Human vs. Machine: Underwriting Decisions in Finance

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ABSTRACT

Using a randomized experiment in the auto lending industry, we provide causal evidence of improved loan profitability and lower loan default rates in the use of algorithmic machine underwriting. Using an experiment in which 140,000 loans are randomly assigned to machine versus human underwriters, we find that machine-underwritten loans generate 10.2% higher profit than human-underwritten loans. Otherwise identical loans underwritten by machines not only have higher APRs but also have a 6.8% lower incidence of default. Importantly, the performance gap is more pronounced with more complex loans. Moreover, the categorization of consumer credit profiles leads to discontinuities for human-underwritten loans. At the threshold, default rates are 40.2% higher, and generate 24.7% less profit for human underwriters. These results are consistent with a human mind's limited capacity in handling complex analysis, and agency conflicts in the underwriting process.

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I. Introduction

The rapid development of technology in the last few decades has transformed many facets of financial markets. In securities markets, algorithmic trading has improved market liquidity (Hendershott et al., 2011) and price discovery (Chaboud et al., 2014). Fintech lenders and blockchain payments are also disrupting the finance industry (Goldstein et al., 2019). A focal point of these developments is that a growing range of financial decision making tasks are being automated through the use of big-data analysis and advanced statistical tools. However, our knowledge of the net benefits of automating financial decisions and how it impacts business efficiency and resource allocation is still limited.

Firms have started automating decision making and pricing in consumer lending: Algorithms now make credit decisions without human intervention at some lenders. Automation can potentially save time and payroll costs, increase accuracy, and mitigate conflicts of interest. Kahneman (1973) describes the human limits in attention and information processing. Accordingly, tasks such as data collection, data processing, and numerical pattern prediction are strong candidates for automation (Chui et al., 2016). If loan underwriting profitability relies on such complex and perhaps non-linear interactions of dozens of variables, then machine decision-making may outperform that of humans.

However, delegating financial decisions to machines can come at a cost of losing soft information. For example, human underwriters can review more nuanced information for borrowers with thin credit files and low income. If soft information plays an important role in the underwriting process, then an experienced underwriter may retain an advantage over the machine. Moreover, automation does not always improve speed and flexibility for financial institutions—notably when the Small Business Administration launched the Paycheck Protection Program in response to COVID-19 (Levitt, 2020). Consequently, it is important to understand the relative performance of machine and human underwriters and how their performance is affected by loan application complexity or borrower riskiness. Using a randomized experiment in the automotive finance industry, this paper examines these conflicting hypotheses.

Using realized cash flows and default rates, our paper quantifies the difference in loan profitability, default risk, and loan pricing in a setting in which underwriting is randomly assigned to machine and human underwriters. Importantly, we also compare the performances for loans with different characteristics to shed light on the underlying channels for the difference in performance. The experiment is conducted by an indirect lender that started automating part of its underwriting process in 2012. Prior to the experiment, when a consumer applied for a loan to purchase a car from an auto dealer, a human underwriter received the credit application from the dealer, evaluated the risk, and determined the loan price and terms. Since 2012, incoming applications are assigned to human and machine underwriters based on a random draw. This randomization results in approximately 140,000 subprime auto loans across over 4,000 U.S. car dealerships acquired by the same financier—with half of the loans underwritten by humans and the other half by machine.

Our setting focuses on the indirect financing channel, in which financing is negotiated between the auto dealer and the car buyer and then sold at auction to lenders who service the loan. The lender bids on approximately 1 million loans each year. After the lender submits a bid, the loan terms and pricing are compared to three to ten other lenders and the best bid is chosen by the dealership. Therefore, the underwriter faces potential agency conflicts where on one hand, she needs to optimally price the loan based on the risk profile, and on the other hand, she needs to maintain a competitive price to keep a high chance at winning the auction, all while maximizing her monthly commission.

We find that machine-underwritten loans are significantly more profitable than human underwritten loans originated in the same month. The profitability of uncensored machine-underwritten loans is 9.5% ($p < 0.01$) higher than human-underwritten loans (a 2.5% increase relative to the baseline profit of 26.4% for human-underwritten loans). The profitability of machine-underwritten loans for the full sample, which includes realized and estimated profit on loans that have not come to term, is 10.2% higher ($p < 0.01$). The results are robust to using different specifications and controls.

Next we examine the source of this difference in profit and find that different loan pricing explains part of the results. The underwriter has discretion to set the interest rate (APR) and the discount (i.e., the discount from par value that the lender pays for the loan). Human-underwriters offer a significantly lower APR (44.2 basis points). The difference in pricing holds even after controlling for the risk profile of the loans. A lower APR increases the chance of the lender in winning the auction but lowers the profitability of the loan. Human underwriters appear more conservative in maintaining their chances at winning the auction.

We next compare the default risk of human- and machine-underwritten loans. The finding that machine-underwritten loans have a higher APR suggests that machines select a riskier set of loans to fund. Interestingly, the default rate of machine-underwritten loans is 6.8% *lower* than that of human-underwritten loans (a 1.6% decrease relative to human underwritten loans with a mean default rate of 23.5%). Machine-underwritten loans also experience lower early default rates in the first 24, 30 and 36 months of their life. The decline in early default rates relative to human underwriting means are 6.9%, 8% and 8.3%, respectively. These findings suggest that machine-underwritten loans not only have higher prices but also are less risky. Overall, these findings suggest that the machine's higher profitability comes from better risk-adjusted pricing. Offering lower prices for loans with similar characteristics is consistent with incentives to win the loan auction due to potential conflicts of interest related to compensation structures.[1].

To shed light on potential channels explaining the difference in performance, we examine how loan characteristics differentially affect loan profitability across underwriter type. A main argument against automated underwriting is that manual underwriting can better handle complex borrowers with poor credit history or low income (Ayres, 2008; Finlay, 2008; Staff, 2011). We compare the human-machine profit differential across different quantiles of FICO score and debt-to-income (DTI) ratio. We find that the machine 'premium' mainly

[1]The empirical literature connecting private benefits with production targets is thick (e.g., Daniel et al. (2002); Tzioumis and Gee (2013); Chan et al. (2014); Larkin (2014); Liebman and Mahoney (2017)

comes from loans with low FICO score and high DTI—the riskiest borrowers. The relationship is almost monotonic across quantiles of FICO and DTI. Moreover, the relationship is stronger for borrowers with a history of bankruptcy. The machine premium is 20.8% higher on loans with below median FICO, above median DTI, and with prior bankruptcy (a 5.5% increase relative to the baseline of 26.5% for human). These results suggest that the machine outperforms human underwriters mainly for riskier loans, perhaps due to its better capacity to analyse the complexity of high-risk loans.

Next, we compare the performance of machine and human underwriters around a critical loan-to-value (LTV) cutoff used by the lender to categorize consumer credit profiles for human underwriters. The lender imposes restrictions to high-risk borrowers with an LTV above 125%. If the incentives of human underwriters are not fully aligned with the lender, the underwriters might have a preference for high-risk borrowers just below the 125% LTV. Underwriters can submit competitive bids for high-risk borrowers just below the threshold, while still complying with the firm's guidance. Consistent with this intuition, we observe a cluster of human-underwritten loans right at LTV of 125%. We find that humans underwriters are 6.4 times more likely to accept loans below the cutoff than in the case of automated underwriting. Moreover, the likelihood that a borrower has prior bankruptcy is 18% higher for human underwritten loan at this LTV threshold when compared to the rest of the sample. Importantly, the machine profit premium increases to 24.7% for loans below the cutoff, and human underwritten loans are 40.2% more likely to default in the first 36 months. The disproportionate funding of riskier loans just below the LTV guideline is consistent with underwriter bias or conflict of interest.

Finally, we examine how machine underwriting affects efficiency—specifically, the timing of funding. The data reports the time between when the vehicle buyer signs the sales contract and when the lender funds the loan. We find that the time to fund declines by 4.3% for machine-underwritten loans, suggesting that machine-underwriting also improves the efficiency of the lending business.

This paper contributes to the literature on the role of technology in finance. Technology is using unconventional data (digital and social footprints) to provide solutions that can complement and potentially substitute traditional credit bureau scores (Berg et al., 2019; Agarwal et al., 2020). Other studies show that investors adopting automated robo-advisors achieve better outcomes (D'Acunto et al., 2019; Coleman et al., 2020). There are evidences that Fintech lenders improve efficiency (processing time and default rate) in mortgage lending (Fuster et al., 2019), and reduce customer discrimination (Bartlett et al., 2019).

Our paper focuses on one important segment of consumer lending: auto loans. More than one-third of U.S. households held vehicle-related debt in 2016 (Bricker et al., 2017), and the size of this debt is increasing; the total vehicle loan balance in the U.S. was $717 billion in 2008 and over $1.1 trillion in 2018 (Zabritski, 2018). We document a novel randomized experimental setting that shows automated underwriting improves subsequent loan performance and profitability in the subprime auto lending market. A serious issue surrounding recent studies analyzing the impact of Fintech innovations in financial services is the selection problem: customers who choose to use Fintech products can be different from traditional customers in ways that influence loan outcomes. Moreover, firms providing Fintech services are likely very different from the legacy firms in dimensions unrelated to the technology. In our setting, otherwise identical loans are split randomly between human and machine underwriters, which allows us to tease out the effect of machine adoption on loan performance.

Our paper is most closely related to Fuster et al. (2019): They describe how technology assists human underwriters in processing information. While focusing on the time-efficiency of FinTech lenders in comparison to legacy lenders, the authors also find a lower default rate for FinTech mortgages. They attribute the lower default of FinTech mortgages to FinTech firms attracting less risky borrowers relative to legacy lenders. In our setting, all the loans are originated by the same lender and have similar borrower characteristics. While Fuster et al. (2019) attribute the lower default rate to FinTech firms borrower selection, our setting looks at randomly assigned borrowers to identify the effect of the machine decision-making, especially for complex loans. Moreover, we contribute to the literature on the role of technology in finance (D'Acunto et al., 2019; Coleman et al., 2020; Berg et al., 2019; Agarwal et al., 2020) by providing evidence of the efficiency of technology adoption in auto lending market.

Our paper also contributes to the finance literature centered on limited attention. The model of Hirshleifer and Teoh (2003) shows that, due to limited attention, information presented in salient, easily processed forms can be absorbed more easily than less salient information. For example, there are evidence that investors pay more attention to more general and familiar information in the stock market (Peng and Xiong, 2006; Corwin and Coughenour, 2008; Lou, 2014). In our paper, the agent (human underwriter) may be bound by his limited attention such that he cannot process a large number of variables associated with a credit application, leading to the inferior performance compared to the machine underwriter. Our results reveal that the difference between human and machine is most important when the loan underwriting complexity is highest.

The remainder of the paper is organized as follows. In section II, we provide a brief overview of indirect auto financing and describe the implementation of machine decision-making in loan underwriting. In section III, we describe our data on individual auto loans. Section IV describes the main results. In section V, we investigate the channels that explain the machine's outperformance. Section VI concludes.

II. Overview of the auto financing service and the experiment

A. *The indirect auto financing service*

In this section, we briefly describe the practice of indirect auto lending to show the workflow that an underwriter performs for a typical loan. The indirect auto financing process starts at an auto dealership. A customer walks into the dealership to look for a vehicle. After finding a car she wants to buy, the customer and the dealer negotiate and agree on a price. If the customer decides to finance the purchase with a loan, but the dealership does not finance the loan directly, the dealership agent uses an indirect auto financing service. With this service, the dealer originates the auto loan, then sells the loan to a financial institution immediately after completing the sales transaction. First, the dealer submits the customer's credit application to multiple potential lenders at the time of purchase (typically through an online system). After reviewing the information, potential lenders submit their bid for the loan, and the dealer accepts the bid that offers the highest profit for the dealer that is acceptable to the consumer. The dealer then completes the transaction with the vehicle buyer. Over the next several days, the lender verifies the borrower's information in the credit application. If this screening does not flag any problem, the lender acquires the loan and pays the dealer. If the verification process fails to confirm the details in the loan application, the loan is renegotiated and sold to the lender at a discount reflecting its higher risk.

After obtaining the loan, the lender collects monthly payments from the borrower. The lender retains the property right to the vehicle until the loan has been paid in full, so the vehicle acts as a collateral. In case a borrower defaults, the lender can attempt to repossess the vehicle, and sell it at a commercially reasonable price, usually at a public auction. If the vehicle sells for more than the outstanding loan amount net the recovery cost, then the borrower receives the balance. If there is an outstanding loan amount even after the sale of the repossessed vehicle, then the lender can sue the borrower for the remaining balance. If the lender wins a judgment against the borrower, it can attempt to collect additional funds from the borrower, for example, by garnishing the borrower's wage. In the subprime auto loan market, the interest rates are high (19.3% on average in our sample), and defaults are frequent (average default rate is 23.6%), so recovery activity after default is common.

There are over 65,000 financial institutions across the U.S. that finance auto loans, including banks and non-bank lenders such as finance companies. The market is competitive, and no single firms holds more than 6% market share (Baines and Courchane, 2014). Our data provider has been in the business for several decades and is one of the top 20 finance companies in terms of market share. It buys loans from thousands of dealerships in more than forty states (Figure 1) and securitize the loans. It is therefore a good representative of lending firms in this market.

B. The underwriting process

The underwriters at our lending firm conduct direct transactions with the dealers. After receiving credit application, they review borrower's information, decide to accept or reject the application, and bid for the accepted loans in a competing market. Lenders typically have a guideline for underwriters using which they can evaluate the risk profile of the applicants. Figures Internet Appendix IA.1 and IA.2 show examples of these guidelines for two typical firms in the industry. The underwriters consider a host of factors such as credit scores, income, employment status, nature of the job and employment time, residence time, and past bankruptcy records. They also consider the type and model of the car, whether it is used or new, and the resale value. They assess the risk profiles based on these guidelines and decide on the acceptance and pricing of the loans. In some cases, dealers convey additional information to the human underwriter that helps the borrower receive credit.

C. *Implementation of machine underwriting*

At the end of 2012, the company launches an automated underwriting system that can fully replace human underwriters in making lending decisions. They decide to use the machine underwriter concurrently with the human underwriter team. Essentially, this is a randomized experiment to evaluate the effectiveness of the machine underwriter. Since the system adoption, each credit application that the firm receives is randomly assigned to either the machine underwriter (with probability 50%) or a human underwriter. The machine underwriter processes all the tasks that a human underwriter typically does.

We use data on this randomized experiment to compare the performance of loans underwritten by the machine versus humans. We observe loan and borrower characteristics in the data along with an indicator for different underwriters, including the machine. We do not see the rejected loans, but the number of machine-underwritten loans are roughly the same as human-underwritten loans, suggesting that the machine accepts or wins the bidding as frequently as humans.[2]

III. Data

Our novel dataset includes all loans that the indirect financing firm acquires in forty states between 1995 and July 2019. In total, we observe key features of more than 320,000 loans that originate at 4,412 dealerships located in 1,902 U.S. ZIP codes. For each transaction, the data include characteristics of the borrower (e.g., income, credit score, home ownership, bankruptcy history), the vehicle (e.g., book value, age, mileage), and the loan (e.g., price, term, amount financed, default). We can also observe loan outcomes up until the end of the data timeline (July 2019). If a loan's status is complete, we know if the loan is paid in full (on original schedule or paid early) or default. In the case of a default, we also

[2]However, near the end of the sample, more loans were designated for machine underwriting. The management team of the lender felt increasingly confident in the performance of the automated underwriting process.

observe how much the lender recovers (from selling the vehicle and collections from the borrower) and how much remaining loan balance is lost due to the default. For ongoing loans, we observe the payments up to the final date of the data timeline. The main results compare the performance of machine and human starting from the beginning of 2013 when the experiment starts. But we also use the loans originated before 2013 to build a credit model that predicts the performance of the ongoing loans.

A. *Measuring of profitability*

To assess the performance of completed loans, we construct a profitability measure that calculates the present value of the cash flows received from the borrowers divided by the initial investment to acquire the loan. The measure takes into account the discount from the face value to the lender as well as the principal loss after recovery in case of a default. For a loan that is fully paid off, the profit is calculated as the sum of present values of monthly payments minus the initial investment. For a loan that defaults in a certain period, profit is the sum of present values of monthly payments up to the point of default, plus the discounted value of the recovered losses from the collections, minus the initial investment. We then calculate the percentage profit as the profit scaled by the initial investment.

$$Profit = \sum_{d} PV(payment_d) + PV(Recovery|Default)] - Initial\ investment \tag{1}$$

$$Profit\ ratio = Profit/Initial\ investment \tag{2}$$

where *Initial investment* is equal to the amount financed, minus the discount from the face value to the lender, plus any participation fee paid to the dealer.

For the ongoing loans, we only observe the actual payments and the default action before the end of our sample period in July 2019. Therefore, we estimate the expected profit using the projected estimates for future payments, the probability of future default events, and the expected loss given default. Our profit estimate is as below:

$$Profit = \sum_d q_d[\sum_{i=1}^{d-1} PV(payments_i) + PV(Recovery_d|Default_d)] + (1 - \sum_d q_d)PV(all\ payments) - Initial\ investment \quad (3)$$

where q_d is the default probability estimated from the uncensored loans in the data.

To estimate the default probabilities, we first estimate the default probability for ongoing loans as a function of the age of the loans in months (d_t) and other loan characteristics. We use machine learning algorithms, including logistic regression, random forest, and neural network, and a stacked ensemble model that combines all these models. We use all the uncensored loans in our sample with all potential default predictors available including the FICO score, DTI, LTV ratio, prior bankruptcy, loan amount, homeownership, the dealer ID, macroeconomics variables such as the interest rate and US corporate BBB spread, and vehicle information such as make, model, mileage, and age. We train our models using 70% of the sample and test and adjust the hyperparameters using the 30% test sample. The stacked model yields the best out of sample results based on both the F1-score and the AUC (Area Under The Curve) of ROC (Receiver Operating Characteristics) curve. It yields an F1-score of 0.68 and an AUC of 0.711. We then use the stacked model to predict the default rate of the ongoing loans. This yields the aggregate default rate of each loans during its lifetime. To estimate the default rates for each month, we then project the aggregate default rate on the default trajectory estimated from the uncensored loans using a polynomial regression of order 5 as in Figure 2. This yields the default likelihood of each loan in each period, q_d. Figure 2 depicts the average predicted default rate in each period for post-2012 loans. The likelihood of default is low initially but rises quickly until around 18 months after loan origination, then falls until the end of the loan life cycle.

Second, we estimate the recovery given default. We first calculate the recovery amount as a percentage of gross default for all completed loans that default. We then estimate a regression of the percentage recovery on loan characteristics, vehicle characteristics, dealer ID, age of the loan, and a host of other variables discussed above. Post regression, we generate the expected recovery percentage for all the ongoing loans as a function of the age of the loan.

Third, we calculate the expected payments collected from the borrower, which represent the first two inputs to equation 3. To do this, we consider the default event in each period as a state of the world with probability q_d. The total payments in each state are equal to the cumulative payments up to that period in present value, plus the present value of recovery amount given default (recovery percentage times the remaining principal). The last state is the scenario in which the loan completes without default (probability $1 - \sum_d q_d$).

Finally, the initial investment is equal to the amount financed, minus the discount from the face value to the lender, plus any participation fee paid to the dealer. The percentage profit is calculated as the sum of expected payments divided by initial investment.

Throughout the paper, we report the results both for the completed loans using the actual cash flows and for the ongoing loans using the expected profit.

B. *Descriptive statistics*

We use the full sample starting from 1995 to construct the profit measures as described in subsection III.A. Because the experiment starts at the end of 2012, we focus on loans that are originated after 2012 and have at least 12 months of data to compare the performance of human and machine. There are more than 140,000 loans in this period, about half of the loans are ongoing, and half are complete (they either reach the end of loan duration, default halfway, or are prepaid halfway). 50.4% of loans in this period are machine-underwritten deals.

We describe loan, borrower, and vehicle characteristics underwritten by human and machine separately in Table I. All variables are winsorized at 1% and 99% level. The vehicle characteristics in the machine sample are similar to those in the human sample. In terms of loan characteristics, there is also no remarkable difference in the duration of the loan (69 months on average) or the amount financed (slightly more than $17,800 on average). These terms are typically negotiated between the dealer and the customer. The human loans have a higher average FICO score and are more likely to own a house, but they are more likely to have prior bankruptcy and a higher DTI ratio.

The machine charges a higher APR of around 50 basis points and obtains loans with slightly larger discounts. Loan outcomes show a clear difference in performance. The default likelihood in human-underwritten loans is 24.5%, about three percentage point higher than the default ratio of machine-underwritten loans.

Overall, from the simple univariate comparison, we can see that machine underwriter tends to price the loan more aggressively and achieve better outcomes in terms of the default rate. In the next step, we compare the performance of machine and human loans in a more rigorous setting.

IV. Machine vs. human in loan outcomes

A. *Profit*

In this section, we compare the profitability of the loans underwritten by machine and human. Our identification comes from the fact that loan applications are randomly assigned to either machine or human underwriters. Therefore, any difference in loan outcome can be attributed to the performance difference between the machine and human. Importantly, the borrowers or the dealers are not aware of the lender's experiment, so there is no concern about self-selection of dealers or borrowers into certain type of loans. We run the OLS regression:

$$Profit = \alpha + \beta machine\_dummy + \gamma Controls + \epsilon \tag{4}$$

Our main variable is *Machine*, a dummy that equals one if the deal is underwritten by the machine, and zero if underwritten by human. We do not use any control variables except for origination year-month fixed effects in the baseline estimates, as the applications are randomized and the observed characteristics of the originated loans in the sample are in fact the choices made by the machine or human. Nevertheless, we also report all the results with a full set of controls including loan, borrower, and vehicle characteristics in the appendix. All regressions are clustered by year-month and dealer ID (2-way clustering).

Table II reports the results. Column (1) shows that the coefficient of *Machine* is positive and economically and statistically significant at 1% level for the uncensored loans. Compared to human underwriters, the machine generate 2.5 percentage point higher profit, a 9.5% improvement relative to the mean profit ratio of 26.4% for humans. Column (2) of Table II reports the regression result for the *completed* loans. The completed loans include both the uncensored loans and loans whose original term would end after the end of our sample period, but they either defaulted or were prepaid during our sample period. 58.7% the loans in our sample are completed. The results show that the machine loans generate 2.75 percentage point higher profit on these completed loans.[3] Further, Columns (3) and (4) show that the machine generates a statistically and economically significant higher profit of 2.7 percentage points whether we look at the censored loans or the full sample. These correspond to 10.2% improvements over the human profitability.

Table IA.1 shows that the results hold as strongly if we control for a full set of observable characteristics in our sample. These characteristics include LTV, loan amount, terms in month, FICO score, homeownership, income, DTI, whether the vehicle is used or new, vehicle age, whether the vehicle is imported, whether it is classified as a luxury car, and year-month, dealer, make, and model fixed effects.

Overall, using a clean randomized setting, these results suggest that the machine picks and price loans that yield a significantly larger profit, and these results are highly consistent for different sub-samples of the data and using a full set of control variables.

[3]The baseline profit is lower at 17.6% for the completed loans by construction, as the subsample of loans completed during our period contains disproportionately higher percentage of defaulted or prepaid loans.

B. Pricing

The machine outperformance can be potentially attributed to a better pricing strategy or better evaluation of the default risks. Here we compare the pricing of the loans underwritten by machine and human. We estimate a regression of the APR on *Machine* and other controls:

$$APR = \alpha + \beta machine\_dummy + \gamma Controls + \epsilon \tag{5}$$

Similar to the results on profitability, we first estimate the results without controls with year-month fixed effects, and then report the results using a full set of controls described above. Standard errors are clustered by year-month and dealer. Table III shows that machine loans have a significantly higher APR of 46.2 basis points for uncensored loans. The results are 44.1 and 44.2 for the censored loans and the full sample. The t-statistics vary from 11.22 to 12.79, suggesting statistically distinguished pricing patterns that can reflect different pricing strategies of human and machine. The pricing difference also holds after controlling for observable loans characteristics.

These loans are originated in the same month and are randomly assigned to machine and human, making such a different pricing patterns more striking. The underwriters in our setting compete with three to ten other bids from other lenders. Therefore, human underwriters might be more lenient on offering lower prices to increase their chance of winning the auction. However, based on the ratio of the underwritten loans, we do not observe that human underwriters show a better chance at winning the auctions in general.

Overall, these results is consistent with human underwriters either picking less risky loans or showing some agency conflicts that incentivize them to offer more conservative prices to win the auctions and potentially earn a commission. In the next section, we examine the riskiness of the loans originated by human and machine.

C. Default rate

The finding that machine-underwritten loans have a higher APR suggests that machines may select a riskier set of loans to fund. Table IV compares the default rates between human and machine loans. Interestingly, Column (1) of Panel A shows that the machine-underwritten loans are 1.7% less likely to default, which is equivalent to 5.3% improvement over the baseline default rate for humans. The machine also shows 7.2% and 6.8% less default rate for censored loans and the overall sample.

Moreover, we compare the early default rates between the machine and human. We look at actual early default rates within 12 months, 18 months, 24 months, 30 months, and 36 months of origination. (Fuster et al. (2019) also use similar measures of default within one year and two year horizons). Our d month default measure is a dummy that equals 1 if the default event occurs within the first d months of origination. The sample contains loans with an origination date of at least 36 months before the end of our sample period.

Results are presented in Panel B of Table IV. The results show that the baseline default rates in the first 12 and 18 months are relatively small at 3.3% and 6.9% respectively, and there is no performance difference between machine and human loans. However, the human underwritten loans show a significantly higher default rate over the 24 months, 30 months, and 36 months horizons. The machine underwriter shows a better performance as the horizon increases and yields 6.9%, 8%, and 8.3% less default relative to human over the first 24 months, 30 months, and 36 months respectively. Moreover, Table IA.2 shows that the results are even stronger after controlling for the observed characteristics.

These results suggest that machine might have a better performance in evaluating the default risk of subprime loans in the sample. These findings can also complement the results in Fuster et al. (2019), who compares the loans between FinTech and legacy lenders and show that FinTech lenders experience lower default rate in the mortgage market. While Fuster et al. (2019) attributes the results to different borrower types selecting the FinTech lenders, our results show an improvement caused by machine underwriters.

D. Processing Time

We also compare the machine with humans in terms of processing time, which reflects the time efficiency of the origination process. We use the number of days between the date of vehicle purchase and loan funding, $Time\_to\_fund$. This measure indicates how fast an underwriter conducts the verification process and pay the dealer. Table V reports the results. The machine loans show a 0.77 faster processing time for the uncensored loans and 0.51 for the full sample. This time measure includes a wider range of processes taken place between the lender and the dealers, and the time difference implies that the time efficiency is reflected in the overall timing of the origination process.

V. The underlying channels behind the machine premium.

A. Machine premium in more complex loans

In this section, we investigate the possibility that the complexity of risky loans can contribute to the difference in profitability between machine loans and human. Kahneman (1973) points out human limited attention and cognitive resources in processing information. In our context, when the complexity of loans increases, human underwriters may find it increasingly difficult to analyze the risk and price the loan. Therefore, we expect the gap in performance between machine and human to increase as the complexity increases.

We compare the machine premium across three key debtor's characteristics: FICO score, debt-to-income (DTI) ratio, and prior bankruptcy record. Customers who defaulted before are more likely to default again. Customers with either low FICO score or high DTI are also perceived to be riskier in their repayment capability. Furthermore, low FICO score and high DTI are both associated with low income. Low-income customers statistically have stronger monthly income swings than middle-income customers,[4] and such income volatility can make it more complicated to predict the loan performance.

First, to see the change in machine premium across quantiles of FICO and DTI, we estimate the machine premium across these two dimensions and plot the results in Panel A of Figure 3. While the machine does not show a sizable premium for high-FICO and low DTI loans, it shows a remarkably better performance for borrowers with low FICO and high DTI. Importantly, Panel B of Figure 3 shows that this pattern is even more substantial in the subsample of borrowers with prior bankruptcy, whereas it is not as strong for borrowers without a bankruptcy record (Figure 3, Panel C).

Second, we put our observation in formal tests. We use three dummy variables for FICO, DTI, and prior bankruptcy. *Low FICO* is an indicator equal to one if the debtor's FICO score is below the median FICO score in the sample. *High DTI* is an indicator equal to one if the debtor's DTI is above the median DTI. *Bankruptcy* is an indicator equal to one if the customers have prior bankruptcy. We also construct variable *FICO_DTI_BK*, which equals one if all three variables are equal to one. We estimate a regression of loan profit on *Machine*, a characteristics dummy, and the interaction of *Machine* and that dummy. Results are reported in Table VI.

In column 1, the interaction of *Machine* and *Low FICO* have a positive and significant coefficient ($p < 0.01$). For a loan with low FICO score, the machine outperforms humans by 12.5% (3.4 percentage point higher than the baseline human-underwriting profit of 27.1%). Similarly, when we look at loans with high DTI in column 2, the effect of machine is also positive and significant ($p < 0.01$). The machine profit premium over humans is 12.5% (3.3 percentage point higher than the baseline profit of 26.5%). The machine also outperforms humans by 12.6% for customers with prior bankruptcy records. Finally, in column 4 we look at cases where the complexity is largest: customers who have below median FICO, above median DTI, and prior bankruptcy record. The machine premium is 20.8% higher (a 5.5%

[4]https://www.nytimes.com/interactive/2017/05/31/business/31-volatility.html. The graph is based on data from JP Morgan Chase customers

increase relative to the baseline of 26.5% for human). These results suggest that the machine outperforms human underwriters mainly for riskier loans, perhaps due to its better capacity to analyse the complexity of high-risk loans.

B. Machine premium at critical LTV cutoff

Next, we compare the performance of machine and human around the critical LTV cutoff used by the lender to guide underwriters. The lender imposes restrictions on high-risk borrowers with an LTV above 125%. If incentives of human underwriters is not fully aligned with the lender, they might have a preference for high-risk borrowers just below the 125% LTV. The reason is that underwriters can submit competitive bids at a reasonable price for high-risk borrowers just below the 125% LTV. This helps them increase the chance of winning the bid, while they still comply with the firm's guidance.

The changing behavior of underwriters around an arbitrary cutoff has been documented before. Keys et al. (2010) provide evidence that there are significantly more loans with FICO score just above 620 than those with FICO score just below 620. The reason is that loans with FICO score higher than 620 are more likely to be securitized. But loans just above the cutoff are more likely to default than those just below. Griffin and Maturana (2016) also show that loan originators are more likely to conduct financial misrepresentation on loans with FICO 620 than on loans with FICO 619.

We first look at the percentage of the human-underwritten loans around the LTV 125% cutoff. If human underwriters prefer loans right at the cutoff, while the machine does not have such preference, we expect the percentage of human-underwritten loans increases at the cutoff. Figure 4 shows that the percentage of human-underwritten loans is noticeably higher right at the cutoff of LTV 125%. Humans underwriters are 6.4 times more likely to accept loans just below the cutoff than in the case of automated underwriting.

Moreover, we find that the borrowers funded by human underwriters at the cutoff are considerably more likely to have a history of bankruptcy. Table VII analyses the loans around the LTV cutoff (loans with LTV from 122.5% to 127.5%) and reports that the likelihood that a borrower has prior bankruptcy is an additional 18 percentage point higher for human loans relative to the machine loans at the cutoff. Here the *LTV125* is an indicator that equals one if the loan's round LTV value is 125. Column (2) shows that the results hold after controlling for other loan, borrower, and vehicle characteristics and using dealer fixed effects.

Next, Panel A of Table VIII compares the profitability of machine versus human for loans around the cutoff. The results show that the machine premium increases to 24.7% for loans at the cutoff (6.7 percentage point larger than the baseline human profit ratio of 27.1%). Column 2 shows that the results do not change after including the controls.

Finally, we compare the default rates for humane and machine loans around the cutoff. Panel B of Table VIII shows that the higher default rates of human underwritten loans are much more pronounced for loans around the LTV cutoff. For example, human loans have 8.2 percentage point higher default rate for loans with LTV of 125, which is a sizable 40.2% higher default relative to the machine default rate.

Overall, the results in this section suggest that human underwriters are considerably more likely to originate otherwise riskier loans below the critical LTV cutoff, and these loans show sizably higher default rates and lower profitability. The disproportionate funding of the riskier loans just below the LTV guideline by the lender, without incorporating the risk into the price, can be consistent with certain biases or conflicts of interests.

VI. Conclusion

In this paper, we examine the effect of adopting machine decision-making in auto loan underwriting. Our setting is an experiment in which loan applications are randomly assigned to machine or human underwriting. The results show that algorithmic underwriting outperforms human: loans underwritten by machines result in higher loan profits and lower default rates. This result is consistent with a key finding in the literature on the role of technology in finance—automation improves efficiency.

We investigate two mechanisms that gives rise to the difference in performance. We find that the improvement in machine performance is attributable to loan complexity, and in cases where humans potentially face a conflict of interest. We interpret these results as evidence of bias and limited capacity by human underwriters.

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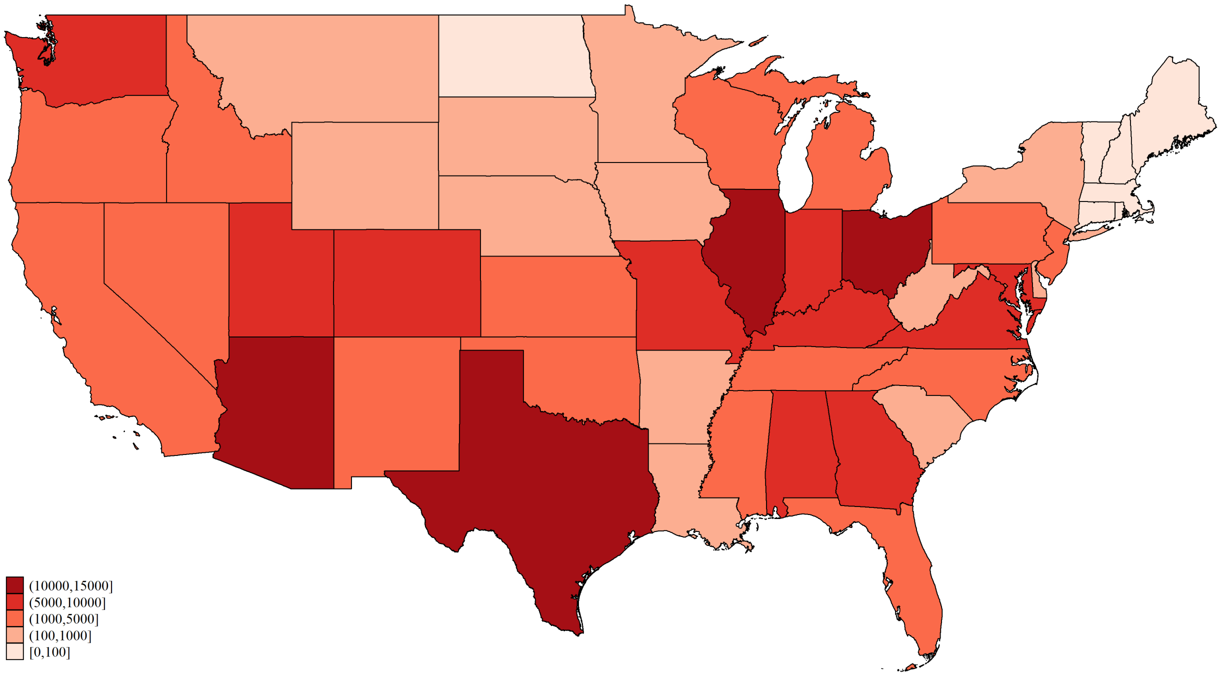


Figure 1. Geographic distribution of loans. This map presents the geographic distribution of loans originated after 2012.

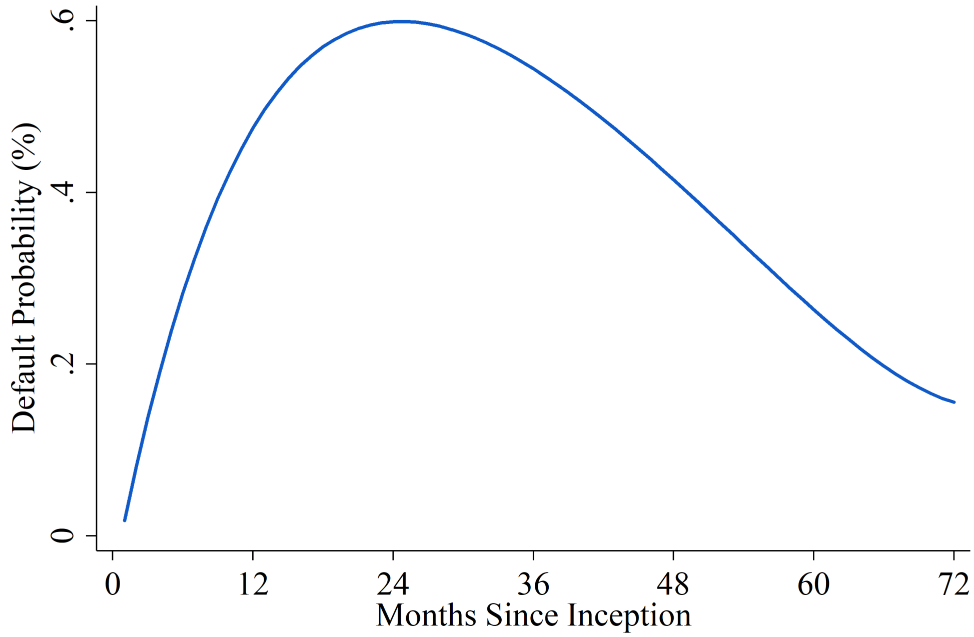
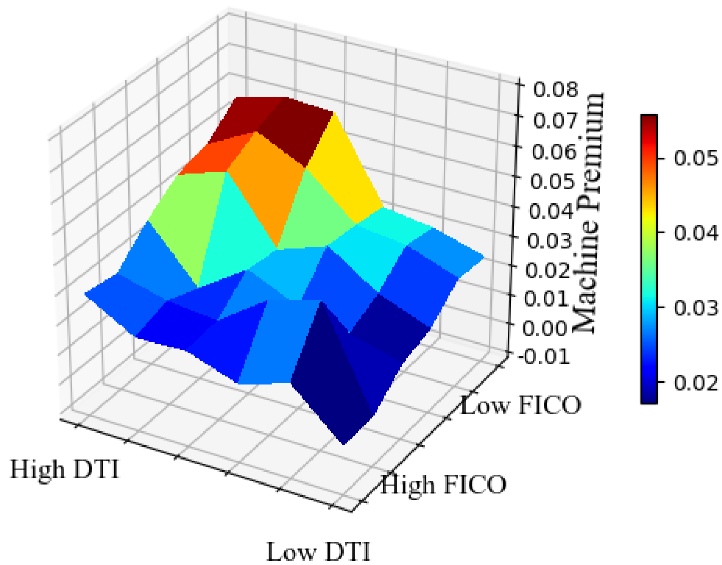
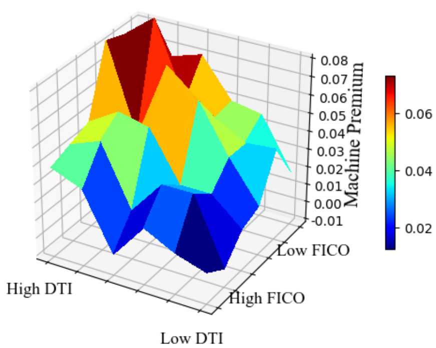


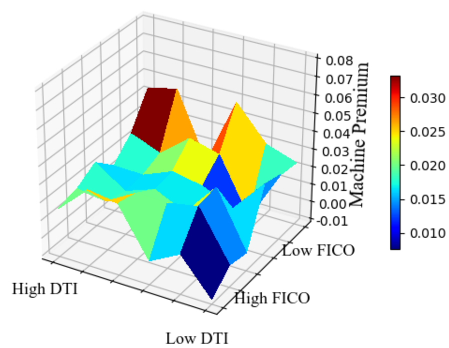
Figure 2. Predicted default probability. This figure presents a line plot of the predicted probability of default during the life cycle of loans originated after 2012.



(a) All Sample



(b) With Bankruptcy



(c) No Bankruptcy

Figure 3. Machine premium in complex loans. These figures show the machine profit premium across two dimensions of customer characteristics (FICO score and debt-to-income). Panel A includes all sample. Panel B includes only debtors who had prior bankruptcies. Panel C includes only debtors who had no bankruptcy history.

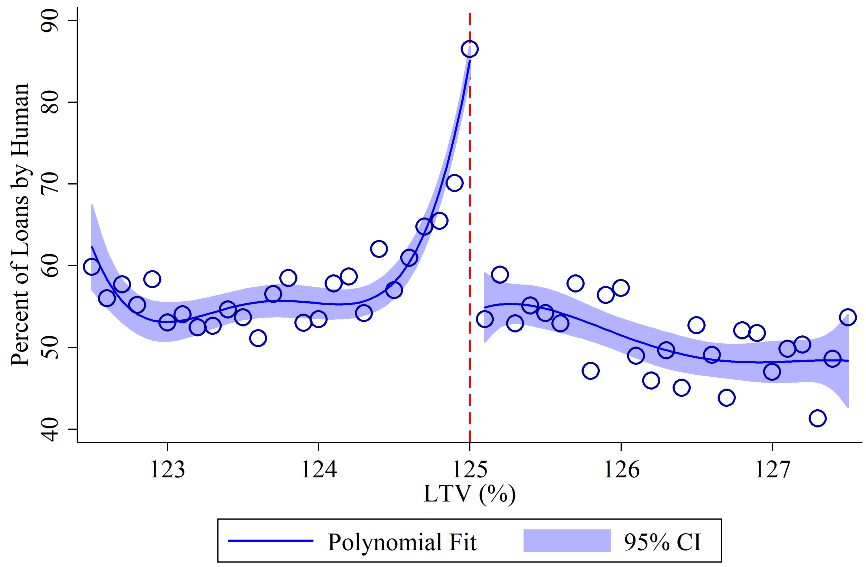


Figure 4. Loan distribution around LTV threshold of 125%. This figure presents the percentage of loans underwritten by humans around the loan-to-value threshold of 125%

Table I. Summary statistics of human- and machine-underwritten loans. This table reports separate summary statistics for the human-underwritten loans and the machine-underwritten loans, between Jan 2013-July 2019. The number of observations, mean, and standard deviations are reported for loan outcomes, loan characteristics, borrower characteristics and vehicle characteristics.

	Human			Machine		
	count	mean	sd	count	mean	sd
Default indicator	69945	0.245	0.430	70990	0.213	0.410
APR	69945	0.186	0.023	70990	0.191	0.023
Discount	69945	687.302	421.163	70990	697.141	416.945
Loan to value	69945	1.314	0.169	70988	1.340	0.167
Term (months)	69945	69.180	5.547	70990	69.352	5.488
Amount financed	69945	17828.711	4050.808	70990	17847.663	4215.364
Credit score	67159	530.851	48.500	67481	525.879	46.872
Bankruptcy	69945	0.529	0.499	70990	0.343	0.475
Homeowner dummy	69945	0.046	0.210	70990	0.037	0.190
Gross monthly income	69945	4619.552	2085.677	70990	4246.897	1746.682
Debt payments/ Income	69938	0.390	0.086	70973	0.379	0.087
Vehicle age in years	69936	2.680	1.848	70967	2.747	1.895
Vehicle book value	69945	13858.690	3969.549	70988	13601.235	3993.565
Vehicle mileage	69943	40614.427	21797.791	70989	41037.718	22555.729
Vehicle make reliability	69945	53.001	17.238	70990	53.318	17.434
Vehicle import dummy	69945	0.664	0.472	70990	0.685	0.465
Vehicle luxury dummy	69945	0.037	0.188	70990	0.033	0.178

Table II. Effect of machine underwriting on profit ratio. This table reports estimates from panel regressions of profitability on whether the loan is underwritten by the machine. The dependent variable is the loan-level profit ratio (profit/initial investment). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. 'Not-censored' loans are those expected to be completed within our sample period. 'Completed' loans are those that have completed during our sample period. 'Censored' loans are those expected to be completed beyond our sample period. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Not-Censored	Completed	Censored	All
Machine	0.025***	0.028***	0.027***	0.027***
	(4.41)	(6.63)	(9.44)	(9.66)
Constant	0.264***	0.176***	0.264***	0.264***
	(60.95)	(37.79)	(99.09)	(95.34)
Observations	18887	82468	119512	140498
Adjusted R^2	0.004	0.030	0.023	0.021

Table III. Effect of machine underwriting on loan pricing. This table reports estimates from panel regressions of initial pricing on whether the loan is underwritten by the machine. The dependent variable is the original interest rate of a loan (*APR*). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. 'Not-censored' loans in column 1 are those expected to be completed within our sample period. 'Censored' loans in column 2 are those expected to be completed beyond our sample period. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
	Not-Censored	Censored	All
Machine	0.462***	0.441***	0.442***
	(12.79)	(11.22)	(12.37)
Constant	18.718***	18.661***	18.671***
	(402.73)	(403.22)	(426.95)
Observations	18899	120023	141023
Adjusted R^2	0.041	0.050	0.045

Table IV. Effect of machine underwriting on default probability. This table reports estimates from panel regressions of default rate on whether the loan is underwritten by the machine. *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. The dependent variable in Panel A is an indicator equal to one if the loan defaults, and zero otherwise. 'Not-censored' loans are those expected to be completed within our sample period. 'Censored' loans are those expected to be completed beyond our sample period. The dependent variables in column (1) to (5) of Panel B are indicators equal to one if the loan defaults within 12 months, 18 months, 24 months, 30 months and 36 months of the loan origination, respectively. The samples in columns (1)-(5) of panel B include loans with at least 36 months of data. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Default Probability

	(1)	(2)	(3)
	Not-Censored	Censored	All
Machine	-0.017*	-0.016***	-0.016***
	(-2.31)	(-3.92)	(-4.03)
Constant	0.323***	0.222***	0.237***
	(47.79)	(52.30)	(52.89)
Observations	18899	120023	141023
Adjusted R^2	0.003	0.052	0.050

Panel B: Early Default Probability

	(1)	(2)	(3)	(4)	(5)
	12M Def	18M Def	24M Def	30M Def	36M Def
Machine	-0.000	-0.003	-0.008*	-0.013**	-0.017***
	(-0.07)	(-1.17)	(-2.63)	(-3.38)	(-3.97)
Constant	0.033***	0.069***	0.116***	0.163***	0.205***
	(32.13)	(33.68)	(40.60)	(44.05)	(45.97)
Observations	91498	91498	91498	91498	91498
Adjusted R^2	0.001	0.001	0.001	0.001	0.002

Table V. Effect of machine underwriting on loan funding time. This table reports estimates from panel regressions of funding time on whether the loan is underwritten by the machine. The dependent variable is the number of days it takes between the vehicle purchase and the funding of the loan by the lender. *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. 'Not-censored' loans in column 1 are those expected to be completed within our sample period. 'Censored' loans in column 2 are those expected to be completed beyond our sample period. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
	Not-Censored	Censored	All
Machine	-0.772**	-0.457***	-0.505***
	(-3.44)	(-3.66)	(-3.99)
Constant	10.504***	11.855***	11.662***
	(44.10)	(66.38)	(65.07)
Observations	18868	119616	140585
Adjusted R^2	0.015	0.054	0.053

Table VI. Effect of machine underwriting on profit ratio across different customer characteristics. This table reports estimates from panel regressions of profitability on whether the loan is underwritten by the machine, and on different risk characteristics of customers. The dependent variable is the loan-level profit ratio (profit/initial investment). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. *Low FICO* is an indicator equal to one if the debtor's FICO score is below the median FICO in the data, and zero otherwise. *High DTI* is an indicator equal to one if the debtor's DTI is above the median DTI, and zero otherwise. *Bankruptcy* is an indicator equal to one if the debtor had bankruptcy before, and zero otherwise. *FICO_DTI_BK* is an indicator equal to one if *Low FICO*, *High DTI* and *Bankruptcy* are all equal to 1, and zero otherwise. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Profit ratio	(2) Profit ratio	(3) Profit ratio	(4) Profit ratio
Machine	0.020***	0.019***	0.018***	0.020***
	(7.30)	(7.60)	(6.45)	(8.19)
Low FICO	-0.021***			
	(-5.40)			
Machine × Low FICO	0.014***			
	(3.69)			
High DTI		-0.008*		
		(-2.58)		
Machine × High DTI		0.014***		
		(3.91)		
Bankruptcy			-0.017***	
			(-3.52)	
Machine × Bankruptcy			0.016**	
			(3.17)	
FICO_DTI_BK				-0.022***
				(-3.90)
Machine × FICO_DTI_BK				0.035***
				(6.59)
Constant	0.271***	0.265***	0.270***	0.265***
	(130.64)	(113.84)	(111.86)	(125.17)
Observations	134234	134234	134234	134234
Adjusted R^2	0.021	0.020	0.020	0.021

Table VII. The association between human underwriting and prior bankruptcy around LTV threshold of 125%. This table reports the association between human underwriting and prior bankruptcy around the LTV threshold of 125%. The sample includes loans with LTV ranging from 122.5% to 127.5%. LTV125 is an indicator equal to one if the rounded value of the loan's LTV is equal to 125%, and zero otherwise. *Human* is an indicator equal to one if the loan is underwritten by a human underwriter, and zero if the loan is underwritten by the machine. *Bankruptcy* is an indicator equal to one if the debtor had prior bankruptcy, and zero otherwise. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Bankruptcy	Bankruptcy
Human	0.171***	0.087***
	(9.54)	(6.28)
LTV125	-0.060***	-0.034**
	(-4.71)	(-3.22)
Human × LTV125	0.180***	0.117***
	(12.09)	(9.43)
Constant	0.400***	2.711***
	(18.52)	(8.44)
Observations	17640	17007
Adjusted R^2	0.079	0.369
Controls	No	Yes

Table VIII. Effect of machine underwriting around LTV threshold of 125%. This table reports the effect of machine underwriting around the LTV threshold of 125%. The samples in both panels include loans with LTV ranging from 122.5 to 127.5. LTV125 is an indicator equal to one if the rounded value of the loan's LTV is equal to 125, and zero otherwise. *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. The dependent variable in Panel A is the loan-level profit ratio (profit/initial investment). The dependent variables in Panel B are the same early default probabilities used in Panel B of Table IV. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Profit

	Profit ratio	Profit ratio
Machine	0.020**	0.018**
	(3.23)	(2.73)
LTV125	-0.030***	-0.036***
	(-3.84)	(-4.95)
Machine × LTV125	0.047***	0.051***
	(4.65)	(4.86)
Constant	0.271***	-0.116
	(56.64)	(-0.48)
Observations	17524	16892
Adjusted R^2	0.023	0.055
Controls	No	Yes

Panel B: Early Default Probability

	(1)	(2)	(3)	(4)	(5)
	12M Def	18M Def	24M Def	30M Def	36M Def
Machine	0.001	0.007	0.003	-0.003	-0.005
	(0.24)	(1.46)	(0.43)	(-0.31)	(-0.55)
LTV125	0.002	0.012*	0.029***	0.049***	0.057***
	(0.41)	(2.04)	(3.99)	(5.46)	(5.15)
Machine × LTV125	-0.002	-0.018	-0.048***	-0.057***	-0.082***
	(-0.32)	(-1.82)	(-3.70)	(-5.47)	(-6.22)
Constant	0.034***	0.066***	0.114***	0.161***	0.204***
	(15.42)	(17.95)	(21.51)	(21.86)	(24.00)
Observations	12091	12091	12091	12091	12091
Adjusted R^2	0.000	0.000	0.002	0.005	0.006

Table IX. Profitability of quick-funding loans versus normal loans. This table examines the impact of quick funding cases on profit ratio. The dependent variable is the profit ratio (profit/initial investment). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. *QuickLoan* is an indicator equal to one if the loan is funded within 3 days of the contract date, and zero otherwise. 'Not-censored' loans are those expected to be completed within our sample period. 'Censored' loans are those expected to be completed beyond our sample period. The regressions in Panel A do not include controls. The regressions in Panel B control for loan characteristics (vehicle payment/income ratio), borrower characteristics (credit score squared, bankruptcy history), vehicle characteristics (age, book value, mileage, reliability rating, import dummy, luxury dummy), and dealership fixed effects. Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: No Controls

	(1)	(2)	(3)
	Not-Censored	Censored	All
Machine	0.024***	0.026***	0.026***
	(4.33)	(9.33)	(9.59)
QuickLoan	-0.016	-0.026***	-0.023***
	(-1.45)	(-3.63)	(-3.78)
Machine × QuickLoan	0.006	0.026**	0.021**
	(0.44)	(2.86)	(2.81)
Constant	0.265***	0.265***	0.265***
	(63.27)	(108.56)	(103.96)
Observations	18887	119512	140498
Adjusted R^2	0.004	0.023	0.021

Panel B: With Controls

	(1)	(2)	(3)
	Not-Censored	Censored	All
Machine	0.025***	0.028***	0.028***
	(6.32)	(10.49)	(11.69)
QuickLoan	0.014	-0.007	-0.003
	(1.31)	(-1.15)	(-0.66)
Machine × QuickLoan	-0.011	0.021*	0.016*
	(-0.89)	(2.49)	(2.20)
Constant	0.324***	0.072**	0.122***
	(7.17)	(2.97)	(5.38)
Observations	17849	113436	133691
Adjusted R^2	0.045	0.063	0.061

For Online Publication

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Auto Financing Guidelines

Lender Requirements:

Lender Name:	[redacted]
Type:	Non Prime to Prime Auto Loans
Minimum FICO:	Generally 550 (can go as low as 525 depending on situation)
Minimum Age:	19
Minimum Residence:	6 Months or 2 years in Area
Minimum Employment:	12 Months History
Minimum Income:	$1900
Max DTI (gross/net):	50%
Bankruptcy Exclusion:	Re-established/Discharged
Repossessions:	1 year or older

Deal Parameters:

Max Advance to Dealer:	125% of NADA Clean Retail
Dealer Discount:	Discount Fee may apply
Down Payment:	0-20%
Amount Financed:	$5,000 to $100,000
Term Range:	24-72 Months
Rate Range:	3.99% to State Max depending on credit
Finance Sales Tax:	Yes
Finance Gap:	Max sale price $800
Finance Warranty:	$2500 max 12 month 12,000 miles minimum coverage If PAF warranty isn't sold, $100 fee will be deducted from advance
Dealer Compensation (fee/reserve):	N/A
Processing Fee:	TBD

Collateral Requirements:

New and/or Used Autos:	Both acceptable
Max Collateral Age:	2006 and newer
Max Mileage:	100,000 (exceptions considered)
Ineligible Vehicles:	Salvage titles/buybacks not acceptable
Value Collateral:	NADA Clean Retail +/- Mileage +/- Options

Possible Stip Requirements:

Proof of Income	Telephone/Electric Bill
Proof of Residence	Valid Driver's License
References	Proof of Insurance

Figure IA.1. Lender A's Underwriter Guideline

Standard Program Guidelines

The Standard Program is [redacted]'s most popular program. Dealers rely on this program as the backbone of their sub-prime finance business. Customers with credit score 0-599 fall into the Standard Program tier. Benefits include:

- On-the-spot approval
- No minimum credit score
- No minimum amount financed
- No minimum income
- No minimum job time
- No minimum residence time
- Hard-to-prove incomes accepted
- Previous repossessions – no problem!
- No maximum vehicle age
- Bankruptcies OK (see BK Policy)
- No maximum vehicle mileage

Program Requirements

Credit Score:	599 & Below
PTI:	
Bureau Time:	No Min
Good Trades:	
Max Term:	42-72
Rates:	Up to max state usury
Down Payment:	10%
Max LTV:	140%
Min Discount:	$75
Vehicle Age:	No Max

Stipulation Requirements

- Proof of Income
- Proof of Insurance
- Driver License
- Completed/Signed Credit Application
- 10 References
- Proof of Residence
- Landline/Cell Phone Bill

Figure IA.2. Lender B's Underwriter Guideline

Table IA.1. Effect of machine underwriting on profit ratio, with controls. This table reports estimates from panel regressions of profitability on whether the loan is underwritten by the machine. The dependent variable is the loan-level profit ratio (profit/initial investment). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. 'Not-censored' loans are those expected to be completed within our sample period. 'Completed' loans are those that have completed during our sample period. 'Censored' loans are those expected to be completed beyond our sample period. The regressions control for loan characteristics (vehicle payment/income ratio), borrower characteristics (credit score squared, bankruptcy history) and vehicle characteristics (age, book value, mileage, reliability rating, import dummy, luxury dummy). Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Not-Censored	(2) Completed	(3) Censored	(4) All
Machine	0.024***	0.036***	0.033***	0.032***
	(6.49)	(11.56)	(12.59)	(13.81)
Constant	0.307***	0.292***	0.081**	0.129***
	(6.94)	(9.51)	(2.88)	(5.33)
Observations	17845	75993	97298	117551
Adjusted R^2	0.046	0.092	0.055	0.054

Table IA.2. Effect of machine underwriting on loan pricing. This table reports estimates from panel regressions of initial pricing on whether the loan is underwritten by the machine. The dependent variable is the original interest rate of a loan (*APR*). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. 'Not-censored' loans in column 1 are those expected to be completed within our sample period. 'Censored' loans in column 2 are those expected to be completed beyond our sample period. The regressions control for loan characteristics (vehicle payment/income ratio), borrower characteristics (credit score squared, bankruptcy history) and vehicle characteristics (age, book value, mileage, reliability rating, import dummy, luxury dummy). Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Not-Censored	(2) Censored	(3) All
Machine	0.194***	0.211***	0.216***
	(10.58)	(8.31)	(9.06)
Constant	24.584***	23.009***	22.645***
	(56.04)	(63.09)	(70.51)
Observations	17857	97666	117933
Adjusted R^2	0.408	0.457	0.440

Table IA.3. Effect of machine underwriting on default probability. This table reports estimates from panel regressions of default rate on whether the loan is underwritten by the machine. The dependent variable is an indicator equal to one if the loan defaults, and zero otherwise. 'Not-censored' loans are those expected to be completed within our sample period. 'Censored' loans are those expected to be completed beyond our sample period. The regressions control for loan characteristics (vehicle payment/income ratio), borrower characteristics (credit score squared, bankruptcy history) and vehicle characteristics (age, book value, mileage, reliability rating, import dummy, luxury dummy). Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Not-Censored	(2) Censored	(3) All
Machine	-0.037***	-0.036***	-0.037***
	(-6.11)	(-8.61)	(-9.96)
Constant	0.342***	0.449***	0.362***
	(7.01)	(11.82)	(11.81)
Observations	17857	97666	117933
Adjusted R^2	0.091	0.088	0.092

Table IA.4. Effect of machine underwriting on loan funding time. This table reports estimates from panel regressions of funding time on whether the loan is underwritten by the machine. The dependent variable is the number of days it takes between the vehicle purchase and the funding of the loan by the lender. *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. 'Not-censored' loans in column 1 are those expected to be completed within our sample period. 'Censored' loans in column 2 are those expected to be completed beyond our sample period. The regressions control for loan characteristics (vehicle payment/income ratio), borrower characteristics (credit score squared, bankruptcy history) and vehicle characteristics (age, book value, mileage, reliability rating, import dummy, luxury dummy). Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
	Not-Censored	Censored	All
Machine	-0.723***	-0.629***	-0.645***
	(-5.43)	(-9.86)	(-10.97)
Constant	6.745***	11.159***	10.135***
	(6.06)	(20.08)	(24.20)
Observations	17827	97379	117616
Adjusted R^2	0.191	0.183	0.180

Table IA.5. Effect of machine underwriting on profit ratio across different customer characteristics. This table reports estimates from panel regressions of profitability on whether the loan is underwritten by the machine, and on different risk characteristics of customers. The dependent variable is the loan-level profit ratio (profit/initial investment). *Machine* is an indicator equal to one if the loan is underwritten by the machine, and zero if the loan is underwritten by a human underwriter. *Low FICO* is an indicator equal to one if the debtor's FICO score is below the median FICO in the data, and zero otherwise. *High DTI* is an indicator equal to one if the debtor's DTI is above the median DTI, and zero otherwise. *Bankruptcy* is an indicator equal to one if the debtor had bankruptcy before, and zero otherwise. *FICO_DTI_BK* is an indicator equal to one if *Low FICO*, *High DTI* and *Bankruptcy* are all equal to 1, and zero otherwise. The regressions control for loan characteristics (vehicle payment/income ratio) and vehicle characteristics (age, book value, mileage, reliability rating, import dummy, luxury dummy). Standard errors are adjusted for clustering, and t-statistics are shown in parentheses below the coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Profit ratio	(2) Profit ratio	(3) Profit ratio	(4) Profit ratio
Machine	0.021***	0.023***	0.018***	0.023***
	(7.98)	(9.06)	(6.44)	(9.51)
Low FICO	-0.011***			
	(-3.60)			
Machine × Low FICO	0.015***			
	(4.52)			
High DTI		-0.006*		
		(-2.55)		
Machine × High DTI		0.012***		
		(3.66)		
Bankruptcy Indicator (=1) prior to Loan			-0.008*	
			(-2.42)	
Machine × Bankruptcy Indicator (=1) prior to Loan			0.027***	
			(6.52)	
FICO_DTI_BK				-0.006
				(-1.41)
Machine × FICO_DTI_BK				0.038***
				(8.61)
Constant	0.144***	0.125***	0.117***	0.106***
	(5.74)	(5.53)	(4.96)	(4.73)
Observations	133691	133691	133691	133691
Adjusted R^2	0.061	0.061	0.061	0.061