Invisible Primes: Fintech Lending with Alternative Data

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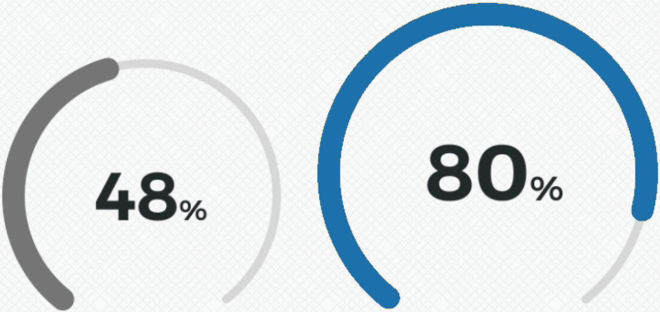
Four in five Americans

have never defaulted on a credit product, yet less than half have access to prime credit.* The implication is eye-opening. With a smarter credit model, lenders could approve almost twice as many borrowers, with fewer defaults.



Americans who have access to prime credit

Americans who never defaulted on a credit product

* According to an Upstart retrospective study completed in December 2019.

Credit score is central to credit decisions

Lenders **primarily use credit scores** to evaluate the probability that an individual will repay loans

- GSEs have a minimum credit score of 620
- Marcus and SunTrust have a minimum credit score of 660 for personal loan, 680 for SoFi

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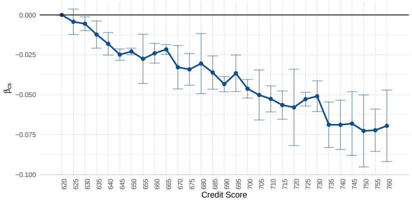
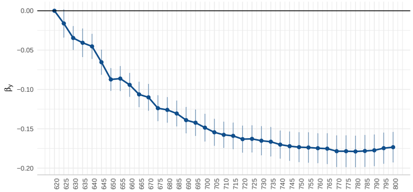
Credit score is a **good predictor of default**, in general

Credit card defaults

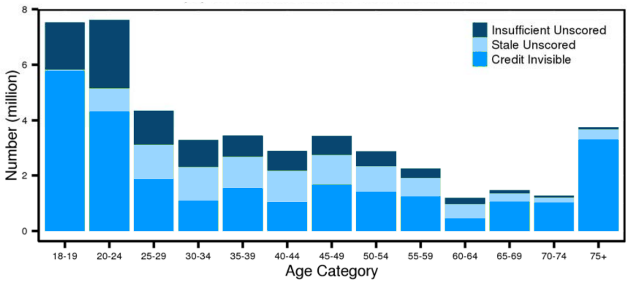


Mortgage defaults



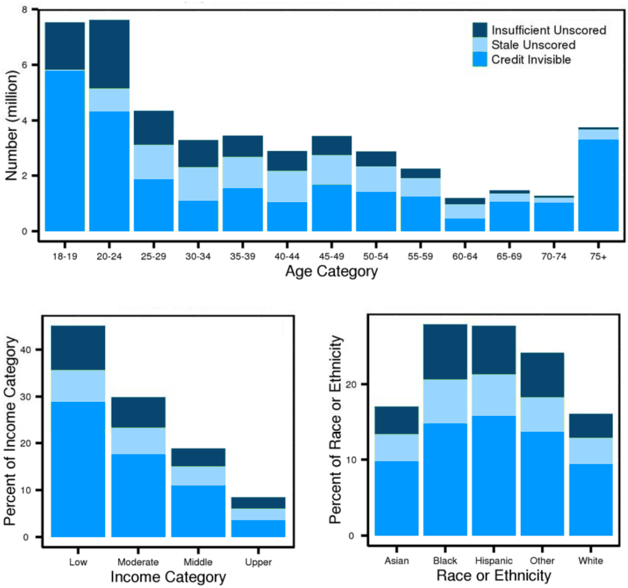
“FICO scores are good, but they’re ***not perfect****.”*
— Roger Hochschild, Discover Financial Services CEO

Credit Invisibles



(Source: The CFPB Office of Research)

Credit Invisibles



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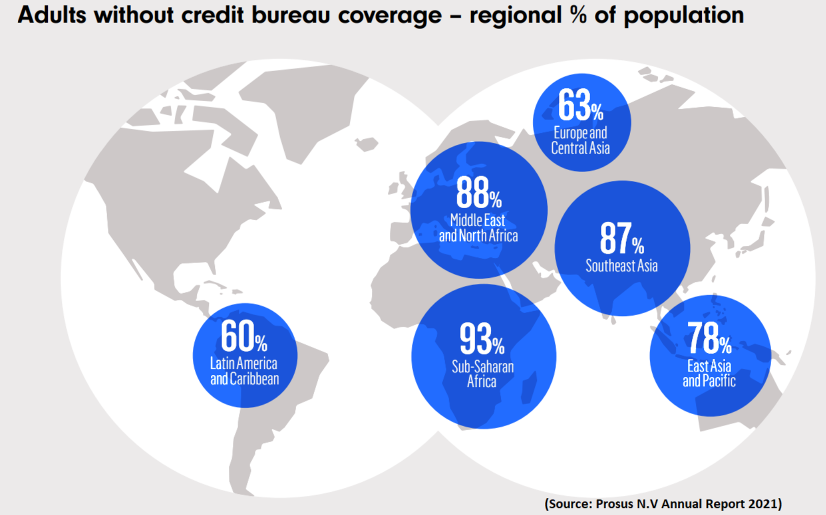

Invisible Primes?

The advent of fintech lenders has the potential to identify the prime borrowers among the credit invisibles

- Sophisticated algorithms
- Alternative data
- Online presence

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- Broader credit access?
- Types of data?
- Profitable to lend to invisible primes?
- Are borrowers better off?

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Empirical Challenge:

- Observing the counterfactual

Our Setting: Upstart

- Anonymized administrative data from Upstart, a major fintech lender

- Why Upstart?
  - Use non-traditional variables such as education and job history for underwriting
  - CFPB granted a no-action letter (NAL) to Upstart regarding its automated model
  - Counterfactual based on a model developed by CFPB

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- Similar results from publicly available mortgage data

Data

- 770,523 loans and 2,374,912 disqualified applications from 2014 to 2021 (Q1)
- Access to all credit report variables and performance data
- Information on education, the type of the device (smartphone/computer) used by applicants, the operating system, the employment type and tenure, etc.

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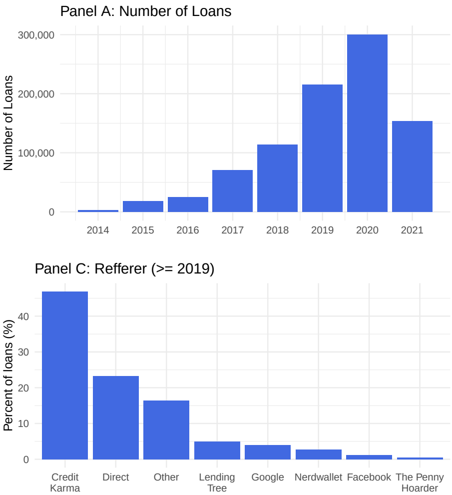
- **Upstart's probability of default estimate**
- **Traditional model** - the counterfactual
- A **panel** of both the funded *and* rejected applicants

Upstart's Loan Growth and Source



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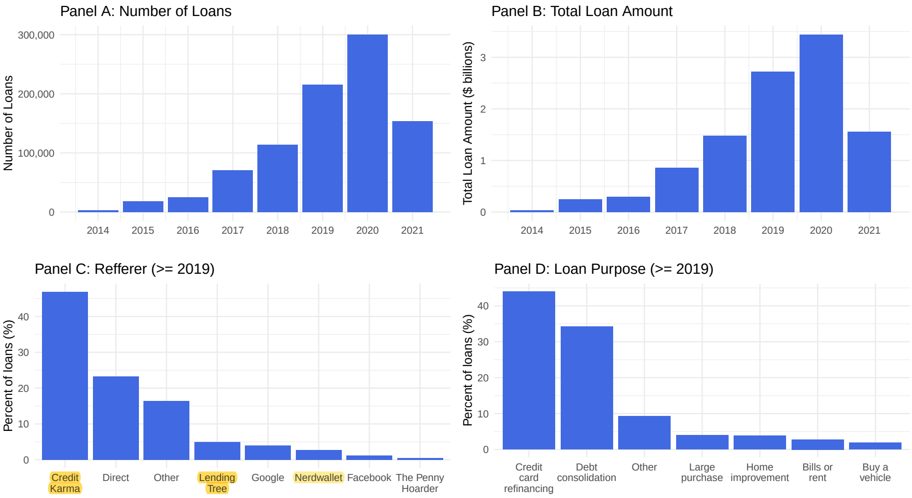
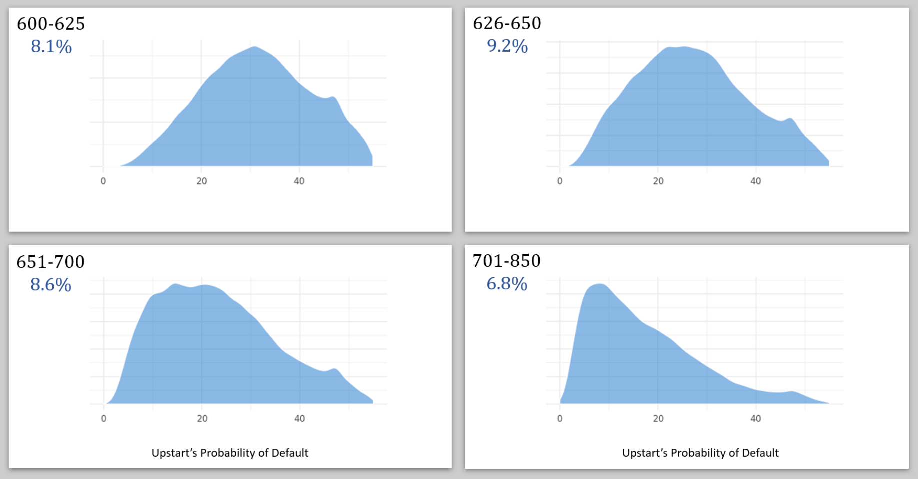


Descriptive Statistics: Funded vs. Disqualified Applications

	Disqualified	Funded
Number of Obs	2,374,912	770,523
Credit Score	589.058	653.996
Age of the borrower	37.106	37.674
Annual income	54,258	66,958
Debt-to-income	19.861	18.237
Number of accounts	17.050	18.624
Credit history in years	9.163	11.014
Total credit balance	68,263	120,394
Credit card utilization	58.366	66.940
Has a mortgage	0.151	0.293
Inquiries (last 6 months)	2.589	1.037
College degree	0.247	0.445
Hourly worker	0.562	0.451
Years at job	4.362	5.367
Purpose = consolidation	0.629	0.788
Used device type = computer	0.263	0.324
Used a Mac	0.228	0.283
Used an iPhone	0.585	0.644

Predictability of Default



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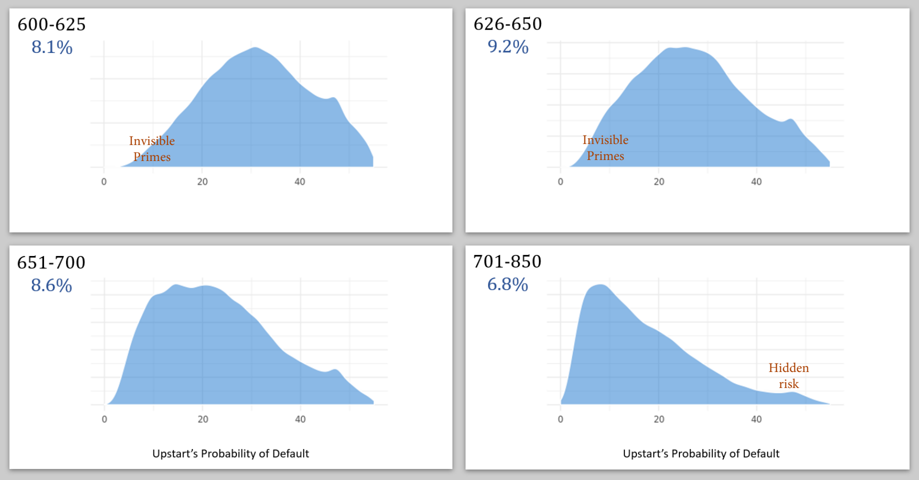

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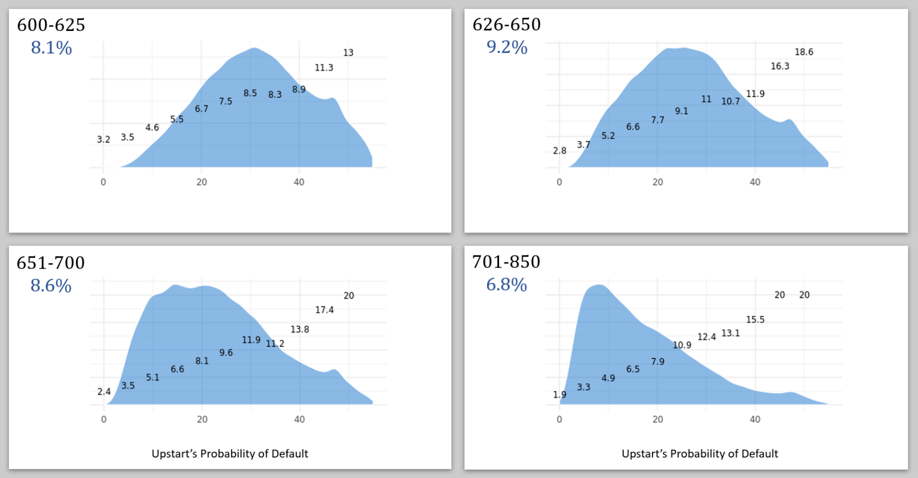

Alternative data and/or sophisticated model?

Main drivers of Upstart's credit model

	(1)	(2)	(3)	(4)	(5)	(6)
Credit score/100	-0.112***	-0.111***	-0.113***	-0.115***	-0.111***	-0.115***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
log(Annual income)	-0.045***	-0.042***	-0.038***	-0.047***	-0.042***	-0.038***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Debt-to-income	0.001***	0.0005***	0.0005***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age of the borrower	0.004***	0.003***	0.005***	0.004***	0.004***	0.004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age of the borrower^2	-0.00003***	-0.00003***	-0.00004***	-0.00003***	-0.00003***	-0.00003***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
log(Number of accounts)	0.004***	0.009***	0.005***	0.005***	0.003***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Number of inquiries)	0.035***	0.033***	0.035***	0.033***	0.034***	0.032***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
log(Total balance)	-0.008***	-0.006***	-0.008***	-0.007***	-0.008***	-0.006***
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
log(Credit history)	-0.027***	-0.025***	-0.028***	-0.027***	-0.026***	-0.026***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
log(Loan amount)	0.00004	0.002***	0.0002	0.003***	0.0002	0.004***
	(0.001)	(0.0005)	(0.001)	(0.0005)	(0.0005)	(0.0005)
Zip code × Year	Y	Y	Y	Y	Y	Y
Loan Term × Year	Y	Y	Y	Y	Y	Y
Educational attainment	N	Y	N	N	N	Y
Employment type	N	N	Y	N	N	Y
Loan purpose	N	N	N	Y	N	Y
Device/Technology	N	N	N	N	Y	Y
N	770,299	770,299	748,796	770,299	687,370	667,777
R^2	0.431	0.451	0.435	0.439	0.439	0.463
Maximum economic impact		0.042	0.028	0.028	0.047	0.056

Education Exchange Rates

- Conditional on credit score, loan amount, and age:
  - To go from high school or less to an advanced degree: $107k
  - From associate to advanced: $114k
  - From college to advanced: $22k

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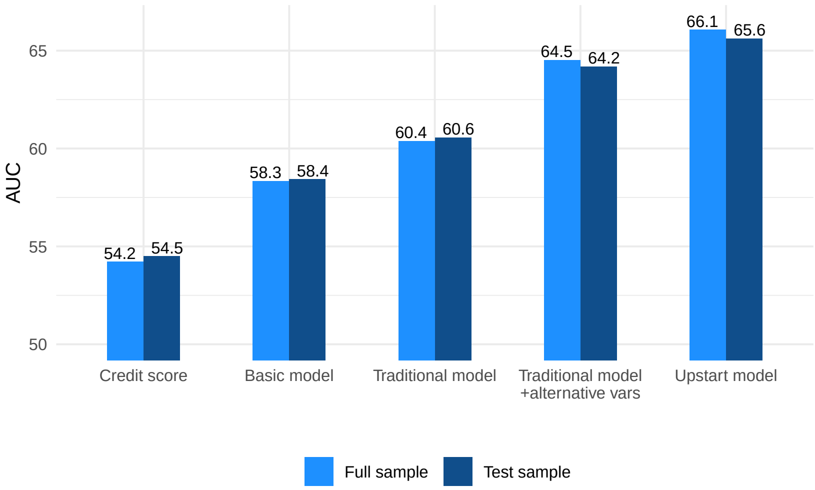
- Conditional on age, income and loan amount:
  - High school to Advanced: 37 points
  - Associate to Advanced: 23 points
  - College to Advanced: 4 points

Alternative data significantly contributes to the predictive power



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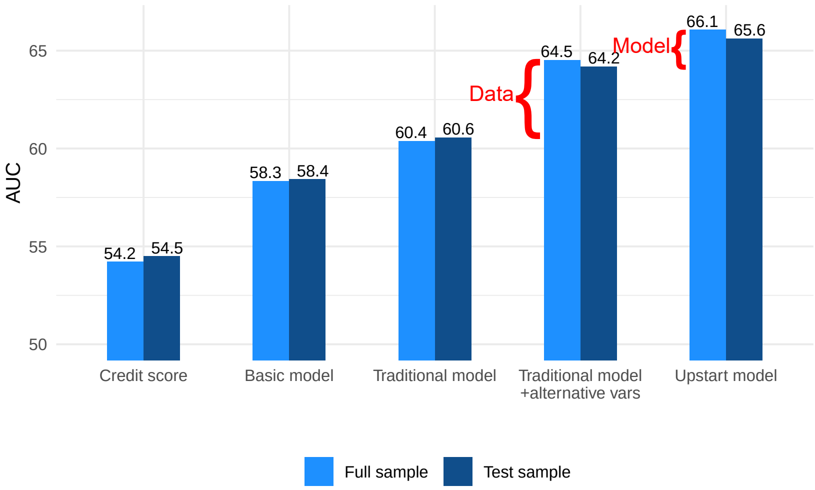
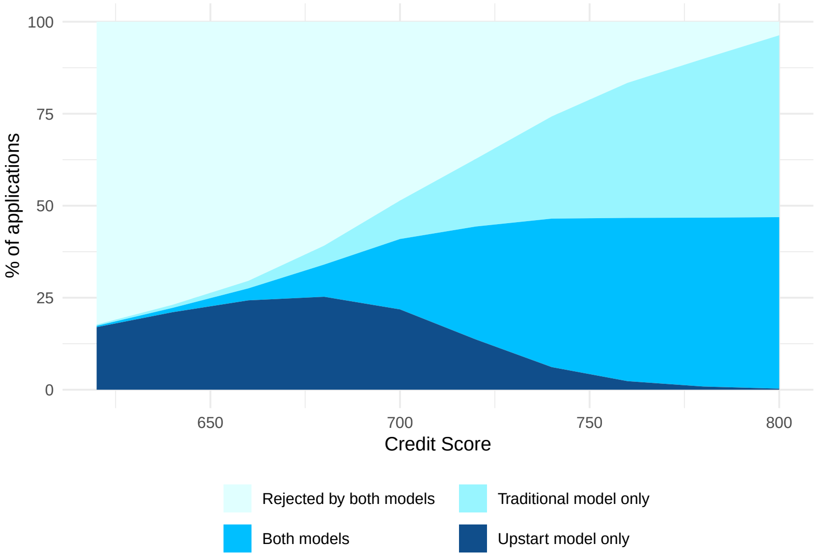
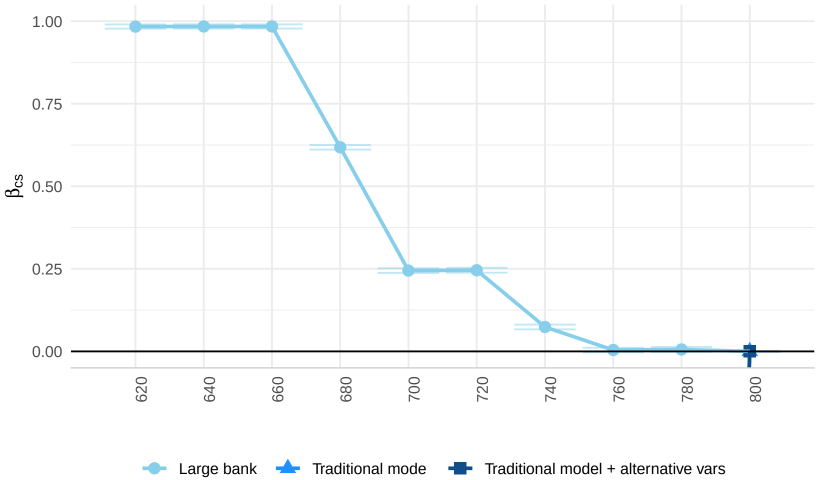


Does the use of alternative data improve credit access?

Upstart is more likely to approve applicants with low credit scores



Traditional vs. Upstart: Rejection rate



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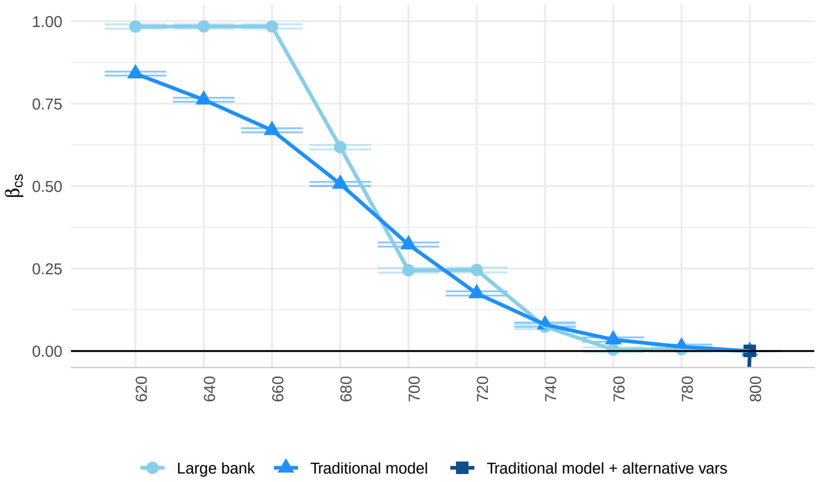
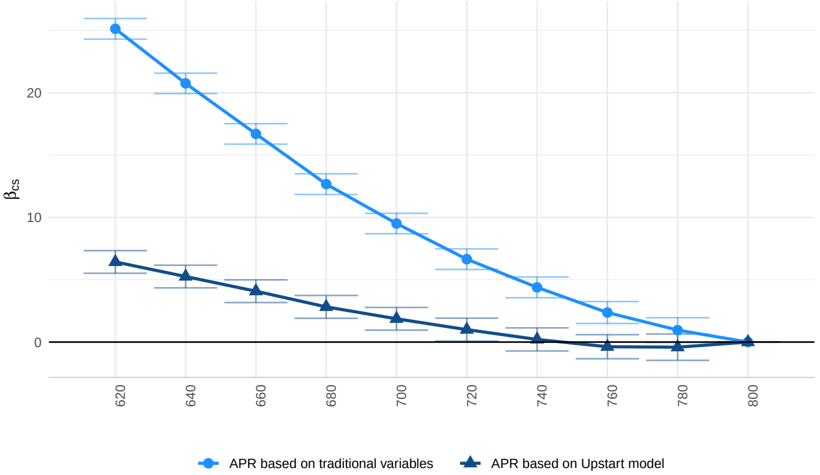


Traditional vs. Upstart: Interest rate difference



Who benefits the most due to the use of alternative data?

Borrower Differences

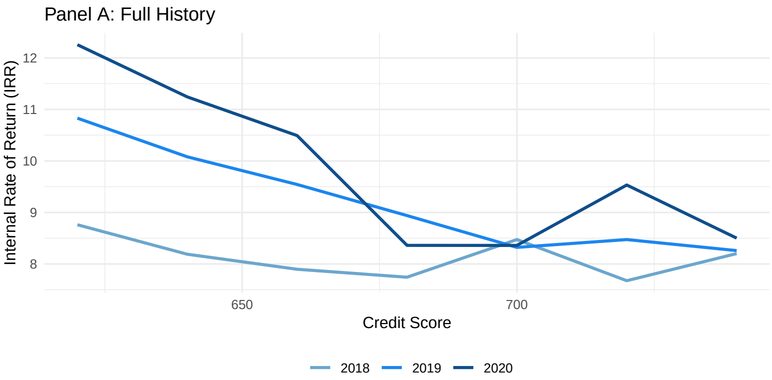
	Rejected by Trad. Model		Trad. APR - Upstart APR	
	(1)	(2)	(3)	(4)
Credit score/100	-0.660***		-15.229***	
	(0.001)		(0.033)	
Credit score $<$ 660		0.332***		9.067***
		(0.003)		(0.068)
Income $<$ 55k	-0.108***	-0.128***	-4.996***	-4.859***
	(0.001)	(0.002)	(0.028)	(0.033)
Advanced degree	0.067***	0.046***	4.153***	3.615***
	(0.002)	(0.002)	(0.041)	(0.051)
College degree	0.036***	0.016***	2.762***	2.521***
	(0.001)	(0.002)	(0.029)	(0.035)
Salaried employee	0.027***	0.032***	1.648***	1.506***
	(0.001)	(0.002)	(0.027)	(0.033)
Thin credit file	0.032***	0.005***	-0.578***	-0.774***
	(0.001)	(0.002)	(0.027)	(0.033)
Credit score $<$ 660 $\times$ Income $<$ 55k		0.048***		-0.615***
		(0.003)		(0.064)
Credit score $<$ 660 $\times$ Advanced degree		0.024***		1.085***
		(0.003)		(0.095)
Credit score $<$ 660 $\times$ College degree		0.024***		0.100
		(0.003)		(0.067)
Credit score $<$ 660 $\times$ Salaried employee		-0.013***		0.476***
		(0.002)		(0.064)
Credit score $<$ 660 $\times$ Thin credit file		0.047***		-0.285***
		(0.003)		(0.064)
Zip code	Y	Y	Y	Y
N	717,524	717,524	717,524	717,524
Adjusted R^2	0.267	0.149	0.335	0.243

Regional Differences

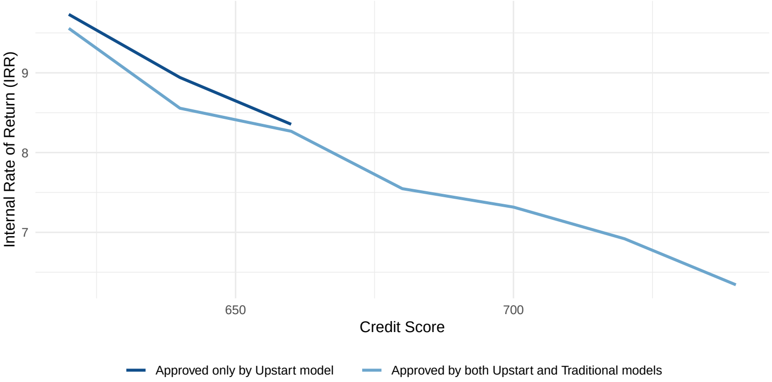
	Dep.var = Rejected by trad. model			Dep. var = Trad. APR - Upstart APR		
	(1)	(2)	(3)	(4)	(5)	(6)
Minority fraction in middle third	0.014***			0.569***		
	(0.003)			(0.065)		
Minority fraction in top third	0.023***			0.823***		
	(0.004)			(0.125)		
Fraction of renters in middle third		0.007**			0.228***	
		(0.003)			(0.076)	
Fraction of renters in top third		0.014***			0.610***	
		(0.003)			(0.104)	
Foreign born fraction in middle third			0.012***			0.671***
			(0.003)			(0.088)
Foreign born fraction in top third			0.022***			0.960***
			(0.004)			(0.109)
Credit score	-0.006***	-0.006***	-0.006***	-0.141***	-0.141***	-0.141***
	(0.00004)	(0.00004)	(0.00004)	(0.002)	(0.002)	(0.002)
log(Annual income)	0.137***	0.138***	0.137***	7.248***	7.271***	7.243***
	(0.003)	(0.003)	(0.003)	(0.060)	(0.059)	(0.061)
Debt-to-income	0.002***	0.002***	0.002***	0.029**	0.029**	0.029**
	(0.001)	(0.001)	(0.001)	(0.011)	(0.011)	(0.011)
State	Y	Y	Y	Y	Y	Y
N	736,896	736,896	736,902	736,896	736,896	736,902
Adjusted R^2	0.283	0.283	0.283	0.368	0.368	0.368

Is lending to ‘invisible primes’ value enhancing for the lender?

Internal Rate of Return: 3-year loans, full history

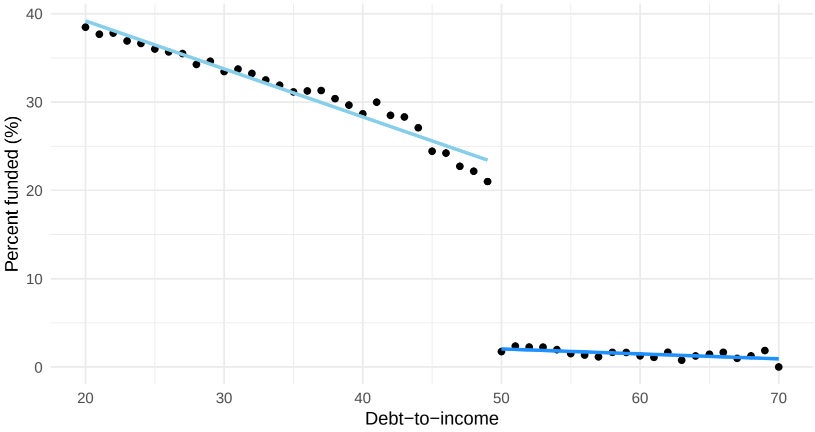


Internal Rate of Return: By Model Outcome



Are the borrowers better off?

We exploit a discontinuity in the probability of approval



Fuzzy RDD

$$Funded_i = \beta_0 + \beta_1 \times I(\text{DTI} > 50\%) \times \text{DTI} + \boldsymbol{\beta_2 X} + \mu_{zt} + \eta_i \tag{1}$$

$$Y_i = \gamma_0 + \gamma_1 \times \widehat{Funded}_i + \gamma_2 \times \text{DTI} + \boldsymbol{\Gamma_3 X} + \mu_{zt} + \mu_i \tag{2}$$

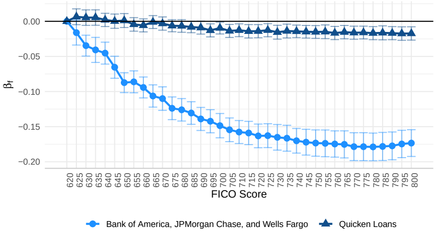
The Effects of Credit Access: RD

	Credit score ≤ 660			Credit score ≥ 660		
	Credit card delinq	Credit score change	Mortgage	Credit card delinq	Credit score change	Mortgage
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Funded}$	-0.198*	0.087***	0.134*	-0.074	0.012	0.010
	(0.102)	(0.026)	(0.072)	(0.074)	(0.015)	(0.087)
Debt-to-income	-0.003*	0.001***	0.002*	-0.004	0.001*	0.003
	(0.002)	(0.0004)	(0.001)	(0.003)	(0.001)	(0.003)
Credit score	-1.949	-6.627***	1.039	3.851***	-3.843***	2.323**
	(1.574)	(0.382)	(1.155)	(1.135)	(0.209)	(1.113)
Credit score2	9.455***	0.323	-0.822	-0.283	-0.672***	0.854
	(0.812)	(0.206)	(0.527)	(0.699)	(0.137)	(0.628)
log(Annual income)	-0.030***	-0.003	0.031***	-0.035**	0.008**	0.025
	(0.010)	(0.002)	(0.006)	(0.017)	(0.003)	(0.017)
Age of the borrower	-0.004**	-0.00003	0.002*	-0.001	-0.001	0.002
	(0.002)	(0.0005)	(0.001)	(0.003)	(0.001)	(0.003)
Age of the borrower^2	0.00004**	0.00000	-0.00002	-0.00001	0.00000	-0.00003
	(0.00002)	(0.00000)	(0.00001)	(0.00003)	(0.00001)	(0.00003)
log(Number of accounts)	0.048***	-0.006***	0.022***	0.023	-0.004	0.021
	(0.009)	(0.002)	(0.006)	(0.018)	(0.004)	(0.015)
log(Number of inquiries)	0.008	-0.010***	0.007**	-0.005	-0.010***	0.027***
	(0.006)	(0.002)	(0.003)	(0.011)	(0.002)	(0.010)
Total liabilities	7.150***	-1.333***	1.326	3.817***	-0.719***	-4.806
	(0.973)	(0.239)	(2.720)	(1.046)	(0.216)	(3.207)
Credit history	-5.817***	2.187***	-0.203	-2.042*	1.577***	2.205*
	(0.936)	(0.231)	(0.604)	(1.124)	(0.227)	(1.173)
log(No of recently opened accounts)	-0.067***	-0.010***	0.004	-0.018	-0.027***	0.020*
	(0.008)	(0.002)	(0.005)	(0.015)	(0.003)	(0.011)
log(Pct. of revolving liabilities)	0.055***	-0.018***	-0.053***	0.044***	-0.022***	-0.082***
	(0.005)	(0.001)	(0.004)	(0.009)	(0.002)	(0.010)
log(Pct. of mortgage liabilities)	0.020***	-0.004***		0.008	-0.004**	
	(0.005)	(0.001)		(0.010)	(0.002)	
Credit card utilization	9.374***	-8.078***	1.465***	0.016	-5.398***	3.480***
	(0.726)	(0.182)	(0.435)	(0.876)	(0.182)	(0.833)
log(Pct. trades ever delinquent)	0.055***	-0.010***	-0.003***	0.068***	-0.009***	-0.002
	(0.001)	(0.0003)	(0.001)	(0.002)	(0.0004)	(0.002)
Zip code × Year	Y	Y	Y	Y	Y	Y
N	29,692	29,692	21,183	13,171	13,171	7,890
Adjusted R^2	0.320	0.304	0.039	0.317	0.498	0.231

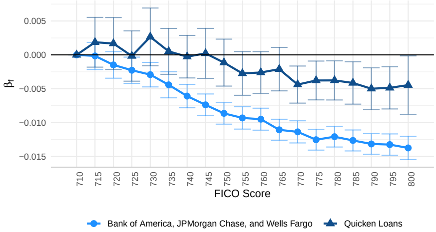
External Validity

- We compare the performance of mortgages originated by the three largest banks (Bank of America, Chase and Wells Fargo) to the performance of mortgages originated by Quicken Loans.
- FICO is not a good predictor of default for a fintech lender like Quicken borrowers

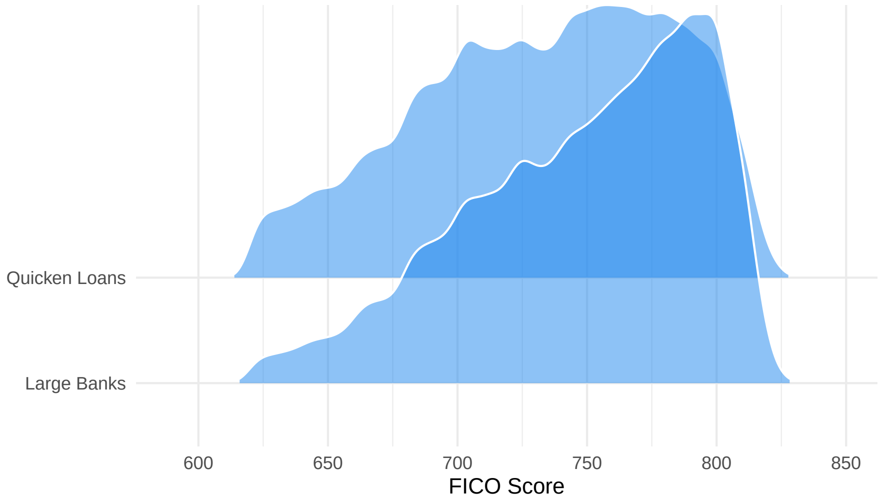
Panel A: Non-agency mortgages



Panel B: Mortgages sold to Freddie Mac



FICO Score Distribution



Conclusion

- A superior ability to predict default translates into broader access to credit
- Benefits for low-score borrowers on both the extensive and intensive margins
- Significant decrease in other liabilities defaults, increase in credit score and home purchase
- These positive findings do not refute arguments around some of the potential concerns around privacy and potential for statistical discrimination
- However, they do show that there are quantifiable benefits to both borrowers and lenders