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FinTech Lending

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Abstract

In this article, we review the growing literature on financial technology (FinTech) lending—the provision of credit facilitated by technology that improves the customer–lender interaction or used in lenders' screening and monitoring of borrowers. FinTech lending has grown rapidly, though in developed economies like the United States it still accounts for only a small share of total credit. An increase in convenience and speed appears to have been more central to FinTech lending's growth than improved screening or monitoring, though there is certainly potential for the latter, as is the case for increased financial inclusion. The COVID-19 pandemic has shown potential vulnerabilities of FinTech lenders, although in certain segments they have displayed rapid growth.

1. INTRODUCTION

The last decade has brought financial technology (FinTech) lending to the forefront of debates among academics, regulators, and policy makers. In some areas, such as the US mortgage market, FinTech lenders have established themselves as major players. Other business models have disappointed—a particularly vivid example is the closing of the former peer-to-peer lending platform LendingClub to retail investors in 2020. New FinTech business models are currently in the spotlight, most notable the so-called buy-now-pay-later (BNPL) firms, with Swedish BNPL-provider Klarna breaking into the ranks of the five most valuable banks in Europe.[1]

In this article, we review the emerging scientific literature on FinTech lending and point out directions for further research. We define FinTech lending as the use of technology to provide lending products. The use of technology has two main flavors: First, technology can be used to improve the customer–lender interaction (for example, with a fully online application process), giving rise to a better user experience, faster processing times, and lower operational costs; and second, it can be used in borrower screening or monitoring, for example, by using alternative data sources or machine learning (ML) methods.

In Section 2, we provide estimates of the market size of FinTech lending as well as statistics on the market capitalization (or valuation for private firms) of key FinTech players. This section provides evidence about the importance of FinTech lending in various lending markets as well as market expectations regarding which business models are seen as particularly promising going forward.

In Section 3, we discuss the empirical evidence on both flavors of FinTech lending. We summarize the recent literature on lending efficiency of FinTech lenders as well as the performance of FinTech lenders in screening and monitoring borrowers. We also provide insights into the human-versus-machine debate, that is, the question of whether humans have an edge in screening or monitoring borrowers vis-à-vis well-trained algorithms.

Section 4 discusses an important issue at the forefront of the current debate: What are the real effects of FinTech lending—in particular, who are the losers and who are the winners of FinTech lending? We discuss evidence both on the access to credit (extensive margin) as well as changes in pricing in the cross-section of borrowers (intensive margin). We also discuss recent evidence on the impact of FinTech lending on discrimination and how FinTech lending interacts with data privacy concerns.

Section 5 assesses the performance of FinTech lending during the COVID-19 pandemic, which was arguably the first major shock to this sector and thus provides insights into the resilience of these new lending models. Section 6 concludes with an outlook for future developments and priority areas for further research.

Our aim is not to exhaustively cover the rapidly growing academic literature in this area but to provide some emerging takeaways and point out areas where we think additional evidence would be particularly valuable. We focus exclusively on FinTech in lending markets. Within lending markets, we focus on lending to households and firms for investment or consumption purposes, and we omit securities lending and lending in the nascent field of cryptocurrency markets. Other recent overview articles—in some cases with a broader focus—include Agarwal & Zhang (2020), Allen, Gu & Jagtiani (2021), Branzoli & Supino (2020), Thakor (2020), and Vives (2019).

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[1]In a new funding round in July 2022, shortly before this article went to press, Klarna's valuation plunged by 85%. One of the contributing factors is an increase in competition, such as the announcement by Apple to enter the BNPL market. The underlying argument—BNPL business models being in the spotlight—continues to be valid.

2. DEFINITION AND MARKET SIZE

2.1. Definition of FinTech Lending

In its broadest definition, FinTech refers to the use of technology to provide financial services (e.g., see BIS 2018; FSB 2019). More specifically, FinTech lending can be defined based on the nature of the customer–lender interaction or on the technology that is used to screen and monitor borrowers.[2]

- Customer–lender interaction: The lending process can give rise to the FinTech label if the customer–lender interaction is purely app-based or purely online (e.g., see Buchak et al. 2018; Fuster et al. 2019). Such a lending process can lower processing times, lower operational costs, and improve the user experience. It increases lender elasticity to demand shocks and decreases errors that may arise from human interaction in the lending process. It may be particularly attractive to borrowers who value convenience over personal interaction and advice.
- Screening and monitoring: The screening and monitoring technology can give rise to the FinTech label if a lender uses technology with the goal of improving traditional bank models for screening and/or monitoring of borrowers. Technology can be used to either expand the set of information (e.g., the use of digital footprints; see Berg et al. 2020) or improve the information content of a given set of information (e.g., via ML algorithms; see Fuster et al. 2022). Such a use of technology can affect default and recovery rates, alter price and nonprice terms, and affect the set of borrowers that get access to finance.

Many traditional banks have invested in technology, allowing loan applications to be handled online and/or using nonstandard data sources to screen and monitor borrowers. Many researchers therefore add additional criteria to ensure that traditional banks do not fall under the FinTech label. These qualifications include the requirement for FinTech lenders to come from outside the incumbent banking system (e.g., see Cornelli et al. 2020; Ziegler et al. 2021) or a requirement that lenders do not take deposits to qualify as FinTech lenders (e.g., see Gopal & Schnabl 2021).

Researchers should be aware that FinTech lending is not uniquely defined and that many traditional banks have invested heavily in technology, so that differences between FinTech firms and traditional banks tend to have attenuated over time. The current practice of defining FinTech lenders uses a mix of features that include the characteristics of the customer–lender interaction, the screening and monitoring technology, as well as additional qualifications not directly linked to the underlying use of technology and that instead also reflect differential regulatory treatment.

2.2. Market Size: The US Market

We start by providing an overview about the market size of FinTech lending in the United States. The United States serves as a natural starting point because it is a major market for FinTech lending and its data availability and quality are better than in most other countries. **Table 1** provides US lending volumes both for the entire market and for FinTech lending. **Table 1a** provides the amount of outstanding loans at the end of 2020 for three key lending segments: mortgage lending ($16.8 trillion)[3], consumer credit ($4.2 trillion), and business lending ($2.6 trillion). **Table 1b** and **Table 1c** provide estimates for FinTech lending. The statistics on FinTech lending in

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[2]Furthermore, FinTech can help to lower search costs for borrowers and lenders, thereby allowing lenders to enter new geographic markets (see Basten & Ongena 2020; Thakor 2020).

[3]Of these, $11.7 trillion are for residential mortgages on 1- to 4-unit properties, which is the main segment where FinTech mortgage lenders are active.

Table 1 Financial technology (FinTech) lending volumes: the case of the United States

A: Size of entire lending market (outstanding volumes)			
Segment	**Source(s)**	**Q4/2020 (USD billion)**	**Growth per annum 2016–2020**
Mortgage loans	Fed. Reserve (2022b)	16,781	4.0%
Consumer credit	Board Gov. Fed. Reserve Syst. (2022)	4,186	3.6%
Commercial and industrial loans	Fed. Reserve (2022a)	2,600	5.7%
B: Estimates of FinTech lending (new lending)			
Segment	**Source(s)**	**2020 (USD billion)**	**Growth per annum 2016–2020**
FinTech mortgage lending	Jagtiani, Lambie-Hanson & Lambie-Hanson (2021); authors' calculations based on Home Mortgage Disclosure Act (HMDA) filings	565	32.5%[a]
FinTech consumer lending	Ziegler et al. (2021)	38	11.9%
FinTech business lending	Ziegler et al. (2021)	31	43.1%
C: FinTech lending for subsegments and major players (new lending)			
Segment	**Source(s)**	**2020 (USD billion)**	**Growth per annum 2016–2020**
Rocket Mortgage (formerly Quicken Loans)	Rocket Co. (2020)	320	35%
Secured non-real estate commercial and industrial loans by FinTech lenders	Gopal & Schnabl (2021); authors' calculations based on Uniform Commercial Code filings	11	11%
LendingClub	LendingClub (2017); US Sec. Exch. Comm. (2020a)	4	−16%
Prosper	US Sec. Exch. Comm. (2016)	2	−9%
Buy-now-pay-later: Afterpay, Klarna, and Affirm combined	Afterpay (2021); Klarna (2021); US Sec. Exch. Comm. (2020b)[b]	25	>100%

[a]Note that 2020 was an extraordinary year in the US mortgage market due to very high refinancing activity (Fuster et al. 2021). Therefore, a potentially better measure of the evolution of FinTech lenders' importance is their market share in new originations, which increased from 9% in 2016 to 14% in 2021. In our calculations, we use the list of ten FinTech lenders from Jagtiani, Lambie-Hanson & Lambie-Hanson (2021), who in turn combine and update the lists from Buchak et al. (2018) and Fuster et al. (2019).

[b]For Klarna and Afterpay, we converted stocks into flows using the average duration of the loans provided in the annual reports.

Table 1b and **Table 1c** are based on new lending, as opposed to the stock of outstanding loans given in **Table 1a**. Data on the stock of FinTech lending are typically not easy to collect and are unreliable (for details, see Ziegler et al. 2021). Two key takeaways stand out.

Takeaway 1: FinTech lending currently constitutes a small share of overall lending in the United States, but FinTech growth rates outpace lending growth rates for the entire market. FinTech lending is generally dwarfed by the amount of outstanding loans (held in the traditional banking sector or securitized). In the mortgage market, where FinTech lending (mainly Rocket Mortgage) has gained a significant presence, the FinTech market share of new lending (including refinancings) reached a new high of approximately 14% in 2020.[4] Nevertheless, even

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[4]This calculation uses a list of ten FinTech lenders from Jagtiani, Lambie-Hanson & Lambie-Hanson (2021), who in turn combine and update the lists from Buchak et al. (2018) and Fuster et al. (2019). Given that some

in this banner year, the annual FinTech lending volume amounted to only approximately 3.5% of the outstanding stock of mortgages. In all other areas, the importance of FinTech lending is significantly lower. FinTech lending can be a major player in certain subcategories; however, these subcategories are often not large from an overall market perspective.[5] Growth rates of FinTech lending have been higher than growth rates in the traditional banking system in the United States over the past years. Going forward, the importance of FinTech lending for capital allocation, financial stability, and macroeconomic outcomes is likely to depend on whether FinTech lenders continue to serve specialized niches or are able to gain a significant presence in major parts of the US lending market aside from residential mortgages.

Takeaway 2: FinTech lending has gained double-digit market share in the mortgage market and experiences high growth rates in the BNPL market. Marketplace consumer lending was important early on but has not displayed much growth in recent years. FinTech lending has clearly gained a strong presence in the mortgage market, with a FinTech lender, Rocket Mortgage, being the largest mortgage originator in the United States. The US mortgage market is an unusual credit market in that most loans are securitized via the government-backed firms Fannie Mae, Freddie Mac, and Ginnie Mae, which also insure the loans' default risk and effectively dictate the underwriting criteria. The key comparative advantage of FinTech lenders in this market, therefore, hinges on a more efficient process and not on screening customers with alternative data or ML algorithms (see Fuster et al. 2019).

Interestingly, marketplace lending—which has been heavily researched in academic papers— plays a relatively minor role in the FinTech lending space. LendingClub and Prosper, for example, have not expanded lending volumes over the 2016–2020 period. Marketplace lending has evolved over time from a peer-to-peer business model, where retail investors fund retail loans, to a model that relies heavily on institutional funding. Hildebrandt, Puri & Rocholl (2017) show evidence of adverse selection for retail lenders in the early days of peer-to-peer lending in Prosper, when sophisticated investors acting as group leaders certified the loans. Balyuk & Davydenko (2019) show that in recent years more than 90% of the loans on Prosper are done by institutions.[6] LendingClub has recently shut down its platform for retail investors (Renton 2020).

In two segments, FinTech lending significantly expanded over the 2016–2020 period. First, FinTech business lending expanded 43% per annum and now stands at $31 billion in 2020 (Ziegler et al. 2021). The majority of FinTech lending is not provided by marketplace lenders but by balance sheet lenders (see Ziegler et al. 2021).[7] Second, we estimate FinTech lending in the BNPL segment to be $25 billion in the United States, with growth rates >100% over the last 4 years. Little academic research has been done on the BNPL segment, even though BNPL has already

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existing lenders may have transformed into FinTech lenders in recent years, and some new entrants are not part of these lists yet, the 14% market share most likely understates the true market share of current FinTech mortgage lenders.

[5]A specific example is provided by TransUnion (2019), which states that FinTechs have gained a market share of 38% in the unsecured personal loan market. The volume of unsecured personal loans, according to TransUnion (2019), is $138 billion; thus, the unsecured personal loan market comprises less than 5% of consumer credit volume in the United States.

[6]Similarly, Vallee & Zeng (2019) document that in 2017 only 13% of LendingClub's investors were retail investors, with the majority of funds coming from institutional investors (55%) and managed accounts (29%). For a description of the early phase of marketplace lending, see Morse (2015).

[7]Relative to household lending, less research has been done on FinTech business lending in the United States, although papers are starting to emerge (Balyuk, Berger & Hackney 2020; Barkley & Schweitzer 2021; Gopal & Schnabl 2021).

Table 2 Market capitalization/valuation of financial technology (FinTech) lenders[a]

Firm	Valuation (USD billion)	Type (date)
Mortgage market lenders		
Rocket Companies	35.2	Market capitalization
Marketplace lenders		
LendingClub	2.8	Market capitalization
Prosper	<1.0	Latest funding round (Sept. 2017)
OnDeck	0.1	Deal value (acquired by Enova on Oct. 13, 2020)
Buy-now-pay-later lenders		
Klarna	45.6	Funding round (June 2021)[b]
Afterpay	29.0	Deal value (takeover announced by Square on Aug. 2, 2021)
Affirm	18.0	Market capitalization

[a]This table depicts the market capitalization as of August 30, 2021, of a selective set of FinTech lenders that have significant activity in the United States.
[b]In a new funding round in July 2022, shortly before this article went to press, Klarna's valuation decreased to $6.7 billion. However, even after the new funding round, Klarna's valuation exceeds LendingClub's concurrent market capitalization by a factor of five.
For nonlisted firms, the valuation is based on the latest funding round or takeover date.
Data from Datastream (2021).

drawn significant attention by regulators in the United States and other countries (FCA 2021; Lott 2021).[8]

The market shares and growth prospects of various FinTech business models are also reflected in their market capitalizations (see **Table 2**). At the end of August 2021, Rocket Companies (the parent company of Rocket Mortgage) had a market capitalization of $34 billion, and valuations of the three major BNPL providers varied between $18 and $46 billion. In contrast, the market valuation of the well-known marketplace lenders LendingClub ($2.8 billion), Prosper (<$1 billion), and OnDeck ($0.1 billion) was an order of magnitude smaller. That said, a company with a similar business model, Upstart, saw a rapid rise in valuation over the course of 2020 and stood at $16.8 billion as of the end of August 2020.[9] Overall, the statistics on market capitalization support the fact presented above: While many marketplace lenders have struggled to cope with expectations, FinTech lending in the mortgage market as well as in the BNPL segment is on the rise.[10]

2.3. Market Size: The Non-US Markets

Claessens et al. (2018), Cornelli et al. (2020), and Ziegler et al. (2021) provide excellent overviews of FinTech credit volumes and other alternative forms of lending globally. The primary data come from an alternative finance survey conducted by the Cambridge Center for Alternative Finance (CCAF), capturing 703 firms as of 2020.

Cornelli et al. (2020) identify a key trend globally: the rise of BigTech credit. BigTech credit is defined as lending by large companies whose primary business is technology. BigTech credit

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[8]Berg et al. (2020) analyze lending in the BNPL market with a focus on the screening technology used in this segment of the market. However, little research has been done on the consequences of the rise in BNPL lending on consumers.
[9]Upstart evaluates applicant credit risk for partner banks that originate personal loans and car refinance loans, which they then either hold on balance sheet or sell off to institutional investors.
[10]While we focus on firms that are directly active in the lending business, FinTech has impacted many intermediary steps in the lending process, with independent firms often providing services to bank and nonbank lenders (for an overview in the mortgage segment, see Choi, Kaul & Goodman 2019). As an example, Black Knight, a software, data, and analytics provider in this area, had a market capitalization of $11.7 billion as of August 2021.

growth has outpaced FinTech credit and—as of 2019—makes up three-quarters of the combined BigTech plus FinTech credit volume worldwide. For an in-depth discussion, we refer the reader to FSB (2019), Frost et al. (2019), Stulz (2019), and Cornelli et al. (2020).

Ziegler et al. (2021) provide cross-country statistics and analysis of alternative lenders, including FinTech lending. The United States is the second-largest market for FinTech lending worldwide, dominated only by China (though volumes in China are declining due to regulatory changes there). Four countries have a larger market share for FinTech lending than the United States: China, Indonesia, Korea, and Kenya. FinTech market share tends to be higher in countries with higher GDP per capita, in countries with lower banking competition, and in countries with less stringent banking regulation (Claessens et al. 2018; Cornelli et al. 2020). However, high-quality data on both FinTech and traditional lending are scarce in many countries, and cross-country drivers of FinTech penetration and the real consequences of higher FinTech penetration clearly remain an important area for future research.

3. DIFFERENCES BETWEEN FINTECH AND TRADITIONAL BANK BUSINESS MODELS

3.1. Customer–Lender Interaction

Takeaway 3: Key competitive advantages of FinTech lenders are faster processing times and an improved user experience, which allow for more elastic loan supply but also have the potential to induce overborrowing by naïve consumers. At the heart of many FinTech business models lies an improvement in the process through which customers and lenders interact. FinTech lenders have streamlined the lending process, thereby improving user experience, accelerating processing times, and minimizing (error-prone) human input. Three examples illustrate this innovation. First, the key benefit that Rocket Mortgage emphasizes on its web page is neither pricing nor credit access but a streamlined process ("Our streamlined application syncs with your bank to get you accurate numbers, fast.") (Rocket Mortgage 2021). Second, in a survey conducted by Klarna, 50% of smartphone users said it is too much trouble to type in a bank account number or social security number to qualify for a loan. BNPL firms have therefore implemented instant loans requiring just a name and an email address and use this information, together with digital footprints collected from applicants' online behavior, to make a credit decision (Berg et al. 2020; Crosman 2017). Third, payment firms like Square and PayPal offer short-term loans to merchants. These so-called merchant cash advances (MCAs) are not necessarily cheap (rates can exceed 10%), but the convenience of getting a loan is the key. Square, for example, markets its lending products by stating "No long forms to fill out" and "You'll usually know if you're approved right away" (Square 2021).

The anecdotal evidence cited above has also been shown in rigorous academic studies. Buchak et al. (2018) point out that FinTech lenders seem to offer convenience rather than cost savings to borrowers, while Fuster et al. (2019) document a 20% improvement in processing time in the context of US mortgage lending. Hau et al. (2021) note that firms active on Alibaba's platform can fill out a credit application in 3 minutes, the approval takes 1 second, and the process involves 0 human interaction (the 3–1–0 model). Berg et al. (2020) show that a German e-commerce firm extends credit to its customers requiring only the name, address, and email address of the customers to make a credit decision. In all cases, the key innovation is not necessarily a better credit decision but more convenience for applicants.

A more efficient lending process affects credit supply beyond user experience and beyond savings in operational costs. First, FinTech lenders can provide credit more elastically when demand increases, as has been shown in the context of the US mortgage market (Fuster et al. 2019, 2021).

This flexibility reflects the increased use of automation as well as the emphasis on centralized operations, which enable labor specialization in the underwriting process (as opposed to an individual underwriter in a branch conducting the entire process) and therefore facilitates capacity adjustments.

Second, the ability to borrow without any required effort might induce consumers to over-borrow, especially when it comes to unsecured loans such as BNPL. In contrast to FinTech lending, traditional credit application processes take significant time and effort. Consumers with a tendency for impulse buying and a taste for immediate gratification can be induced to borrow too much. While self-control problems have been associated with overborrowing for easy-to-use credit cards (see Benton, Meier & Sprenger 2007; Heidhues & Kőszegi 2010), research on the consequences of one-click FinTech lending remains scarce. One exception is the work by Di Maggio & Yao (2021), who compare default rates between FinTech and bank borrowers using unsecured personal loans. They find that FinTech borrowers become delinquent at substantially higher rates (even controlling for other observable characteristics) and provide evidence that these borrowers use the additional credit not to consolidate existing debt but to support additional expenditures (such as buying a car).

3.2. Screening and Monitoring

Takeaway 4: FinTech lenders can potentially improve screening and monitoring by using nontraditional data sources and new methodologies, but evidence on the extent to which the growth in FinTech lending has been driven by a significant competitive advantage over banks in terms of screening and monitoring is limited. Various researchers have analyzed the usefulness of nontraditional data sources for credit scoring and lending decisions. A first wave of research made use of publicly available data from marketplace lenders to analyze the usefulness of nontraditional data sources for screening and monitoring of borrowers. These nontraditional data sources and alternative ways of screening include soft information in marketplace lending (Iyer et al. 2016), friendship, social network, group leader data (Hildebrandt, Puri & Rocholl 2017; Lin, Prabhala & Viswanathan 2013), as well as text-based analysis of applicants' listings (Dorfleitner et al. 2016; Gao, Lin & Sias 2021; Netzer, Lemaire & Herzenstein 2019). Most of these papers show that the predictive power of credit scores improves by using nontraditional data sources. However, these results should be interpreted with caution. First, the improvement in the predictive power of credit scores is often lower than the improvement in credit scores brought by relationship-specific information that banks have access to.[11] Second, an improvement in predictive power does not map one-to-one into a competitive advantage vis-à-vis other lenders. Third, many FinTechs innovate both the customer–lender interaction as well as screening and monitoring technology, making it hard to empirically disentangle the effect of better screening and monitoring on the FinTech market share. This cautious note is supported by the fact that—even though many of the papers cited above use marketplace lending data—marketplace business models have not been very profitable in practice, as discussed earlier.[12]

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[11]For the value of relationship-specific information for credit scoring and lending, see Mester, Nakamura & Renault (2007); Norden & Weber (2010); and Puri, Rocholl & Steffen (2017). Berg et al. (2020) document that bank-internal ratings provide a larger improvement in predictive power than many alternative data sources used in FinTech lending studies. This evidence should be interpreted with care, as results stem from different samples of borrowers. We are not aware of any study that would compare predictive power of bank-internal ratings to ratings from FinTech lenders for the same sample of borrowers at the same time.

[12]An alternative way to study the use of alternative data is to examine how much of the variation in the interest rates within a given lender type can be explained by standard information available in credit reports.

A complementary set of studies examine the value of more sophisticated ML models for credit scoring and loan performance prediction. The evidence indicates that out-of-sample predictive performance can indeed be improved by the adoption of ML when compared with more traditional approaches (e.g., Fuster et al. 2022; Gambacorta et al. 2019; Khandani, Kim & Lo 2010; Sadhwani, Giesecke & Sirignano 2021), although the size of the improvements varies across applications.

The evidence comparing realized delinquency rates between FinTech and bank loans for borrowers with otherwise similar observable characteristics has been mixed. In the US mortgage market, Buchak et al. (2018) find no differences based on data from Fannie Mae and Freddie Mac, while Fuster et al. (2019) find lower delinquency rates for FinTech-originated loans in the riskier Federal Housing Administration (FHA) segment. In contrast, Di Maggio & Yao (2021), as discussed above, find higher delinquency rates for FinTech unsecured loans.

A second wave of research has looked into lending by firms that have exclusive access to customer data such as BigTech, telecommunication, e-commerce, and payment firms. Cornelli et al. (2020) document that BigTech credit growth has far outstripped credit growth by other FinTech lenders in recent years. Hau et al. (2021) show how a major BigTech firm in China uses data collected about firms active on its platform to build a lending business, and Gambacorta et al. (2020) find that BigTech credit is much less sensitive to local collateral values than traditional bank lending. Berg et al. (2020) document the use of digital footprints by an e-commerce firm that can track customer behavior on its website. Agarwal et al. (2020) document the use of mobile phone data for credit scoring, while Parlour, Rajan & Zhu (2021) and Ghosh, Vallee & Zeng (2021) highlight complementarities between payment processing and lending.

A common theme of this strand of literature is that some firms have a competitive advantage in providing loans to their own customers. In essence, these FinTech business models are not too different from companies providing short-term trade credit or leasing and financing for their products (e.g., for lending by captive finance subsidiaries; see Gopal & Schnabl 2021; Murfin & Pratt 2019). The competitive advantage can arise either from a better ability to screen borrowers or from a better ability to enforce contracts and to liquidate collateral (e.g., for e-commerce platforms offering loans to merchants selling via their platform). As a drawback, the competitive advantage is typically limited to a specific set of borrowers and may not easily scale beyond the existing customer base.

Recent research has also studied whether human beings or machines are better at screening and monitoring (man versus machine). Berg (2015) shows that human loan officers are able to reduce loan default rates by 50% relative to a lending decision based purely on bank-internal ratings. Costello, Down & Mehta (2020) provide similar evidence, showing that a combination of a machine-generated credit model and human intervention improves loan outcomes relative to outcomes using the machine-generated credit model alone. In contrast, Jansen, Nguyen & Shams (2021) document that algorithmic underwriting outperforms the human underwriting process, though in a setting where humans only have access to the same set of hard information as the machine. Laudenbach, Pirschel & Siegel (2021) focus on human involvement in the workout process of consumer loans and find that personal communication improves recovery rates relative to nonhuman forms of interaction with the borrower.

Buchak et al. (2018) find that for mortgages, the R-squared value in regressions of interest rates on standard borrower characteristics is slightly lower for FinTech lenders, potentially in line with these lenders using additional information in their pricing. Di Maggio & Yao (2021) obtain the opposite result for personal loans, which they interpret as soft information deficiency for FinTech lenders.

It is also worth noting in this context that many lending decisions are much more complicated than just predicting a borrower's default probability as if it were a fixed innate characteristic. Default probabilities are endogenous to loan size, interest rate, maturity, and potentially other loan features that the lender can adjust for a given applicant or that borrowers will endogenously sort into depending on the lender's supply schedule. Furthermore, to maximize profitability, lenders also need to predict the loss given default, the probability of the borrower taking out another loan in the future, and other factors that could affect loan profitability. It is an open question to what extent FinTech lenders are using randomization (or other techniques to recover causal effects) in order to improve the accuracy of their prediction models out-of-sample.[13]

The relative importance of drivers of FinTech lending growth might also differ across countries. It is plausible that FinTech advances in customer–lender interaction (convenience) are more important drivers of FinTech credit growth in advanced economies, where screening and monitoring was already rather advanced before the rise of FinTech lending. In countries that were lacking basic data on borrower creditworthiness, FinTech advances are more likely driven by improvements in screening and monitoring. However, cross-country research on the importance of screening/monitoring improvements by FinTech firms is scarce.[14]

3.3. Regulation

Takeaway 5: FinTech lenders (and other nonbanks) are generally subject to fewer regulations than banks, which has likely contributed to their growth. FinTech lending has been facilitated by a more lenient regulatory treatment vis-à-vis established lenders in some jurisdictions. For example, research has argued that increases in regulatory capital requirements for traditional lenders in the United States have led to an increased market share of FinTech lenders both in the mortgage market (Buchak et al. 2018) and in small business lending (Gopal & Schnabl 2021).

There are at least two types of regulatory differences between FinTech lenders and traditional banks. First, FinTech lenders are typically nondepository institutions and therefore fall outside the scope of some of the traditional banking regulation. The regulatory advantage of FinTech lenders is thus not driven by their lending technique but rather by differences in funding sources. This regulatory advantage is also not unique to FinTech lenders, and other shadow banks benefit from it as well. Indeed, in the US mortgage market, nonbank lenders that still use "standard" technology (with local branches, etc.) have also experienced sizeable market share growth in recent years (for further discussion, see Kim et al. 2022).

Second, FinTech lenders have established new products that have partially been outside of the traditional realm of lending laws. In particular, BNPL products are typically legally structured as deferred payments and can therefore fall outside the scope of consumer credit acts (FCA 2021). The regulation of consumer lending products and the design of consumer credit acts varies significantly from country to country, so any advantage that FinTech lenders might have will likely vary across countries.

Overall, regulatory differences between traditional banks and FinTech lenders as well as the regulation of new products offered by FinTech lenders is an important area for future research. We provide some additional outlook in the conclusion (Section 6).

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[13]DeFusco, Tang & Yannelis (2021) use data from a Chinese FinTech lender that experimentally cut the cost of consumer installment loans by 40%, presumably to learn about the effects on take-up, loss rates, and profitability.

[14]Cornelli et al. (2019, chapter 4) provide a discussion on drivers of FinTech small- and medium-sized enterprise (SME) lending in Asia. Claessens et al. (2018) and Cornelli et al. (2020) discuss drivers of FinTech credit growth in a cross-country setting.

4. DISTRIBUTIONAL EFFECTS

As the lending landscape changes, a central question is how these changes affect the distribution of credit, in terms of access to and costs of loans, which in turn may affect real outcomes such as consumer spending or firm growth.[15] At least four aspects need to be considered in thinking about this question. First, the reliance on new data can allow assessing the creditworthiness of borrowers that were previously unscorable, for instance, due to a missing credit history. Second, the use of more sophisticated scoring models (on a given set of data) will lead to more dispersion in scores, and thus some borrowers will gain and others lose—the question then being who is in these groups. Third, reliance on algorithmic lending could reduce implicit or explicit biases of human loan officers against certain types of borrowers. Fourth, to the extent that there is advantageous or adverse selection of borrowers into loans by FinTech lenders, this may affect the cost not only of these FinTech loans but also of the loans of traditional lenders (as their set of loan applicants changes). We discuss these issues in turn.[16]

Takeaway 6: The availability of nontraditional data has the potential to expand access to credit for previously excluded borrowers, but direct evidence is scant. Growing evidence shows that in developing economies, BigTech firms are able to expand credit access to previously unserved or underserved households and firms (e.g., Frost et al. 2019; Hau et al. 2019, 2021), which likely reflects at least in part their access to rich data on these borrowers.[17] However, direct evidence on the role of richer data in changing the distribution of credit is still rather thin. In their study of digital footprints in Germany, Berg et al. (2020) find that the predictive power of the footprint variables for subsequent delinquency was equally strong for otherwise unscorable customers (who did not have a standard credit score) as for scorable ones, suggesting the potential for increased financial inclusion. In practice, when the e-commerce firm studied by Berg et al. (2020) introduced the digital footprint, there was some reshuffling of credit access from customers who did have a standard credit score in the low-to-medium range but an unfavorable footprint to customers without a standard credit score but a favorable footprint. Jagtiani & Lemieux (2019) study loans originated by LendingClub in the 2007–2015 period and find that the correlation between borrowers' FICO credit score and the rating grade assigned by LendingClub decreased steadily over this period, suggesting increased use of alternative data. Using data from Upstart, a FinTech platform in the United States that uses alternative data for credit scoring, Di Maggio, Ratnadiwakara & Carmichael (2022) provide complementary evidence, showing that borrowers with low standard credit scores and short credit histories have higher acceptance probabilities and pay lower interest rates compared with a traditional lending model.

An important question when it comes to the use of new data for credit scoring is whether every potential borrower's data are automatically available to lenders or the borrower has control over the data that can be accessed. In the latter case, it is possible that differential privacy preferences or trust in (bank and nonbank) financial institutions determines who makes their data available, which in turn affects both the overall informativeness of the data and how the data may impact the distribution of credit. For instance, Tang (2020) finds that loan applicants attach value to not

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[15]For real effects on the consumer side, see Chava et al. (2021) and Di Maggio & Yao (2021). For real effects of FinTech lending on SMEs, see Eça et al. (2021); Gopal & Schnabl (2021).

[16]A number of papers analyze distributional effects in the context of peer-to-peer and marketplace lending. These business models are not the main focus of our review. For a general overview of peer-to-peer and marketplace lending, see Morse (2015). For distributional effects, see Jagtiani & Lemieux (2017); Tang (2019); and de Roure, Pelizzon & Thakor (2022).

[17]Another possible driver is that BigTechs have more powerful contract enforcement methods than banks. For instance, an SME that does not repay could be excluded from the platform.

having to disclose a social network ID or employer contact information. Furthermore, women and older applicants are particularly reluctant to disclose such information. The gender gap is also emphasized by Chen et al. (2021), who find, based on survey data from 28 countries, that women are less willing to share personal data and worry more about their safety; this is likely an important contributor to the documented gender gap in FinTech product use.[18] He, Huang & Zhou (2020) analyze data sharing in equilibrium, showing that data sharing can make the entire financial industry better off yet leave all borrowers worse off even when individual borrowers have full control over access to their data.

Takeaway 7: The use of more sophisticated statistical models aligns credit scores more closely with true underlying default probabilities, which can lead to increased dispersion in credit costs across and within demographic groups; conversely, reduced reliance on lending decisions by potentially biased humans can increase credit access for minority groups. Turning to the second issue, the use of more sophisticated scoring models on a given set of data, Fuster et al. (2022) first show formally that under mild assumptions a move to more sophisticated models (e.g., ML models) will increase the dispersion of scores around an unchanged mean, so that some borrowers will gain (in the sense of being assessed as less risky than before) while others lose. They then study in the context of the US mortgage market which groups of society might be most likely to gain if lenders transition from traditional technology (in their context, logit models) to more sophisticated ML models (random forests or XGBoost). They find that non-Hispanic White and Asian borrowers—groups that already tend to have better access to credit—are more likely to gain than Hispanic and Black borrowers. Furthermore, using a simple credit market equilibrium model, Fuster et al. (2022) predict an increase in the dispersion of interest rates across and within these groups while, on the extensive margin (being offered a loan at all), all groups see small improvements.[19]

There are different possible drivers of such unequal effects. One possibility is that the ML algorithm uses available borrower characteristics (such as income, credit score, or collateral value) to effectively proxy for, or triangulate, borrowers' race. This would arguably sidestep fair-lending regulation, which does not allow for lending decisions to be based on race and certain other personal characteristics. However, in this application, the study finds that the improved predictive power from ML models is primarily due to their increased flexibility to learn how nonlinear combinations of characteristics predict default.

A potential increase in statistical discrimination (even when legal) could be offset by an elimination of taste-based discrimination: FinTech lending can be beneficial for minority groups in the population because human loan officers' biases play less of a role (or no role) when algorithms decide.[20] A study addressing this question in a highly developed market is by Bartlett et al. (2021). These authors rely on data from the US mortgage market and use the list of FinTech lenders from Buchak et al. (2018) to study whether loans from these lenders display a lower gap in interest rates

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[18]Armantier et al. (2021) document differences in trust in different types of intermediaries (banks, FinTechs, BigTechs) and that the COVID-19 pandemic has led to a reported decline in the willingness to share personal data. Yang (2021) exploits a negative shock to trust in banks (due to the Wells Fargo scandal) to show that decreased trust in banks leads to faster expansion of FinTech mortgage lending.

[19]Huang et al. (2020) compare the effects on predicted default probabilities for Chinese SME loans granted by the FinTech lender MYbank when both nontraditional data and machine learning are used for prediction. They find that the smallest firms are most likely to gain from the move to more data and more sophisticated models, but (unlike when studying the source of performance improvements) the authors do not decompose which aspect is more important for this conclusion.

[20]For a more extensive discussion of technological innovation and discrimination, see Morse & Pence (2020).

between Black and Latinx (minority) groups versus other groups. The results are mixed: For conventional mortgages securitized by Fannie Mae and Freddie Mac, the within-lender rate premia paid by minority borrowers relative to otherwise observationally identical nonminority borrowers are just as large for FinTech lenders as for others. For FHA loans, which are an important financing source for minority borrowers, the rate premia for FinTech loans are slightly smaller, suggesting a potential reduction in discrimination. However, the differences between FinTech and non-FinTech lenders are only approximately 1 basis point (relative to a baseline difference of 4–5 basis points for purchase mortgages and 1–2 basis points for refinances).[21]

In the context of the US Paycheck Protection Program (PPP) targeted at small- and medium-sized enterprises (SMEs) during the COVID-19 pandemic (further discussed in Section 5), Howell et al. (2022) show that lenders that rely more on automation—FinTechs but also larger banks—originated more PPP loans to minority-owned businesses. They are able to observe some banks that increased their degree of automation during the PPP and find in a difference-in-differences analysis that these banks significantly increased their share of loans to minority-owned businesses after increasing the automation of their lending process. The results are consistent with automation reducing opportunities for racial discrimination.

Other work focuses on potential (rather than realized) effects of replacing human loan officers by algorithmic decisions. Dobbie et al. (2021) study data from a high-cost lender in the United Kingdom and document bias against immigrant and older applicants, which they ascribe to an incentive problem (with loan officers maximizing a short-term outcome rather than longer-term profits to the firm). They then show that a decision rule based on ML could simultaneously increase profits and eliminate bias. Tantri (2021) conducts a similar analysis in the context of a developing economy (India), where much less hard information is available. Loan officers in this context have access to soft information, which the ML model does not have. Nevertheless, the paper finds that an ML algorithm would do better than loan officers in terms of lending efficiency without decreasing the share of loans that go to historically disadvantaged groups.[22] These results suggest that using the hard information efficiently may more than offset the loss of soft information and that if there were ML bias against disadvantaged groups, this might still be no worse than the bias of human loan officers, whether it arises for misaligned incentives or prejudice/stereotyping.

Takeaway 8: Little evidence has been found so far, at least in developed economies, that FinTech lenders have extended credit to borrowers previously underserved by banks, except in specialized niche segments. Many of the studies mentioned above focus on potential impacts of certain features of FinTech lending on the distribution of credit. We now turn to empirical evidence on what has actually happened so far, focusing primarily on the United States. It appears that FinTech lending has mostly substituted for bank lending, meaning that borrowers who got loans from FinTechs would otherwise likely have been able to obtain them from banks or other sources.

Buchak et al. (2018) and Fuster et al. (2019) study loan- and location-level characteristics to assess whether FinTech mortgage lenders have expanded access to loans for borrowers or in locations with otherwise low access to finance. When looking within nonbanks only (to hold regulatory influences and financing sources constant), the evidence is mixed: While, for instance, FinTech

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[21]The discussed baseline results cover 2009–2015. Using a separate sample covering 2018–2019, where the data allow for more precise measurement of total loan costs, there are no significant differences in minority interest premia between FinTech and non-FinTech lenders, although for FHA refinances, FinTech lenders do not charge more to minorities.

[22]Also relying on data from India, D'Acunto et al. (2021) document that the introduction of a robo advising tool on a peer-to-peer platform substantially reduced lenders' discrimination and improved their performance.

share is higher in census tracts with lower credit scores, it does not strongly correlate with local or individual income. Also, FinTech market shares are higher in locations with higher bank branch densities and where borrowers are older and more educated, suggesting that obtaining mortgages online may (at least over the period studied, which ended in 2016) be most attractive to experienced borrowers. Consistent with this, FinTech lenders specialized in refinancing and (even within purchase loans) had a lower first-time homebuyer share than other nonbanks.

Jagtiani, Lambie-Hanson & Lambie-Hanson (2021) study Home Mortgage Disclosure Act (HMDA) data for 2016–2019 and find evidence more suggestive of FinTech lenders expanding access to credit. In particular, they find higher FinTech shares in locations with higher application denial rates by non-FinTech lenders in the previous year. Furthermore, based on advertisement and direct mail data, these authors document that FinTech lenders are more likely to reach out to borrowers outside of metropolitan areas.[23] However, they do not find that FinTech lenders are more likely to make small-dollar loans (under \$70,000), even though (if they have lower per-loan origination costs) FinTech lenders should have a comparative advantage to do so.

Di Maggio & Yao (2021) use credit report data in the 2012–2017 period to study unsecured personal loans. They find that while FinTech lenders in this market initially grew by lending predominantly to low-credit-score borrowers, over time they moved to higher-quality borrowers, although these borrowers tend to have higher credit utilization. FinTech borrowers pay higher interest rates and are more likely to default.

For small business lending, Gopal & Schnabl (2021) show that FinTech lenders (and other finance companies) gained substantial market share in 2010–2016 and increased their lending the most in areas where the Big Four banks reduced their lending in the wake of the crisis. Balyuk, Berger & Hackney (2020) find that FinTech lending (in their case from two marketplace lenders) tends to substitute for loans by large/out-of-market banks more than for loans by small/in-market banks, consistent with FinTechs having a comparative advantage in processing of hard information. Conversely, Beaumont, Tang & Vansteenberghe (2021) find that French FinTech platforms expand credit access of collateral-constrained SMEs by offering them unsecured loans.

These empirical findings should inform further conceptual analysis of the interaction between different lender types (banks, FinTechs, and other shadow banks). The industrial organization of a lending market may depend, among other things, on different players' regulation, funding, cost structure, and ability to effectively screen and monitor borrowers. But, of course, borrower preferences (in terms of online versus offline convenience, personal interaction, privacy, etc.) also play an important role. Integrating these factors to understand how equilibrium outcomes may evolve is an important area for further research.

5. FINTECH LENDING AND THE COVID-19 PANDEMIC

The decade after the global financial crisis of 2008 witnessed few large-scale negative shocks to asset prices or household and firm balance sheets. Thus, the period in which FinTechs grew was a period of stability. The onset of the COVID-19 pandemic in early 2020 changed all this. The pandemic was arguably the first large-scale shock that the newly minted FinTechs had to face. Were FinTech lenders able to maintain the flow of credit or even expand their market shares?

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[23] Dolson & Jagtiani (2021) also use the direct mail offer data to study supply differences between banks, nonbanks, and FinTech lenders, for both personal loans and mortgages. They find that, overall, FinTech lenders are more likely than banks to send offers to subprime borrowers while, within nonbanks, patterns differ somewhat between personal loans (where some evidence suggests that FinTech lenders attempt to "cream-skim") and mortgages.

Did defaults of FinTech loans evolve differently from those on bank loans? Research has begun to address these kinds of questions for both advanced and developing economies.

Takeaway 9: FinTechs expanded credit flows in segments where they had continued access to funding during COVID-19, but the pandemic period also revealed vulnerabilities in the FinTech lending approach. Fuster et al. (2021) show that FinTech lenders gained market share in the US mortgage market over the course of 2020, especially for loans that are thought to be more time-consuming and complex to underwrite (namely mortgages for new purchases, as opposed to refinances, and mortgages to low-credit-score borrowers).[24] This finding is consistent with FinTech lenders being better able to scale up (or maintain their lending efficiency) during a time when working from home, social distancing, and other pandemic restrictions made it difficult for traditional lenders to expand their workforce in the face of a strong increase in mortgage demand (primarily for refinancing, fueled by the low long-term interest rates). The fact that lender markups were at historical highs over this period (Fuster et al. 2021) made FinTech mortgage lenders very profitable: For instance, Rocket Mortgage's parent company, Rocket Companies, reported $9.4 billion in profits for 2020, relative to less than $1 billion for 2019.

Different FinTech lenders participated in the distribution of loans under the US PPP. These loans are partly forgivable to the extent used for payroll or other allowable expenses and otherwise convert to attractive loans carrying a 1% interest rate. As the loans are guaranteed by the US Small Business Administration (SBA), they required no underwriting or investments in credit quality assessments. During the initial wave, banks struggled to fulfill the demand for these loans (Balyuk, Prabhala & Puri 2021), so the SBA also admitted a number of FinTech lenders to participate. These lenders gained market share in relatively smaller loans, particularly in locations with fewer banks. As Erel & Liebersohn (2020) show, compared to bank loans, the FinTech loans reached areas that were more affected by COVID-19 and, within a given county, were more likely to reach areas with fewer bank branches, lower incomes, and higher share of minorities, as well as new borrowers without existing bank relationships.[25] Thus, FinTechs seem to have expanded the set of borrowers to those less reachable by traditional banks and not just substituted for otherwise easily available bank loans.

Research shows some evidence that the high PPP market share of FinTechs may have partly reflected lower-quality credit flows by these lenders. Griffin, Kruger & Mahajan (2021) develop different metrics suggesting potential misreporting on approved PPP loan applications and find that FinTech loans have a substantially higher incidence of suspicious features than loans from traditional lenders (though the share of loans with suspicious features varies substantially even across FinTech lenders). This suggests that at least for some of the FinTech lenders that participated in this program, many of which were new entrants with little reputation to protect, due diligence processes may have been lacking.[26]

Also, in stark contrast to the important role of FinTechs in originating mortgages and distributing PPP loans, Ben-David et al. (2021) document that regular small business lending through a

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[24]The market share of FinTech lenders grew both relative to other nonbanks and in the market overall, in part because nonbanks as a whole gained market share from banks over 2020.

[25]See also Chernenko & Scharfstein (2022), Fei & Yang (2021), and Howell et al. (2022), who all show that minority-owned businesses were more likely to obtain PPP loans from FinTech lenders, even within location.

[26]Of course, this does not mean that technology itself was not beneficial for lending efficiency over this period. Kwan et al. (2021) use a measure of information technology (IT) sophistication within banks participating in the PPP and find that more IT-sophisticated banks originated more PPP loans within a given location, especially in areas with more severe COVID-19 outbreaks, higher levels of Internet use, and higher bank competition.

marketplace lending platform came to a halt in March 2020, likely due to the lenders' funding drying up at that time, thus making lenders financially constrained. The difference to the mortgage market highlights that funding stability (as is the case in the US mortgage market where most loans are securitized in government-backed pools) is crucial for FinTechs and other nonbanks to maintain the flow of credit during stress situations.

Bao & Huang (2021) compare FinTech and bank loans in China during the pandemic, studying both the distribution of new lending and delinquency rates on preexisting loans. FinTech lenders increase loan originations more strongly after the start of the pandemic, in particular to borrowers that did not have a previous lending relationship. Furthermore, FinTech loans tilted more toward relatively lower-income borrowers and areas more affected by the pandemic, similar in spirit to the PPP findings of Erel & Liebersohn (2020) discussed above. Turning to loan performance, Bao & Huang (2021) focus on loans originated prior to but still active at the onset of the pandemic. Delinquency rates remain steady for bank loans but substantially increase for FinTech loans in the 6 months after the pandemic starts. These differences are only to a small extent explained by observable differences in loan or borrower characteristics. For a subset of borrowers, the authors are able to match FinTech and bank loan records and find that borrowers tend to default on FinTech loans first. Such behavior may reflect a view by borrowers that FinTech loan defaults are less consequential for their future access to credit than bank loan defaults.[27]

6. CONCLUSIONS

In this article, we have reviewed the growing literature on FinTech lending—the provision of credit facilitated by technology that improves the customer–lender interaction or lenders' screening and monitoring of borrowers. Our review is a snapshot of where FinTech lending stands as of now. Given the dynamic growth of FinTech lending, the field is likely to develop further, and we see several areas that are important for academics, regulators, and policy makers to closely monitor going forward.

First, adoption of FinTech lending is plausibly path-dependent. Many borrowers have interacted with FinTech lenders for the first time over the past years, and their experiences are likely to shape the adoption of FinTech lending going forward. Have FinTech lenders reaped the low-hanging fruits, with any additional gain in market share becoming subsequently harder to achieve? Or does past FinTech growth fuel future FinTech growth, as borrowers have become acquainted with the new form of financing?

Second, many FinTech lending models have not been tested in protracted recessions, though COVID-19 provided the first glimpse of how FinTech lending performs in turbulent times. If FinTech lending gains a significant market share in many lending markets, cyclicality of loan supply and effects on financial stability will come to the forefront of the discussion among academics, policy makers, and regulators.

Third, the growth of FinTech lending has also put FinTech lenders in the spotlight of governments and regulators. Examples include the Woolard Review on unsecured (FinTech) consumer lending in the United Kingdom and the Chinese government's decision to break up Alipay. Regulation is likely to play a significant role for FinTech lending going forward, in particular in areas where FinTech lending has been spurred by a more lenient regulatory treatment vis-à-vis established lenders.

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[27]In a setting with centralized credit reporting like the United States, this would not be the case, as FinTech and traditional lenders report in the same way.

Fourth, payment data are of crucial importance for many bank rating models. FinTech payment firms have achieved significant growth in recent years—for example, Alipay in China and PayPal, Square, and Stripe in the United States. These payment firms may disrupt access to valuable payment data for traditional banks (Parlour, Rajan & Zhu 2021), and may themselves use payment data to screen borrowers, which could in turn further incentivize consumers to use their payment services (Ghosh, Vallee & Zeng 2021).

Overall, the field of FinTech lending is dynamic and provides a host of important and interesting research questions to answer. The development of the field will impact credit access and welfare of almost all countries, firms, and households worldwide. This review has provided an overview about the current state of research on FinTech lending as well as guidance on where to look going forward.

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