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Alan Chernoff
Rutgers University

Julapa Jagtiani
Federal Reserve Bank of Philadelphia

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The Role of Bank-Fintech Partnerships in Creating a More Inclusive Banking System

Alan Chernoff
Rutgers University

Julapa Jagtiani*
Federal Reserve Bank of Philadelphia

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Abstract

Fintech firms are often viewed as competing with banks. Instead, more recently, there has been growth in partnership and collaboration between fintech firms and banks. These partnerships have allowed banks to access more information on consumers through data aggregation, artificial intelligence/machine learning (AI/ML), and other tools. We explore the demographics of consumers targeted by banks that have entered into such partnerships. Specifically, we test whether banks are more likely to extend credit offers (by mail) and/or credit originations to consumers who would have otherwise been deemed *high risk* either because of low credit scores or lack of credit scores altogether. Our analysis uses data on credit offers based on a survey conducted by Mintel, as well as data on credit originations based on the Federal Reserve's Y-14M reports. Additionally, we analyze a unique data set of partnerships between fintech firms and banks compiled by CB Insights to identify the relevant partnerships. Our results indicate that banks are more likely to offer credit cards and personal loans to the *credit invisible* and *below-prime* consumers — and are also more likely to grant larger credit limits to those consumers — after the partnership period. Similarly, we find that fintech partnerships result in banks being more likely to originate mortgage loans to nonprime homebuyers and that they increase the mortgage loan amounts that banks grant to nonprime buyers as well. Overall, we find that these partnerships could help to move us toward a more inclusive financial system.

Keywords: Fintech, alternative data, fintech partnership, financial inclusion, credit invisible

JEL Classification: G21, G28, G18, L21

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*Correspondence to Julapa Jagtiani, Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA 19106, julapa.jagtiani@phil.frb.org. Comments and suggestions from Bill Spaniel, Mitchell Berlin, Bob Hunt, Leonardo Gambacorta, Jon Frost, Giulio Cornelli, Christopher Finger, and Jeanne Rentezelas are appreciated. We thank Kevin Bazer for his dedicated assistance with the analysis using the confidential Y-14M data set. Thanks also to Andy Kish and Anna Veksler for their assistance related to the Mintel data on credit offers. Alan Chernoff worked on this paper while serving as a research intern at the Federal Reserve Bank of Philadelphia.

I. Introduction

Financial technology firms, also known by the popular portmanteau *fintech* firms, have firmly established themselves as a feature on the financial landscape. Fintech may have once been the Wild West of the world of finance, but over the past decade, it has been domesticated and integrated into the financial infrastructure that was previously dominated solely by large banking institutions. Partnerships between the largest banking institutions and fintech firms have been especially noteworthy. Banks and bank holding companies (BHCs) have been entering into partnerships with fintech firms to gain access to the latest technology, more complex algorithms, and nontraditional (alternative) consumer data.

The advent of these partnerships is certainly not surprising. Fintech firms have been responsible for a number of new financial innovations, including new financial metrics, new data aggregation methods, and new ways of analyzing consumer credit risk. It is well-accepted in banking and fintech literature that traditional banking companies can benefit from having access to this technology and that fintech firms can benefit from the scale and customer bases of well-established banks. As fintech firms have moved steadily into the consumer lending space, it is worth noting that fintech firms in this space seem to behave differently than banks that are already offering similar products. Some fintech firms have extended credit, or credit offers, to previously underserved consumers and small business owners, as seen in Jagtiani and Lemieux (2019, 2018); Cornelli, Frost, Gambacorta, and Jagtiani (2022); and Dolson and Jagtiani (2021). It stands to reason that the technology underpinning fintech lending practices, if adopted by traditional banking companies, would allow said banking companies to gain a more wholistic view of consumers' financial situations and potentially start to engage in practices more akin to those of fintech firms themselves.

In this paper, we explore if and how the connections between banks and fintech firms, once established, may affect the behavior of the banks that form those connections. In other words, our goal is to establish how the partnerships between traditional banking companies and fintech firms influence the lending behavior of the former — that is, whether the activities of the banks that have partnered with fintech firms start to resemble those of the fintech firms themselves. Specifically, we posit the following questions: Would the lending behavior of banking institutions change after a fintech partnership, and would this change in lending behavior vary across different loan products (we focus on mortgages, unsecured personal loans, and credit cards)? Additionally, would this behavior only have an impact on credit *offers* (i.e., the supply side of credit) made by traditional banks, or would it manifest in actual loan *originations*, as well?

We apply logit regression models to estimate the probability of bank behavior changing, conditioned on a bank entering a fintech partnership. We first examine how the probability of a bank extending a *credit offer* to a consumer with a low credit score (below prime) or a lack of credit history (thin file) is affected by said bank's entrance into a partnership with a fintech firm. We then proceed to study the probability of loan *originations* occurring for those below-prime and thin-file consumers after a fintech partnership. Exploring both avenues is important because of the different aspects of the lending market to which each model provides insight. Ultimately, credit offers are a measure of the willingness of financial institutions to offer loans to those *underserved* consumers. Since consumers may be receiving several offers and only pursue one loan at a time, examining originations serves to control for any change in demand from consumers.

Our results demonstrate that there does appear to be a statistically significant difference in the lending behavior of a bank following a partnership with a fintech firm. Banks are more likely to extend personal loans and credit offers to consumers who would otherwise have difficulty accessing credit. Origination behavior also changes post-partnership, with banks providing larger credit limits for below-prime consumers following partnerships with fintech firms.

The rest of this paper proceeds as follows. Section II contains a review of the relevant literature, and Section III contains an in-depth description of the data used with regards to bank and fintech partnerships, credit offers, and loan originations. Section IV summarizes the preliminary analysis from the plots of the relevant data and presents additional statistical analysis to control for other key factors that could also impact a bank's credit decisions. The empirical results are highlighted in Section V, and Section VI concludes.

II. Related Literature

The adoption of new technology within the banking sector is hardly a novel phenomenon. The Financial Stability Board (FSB, 2017) defines fintech as "technology-enabled innovation in financial services that could result in new business models, applications, processes, or products with an associated material effect on the provision of financial services." Under such a broad definition, fintech is indeed composed of ATMs, online services, and peer-to-peer (P2P) lending applications, as well as everything in between.

Previous studies have examined the role of technology in banking, from online banking to the adoption of ATMs. DeYoung, Lang, and Noelle (2007) find that Internet adoption in the late 1990s led to stronger financial performance from 1999 to 2001 in banks that implemented transactional banking websites versus banks that did not. Saloner and Shepard (1995) have an earlier study on how adopting the ATM helped maintain the banking network, delaying a decline in the number of branches and the value of deposits.

More recently, Kutzbach and Pogach (2023) use data on Paycheck Protection Program (PPP) loans during the COVID-19 pandemic to suggest that banks that more heavily engage with fintech may have a comparative advantage over banks that do not.[1] They find that technology-oriented banks were able to reach a wider pool of borrowers who were previously outside of their branch network, while retaining the ability to lend to borrowers who were within their network. Additional evidence for the recent benefits of fintech inclusion comes from Babina, Buchak, and Gornall (2022). The authors find that government policies encouraging open banking would lead to an increase in banks' investment in new technologies used for sharing consumer data, as well as an increase in venture capital investment in fintech firms. This increase in fintech investment in response to open banking represents evidence for the perceived value-added from data aggregation enabled by open banking.

Fintech also played a role in distributing PPP loans to those business owners who did not have an established banking relationship. Pierri and Timmer (2020) find that technological and IT adoption helped banks weather the 2008 financial crisis by originating better-performing mortgages, providing stability during the crisis. They conclude that banks with significant technological investment were able to select better borrowers, resulting in the loans originated by these technologically invested banks experiencing lower delinquency rates, controlling for traditional credit scores.

While fintech firms such as LendingClub, Finicity, Plaid, and Stripe may be recent additions to the financial landscape, financial technology itself has been around and evolving for decades. What distinguishes modern-era innovation from ATMs or online banking is the rate at which innovations are being successfully implemented. The evolution of banking has picked up significant speed as computing capacity has improved and as large amounts of consumer data have become readily available. Access to financial technology has also been democratized in recent years through cloud computing and storage, as well as through various partnerships.

Although the effects of partnerships between banking institutions and fintech firms have not been fully documented in the existing literature, there has been notable exploration of the behavior of fintech firms in marketplace lending. The niche in which fintech firms find themselves

[1] A PPP loan is a small business loan backed by the Small Business Administration (SBA) during the COVID-19 pandemic, which started in March 2020. The goal was to help small businesses keep their workforces employed during the COVID-19 crisis.

remains opaque, with some research proposing that these firms serve as complements to the existing banking structure and other research positing that fintech firms are merely substitutes. The results of this paper may lend evidence to the *fintechs as complements* hypothesis and suggest that, in particular, fintech firms extend credit and services to traditionally underserved segments of the population. However, with the growth of mergers between fintech firms and banking institutions, we would also expect both to eventually merge their behaviors. This may support the *fintechs as substitutes* hypothesis in the future, and it may potentially even provide evidence that fintech firms and banks will indeed be reaching out to the same consumer pools post-partnership. We examine both hypotheses for the role of fintech firms in this paper.

The *fintechs as substitutes* hypothesis sees ample support in Tang (2019), who finds that fintech firms are likely to serve the same borrowing pool as larger banks in the consumer credit market. The paper establishes that fintech firms only complement the existing banking structure with regard to small loans. Within this framework, fintech firms would merely establish themselves by offering more efficient services than traditional banks. Fuster, Plosser, Schnabl, and Vickery (2019) find evidence of this in the mortgage market; they argue that fintech firms establish themselves with more efficient services, rather than appealing to a different class of clientele. They additionally find no evidence of fintech firms targeting underserved consumers.

Chava, Ganduri, Paradkar, and Zhang (2021) study the credit scores and default rates of consumers who borrow from marketplace lenders (MPLs) and ultimately find that borrowing from MPLs may have short-term positive effects but can be detrimental when seen over a longer time frame. They find that, while MPL consumers experience an increase in credit scores after the origination of an MPL loan, this is merely due to a decline in credit utilization from traditional banking services, supporting the idea that MPLs are substitutes for banks. The consumers that they examine experience higher default rates than traditional bank borrowers, ultimately resulting in lower credit scores after approximately two months.

Buchak, Matvos, Piskorski, and Seru (2018) find evidence of a small difference between mortgage borrowers at fintech firms and mortgage borrowers at traditional banks. Specifically, they show that fintech borrowers have a $7,000 lower median annual income than that of borrowers at traditional banks. This result is inconsistent with the fintechs as substitutes hypothesis. However, they also determine that fintech lenders charge a slight premium over traditional bank rates, suggesting that fintech borrowers may not be underserved; instead, they are choosing to borrow from fintech firms and paying a premium rate for enhanced transparency and convenience.

There has also been ample research supporting the *fintechs as complements* hypothesis. De Roure, Pelizzon, and Tasca (2016) find that P2P lenders in the German market are more likely to serve risky segments of the market that traditional banks are not willing, or not able, to service but charge a higher price to compensate for the additional risk. De Roure, Pelizzon, and Thakor (2022) also find that riskier borrowers tend to leave traditional banks for fintech lenders; thus, fintech firms could potentially promote a healthier banking system. Erel and Liebersohn (2020) investigate fintech firms' role in the response to the demand from the PPP. They find that fintech firms cater to clientele in zip codes with fewer bank branches, lower incomes, and larger minority population shares. They conclude that fintech firms expand the supply of financial services overall, rather than acting as redistributors.

Further evidence comes from Jagtiani and Lemieux (2018), who investigate fintech behavior by closely examining the activities of LendingClub. They use account-level data to find that fintech firms provide credit access to areas underserved by the traditional banking sector. Jagtiani and Lemieux (2019) investigate LendingClub activities further and find that fintech firms provide funding to below-prime consumers at lower costs compared with traditional banks. Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021) find similar evidence in the mortgage markets. Their investigation of fintech activity by examining fintech mortgage origination finds that these fintech mortgage loans are more likely to be originated in zip codes with higher denial rates from traditional lenders, as well as in areas with lower average credit scores.

Additional research suggests that fintech firms tread the line between complements and substitutes. Cornaggia, Wolfe, and Woongsun (2018) investigate the role of fintech firms in the unsecured loan market. They find evidence of declining loan volumes from the higher-risk segments of borrowers for traditional banks when fintech firms enter their markets, implying that fintech firms are competing for the same customers. However, they also conclude that fintech firms may be offering lower interest rates than traditional banks for *less risky borrowers*. Cornaggia, Wolfe, and Woongsun (2018) are unable to find data on fintech rates for high-risk borrowers directly. Given the departure of high-risk clientele from traditional banks in favor of fintech lenders, it may be inferred that fintech firms are also offering lower interest rates to higher-risk borrowers than banks do. When Di Maggio and Yao (2021) investigate the foray of fintech firms into the credit markets, they notice that consumers who receive fintech personal loans tend to have higher credit utilization ratios than traditional bank borrowers, despite fintech firms' clientele having higher incomes and better credit histories on average. These borrowers may have already hit their credit limit from traditional banks and thus have moved to fintech lenders for additional credit needs.

Our preliminary hypothesis — that banks into entering partnerships with fintech firms for their technology will begin to act in similar ways to the fintech firms themselves — has seen support from existing research. Kutzbach and Pogach (2023) find that banks that utilize fintech begin to operate more similarly to fintech firms. They suggest that banks with significant technology adoption operate as a hybrid between fintech firms and traditional banks, based on their examination of PPP loan volume during the COVID-19 pandemic. Interestingly, there exists evidence for the converse hypothesis as well: Instead of banks changing to resemble fintech firms, fintech firms may be changing to resemble banks. Navaretti et al. (2017) go into detail examining the ways in which fintech firms and banks have come to resemble one another, whether due to regulatory or competitive pressures. They note that while the largest contribution of fintech firms may sometimes be to offer new services, fintech firms are more likely to find new ways to offer existing services as well. They suggest that most of these technological innovations are ripe for adoption by the existing banking infrastructure.

Conversely, Hughes, Jagtiani, and Moon (2022) find that LendingClub, one of the largest fintech consumer lenders, resembled a small bank (a peer group of banks similar in size to LendingClub) in 2013. However, within three years, it began to take on more credit risks as its lending efficiency increased and became more akin to the most efficient group of banks (the largest banks, which were much larger than its peer group), further suggesting that, as fintech firms mature in their use of alternative data and complex modeling, they begin to exhibit the enhanced efficiency that traditional banks could only achieve through scale. Just as banking behavior begins to resemble that of fintech firms, fintech firm behavior begins to resemble that of banks.

Our contribution to the literature is to build on what has been examined previously, as well to test an alternative view of what has been previously posited, using a novel data set: partnerships between banks and fintech firms. Rather than examining if banks become more like fintech firms through technological adoption, or if fintech firms become more like banks as their scale and reach improve, we directly see if partnerships between the two entities cause a notable change in behavior. By examining loan *offerings* and loan *originations* at the individual loan level, we can detect if banks begin to target similar demographics as fintech firms following partnerships with the firms in question. The distinctions between the *fintechs as substitutes* and *fintechs as complements* theories become hazier as the distinctions between fintech firms and banking firms become hazy themselves. Perhaps, in the coming years, the primary distinction between fintech firms and banks will be merely the age of the institution, as the practices of both entities begin to converge to a similar or even indistinguishable set of behaviors.

III. The Data

The analysis conducted in this paper uses data from several different sources. First, data on credit offers come from the monthly household survey conducted by Mintel Comperemedia, Inc. (and the TransUnion LLC Match File) on credit offers they received. Note that the data that we received from TransUnion were depersonalized. Second, data on loan originations come from loan-level data from the Y-14M reports submitted monthly by large BHCs that are subject to Comprehensive Capital Analysis and Review (CCAR) stress testing. Third, data on partnerships between fintech firms and banking institutions are sourced from the partnership data maintained by CB Insights.

III.1 Data on Credit Offers

Our analysis in this paper starts with an examination of the supply side of credit (proxied by credit offers, or willingness to lend) and how these credit offers by banks may be altered by their partnerships with fintech firms. The credit offer data come from the Mintel Comperemedia, Inc. Direct Mail Monitor Data and the TransUnion LLC Match File (depersonalized data). Together, this data set is a monthly survey of the credit offers received by anonymous households and the characteristics of the potential depersonalized consumers, in question. A random sample of 8,000 households is surveyed every month, in which information is collected on the credit offers sent to these consumers. Any consumers not surveyed are thus excluded from the sample and subsequently from our analysis. This information includes the name of the credit-offering entity and details about the offer, as well as consumer characteristics. Consumer credit scores, the primary metric of creditworthiness as based on previous credit performance, are aggregated by TransUnion. The credit score collected by TransUnion is then merged with the credit offer data from Mintel, creating what we refer to hereafter as the Mintel/TU data set. Altogether, the Mintel/TU data set provides a comprehensive overview of the supply side of financial product offerings at the individual consumer level.

From this data, we examined individual financial product offerings for each banking institution surrounding their partnership with a fintech firm.[2] For our sample, we examined all

[2] It should be noted that, although the Mintel/TU data set provides the "weights" that could be used to proxy total national mail volume for each bank, we do not use the weights in our analysis. The Mintel/TU data set provides these weights as a way for researchers to calculate a true aggregate of the credit offers made by each lender. Instead, we use the raw counts of the offers in our analysis. The reason is that we only focus on those offers that may be affiliated with a fintech partnership (other credit offers and the overall volume of offers by each lender are not relevant). The total offer volume estimated from the weights provided by Mintel/TU data set would not be relevant to the research question in this paper.

offerings for the financial products that were contained in the Mintel/TU data set available from the time frames analyzed. The financial products examined are mortgage loans, personal loans, and credit cards offered to consumers. The data used in the analysis of this paper are restricted to offers occurring within each of the three quarters around the partnership date: I quarter during which a partnership between a bank and fintech firm occurred, the prior quarter, and the quarter following the partnership quarter. This, in effect, creates an event study of bank behavior during the periods surrounding the occurrence of a partnership between a bank and a fintech firm.

This event study contained loan offers from 2016 to 2021. Initially, we identified over a dozen banks with relevant fintech partnerships based on the CB Insights database. In the next step, in which we tried to match fintech partnership events with data on credit offerings using the Mintel/TU data set, some banks with fintech partnerships were dropped because of data unavailability/limitation. Only 10 banks from the initial list contained adequate loan offerings on the Mintel/TU data set: Bank of America, Barclays, JPMorgan Chase, Citibank, Cross River Bank, First National Bank of Omaha, Santander, TD Bank, Union Bank, and Wells Fargo. Our credit offering data set associated with these 10 banks contains 1,943 mortgage offerings, 5,878 personal loan offerings, and 33,172 credit card offerings. The Mintel/TU data set provides additional characteristics for each of the credit offerings, including the credit score of the consumer to whom the credit product was offered.

The four largest banks in our Mintel/TU credit offer data set are Bank of America, Chase Bank, Wells Fargo, and Citibank. These banks were likely to have had fintech partnerships, offers for all credit types, and large amounts of data on credit offerings in multiple periods. One of the key observations is how much variation occurs across years for the banks in question in all three of the financial products examined. **Figure 1** presents the credit offers made by these four banks both by year and by breakdowns of loan type by year. Across all four banks, more than 80 percent of the credit offers in each year are credit card offers. Regarding the distribution of credit scores of those consumers who received credit offers from these four banks, we examine the score distribution by type of credit products by year for each bank (the plots of which are not shown in this paper). For mortgage offers, more than half of all the mortgage offers in each year were given to consumers with a credit score higher than 700. For personal loan offers and credit card offers, the share of credit offers to below-prime consumers increases across all four banks for personal loan offers and credit card offers, relative to the share in mortgage offers. Overall, it does not appear that lending practices toward below-prime consumers have had a solid pattern at these sampled banks. We hypothesize that credit offers to potentially underserved consumers may instead be related to the banks' ability to use the technology and resources of fintech firms to target this previously under-accessed market space.

III.2 Data on Credit Originations

The Mintel/TU data set has allowed us to examine the supply side of the credit market and how the behavior of banking institutions may change after partnering with fintech firms. After examining credit *offerings*, the next logical step would be to investigate credit *originations*; it becomes intuitive to explore whether the changes in credit offering behavior actually resulted in a meaningful change in credit originations as well. For this, we use loan-level data on mortgage and credit card originations from the Federal Reserve's Y-14M reports. These are detailed monthly reports on the loan portfolios of BHCs, savings and loan holding companies (SLHCs), and intermediate holding companies (IHCs) that hold more than $100 billion in total assets (the largest U.S. banks that were subject to CCAR stress testing).[3] Personal loans were not included in the origination analysis since they are not collected at the loan level in the Y-14M reports. We take a random sample of 1 percent of credit card originations and 10 percent of mortgage originations for the sampled banks in the event study.

From this data set, we have information about the loan characteristics (loan amount, credit limit, loan origination date, etc.) and the consumers' characteristics (zip code, FICO score as of loan application, etc.). We assign the binary dependent variable a value of 1 if the loan was given to a consumer with a low credit score (below a given threshold), based on the consumer's FICO score as of the loan application date, or a consumer with a missing FICO score; and a value of 0 otherwise (if the loan was given to a consumer with higher FICO score). Logistic regressions are modeled on the originated loans using bank partnerships as the independent variable of interest, just as in the case of credit offerings described earlier. These regressions are run for 994,012 credit card originations and 205,038 mortgage originations for the five banks analyzed during the period 2016–2021.

III.3 Loan Amount and Total Credit Limits

In addition to exploring the impact of fintech partnerships on the likelihood of increased access to credit for low-score and thin-file consumers, we also examine the impact on loan amounts (for mortgages) and total credit limits (for credit cards). Linear regressions are run using the log

[3] The asset threshold for Y-14M reporting was recently increased from $50 billion (before 2019) to $100 billion. Because of this change, those BHCs with assets between $50 billion and $100 billion stopped submitting Y-14M reports after 2019. We include all BHCs in our analysis as long as they were still submitting Y-14M reports when they entered into fintech partnerships.

transformation of the loan amount and credit limit variables as the dependent variable for a subset of the loans originated in the logistic regressions. Here, we look only at below-prime and thin-file consumers and estimate whether fintech partnership activity may have affected the loan amount (for mortgage origination) and/or credit limit (for credit cards) of the loans made to this segment of consumers. For this analysis, we use data from the same 2016–2021 time period for both credit card and mortgage originations.

For the analysis of credit card originations, we use two different FICO score thresholds (below 660 or below 680) to identify below-prime consumers. Our initial credit card sample includes 225,282 credit card originations for thin-file and below-prime consumers (with a FICO score below 680 or with no FICO score on record). The sample observation decreases to 151,021 credit card originations for thin-file or below-prime consumers (with a FICO score below 660 or with no FICO score on record). For the analysis of mortgage originations, our initial sample includes 18,587 mortgages originated to consumers with a FICO score below 680 or with no FICO score on record, and the mortgage sample observation includes 10,344 mortgages originated to consumers with a FICO score below 660 or with no FICO score on record.

III.4 Data on Fintech Partnerships

Partnership data are assembled using data provided by CB Insights, which keeps a detailed list of partnerships between fintech firms and other companies listed in its database. Large banking companies seem to enter into various partnerships more frequently than smaller banks. We started the partnership data collection with a complete data set of all types of partnerships with the relevant banks. Not all the partnerships that banks enter into would be relevant to their credit decision processes; thus, specific bank partnerships were then further investigated to include only those deemed relevant partnerships. **Appendix I** presents detail on the criteria used to screen for the relevant partnership data for our analysis. **Appendix II** presents the final list of all the firms and partnerships that are sourced from the CB Insights database.

Our analysis focuses on those partnerships between banks and fintech firms that could potentially impact a lender's credit decision. These partnerships may give banks access to technology that can provide alternative metrics with which to assess the creditworthiness of thin-file consumers or provide banks with additional novel data analysis and aggregation methods to help moderate risk and allow more offers to reach consumers with poor credit histories or no credit history.

Although the inner details of the partnerships remain opaque, prime examples of the companies in question that we would expect to be beneficial to large banking institutions would be firms such as Plaid, Finicity, or other data aggregators. Other types of partnerships that are not related to enhancing data or the credit risk evaluation process are not included in our analysis. The process to identify the relevant partnerships is far from trivial, making it likely that such an analysis would either miss partnerships (if the criteria for selection were too rigorous) or include too many partnerships (if the criteria were too lax). Although a less rigorous selection would likely weaken the results, we found it prudent to err on the side of too many partnerships rather than too few.[4]

Ultimately, there are approximately 30 partnerships identified as being relevant for banks' credit decisions during the period 2016–2020,[5] with the majority of these partnerships occurring between 2018 and 2020. **Figure 2** shows the number of relevant partnerships we collected from CB Insights, broken down by year. These partnerships were concentrated within just over a dozen banks. We looked to match these banks with the credit offering data from the Mintel/TU data set and with loan origination data from the Y-14M reports. This matching process left us with 10 banks in the final sample that have a sufficiently large number of credit offers in the Mintel/TU data set and only seven banks in the final sample with sufficient and reliable data on the loan originations data set.

The partnership dates provided by CB Insights are those at which the details of the partnerships were released to the public. Given this, there are reasons to believe that there would be a required onboarding process once a bank enters into a partnership with a fintech firm before the technologies of the firm could be adequately utilized. As a result, it is unlikely that the effects of a partnership would be felt immediately. To account for this delay, we use loan and credit offers from the banks entering into these partnerships in the quarter preceding the partnership, as well as those in the quarter of the partnership itself, as a control group. These loans are used as typical offers that the banks in question would have made prior to engaging in activities similar to those of a fintech firm. The characteristics of the offerings and (eventually) originations from these quarters are then compared with those from the following quarter to test whether there is an increase in the

[4] It is also worth noting that the list of partnerships and dates supplied by CB Insights may not be exhaustive and that there may be additional partnerships that could have proven beneficial to consumers with poor credit ratings, potentially strengthening the results found in this paper. However, since this was treated as an event study, only dates corresponding to the partnerships analyzed were used, with the CB Insights data set serving as the primary arbiter of available partnerships and their relevant dates.

[5] Although partnerships were selected only from 2016 to 2020, loan data were extended to 2021 to account for the post-partnership observation (the quarter following partnerships made during the last quarter of 2020).

probability of a loan being offered to a below-prime or thin-file consumer in the subsequent quarter.

IV. The Empirical Analysis

IV.1 Logistic Analysis of Fintech Partnerships and Banks' Credit Offerings

In our empirical analysis of the impact of fintech partnerships on credit offers by banks, we utilize characteristics of the credit offers from the Mintel/TU data set in conjunction with partnership data derived from CB Insights. The dependent variable is a binary variable that takes a value of 1 if the credit product in question was offered to a consumer with nonprime characteristics — i.e., those with a low credit score (below a given threshold) or those without a credit score. It is assigned a value of 0 otherwise. We assign two different thresholds (below 660 and below 680) for consumers to be classified as below-prime, and we report results using both thresholds. This helps confirm that our results are robust and not sensitive to slight variations in how the below-prime segment is defined across lenders.

From the set of credit offers (mortgage loans, personal loans, and credit cards offers) during the periods in question, the models test whether there exists a significant relationship between a bank entering into a fintech partnership and the likelihood that a credit offer would be made to a nonprime consumer. An association between the periods during which banks had entered into partnerships with fintech firms and the credit offers in those periods would manifest as an increase in the probability of an offer to a below-prime or thin-file consumer, thus potentially expanding credit access to those underserved consumers.

In Model (1), we analyze whether entering into a partnership with a fintech firm affected the probability of a bank offering a loan to a below-prime or thin-file consumer. For the banks chosen, loan offers (and eventually originations) in the quarters before, during, and after the partnerships were used as the primary data set, with loan offers and originations from the quarters following the partnerships used as the comparison groups. To study the relationship between credit offers and fintech partnerships, we use a logistic regression **Model (1)** below to estimate the following specification:

$$P(Nonprime\ Credit\ Offer) = G(\beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank) \qquad (1)$$

where *Nonprime Credit Offer* is a binary variable that takes on a value of 1 if the loan analyzed was offered to a below-prime or thin-file consumer and takes on a value of 0 otherwise. The regressor, *t.1,* is a binary variable that takes on a value of 1 if the loan analyzed was offered in the quarter following the partnership quarter and a value of 0 otherwise. *Year* and *Bank* are fixed-effect variables to absorb time-varying factors that may vary across the year of loan offering as well as the size and scope of a bank offering a given loan.

The logistic regression model was then run separately for mortgage offers, personal loan offers, and credit card offers to examine if different offerings were affected differently by banks entering into partnerships with fintech firms. In addition, in a separate analysis, personal loan offers and credit cards offers were grouped together for a final model to see if an overall change in a bank's behavior could be detected. The logistic regression results are presented in **Table 1** (for the threshold credit score being less than 660) and **Table 2** (for the threshold credit score being less than 680) for mortgage offers, personal loan offers, card offers, and the combined personal loan and credit card offers as a group of financial products.

As mentioned earlier, for robustness and to ensure that the results are not sensitive to slight variations in how the below-prime segment is defined across lenders, we run separate regressions using two different credit score cutoff thresholds: 660 and 680. The *Nonprime Credit Offer* variable, therefore, includes: (1) loans offered to consumers with no credit on file or those with a credit score below *660*, or (2) loans offered to consumers with no credit on file or those with a credit score below 680. Results of the 660 and 680 cutoff thresholds are reported for each of the financial products in **Tables 1** and **Table 2**, respectively.

IV.2 Logistic Analysis of Fintech Partnerships and Banks' Loan Originations

The next step of our study is to determine if loan origination behavior changed post-partnership for banks that partnered with fintech firms, using **Model (2)**. To examine this, a similar analysis was run using Y-14M data on credit card and mortgage originations. As noted earlier, Y-14M data do not contain loan-level information on personal loans. Mirroring the methodology of the loan offering analysis, our models took the form of the following logistic regression:

$$P(Nonprime\ Credit\ Origination) = G(\beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank) \qquad (2)$$

where *Nonprime Credit Origination* is a binary variable that takes on a value of 1 if the loan analyzed was made to a nonprime consumer (with no credit history on file or with a designated below-prime score); it takes on a value of 0 otherwise. The variables *t.1*, *Year*, and *Bank* are defined the same as in the prior regression, incorporating a subset of the same partnerships and banks as the prior analysis.[6] As in the credit offering model, we apply two different thresholds for the below-prime designations, with the cutoff points for what qualified as a below-prime score being a FICO score below 680 or a FICO score below 660, depending on the model. The logistic regression results for credit card originations and mortgage originations (for both FICO score thresholds) are presented in **Table 3**. Note that the credit score thresholds for the loan origination analysis are based on FICO scores, rather than the credit score (from TransUnion) used earlier in the analysis of credit offers. They are not identical scores but close enough for the purpose of our analysis given the data constraint, in which the Mintel/TU data set reports its version of a credit score and the Y-14M data set reports FICO scores.

IV.3 Regression Analysis of Fintech Partnerships and Loan Amounts

The origination data lent themselves well to additional analysis about a bank's willingness to grant larger loans to some nonprime consumers. The loan-level data from the Y-14M reports contain total credit limits (for credit cards) and loan amounts (for mortgages). We construct models, with the dependent variable being the mortgage loan amount (or the total credit limit for credit cards), to examine whether banks would be more willing to grant larger loans to some nonprime consumers after entering into a partnership with a fintech firm. Using better data and modeling, banks might be better able to identify some nonprime consumers (based on traditional measures like credit scores) who are, in fact, not likely to default. If so, we should observe an increase in banks' willingness to grant larger loans to these nonprime consumers. Our analysis in **Model (3)** uses a simple linear model to explore this potential impact.

The sample observations include only *nonprime* consumers, i.e., those previously designated as being below-prime or thin-file consumers. The models for loan size (or total credit limit) for nonprime consumers take the following form:

$$Log\ (Loan\ Size\ or\ Credit\ Limit) = \beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank \qquad (3)$$

where *t.1*, *Year*, and *Bank* are defined the same as in the prior regressions. The response variable, *Log (Loan Size or Credit Limit)*, is the log transform of the credit limit on credit cards (or the size of the mortgage loan) that was extended to a nonprime consumer. We estimate separate models of mortgage loan size and credit card limit to determine whether banks are substantially changing

[6] Since Y-14 bank data are only collected for larger banks that are subject to CCAR stress testing, our analysis involving loan *originations* only includes these large banks. Bank names have been removed in Table 3 to maintain confidentiality. The analysis of credit *offerings* includes a larger sample of banks based on the Mintel/TU data set.

their credit decisioning behavior following fintech partnerships. We hypothesize that, in addition to targeting a different consumer pool by reaching out more to nonprime consumers, banks may also engage more with their existing nonprime borrowers by allowing larger credit amounts, which would be captured by this model. The ordinary least squares (OLS) regression results are presented in **Table 4** for credit card limits and mortgage loan amounts.

V. The Empirical Results

V.1 The Effect of Fintech Partnerships on Credit Offerings

The results are presented in **Table 1** for mortgage offers, personal loan offers, credit card offers, and both personal loan and credit card offers combined, based on the below-prime threshold (with a credit score below 660). And, **Table 2** presents the results for mortgage offers, personal loan offers, credit card offers, and both personal loan and credit card offers combined when the below-prime threshold (with a credit score below 680).

The overall results indicate that there are statistically significant changes in the behavior of banking institutions following partnerships with the selected fintech firms. The probability of a loan being offered by a bank to a potential *nonprime* borrower (with a low credit score or no credit score on file) consistently increased in the quarter following a partnership with a fintech firm. It is also worth noting that the degree of significance varies across the financial products offered.

For mortgage offers, the coefficients of t.1 are positive for below-prime consumers, regardless of the below-prime thresholds used (a credit score below 660 in Table 1 and a credit score below 680 in Table 2), but they are not statistically significant. Unlike the coefficients for mortgage offers, the coefficients for personal loan offers and credit card offers are consistently positive (as expected) for both a credit score being less than 660 (in Table 1) and less than 680 (in Table 2), and they are all statistically significant at the 1 percent level.

The results for the combined personal loan offers and credit card offers in Tables 1 and 2 also show a statistically significant (at the 1 percent level) positive coefficient of the t.1 indicator, 0.128 in both cases (when below prime is defined as having a credit score below 660 and when it is defined as having a credit score below 680). When these results are broken down for personal loans and credit card offers, the t.1 indicator maintains a significant positive coefficient: 0.161 for personal loan offers and 0.142 for credit card offers. In all these cases, the results indicate that the behavior of banks changed postpartnership, and in the positive direction, with a higher probability of credit card and personal loan offerings to below-prime borrowers.

The results for mortgages were notably different. Although the coefficients of the t.1 dummy (0.086 for both tables) had the expected (positive) signs, they are not statistically significant. This is likely due to the nature of mortgage offers. Literature shows that most mortgage offers are meant for refinancing an existing mortgage, rather than for home purchase; see Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021). In other words, most mortgage offers have been made to people who already own a home and are thus less likely to be affected by fintech partnerships. In addition, Dolson and Jagtiani (2021) show that mortgage offers (based on the Mintel/TU data set) are mostly offered by nonbank and fintech lenders. This is consistent with **Figure 1,** in which the share of mortgage offers is less than 5 percent of all credit offers at our sample banks.

V.2 The Effect of Fintech Partnerships on Loan Originations

Our examination of the effects of fintech partnerships extends beyond credit offerings to the actual loan originations – considering both the supply side from lenders and the demand side from borrowers. The origination data are only available for credit cards and mortgages. Personal loan data are not available at the loan level in the monthly Y-14M database.

The results on the probability of granting credit to below-prime consumers are presented in **Table 3** for credit card issuance and mortgage origination. Overall, the results show evidence of banking institutions changing behavior post-partnership as well. However, the results for loan originations are notably different from those reported earlier for credit offers.

Credit Cards: Credit card origination models initially showed insignificant coefficients when all the sample banks were included in the analysis. However, two of the banks in question saw an incredibly steep decline in their credit card origination data. After the removal of these anomalous banks, **Table 3** shows that credit card origination models did become statistically significant negative results in Column 3 (when below prime is defined as a FICO score below 680 or no FICO score) but remain insignificant in Column 1 (when below prime is defined as a FICO score below 660 or no FICO score). While banks are more likely to send credit card offers to below-prime consumers after the start of a partnership with a fintech firm, the increased credit offers do not seem to result in increased issuance of credit cards to those nonprime consumers.

It is also important to note that our sample of lenders that is included in the analysis of credit *offers* is different from the sample of lenders in the credit *originations* analysis. Specifically, while any bank could be included in the analysis of credit card offers (using the Mintel/TU data set), only the largest banks that are subject to CCAR stress testing could be included in the credit card originations data (non-CCAR banks do not report Y-14M data). For these reasons, the results may be at least partially driven by nonrandom sample banks, rather than the lack of demand for credit.

Mortgages: Unlike the results for credit card issuance, the results for mortgage origination to below-prime borrowers after a fintech partnership show statistically positive coefficients for both FICO score thresholds (a 660 threshold in Column 2 and a 680 threshold in Column 4 of **Table 3**). While the partnerships did not seem to significantly impact mortgage *offers* to nonprime consumers (based on the Mintel/TU data set as reported in Tables 1 and 2), we find that for CCAR banks, partnerships did seem to be positively related to an increased likelihood of mortgage originations to below-prime consumers. Again, this may be at least partially explained by the fact that the banks included in the mortgage offers analysis are not the same banks included in the mortgage originations analysis. Our results on mortgages overall show that fintech partnerships during the sample period at large CCAR banks had the potential to expand mortgage credit access to nonprime consumers (and, potentially, first-time homebuyers).

V.3 The Effect of Fintech Partnerships on Loan Amounts

Using the same loan origination data from the Y-14M reports, we explore the potential for banks to grant larger loans to nonprime consumers following fintech partnerships. The analysis focuses on mortgage loan amount and credit card limits. The results are presented in **Table 4** for credit limits on new credit cards that were issued after the partnership (Columns 1 and 3) and for the loan size of newly originated mortgages originated after the partnership period (Columns 2 and 4).

Credit Cards: Credit limits were found to have increased by 0.9 percent for nonprime consumers (with a FICO score below 660 or no score) following a fintech partnership period. The coefficients are statistically significant at the 5 percent level, as shown in Column 1 of Table 4. The coefficient becomes insignificant when the analysis includes a larger segment of nonprime consumers — that is, when the analysis also includes those with FICO scores between 660 and 680, as shown in Column 3 of Table 4. The additional data and analysis available to banks through fintech partnerships may have given them a better picture of nonprime consumers with scores below 660 than it did for consumers with scores between 660 and 680. Overall, our analysis suggests that nonprime consumers at large CCAR banks tend to get a larger credit limit following the fintech partnership period.

The results overall also suggest that, while fintech partnerships do not result in CCAR banks issuing more cards to nonprime consumers (**Table 3**), partnerships do effectively expand credit access to nonprime consumers by allowing them to access larger credit limits (**Table 4**) on cards issued by these large banks.

Mortgages: Recall that fintech partnerships result in CCAR banks originating more mortgage loans to nonprime borrowers (**Table 3**). Specifically, banks are more likely to originate mortgage loans to these nonprime consumers, with a statistically significant 0.053 coefficient on the partnership indicator at the FICO score below 680 threshold and a statistically significant 0.076 coefficient on the partnership indicator at the FICO score below 660 threshold. In addition to an increased likelihood of granting loans to nonprime consumers, the results in **Table 4** show that these large banks also grant *larger* loans to their nonprime mortgage borrowers following the fintech partnership period. Mortgage loan amounts at these sample banks increased by 2.4 percent (statistically significant at the 10 percent level for the FICO score below 660 threshold).

Overall, the story told by credit card and mortgage originations, as well as by mortgage loan amount and credit card limits, adds additional context to the results from the credit offering models. Bank behavior does indeed appear to change following a partnership with a fintech firm. When focusing on the impact that fintech partnerships have on the actual loan originations at large banks, we find that banks tend to grant larger credit limits on credit cards to nonprime consumers. In addition, after entering a fintech partnership, banks are more likely to grant mortgage credit to nonprime consumers, and they are also more likely grant larger mortgage loans to these nonprime borrowers.

VI. Conclusions

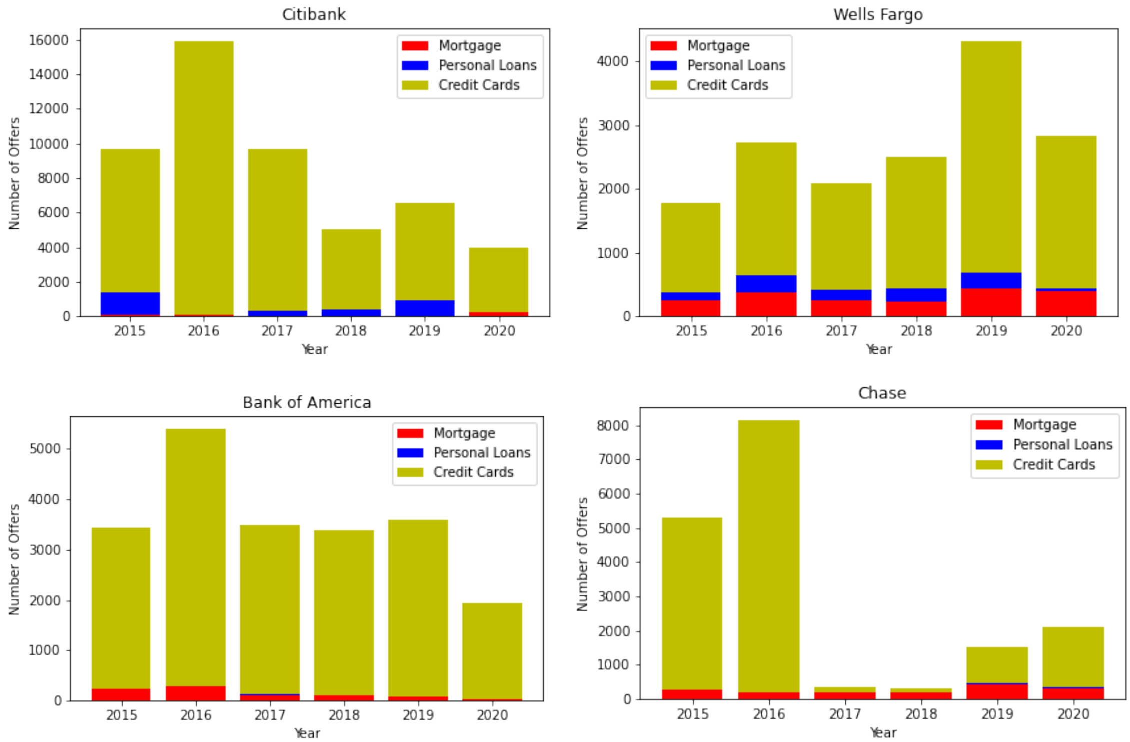
Examining the effects of fintech integration within the traditional banking structure remains a nontrivial task. Previous studies find evidence of fintech firms targeting nonprime consumers more so than traditional banks when it comes to loan offerings and originations. Given this behavior of fintech firms in regard to consumer lending, we can hypothesize how banking institutions would likely behave after adopting fintech methods and technology. We do find evidence in support of our hypothesis, as our results show that traditional banking behavior does change following a partnership with a fintech firm. We find that the probability of credit offerings and loan originations for certain financial products is likely to increase following a fintech partnership, and we also find the potential for increases in credit card limits and mortgage loan amounts.

Our results indicate that, after the fintech partnership period, banks offer larger credit limits on credit cards issued to their nonprime consumers. In addition, these large banks are more willing to grant mortgage loans to nonprime consumers and are willing to grant larger loans to their nonprime mortgage borrowers. Fintech firms are continuing to solidify their space within the financial markets. Fintech methods and behaviors have become sufficiently distinct to the point that some of the largest banking institutions are beginning to emulate them. While our results on loan originations are based on the behavior of large CCAR banks, we suspect that the impact of fintech partnerships could be even more significant for smaller banks, especially those with limited access to current technology because of their resource constraints. Banks' behavior evolves to look more like that of fintech firms in their credit decisioning and in their willingness to reach out to more to nonprime consumers following fintech partnerships.

Given the large unbanked, thin-file, and credit-invisible population in the U.S.,[7] fintech partnerships have an important role to play in expanding credit access to this underserved population. Our overall findings are consistent with the hypothesis that partnerships between traditional banks and fintech firms have the potential to move us closer to a more inclusive financial system.

[7] The Federal Deposit Insurance Corporation (FDIC, 2022) estimated that 4.9 percent of American households (about 5.9 million households) are unbanked (nobody in the household has an account with a bank or a credit union). In addition, the Consumer Financial Protection Bureau (CFPB, 2016) estimated that 26 million American consumers are *credit invisible*, with no credit file with any of the three major credit bureaus, and that another 19 million American consumers are *credit unscorable*, with a credit record, but no score, because their history is either too thin or too stale.

Figure 1: Credit Offers (Not Originations) by Year and Type of Credit Products



Data Source: Monthly Household Survey by Mintel Comperemedia, Inc.

Figure 2: Number of Sampled Fintech-Bank Partnerships by Year (2016–2020)

Data Source: CB Insights

Table 1: Logistic Regression — Credit Offers When Below-Prime Is Defined as Having Credit Score Below 660

The analysis in this table examines the impact of fintech partnership on the likelihood that a credit offer by banks be made to a nonprime consumer — using **Model (1).** The models contain fixed effects for the **year** of credit offer and the **bank** that offers the credit to nonprime consumers — using the year 2016 and Bank of America as the excluded categories (base case). The data sampled consist of individual loan-level credit offers from 2016 to 2021. The dependent variable, *Nonprime Credit Offer*, is a binary variable that takes on a value of 1 if the loan is offered to a nonprime consumer, and a value of 0 otherwise. Note: The ***, **, and * represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Model (1): $P(Nonprime\ Credit\ Offer) = G(\beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank)$

Variable	Mortgage Offers	Personal Loan Offers	Credit Card Offers	Personal Loan & Credit Card
(Intercept)	0.227483	-12.3009	-0.95162***	-0.94522***
	(0.801893)	(187.314)	(0.07968)	(0.07915)
t.1	0.085954	0.1607**	0.1423***	0.12778***
	(0.115031)	(0.0625)	(0.02466)	(0.02249)
year2017	-0.00653	-0.3267	0.12578***	0.10876**
	(0.568126)	(1.234)	(0.04538)	(0.045)
year2018	-0.29694	-0.2854	0.14003***	0.11154**
	(0.573886)	(1.2276)	(0.04948)	(0.04752)
year2019	-0.38891	-0.5772	0.30659***	0.15748***
	(0.565466)	(1.2272)	(0.04544)	(0.04443)
year2020	-0.2418	-0.3197	0.1481***	0.14165***
	(0.557537)	(1.2301)	(0.04933)	(0.04822)
year2021	0.073895	-0.5662	-0.42409***	-0.411***
	(0.632435)	(1.6844)	(0.08048)	(0.07973)
BankBarclays		11.9345	0.64503***	-0.12355
		(187.31)	(1.00263)	(0.19817)
BankChase	-1.18744**	11.9554	0.21978***	0.29927***
	(0.598264)	(187.3103)	(0.08484)	(0.08397)
BankCitibank	-1.01594*	11.6077	0.61258***	0.60583***
	(0.5934)	(187.3099)	(0.07036)	(0.06976)
BankCrossRiver		13.6271		1.66069***
		(187.3099)		(0.07864)
BankOmaha	-1.10109	11.112	0.29063**	0.16513
	(0.999059)	(187.3102)	(0.14665)	(0.13483)
BankSantander	-1.00659	12.4715	-0.14074	0.41862*
	(1.470193)	(187.3143)	(0.33395)	(0.23965)
BankTD		13.0051	-0.39354***	0.29572***
		(187.31)	(0.11758)	(0.09552)
BankUnion	0.041888		0.37643	0.39898
	(1.530179)		(0.36412)	(0.3638)
BankWellsFargo	-0.78157	12.1945	0.31364***	0.37043***
	(0.589672)	(187.31)	(0.0729)	(0.07215)
Observations:	N=1,943	N=5,878	N=33,172	N=39,050

Data Source: Mintel/TransUnion database and CB Insights database.

Table 2: Logistic Regression — Credit Offers
When Below-Prime Is Defined as Having Credit Score Below 680

The analysis in this table examines the impact of fintech partnership on the likelihood that a credit offer by banks is made to a nonprime consumer — using **Model (1).** The models contain fixed effects for the **year** of credit offer and the **bank** that offers the credit to nonprime consumers — using the year 2016 and Bank of America as the excluded categories (base case). The data sampled consist of individual loan-level credit offers from 2016 to 2021. The dependent variable, *Nonprime Credit Offer*, is a binary variable that takes on a value of 1 if the loan is offered to a nonprime consumer, and a value of 0 otherwise. The ***, **, and * represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Model (1): $P(Nonprime\ Credit\ Offer) = G(\beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank)$

Variable	Mortgage Offers	Personal Loan Offers	Credit Card Offers	Personal Loan & Credit Card
(Intercept)	0.227483	-12.3009	-0.95162***	-0.94522***
	(0.801893)	(187.314)	(0.07968)	(0.07915)
t.1	0.085954	0.1607**	0.1423***	0.12778***
	(0.115031)	(0.0625)	(0.02466)	(0.02249)
year2017	-0.00653	-0.3267	0.12578***	0.10876**
	(0.568126)	(1.234)	(0.04538)	(0.045)
year2018	-0.29694	-0.2854	0.14003***	0.11154**
	(0.573886)	(1.2276)	(0.04948)	(0.04752)
year2019	-0.38891	-0.5772	0.30659***	0.15748***
	(0.565466)	(1.2272)	(0.04544)	(0.04443)
year2020	-0.2418	-0.3197	0.1481***	0.14165***
	(0.557537)	(1.2301)	(0.04933)	(0.04822)
year2021	0.073895	-0.5662	-0.42409***	-0.411***
	(0.632435)	(1.6844)	(0.08048)	(0.07973)
BankBarclays	--	11.9345	0.64503	-0.12355
		(187.31)	(1.00263)	(0.19817)
BankChase	-1.18744**	11.9554	0.21978***	0.29927***
	(0.598264)	(187.3103)	(0.08484)	(0.08397)
BankCitibank	-1.01594*	11.6077	0.61258***	0.60583***
	(0.5934)	(187.3099)	(0.07036)	(0.06976)
BankCrossRiver	--	13.6271	--	1.66069***
		(187.3099)		(0.07864)
BankOmaha	-1.10109	11.112	0.29063**	0.16513
	(0.999059)	(187.3102)	(0.14665)	(0.13483)
BankSantander	-1.00659	12.4715	-0.14074	0.41862*
	(1.470193)	(187.3143)	(0.33395)	(0.23965)
BankTD	--	13.0051	-0.39354***	0.29572***
		(187.31)	(0.11758)	(0.09552)
BankUnion	0.041888	--	0.37643	0.39898
	(1.530179)		(0.36412)	(0.3638)
BankWellsFargo	-0.78157	12.1945	0.31364***	0.37043***
	(0.589672)	(187.31)	(0.0729)	(0.07215)
Observations:	N=1,943	N=5,878	N=33,172	N=39,050

Data Source: Mintel/TransUnion database and CB Insights database.

Table 3: Logistic Regression
Credit Card and Mortgage Loan Originations

The analysis in this table examines the impact of fintech partnership on the likelihood that a bank-issued credit card or mortgage is made to a nonprime consumer — using **Model (2).** The models contain fixed effects for the **year** of credit offer and the **bank** that offers the credit to nonprime consumers — with the year 2016 as the excluded categories (base case). The coefficients of individual bank's fixed-effect variables are not reported here. The data sampled consist of individual loan-level credit card and mortgage originations from 2016 to 2021. The dependent variable, *Nonprime Credit Origination*, is a binary variable that takes on a value of 1 if the loan was issued to a nonprime consumer (with FICO score below the given threshold or with no score on file), and a value of 0 otherwise. The ***, **, and * represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Model (2): $P(Nonprime\ Credit\ Origination) = G(\beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank)$

Variable	(1) Credit Card Origination (FICO < 660)	(2) Mortgage Origination (FICO < 660)	(3) Credit Card Origination (FICO < 680)	(4) Mortgage Origination (FICO <680)
(Intercept)	-0.77464***	-3.21659***	-0.59131***	-2.58961***
	(0.019871)	(0.112036)	(0.018304)	(0.085807)
t.1	-0.00699	0.075907***	-0.01336**	0.052872***
	(0.006222)	(0.022251)	(0.005352)	(0.016956)
year2017	-0.05476***	0.099711	-0.02706***	0.102713
	(0.010892)	(0.083202)	(0.009423)	(0.065875)
year2018	-0.09768***	-0.11616	-0.06931***	-0.06883
	(0.011159)	(0.08503)	(0.009633)	(0.067122)
year2019	-0.1111***	-0.53137***	-0.08571***	-0.41128***
	(0.010883)	(0.084708)	(0.009403)	(0.066718)
year2020	-0.20912***	-0.63314***	-0.16544***	-0.58308***
	(0.012248)	(0.08972)	(0.010497)	(0.070525)
year2021	-0.29527***	-0.83752***	-0.25509***	-0.74041***
	(0.02067)	(0.149207)	(0.017494)	(0.113097)
Bank Fixed-Effect	-- Yes—	-- Yes--	-- Yes—	-- Yes—
Observations:	N=994,012	N=205,038	N=994,012	N=205,038

Data Source: Y-14M monthly reports and CB Insights

Table 4: Regression Analysis
Credit Card Limits and Mortgage Loan Amounts

The analysis in this table examines the impact of fintech partnership on the likelihood that a credit card limit or mortgage loan issued by the bank to a nonprime consumer would increase after the bank's partnership with a fintech vendor — using **Model (3).** Columns (1) and (2) report results when the below-prime cutoff point is a FICO score below 660. Columns (3) and (4) report results when the below-prime cutoff point is a FICO score below 680. The models contain fixed effects for the **year** of credit offer and the **bank** that offers the credit to nonprime consumers — with the year 2016 as the excluded categories (base case). The coefficients of individual bank's fixed-effect variables are not reported here. The data sampled consist of individual loan-level credit card and mortgage originations from 2016 to 2021. The dependent variable, $Log\ (Credit\ Card\ Limit)$ is the log transform of the credit limit in U.S. dollars on file for the credit card and mortgage loan originated. The ***, **, and * represent statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Model (3): $Log\ (Credit\ Card\ Limit\ or\ Loan\ Amount) = \beta_0 + \beta_1 * t.1 + \alpha_2 * Year + \alpha_3 * Bank$

Variable	(1) Credit Card Limit (FICO < 660)	(2) Mortgage Loan Amount (FICO < 660)	(3) Credit Card Limit (FICO < 680)	(4) Mortgage Loan Amount (FICO <680)
(Intercept)	6.644377***	11.76949***	6.809235***	11.82662***
	(0.014299)	(0.072511)	(0.013478)	(0.052632)
t.1	0.009281**	0.024021*	0.00231	0.010422
	(0.004722)	(0.014253)	(0.004141)	(0.010211)
year2017	-0.10793***	0.204883***	-0.07509	0.216965***
	(0.00834)	(0.052689)	(0.007281)	(0.03938)
year2018	-0.07134***	0.214724***	-0.0347***	0.22375***
	(0.008541)	(0.05366)	(0.007459)	(0.040017)
year2019	-0.09943***	0.313047***	-0.0604***	0.311028***
	(0.008296)	(0.053822)	(0.007249)	(0.039978)
year2020	-0.14537***	0.516954***	-0.12996***	0.444798***
	(0.009365)	(0.058186)	(0.008125)	(0.043093)
year2021	-0.18689***	0.6884***	-0.17016***	0.563161***
	(0.015763)	(0.095304)	(0.013622)	(0.069772)
Bank Fixed-Effect	-- Yes--	-- Yes--	-- Yes--	-- Yes--
Observations:	N=151,021	N=10,344	N=225,282	N=18,587

Data Source: Y-14M monthly reports and CB Insights

References

Babina, Tania, Greg Buchak, and Will Gornall (2022). "Customer Data Access and Fintech Entry: Early Evidence from Open Banking." Stanford University Graduate School of Business Research Paper.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2018). "Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks." *Journal of Financial Economics* 130(3), pp. 453–83.

CFPB (2016). "Who Are the Credit Invisibles? How to Help People with Limited Credit Histories." December. Available at 201612_cfpb_credit_invisible_policy_report.pdf (consumerfinance.gov).

Chava, Sudheer, Rohan Ganduri, Nikhil Paradkar, and Yafei Zhang (2021). "Impact of Marketplace Lending on Consumers' Future Borrowing Capacities and Borrowing Outcomes." *Journal of Financial Economics* 142(3), pp. 1186–208.

Cornaggia, Jess, Brian Wolfe, and Yoo Woongsun (2018). "Crowding Out Banks: Credit Substitution by Peer-to-Peer Lending." Paper submitted to First New York Fed Conference on Fintech.

Cornelli, Giulio, Jon Frost, Leonardo Gambacorta, and Julapa Jagtiani (2022). "The Impact of Fintech Lending on Credit Access for U.S. Small Businesses." Federal Reserve Bank of Philadelphia Working Paper 22-14.

De Roure, Calebe, Loriana Pelizzon, and Paolo Tasca (2016). "How Does P2P Lending Fit into the Consumer Credit Market?" Deutsche Bundesbank Discussion Paper 30.

De Roure, Calebe, Loriana Pelizzon, and Anjan Thakor (2022). "P2P Lenders versus Banks: Cream Skimming or Bottom Fishing?" *Review of Corporate Finance Studies* 11(2), pp. 213–62.

DeYoung, Robert, William W. Lang, and Daniel L. Nolle (2007). "How the Internet Affects Output and Performance at Community Banks." *Journal of Banking & Finance* 31(4), pp. 1033–60.

Di Maggio, Marco, and Vincent Yao (2021). "Fintech Borrowers: Lax-Screening or Cream-Skimming?" *Review of Financial Studies* 34(10), October, pp. 4565–618.

Dolson, Erik, and Julapa Jagtiani (2021). "Which Lenders Are More Likely to Reach Out to Underserved Consumers: Banks Versus Fintechs Versus Other Nonbanks?" Federal Reserve Bank of Philadelphia Working 21-17.

Erel, Isil, and Jack Liebersohn (2020). "Does FinTech Substitute for Banks? Evidence from the Paycheck Protection Program." NBER Working Paper No. 27659.

FDIC (2022). "2021 FDIC National Survey of Unbanked and Underbanked Households." November 14. Available at 2021 FDIC National Survey of Unbanked and Underbanked Households.

FSB (2017). "Financial Stability Implications from FinTech." June 27. Available at www.fsb.org/wp-content/uploads/R270617.pdf.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery (2019). "The Role of Technology in Mortgage Lending." *Review of Financial Studies* 32(5), May, pp. 1854–99.

Hughes, Joseph P., Julapa Jagtiani, and Choon-Geol Moon (2022). “Consumer Lending Efficiency: Commercial Banks versus a Fintech Lender.” *Financial Innovation*, 8, April 2022. Available at doi.org/10.1186/s40854-021-00326-1.

Jagtiani, Julapa, Lauren Lambie-Hanson, and Timothy Lambie-Hanson (2021). “Fintech Lending and Mortgage Credit Access.” *Journal of FinTech* 1 (1), 2021.

Jagtiani, Julapa, and Catharine Lemieux (2018). “Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks?” *Journal of Economics and Business* 100, November–December 2018, pp. 43–54.

Jagtiani, Julapa, and Catharine Lemieux (2019). “The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from LendingClub Consumer Platform.” *Financial Management* 48(40), Winter 2019, pp. 1009–29.

Kutzbach, Mark, and Jonathan Pogach (2023). “Bank Technology and the COVID-19 Pandemic.” FDIC CFR Working Paper 2022-02. https://www.fdic.gov/analysis/cfr/working-papers/2022/cfr-wp2022-02.pdf

Navaretti, Giorgio Barba, Giacomo Calzolari, José Manuel Mansilla-Fernandez, and Alberto F. Pozzolo (2017). “Fintech and Banking. Friends or Foes?” *European Economy – Banks, Regulation, and the Real Sector.*

Pierri, Nicola, and Yannick Timmer (2020). “Tech in Fin Before FinTech: Blessing or Curse for Financial Stability?” IMF Working Paper 20/14.

Saloner, Garth, and Andrea Shepard (1995). “Adoption of Technologies with Network Effects: An Empirical Examination of the Adoption of Automated Teller Machines.” *RAND Journal of Economics* 26(3), pp. 479–501.

Tang, Huan (2019). “Peer-to-Peer Lenders Versus Banks: Substitutes or Complements?” *Review of Financial Studies* 32(5), pp. 1900–38.

Appendix I
Fintech Partnership Data — Selection Criteria
Source: Authors' analysis based on the CB Insights database

In determining whether the fintech partnerships reported in the CB Insights database would be relevant for our research, we follow the steps described below.

First, we compile a list of all relevant fintech partnerships listed by CB Insights. The initial comprehensive list contains approximately 10,000 partnerships between tech firms and financial firms for the period 2002–2021. Each of the collected partnership transactions are classified as "vendor-client," "partner-partner," "licensee-licensor," or "supplier-distributor."

Second, we restrict the sample period to include only partnerships that were announced from 2016–2020. In addition, we select only partnerships that involve banks and/or BHCs as one of the entities. We exclude all partnerships not involving a bank or a BHC. Also, because some of the partnership announcements are reported twice on the CB Insights database (once for each partner entity), we remove the duplicate partnership records.

Third, we narrow down the type of partnerships to match the purpose of our study.

1. CB Insights assigns a *sector* variable for each of the partnerships. From the general "inter-business relationships" sector classified by CB Insights, we restrict our search further to include only the subsectors classified as "Internet," "Mobile & Telecommunications," "Software (non-internet/mobile)," and "Computer Hardware & Services."
2. CB Insights also provides information on the *sources* (*purposes*) of the partnership data. So, for those partnerships that were included in (1), we further investigate the source, and only the partnerships that were explicitly enacted for the exchange of consumer data, software, or related purposes are included in our sample.
3. All partnerships that appeared to have no bearing on enhancing the credit-decisioning processes of banks were removed from our analysis. For illustration purposes, we use **Table A1** to present examples of partnership characteristics that:
    3.1) clearly should be included in the analysis;
    3.2) clearly should **not** be included in the analysis; and
    3.3) some borderline cases that were determined by us (judgmental) to be relevant (or not relevant) for a bank's credit decisioning process.

Table A1
Example of Our Fintech Partnership Data and the Selection Criteria

Example	Partnership (Date)	Partnership Description and Decision Criteria
3.1 Clearly should be included	Wells Fargo and Finicity (April 2017)	Source: www.businesswire.com/news/home/20170404006453/en/Finicity-Wells-Fargo-Ink-Data-Exchange-Deal/ Reasoning: This partnership is outlined as an explicit agreement between Wells Fargo and Finicity (a data aggregator, now part of Mastercard Co.) that shares customer data from Wells Fargo with Finicity and also allows Wells Fargo to implement financial management tools from the Finicity financial data application programming interface (API). This is clearly the type of partnership that we were hoping to include in our analysis — one where a large banking firm benefits from the use of technology and alternative data from a fintech, AI, or similarly related firm.
3.2 Clearly should not be included	TD Bank and WEConnect International (March 2020)	Source: www.newswire.ca/news-releases/td-bank-group-and-weconnect-international-work-together-to-fund-training-for-women-owned-businesses-in-quebec-879311001.html Reasoning: This partnership between TD Bank and WEConnect International only satisfies our criteria at the surface level. WEConnect International is classified a fintech firm, as it exists largely in the intersection between technology and finance/business. CB Insights even classifies it under the "Computer Hardware & Services" sector. However, WEConnect International is primarily concerned with women-owned business enterprises and is focused on facilitating the growth and success of women-owned businesses. While this might nominally be classified as a partnership between a fintech firm and a large bank, it is clear that such a partnership would not be relevant to our study because it would not impact TD Bank's lending activities and/or credit decisioning process. Thus, it has been excluded from our analysis.
3.3A Borderline (being included)	Santander Bank and Kabbage (April 2016)	Source: www.businessinsider.com/fintech-briefing-bbvas-plan-to-compete-with-fintechs-sme-partners-to-boost-sme-lending-barclays-offer-apple-pay-2016-4 Reasoning: This partnership announced a pilot program that would allow small and medium-sized enterprises (SMEs) to get same-day working capital loans. Through this partnership, Santander benefits from gaining access to Kabbage's data aggregation platform, while Kabbage gains access to Santander's customer data. While SME loans would not necessarily extend to some of the loan products (mortgages, credit cards, and personal loans) analyzed in our paper, the proliferation of new technologies and alternative data usage throughout Santander would likely increase the potential for Santander to change its loan offering and origination patterns for

		other financial products as well. For these reasons, this is included in our analysis. We felt it would be prudent to err on the side of overinclusion, which would result in more robust findings, even though some of those findings are less likely to be significant.
3.3B Borderline (being excluded)	Santander Bank and Sherpa.ai (July 2020)	Source: www.analyticsinsight.net/augmenting-business-potential-with-world-class-ai-capabilities/ Reasoning: Sherpa.ai is a fintech firm providing predictive algorithms, natural language processing, federated learning, and more. Sherpa.ai has done research in the development of federated learning, a type of ML that uses multiple local data sets. This is the reason that the article cited above briefly mentions a partnership between Sherpa.ai and Santander Bank. Given the nature of federated learning, which is largely used in fields such as health care — in which health information needs to be stored locally so as not to be easily accessible to outside sources — we determine that it is unlikely for the partnership to impact Santander's credit decisioning process. Instead, it is more likely that Santander would utilize the technology and resources of Sherpa.ai to enhance the security of its algorithms and data storage capabilities.

Appendix II

List of Partnerships Between Banks and Selected Fintech Firms

Source: Authors' analysis based on the CB Insights database

Bank Name	Bank Role	Partner Role	Partner Name	Date
Santander Bank	Partner	Partner	Kabbage	4/5/2016
Citibank	Partner	Partner	FIS/Paypal	12/15/2016
Fifth Third Bank	Client	Vendor	AxiomSL	2/15/2017
Wells Fargo Bank	Partner	Partner	Finicity	4/5/2017
JPMorgan Chase	Partner	Partner	Finicity	7/11/2017
Citibank	Partner	Partner	FIS/Trax	10/16/2017
Fifth Third Bank	Client	Vendor	FIS	12/7/2017
Wells Fargo Bank	Client	Vendor	Personetics Technologies	2/28/2018
Citibank	Client	Vendor	Personetics Technologies	3/5/2018
Union Bank	Client	Vendor	FIS/Profile	5/3/2018
JPMorgan Chase	Client	Vendor	Kasisto	6/20/2018
Citibank	Partner	Partner	HighRadius	7/12/2018
Citibank	Partner	Partner	HighRadius	7/13/2018
JPMorgan Chase	Partner	Partner	Plaid Technologies	10/23/2018
Citibank	Licensee	Licensor	Feedzai	12/17/2018
Cross River Bank	Partner	Partner	Stripe	1/9/2019
Toronto-Dominion Bank	Partner	Partner	Avant	3/25/2019
First National Bank of Omaha	Partner	Partner	Upstart	4/8/2019
Citibank	Partner	Partner	Betterment	7/24/2019
JPMorgan Chase	Client	Partner	Persado	8/13/2019
Barclays	Partner	Partner	Betterment	7/24/2019
Wells Fargo Bank	Partner	Partner	Plaid Technologies	9/19/2019
Citibank	Partner	Partner	Trumid	11/12/2019
Citibank	Client	Vendor	Temenos	11/19/2019
Citibank	Client	Vendor	HighRadius	12/4/2019
Citibank	Partner	Partner	Wealthfront	12/6/2019
Wells Fargo Bank	Partner	Partner	Wealthfront	12/6/2019
Union Bank	Partner	Partner	FIS	1/15/2020
Cross River Bank	Partner	Partner	Upstart	1/16/2020
Barclays	Partner	Partner	Trumid	2/19/2020
Bank of America	Partner	Partner	AlphaSense	5/12/2020
Citibank	Client	Vendor	TruValue Labs	9/30/2020
Citibank	Partner	Partner	Moneyhub	12/8/2020
Fifth Third Bank	Client	Vendor	Blend	12/17/2020