrowers. On the basis of a myriad of standardised (hard) or nonstandardised (soft) information, lenders decide on *whether* and if so *how much* to bid for a loan listing. A loan is realised when the requested amount is fully underwritten; otherwise, it is deemed unsuccessful. The natural question lies in this anonymous environment; that is, how do individual lenders evaluate borrowers?

In a typical P2P platform, the hard information available to lenders typically includes the borrower's age, gender, income range, education, work experience, home ownership status, borrowing history on the platform, and credit grading assigned by the platform. The soft information, which includes both information that cannot easily be quantified and data that is quantifiable but not typically used by banks, comprises residential address, photograph, friend network on the platform, and narratives. Following this conjecture, a number of articles have investigated the benefits of hard and soft information to predict funding success, pricing, and probability of default.

Duarte *et al.* (2012) examine whether the trustworthiness of an individual borrower assessed through appearance affects the lending decisions of investors. They initially asked 25 independent Mturk workers to evaluate and rate borrowers' trustworthiness and their will to pay based on a picture posted. Subsequently, the average of the scores was calculated across these workers. This empirical study shows that people deemed trustworthy could obtain a loan with high probabilities and pay low interest rates. Furthermore, trustworthy borrowers tend to have better credit scores and lower default rates than untrustworthy ones.

Motivated by the literature on adverse selection and signaling, Lin *et al.* (2013) argue that friendships signify credit quality in online credit market. The authors employ a loan-listing sample on Prosper.com from 2007 to 2008 and find that friendships could increase the probability of a successful listing and reduce interest rates. In addition, friendships are also associated with decreased *ex post* default rates. This effect is emphasised when the hierarchy of friendship, which is measured by the roles and identities of among friends, is high.

Iyer *et al.* (2016) also demonstrate that standard financial and soft/nonstandard information contribute to inferences about the quality of small borrowers. The authors use a dataset from Prosper.com between 2007 and 2008, which contains all credit information variables displayed on a borrower's loan listing and the text of the listing, and show that peer lenders could predict the borrowers' likelihood of default better than the borrower's exact credit score by using nonstandard or soft sources of information.

Michels (2012) investigates a specific type of soft information, namely the unverifiable disclosure of a borrower. He utilises data on three-year unsecured loans from Prosper.com and concludes that an additional unverifiable disclosure is associated with a 1.27 percentage point



reduction in interest rates and an eight percent increase in bidding activity. The effect of these disclosures is stronger for borrowers with relatively poor credit than for those whose credit is good. Moreover, unverifiable disclosures are negatively associated with future loan defaults.

A key difference between P2P and bank lending is that individual lenders, who are not finance experts, tend to exhibit behavioral biases. For example, Lin and Viswanathan (2016) confirm the existence of home bias in the online lending market. They conduct a dyadic analysis of daily transaction data on Prosper.com and show that lenders tend to invest in borrowers from their own state. For identification, they design a quasi-experiment at the listing level that exploits the movement of borrowers across state boundaries as an exogenous variation, and find that the number of origination state bids decreases while bids from destination states increase.

Herzenstein *et al.* (2011) document evidence of “herding” among Prosper lenders, whereby borrower listings that have attracted a large number of lenders are more likely to receive further funding. Zhang and Liu (2012) further distinguish between rational and irrational herding. They find that lenders engage in active observational learning (rational herding) instead of passively mimicking their peers (irrational herding). In other words, they infer the creditworthiness of borrowers by observing peer lending decisions and use publicly observable borrower characteristics to moderate their inferences.

Paravisini *et al.* (2017) estimate risk aversion in the financial decisions of investors and the elasticity of wealth using data from the Lending Club. Given that the same individuals invest repeatedly, the authors construct a panel dataset to disentangle heterogeneity in attitudes toward risk across investors. They note that wealthy investors are risk averse on average, and investors increase their risk aversion after a negative housing wealth shock.

### 3.6.2 Incentives and mechanism design in P2P platforms

A second set of literature focuses on the design of incentives and mechanisms in P2P lending platforms. The bulk of the business revenue of such platforms comes from volume-based service fees payable for each successful loan origination. Unlike banks, P2P platforms serve as a marketplace, a screening agency, and a matchmaker. Platforms often fail to assume borrower credit risk but can take the fee when facilitating a loan. The service fee varies according to the credit rating of the borrower. It follows that each P2P platform has an incentive to maximise the volume of loans facilitated and design its mechanism as a tool to maximise its own profit. Since inception, Prosper Marketplace and Lending Club have learned from the market and experimented with different mechanism designs. These alterations provide opportunities for researchers to understand the underlying economics of P2P lending.

Four articles are in this category. Wei and Lin (2017) compare two approaches to marketplace lending, namely the auction-based and posted-price mechanisms. In auction-based lending, the “crowd” determines the “price” (interest rate) of the transaction through an auction process. In posted-price lending, the platform determines the interest rate on the basis

of its own “grading” of the borrower. Through building a game theory based model of market mechanisms, the authors predict that the posted-price mechanism benefits borrowers and lenders through the rapid deployment of funds but increases the interest rates paid by borrowers, thereby increasing the loan default risk. When a change in social welfare is examined, the posted-price mechanisms decrease overall social welfare even though they can increase the platform surplus.

Hildebrand *et al.* (2017) exploit a mechanism design experiment on Prosper in which “group leaders” in the bidding process were rewarded with a one-off origination fee. In particular, they investigate group leader bids in the presence of origination fees and find that these bids are (although wrongly) perceived as a signal of good loan quality, thereby decreasing interest rates. However, these loans have higher default rates compared with other types. This means that in the longer term, the reputation of the platform is harmed. Consistent with this conjecture, these adverse incentives are overcome simply by having sufficient “skin in the game” when no origination fee is present.

Vallee and Zeng (2019) investigate how platforms can maximise their utility through strategic information provision. They argue that P2P lending is a new paradigm wherein platforms and investors jointly produce information, unlike traditional lending in which banks are the exclusive information provider. In this new paradigm, the provision of additional information from the platform to sophisticated investors may increase adverse selection and harm the trading volume of the platform. Therefore, it must trade off improving screening outcomes with the adverse selection problem in order to maximise trading volume.

Vallee and Zeng (2019) construct a theoretical model to show that the optimal strategy for a platform is to provide intermediate levels of prescreening intensity and information to investors. To test this model, they employ data from Lending Robot collected between 2014 and 2017 and find that sophisticated investors actively screen loans and improve investment performance. However, this outperformance declines with increased screening cost (substituted by the reduction information about the characteristics of borrowers by Lending Club after 7 November 2014). Their results are consistent with those seen in the platforms that manage adverse selection and produce intermediate-level information.

Another challenge faced by P2P platforms is the process of how to increase borrowers’ willingness to pay using soft techniques. Du *et al.* (2020) test several behavioral mechanisms in a natural field experiment seeking to mitigate moral hazard problems in P2P lending. They set up a medium-sized P2P lending website in China that sent out reminder messages prior to the due date of loan repayments. To embed behavioral mechanisms in the reminder messages, the authors designed a  $2 \times 3$  field experiment in which one dimension was the variation in message content (neutral, positive expectations, or adverse consequences) and the other whether or not the lender’s identity was revealed. The platform was set to send out the first message immediately after the loan is approved, the second on the day before the first due

date, and the last at 30 days after the final due date if the loan was still unpaid by then. Looking at loans approved during the period 1-31 May 2016, the study shows that text message reminders expressing positive expectations increase the likelihood of borrowers' repayment in both the long and short term, whereas message reminders emphasizing the adverse consequences of failure to repay have a short-term influence on the likelihood of repayment.

### 3.6.3 Interrelationship between P2P lending and bank finance

P2P lending provides online unsecured lending and thus partly overlaps with the services provided by banks. An important question is whether P2P lending serves as a substitute for, or a complement to, banking. This is a legitimate query, since if P2P lending as a technology-based new business model is substituting for banks' traditional services, banks should be alarmed about losing clients to technology companies. However, if the P2P lending industry is mainly servicing a group of borrowers who are unbanked or would be turned away by traditional lending institutions, then it complements the banking system and improves financial inclusion.

To explore the interrelationship between banking and P2P lending, Tang (2019) proposes a conceptual framework to predict the effect of a negative shock to the bank credit supply on the quantity and composition of P2P loans. The study predicts that if P2P platforms and banks are perfect substitutes, then a negative shock to the bank credit supply will increase P2P lending volume and decrease average P2P borrower quality. If the relationship is perfectly complementary, then a reduction in banking supply would lead to increased lending volume and average borrower quality. For the intermediate case, negative shock would increase lending volume. To test these predictions empirically, Tang uses a difference-in-differences method with counties suffering from the regulation of FAS 166/167 in 2010 as the treatment groups. A dataset consisting of the P2P lending data from Lending Club 2009-2012 was used to construct the county-level variables. Tang finds that P2P lending expands in markets with tightened bank credit supply, and could therefore substitute for banking through low-quality bank borrowers migrating to P2P platforms. In addition, P2P lenders also complement banks by providing smaller loans.

Butler *et al.* (2017) examine the same question using a different approach. They draw on the loan listings data from Prosper over the period 2008-2010 and use county-level bank deposits and the number of FDIC-insured bank branches within a county to substitute for access to bank financing. Their study finds that borrowers living in areas with good access to bank finance request P2P loans with low interest rates. This effect is stronger for borrowers with poor credit ratings and those seeking smaller loans. Their evidence supports a substitute relationship between banks and the P2P lending industry.

Other studies have found evidence that marketplace lending can be a complement to bank credit. Balyuk (2019) and Chava *et al.* (2017) find that marketplace lending has improved credit access for consumers who cannot access credit from traditional banks. Using

data from the Lending Club, Jagtiani and Lemieux (2018) find that marketplace lending has penetrated areas that may be underserved by traditional banks, such as borrowers in highly concentrated markets and areas with fewer bank branches *per capita*.

Since its inception in 2005, the fintech innovation of P2P lending has received substantial scholarly investigation. Our review suggests that even in an online anonymous environment such as this, individual lenders rely on a battery of hard (credit grade, income, history, and other quantifiable information of this nature) and soft (appearance, friend network, voluntary disclosure, etc.) information to assess borrowers, but also exhibit human biases. However, the platform plays an essential role as information intermediary and market maker. To maximise its (volume-based) revenue, the platform will strategically manage its screening intensity and provision of information to investors, and employ different mechanisms to facilitate quicker deployment of funds. In terms of the interrelationship between marketplace lending and bank lending, the former can either substitute for or complement the latter, depending on the circumstances. Finally, we note that existing studies mostly use data from two large US-based marketplace lending platforms (Prosper and Lending Club), although such lending is a global phenomenon. For example, the P2P lending market in China is larger than the rest of the world combined. Hasan *et al.* (2020) comment on the impact of regional social capital in marketplace lending, and Li *et al.* (2020) on the reintermediation of Chinese P2P lending platforms.

### 3.7 Big Data and AI in Finance

This section reviews articles on the use of big data and AI in finance. The exponential growth in the amount of available and potentially valuable data collected via the web, smartphones, social media, sensors, and cloud computing provides an alternative source of information to facilitate financial decisions. AI, or robots that perform the cognitive functions of human beings, can provide and execute financial advice through automated algorithms on digital platforms. This trend is particularly true in the financial sector, where AI is considered as the “new physics in financial services”. The World Economic Forum has identified over 60 use cases of AI across six areas including deposits and lending, insurance, payments, investment management, capital markets, and market infrastructure (WEF, 2018). In these industries, AI helps to improve credit screening, verify identities, estimate insurance risk, and automate financial advice.

Tambe (2014) examines whether the IT investment of firms pays off by analyzing the returns of firms investing in big data. It employs the LinkedIn skills database as a means to obtain firm-level measurements of employees’ skills in Hadoop (a technology central to the early wave of big data investment) over the period 2006-2011. Tambe finds that Hadoop investment is associated with three percent faster productivity growth. However, this growth is confined to firms with large amounts of data assets and that operate in labor markets where complementary technical skills are provided by other firms. These findings highlight the

importance of geography, skill acquisition channels, and firm investment in productivity growth during the spread of new technology.

Berg *et al.* (2018) investigate the importance of digital footprints for consumer lending. They reveal that even simple and easily accessible variables from the digital footprint can be equal to or even exceed the information content of credit bureau scores for predicting consumer default.

Zhu (2019) explores the role of big data as a firm governance mechanism. Relying on consumer transactions and satellite images data, Zhu shows that firms which use data collected by online consumer trading platforms and satellites have more informative stock prices. Furthermore, increased price informativeness disciplines managers through reducing their extraction of information rents and improving their investment efficiency.

D'Acunto *et al.* (2019) study the benefits and pitfalls of robo-advising. They use an automated portfolio optimiser introduced by a brokerage firm to its clients in India and conclude that clients who receive robo-advice have more diversified portfolios and are less prone to behavioral biases (such as disposition effect, trend chasing, and the rank effect) than those in the control group. The effect of robo-advising on portfolio diversification and performance is particularly pronounced for *ex ante* undiversified investors.

In summary, the vast amount of data, in conjunction with advances in AI, have become key factors driving innovation in recent years. Our review shows that firms' IT-related investment leads to measurable productivity growth, and alternative data (including data from nontraditional sources) can help to enhance decision making and fraud detection capabilities. On the other hand, there is a convergence whereby financial institutions are seeking to differentiate themselves by using AI to build new products and data ecosystems, and tech giants and other startups are applying for full financial service licenses and becoming financial conglomerates.

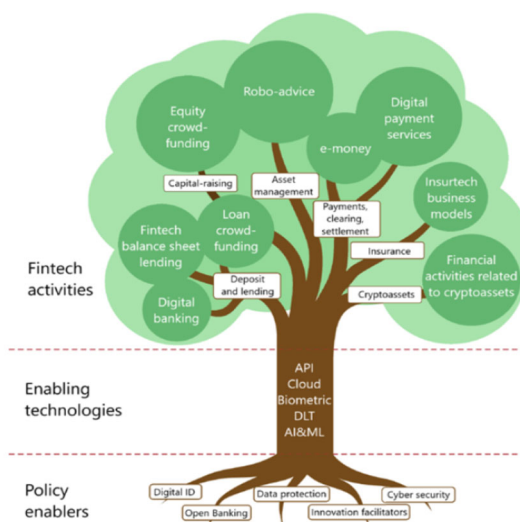
While the potential benefits of AI to financial institutions are immense, the challenges of execution and the timeline to realise value are often underestimated. Incumbent institutions possess extensive datasets already, but often struggle to deploy it effectively in AI applications. In these institutions, legacy technology infrastructure and rigid operating models are additional hurdles to the effective deployment of AI. On the other hand, there are challenges related to data ownership, the ethical use of data, and algorithmic biases in financial services. These challenges have welfare implications for consumers, the market, and the financial ecosystem.

### 3.8 The Correlation of Different Topics

The seven topics that we discussed above are inherently correlated. For example, AT relies heavily on big data and AI (Qin, 2012). Crowdfunding consists of equity-, reward-, donation-, and debt-based crowdfunding. P2P lending is a subset of debt-based crowdfunding, and the techniques used in loan screening and scoring are very similar to those found in fintech

lending (Jagtiani and Lemieux, 2019).

To further illustrate these relationships, we draw upon a conceptual framework for the taxonomy of the fintech environment proposed by Ehrentraud *et al.* (2020), namely the “Fintech Tree”.



Source: FSI Insights on policy implementation No. 23: Policy responses to Fintech: A cross-country overview

The fintech tree distinguishes three categories, namely fintech activities, enabling technologies, and policy enablers. At the top of the tree are the various forms of fintech activities (or the technologically enabled provision of financial services), which can be broadly divided into the following financial services categories; (i) deposits and lending; (ii) capital-raising and alternative sources of funding; (iii) asset management, trading, and related services; (iv) payments, clearing, and settlement services; (v) insurance; and (vi) cryptoassets. These activities encompass the topics addressed in this paper such as AT, cryptocurrencies, crowdfunding, P2P lending, and fintech lenders.

The trunk of the tree comprises a number of “enabling technologies” that present new opportunities and have a large number of use cases in the financial industry. These include, but are not limited to, AI, application programming interfaces (API), machine learning (ML), biometric-based identification and authentication (biometrics), cloud computing (CC), quantum computing (QC), and DLT. These enabling technologies interact and are mutually reinforcing. Our focus on textual analysis and blockchain falls into this category.

At the roots of the fintech tree are the policy enablers that create the foundation of the digital infrastructure required for providing such services. They include national broadband networks, digital IDs, data protection, and cyber security frameworks, and other financial innovation facilitators (innovation hubs, regulatory sandboxes, and accelerators). For example, Ehrentraud *et al.* (2020) survey the policy responses to fintech across 30 jurisdictions and finds that authorities worldwide are pursuing a range of approaches to regulating fintech

activities and must balance several different objectives when formulating policies. Policymakers face the challenge of maximizing the benefits of fintech while minimizing potential risks to the financial system.

#### **IV. Discussion and Conclusion**

Although the financial industry has traditionally been an early adopter of IT, the recent wave in fintech is unprecedented in terms of the new business models associated with the use of AI, blockchain, cloud computing, data analytics, and the IoT. Although a consensus on the definition of fintech is not comprehensively aligned, it is clear that there is a rapidly growing literature on how technology is transforming the landscape of financial services.

Our literature review of fintech-related papers published in the leading finance, accounting, and management journals in the past decade demonstrates that conventional theories in finance (e.g., contracting theories, information asymmetry, adverse selection, modern portfolio theory, capital asset pricing model, and behavioral biases) remain useful in explaining the numerous economic issues surfacing in fintech. On the one hand, technology-enabled alternative data sources, coupled with rapid computing power, can help to improve financial decisions. On the other, however, technology simultaneously enhances the chance of fraud (such as cryptocurrencies) and fraud detection (such as big data analytics and governance).

Our review also reveals the diverse nature of fintech research questions, which is to be expected given the diversity of fintech activities and their underlying enabling technologies. Existing research on fintech is weakly connected with no coherent research agenda overall. Despite this inadequacy, several high-level themes emerge as important directions for future research efforts.

The first research agenda aims to investigate the changing industrial structure and organisation of financial services arising from the new technologies. For example, what products and services do fintech companies provide in competition with traditional services? In what ways are their value creation models different from those of conventional financial service providers? Within the sectors in financial service (payment, lending, transfer, capital markets, insurance, personal finance, wealth management, etc.), which are particularly vulnerable to new technologies, and why? What is the long-term effect on the market of the “evolution” and “revolution” paths of fintech? This reflects a ‘new market equilibrium’ in the financial industries, a phrase coined by Goldstein *et al.* (2019). Studies that formulate analytical frameworks and/or collect empirical evidence to understand these questions will be important in advancing new directions for theoretical and empirical research in this area.

The second strand for future research tackles the rise of alternative finance and new forms of financial intermediation. Our literature review has demonstrated considerable interest in investigating the rise of loan- and equity-based crowdfunding, as well as the role

of fintech platforms for providing financial services. These studies focus on the understanding of the mechanisms used by crowd-funded markets and their relationship with traditional sources of finance such as banks and capital markets. However, the evolution of fintech platforms shows a clear trend away from “de-intermediation” towards “reintermediation” (Balyuk and Davydenko, 2019). Taking P2P lending as an example, this was first introduced in 2005 as a fintech innovation that enabled individuals to borrow directly from other individuals, thereby omitting the financial institution as the middleman. However, over time, P2P platforms in the US and elsewhere have evolved from being mere meeting places for borrowers and lenders to a service resembling delegated asset management, whereby lenders’ money is invested in loans for a fee chosen by the platform at a price that the platform deems appropriate. These new forms of financial intermediaries, powered by machine learning and AI, impose new risks but are completely unregulated. For example, Li *et al.* (2020) discuss the ethical challenge of P2P platforms skimming off the cream of both lenders and borrowers through strategic information provision, fast trading, and price manipulation.

A third research agenda, which provides ample research opportunities but is not sufficiently addressed in current finance and economics studies, is the regulation of fintech. From a legal point of view, regulation is needed when market failure occurs or when the uncontrolled use of technology causes a subversion of justice, often involving violations of rights or the inequitable distribution of benefits. Welfare issues should be considered when evaluating the effects of fintech. Technological innovation in financial services opens up new opportunities but also comes with potential risks to consumers and investors and to financial stability and integrity in general, which can be mitigated by financial regulation. Topics in this category are large and diverse. Examples include cryptofinance, digital currencies, and cybersecurity risks; data and identity issues; and financial institutions’ use of AI. In designing fintech regulations, regulators seek to provide clear rules, maintain market integrity, and encourage fintech innovations (Jagtiani and John, 2018). Brummer and Yadav (2019) propose several regulatory strategies in dealing with the potential risks posed by fintech, including informal guidance, no-action letters, regulatory sandboxes, licensing versus chartering forms of organisation, and other pilot programs.

We conclude by addressing the limitation of this study. Our literature review has surveyed the content of eight leading journals in finance, management, and accounting, which necessarily reflects their editors’ view on the first-order questions in fintech. Kavuri and Milne (2018) provide a comprehensive review that includes articles from other social science disciplines, applied engineering, and computer science. In addition, the studies reviewed here exhibit a strong US focus even though fintech is an international phenomenon that involves other important leading markets such as China and India. For example, by any measure of size, the Chinese P2P lending market is larger than the combined markets worldwide (He and Li, 2020). This review also aims to provide scholars unfamiliar with fintech with a quick grasp



of the important current work in this interdisciplinary field. The value of fintech research lies in its potential to advance our understanding of the interaction between the disciplines of finance, accounting, law, and technology. Scholars should explore this field further by taking novel and interdisciplinary approaches.

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