Rise of the Machines: The Impact of Automated Underwriting

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Motivation

- Technology has transformed the lending industry
  - Lenders increasingly automate underwriting.
  - The effects of these changes are widely debated.
  - Complete automation of underwriting risks the loss of human expertise
- It remains unclear to what extent the impact of FinTechs and ML models is attributable to the replacement of humans with machines.

This paper:

- Using a randomized experiment, we directly compare human underwriting with full automation in consumer lending markets and shed light on mechanisms that give rise to the differential outcomes.

Human versus machine

- Automation potentially saves time and labor costs, while increasing accuracy, and mitigating conflicts of interest.
  + Kahneman (1973) describes the human limits in information processing.
  + Tasks such as data collection, data processing, and numerical pattern prediction are strong candidates for automation (Chui et al., 2016).
  + Automated lending helps improve mortgage application processing time and reduce discrimination (Fuster et al., 2019; Bartlett et al., 2019; D'Acunto et al., 2020).
  + In marketplace lending, sophisticated investors who invest automatically outperform unsophisticated investors (Vallée and Zeng, 2019).
  + Loans officers have incentives to manipulate hard information to get applications approved (Berg et al., 2013).
- But, full automation can come at a cost
  - Human underwriters can review more nuanced borrower information when credit files are thin (Iyer et al., 2016).
  - Costello et al. (2020) find that human discretion incrementally improves on machine recommendations.
  - Automation does not always improve speed and performance for financial institutions (Brogaard et al., 2020).

The Experiment

- A Top 10 auto lender launched an automated underwriting system in 2013 that replaces human underwriters in making lending decisions. The firm has been in the business for decades and acquires loans from more than 4,000 auto dealerships across the U.S.
- **Randomized experiment:** the firm uses the machine concurrently with human underwriters. Each loan application is randomly assigned to either the machine (probability 50%) or human underwriters.
- Approximately, 2 million loan applications from 4,000 dealerships across 40 states were randomly assigned to either the machine- or human underwriters, resulting in 140,000 loans.
- We compare terms and subsequent performance of machine-underwritten loans with human-underwritten loans.

Preview of main results

- The profitability of machine-underwritten loans is 10.2% higher than that of human-underwritten loans.
- Human-underwriters offer a significantly *lower* APR.
- Default probability of human-underwritten loans is *higher* than that of machine-underwritten loans.
- The gap in performance is significantly larger for applications:
  - **where potential for agency conflict is high**; and
  - **where default prediction is more difficult (those with greater complexity).**

Contribution

1. By directly comparing human underwriting with full automation, we shed light on the role of automation in financial technology adoption.
   - ★ As lenders and insurance companies increasingly shift from human and machine-aided human processes to full automation, our apples-to-apples comparison is particularly informative about the possible outcomes of this transition.
2. The adoption of technology and alternative data in lending
3. Agency problem in lending

Contribution

1. By directly comparing human underwriting with full automation, we shed light on the role of automation in financial technology adoption.
2. The adoption of technology and alternative data in lending
   - Digital and social footprints can be used to develop new effective credit scoring systems (Berg et al., 2020; Agarwal et al., 2019)
   - Algorithmic lenders reduce customer discrimination (Bartlett et al., 2019; D'Acunto et al., 2020), and outperform traditional lenders in terms of processing time and default probability (Fuster et al., 2019)

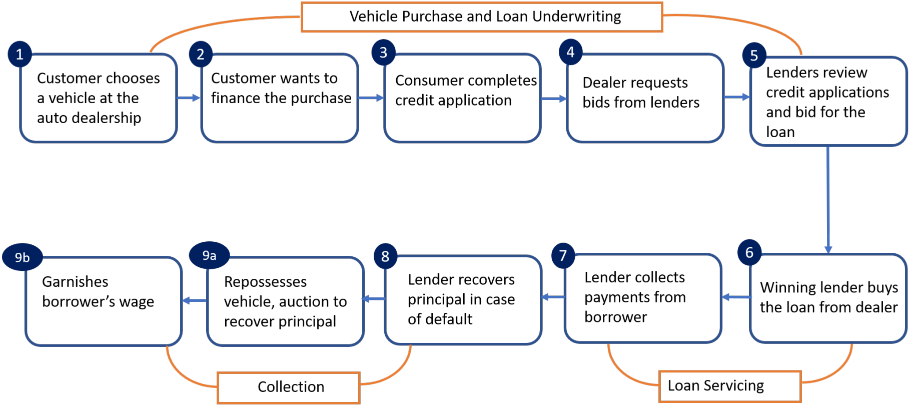
   ★ *Our results show that the difference in performance between FinTech and traditional lenders can be at least partially attributed to a more widespread use of automation.*
3. Agency problem in lending

Contribution

1. By directly comparing human underwriting with full automation, we shed light on the role of automation in financial technology adoption.
2. The adoption of technology and alternative data in lending
3. Agency problem in lending
    - Volume-based incentives for loan officers lead to lower lending standards and higher default rates (Heider and Inderst, 2012; Agarwal and Ben-David, 2018).
    - Gaming behavior around discrete cutoffs in loan origination (Keys et al., 2010; Griffin and Maturana, 2016)

★ *We show that humans are more likely to approve and fund loans right below a critical loan-to-value cutoff. When underwritten by humans rather than the machine, these loans have lower APR and riskier profiles at origination and perform poorly ex post.*

The lending process



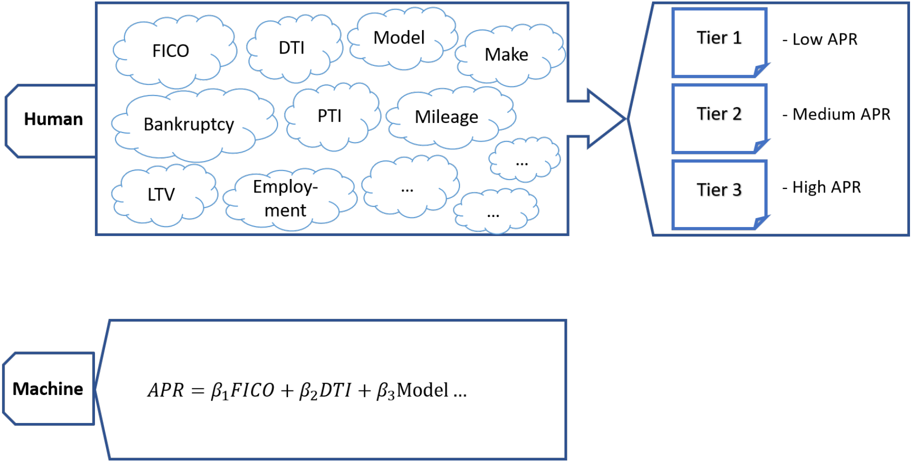
Underwriter guideline example

AAA Guidelines

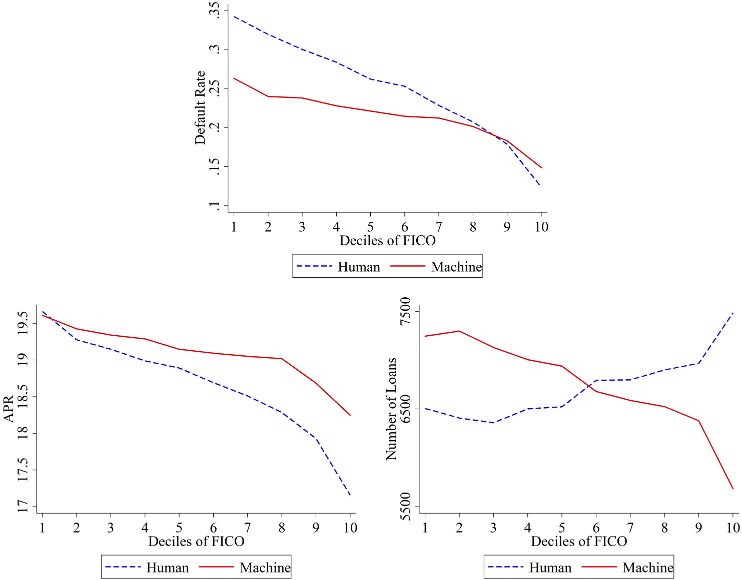
'AAA' any Titanium, Platinum, Gold or Standard program deal and receive lower APRs and dealer discounts. AAA deals must be structured to meet the deal requirements listed below. 'AAA' deals are available on vehicles of any age and mileage. Dealers may add up to 2% participation with no chargebacks (Gold, Platinum, and Titanium only).

Credit Score Range	Tier	Min. Payment	Min. Down Payment	Max LTV	A.P.R.	Discount
	1	$300	10%	110%	5.99%	$250
780+	2	$300	10%	120%	7.99%	$450
	3	$300	10%	125%	9.99%	$500
	1	$300	20%	100%	7.99%	$400
725-779	2	$300	15%	110%	9.99%	$600
	3	$300	10%	115%	11.99%	$700
	1	$275	25%	90%	9.99%	$500
680-724	2	$275	15%	100%	11.99%	$700
	3	$275	10%	105%	13.99%	$800
	1	$275	30%	80%	12.99%	$700
625-679	2	$275	20%	90%	14.99%	$800
	3	$275	15%	95%	15.99%	$900
	1	$250	35%	75%	15.99%	$800
575-624	2	$250	25%	80%	16.99%	$900
	3	$250	20%	85%	18.99%	$1,000
	1	$250	40%	65%	22.99%	$1,250
525-574	2	$250	40%	70%	22.99%	$1,500
	3	$250	40%	75%	22.99%	$1,750
	1	$250	45%	60%	24.99%	$1,500
300-524	2	$250	45%	65%	24.99%	$1,750
	3	$250	45%	70%	24.99%	$2,000
	1	$250	35%	75%	15.99%	$800
0	2	$250	30%	85%	16.99%	$900
	3	$250	25%	90%	18.99%	$1,000
	1	$250	35%	60%	24.99%	$1,500
Default	2	$250	30%	65%	24.99%	$1,750
	3	$250	25%	70%	24.99%	$2,000

Differences in the underwriting process



Human and machine decision criteria Criteria



Loan profitability

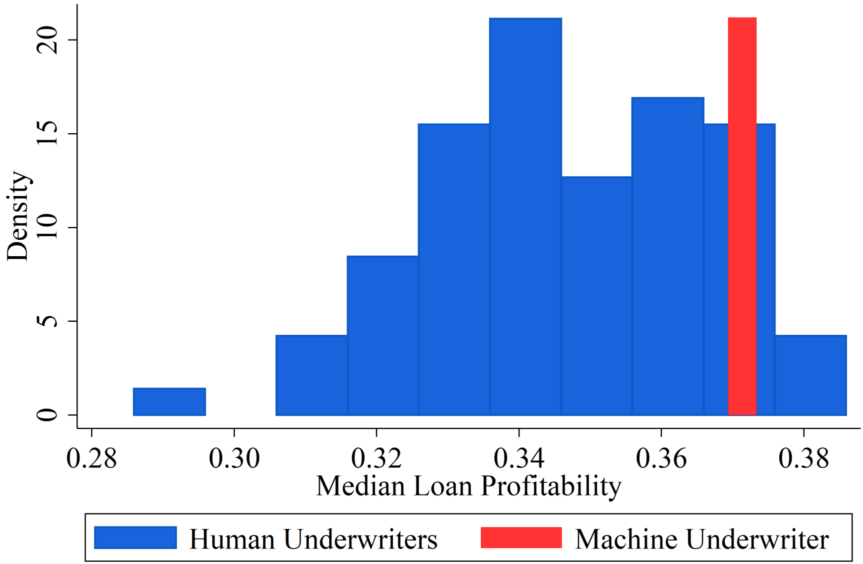
Sample:	(1) Uncensored	(2) Completed	(3) Censored	(4) All
Machine	0.025***	0.028***	0.027***	0.027***
	(4.41)	(6.63)	(9.44)	(9.66)
Year-Month FE	YES	YES	YES	YES
Observations	18887	82468	119512	140498
Adjusted R^2	0.004	0.030	0.023	0.021

The machine generates 2.7 percentage points higher profit — a 10.2% improvement relative to human-underwritten loans' profitability of 26.4%.

Loan profitability, with controls

	(1)	(2)	(3)	(4)	(5)
Sample:	Uncensored	Completed	Censored	All	All
Machine	0.020***	0.025***	0.025***	0.024***	0.027***
	(5.88)	(8.66)	(9.90)	(11.13)	(9.66)
Loan-to-Value	-0.149***	-0.218***	-0.118***	-0.124***	
	(-7.15)	(-17.58)	(-11.46)	(-13.55)	
Loan Amount	-0.000***	-0.000***	-0.000***	-0.000***	
	(-7.59)	(-9.71)	(-15.12)	(-17.92)	
Term (months)	0.002***	-0.000	0.003***	0.003***	
	(5.36)	(-0.78)	(12.32)	(14.02)	
Discount	0.000***	0.000***	0.000***	0.000***	
	(6.75)	(6.02)	(13.99)	(13.91)	
Credit Score	0.000***	0.001***	0.000***	0.000***	
	(4.36)	(16.02)	(13.21)	(13.70)	
Homeowner Indicator	-0.006	0.008	0.002	0.001	
	(-0.47)	(1.18)	(0.44)	(0.29)	
Bankruptcy	0.028***	0.073***	0.031***	0.030***	
	(5.39)	(12.69)	(9.01)	(9.96)	
Debt-to-Income Ratio	-0.082***	-0.008	-0.012	-0.011	
	(-3.87)	(-1.19)	(-1.08)	(-1.56)	
New Car Indicator	-0.018*	-0.044***	-0.019***	-0.020***	
	(-1.80)	(-6.71)	(-3.42)	(-4.00)	
Car Age (years)	-0.007***	-0.011***	-0.005***	-0.006***	
	(-2.99)	(-8.64)	(-4.65)	(-5.47)	
Year-Month FE	YES	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES	NO
Car Make FE	YES	YES	YES	YES	NO
Car Model FE	YES	YES	YES	YES	NO
Observations	17796	78806	113379	133629	140498
Adjusted R^2	0.045	0.097	0.065	0.062	0.021

Loan profitability



Loan interest rate (APR %) APR

	(1)	(2)	(3)	(4)
Sample:	Uncensored	Completed	Censored	All
Machine	0.462***	0.387***	0.441***	0.442***
	(12.79)	(10.39)	(11.22)	(12.37)
Year-Month FE	YES	YES	YES	YES
Observations	18899	82468	120023	141023
Adjusted R^2	0.041	0.037	0.050	0.045

Machine underwritten loans are priced 44.2 basis points higher than those underwritten by humans in the uncensored sample.

Loan default probability

Default

	(1)	(2)	(3)	(4)
Sample:	Uncensored	Completed	Censored	All
Machine	-0.017**	-0.020***	-0.016***	-0.016***
	(-2.31)	(-3.26)	(-3.92)	(-4.03)
Year-Month FE	YES	YES	YES	YES
Observations	18899	82468	120023	141023
Adjusted R^2	0.003	0.009	0.052	0.050

Machine-underwritten loans are 1.6 percentage points *less* likely to default, which is equivalent to 6.8% improvement over the default rate for human-underwritten loans.

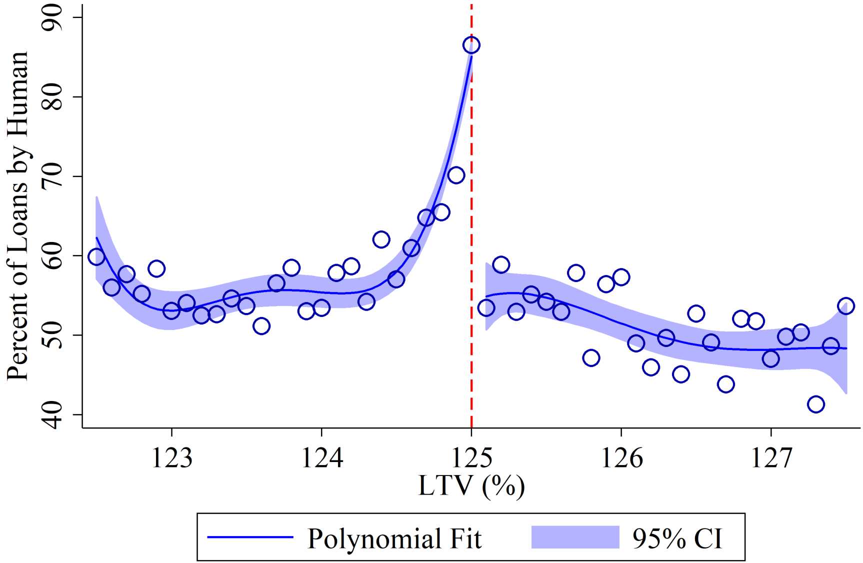
Two potential channels

1. **Agency conflicts**
2. **Loan complexity**

Difference in performance around the LTV cutoff

- The lender imposes restrictions on high-risk borrowers with a loan-to-value ratio (LTV) above 125%, requiring exceptions and a higher APR.
- Underwriters can submit bids at a competitive price for high-risk borrowers just below the 125%.
- If human underwriters want to maximize their chance of winning the auctions, they will strongly prefer risky borrowers just below the 125%.
- Keys et al. (2010) find that the number of loans surges at FICO score just above 620 (threshold to securitize), but these loans have higher default probability

Percentage of human-underwritten loans around LTV 125%



Borrower risk factors around LTV 125%

	(1)	(2)	(3)
Dep Var:	FICO	DTI	Bankruptcy
Human	0.119***	0.061***	-0.166***
	(5.61)	(3.29)	(-4.64)
LTV125	0.077*	-0.072*	-0.209***
	(1.92)	(-1.86)	(-6.44)
Human $\times$ LTV125	-0.208***	0.129***	0.324***
	(-4.60)	(2.93)	(8.10)
Year-Month FE	YES	YES	YES
Observations	17640	17636	17640
Adjusted R^2	0.010	0.027	0.014

Default probability around LTV 125%

Dep Var:	(1) DEF^{12}	(2) DEF^{18}	(3) DEF^{24}	(4) DEF^{30}	(5) DEF^{36}
Machine	0.001	0.005	-0.003	-0.007	-0.012
	(0.33)	(0.97)	(-0.47)	(-0.85)	(-1.36)
LTV125	0.003	0.011*	0.029***	0.056***	0.065***
	(0.75)	(1.74)	(4.02)	(5.86)	(5.66)
Machine × LTV125	-0.004	-0.016	-0.043***	-0.060***	-0.080***
	(-0.56)	(-1.47)	(-3.38)	(-4.17)	(-4.61)
Year-Month FE	YES	YES	YES	YES	YES
Observations	12091	12091	12091	12091	12091
Adjusted R^2	0.000	0.000	0.002	0.005	0.006

At 36 months, machine-underwritten loans have an 8 percentage points (38.1%) *lower* default rate for loans with LTV just below 125%.

APR around LTV 125%

	(1)	(2)	(3)
Sample:	LTV:124-126	LTV:122.5-127.5	LTV:120-130
Human	-0.167**	-0.193***	-0.218***
	(-2.56)	(-4.37)	(-6.43)
Below Cutoff	0.152	0.177**	0.086*
	(1.52)	(2.38)	(1.97)
Human $\times$ Below Cutoff	-0.274***	-0.209***	-0.140***
	(-3.14)	(-3.51)	(-3.29)
Year-Month FE	YES	YES	YES
Dealer FE	YES	YES	YES
Car Make FE	YES	YES	YES
Car Model FE	YES	YES	YES
Controls	YES	YES	YES
Observations	8407	16946	30135
Adjusted R^2	0.390	0.402	0.406

Below the LTV of 125%, within the LTV bandwidth of 124 to 126, humans underwrite loans with an APR that is incremental 27.4 basis points lower than the machine underwrites.

Loan Profitability around LTV 125%

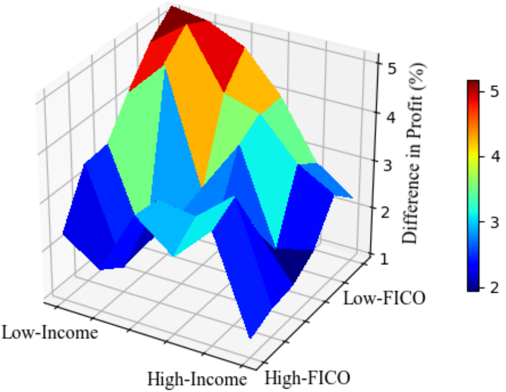
	(1)	(2)
Dep Var:	Loan Profit	Loan Profit
Machine	0.023***	0.016**
	(3.96)	(2.58)
LTV125	-0.033***	-0.042***
	(-3.91)	(-5.74)
Machine × LTV125	0.052***	0.053***
	(4.29)	(4.22)
Year-Month FE	YES	YES
Dealer FE	NO	YES
Car Make FE	NO	YES
Car Model FE	NO	YES
Controls	NO	YES
Observations	17524	16831
Adjusted R^2	0.024	0.059

The machine *premium* increases to 27.9% for loans just below the cutoff — a 7.5 percentage points increase relative to the profitability of 26.9% for human-underwriters.

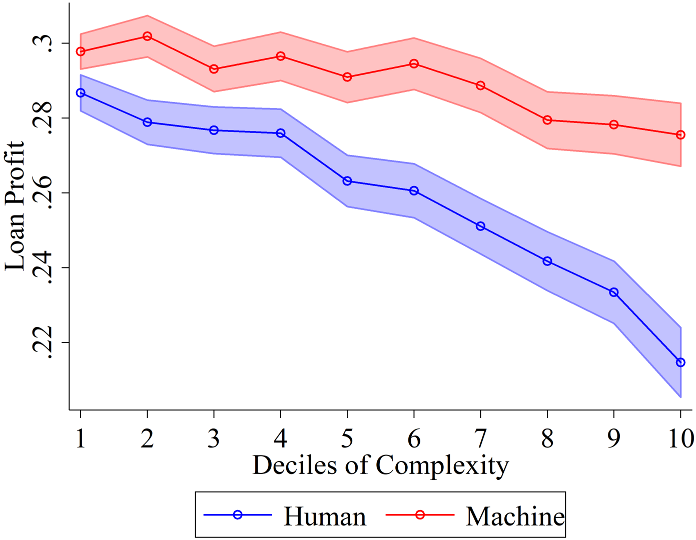
How does loan performance change with complexity?

- Default prediction might be more difficult for certain loans.
- For example, thin credit files and low income might increase the complexity of underwriting.
    - Low-wage borrowers have more income volatility, less insurance, etc.
- Human underwriters may find it increasingly difficult to analyze the risk of these loans.
- On the other hand, human underwriters can review more nuanced information, and their discretion can be helpful in these cases
- We compare the loan performance for loans with varying degrees of complexity
- We quantify loan complexity as the expected magnitude of the forecast errors for predicting default.
    - This magnitude captures the difficulty in accurately predicting loan outcomes.

Machine premium across FICO and DTI



Loan profit across deciles of complexity FICO & DTI



Profitability of complex loans Heatmap

	ML Model		Linear Model	
	(1)	(2)	(3)	(4)
Dep Var:	Loan Profit	Loan Profit	Loan Profit	Loan Profit
Machine	0.028***	0.031***	0.028***	0.031***
	(11.52)	(12.48)	(11.40)	(12.45)
Complexity	0.025***	0.041	0.031***	0.042
	(6.95)	(1.11)	(8.76)	(1.11)
Machine × Complexity	0.010***	0.008**	0.009***	0.008**
	(3.71)	(3.07)	(3.46)	(3.23)
Default LL	-0.073***	-0.096***	-0.077***	-0.096***
	(-12.93)	(-9.69)	(-13.93)	(-9.68)
Machine × Default LL	0.002	0.003	0.002	0.003
	(0.67)	(0.90)	(0.70)	(0.86)
Constant	0.260***	0.251***	0.260***	0.253***
	(132.59)	(20.37)	(129.92)	(22.95)
Year-Month FE	YES	YES	YES	YES
Dealer FE	NO	YES	NO	YES
Car Make FE	NO	YES	NO	YES
Car Model FE	NO	YES	NO	YES
Controls	NO	YES	NO	YES
Observations	134180	133629	134180	133629
Adjusted R^2	0.053	0.088	0.056	0.088

Conclusion

- We use a randomized experiment to evaluate the outcome of automating loan underwriting process.
- Machine-underwritten loans generate more profit, have lower default probability, and have higher interest rates than human-underwritten loans.
- The machine premium is considerably larger at a critical underwriting threshold, where the potential for agency conflict is high.
- The machine profit premium is considerably larger for more complex loans.

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Prepayment rate

	(1)	(2)	(3)
Sample:	Uncensored	Censored	All
Machine	0.008	0.004	0.005
	(0.89)	(1.03)	(1.14)
Constant	0.548***	0.310***	0.337***
	(75.35)	(62.67)	(67.81)
Observations	18899	120023	141023
Adjusted R^2	0.002	0.064	0.082

Loan interest rate (APR), with controls APR

	(1)	(2)	(3)	(4)
Sample:	Uncensored	Censored	All	All
Machine	0.313***	0.284***	0.293***	0.442***
	(15.19)	(12.36)	(13.31)	(12.37)
Loan-to-Value	1.056***	1.313***	1.260***	
	(10.70)	(17.14)	(17.99)	
Loan Amount	-0.000***	-0.000***	-0.000***	
	(-9.00)	(-8.41)	(-9.90)	
Term (months)	0.003	-0.025***	-0.014***	
	(0.78)	(-6.45)	(-4.74)	
Discount	0.002***	0.002***	0.002***	
	(17.96)	(21.23)	(20.99)	
Credit Score	-0.014***	-0.010***	-0.011***	
	(-28.66)	(-21.89)	(-22.82)	
Homeowner Indicator	-0.409***	-0.264***	-0.286***	
	(-7.28)	(-9.73)	(-11.42)	
Bankruptcy	-0.800***	-0.609***	-0.649***	
	(-14.37)	(-15.51)	(-16.39)	
Debt-to-Income Ratio	0.055	-0.062	-0.054	
	(0.35)	(-1.13)	(-1.58)	
New Car Indicator	-0.026	0.100*	0.076	
	(-0.36)	(1.79)	(1.52)	
Car Age (years)	0.041***	0.088***	0.084***	
	(2.74)	(8.50)	(8.72)	
Year-Month FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	NO
Car Make FE	YES	YES	YES	NO
Car Model FE	YES	YES	YES	NO
Observations	17807	113863	134126	141023
Adjusted R^2	0.423	0.463	0.450	0.045

Loan default probability, with controls Default

	(1)	(2)	(3)	(4)
Sample:	Uncensored	Censored	All	All
Machine	-0.024***	-0.021***	-0.021***	-0.016***
	(-4.40)	(-5.62)	(-6.59)	(-4.03)
Loan-to-Value	0.231***	0.145***	0.162***	
	(9.42)	(9.90)	(11.99)	
Loan Amount	0.000***	0.000***	0.000***	
	(2.98)	(9.35)	(10.23)	
Term (months)	0.003***	-0.001***	0.000	
	(5.24)	(-4.03)	(0.30)	
Discount	0.000***	0.000***	0.000***	
	(18.89)	(16.96)	(18.65)	
Credit Score	-0.001***	-0.001***	-0.001***	
	(-16.78)	(-14.12)	(-16.07)	
Homeowner Indicator	-0.042*	-0.038***	-0.040***	
	(-1.96)	(-5.58)	(-5.86)	
Bankruptcy	-0.085***	-0.059***	-0.063***	
	(-7.34)	(-12.64)	(-14.52)	
Debt-to-Income Ratio	0.225***	0.035*	0.032**	
	(8.23)	(1.86)	(2.61)	
New Car Indicator	0.015	0.025***	0.025***	
	(0.98)	(2.86)	(3.12)	
Car Age (years)	0.011***	0.010***	0.011***	
	(3.62)	(6.75)	(7.85)	
Year-Month FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	NO
Car Make FE	YES	YES	YES	NO
Car Model FE	YES	YES	YES	NO
Observations	17807	113863	134126	141023
Adjusted R^2	0.093	0.106	0.109	0.050

Recovery from defaulted loans Default

Dep Var:	Recovery from Car Liquidation		Net Loss	
	(1)	(2)	(3)	(4)
Machine	0.015***	0.015***	-0.013***	-0.016***
	(4.69)	(4.39)	(-2.75)	(-3.19)
Age of Default (mth)	-0.007***	-0.007***	0.000	0.000
	(-42.11)	(-43.75)	(0.94)	(0.93)
Loan Amount		0.000***		0.000***
		(8.66)		(6.79)
Term (months)		0.001		0.002**
		(1.43)		(2.30)
Discount		0.000		0.000***
		(0.99)		(3.30)
Credit Score		0.000		-0.000***
		(1.57)		(-5.00)
Homeowner Indicator		-0.016**		0.008
		(-2.41)		(0.63)
Bankruptcy		0.010***		-0.019***
		(2.79)		(-3.40)
Debt-to-Income Ratio		0.009		0.021*
		(1.35)		(1.88)
New Car Indicator		-0.057***		-0.103***
		(-8.07)		(-7.69)
Car Age (years)		-0.010***		0.036***
		(-7.34)		(14.01)
Year-Month FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES
Car Make FE	YES	YES	YES	YES
Car Model FE	YES	YES	YES	YES
Observations	31176	30143	23850	23021
Adjusted R^2	0.174	0.191	0.096	0.110

Book value inflation? Residual from hedonic regression

	(1)
Dep Var:	Car Book Value
New Car Indicator	4221.199***
	(32.01)
Car Age (years)	-892.782***
	(-59.88)
Car Mileage	-0.055***
	(-34.87)
Remaining Warranty (years)	-46.148***
	(-3.87)
Remaining Warranty (mileage)	0.002
	(1.01)
Constant	18239.225***
	(265.99)
Car Make FE	YES
Car Model FE	YES
Observations	134145
Adjusted R^2	0.820

Difference in APR residuals

	(1) Uncensored	(2) Completed	(3) Censored	(4) All
Human	0.064**	0.051***	0.063***	0.063***
	(2.73)	(4.64)	(5.86)	(6.22)
Constant	-0.013	-0.008	-0.035**	-0.032*
	(-0.61)	(-0.63)	(-2.99)	(-2.60)
Year-Month FE	YES	YES	YES	YES
Observations	18127	79062	113977	134126
Adjusted R^2	0.010	0.002	0.004	0.004

Difference in APR residuals, with controls

	(1) Uncensored	(2) Completed	(3) Censored	(4) All
Human	0.056*	0.037***	0.041***	0.045***
	(2.49)	(3.85)	(4.71)	(5.42)
Loan Amount	0.000	0.000***	0.000***	0.000***
	(0.51)	(6.54)	(9.75)	(9.52)
Term (months)	-0.005**	-0.011***	-0.016***	-0.012***
	(-3.17)	(-8.85)	(-9.78)	(-10.59)
Credit Score	0.001***	0.001***	0.002***	0.002***
	(4.55)	(13.27)	(17.34)	(16.74)
Debt-to-Income Ratio	-0.158*	0.015	0.013	0.003
	(-2.19)	(0.75)	(0.48)	(0.14)
Discount	0.001***	0.001***	0.001***	0.001***
	(12.12)	(19.65)	(18.84)	(19.62)
Loan-to-Value	-0.207**	-0.197***	-0.214***	-0.224***
	(-3.28)	(-5.63)	(-7.12)	(-7.57)
Homeowner Indicator	-0.020	0.009	0.019	0.010
	(-1.00)	(0.53)	(1.21)	(0.76)
Bankruptcy	0.017	0.063***	0.092***	0.078***
	(0.62)	(4.84)	(6.53)	(6.10)
New Car Indicator	-0.033	-0.013	-0.009	-0.012
	(-1.09)	(-0.65)	(-0.37)	(-0.59)
Car Age (years)	0.007	0.022***	0.027***	0.026***
	(0.73)	(5.16)	(7.41)	(7.69)
Constant	-0.254	-0.415***	-0.297*	-0.421***
	(-1.18)	(-4.01)	(-2.30)	(-4.44)
Year-Month FE	YES	YES	YES	YES
Dealer FE	YES	YES	YES	YES
Car Make FE	YES	YES	YES	YES
Car Model FE	YES	YES	YES	YES
Observations	17807	78806	113863	134126
Adjusted R^2	0.084	0.080	0.098	0.093

Profitability across two borrower risk dimensions, with controls Complex

Dep Var:	(1) Loan Profit	(2) Loan Profit	(3) Loan Profit
Machine	0.014***	0.018***	0.018***
	(5.84)	(7.64)	(8.09)
Low FICO	-0.038***		
	(-12.48)		
Machine × Low FICO	0.018***		
	(5.39)		
High DTI		-0.013***	
		(-5.42)	
Machine × High DTI		0.012***	
		(3.62)	
Low FICO-High DTI			-0.017***
			(-5.15)
Machine × Low FICO-High DTI			0.024***
			(6.63)
Year-Month FE	YES	YES	YES
Dealer FE	YES	YES	YES
Car Make FE	YES	YES	YES
Car Model FE	YES	YES	YES
Controls	YES	YES	YES
Observations	133629	133651	133629
Adjusted R^2	0.061	0.062	0.063

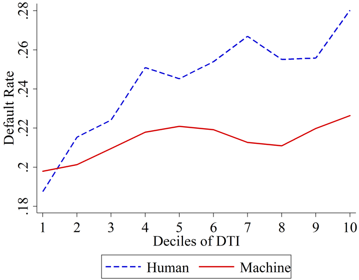
Profitability across two borrower risk dimensions, subsamples Complex

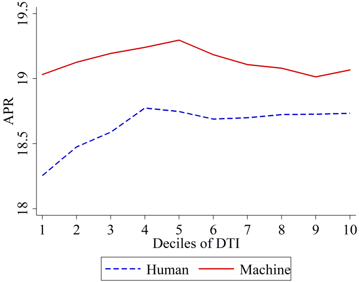
	(1)	(2)	(3)
Sample:	Not-Censored	Completed	Censored
Machine	0.016**	0.014***	0.020***
	(2.78)	(3.59)	(7.62)
Low FICO-High DTI	-0.024**	-0.042***	-0.020***
	(-2.70)	(-7.45)	(-4.72)
Machine × Low FICO-High DTI	0.030**	0.045***	0.023***
	(3.07)	(8.72)	(5.33)
Constant	0.270***	0.187***	0.266***
	(69.31)	(49.43)	(126.42)
Year-Month FE	YES	YES	YES
Observations	18245	79417	113961
Adjusted R^2	0.005	0.032	0.023

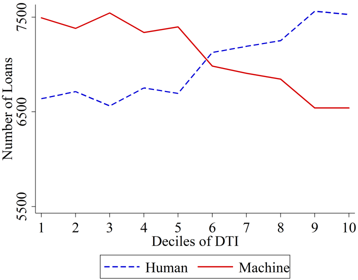
Profitability across quartiles of risk dimensions Complex

	(1)	(2)
Dep Var:	Loan Profit	Loan Profit
Machine	0.041***	0.013***
	(7.24)	(4.26)
FICO Quantiles=2	0.015***	
	(3.62)	
FICO Quantiles=3	0.025***	
	(5.14)	
FICO Quantiles=4	0.032***	
	(5.23)	
Machine × FICO Quantiles=2	-0.013*	
	(-2.61)	
Machine × FICO Quantiles=3	-0.020***	
	(-3.97)	
Machine × FICO Quantiles=4	-0.022***	
	(-3.49)	
DTI Quantiles=2		-0.004
		(-1.39)
DTI Quantiles=3		-0.009*
		(-2.34)
DTI Quantiles=4		-0.011*
		(-2.53)
Machine × DTI Quantiles=2		0.013**
		(3.10)
Machine × DTI Quantiles=3		0.017**
		(3.26)
Machine × DTI Quantiles=4		0.023***
		(4.92)
Constant	0.243***	0.267***
	(42.04)	(113.78)
Year-Month FE	YES	YES
Observations	134234	134212
Adjusted R^2	0.021	0.020

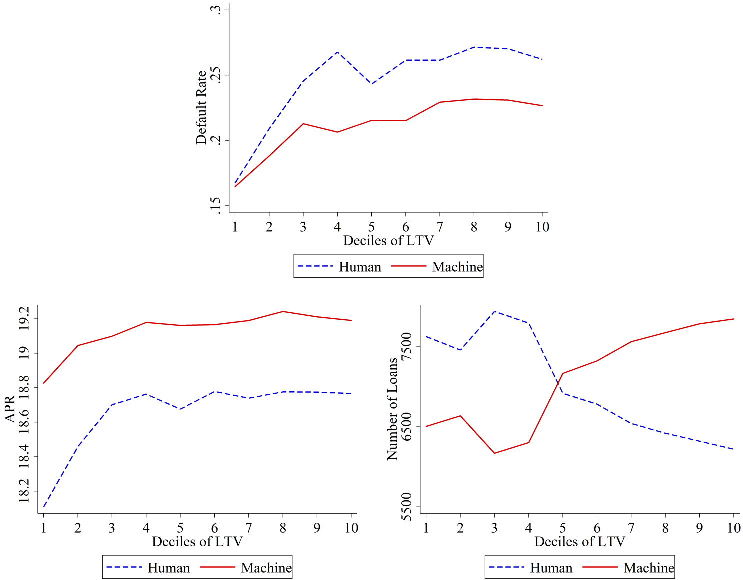
Human and machine decision criteria - DTI Criteria





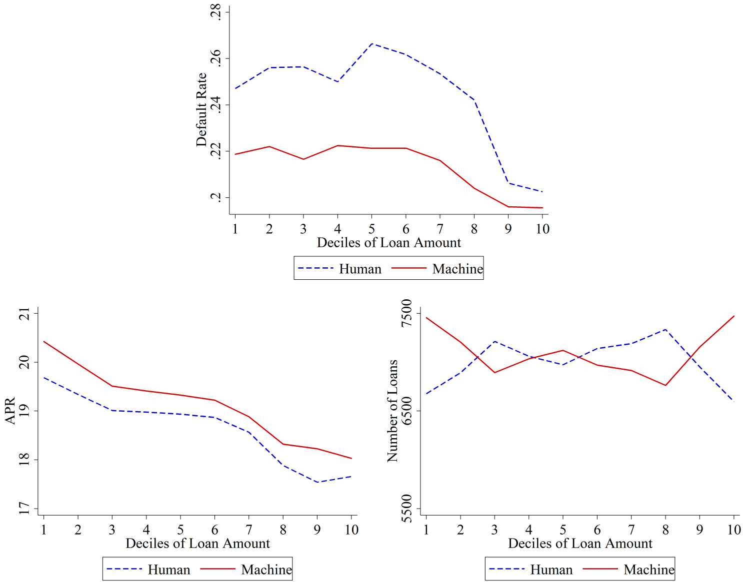


Human and machine decision criteria - LTV Criteria

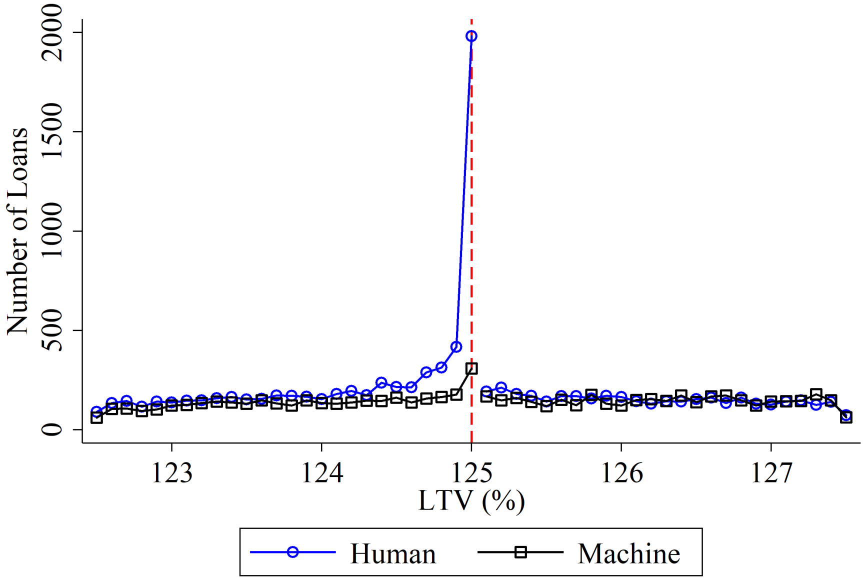


Human and machine decision criteria - Loan Amount

Criteria

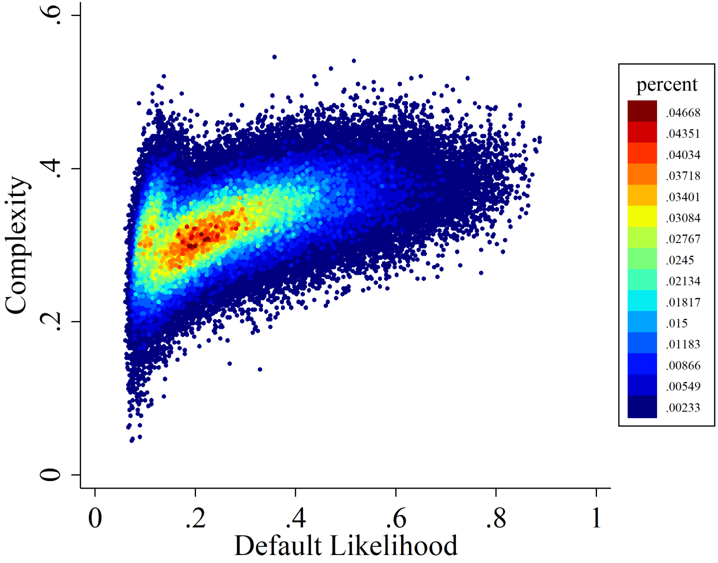


Number of loans around LTV 125%

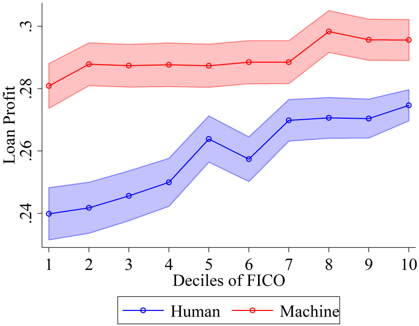


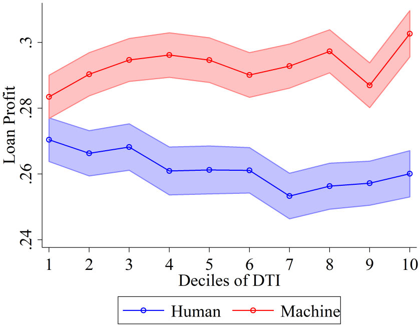
Relationship between complexity and default likelihood

Back



Loan profit across deciles of credit score and DTI Complexity





Number of loans and deciles of complexity Complexity