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Fintech Innovations in Banking

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Fintech Innovations in Banking: Fintech Partnership and Default Rate on Bank Loans

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Abstract

We explore whether banks could leverage data and technology to expand their customer base without taking on more credit risk. Previous studies have not explored the impact of fintech partnerships on the quality of banks' loan portfolios. Our analysis utilizes data on relevant bank–fintech partnerships and loan-level data from Y-14M reports. For credit cards, we find that banks that had fintech partnerships extended larger lines of credit to consumers with low credit scores or missing credit scores. We also find that credit card default rates declined among nonprime borrowers with missing credit scores. For mortgages, unlike credit cards, our sampled banks did not grant larger mortgage loans to nonprime borrowers, however, the fintech tools seem to have improved the effectiveness of banks' credit decisions, resulting in a decline in mortgage default rates. Further analysis of the interest rate spread residual shows that, after gaining access to fintech tools, banks were better able to differentiate between nonprime borrowers that were good credit risks and those that were not. This was evident in the pricing of the loans after the banks entered partnerships. This allowed banks with access to fintech tools to attract creditworthy nonprime borrowers by giving them (appropriately) discounted mortgage rates relative to the traditional risk pricing models. Those banks continued to charge risky nonprime borrowers a large risk premium on their mortgages. Overall, fintech partnerships have made it possible for banks to offer a larger credit card line and charge a lower mortgage interest rate to some nonprime borrowers while seeing nonprime defaults decline on average.

Keywords: Fintech partnership, alternative data, AI, mortgage default, mortgage rate, credit limits
JEL Classification: G21, G28, G18, L21

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I. Introduction

Fintechs partnering with banks and the use of artificial intelligence (AI) in banking have become increasingly common. On the positive side, fintechs can provide banks with new types of innovative financial products and services and banks can provide fintechs access to the payments system and customer base, allowing fintechs to provide high-quality banking services to retail consumers without a banking license. On the downside, there have been concerns about the impacts on consumers, safety and soundness in the banking system, and the future of finance overall. In this paper, we focus on a specific type of bank–fintech partnership and explore the impacts.

A debate has emerged regarding whether fintech tools could help banks expand their customer base without exposing banks to additional default risk. Chernoff and Jagtiani (2024) found that when financial institutions have access to fintech tools, their customer base expands to include some creditworthy customers whose information was not readily available without the fintech tools. Chernoff and Jagtiani (2024) stopped short of investigating whether the benefit of the expanded customer base might be outweighed by greater exposure to default risk, compromising the safety and soundness of the banking system.[1]

In general, one could easily increase the customer base by lowering credit standards. However, granting loans to borrowers who do not have the ability to repay would be bad for both the banks and the borrowers in the long run. For the banks, reduced credit standards would lead to increased nonperforming loans and credit losses, causing harm to bank shareholders, the federal safety net, and taxpayers at large. For the borrower, taking on loans that they would not be able to repay could lead to loan defaults or even bankruptcy, impairing their ability to access credit in the future. Thus, it is important that the granting of credit to more customers is not achieved through lowering banks' credit standards.

An alternative approach would be for banks to improve their ability to understand their customers' financial well-being and to identify the potential "good" borrowers from a nonprime pool of consumers. It has been well documented in the literature that the customer base could be expanded through banks' access to fintech tools — see Cornelli et al. (2024), Jagtiani and Lemieux (2019), Erel and Liebersohn (2022), and Jagtiani and Lemieux (2018). However, what has been

[1] Specifically, Chernoff and Jagtiani (2024) explored the credit card and mortgage lending behavior of large CCAR banks (all Y-14 reporters) after they formed partnerships with fintech firms, which granted the banks to access more fintech tools, including automated underwriting models, artificial intelligence and machine learning (AI/ML) underwriting models, and alternative data, for use in assessing borrower creditworthiness.

missing in the literature is a detailed look at how expanded credit access through fintech tools has affected default rates at banks.

A few studies find mixed results regarding the impact and potential unintended consequences of fintech tools. Chu et al. (2023) find evidence of price discrimination along gender lines when using algorithmic underwriting systems (rather than manual underwriting systems) for mortgage lending. The AI underwriting models learned that female borrowers are less price-sensitive, thus assigning a higher mortgage rate to female loan applicants to maximize profit for the lenders.

In this paper, we attempt to fill the literature gap by investigating the impacts of applying fintech tools in credit decisioning on the potential risk to lenders, taxpayers, and the financial system overall. Specifically, in addition to exploring the impact of fintech tools on credit card origination and performance, we focus on mortgage origination, mortgage rates, and mortgage defaults at the largest banks, that have been subject to the Comprehensive Capital Analysis and Review (CCAR) stress testing conducted by the Federal Reserve, during the periods before and after the banks enter a relevant fintech partnership.

First, we will confirm the results from earlier studies that the use of fintech tools that incorporate alternative data and AI/ML modeling in the credit approval process leads to banks extending credit to those borrowers who were previously unlikely to be granted credit. Second, we explore whether this use of fintech tools tends to impact banks' default risk — either by adding more risk to the bank (resulting in higher default rates) or by lowering the bank's default risk through enhanced visibility of consumer credit risk. Third, we investigate risk pricing before and after a bank entering a fintech partnership. Our findings suggest that collaboration between banks and fintech can potentially expand the provision of credit without significant increases in default risk. Both the banks and their borrowers could benefit from the banks having access to alternative data and more advanced credit modeling tools to better identify creditworthy borrowers.

Next, we will elaborate on how access to fintech tools can help banks identify "good" borrowers. Traditional underwriting systems for credit cards and mortgages rely on information reported by the three big nationwide credit reporting agencies ("NCRA") that provide consumer credit reports: Equifax, TransUnion, and Experian. Credit scores are developed from this information and used to rate a borrower's ability to repay. The two most used credit scores are FICO and VantageScore. It would be helpful to understand what inputs are being used in these credit scoring models. For example, FICO reports that the information used to create its credit score (and the weighting of the information) is as follows: payment history (35%), amounts owed (30%), length of credit history (15%), new credit (10%) and credit mix (10%). Some other information, so-called alternative data, that is likely to play a big role in consumers' ability to pay back a loan is not used in the credit scoring process. Variables such as employment history, salary, education, rent payments, homeownership, and total wealth (all assets including investments) are also not considered in the credit scoring process. In addition, some consumers with data deficits (sometimes referred to as "thin-file" consumers) have difficulty obtaining a credit score if they are new to the financial and payment systems.

Brevoort, Grimm, and Kambara (2015) identify three types of "thin-file" consumers. First, the credit invisibles (26 million people in 2015) are people with zero NCRA credit records. They have never taken out a reportable loan or credit card. Second, the insufficient unscorables with thin credit files (9.9 million people in 2015) are people with some NCRA credit records but not enough to generate a credit score. This often happens when a consumer has too few accounts or only recently opened accounts.[2] Third, the stale unscorables (9.6 million people in 2015) are people who have not had any reported credit activity in a long time. In 2022, Experian estimated that 62 million Americans had a thin credit file — up from the almost 46 million estimated in Brevoort, Grimm, and Kambara (2015). Being able to identify the consumers in these groups that have a high likelihood of repaying their loan (and therefore are a good credit risk) would allow a bank to increase the loans to these consumers without increasing their credit risk.

Software as a service ("SaaS") companies are fintechs that provide subscribers (banks in this case) with a platform to run applications on a cloud infrastructure.[3] These companies allow banks to bring new products to market without the development issues inherent in dealing with legacy technology systems that may exist in their own institutions. Many also provide the ability to access data on payments, income, assets and credit in real time, so alternative data can be incorporated into lending decisions in a seamless manner. Unlike these fintech tools, the traditional credit scores from NCRAs are often refreshed only once a month. Therefore, having access to real-time information to make lending decisions is an important advantage that could be achieved through bank–fintech partnership.

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[2] Experian defines a thin-file consumer as someone with fewer than five credit accounts. https://www.experian.com/blogs/ask-experian/what-is-a-thin-credit-file-and-how-will-it-impact-your-life/#:~:text=A%20thin%20credit%20file%20typically,according%20to%20an%20Experian%20report.

[3] NIST defines SaaS as the capability provided to the buyer to use the provider's applications running on a cloud infrastructure. The applications are accessible from various client devices through either a thin client interface, such as a web browser (e.g., web-based email), or a program interface. The buyer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities, with the possible exception of limited user-specific application configuration settings.

The rest of the paper is organized as follows. The review of related literature is presented in Section II. We describe the data collection, screening, and basic statistics of the data in Section III. The empirical approach and specific models are presented in Section IV. The empirical results are discussed in Section V as follows: credit card analysis in Section V.1, mortgage analysis in Section V.2, and interest rate risk premium analysis in Section V.3. The concluding remarks and potential policy implications are presented in Section VI.

II. Related Literature

Allen, Gu, and Jagtiani (2021) present a comprehensive fintech literature survey with relevant research studies and policy discussion around the various aspects of fintech. One of the research themes relates to using fintech tools to enhance credit access and economic development. A number of studies have found that fintech tools including alternative data have resulted in increased access to credit, particularly for below-prime and thin-file consumers. Beck, Demirgüç-Kunt, and Levine (2007) demonstrated a positive relationship between financial access and economic development, implying that increased credit access benefits economic development.

In addition to enhancing credit access and economic development, fintech tools have been found to reduce the cost of credit to consumers while also expanding financial access. Fuster et al. (2022) examined the mortgage market and find that using ML models resulted in more borrowers having access to mortgage credit. Jagtiani and Lemieux (2019) use loan-level data from the LendingClub consumer lending platform and Y-14M bank stress test data. They found that the use of alternative data allowed some below-prime consumers to receive personal installment loans at a much lower cost (compared with credit card borrowing), and that the default rate of these invisible prime borrowers was similar to that of highly rated consumers with top credit scores (760 or higher). In addition, they found that for the same risk of default, borrowers were required to pay smaller interest rate spreads on their fintech personal installment loans relative to traditional alternatives such as credit card borrowing. Di Maggio and Yao (2021) provided complementary evidence, showing that fintech borrowers with low standard credit scores and short credit histories have higher acceptance probabilities and pay lower interest rates compared to a traditional lending model.

Croux et al. (2020) identified alternative data variables and tested their predictive power; they found that the variables are important predictors, even after controlling for traditional risk characteristics and local economic factors. Di Maggio, Ratnadiwakara, and Carmichael (2022) also found that alternative data contribute significantly to enhancing predictive power with regard to the likelihood of default. Credit risk models that utilize alternative data help to expand credit access to low-score borrowers, whose default rates are substantially lower than their credit score would otherwise suggest. Jagtiani, Lemieux, and Goldstein (2025) built on previous studies by showing that the fintech tools continued to provide greater predictive power than the traditional risk measures in a declining economic environment outside of the development data period. The superior results from using fintech tools and AI/ML underwriting hold even in adverse economic conditions, namely the economic downturn from the COVID-19 pandemic.

Fintech tools have also been found to enhance banking efficiency and default prediction accuracy. Hughes, Jagtiani, and Moon (2022) found that LendingClub became more efficient (based on minimizing loan loss controlling for risk, using bank efficiency frontier analysis) than other lenders in its peer group size as of 2016 (after more alternative data were incorporated into its credit scoring and pricing) compared with 2013. Berg, Fuster, and Puri (2022) also pointed out that the use of more complex credit risk models by fintech lenders improves accuracy in predicting consumers' true underlying default probabilities. Jansen, Nguyen, and Shams (2025) explored performance in auto lending and found higher loan profits and lower loan defaults, especially when dealing with riskier and more complex borrowers. Fuster et al. (2019) found that nontraditional, algorithm-wielding fintech mortgage lenders are 20 percent faster in processing speed over traditional lenders without a corresponding increase in defaults.

Moreover, it has been documented that fintech tools have been effective in filling the credit gaps in areas where there are not sufficient banking services. Dolson and Jagtiani (2024) explored credit supply to underserved consumers, using data on credit offers made by fintech lenders versus traditional lenders. They found evidence suggesting that fintech lenders attempt to reach consumers with lower credit scores and lower income relative to traditional lenders. Similarly, using evidence from a fintech platform, Basten and Ongena (2024) found that online banking has allowed banks to extend mortgage loans to clients in regions where banks lack branches, reputation, staff, or local expertise. And Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021) explored the mortgage market and find evidence suggesting that more borrowers turned to mortgage fintech lenders in areas where there were higher denial rates by traditional lenders in the previous period.

While some sophisticated traditional lenders have attempted to utilize nontraditional data in their credit decisions, it has been uncommon. The additional information used by the more sophisticated lenders included information about the borrowers and their local economic conditions. This additional information beyond consumer credit scores affected interest rates, fees, credit limits, and rewards on credit cards that these banks originated — see Ru and Schoar (2020); Agarwal et al. (2023); Horvath, Kay, and Wix (2023); and Agarwal and Zhang (2016).

In attempting to access fintech tools, some lenders decide to build their own in-house technology, rather than establishing fintech partnerships. A few studies have looked at the impact of IT investment on lending decisions. He, Jiang, Xu, and Yin (2022) examine IT spending at banks located in areas where LendingClub was granted entry between 2010 and 2016. They find that the entry of LendingClub induced local commercial banks in the area to spend more on their IT investments. Pierri and Timmer (2022) found that mortgages originated by banks with higher IT spending tend to perform better, consistent with a better borrower screening argument. Kutzbach and Pogach (2024) found similar results, with technologically adept banks originating significantly more COVID-19-era Paycheck Protection Program (PPP) loans, which were utilized by small businesses, than their peer banks.

There are drawbacks in these studies that focus on IT spending, as the researchers did not have access to data on banks' specific IT investment categories. More importantly, while fintech tools and IT could potentially be developed internally, the AI/ML underwriting models cannot be successful without a large amount of high-quality data on prospective borrowers.[4] Fintech partnerships allow banks to utilize much bigger datasets, including those data points not available to banks internally. Unlike these studies, we use data on fintech partnerships, allowing us to zero in on the impact of fintech tools (and more high-quality data) on bank lending, pricing, and loan performance.

Next, we will discuss the literature that contributes to our empirical strategy in this paper when designing credit decisioning models and default risk models for two main financial products — credit cards and mortgages.[5] Buchak et al. (2018) argue that fintech lenders became bigger players in this space as they utilized their comparative advantage over traditional banks in accessing today's technology and exploiting regulatory arbitrage opportunities.

In modeling credit card defaults, we control for local economic conditions, average local income, and other consumer characteristics. Agarwal and Liu (2003) find that county unemployment rates and state average income are important in predicting credit card delinquency. Credit card defaults are also affected by consumers' social networks, demographic factors, and bank

[4] The absence of sufficient quality data available to banks has been documented in Berger et al. (2024).

[5] These two products represent the largest consumer credits — with outstanding credit card balances of $1.21 trillion as of the first quarter of 2025 and $1.79 trillion in mortgages loans originated in 2024. See Credit Card Debt Statistics (2025): See the Trends and U.S. Mortgage Originations Forecast 2026| Statista

account behavior — see Kim, Cho, and Ryu (2018); Calli and Coskun (2021); Agarwal et al. (2018); and Hibbeln et al. (2020).

For the mortgage default prediction models, we control for the various factors identified in previous studies as being important in determining mortgage defaults. In addition to credit scores, we control for the combined loan-to-value (CLTV) ratio and debt-to-income (DTI) ratio following the literature — see Di Maggio, Kemani, and Korganokar (2019); Shi and Downs (2015); Nowak, Smith, and Thibodeau (2024); and Foote, Loewenstein, and Willen (2019); Farzad (2019); Lazarov and Hinterschweiger (2018); Babii, Chen, and Ghysels (2019); and Davis et al. (2023). We also control for the home price index (HPI), as house prices have been documented to play a role in determining demand for homes, collateral value, and the likelihood of a mortgage being underwater, thus affecting mortgage defaults — see Di Maggio, Kemani, and Korganokar (2019) and Hatchondo, Martinez, and Sanchez (2015). We also control for whether it is a new purchase or refinancing. Refinanced mortgages behave differently than purchase mortgages, and they are less accessible for sub-prime borrowers than prime borrowers — see Shi and Downs (2015); Lambie-Hanson and Reid (2018), and Abel and Fuster (2021). In addition, we focus only on first-lien residential mortgages to control for defaults that may be driven by willingness to pay (rather than ability to pay) motivated by changes in consumers' debt payment priority — see Jagtiani and Lang (2011); and Calem, Jagtiani, and Lang (2017).

III. The Data

Our primary goal in this paper is to explore the impact of fintech partnerships on bank loan default rates, using proprietary and unique datasets. We first test whether banks made more loans to nonprime consumers after partnering with a relevant fintech firm. Then, we explore how the loans to nonprime and thin-file borrowers performed during the 24 months after origination.[6] To accomplish this, we use data from two different sources. First, data on partnerships between fintech firms and banks are sourced from the partnership data maintained by CB Insights, and we supplemented this with additional internal proprietary data. Second, we obtained loan-level data on loan origination and loan performance for mortgages and credit cards from FR Y-14M reports filed by large banking institutions that are subject to annual CCAR stress testing. We focus on the banks that we identified as being in partnerships with relevant fintech firms. We explore the impact of fintech partnerships, using credit originations from the banks that entered into these fintech

[6] We also looked at 12-month window after origination. The results are similar for both the 12-month and 24-month window, with slightly stronger results when the 24-month window is used.

partnerships, during the period preceding the partnership (as a control group) as well as the period after the partnership.

Fintech Partnership Data: Our initial steps in collecting fintech partnership data follow Chernoff and Jagtiani (2024) by using the CB Insights database, to obtain a detailed list of partnerships between fintech firms and other companies. Our analysis focuses on those partnerships (with banks) that could potentially affect the banks' credit decision. Ultimately, we have a total of 51 partnerships identified as being relevant for banks' credit decision during the period 2016–2022, most of which occurred between 2018 and 2022.[7]

It should be noted that the partnership dates provided by CB Insights are the dates on which the details of the partnerships were released to the public and thus do not necessarily reflect the actual implementation date or adequately disclose the scope of the partnership. Moreover, we recognize that the effects of a partnership would not be felt immediately.

For the purpose of the study, we focus on seven fintech firms that could make the relevant fintech tools available to banks. Each of the seven fintech firms has a slightly different focus, but all are considered SaaS companies. Banks that partner with these fintechs have access to the infrastructure needed to do such things as speed payments, provide end-to-end digital solutions for consumer banking (including mortgages and credit cards), or integrate data from multiple sources into their loan approval process. By using SaaS firms, banks do not incur the costs required to develop and maintain in-house solutions and overcome issues associated with legacy technology systems and can speed delivery of new products. Details (from Bloomberg company profiles) about these fintech firms are shown in **Table 1,** and the share of each fintech partner in our analysis is shown in **Figure 1**.

Loan-Level Sample: The next source of data is loan-level data for mortgages and credit cards obtained from financial institutions that are FR Y-14M reporters and that have fintech partnerships in the CB Insights database. The Y-14M reports 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 US banks that are subject to CCAR stress testing). This dataset contains information about the loan characteristics (loan amount, credit limit, loan origination date, etc.) and the consumers' characteristics (zip code, consumer credit score as of loan application, loan payments, delinquency status, etc.).

[7] For some analyses of credit cards, partnership data from 2011, 2012, and 2013 are also included. Overall, the regression analysis includes a total of 38 partnerships for credit cards and 50 partnerships for mortgages.

Our data period is primarily based on the partnership dates between banks and fintech firms. We use loan-level data from Y-14M during the period 2011 to 2024 for our credit cards analysis and the period 2016 to 2024 for our mortgages analysis.[8] Our loan sample consists of a 5% random sample of credit card originations and the entire dataset of mortgage originations from Y-14M monthly reports for those loans originated during the relevant window around the partnership dates. The relevant windows are during the six months before a fintech partnership date (t-6) and nine months after the partnership date (t+9). We expect the effects of a partnership would not be felt immediately. The post-partnership window is three to nine months after the partnership date (from t+3 to t+9).

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. For both credit cards and mortgages, loans that were originated during the post-partnership period constitute the treatment group. Loans that were originated during the six months to three months before (t-3) a partnership date constitute the control group. We carve out this three-month radius around each of the partnership dates to account for a financial institution's strategic testing and acclimation to the new tools.

Data on the Borrowers: We define nonprime consumers to include those who are below-prime and borrowers with no (missing) credit scores as of the loan application date. Below-prime consumers are those with a credit score at origination of 660 or below for both credit cards and mortgages.[9] The binary dependent variable (in the logistic analysis) takes a value of 1 if the loan was given to a nonprime consumer and a value of zero otherwise.

Credit Cards: For each credit card loan, we collect the account's origination date, the borrower's income at origination, whether the borrower has other non-credit card banking relationships with the card's originator (including a deposit account or loans held by the originator but not serviced by them), whether the borrower has another credit card with the card's originator, the original credit limit of the card, and whether the card became delinquent (defined as 60+ days past due (DPD)) within 12 or 24 months after origination. Only consumer cards are included in the analysis. Business cards and corporate cards are excluded. Credit cards that were acquired by the reporting bank are also excluded from the analysis, because these acquired credit card accounts

[8] Note that while the data were collected for these periods (up to 2024), only loan observations that were originated two years before the end of our data collection period are included in the default analysis — to allow a two-year observation window for default behavior during 24 months after origination.
[9] We also explored an alternative credit score threshold for mortgages of a 680 or below credit score at origination cut off for nonprime. The results are consistent with those reported in this paper.

were not originated by the bank using the fintech tools.[10] On average, 46 percent of credit card originations in our sample (both during the pre- and post-partnership period) went to nonprime borrowers with a credit score below 680 or missing credit scores; and 39 percent went to nonprime borrowers with a credit score below 660 or missing credit scores. However, we find significant variation across the sampled banks. Volume also varies significantly across banks.[11] For robustness testing, we also ran the analysis with and without the unusual observations,[12] and the results are robust in terms of the impact on credit expansion but the impact on default rates changes significantly.

Mortgages: For each mortgage borrower, we collect the associated close date, the principal balance at origination, the front-end debt-to-income (DTI) ratio at origination, whether the mortgage is an FHA or VA residential mortgage, the combined loan-to-value (CLTV) ratio at origination, whether the purpose of the mortgage is to purchase a home or to refinance an existing mortgage, and whether the mortgage became delinquent (defined as 120+ DPD) within 24 months after origination. Unlike with credit cards, there is not an easy way in the Y-14M reports to distinguish acquired mortgages from originated mortgages. To address this, we use only mortgages whose first appearance within the Y-14M reports was within six months of the mortgage's associated close date.[13]

Loan Performance Data: We examine the impact of bank–fintech partnerships on loan performance, focusing on mortgages and credit cards that were originated to nonprime consumers during the period before versus after the full partnership implementation date. We identify loans that became delinquent — defined as 60+ DPD for credit cards (within 12 or 24 months after origination) and defined as 120+ DPD for mortgages (within 24 months after origination). If the empirical results show that loans made to nonprime borrowers had the same delinquency rate during pre- and post-partnership, then we could say that banks were able to extend credit to nonprime (below-prime and thin-file) borrowers without exposing themselves to more risk.

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[10] Credit cards with very small credit limits (less than $100) and credit cards associated with borrowers whose reported incomes were unusually high (in excess of $1 billion) are also removed from the sample.
[11] For example, one of the sampled banks had only about 13,000 credit card originations, but 84 percent went to borrowers with missing credit scores or credit score below 660. Another sampled bank had more than 2.5 million credit card originations, and 53 percent went to borrowers with missing credit scores or credit score below 660.
[12] Our data show that one of the banks follows a much different strategy than others in their risk taking and pricing. While the results on credit expansion remain robust, the results on default rate changed significantly when observations associated with that specific banks are removed from the analysis.
[13] Mortgages with very small principal balances (less than $10,000) and mortgages with reported DTIs below zero at origination are deleted from the sample.

Economic Variables: To account for localized macroeconomic-dependent lending strategy adjustments by the banks, we acquire an economic control variable for the credit card observations, the initial unemployment insurance claims, and an economic control variable for the mortgage observations, the home price index. The number of initial unemployment insurance claims, provided by the United States Department of Labor, is at the U.S. state level. The series is also reported by the Department of Labor on a weekly basis. We match each credit card's account origination date to the closest week-end date in the series and then match the borrower's state of residence to identify the appropriate value of initial unemployment insurance claims. The home price index is seasonally adjusted, at the United States census region level, reported monthly, and provided by the Federal Housing Finance Agency. The values are matched to the mortgage observations on the state associated with the borrower aggregated into their respective United States census regions and the month and year of the mortgage's close date.

Interest rate spread data: In exploring whether interest rates that banks charge to nonprime borrowers are set differently before versus after the fintech partnership, we collect data on interest rates from the mortgage loan contracts (from Y-14M reports) and calculate the risk premium above risk-free rate that banks charge to compensate for the additional credit risk. We define the risk-free rate as the market yield on the United States Treasury securities with a maturity identical to that of the mortgage (as of the reporting date closest to the mortgage's close date).[14] For adjustable-rate mortgages, we match the maturity of the Treasury security with the time until the initial rate reset (instead of maturity date). Note that there are some mortgage loans in the sample with maturities that cannot be directly matched with Treasury yields because Treasury securities with the same time to maturity do not exist. For example, our sample includes some mortgages with 15-year maturity and some mortgages with 15-year initial reset terms, but a Treasury security with a 15-year maturity does not exist. To address this data issue, we interpolate the yield curve to derive a 15-year yield using the popular monotone convex method, as described in Hagan and West (2006) and available via the TensorFlow library written in Python.[15] We then subtract the appropriate risk-free rate from the original mortgage interest rate to obtain the risk premium, the so-called interest rate spread. We explore whether the interest rate spread that a bank charges to its nonprime

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[14] Interest rates for the various maturities of Treasury securities are collected from Federal Reserve Bank of St. Louis FRED database. Link: https://fred.stlouisfed.org/graph/?g=1JpW5

[15] For a given reporting date, our inputs for the monotone convex method are the market yields on the Treasury securities with maturities of one month, three months, six months, one year, two years, three years, five years, seven years, 10 years, 20 years, and 30 years. For more details on the TensorFlow library written in Python, see https://github.com/google/tf-quant-finance/tree/master

borrower became more accurately priced, according to the borrower's true default risk, after the fintech partnership.

Table 2 presents a summary of the variables, data sources, and how they are defined.

IV. The Empirical Analysis

The first step in our analysis is to determine whether loan origination behavior changes for banks that partner with fintech firms. The changes in loan decision behavior are observed in two ways: (1) the likelihood of a loan being offered to nonprime borrowers pre- versus post-partnership, using a logistic regression analysis; (2) the size of the credit line or loan amount originated to nonprime consumers pre- versus post-partnership, using ordinary least squares (OLS) regression analysis.

Probability that a credit card would be issued to a nonprime consumer: The dependent variable for this analysis is a binary variable that takes a value of 1 if it is issued to a nonprime consumer and zero otherwise. The sample includes all credit cards issued pre- and post-partnership regardless of their credit ratings. For explanatory variables, we include borrowers' income and whether they have a prior banking relationship, following Berger et al. (2024). Instead of including the borrower's income directly in the regression specification, we create six income brackets, with an income less than $50,000 serving as the base case; this design recognizes that lenders separate prospective borrowers into credit boxes when underwriting rather than make credit decisions based on small differences in two borrowers' underwriting metrics.

Specifically, the set of independent variables for the analysis of credit cards are binary variables indicating whether the loan was originated in the post-partnership period (*3-9 Months Post-Partnership*), a binary variable indicating whether the borrower has no credit score (*Missing Credit Score*), the cross-product term (*3-9 Months Post-Partnership* X *Missing Credit Score*), and the various control factors. The first control factor is an indicator of the borrower's income bracket — *Borrower Income (50K–100K), Borrower Income (100K–250K), Borrower Income (250K–500K), Borrower Income (500K–5M), and Borrower Income (5M+)*. We also control for whether the borrower has had a prior relationship with the bank (*Prior Banking Relationship*), the local economic condition where the loan is located (*Initial Unemployment Claims (State)*), the *Bank Fixed-Effect*, and the *Origination Year Fixed-Effect*. Bank names are not disclosed to protect confidentiality.

Credit limit and default rate on cards issued to nonprime consumers: The dependent variable for the credit limit analysis is the natural log of the credit limit (in US dollar) on each credit card originated to nonprime consumers during the relevant window before and after the fintech partnership. The dependent variable for default rate is a binary indicator for whether the credit card loan became delinquent within 24 months after the card was issued. The sample observation for both the loan amount and the default rate analysis includes only credit cards that were issued to nonprime borrowers. The explanatory variables are identical to those described above (in the logistic analysis for loan origination). The regression results for the credit cards analysis are presented in **Table 3A** for the entire sample and in **Table 3B** when one of the sampled (unusual) banks is removed from the analysis.

Probability that a mortgage loan would be granted to a nonprime borrower: The dependent variable for this analysis is a binary variable that takes a value of 1 if the mortgage borrower is a nonprime consumer and zero otherwise. The sample includes all mortgage loans issued pre- and post-partnership regardless of their credit ratings. For explanatory variables, we include the various underwriting metrics such as front-end debt to income ratio (DTI) and combined loan to value ratio (CLTV). We also include indicators for refinancings and whether the mortgages are FHA and VA originations since they are treated differently by lenders than conventional mortgages. We also interact whether the origination is an FHA or VA mortgage with the post-partnership indicator variable to discern how the partnerships altered firms' approach to mortgages that are neither conventional nor necessarily tied to a borrower with missing credit information.

Specifically, the key independent variables for the mortgage analysis are the same as those in the credit card analysis — binary indicators for *3-9 Months Post-Partnership*, *Missing Credit Score,* and *3-9 Months Post-Partnership* X *Missing Credit Score*. The control factors specific to mortgages are whether it is a GSE loan (FHA or VA Mortgage), the cross product between being a GSE loan and being originated in the post-partnership period (*3-9 Months Post-Partnership* X FHA or VA Mortgage), the debt to income ratio (*Front-End Debt-to-Income Ratio*), whether the loan is larger than the borrower's income (*Front-End Debt-to-Income Ratio (100+)*), a measure of the loan size relative to the home value (*Combined Loan-to-Value Ratio*), whether the loan amount exceeds the value of the home (*Combined Loan-to-Value Ratio (100+)*), and whether the loan is for a home purchase or refinancing (*Refinance Flag*). The other control factors are the local economic conditions where the home is located (proxied by *HPI (Regional))*, the *Bank Fixed-Effect*, and the *Origination Year Fixed-Effect*. Again, bank names are not disclosed to protect confidentiality.

Loan Amount and Loan Quality for mortgages issued to nonprime consumers: We include only nonprime mortgage loans in this portion of the analysis. In exploring the size of loans that banks are willing to offer to nonprime borrowers after the partnership, we define the dependent variable as the natural log of the mortgage loan amount originated to nonprime borrowers. In addition, we investigate the impact of fintech partnerships on the quality of mortgage loans that banks offer to nonprime consumers after the partnership. To explore the impact on loan quality, we define the dependent variable as a binary indicator that takes a value of 1 if the loan became delinquent within 24 months after the mortgage origination month and zero otherwise. The sample observation for both the loan amount and the default rate analysis includes only mortgages that were originated to nonprime borrowers during the relevant windows before and after the partnership. The explanatory variables are identical to those used earlier in the logistic analysis of loan origination. The results for mortgages are presented in **Table 4,** where nonprime borrowers are defined to include those with no credit scores as well as those with credit scores less than 660.[16]

Interest rate spreads analysis: Finally, we examine the interest rate charged on mortgages that banks originated, focusing on loans to nonprime borrowers during the period before versus after the partnership, controlling for the relevant risk factors. We use an OLS regression analysis to determine whether the risk pricing on the loans becomes more accurate and more in line with the true risk (actual default rate) of the borrowers. In other words, we explore whether the interest rate spreads charged during the post-partnership period have a closer relationship to the borrower's actual default behavior. The analysis is conducted in a two-step process as follows.

In the **first stage**, we calculate the spread residual for each of the mortgage loans in our sample. The spread residual is the portion of interest rate spread that cannot be explained by traditional credit risk factors. Specifically, the spread residual is the error term estimated from a regression with interest rate spread as the dependent variable and all the traditional credit risk factors and control factors as independent variables. The dependent variable, interest rate spread, is the difference between the mortgage rate charged by the lending bank and the risk-free interest rate (the rate on a Treasury security with the same time to maturity as the loan). The error term is estimated for each mortgage loan that banks originated to nonprime consumers during the relevant period before and after the partnership. Pre-partnership origination period is defined as six months before the partnership to three months before the partnership (t-6 to t-3). Post-partnership origination period is defined as three months after partnership to nine months after the partnership (t+3 to t+9).

The sample includes only nonprime mortgage loans — with credit scores less than 660 as of mortgage origination date. Those loans associated with people with missing credit scores are

[16] We have also conducted the same analysis where we define nonprime mortgages being below 680 scores (a higher credit score minimum for mortgages than for credit cards), and the results are consistent with those reported in Table 4.

excluded.[17] The (First Stage) regression results are reported in the second column of **Table 5A.** We also report the same analysis but based on more sample observations, using a credit score of 680 as the threshold to define nonprime for mortgages, in **Table 5B**. The results are very similar in both tables, with almost double the number of observations when using the 680 threshold in Table 5B.

Figures 2A and 2B plot interest rate residuals during the pre- versus post-partnership and differentiates between nonprime borrowers that defaulted and those who did not default, where nonprime is defined based on FICO<680 in Figure 2A and based on FICO<660 in Figure 2B. The plots show the decline in average risk premium rate (post-partnership) and shed some light on the reasons for this. We observe a contrast difference in rates that nonprime borrowers were required to pay — based on their true creditworthiness. Despite being nonprime, those who did not default are associated with a negative average interest rate residual during the post-partnership period. These creditworthy nonprime borrowers were over-penalized before the partnership when banks did not have access to the fintech tools.

In the **second stage**, we incorporate the spread residuals estimated in Stage 1 into the analysis of loan default in Stage 2 — to explore whether the spread residuals (the portion of spreads that is not explained by the credit risk factors used by banks in pricing credit risk) became smaller after the partnership. A smaller spread residual during the post-partnership period would imply that the risk premium that banks charge to nonprime mortgage borrowers after the partnership are more accurately reflecting the true default risk of the loan, controlling for relevant risk factors. The dependent variable is a binary indicator that takes a value of 1 for loans that became at least 120 DPD within 24 months after origination and zero otherwise. The (Second Stage) regression results are presented in the third and fourth columns of Table 5A (with a sample consisting of nonprime borrowers with credit score below 660) and Table 5B (with a larger sample consisting of nonprime borrowers with credit score below 680).

V. The Empirical Results

V.1 Impact of Fintech Partnership: Credit Cards

Results reported in Table 3A are derived from the sampled banks that we identified earlier to have entered into a relevant fintech partnership. We explore the impact of fintech partnership on credit card access (column 1), the credit limits on cards that were issued to nonprime consumers (column

[17] We removed consumers with missing scores in this part of the analysis to include credit scores in the regression specifications. The inclusion of the borrowers' credit scores in the first stage of our spread analysis is critical since credit score is a major determinant of the interest rates that banks charge.

2), and the default rate for nonprime consumers (column 3). Loan observations that do not have 24 months observation window after the origination date are excluded from the analysis. The base year for credit card analysis is 2011.

From Table 3A column 1, the dependent variable for the logistic regression results is a binary variable that takes a value of 1 if the card was issued to a nonprime consumer (credit scores below 660 or no credit scores) and zero otherwise. Unlike in Chernoff and Jagtiani (2024), we find that banks were not more likely to issue credit cards to nonprime consumers in the post-partnership period.

However, our results show that there is a significant impact of fintech tools on the credit limit that banks are willing to offer nonprime consumers, as shown in column 2 of Table 3A, where we examine the quantity of credit. The dependent variable for the OLS regression results is the natural log of the credit limit on each credit card originated during the relevant window before (i.e., from six months before partnership date (t-6) to three months before partnership date (t-3)) and after (i.e., from 3 months after partnership date (t+3) to nine months after partnership date (t+9) the fintech partnership date t. Only credit cards that were originated to nonprime consumers are included in the analysis in Columns 2.

We find that among the overall nonprime consumers whose creditworthiness has been confirmed through the fintech tools, banks are more willing to grant larger credit limits on cards issued to those "invisible prime" consumers. In other words, having a fintech partnership gave the banks enough extra information to grant a larger line of credit to nonprime borrowers overall. In addition, the interaction between missing credit score and fintech partnerships is also significantly positive, indicating that the increase in credit limit is even larger for those missing-score consumers.

We then examine how default rates on these credit cards are impacted. In column 3 of Table 3A, the dependent variable is a binary variable that takes a value of 1 if the credit card defaulted within 24 months after origination. Only cards originated to nonprime consumers are included in the analysis in column 3. The likelihood of becoming 60+ DPD in a 24-month window after origination increased overall post-partnership. We find that the default rate, on average, increased for the portfolio of nonprime credit cards after the fintech partnership. When focusing on the subgroup of nonprime with no credit scores only, we find that the coefficient of the interaction between this group and the post-partnership dummy is significantly negative, suggesting that their default rate actually declined after the partnership (relative to default rate of missing-score consumers before the partnership). We also find strong evidence across all nonprime consumers, regardless of whether scores are missing, that they get larger credit lines on cards originated after the partnership. Overall, the partnership seems to have allowed banks to have a much better understanding of the missing-score consumers' creditworthiness relative to other nonprime consumers. In other words, the fintech tools seem to have helped banks better identify creditworthy borrowers among those who do not have credit scores (based on data reported in Y-14M).

Among the control factors, we find that borrowers with a prior banking relationship were more likely to get credit and receive a larger credit line, in line with the literature. In addition, we find that the coefficients on the bank dummy variables (not reported) are significant, indicating that the individual bank's lending strategy has a role to play on how fintech tools are used and their impact. The coefficients of the year of origination are also significant, as were state unemployment claims, supporting the well-documented notion that macroeconomic conditions are an important determinant in credit decisioning.

It is interesting to note that the increase in the overall nonprime default rate was not consistent across all the sampled banks. The breakdown is not reported here because of the confidential nature of the data. However, we note that the overall impact on default rate appears to be driven by one of the banks in the sample, as a result of its unique strategy for nonprime risk pricing. For robustness testing, we rerun the same analysis after removing unusual observations (all associated with this specific bank), and the results are reported in **Table 3B**.

From Table 3B (subsample), the results are consistent with those reported in Table 3A (full sample) in terms of credit card issuance (in column 1) and amount of credit line (in column 2). However, the results on cards delinquency flips (in column 3). The coefficient suggests that the overall nonprime default rate in the post-partnership period was significantly reduced. And now there is no significant difference between missing-score consumers and low-score consumers, as reflected in the insignificant coefficient of the interactive term between missing score and post-partnership.

V.2 Impact of Fintech Partnership: Mortgages

We conduct similar analysis on mortgage loans, and the results are reported in Table 4, when nonprime consumers are defined as having credit scores below 660 or a missing credit score.[18] We have considered using a credit score of 680 as an alternative threshold because higher credit standards are usually required for mortgage eligibility, and confirmed that the results (not reported here) are the same for both credit score thresholds. Loan observations that do not have a 24-month

[18] Note that the reported credit scores are not all FICO scores — some are VantageScores (highest 990).

long observation window after origination are excluded from the analysis. Year of origination dummies are included as control factors, with 2016 as the base year. Bank dummies are also included as control factors (bank names are not disclosed and coefficients are not reported).

In Table 4 column 1, the dependent variable is a binary variable that takes a value of 1 if the mortgage was issued to a nonprime consumer and zero otherwise. In other words, we examine the probability that a mortgage loan that was originated three to nine months after a fintech partnership was a nonprime loan. Consistent with the credit card results, we find that the probability of an originated mortgage loan being nonprime is smaller overall after the fintech partnership. Post-partnership banks, on average, reduced the percentage of their mortgage portfolio held by nonprime borrowers. However, applicants with missing credit scores and those applicants for VA and FHA mortgages benefited from the fintech tools that banks had access to during the post-partnership period.[19] Specifically, we find that a bank's portfolio seems to have an increased proportion of nonprime with missing scores and those who apply for FHA or VA loans after the partnership. So, while mortgage loans to nonprime borrowers declined overall, for those nonprime borrowers who were eligible for a VA or FHA loan, their likelihood of getting a mortgage increased. It seems possible that fintech tools have also helped banks identify nonprime borrowers who are eligible for VA and FHA loans. Both FHA and VA lenders consider income stability, something the fintech tools can help document.

In column 2 of Table 4, the dependent variable is the natural log of the original principal balance on each mortgage originated during the relevant window before and after the fintech partnership. Only mortgages originated to nonprime consumers are included in the analysis. Given that the loan is a nonprime mortgage, we find that fintech partnership has no significant impact on total loan amount. That is, the fintech partnerships had no significant impact on the banks' willingness to offer larger mortgages to nonprime borrowers. While post-partnership banks tend to be more likely to issue mortgage loans to FHA/VA borrowers (as shown in column 1), the loan amount for these borrowers is reduced when fintech tools are used.

In column 3 of Table 4, the dependent variable is a binary variable that takes a value of 1 if the mortgage defaulted (became at least 120 DPD) within 24 months after origination. Only mortgages originated to nonprime consumers are included in the analysis. In looking at defaults post fintech partnership, we find that the overall nonprime mortgage default rate declined, and that

[19] FHA mortgages have less strict credit score requirements, require smaller down payments, and often have lower interest rates. VA loans do not require a down payment, have more lenient credit score requirements, and do not require private mortgage insurance.

there is no significant difference for consumers with low credit cores or missing scores. Past due rate on mortgages associated with missing credit scores borrowers is lower than that of nonprime borrowers overall. Our results from the mortgage analysis demonstrate that fintech tools could be useful to banks in identifying creditworthy borrowers, resulting in a reduction in default rate for banks' mortgage portfolio.

V.3 Impact on Mortgage Rate to Nonprime and Risk Pricing

From column 1 of Tables 5A and 5B, where we estimate spread residuals for each of the mortgage loan observations, we find that higher score borrowers (among those nonprime borrowers with credit score below 680) received a slightly better rate — with a smaller risk premium for higher-score borrowers among those with scores below 680 in Table 5B, controlling for relevant risk characteristics, bank fixed effects, and origination years. When including only a subset of nonprime with credit score below 660 in Table 5A, the sample observation is reduced from about 90,000 loans to about 50,000, and we find that among those with scores below 660, a higher score does not help to reduce the risk premium charged by banks. As expected, we find lower interest rate spreads (smaller risk premium) for FHA or VA mortgage borrowers. We then use the spread residuals calculated from the first step in our analysis in the second step and report the results in columns 2 and 3 of Tables 5A and 5B.

From the last two columns of Tables 5A and 5B, where the dependent variable is default probability, we find the coefficients of spreads are all positive and significant at the 1 percent level, indicating that banks charge a higher interest rate spread (risk premium) for loans that defaulted (with higher default probability). The coefficient on the interactive term between interest rate spread and post-partnership period is significantly negative in column 2, indicating that overall interest rate spreads that banks charge to nonprime borrowers is smaller on average for nonprime loans that were originated post-partnership. The results suggest that fintech partnerships may have allowed banks to have a more complete understanding of the borrowers' financial life and their ability to pay back the loans — resulting in banks choosing low-risk borrowers from the nonprime pool and charging a smaller risk premium to these borrowers. This is consistent with the results found in Table 4, which indicate a lower default rate for nonprime mortgage loans that were originated after the partnership.

The coefficients of the spread residuals are significant in determining defaults, controlling for borrowers' credit scores and other relevant risk factors. This means there are some factors that are important in determining default (and should be used in determining interest rates), and these factors are not correlated with the traditional factors that banks use in mortgage risk pricing.

The negative coefficient on the spread residual variable (in the last column of Tables 5A and 5B) indicates smaller spread residuals for loans that became delinquent within 24 months after origination. This is probably driven by the fact that banks generally charge a high risk-premium across all nonprime borrowers. Thus, the pricing (high risk premium) would be more accurate for those loans that are truly risky (become 120+DPD) nonprime borrowers, thus smaller spread residuals for these loans. The pre-partnership pricing process penalizes those creditworthy nonprime borrowers who did not become 120+DPD. In other words, the invisible prime borrowers in the nonprime pool had to pay more than what lenders would need to compensate for the risk they take. We expect the degree of mispricing to be smaller after the partnership (resulting in smaller risk premium for loans to creditworthy nonprime borrowers). The negative coefficient on the spread residual in column 3 is consistent with our argument that the degree of mispricing pre-partnership (i.e., banks charging high risk premium for all nonprime) is smaller for those who actually became delinquent on their mortgages.

The coefficient of the interactive term between spread residuals and the post-partnership dummy is positive and weakly significant at the 10 percent level in Table 5B (including all loans to borrowers with credit score below 680) but insignificantly positive in Table 5A (including a much smaller sample with only loans to borrowers with credit scores below 660). The positive coefficients here in conjunction with the (larger) negative coefficient of spread residual imply that the degree of mispricing may become a smaller negative for those loans that defaulted, although this impact is not significant statistically. All other risk/control factors, including credit scores, are included in the analysis and the results are as expected.

Overall, we find that banks that have access to fintech tools (through fintech partnerships) tend to have a more accurate risk pricing process such that the interest rates charged on mortgage loans to nonprime borrowers are more tightly correlated with the actual default risk for each individual nonprime borrower. We also find that the overall default rates become smaller among nonprime borrowers as the fintech tools also allow banks a better selection and screening process, resulting in increased share of creditworthy borrowers within the nonprime segment.

VI. **Conclusions**

Research has shown that lending by fintech firms has the potential to reach nonprime (low-score and thin-file) consumers, especially those nonprimes who are creditworthy. We investigate whether the same could be true for banks that have access to fintech tools. One way for banks to expand their customer base is by lowering credit standards. This would, however, be harmful to the banks themselves (increased credit losses) and to the borrowers (increased likelihood of default and bankruptcy, causing long-term damage). We explore whether banks could utilize better data and technology through fintech partnerships to expand their customer base (into nonprime consumer segment) while simultaneously improving their balance sheet through reduced default rates, thus enhancing the strength of the banking industry and promoting economic growth.

Previous research has not investigated the impact of fintech partnerships on the quality of a bank's loan portfolio after partnering with a fintech. While a few papers on bank IT spending and loan quality have been examined (i.e., that banks with high IT spending tend to originate mortgages with better performance), IT spending generally includes a variety of technology research and development, which may not be related to the credit decisioning process. In addition, the key factors in enhancing the lending decision process rely on better-quality data and more data from outside the bank's own book. Thus, a partnership between the bank and fintech (data aggregators and AI vendors) would provide a more direct measure of access to the relevant fintech tools. We take the analysis one step further by using information on relevant fintech partnerships that banks have undertaken.

Our results show that the relevant fintech partnerships changed banks' behavior to more closely resemble that of fintech lenders. For credit cards, banks that had fintech partnerships extended larger lines of credit to consumers with low credit scores or missing credit scores. We also find that a fintech partnership reduces the credit card default rate among those thin-file (no credit score) consumers. The impact on credit card defaults among low-score consumers varies depending on the bank's strategy and pricing approach. Overall, we find a significant impact of fintech partnerships on banks' lending to thin-file consumers as those consumers are more likely to be granted larger lines of credit and are less likely to become delinquent (60+DPD) within 24 months after the credit card issuance date.

For mortgages, banks with fintech partnerships saw a significant decline in the delinquency rate (120+DPD within 24 months after the mortgage origination date) of nonprime or thin-file borrowers. Unlike credit cards, the banks in our sample did not grant larger mortgage loans to nonprime borrowers, however, the fintech tools seem to have improved the banks' effectiveness in their credit decisioning, resulting in a decline in mortgage default rates. Further analysis of the interest rate spread residual shows that banks were better able to differentiate good versus bad nonprime borrowers after the partnership. We observe significant difference in mortgage rates that banks charge to defaulted versus non-defaulted (nonprime) borrowers after the partnership, while all nonprime borrowers were charged equally large interest rate risk premiums regardless of their true creditworthiness before the partnership. Fintech tools allow banks to attract creditworthy nonprime borrowers by giving them a discounted rate relative to the traditional risk pricing models. Risky nonprime borrowers continue to be charged a large risk premium on their mortgages after the partnership.

Overall, fintech partnerships have made it possible for banks to offer a larger loan and charge a lower interest rate to some nonprime borrowers while seeing defaults decline on average. Banks can leverage fintech tools, including alternative data, to better identify nonprime customers who can repay their indebtedness. This is good news for banks, consumers, and the economy. However, the impacts vary depending on the bank's own strategy. Our findings imply that while partnerships between banks and fintech and AI vendors could potentially increase access to credit without significant, negative effects on default rates, it is important that the banks understand fully how their credit decisions are made and how their financial safety and soundness might be affected when utilizing fintech tools provided by outside vendors.

References

Abel, Joshua, and Andreas Fuster. 2021. "How Do Mortgage Refinances Affect Debt, Default, and Spending? Evidence from HARP." *American Economic Journal: Macroeconomics* 13 (2): 254–91.

Agarwal, Sumit, Souphala Chomsisengphet, Chunlin Liu, Changcheng Song, and Nicholas S. Souleles. 2018. "Benefits of Relationship Banking: Evidence from Consumer Credit Markets." *Journal of Monetary Economics* 96:16–32.

Agarwal, Sumit, Wenli Li, Raluca Roman, and Nonna Sorokina. 2023. "The Opioid Epidemic and Consumer Credit Supply: Evidence from Credit Cards." Working Paper 23–28. Federal Reserve Bank of Philadelphia.

Agarwal, Sumit, and Chunlin Liu. 2003. "Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors." *Journal of Economics and Finance* 27 (1): 75–84.

Allen, Franklin, Xian Gu and Julapa Jagtiani. 2021. "A Survey of Fintech Research and Policy Discussion," *Review of Corporate Finance* 1 (3–4): 259–339.

Babii, Andrii, Xi Chen, and Eric Ghysels. 2019. "Commercial and Residential Mortgage Defaults: Spatial Dependence with Frailty." *Journal of Econometrics* 212 (1): 47–77.

Basten, Christoph, and Steven Ongena. 2024. "Mortgage Lending Through a Fintech Web Platform. The Roles of Competition, Diversification, and Automation." *Journal of Banking & Finance* 163 (C).

Beck, Thorsten, Asli Demirgüç-Kunt, and Ross Levine. 2007. "Finance, Inequality, and the Poor." *Journal of Economic Growth* 12 (1): 27–49.

Berg, Tobias, Andreas Fuster, and Manju Puri. 2022. "FinTech Lending." *Annual Review of Financial Economics* 14 (1): 187–207.

Berger, Allen N., Christa H. S. Bouwman, Lars Norden, Raluca A. Roman, Gregory F. Udell, and Teng Wang. 2024. "Piercing through Opacity: Relationships and Credit Card Lending to Consumers and Small Businesses During Normal Times and the COVID-19 Crisis." *Journal of Political Economy* 132 (2): 484–551.

Brevoort, Kenneth, Philip Grimm, and Michelle Kambara. 2015. "Credit Invisibles." 15–1. Consumer Financial Protection Bureau Office of Research Reports Series. Consumer Financial Protection Bureau.

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): 453–83.

Calem, Paul S., Julapa Jagtiani, and William Lang. 2017. "Foreclosure Delay and Consumer Credit Performance." *Journal of Financial Services Research* 52 (3): 225–51.

Calli, Busra Alma, and Erman Coskun. 2021. "A Longitudinal Systematic Review of Credit Risk Assessment and Credit Default Predictors." *SAGE Open* 11 (4).

Chernoff, Alan, and Julapa Jagtiani. 2024. "The Role of Bank–FinTech Partnerships in Creating a More Inclusive Banking System." *Journal of Digital Banking* 8 (4): 330–54.

Chu, Yongqiang, Chunxing Sun, Bohui Zhang, and Daxuan Zhao. 2023. "Fintech and Gender Discrimination." *SSRN Electronic Journal*, January.

Cornelli, Giulio, Jon Frost, Leonardo Gambacorta, and Julapa Jagtiani. 2024. "The Impact of Fintech Lending on Credit Access for U.S. Small Businesses." *Journal of Financial Stability* 73 (2024) 101290.

Croux, Christophe, Julapa Jagtiani, Tarunsai Korivi, and Milos Vulanovic. 2020. "Important Factors Determining Fintech Loan Default: Evidence from a LendingClub Consumer Platform." *Journal of Economic Behavior & Organization* 173: 270–96.

Davis, Morris, William Larson, Stephen D. Oliner, and Benjamin R. Smith. 2023. "A Quarter Century of Mortgage Risk." *Review of Finance* 27 (2): 581–618.

Di Maggio, Marco, Amir Kermani, and Sanket Korgaonkar. 2019. "Partial Deregulation and Competition: Effects on Risky Mortgage Origination." *Management Science* 65 (10): 4676–711.

Di Maggio, Marco, Dimuthu Ratnadiwakara, and Don Carmichael. 2022. "Invisible Primes: Fintech Lending with Alternative Data." NBER Working Paper 29840. National Bureau of Economic Research, Inc.

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

Dolson, Erik and Julapa Jagtiani. 2024. "Which Lenders Are More Likely to Reach Out to Underserved Consumers: Banks Versus Fintechs Versus Other Nonbanks?" *Journal of Alternative Finance* 1 (1): 35–66.

Erel, Isil, and Jack Liebersohn. 2022. "Can FinTech Reduce Disparities in Access to Finance? Evidence from the Paycheck Protection Program." *Journal of Financial Economics* 146 (1): 90–118.

Farzad, Taghi. 2019. "Determinants of Mortgage Loan Delinquency: Application of Interpretable Machine Learning." Job Market Paper. University of California, Riverside.

Foote, Christopher L., Lara Loewenstein, and Paul S. Willen. 2019. "Technological Innovation in Mortgage Underwriting and the Growth in Credit: 1985–2015," Federal Reserve Bank of Boston, working paper #19-11.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther. 2022. "Predictably Unequal? The Effects of Machine Learning on Credit Markets." *Journal of Finance* 77 (1): 5–47.

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

Hagan, Patrick and Graeme West. 2006. "Interpolation Methods for Curve Construction." *Applied Mathematical Finance* 13 (2): 89–129.

Hatchondo, Juan Carlos, Leonardo Martinez, and Juan M. Sánchez. 2015. "Mortgage Defaults." *Journal of Monetary Economics* 76 (C): 173–90.

He, Zhiguo, Sheila Jiang, Douglas Xu, and Xiao Yin. 2022. "Investing in Lending Technology: IT Spending in Banking." NBER Working Paper 30403. National Bureau of Economic Research, Inc.

Hibbeln, Martin, Lars Norden, Piet Usselmann, and Marc Gürtler. 2020. "Informational Synergies in Consumer Credit." *Journal of Financial Intermediation* 44.

Horvath, Akos, Benjamin Kay, and Carlo Wix. 2023. "The COVID-19 Shock and Consumer Credit: Evidence from Credit Card Data." *Journal of Banking & Finance* 152:106854.

Hughes, Joseph P., Julapa Jagtiani, and Choon-Geol Moon. 2022. "Consumer Lending Efficiency: Commercial Banks Versus a Fintech Lender." *Financial Innovation* 8 (1): 1–39.

Jagtiani, Julapa, and William Lang. 2011. "Strategic Default on First and Second Lien Mortgages During the Financial Crisis." *Journal of Fixed Income* 20 (4): 7–23.

Jagtiani, Julapa, and Catharine Lemieux. 2018. "Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks?" *Journal of Economics and Business* 100: 43–54.

Jagtiani, Julapa, and Catharine Lemieux. 2019. "The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform." *Financial Management* 48 (4): 1009–29.

Jagtiani, Julapa, Catharine Lemieux, and Brandon Goldstein. 2025. "Did Fintech Loans Default More During the COVID-19 Pandemic? Were Fintech Firms 'Cream Skimming' the Best Borrowers?" *Journal of Credit Risk* 21(1), 93–144. DOI: 10.21314/JCR.2024.010

Jagtiani, Julapa, Lauren Lambie-Hanson, and Timothy Lambie-Hanson. 2021. "Fintech Lending and Mortgage Credit Access," *Journal of FinTech* 1 (1): 1–50.

Jansen, Mark, Hieu Quang Nguyen, and Amin Shams. 2025. "Rise of the Machines: The Impact of Automated Underwriting." *Management Science* 71 (2): 955–75.

Kim, Hyeongjun, Hoon Cho, and Doojin Ryu. 2018. "An Empirical Study on Credit Card Loan Delinquency." *Economic Systems* 42 (3): 437–49.

Kutzbach, Mark J. and Jonathan Pogach. 2024. "Financial Technology and Relationship Lending: Complements or Substitutes?," *Journal of Financial Intermediation* 59(C).

Lambie-Hanson, Lauren, and Carolina Reid. 2018. “Stuck in Subprime? Examining the Barriers to Refinancing Mortgage Debt.” *Housing Policy Debate* 28 (5): 770–96.

Lazarov, Vladimir, and Marc Hinterschweiger. 2018. “Determinants of Distress in the UK Owner-Occupier and Buy-to-Let Mortgage Markets.” Bank of England Working Paper 760. Bank of England.

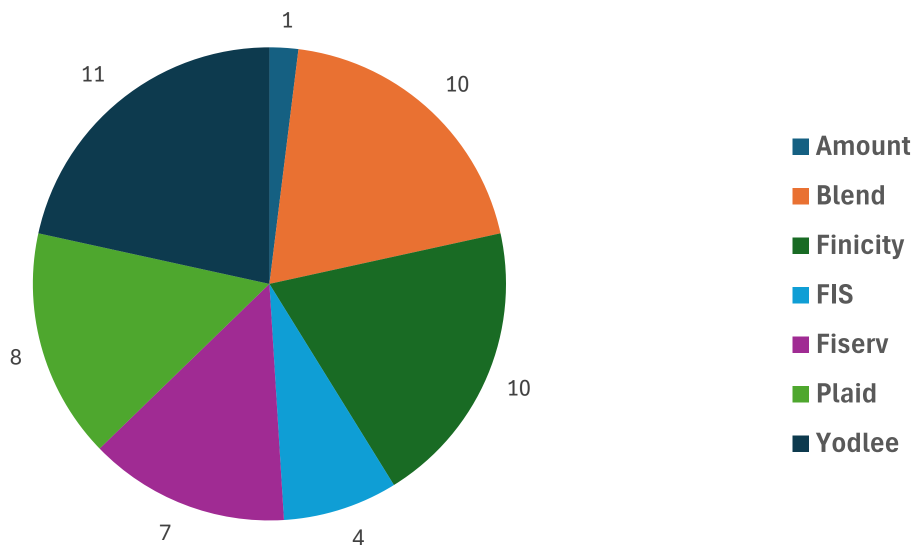
Nowak, Adam, Patrick Smith, and Mark Thibodeau. 2024. “Debt-to-Income as a Measure of Ability to Repay.” *SSRN Electronic Journal*, July.

Pierri, Nicola, and Yannick Timmer. 2022. “The Importance of Technology in Banking During a Crisis.” *Journal of Monetary Economics* 128 (C): 88–104.

Ru, Hong, and Antoinette Schoar. 2020. “Do Credit Card Companies Screen for Behavioural Biases?” BIS Working Paper 842. Bank for International Settlements.

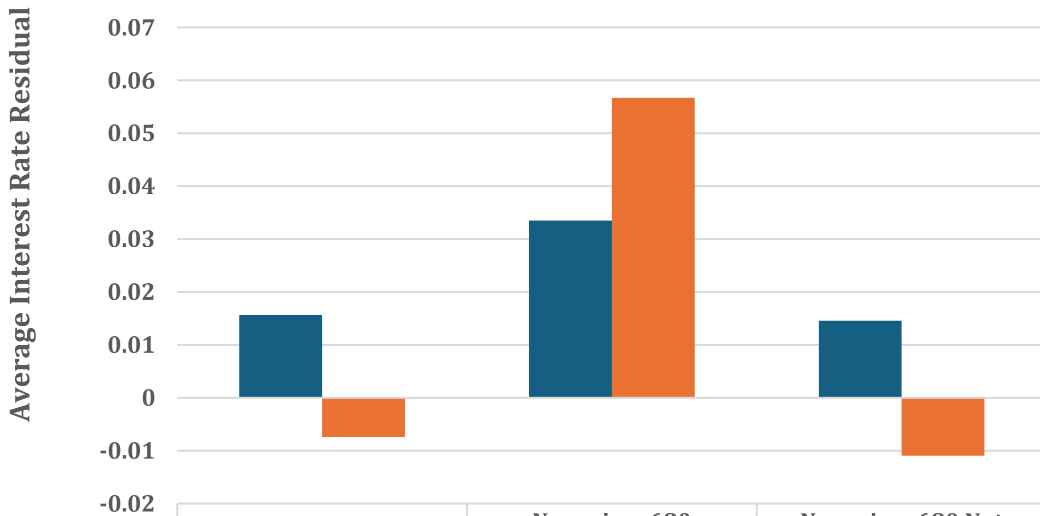
Shi, Lan, and David Downs. 2015. “The Impact of Reversing Regulatory Arbitrage on Loan Originations: Evidence from Bank Holding Companies.” *Journal of Real Estate Finance and Economics* 50 (3): 307–38.

Figure 1: Number of Relevant Bank–Fintech Partnerships Established by Each Fintech Partner



Data Source: Author calculation based on CB Insights.
Note: Only relevant bank–fintech partnerships that involve CCAR banks are included in this analysis.

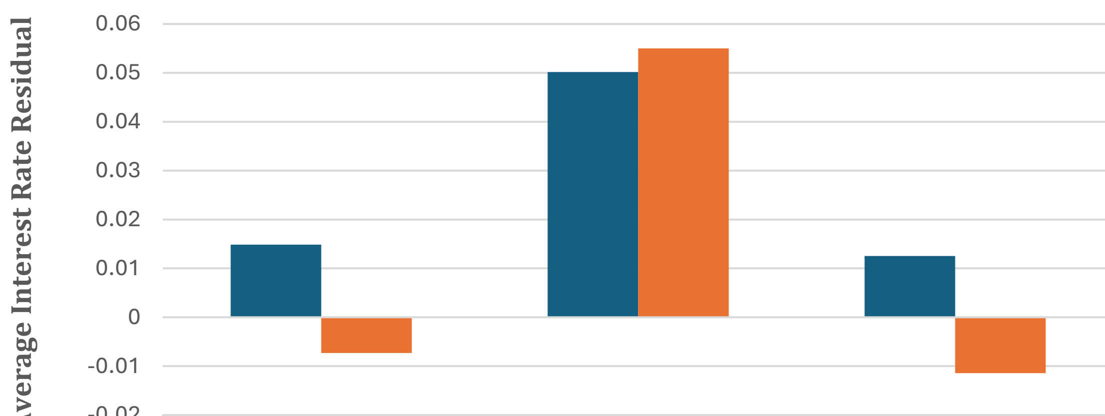
Figure 2A: Average Mortgage Interest Rate Residuals for Borrowers with Credit Score <680 During Pre- Versus Post-Partnership Periods



	All Nonprime 680	Nonprime 680 Delinquent	Nonprime 680 Not Delinquent
Pre-Partnership	0.015622	0.033487	0.014585
Post-Partnership	-0.007417	0.056701	-0.010937

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.
Note: Loan observations with missing scores are excluded from this analysis.

Figure 2B: Average Mortgage Interest Rate Residuals for Borrowers with Credit Score <660 During Pre- Versus Post-Partnership Periods



	All Nonprime 660	Nonprime 660 Delinquent	Nonprime 660 Not Delinquent
Pre-Partnership	0.01487	0.050156	0.012549
Post-Partnership	-0.007302	0.055025	-0.011438

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.
Note: Loan observations with missing scores are excluded from this analysis.

Table 1: Relevant Fintech Firms That Partner with Sampled Banks

Fintech Firm	Year Founded	Bloomberg Description	Firm Description of Alternative Data
Amount, Inc.	2014	Amount, Inc., provides software solutions. The company offers financial technology for banks and financial institutions to digitize their financial infrastructure, which simplifies and improves digital banking experiences. Link: [Amount Inc - Company Profile and News - Bloomberg Markets]	Amount offers a high–velocity digital credit card origination system to streamline and scale the application process and provide consumers with quicker credit decisions. The system allows for personalization of credit limits based on demonstrated responsible credit behavior, credit score improvement, strong payment history, or increased income.
Blend Labs, Inc.	2012	Blend Labs, Inc., designs and develops software. The company offers a platform that focuses on mortgage lending, as well as provides an application experience for the homebuying process for both buyers and lenders. Link: [Blend Labs Inc - Company Profile and News - Bloomberg Markets]	Blend Insights provides lenders and other financial institutions better insights into their customers through responsible and transparent third-party data collection practices from a network of reliable third party data providers. The Blend Income Report provides current and historical employment and income information sent to Blend Insights service by participating data providers. https://blend.com/insights/
Finicity, Inc.	2000	Finicity, Inc., designs and develops software solutions. The company offers data processing software solutions for the financial sector. Link: [Finicity Inc - Company Profile and News - Bloomberg Markets]	Finicity uses open banking data to augment the foundation of credit histories and credit scores by providing real-time insights into cash flow, stable income, and the actual room in someone's monthly budget to afford a loan or a new purchase. https://www.finicity.com/blog/credit-decisioning-ebook/
FIS Global	1968	FIS Global provides financial technology solutions. The company focuses on retail and institutional banking, payments, asset and wealth management, risk and compliance, trade enablement, and transaction processing and record-keeping. Link: [FIS Global - Company Profile and News - Bloomberg Markets]	FIS Global offers a real-time offering of alternative data (attributes and scores) to help financial institutions gain insight into credit-challenged, thin-file, no-credit-file, and nonprime consumer populations to score risk more intelligently and grow the portfolio. https://www.fisglobal.com/products/decision-solutions-for-risk

Fiserve, Inc.	1984	Fiserve, Inc. provides integrated information management and electronic commerce systems and services. The company's solutions include transaction processing, electronic bill payment and presentment, business process outsourcing, document distribution services, and software and systems solutions. Link: Fiserv Inc - Company Profile and News - Bloomberg Markets	Fiserv, Inc. offers the product, Alternative Credit Data, which creates a single customer view based on the customer's identity and bank account information. https://www.carat.fiserv.com/en-us/solutions/alternative-credit-data/
Plaid Technologies, Inc.	2013	Plaid Technologies, Inc., develops and creates APIs for banking data. The company offers APIs that allow developers to programmatically interact with banks and credit cards, giving them access to account and transactional data, including merchant names, street addresses, and geocoordinates. Plaid markets its products and services throughout the United States. Link: Plaid Inc - Company Profile and News - Bloomberg Markets	Plaid lists three types of alternative data that can be used to evaluate thin-file consumers: payment history, asset ownership, and income data. Plaid offers asset verification APIs that instantly provide an up-to-date view of a borrower's bank accounts and assets. Plaid income APIs provide robust data pulls for employment and income verification in seconds. https://plaid.com/resources/lending/credit-invisibles/#How-can-lenders-evaluate-credit-invisibles?
Yodlee, Inc.	1999	Yodlee, Inc., is a technology and applications platform for digital financial services in the cloud. The company's customers include financial institutions, Internet service companies providing innovative financial solutions, and third-party developers of financial applications. Link: Yodlee Inc - Company Profile and News - Bloomberg Markets	Yodlee's customers include financial institutions, internet service companies providing innovative financial solutions, and third-party developers of financial applications. Yodlee provides comprehensive alternative datasets from over 17,000 global data sources covering more than 33 million de-identified individuals. https://www.yodlee.com/data-analytics/alternative-data

Table 2: Data Definitions and Data Sources

Variables	Source	Definition
Origination Year	Y-14M Reports	Year credit card or mortgage was originated
3-9 Mos Post-Partnership	CB Insights	Dummy variable with the value of 1 if credit was originated between 3 and 9 months after a partnership
Initial Unemployment Claims (state)	US Department of Labor	Number of workers applying for unemployment benefits for the first time following job loss in the state where the borrower resides
Borrower Income	Y-14M Reports	Borrower's total annual income obtained at the account's origination
Other Banking Relationships	Y-14M Reports	Dummy variable takes the value of 1 if borrower has a prior relationship with the bank other than a credit card relationship
Other Credit Card Relationships	Y-14M Reports	Dummy variable takes the value of 1 if borrower has a prior credit card with the bank
HPI (Regional)	Federal Housing Finance Agency	The HPI is a weighted, repeat-sales index that measures average price changes in repeat sales or refinancings on the same properties in 363 metropolises. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. The United States is divided into 9 regions to produce regional HPIs.
Front-End Debt-to-Income Ratio	Y-14M Reports	Percentage of a borrower's monthly income that would go toward housing (PITI) expenses. The total liabilities of the borrower, such as the monthly principal, interest, taxes, insurances and association dues, should be divided by the total monthly income of the borrower. This line item should be measured at origination.
Loan-to-Value Ratio	Y-14M Reports	Original loan amount divided by the lesser of the selling price or the appraised value of the property securing the mortgage at origination
Mortgage Interest Rate Spread	Y-14M Reports and the FRED database	Contracted interest rate on mortgages (from Y-14M) minus interest rate on Treasury securities with matching time to maturity (from FRB St. Louis FRED database)
Refinance Flag	Y-14M Reports	Dummy variable with the value of 1 if the loan purpose was refinance

Table 3A: Credit Card Origination, Credit Limit, and Default Rate

Impact of Fintech Partnership on Credit Card Access, Credit Limit, and Default Rate for Nonprime Consumers (Credit Score<660 or Missing Credit Score)

Dependent variable in Column 1 is a binary variable that takes a value of 1 if the card was issued to a nonprime consumer (credit scores below 660 or no credit scores) and zero otherwise. Dependent variable in Column 2 is natural log of credit limit on each credit card originated during the relevant window before and after the fintech partnership. Dependent variable in Column 3 is a binary variable that takes a value of 1 if the credit card defaulted within 24 months after origination. Only cards originated to nonprime consumers are included in the analysis in Columns 2 and 3. Loan observations that do not have 24 months observation window after origination are excluded from the analysis. Year of origination included as control factors. Base year is 2011. Banks are included as control factors (names are not disclosed). The *** and * indicate 1% and 10% level of significance, respectively. The t-values are in parentheses.

Independent Variables	(1) Credit Origination: Prob of Card Holder Being Nonprime	(2) Credit Limit: Natural Log of Credit Limit to Nonprime	(3) Card Default: Prob of Card Being 60+DPD in 24 months
Intercept	-1.5187*** (-41.18)	6.9616*** (376.91)	-1.8492*** (-24.59)
3-9 Months Post-Partnership	-0.1210*** (-34.17)	0.0748*** (39.74)	0.1554*** (25.32)
Missing Credit Score	34.9226 (0.00)	-0.3590*** (-115.26)	-0.3437*** (-29.81)
3-9 Months Post-Partnership X Missing Credit Score	-0.3589 (-0.00)	0.1325*** (38.58)	-0.1078*** (-8.60)
Borrower Income (50K–100K)	-0.2647*** (-95.46)	0.2498*** (192.04)	-0.2763*** (-69.00)
Borrower Income (100K–250K)	-1.0068*** (-245.50)	0.5931*** (260.31)	-0.6397*** (-80.64)
Borrower Income (250K–500K)	-2.0135*** (-131.29)	0.8665*** (90.78)	-0.7422*** (-19.63)
Borrower Income (500K–5M)	-2.1918*** (-72.94)	0.7379*** (41.62)	-0.5513*** (-7.79)
Borrower Income (5M+)	-1.5812*** (-14.11)	0.4030*** (5.81)	-0.4978* (-1.77)
Prior Banking Relationship	0.1661*** (62.07)	0.1613*** (123.79)	-0.4531*** (-111.79)
Initial Unemployment Claims (State)	0.0000*** (4.79)	-0.0000 (-1.30)	-0.0000*** (-24.26)
Bank Fixed-Effect	Included	Included	Included
Origination Year Fixed-Effect	Included	Included	Included
Observations	3,965,577	1,657,071	1,657,093
Adjusted R-Squared	--	0.267	--
Log-Likelihood	-1.84E+06	-1.89E+06	-9.00E+05
Deviance	3.6780E+06	--	1.8006E+06
Pearson Chi-squared	3.63E+06	--	1.66E+06
AIC	--	3.779E+06	--
BIC	--	3.779E+06	--

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.

Table 3B: Credit Card Origination, Credit Limit, and Default Rate (Subsample)
Impact of Fintech Partnership on Credit Card Access, Credit Limit, and Default Rate for Nonprime Consumers (Credit Score<660 or Missing Credit Score)

Dependent variable in Column 1 is a binary variable that takes a value of 1 if the card was issued to a nonprime consumer (credit scores below 660 or no credit scores), and zero otherwise. Dependent variable in Column 2 is natural log of credit limit on each credit card originated during the relevant window before and after the fintech partnership. Dependent variable in Column 3 is a binary variable that takes a value of 1 if the credit card defaulted within 24 months after origination. Only cards originated to nonprime consumers are included in the analysis in Columns 2 and 3. Loan observations that do not have 24 months observation window after origination are excluded from the analysis in Column 3. Year of origination included as control factors. Base year is 2011. Banks are included as control factors (names are not disclosed). The ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. The t-values are in parentheses.

Independent Variables	(1) Credit Origination: Prob of Card Holder Being Nonprime	(2) Credit Limit: Natural Log of Credit Limit to Nonprime	(3) Card Default: Prob of Card Being 60+DPD in 24 months
Intercept	-1.5387*** (-41.22)	7.0333*** (349.99)	-1.8912*** (-24.62)
3-9 Months Post-Partnership	-0.1664*** (-26.49)	0.0912*** (21.28)	-0.0314** (-2.02)
Missing Credit Score	34.4238 (0.00)	-0.3537*** (-72.09)	-0.5640*** (-27.03)
3-9 Months Post-Partnership X Missing Credit Score	0.1125 (0.00)	0.1458*** (24.99)	-0.0044 (-0.18)
Borrower Income (50K–100K)	-0.3576*** (-67.49)	0.3083*** (100.89)	-0.1184*** (-10.17)
Borrower Income (100K–250K)	-0.9537*** (-128.22)	0.6979*** (147.23)	-0.4196*** (-20.94)
Borrower Income (250K–500K)	-1.4425*** (-62.69)	0.9234*** (62.45)	-0.4018*** (-6.27)
Borrower Income (500K–5M)	-1.3134*** (-33.55)	0.8099*** (33.80)	-0.1850* (-1.91)
Borrower Income (5M+)	-1.2203*** (-10.39)	0.3470*** (4.37)	-0.4966 (-1.53)
Prior Banking Relationship	0.2603*** (49.02)	-0.0784*** (-22.27)	-0.4370*** (-32.88)
Initial Unemployment Claims (State)	0.0000*** (10.27)	0.0000 (0.55)	-0.0000*** (-4.46)
Bank Fixed-Effect	Included	Included	Included
Origination Year Fixed-Effect	Included	Included	Included
Observations	1,906,596	382,463	382,485
Adjusted R-Squared	--	0.237	--
Log-Likelihood	-6.04E+05	-4.60E+05	-1.33E+05
Deviance	1.2077E+06	--	2.6618E+05
Pearson Chi-squared	1.72E+06	--	3.75E+05
AIC	--	9.204E+05	--
BIC	--	9.207E+05	--

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.

Table 4: Mortgage Origination, Principal Balance, and Default Rate
Impact of Fintech Partnership on Mortgage Access, Principal Balance, and Default Rate for Nonprime Consumers (Credit Score<660 or Missing Credit Scores)

Dependent variable in Column 1 is a binary variable that takes a value of 1 if the mortgage was issued to a nonprime consumer (credit scores below 660 or no credit scores), and zero otherwise. Dependent variable in Column 2 is natural log of principal balance on each mortgage originated during the relevant window before and after the fintech partnership. Dependent variable in Column 3 is a binary variable that takes a value of 1 if the mortgage defaulted within 24 months after origination. Only mortgages originated to nonprime consumers are included in the analysis in Columns 2 and 3. Loan observations that do not have 24 months observation window after origination are excluded from the analysis. Year of origination included as control factors. Base year is 2016. Banks are included as control factors (names are not disclosed). The ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. T-values are in parentheses.

Independent Variables	(1) Credit Origination: Prob of Mortgage Loan to Nonprime	(2) Credit Limit: Natural Log of $ Loan Amount to Nonprime	(3) Mortgage Default: Prob of 120+DPD within 24 Months
Intercept	-2.6201*** (-50.46)	10.2294*** (428.94)	-5.2551*** (-24.19)
3-9 Months Post-Partnership	-0.1663*** (-11.72)	0.0124 (1.64)	-0.2407*** (-4.10)
D_Missing Credit Score	31.1955 (0.00)	0.2631*** (21.40)	-0.7733*** (-5.76)
3-9 Months Post-Partnership X Missing Credit Score	0.6045 (0.00)	0.0183 (1.29)	0.1627 (1.11)
D_FHA or VA Mortgage	1.6738*** (82.29)	-0.0096 (-1.00)	-0.0000 (-0.00)
3-9 Months Post-Partnership X FHA or VA Mortgage	0.3213*** (13.61)	-0.0418*** (-3.76)	0.1301 (1.57)
Front-End DTI Ratio	-0.0050*** (-9.50)	0.0084*** (40.41)	0.0227*** (12.82)
D_Front-End DTI Ratio>100%	2.4582*** (15.19)	-1.0360*** (-13.71)	-7.3041 (-1.55)
Combined LTV Ratio	0.0154*** (42.47)	0.0068*** (41.55)	0.0210*** (12.96)
D_Combined LTV Ratio>100%	-0.0360 (-1.50)	-0.1478*** (-14.09)	0.0190 (0.26)
D_Refinance Flag	0.0628*** (4.86)	-0.0285*** (-4.36)	0.1105* (1.87)
HPI (Regional)	-0.0039*** (-29.54)	0.0028*** (47.19)	-0.0010** (-1.97)
Bank Fixed-Effect	Included	Included	Included
Origination Year Fixed-Effect	Included	Included	Included
Observations	1,199,228	64,660	64,659
Adjusted R-Squared	--	0.224	--
Log-Likelihood	-1.83E+05	-5.45E+04	-1.28E+04
Deviance	3.6664E+05	--	2.5586E+04
Pearson Chi-squared	1.15E+06	--	1.51E+05
AIC	--	1.091E+05	--
BIC	--	1.094E+05	--

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.

Table 5A Mortgage Spread Analysis
Stage 1: Estimating Spread Residuals for Each Mortgage Loan
Stage 2: Explore Increased Accuracy in Risk Pricing After Fintech Partnership

Dependent variable in Stage 1 is interest rate spread (mortgage interest rate minus risk-free rate (rate on Treasury security with the same time to maturity)). Dependent variable in Stage 2 is a binary indicator that takes a value of 1 for loans that become 120+DPD within 24 months after origination and zero otherwise. Sample includes only nonprime mortgages (**credit scores<660**) that were originated during the relevant pre-partnership and post-partnership periods. Pre-partnership period is defined as 6 months prior to partnership to 3 months after the partnership (t-6 to t-3). Post-partnership period is defined as 3 months after partnership to 9 months after the partnership (t+3 to t+9). Loans that do not have sufficient observations in the performance windows (do not have at least 24 months after origination) are removed from the analysis. The ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. T-values are in parentheses.

Variables	**Stage 1:** Dependent Variable = Interest Rate Spread	**Stage 2:** Dependent Var =Prob 120+DPD within 24 Months After Origination (Risk Score≤ 660)	
Intercept	0.9659*** (12.49)	0.1442 (0.25)	-0.0784 (-0.13)
Interest Rate Spread	--	0.3303*** (8.93)	0.9212*** (13.11)
3-9 Mo Post-Partnership X Interest Rate Spread	--	-0.0737*** (-3.13)	--
Spread Residual	--	--	-0.8338*** (-8.72)
3-9 Mo Post-Partnership X Spread Residual	--	--	0.0054 (0.07)
D_FHA or VA Mortgage	-0.2889*** (-47.46)	0.2894*** (6.82)	0.4530*** (9.94)
Front-End DTI Ratio	-0.0006** (-2.52)	0.0241*** (13.20)	0.0257*** (14.01)
D_Front-End DTI Ratio>100%	-0.1592** (-2.11)	-3.3016*** (-3.17)	-3.3164*** (-3.18)
Combined LTV Ratio	0.0025*** (13.91)	0.0183*** (10.59)	0.0180*** (10.32)
D_Combined LTV Ratio>100%	-0.1896*** (-17.89)	-0.1507* (-1.96)	0.0031 (0.04)
D_Refinance	-0.0363*** (-5.16)	-0.4572*** (-7.08)	-0.4035*** (-6.25)
Credit Score	0.0007*** (6.06)	-0.0086*** (-9.77)	-0.0100*** (-11.24)
HPI (Regional)	-0.0005*** (-6.98)	--	--
Bank Fixed-Effect	YES	--	--
Origination Year Fixed-Effect	YES	--	--
Observations	50,725	50,725	50,725
Adjusted R-Squared	0.281	--	--
Log-Likelihood	-3.90E+04	-1.14E+04	-1.13E+04
Deviance	--	2.2714E+04	2.2605E+04
Pearson Chi-squared	--	5.08E+04	5.12E+04
AIC	7.808E+04	--	--
BIC	7.836E+04	--	--

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.

Table 5B Mortgage Spread Analysis
Stage 1: Estimating Spread Residuals for Each Mortgage Loan
Stage 2: Explore Increased Accuracy in Risk Pricing After Fintech Partnership

Dependent variable in Stage 1 is interest rate spread (mortgage interest rate minus risk-free rate (rate on Treasury security with the same time to maturity)). Dependent variable in Stage 2 is a binary indicator that takes a value of 1 for loans that become 120+DPD within 24 months after origination and zero otherwise. Sample includes only nonprime mortgages (**credit scores<680**) that were originated during the relevant pre-partnership and post-partnership periods. Pre-partnership period is defined as 6 months prior to partnership to 3 months after the partnership (t-6 to t-3). Post-partnership period is defined as 3 months after partnership to 9 months after the partnership (t+3 to t+9). Loans that do not have sufficient observations in the performance windows (do not have at least 24 months after origination) are removed from the analysis. The ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. T-values are in parentheses.

Variables	**Stage 1:** Dependent Variable = Interest Rate Spread	**Stage 2:** Dependent Var =Prob 120+DPD within 24 Months After Origination (Risk Score≤ 680)	
Intercept	1.3874*** (26.41)	0.8185** (1.97)	-0.0160 (-0.04)
Interest Rate Spread	--	0.3521*** (11.87)	1.0904*** (19.16)
3-9 Mo Post-Partnership X Interest Rate Spread	--	-0.0800*** (-4.30)	--
Spread Residual	--	--	-1.0965*** (-13.93)
3-9 Mo Post-Partnership X Spread Residual	--	--	0.1127* (1.78)
D_FHA or VA Mortgage	-0.2933*** (-64.10)	0.2223*** (6.45)	0.4276*** (11.57)
Front-End DTI Ratio	-0.0003* (-1.85)	0.0246*** (16.73)	0.0263*** (17.79)
D_Front-End DTI Ratio>100%	-0.2025*** (-3.39)	-3.8360*** (-3.73)	-3.8231*** (-3.71)
Combined LTV Ratio	0.0035*** (27.06)	0.0188*** (13.73)	0.0172*** (12.39)
D_Combined LTV Ratio>100%	-0.2012*** (-24.81)	-0.1529** (-2.40)	0.0526 (0.81)
D_Refinance	0.0116** (2.33)	-0.4156*** (-8.38)	-0.3921*** (-7.91)
Credit Score	-0.0002** (-2.27)	-0.0098*** (-16.03)	-0.0104*** (-17.03)
HPI (Regional)	-0.0003*** (-7.39)	--	--
Bank Fixed-Effect	YES	--	--
Origination Year Fixed-Effect	YES	--	--
Observations	92,935	92,935	92,935
Adjusted R-Squared	0.273	--	--
Log-Likelihood	-7.05E+04	-1.85E+04	-1.84E+04
Deviance	--	3.6980E+04	3.6723E+04
Pearson Chi-squared	--	9.26E+04	9.31E+04
AIC	1.410E+05	--	--
BIC	1.413E+05	--	--

Data Source: Author calculations primarily based on CB Insights and Y-14 M database, see Table 2.