The Roles of Bank/Fintech Partnership in Creating a More Inclusive Banking System

Central Bank Research Association (CEBRA) Annual Meeting

Columbia University (July 5-7, 2023)

Alan Chernoff and Julapa Jagtiani

Federal Reserve Bank of Philadelphia

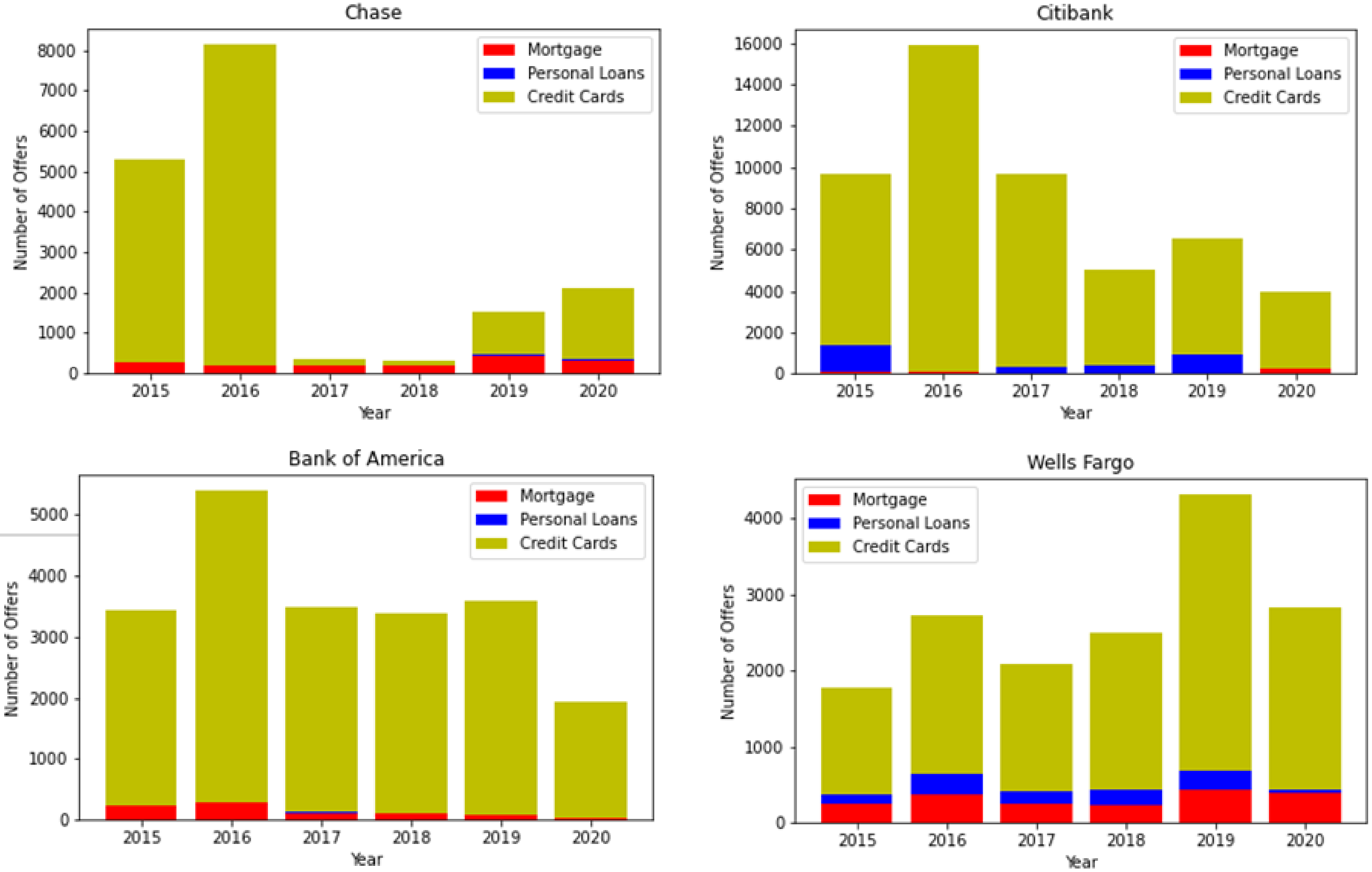
Introduction

- FDIC (2021) -- estimated that 4.5% of American households (5.9 million HHs) are unbanked – nobody in the HH has account with a bank or credit union.
- CFPB (2016) –26 million Americans are "credit invisible" with no credit file with any of the 3 major credit bureaus. In addition, another 19 million American consumers are "credit unscorable" with a credit file but too thin history or stale out-of-date.
- Alternative data could play important roles in expanding credit access:
  - Jagtiani and Lemieux (2019)
  - Cornelli, Frost, Gambacorta, and Jagtiani (2022)
  - Dolson and Jagtiani (2021)
- Alternative data and complex modeling (AI/ML) could potentially be accessible to traditional banks (large and small) through their partnership with fintech platforms.

Fintech and Bank Partnerships

- Previous research into the behavior of fintech lenders find that they are more likely to target segments of the population that lack credit history or low scores.
  - De Roure, Pelizzon, and Tasca (2016) -- P2P lenders in the German market are more likely to serve “risky” segments of the market
  - De Roure, Pelizzon, and Thakor (2022) – “riskier” borrowers tend to leave traditional banks for a fintech lender
- My own research – evidence supporting argument that fintech lenders are more willing to lend to the “credit invisible” consumers if alternative data confirm that they are not risky – personal loans (2018, 2019, 2020, 2021), small business loans (2022), mortgage loans (2021).
- This paper examines if banks may start to emulate the behavior of fintech lenders after they enter a partnership with fintech data aggregators and/or AI vendors

Total 40,000 Credit Offers (mostly credit card offers)

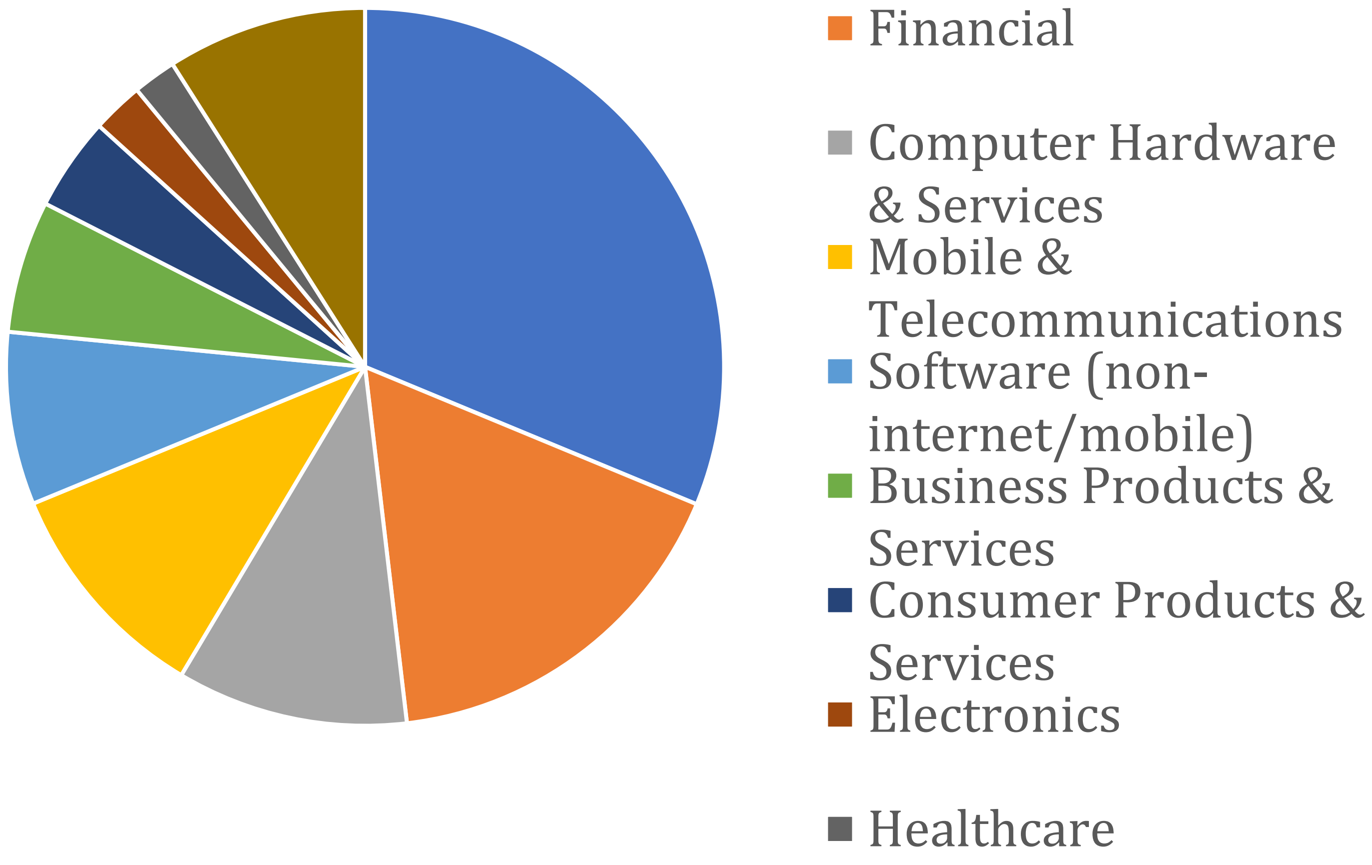


Source: Mintel (survey of credit offers)

Sorting Through Partnership Data

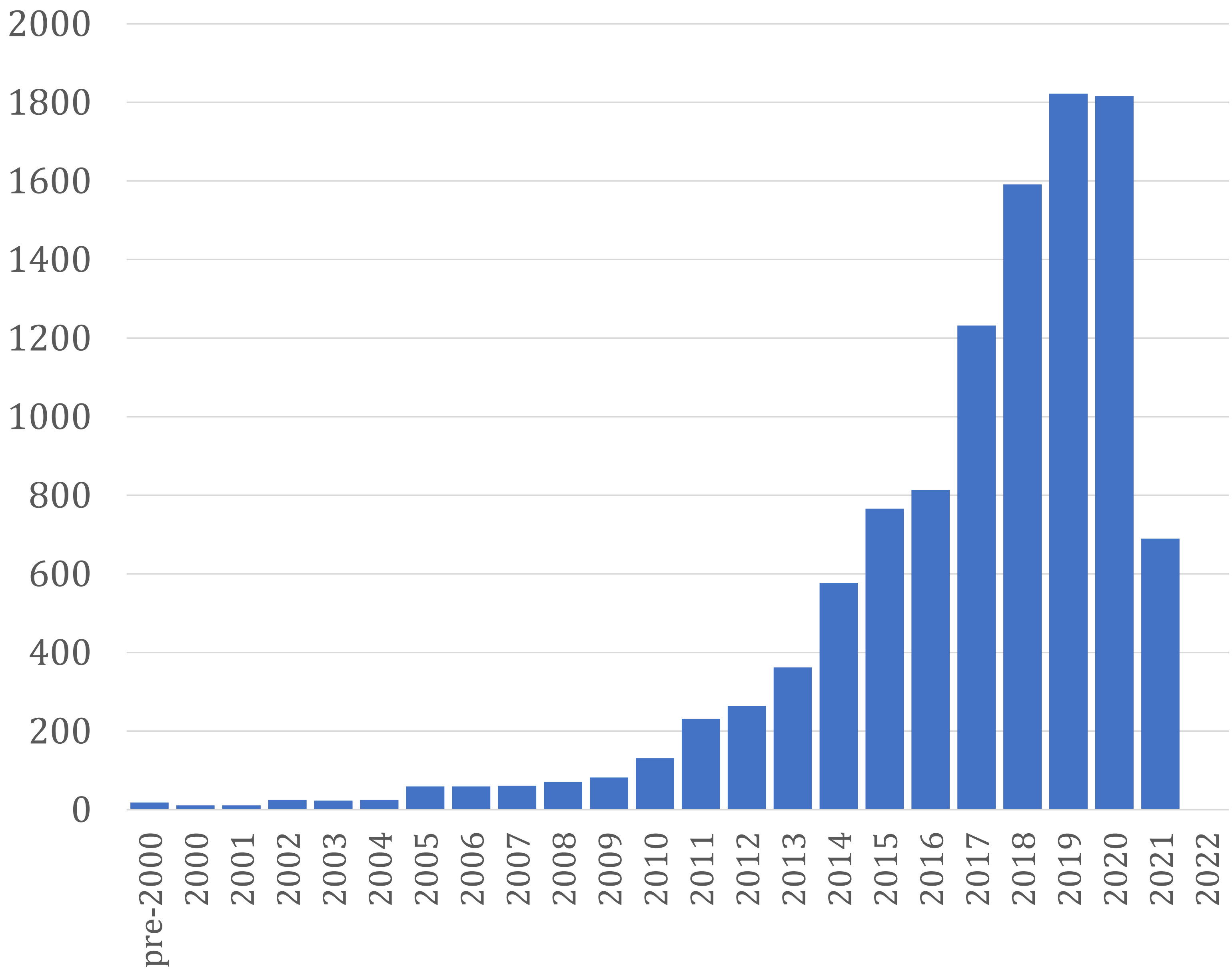
- Over 10,000 partnerships between relevant institutions (banks, BHCs, fintech firms, technology firms) were collected.
- Partnerships that did not involve banks or BHCs were removed, and duplicate partnerships were eliminated.

Share of Fintech Partnership Types (2000-2022)



Source: CB Insights

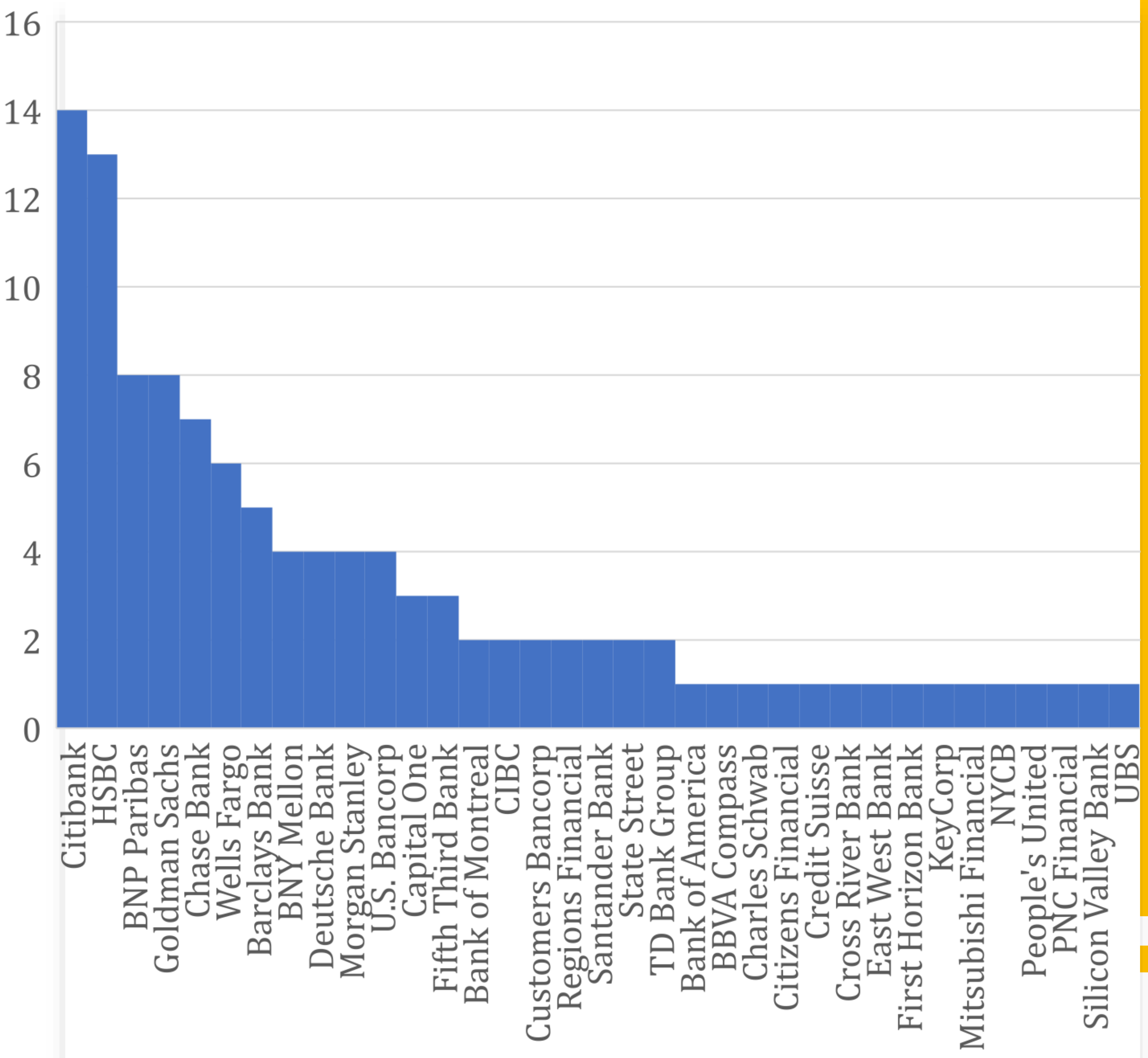
Growth in Fintech Partnerships (with Financial Institutions)



Source: CB Insights

Number of Fintech Partnerships by Bank (2004-2021)

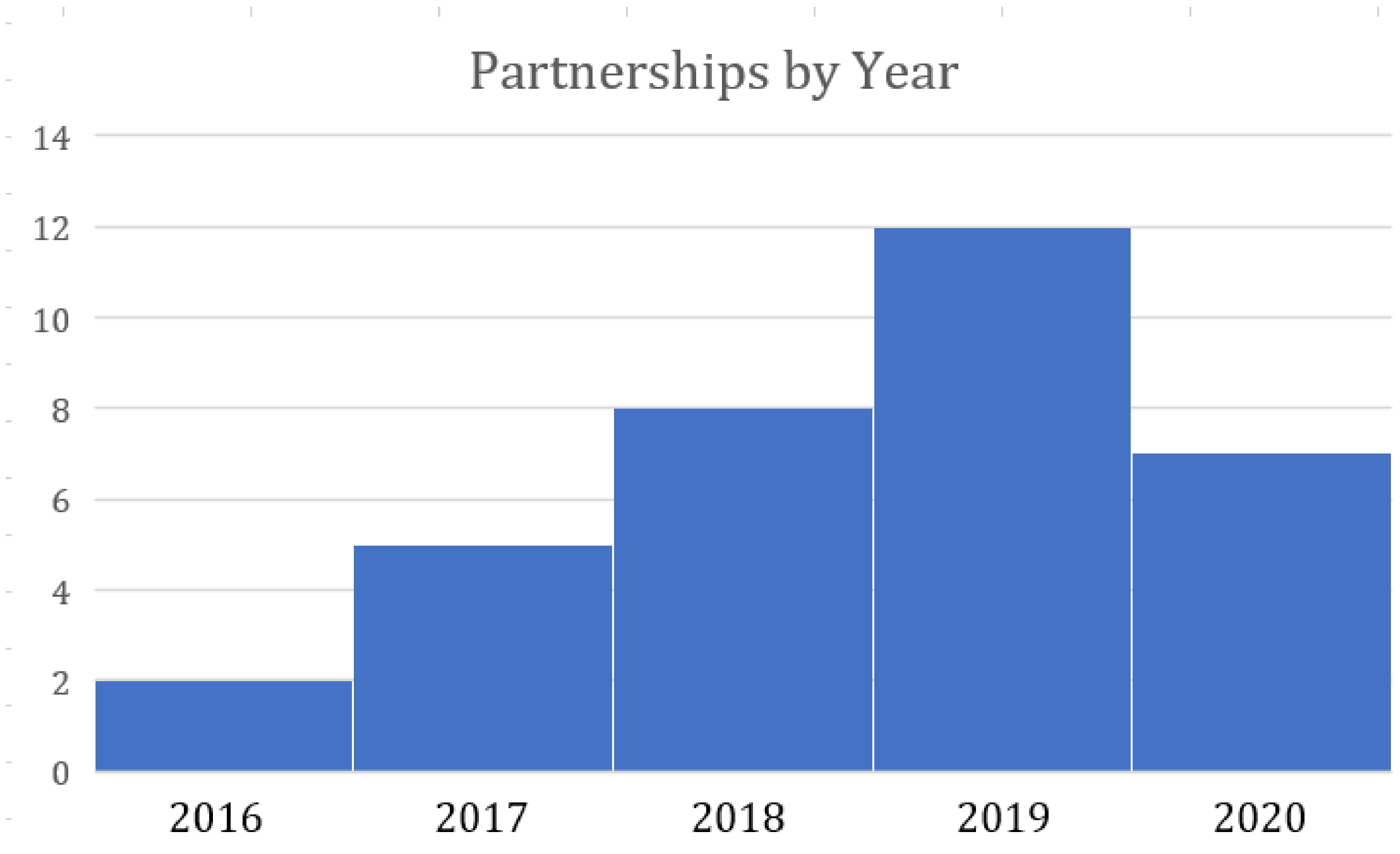
- Focusing on only partnership with banks (and removing double counted partnerships), we have 112 partnerships.
- These partnerships were further analyzed at the individual level, in order to assess whether they resulted in more lending to the underserved post-partnership



Source: CB Insights

Number of Sampled Fintech-Bank Partnerships by Year

Source: Our own analysis based on CB Insights



- Only the relevant partnerships (that involve alternative data and AI/ML fintechvendors) are included in the analysis.
- **Appendix I** presents the selection criteria.
- **Appendix II** lists all the partnership parties and dates.

Our Empirical approach

- **Hypothesis** – The partnerships allow banks to access more information on consumers through the use of data aggregation, AI/ML, and other tools brought by the fintech firms with whom they are partnering.
- We explore whether after partnership, banks would be more likely to offer credit (and eventually originate loans) to consumers who would otherwise be deemed “high risk” -- due to **low credit scores or lack of credit scores**.
- We analyze the credit offers and loan origination behaviors **before** and **after** the partnership – where partnership dates are compiled based on CB Insights.

The Data

Credit Offers by Banks -- from Mintel/TU

- Products: mortgages, personal loans, and credit card offers
- Characteristics of the offers (loan amount, credit limit, APR) and the consumers (VantageScore 3.0, zip code, etc.)

Credit Origination by Banks -- from Y-14M

- Products: mortgages and credit card originations
- Loan characteristics (loan amount, credit limit, APR) and consumer characteristics (FICO score, zip code, etc.)

Bank-Fintech Partnership event date -- CB Insights

- We focus on 10 banks whose data are available from both Mintel/TU and Y-14M reports.
- Partnership during 2016-2020 period.

Likelihood of Credit Extension to "Underserved" Consumers After Fintech Partnership

- Logistic Regressions – whether an **offer** (from Mintel/TU) to the credit invisibles or low scores are more likely to occur after the partnership?
  - Dependent variable: binary variable equal to 1 if a credit offer by a bank was made to a Nonprime consumer (either low score or no score); 0 otherwise.
  - Define "Low Scores" – 1) VantageScore 3.0 <660; 2) VantageScore 3.0 <680
- Logistic Regressions – whether a **loan** (from Y-14M) to the credit invisibles or low scores are more likely to occur after the partnership?
  - Dependent variable: binary variable equal to 1 if a loan originated by a bank was made to a Nonprime consumer (either low score or no score); 0if it was made to a Prime consumer.
  - Define "Low Scores" – 1) FICO <660; 2) FICO <680

Amount of Credit Extended to "Underserved" Consumers After Fintech Partnership

- OLS Regression – whether a loan (from Y-14M) banks made to the "credit invisibles" or low score consumers are likely to **Larger loan** (for mortgages) or **Larger credit limit** (for credit cards) after the partnership?
  - Personal loan origination is not available at loan level on Y-14M report
  - Dependent variable is the log of loan amount (for mortgages) or log of credit limit amount (for credit cards).
  - Define "Low Scores" – 1) FICO <660; 2) FICO <680
- **Post Partnership t.1** – this is a binary variable which is set equal to 1 if the loan was offered or originated in the quarter following the partnership quarter; it is 0 otherwise.
- **Year-fixed effect** and **Bank-fixed effect** are also included in all the analysis as control variables

Personal Loan Offers

Logistic Regression

(Nonprime with VantageScore3.0 <660 or no scores)

Source: Mintel/TU and CB Insights

Dependent Var = 1 if the credit offer was made to nonprime consumers

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	-12.3009	187.314	0.94764
t.1	0.1607	0.0625	0.01013**
year2017	-0.3267	1.234	0.79123
year2018	-0.2854	1.2276	0.81618
year2019	-0.5772	1.2272	0.63812
year2020	-0.3197	1.2301	0.79492
year2021	-0.5662	1.6844	0.73678
BankBarclays	11.9345	187.31	0.94920
BankChase	11.9554	187.3103	0.94911
BankCitibank	11.6077	187.3099	0.95059
BankCrossRiver	13.6271	187.3099	0.94200
BankOmaha	11.112	187.3102	0.95269
BankSantander	12.4715	187.3143	0.94692
BankTD	13.0051	187.31	0.94465
BankWellsFargo	12.1945	187.31	0.94809
Observations:	N=5,878		

Credit Cards Offers

Logistic Regression

(Nonprime with VantageScore3.0 <660 or no scores)

Source: Mintel/TU and CB Insights

Dependent Var = 1 if the credit offer was made to nonprime consumers

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	-0.95162	0.07968	0.00000***
t.1	0.1423	0.02466	0.00000***
year2017	0.12578	0.04538	0.00558***
year2018	0.14003	0.04948	0.00466***
year2019	0.30659	0.04544	0.00000***
year2020	0.1481	0.04933	0.00268***
Year2021	-0.42409	0.08048	0.00000***
BankBarclays	0.64503	1.00263	0.52001
BankChase	0.21978	0.08484	0.00958***
BankCitibank	0.61258	0.07036	0.00000***
BankOmaha	0.29063	0.14665	0.04750**
BankSantander	-0.14074	0.33395	0.67343
BankTD	-0.39354	0.11758	0.00082***
BankUnion	0.37643	0.36412	0.30122
BankWellsFargo	0.31364	0.0729	0.00002***
Observations:	N=33,172		

Personal Loans & Credit Cards Offers

Logistic Regression

(Nonprime with VantageScore3.0 <660 or no score)

Source: Mintel/TU and CB Insights

Dependent Var = 1 if the credit offer was made to nonprime consumers

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	-0.94522	0.07915	0.00000***
t.1	0.12778	0.02249	0.00000***
year2017	0.10876	0.045	0.01565**
year2018	0.11154	0.04752	0.01892**
Year2019	0.15748	0.04443	0.00039***
year2020	0.14165	0.04822	0.00331***
year2021	-0.411	0.07973	0.00000***
BankBarclays	-0.12355	0.19817	0.53299
BankChase	0.29927	0.08397	0.00037***
BankCitibank	0.60583	0.06976	0.00000***
BankCrossRiver	1.66069	0.07864	0.00000***
BankOmaha	0.16513	0.13483	0.22067
BankSantander	0.41862	0.23965	0.08067*
BankTD	0.29572	0.09552	0.00196***
BankUnion	0.39898	0.3638	0.27278
BankWellsFargo	0.37043	0.07215	0.00000***
Observations:	N=39,050		

Mortgage Offers

Logistic Regression

(Nonprime with VantageScore3.0 <660 or no scores)

Source: Mintel/TU and CB Insights

Dependent Var = 1 if the mortgage credit offer was made to nonprime consumers

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	0.227483	0.801893	0.77665
t.1	0.085954	0.115031	0.45493
year2017	-0.00653	0.568126	0.99083
year2018	-0.29694	0.573886	0.60486
Year2019	-0.38891	0.565466	0.49160
year2020	-0.2418	0.557537	0.66451
Year2021	0.073895	0.632435	0.90699
BankChase	-1.18744	0.598264	0.04717**
BankCitibank	-1.01594	0.5934	0.08689*
BankOmaha	-1.10109	0.999059	0.27040
BankSantander	-1.00659	1.470193	0.49356
BankUnion	0.041888	1.530179	0.97816
BankWellsFargo	-0.78157	0.589672	0.18502

Observations: N=1,943

Effect of Partnerships on Credit Offerings

- The probability of a loan being offered by a bank to a nonprime borrower (with a low VantageScore 3.0 or no credit score on file) consistently increased in the quarter following a partnership with fintechs

- The degree of significance varies across the financial products offered

- Personal loans and credit card offers saw the highest probability of increase, with the least change coming from mortgage offerings (correct sign but not significant)

Credit Cards Originations

Logistic Regression

(Nonprime with FICO<660 or no scores)

Source: Y-14M Reports and CB Insights

Dependent Var = 1 if the credit card was issued to nonprime consumers

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	-0.77464	0.019871	0.00000***
t.1	-0.00699	0.006222	0.26102
year2017	-0.05476	0.010892	0.00000***
year2018	-0.09768	0.011159	0.00000***
year2019	-0.1111	0.010883	0.00000***
year2020	-0.20912	0.012248	0.00000***
year2021	-0.29527	0.02067	0.00000***
Bank Fixed-Effect	-- Yes—		
Observations:	N=994,012		

Mortgage Originations

Logistic Regression

(Nonprime with FICO<660 or no scores)

Source: Y-14M Reports and CB Insights

Dependent Var = 1 if the mortgage loan was originated for nonprime consumers

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	-3.21659	0.112036	0.00000***
t.1	0.075907	0.022251	0.00065***
year2017	0.099711	0.083202	0.23076
year2018	-0.11616	0.08503	0.17190
year2019	-0.53137	0.084708	0.00000***
year2020	-0.63314	0.08972	0.00000***
year2021	-0.83752	0.149207	0.00000***
Bank Fixed-Effect	-- Yes--		
Observations:	N=205,038		

Effect of Partnerships on Loan Originations

- The impact of fintech partnerships on loan originations differed somewhat from that the analysis on credit offerings
- Banks did show significant differences in mortgage originations to nonprime consumers post partnership
- Banks did not show significant differences in credit card originations post partnership – probably because credit card approval relies much on credit scores. However, later results show significant impact on credit limits.

Credit Cards Total $ Limits

OLS Regression

(Nonprime with FICO <660 or no scores)

Source: Y-14M Reports and CB Insights

Dependent Var = Log of total $ credit limit for credit card that bank issued to nonprime consumers.

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	6.644377	0.014299	0.00000***
t.1	0.009281	0.004722	0.04936**
year2017	-0.10793	0.00834	0.00000***
year2018	-0.07134	0.008541	0.00000***
year2019	-0.09943	0.008296	0.00000***
year2020	-0.14537	0.009365	0.00000***
year2021	-0.18689	0.015763	0.00000***
Bank Fixed-Effect	-- Yes--		
Observations:	N=151,021		

Note: Only credit cards that were issued to nonprime consumers are included in this analysis. We observe $ credit limit from the same bank before vs. after a partnership.

Mortgages Loan $ Amount

OLS Regression

(Nonprime with FICO<660 or no scores)

Source: Y-14M Reports and CB Insights

Dependent Var = Log of total $ mortgage loan amount that bank made to nonprime consumers.

Variable	Estimate	Std. Error	Pr(>|z|)
Intercept	11.76949	0.072511	0.00000***
t.1	0.024021	0.014253	0.09196*
year2017	0.204883	0.052689	0.00010***
year2018	0.214724	0.05366	0.00006***
year2019	0.313047	0.053822	0.00000***
year2020	0.516954	0.058186	0.00000***
year2021	0.6884	0.095304	0.00000***
Bank-Fixed Effect	-- Yes--		
Observations:	N=10,344		

Note: Only mortgage loans that were made to nonprime consumers are included in this analysis. We observe $ loan amount granted to nonprime borrowers by the same bank before vs. after a partnership.

Effect of Partnerships on Total $ Credit Limits (and $ Loan Amount)

- Following their partnership with a fintech firm, banks were more willing to offer larger loans to “underserved” consumers.
- Total $ credit limit to nonprime borrowers increased significantly for credit cards.
- Nonprime consumers at large CCAR banks tend to get a larger mortgage loans $ amount following the fintech partnership period.

Conclusions

- Following the quarter that a bank enters in to a fintech partnership, the bank is more likely to offer personal loans and credit cards to nonprime consumers – and to grant them larger $ credit limits.
- Similarly, following the partnership, banks are more likely to originate mortgages to nonprime home buyers and to grant them a larger $ mortgage loan amount.
- While the loan origination results are based on the behavior of CCAR banks, we suspect that the impact could be even greater for smaller banks, especially those with limited access to today's technology due to resource constraints.
- A partnership between traditional banks and fintech firms has the potential to democratize access to more data and better technology – and has a potential to move us closer to a more inclusive financial system

Literature Cited

- Cornelli, G., J. Frost, L. Gambacorta and J. Jagtiani (2022). “The Impact of Fintech Lending on Credit Access for U.S. Small Businesses” Philadelphia Fed Working Paper 22-14.
- Croux, C., J. Jagtiani, T. Korivi, and M. Vulanovic (2020) “Important Factors Determining Fintech Loan Default: Evidence from LendingClub Consumer Platform,” *Journal of Economic Behavior & Organization*, Volume 173, May, 270-296.
- De Roure, C., L. Pelizzon, and P. Tasca (2016). “How Does P2P Lending Fit into the Consumer Credit Market?” Deutsche Bundesbank Discussion Paper 30.
- De Roure, C., L. Pelizzon, and A. Thakor (2022) “P2P Lenders versus Banks: Cream Skimming or Bottom Fishing?” *The Review of Corporate Finance Studies* 11, 213–262.
- Dolson, E., J. Jagtiani (2021). “Which Lenders Are More Likely to Reach Out to Underserved Consumers: Banks versus Fintechs versus Other Nonbanks?” Philadelphia Fed Working Paper 21-17.
- Jagtiani, J. and C. Lemieux (2018). “Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks?” *Journal of Economics and Business* 100, November– December 2018, 43–54.
- Jagtiani, J. and C. Lemieux (2019). “The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from LendingClub Consumer Platform.” *Financial Management*, Winter 2019, 48: 4, 1009–1029.
- Jagtiani, J., L. Lambie-Hanson, and T. Lambie-Hanson (2021) “Fintech Lending and Mortgage Credit Access.” *The Journal of Fintech*, June, 1-50.