

# **The Roles of Alternative Data and AI/ML in Fintech Lending**

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# Interesting Fintech Questions

- ❖ **What type of alternative (nontraditional) data are Fintech lenders using?**
- ❖ **What are the benefits and risks of Fintech lending technologies -- Big data, data aggregation, machine learning (ML), artificial intelligence (AI)?**
- ❖ **Impacts on:**
  - **Consumers**
  - **Bank safety and soundness**
  - **Financial stability overall?**



# There have been concerns related to their use of alternative data and AI/ML algorithms by Fintech lenders and data aggregators

## E-Commerce



## Financial Services



## Partners



# Fintech Benefits and Risks?

- ❖ **Richard Cordray (2017) -- Alternative data could paint a fuller and more accurate picture about people's financial lives -- and open up more affordable credit to 26 millions consumers**
  - ❖ **Jagtiani and Lemieux (2018) – find that adding alternative data into the mix allowed some subprime borrowers to receive lower priced credit.**
- ❖ **There are risks associated with data accuracy, stability, representativeness, consumer privacy.**
- ❖ **Fintech lenders use advanced technology and big data to assess creditworthiness, but the process may not be well understood.**



# Regulatory Concerns?

- ❖ **Black Box** -- The ML process is purely data-driven and may not be well understood by the lenders themselves -- Fair Lending issues.
- ❖ **Third-Party Vendor Risk** -- many firms may be using similar algorithms. This interdependency effect could potentially impact financial stability
- ❖ **Systemic Risks** -- will evolve and harder to measure
- ❖ **Trade-Off** – for regulators to balance Fintech regulations and incentives for Fintech innovations.





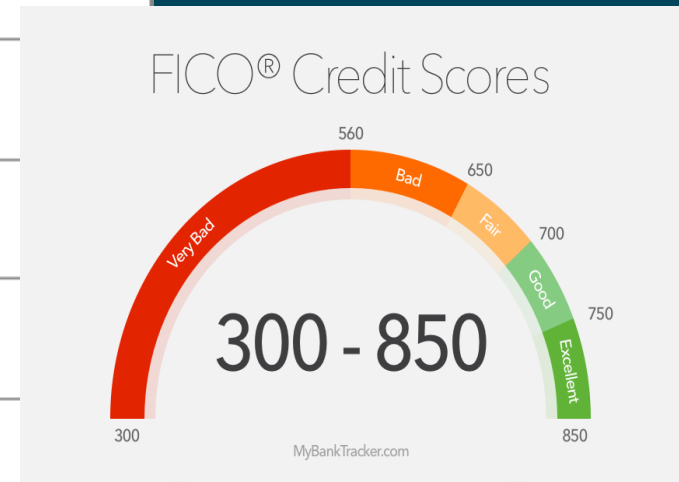
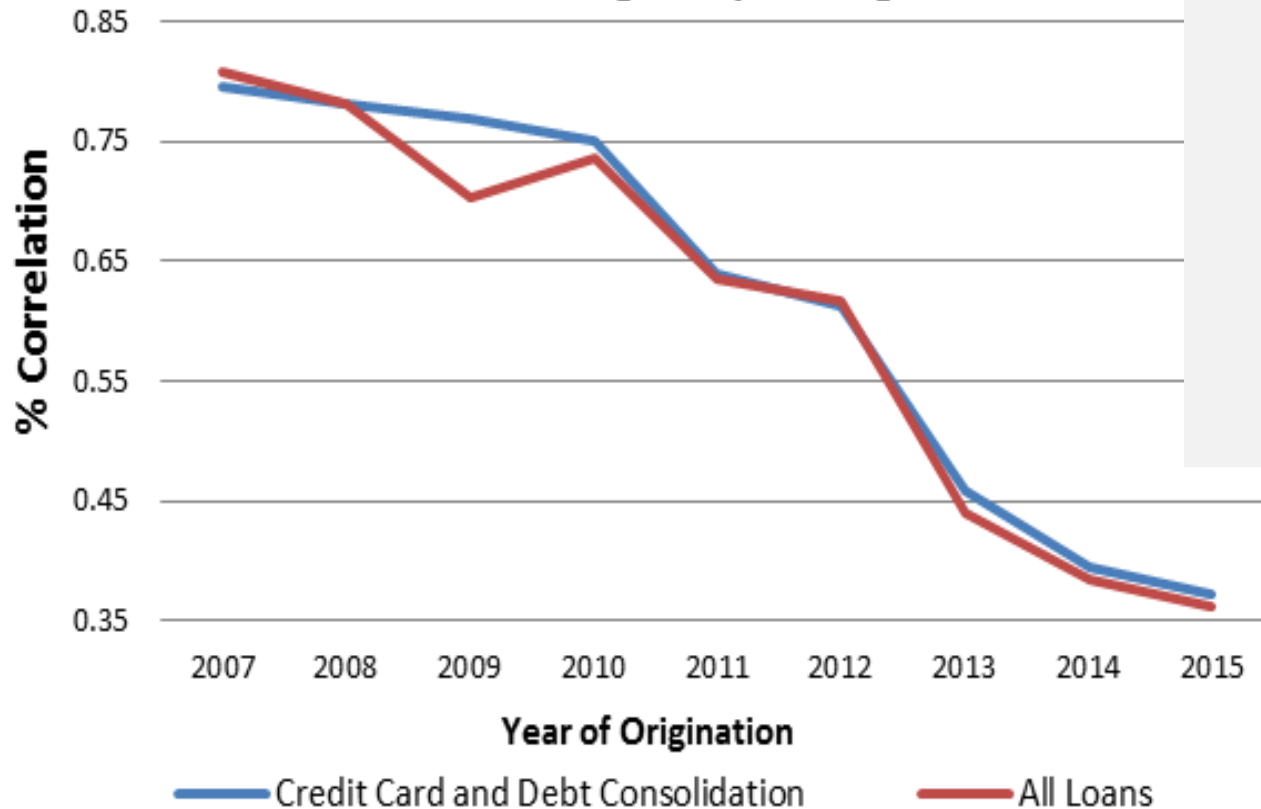
# Fintech vs. Traditional Lenders

- ❖ Fintech P2P lending platforms use advanced technology and better data to provide better and more options of financial services to consumers.
- ❖ Utilizing different business models -- PayPal, Square, Lending Club, Prosper, Kabbage, OnDeck, SoFi, LoanDepot, Better Mortgage, etc.
- ❖ We explore **consumer** lending space:
  - LendingClub data
  - Y-14M data.
- ❖ We also explore **mortgage** lending space:
  - HMDA data (mortgage origination)
  - Mintel data (mortgage credit offers).



# Lending Club Has Increasingly Relied on Alternative Data

Figure 7: Correlation Between Origination FICO and Rating Grade Assigned by Lending Club



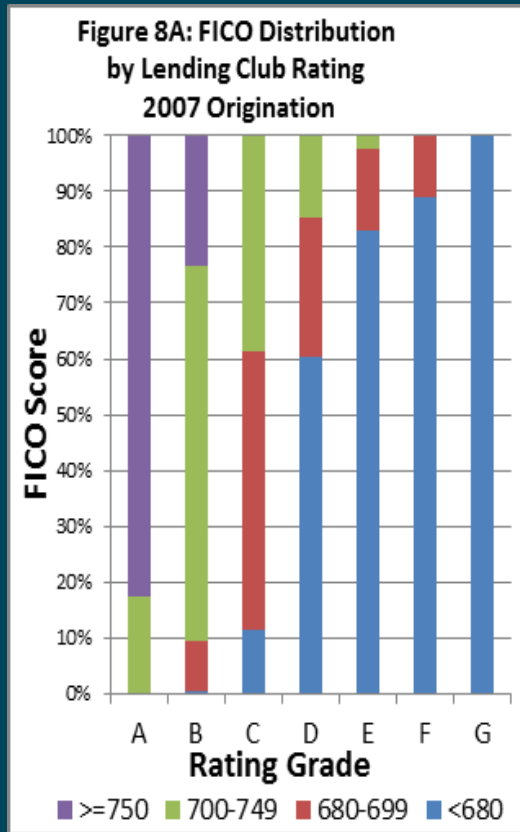
Source: Jagtiani and Lemieux (2018)



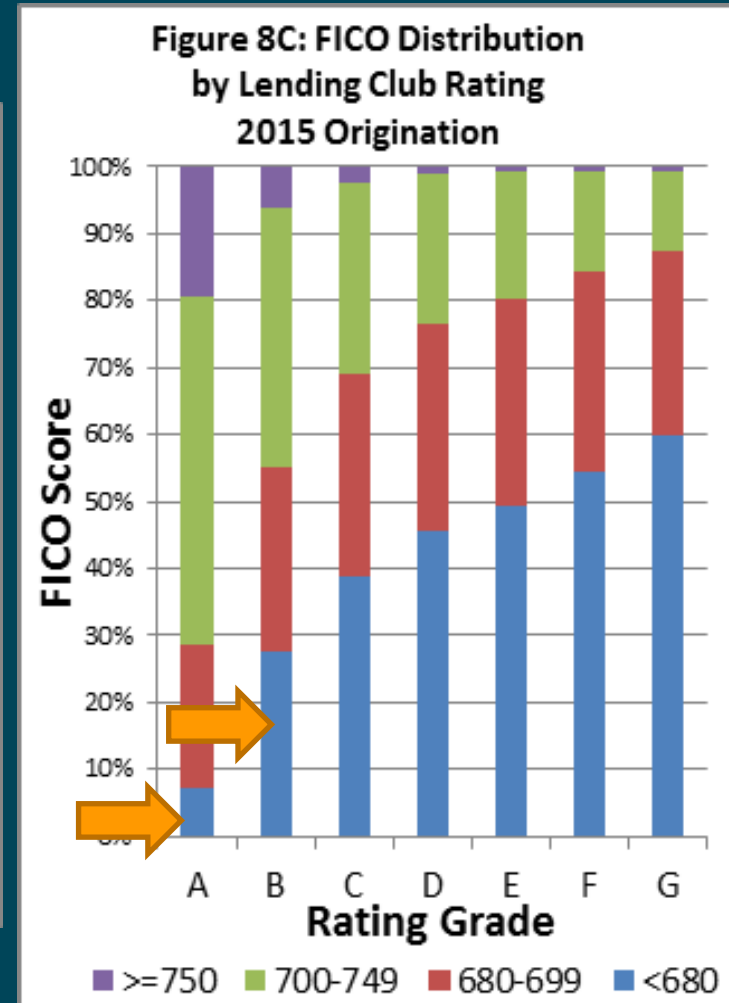
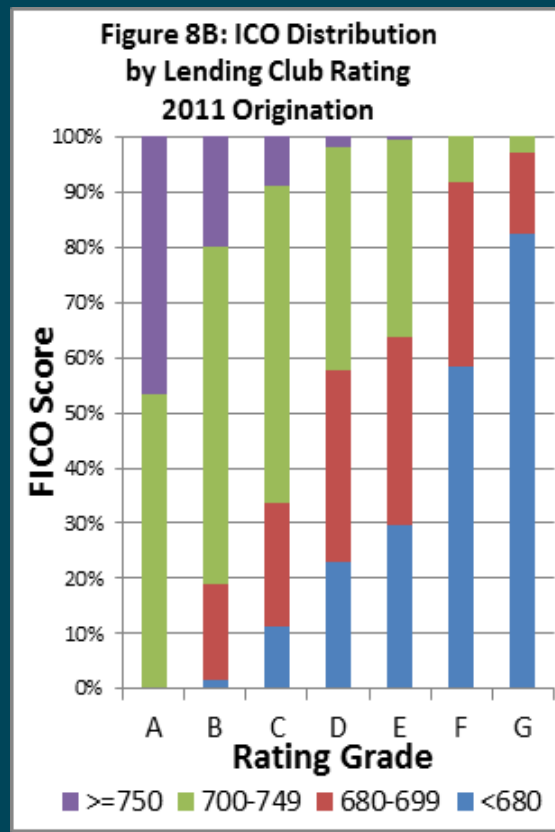
# For 2015 Origination, A-Rated and B-Rated Include 8% and 27% of FICO<680 Borrowers

2015

2007



2011



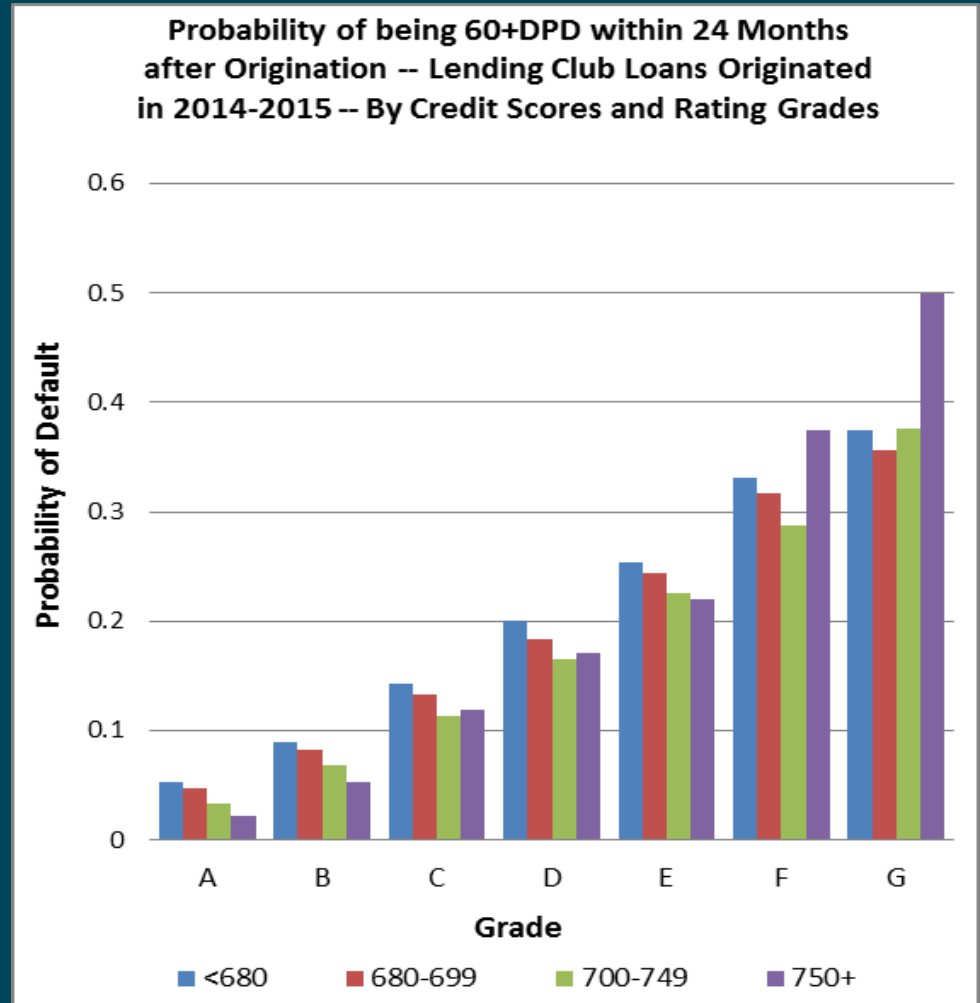
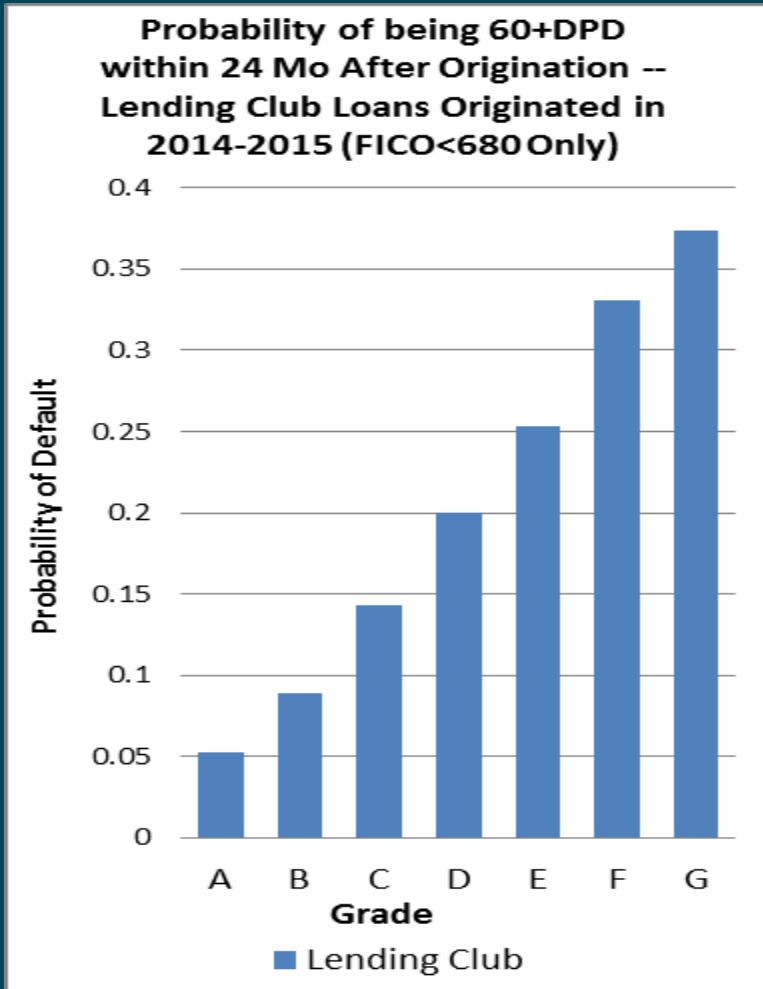
Source: Jagtiani and Lemieux (2018)



# Default Rate – by Rating Grades vs. FICO Scores

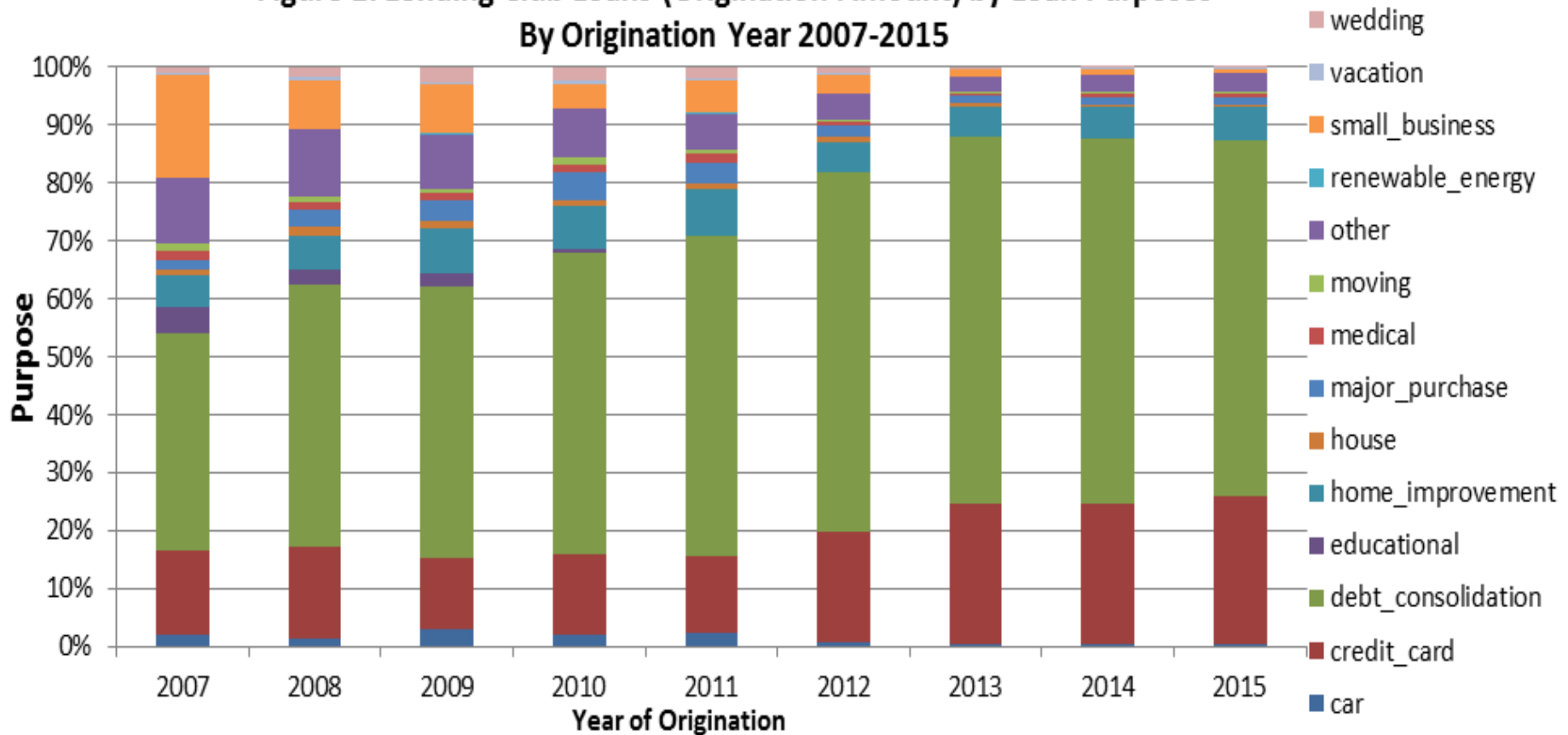
FICO<680 Only

PD is closely related to A-G rating



# LendingClub Consumer Loans Mostly Cards and Debt Consolidation



Figure 1: Lending Club Loans (Origination Amount) by Loan Purposes  
By Origination Year 2007-2015



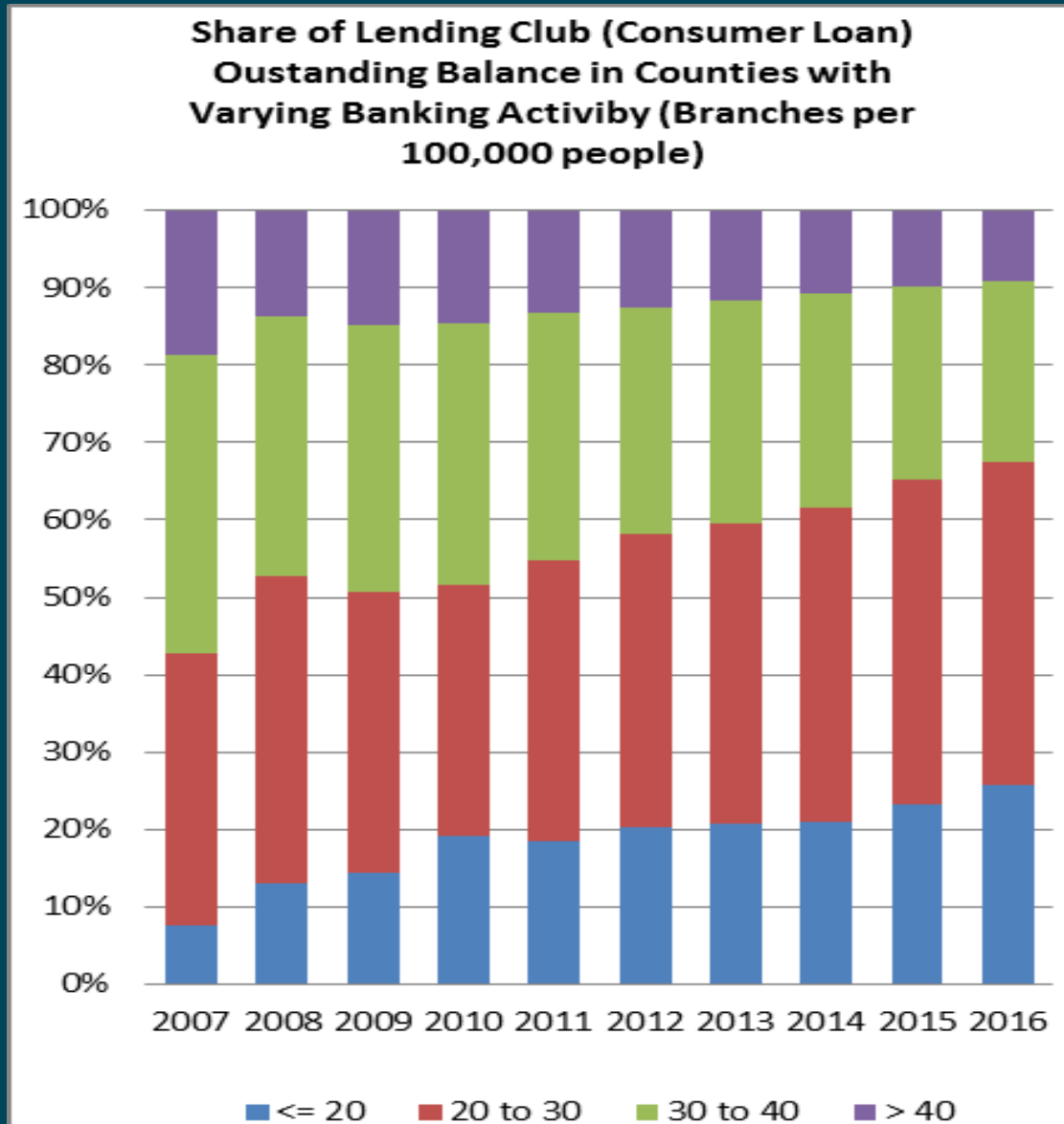
Source: Jagtiani and Lemieux (2018)



# Lower Rates at LendingClub

FICO Segment At Origination	% Average Spread LendingClub		% Ave Spread Bank Y-14M Revolvers Only
	3Year Maturity	5 Year Maturity	
			
660-679	12.0646	15.7089	20.1923
680-699	10.7630	14.3937	19.8465
700-719	9.3477	13.0239	19.1418
720-739	8.12608	11.7484	18.4180
740-759	7.16102	10.5891	17.6569
760-779	6.5303	9.7955	16.8312
780-799	6.0904	9.2009	16.1820
800+	5.6408	8.6312	16.1668

# More Than 50% of LendingClub Loans are in Areas with Less Bank Branches/Capita



# Main Findings from LendingClub Data

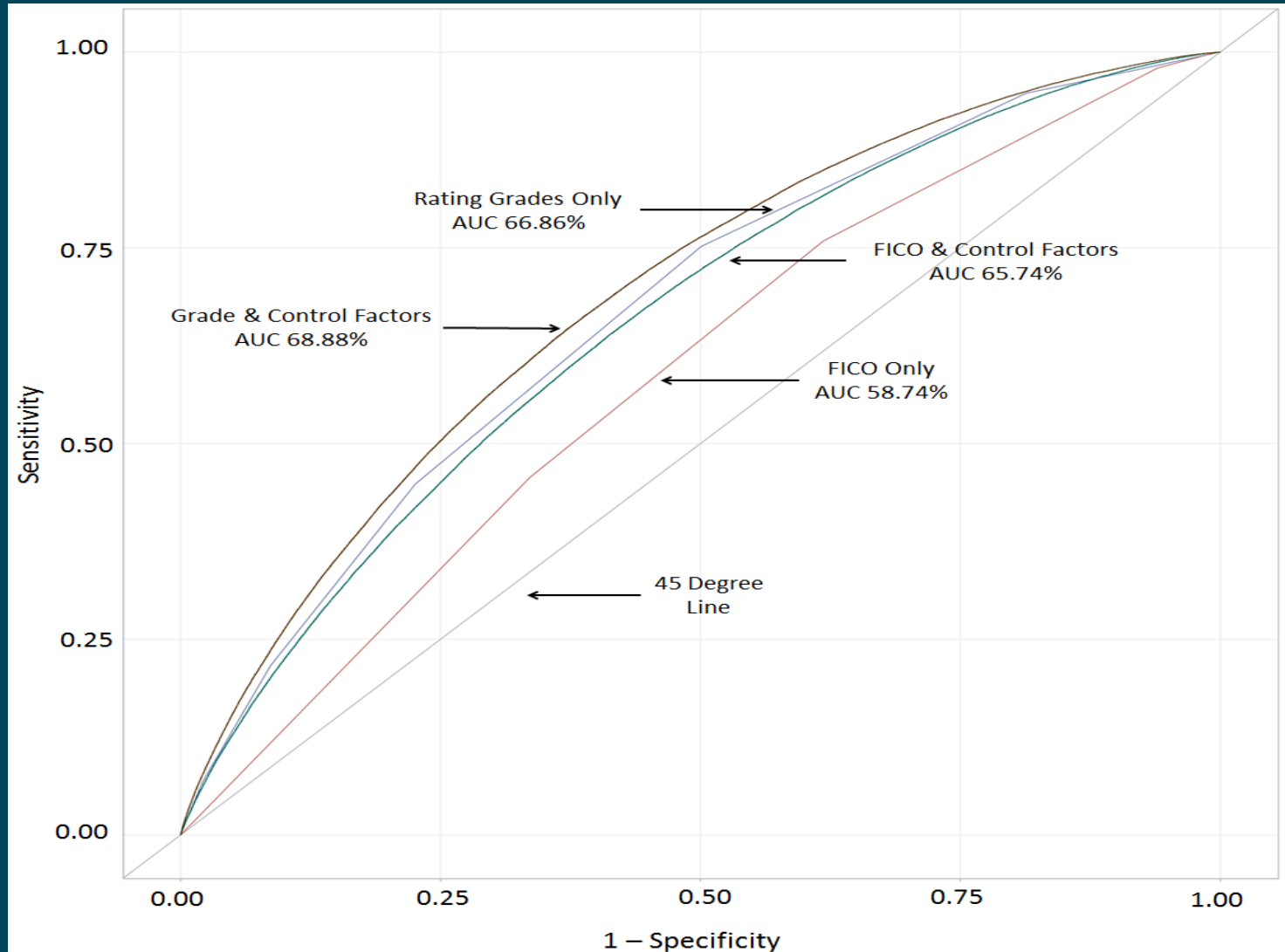
- ❖ Use of alternative data in credit decisions has allowed lenders to identify good borrowers (the “invisible prime”) from the pool of subprime borrowers (based on traditional credit score measures).
- ❖ Allowing them to access credit and at a lower cost than what they would have had to pay otherwise.
- ❖ Given the same credit scores (FICO), on average, consumers pay smaller spreads on loans from LendingClub than from carrying their credit card balances.

Source: Jagtiani and Lemieux (2018)



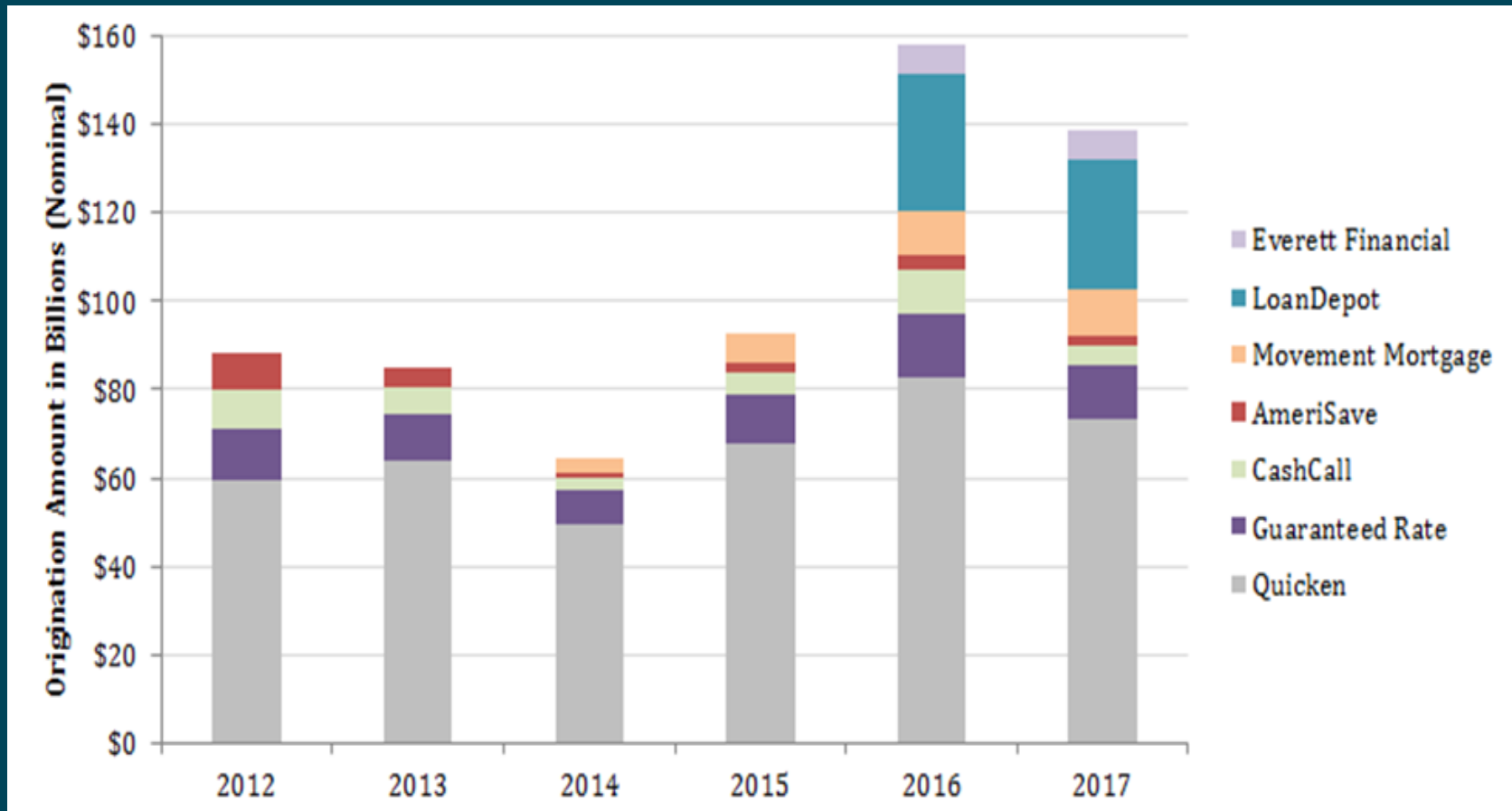
# Discriminatory Power of 4 PD Model Specifications

## Model with rating grades + control factors is best at predicting future defaults





# Fintech Mortgage Origination Volume by Lenders (HMDA)



Source: Jagtiani, Lambie-Hanson, and Lambie-Hanson (2018)

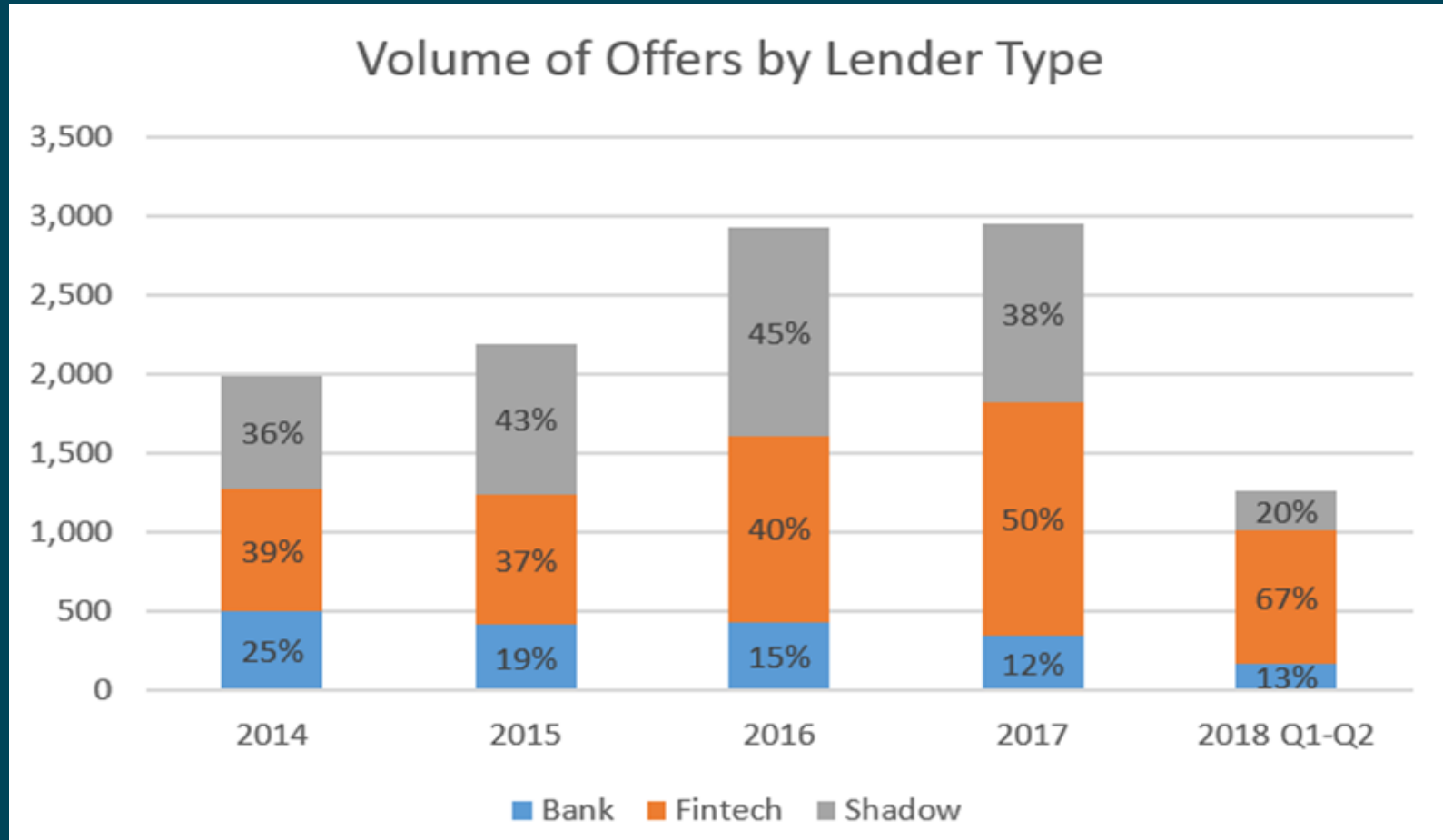


# Main Findings from HMDA Data

- ❖ Fintech mortgages overall are more commonly originated in areas that have had greater non-Fintech denial rates.
- ❖ Consumers turn to mortgage Fintech lenders after being denied by traditional lenders -- filling the credit gaps in underserved community.
- ❖ We observe different behaviors across lenders and consumers in the conventional vs. FHA mortgages -- with mixed results when considering HHI, branch per capita, average household income, etc.



# Mortgage Credit Offers (Intel Direct Mail Offers)



Source: Jagtiani, Lambie-Hanson, and Lambie-Hanson (2018)



# Main Findings from Mintel Data

- ❖ **Fintech lenders tend to market more frequently to low income and low credit score consumers.**
- ❖ **Unlike Fintech consumer loans, mortgage Fintech lenders may not have the same flexibility to utilize alternative data for credit decision, probably due to stringent mortgage origination requirements, especially for FHA loans.**
- ❖ **Policy Question: Would allowing greater potential use of alternative data in mortgage lending be a superior approach to achieve our goals on homeownership than the current federal program through Federal guarantee/subsidies.**

