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What predicts loan repayment at auto capital?

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What Predicts Loan Repayment at Auto Capital?

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PUBLIC PRESENTATION

This work is accepted for presentation, in part or in full, at the Honors Symposium on Friday, April 15.

For my grandmother, June Kinney, who has had an incredible attitude throughout all of the challenges she has faced. She has led by example and taught me never to give up, regardless of the odds, and to never stop smiling.

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Introduction

Auto Capital is a licensed retail sales finance company located in New York State. It operates to extend credit for the purpose of financing automobiles solely from a used automobile dealership, City Motors. Together Auto Capital and City Motors operate as a buy-here-pay-here,[1] a dealership at which customers are extended credit, buy a vehicle, and make payments. Buy-here-pay-here dealerships cater to customers with damaged credit or no credit, referred to as subprime consumers. These customers are much more likely than prime customers are to default on their loans, making these loans high risk. Traditionally, credit score has been used as a primary lending criteria based on the idea that it indicates the likelihood that a borrower will repay future obligations ("Selection and Use of Credit Scores," 2016). However, there are many problems associated with using credit score alone to predict loan repayment. For example, credit scores can be manipulated by lending agencies and through collections agencies. Credit score also may not be an accurate representation of risk (Demyanyk, n.d.). In addition, many people in the U.S. do not have a credit score. Many companies are beginning to use alternative measures to underwrite, but there are no published studies on using this method for subprime auto loans. The purpose of this thesis is to determine if measures other than credit score are predictors of loan repayment for high-risk borrowers.

I tested several alternative measures selected based on non-standard underwriting models in use and on the data I could access. These alternative measures are time-at-job, time-at-

[1] Names have been changed to protect privacy

residence, down payment, payment ratio, and disposable income. Of these measures, only down payment and payment ratio were the significant predictors of loan repayment for the subprime population.

Background

BUY-HERE-PAY-HERE MODEL

The Buy-Here-Pay-Here model (henceforth "BHPH model") originated in the 1970's as a response to the United States savings and loan crisis. Credit was difficult for many to obtain through banks and rising vehicle prices made it prohibitive to buy with cash. In order for dealerships to continue to sell vehicles, they began to set up related finance companies. Dealers then realized they could profit both off the sale of the vehicle and from the loan. This type of model became popular again after the financial crisis in 2008. Consumers again were having difficulty obtaining financing from banks, especially those with poor credit. The BHPH model evolved to cater specifically to customers with damaged credit. The credit scores of customers served typically range from the mid 400's upward to the low 600's. These customers have a much higher default risk than prime customers. In order to be profitable, it is key to select customers that have the highest likelihood of repayment.

INDUSTRY AVERAGE DEFAULT RATE

The industry average for financing customers with these credit profiles results in three of every ten loans failing ("Auto Capital Policy Manual," 2015). This is huge compared to the average prime auto loan default rate of 0.85% (Mantell, 2015). J.D. Byrider BHPH franchisees, a national chain with 134 stores, generally expect a default rate of 25% (Sawyers, 2014; Parker, 2009). These high default rates make customer selection crucial to the success of the business. Gary Tillery, owner of three J.D. Byrider BHPH's in Albuquerque, New Mexico says, "It's strictly the underwriting and collection side that makes you profitable," (Sawyers, 2014). Tillery is shooting for 22% default rate (Sawyers, 2014). With the proper collections and underwriting process, it is possible to lower this default rate. Jonathan Gandolfo, dealer principal of three J.D. Byrider stores in South Carolina, has a default rate of about 16.5% (Sawyers, 2014).

AUTO CAPITAL

Auto Capital was founded in 2009 to cater to the growing subprime population. Initially, Auto Capital was performing at benchmark loan repayment levels. However, in 2014, as more of Auto Capital portfolio matured, Auto Capital began to experience higher and higher repossession and delinquency rates (G. Parks, 2016). At this point management was unable to determine which characteristics caused one loan to perform better than another. Management assumed that loans to customers with higher credit scores would perform better than those made to customers with lower credit scores, but this had not yet been tested.

AUTO CAPITAL INTEREST RATE

Subprime lenders are under scrutiny in the state of New York. Auto Capital uses a standard interest rate of 22.9% for all loans, regardless of credit score. In New York, interest rates can be fixed or varied, so long as they are under the state maximum of 25%. Auto capital uses a standard rate in order to eliminate the possibility of any discrimination or preferential treatment (“Auto Capital Policy Manual,” 2015). This fixed rate also decreases Auto Capital’s legal exposure to the New York State department of financial services and the Consumer Finance Protection Bureau, as dealerships with variable rates are more of a target.

Both New York State and federal regulators are targeting subprime auto lending practices ("NYC Seeks to Remove," 2015). A state senate panel recently met with industry experts and regulators to discuss ways to tighten subprime auto lending laws (Press, 2105). This is largely due to issues with unfair lending practices, specifically interest rate variation. For example, the Department of Justice (DOJ) and the Consumer Financial Protection Bureau (CFPB) ordered Ally Bank and Ally Financial Inc. to pay $18 million in penalties and $80 million in damages to harmed minority borrowers because the CFPB and DOJ determined that minority borrowers paid higher interest rates for auto loans due to dealers varying interest rates (Ficklin, 2015). For the same reason, Toyota Motor Credit was ordered to pay $19.9 million in restitution and American Honda Finance Corporation was ordered to pay $24 million ("CFPB and DOJ Reach," 2016). This happened because these lenders allowed dealers to vary the interest rate charged to consumers.

The CFPB is urging these lenders to switch to a flat interest rate, which would eliminate dealer markups and the potential for discriminatory lending. Ally has not yet made its system compliant and has been ordered to pay harmed consumers every year until Ally eliminates disparities or moves to a flat fee system ("CFPB and DOJ Reach," 2016). Toyota Motor Credit and American Honda Finance Corporation have been forced to reduce the amount interest rates can be varied to a maximum of 1.25 percentage points or to switch to a flat fee (Lutz, 2015 & “CFPB and DOJ Reach," 2016). In order to avoid these legal problems, some lenders such as BB&T have preemptively switched to a flat rate (Henry, 2015).

WHY AUTO CAPITAL NEEDS ALTERNATIVE UNDERWRITING

As banks are loosening their lending policies and beginning to lend to non-prime customers again, Auto Capital is losing its applicants with the highest credit scores (G. Parks, 2016). In addition, Auto Capital is facing more competition in the market. Therefore, Auto Capital would benefit from an alternative way to assess customer qualification. Auto Capital currently uses some alternative measures to qualify a customer, however management is not sure which measures actually predict loan repayment. If Auto Capital management was aware of what indicated a higher probability of loan repayment, it could more accurately filter customers and approve only those with the highest probability for success. A systematic measure such as this would help to decrease default and delinquency, which would increase Auto Capital's profitability without raising additional concerns of discrimination or unfair lending practices.

PROBLEMS WITH CREDIT SCORES

Fair Isaac Corp.'s credit score (FICO) was initially meant to be used in the underwriting process along with vetting potential borrowers by checking tax returns, pay stubs, employers, and so on, to help banks in determining their customers' creditworthiness. However, the FICO score became seen as a stand-alone statistic that communicated the quality of a loan. Lenders stopped vetting potential borrowers and instead relied on credit score alone (Foust & Pressman, 2008). This was a huge problem for people without a credit score and it became a problem for many lenders.

There are many underbanked consumers in the US due to lack of credit score. One in every 10 adults in the United States does not have a credit score ("Millions of consumers," 2015), which is about 26 million people. In addition, 19 million consumers have "unscored" credit records, meaning they do not have a report with recently reported information or they do not have enough credit history for a credit score to be generated ("Millions of consumers," 2015). Even if a consumer does have a credit score, it can be manipulated by both lenders and through the collections agency system.

In the past, lenders have manipulated FICO scores in order to help people qualify for credit cards and mortgages that they could not afford (Foust & Pressman, 2008). Some "credit doctors" began to help borrowers "juice their FICO scores" using legal and illegal tricks (Foust & Pressman, 2008). According to Anthony B. Sanders, a finance professor at Arizona State University and former head of asset-backed research at Deutche Bank in New York, "The more heavily lenders and bankers relied on credit scores, the more mistakes were made" (Foust & Pressman, 2008).

Another way credit scores can be manipulated is through collections agencies. When a collections agency registers an item on a credit report, the only way to improve that credit score is time. It can take seven to ten years for items to disappear completely. As the collection item ages, it affects credit score less. However, whether or not someone pays off the item does not affect the score. A way around this is "pay for delete" in which case if the collections agency is paid, they will delete the item from the credit report. This can have a significant effect someone's credit score. Because of these shortcomings, lenders began to look more closely at FICO scores' ability to predict risk, especially after the subprime housing bubble burst.

In the wake of the Great Recession, many began to blame Fair Isaac, "arguing that its score didn't predict delinquencies as expected" (Foust & Pressman, 2008). For example, when comparing five different groups of borrowers with different FICO scores when their loans were made, the higher the credit score, the larger the increase in serious delinquency rate one year after the loan was made (Demyanyk, n.d.). Serious delinquency is defined as a borrower missing more than two monthly payments or defaulting on a loan (Demyanyk, n.d.). For those with FICO scores between 500 and 600, the rate of serious delinquency doubled from 2005 to 2007, compared to those with FICO scores above 700, whose serious delinquency rate quadrupled in the same time period (Demyanyk, n.d.). Furthermore, the serious delinquency rate for those with FICO scores 700 and above in 2007 was almost the same as the rate in 2005 for those with FICO scores between 500 and 600 (Demyanyk, n.d.). This suggests that credit score did not act as a predictor of default risk like so many believed it was. Discover Financial Services Chief Executive David W. Nelms told analysts "So many people, I think incorrectly, looked at FICO as being the measure of risk," (Foust & Pressman, 2008). Due to these issues, lenders began to create new lending models that did not rely as heavily on credit score.

COMPANIES USING NON-STANDARD UNDERWRITING

There were many other risk measures used before credit score dominated underwriting. For example, income was previously widely used, but only recently has it again been given precedence in some underwriting models. Some believe that income is actually one of the best measures of risk, along with employment tenure, which are not factored into credit scoring models (Biundo, 2015). Many companies are beginning to revert to these methods, using "non-standard" underwriting practices in order to supplement and/or replace systems that rely on credit scores. Many of these new systems claim to be more accurate at predicting loan repayment than systems that rely more heavily on credit score.

ZEST FINANCE

Zest Finance is a company that uses "big" data, defined as large complex data sets containing a variety of data types, to underwrite loans for the subprime population. They analyze thousands of potential credit variables ranging from financial information to technology usage. Douglas Merrill, the founder of Zest Finance, discloses that one signal used is whether someone has given up a prepaid wireless phone number (Hardy, 2015). If they have, it is a bad sign as it indicates someone is willing or has been forced to disappear from those they know (Hardy, 2015). These non-standard data signals help Zest create a better idea of who is going to repay their debt. Zest claims that their model “provides a 40% improvement over the current best in class industry score,” ("Zest Finance," n.d.). Merrill believes that this his method of “data-driven analysis of personality” is a better and more fair method than standard measures because of the difference between ability and willingness to pay (Hardy, 2015). Ability to pay is simply having the money to pay while willingness to pay is the level of importance one places on repaying their debt. Merrill said, “If all you look at is financial transactions, it’s hard to say much about willingness,” (Hardy, 2015). Many other firms are beginning to place increased importance on willingness to pay over ability to pay as well.

UPSTART

Upstart is another company using non-traditional data to underwrite loans based on willingness to pay rather than ability to pay alone. Upstart uses information such as level of education, SAT score, college attended, major, and GPA to determine a loan rate ("Upstart," n.d.). Paul Gu, Upstarts co-founder, said that “If you take two people with the same job and circumstances, like whether they have kids, five years later the one who had the higher G.P.A is more likely to repay the debt,” (Hardy, 2015). He goes on to say, “It’s not a question of whether you can pay, it’s a question of how important you see the obligation,” (Hardy, 2015). The concept, validated by data, is that those who took the extra time to study extra and double check their homework are “through and more likely to honor their debts,” (Hardy, 2015).

SOFI

SoFi is a lending company that also places importance on willingness to pay. SoFi uses an underwriting model based on college attended, major, employment, and income in addition to FICO score ("Great Rates and a Lifetime of Benefits L SoFi," n.d.). SoFi does not specialize in auto loans but will make a personal loan for things such as a vehicle, paying off credit cards, home improvement projects, medical expenses and home mortgages ("Great Rates and a Lifetime of Benefits L SoFi," n.d.).

Earnest

Earnest uses an underwriting model based on monthly cash flow ("Earnest," n.d.). They look at customer bank accounts, income, and spending. If they have enough cash flow to add a loan payment, they will issue the loan.

Car Credit Nation

Car Credit Nation does no credit check financing. In a phone interview with Jack Keller, a sales person at Car Credit Nation in Winchester, Virginia, I learned what is necessary to get a loan; a down payment of $500-$1000, income of at least $300 per month, proof of this income, and proof of residence such as a piece of mail (J. Keller, Personal communication, March, 2016). If someone meets these standards, Car Credit Nation will issue the loan.

AutoZoom

AutoZoom is a company that creates custom scoring models for BHPH dealerships using predictive underwriting. The company has based its model on forty years of underwriting experience and data from over one million BHPH transactions ("AutoZoom," n.d.). AutoZoom claims that use of its model will enable dealerships to make better underwriting decisions. The AutoZoom model incorporates many different variables, including credit score, residence stability, job stability, number of times repossessed, down payment, monthly payment ratio, and income source in order to produce a final score. The dealership sets a benchmark score and then underwrites a loan only if the AutoZoom score is above the benchmark. The total score can also be compared from loan to loan, which allows dealerships to see what measures are producing loans with the best repayment. This enables lenders to improve their underwriting by standardizing acceptable ranges that result in the most successful loans.

Methods

Based on the factors listed above and the data I could collect from Auto Capital, my hypothesis is that disposable income, the time someone has spent at their residence, the time someone has spent at their job, the down payment made, and the payment ratio can be used to predict loan repayment.

VARIABLES

LOAN REPAYMENT

Loan repayment is the dependent variable and is measured as the ratio of the total amount paid divided by the amount of the loan. The total amount paid includes the down payment and the total of monthly payments made. The total amount of the loan varies only slightly from loan to loan with an average loan amount of $10,800 and a standard deviation of $1,430. There is no significant difference in loan amount between the bottom half of the sample and the top half when divided by credit score.

CREDIT SCORE

The FICO credit score was measured as the reported score on file. The credit score should be positively correlated with the dependent variable because credit score is representative of capacity to repay a loan. If someone has a higher capacity for repayment, they should pay a higher percentage of their loan off.

TIME-AT-RESIDENCE

The time-at-residence was measured as how long an individual has lived in their current residence in years. This should be positively correlated with loan repayment because the time someone has lived in one place is representative of the stability of their life and is a predictor of their future intent. If they have been in one home for a long time, it is assumed that they will stay, decreasing the risk that they will run away with the vehicle and increasing the likelihood that they will continue making payments.

Time-at-Job

The time-at-job was measured as how long an individual has held their current job in years. The time-at-job should be positively correlated with loan repayment. This is because the time someone has spent at their job is representative of the stability of their income. If someone has a stable income, the likelihood that they will continue making payments increases.

Payment Ratio

The payment ratio was measured as the monthly payment divided by total monthly income. This should be negatively correlated with loan repayment because those with a high payment in relation to income are more likely to stop payment if their income stream is even slightly reduced.

Down Payment

The down payment was measured in dollars as the total down payment before beginning monthly payments. This should be positively correlated with loan repayment because the down payment contributes to total amount paid and a high down payment is representative of ability to make future payments.

DISPOSABLE INCOME

Disposable income was measured in dollars as the monthly amount remaining after all planned expenses such as taxes, rent or mortgage payment, $250 for miscellaneous expenses and the individual's monthly car payment. These expenses are included for every customer. Additional expenses are self-reported by the customer such as child support, cable bill, phone bill, and insurance. However, the amount of additionally reported expenses is verified through obtaining a copy of the bill. Auto Capital management believes that people are generally honest in reporting additional expenses (G. Parks, 2016). Disposable income should be positively correlated with the dependent variable. This is because if someone has more money to spend, they are more likely to continue making their payment.

POINTS

As a robustness measure, all variables above were then converted into a points system based on the AutoZoom scoring method. For each variable, a conversion into points was created as shown below in Table 1.

Table 1

Points Model Scoring

Disposable Income			**Payment Ratio**			**Down Payment**			**Residence and Job**		
Lower	Upper	Points	Lower	Upper	Points	Lower	Upper	Points	Lower	Upper	Points
300	800	-3	0%	2%	7	0	1	-5	0	1	-1
800	1300	-2	2%	6%	5	1	500	-3	1	3	0
1300	2100	-1	6%	10%	3	500	1000	0	3	5	1
2100	2900	0	10%	14%	1	1000	1500	3	5	7	2
2900	3700	1	14%	18%	0	1500	2000	5	7	+	3
3700	4500	2	18%	22%	-1	2000	2500	7			
4500	5300	3	22%	26%	-3	2500	5000	10			
5300	6100	4	26%	40%	-5						
6100	6900	5									
6900	7700	6									

Notes: the lower range is inclusive

Regression Model

Based on the relationships predicted, the following regression equations were used to test if the independent variables were predictors of loan repayment.

Model 1

$Y_1 = \beta_0 + \beta_1(\text{Credit Score}) + \varepsilon$

Model 2

$Y_2 = \beta_0 + \beta_1(\text{Time at Job}) + \beta_2(\text{Time at Residence}) + \beta_3(\text{Payment Ratio}) + \beta_4(\text{Disposable Income}) + \beta_5(\text{Down Payment}) + \varepsilon$

Model 3

$Y_2 = \beta_0 + \beta_1(\text{Points Time at Job}) + \beta_2(\text{Points Time at Residence}) + \beta_3(\text{Points Payment Ratio}) + \beta_4(\text{Points Disposable Income}) + \beta_5(\text{Points Down Payment}) + \varepsilon$

Model 4

$Y_2 = \beta_0 + \beta_1(\text{Points Time at Job}) + \beta_2(\text{Points Time at Residence}) + \beta_3(\text{Points Payment Ratio}) + \beta_4(\text{Points Disposable Income}) + \beta_5(\text{Points Down Payment}) + \beta_6(\text{Credit Score}) + \varepsilon$

DATA

A random sample of closed loan files with an origination date between when Auto Capital opened in 2009 and the end of 2011 were selected for the starting sample. This date range was chosen in order to ensure the loan was closed as the longest possible loan term is 48 months. I reviewed 264 loan files, with 215 files including credit score and 189 files having all of the data needed to test the desired variables not including credit score. This was partially due to Auto Capital's poor filing system and partially due to some customers not having enough credit history to have a credit score. The 215 files with credit score were used to determine if credit score was a significant predictor of loan repayment in model one. The 189 files were used in models two and three. Only 161 files had data on all variables including credit score. These files were used for model four. Auto Capital verifies income and time at job through paystubs, unemployment awards, SSI/retirement benefits awards letters, and phone calls to employers. Time at residence is also verified through calling property owners and mortgage companies.

The descriptive statistics for the data is shown below in Table 2. The average customer pays 72% of their loan; however, there is a large variation in this as shown by the standard deviation. Loan repayment can go well over 100% due to interest. The average customer has a credit score of 522 and makes a down payment of $500 but this also varies considerably. The average time at residence and time at job is about 6 years, which is well above the median. This is due to a few customers that have lived in the same home and held the same job for 40 years or more.

Table 2

Descriptive Statistics

	Loan Repayment	Credit Score	Payment Ratio	Disposable Income	Down Payment	Time at Residence	Time at Job
Mean	72.0%	521.8	8.2%	$1,454	$628	5.7	6.1
Median	61.8%	524.0	7.7%	$1,082	$500	3.0	2.0
SD	45.6%	62.3	3.9%	$1,071	$515	7.9	9.1
Range	162.6%	299.0	24.0%	$6,849	$4,000	50.0	55.0
Minimum	3.3%	388.0	1.6%	$307	$0	0.0	0.0
Maximum	166.0%	687.0	25.6%	$7,156	$4,000	50.0	55.0

I examined the relationship between loan term, amount of the loan, and credit score in order to ensure these factors did not affect the dependent variable. Credit score and loan term were not correlated (r = .083), nor was credit score and loan amount (r = -.067). Using a difference of means test to compare the top half of the sample with the bottom half based on credit score, no significant difference was found between the loan amounts (p = 0.368) or the loan terms (p = 0.332). Therefore, loan term and loan amount do not have an impact.

In addition, I examined the correlation between predictor variables to ensure there was not a multicollinearity issue. As shown in Table 3, all correlations were between -30% and 30% indicating weak correlation between variables.

Table 3

Correlation Between Predictor Variables

Variable	Credit Score	Payment Ratio	Disposable Income	Down Payment	Years at Residence	Years at Job
Credit Score	100.0%					
Payment Ratio	19.0%	100.0%				
Disposable Income	-11.9%	-26.9%	100.0%			
Down Payment	8.9%	-2.2%	8.9%	100.0%		
Years at Residence	14.9%	8.5%	5.4%	7.1%	100.0%	
Years at Job	-0.3%	-2.1%	-5.5%	-0.4%	17.1%	100.0%

Results

As a control, a linear regression (Model 1) was conducted in order to determine if credit score predicted loan repayment. A significant regression equation was found with regression coefficients and significance shown in Table 4. Credit score was a significant predictor of loan repayment ($p<.0014$). Loan repayment increased 0.00165 for each point of credit score.

An OLS regression, (Model 2) was calculated to predict loan repayment based on time at job, time at residence, payment ratio, disposable income, and down payment. A significant regression was found with regression coefficients and significance shown in Table 4. Of the predictor variables, only down payment and payment ratio were significant ($p <0.05$) predictors of loan repayment. This is surprising as the lack of significance of disposable income suggests that the amount of money one has, or ability to pay, does not influence the amount of their loan that they pay back. Furthermore, this suggests that the stability of one's life as measured by the time at job and time at residence does not influence loan repayment of high-risk borrowers either.

Table 4

Multiple Linear Regression of Loan Repayment by Model

Variable	β	SE(β)	P	Adj. R^2
Model 1				
Intercept	-0.13854	0.26733	0.6048	
Credit Score		0.0005	0.0014	
F(1,215) = 10.49				0.0425
Model 2				
Intercept	0.75304	0.12673	<.0001	
Time at Job	-0.00287	0.00004	0.3929	
Time at Residence	0.00276	0.00336	0.4892	
Payment Ratio	-2.22125	0.00399	0.0267	
Disposable Income	-0.00004	0.00006	0.3022	
Down Payment	0.00033	0.99452	<.0001	
F(5,183) = 8.41			<.0001	0.1647
Model 3				
Intercept	0.55691	0.55691	<.0001	
Points Time at Job	0.01738	-0.01309	0.3650	
Points Time at Residence	0.02895	0.07107	0.1409	
Points Payment Ratio	0.04692	0.04692	0.0275	
Points Disposable Income	-0.01309	0.01738	0.4575	
Points Down Payment	0.07107	0.02895	<.0001	
F(5,183) = 9.46			<.0001	0.1836
Model 4				
Intercept	0.44001	0.30606	0.15260	
Time at Job	-0.00397	0.00379	0.29650	
Time at Residence	0.00106	0.00438	0.80930	
Payment Ratio	-1.78169	1.13365	0.11810	
Disposable Income	-0.00007	0.00004	0.84560	
Down Payment	0.00034	0.00006	<.001	
Credit Score	0.00049	0.00006	0.37820	
F(6, 154) = 6.38				0.1679

Notes: Model 1 N = 215, Model 2 and 3 N = 189, Model 4 N =161

As a robustness measure, a second OLS regression, (Model 3) was also calculated to predict loan repayment based on residence points, job points, payment ratio points, down payment points, and disposable income points. Each original data point was converted into a point value previously determined from a sample AutoZoom score sheet. The scoring method used is detailed in Table 1. A significant regression equation was found with the regression coefficients and significance shown in Table 4. Again, of the independent variables, only down payment points and payment ratio points were significant ($p < 0.05$) predictors of loan repayment. This is in line with the results from model two and suggests once again that stability measures do not predict loan repayment for high-risk borrowers, nor does ability to pay.

A fourth OLS regression was calculated to determine if these results held true when credit score is included in the model. A significant regression equation was found with the regression coefficients and significance detailed in Table 4. Of the independent variables, only down payment was a significant predictor of loan repayment at the five percent significance level. Therefore, down payment was the most significant predictor of loan repayment in the subprime population.

Conclusion

As the subprime auto loan market changes, Auto Capital must adapt in order to stay competitive. Banks are beginning to underwrite to non-prime customers again, causing Auto Capital to lose applicants with the highest credit scores. Furthermore, many Americans do not have a credit score and there is some evidence that credit scores are not necessarily accurate predictors of risk or likelihood of repayment. If Auto Capital continues to use credit score as the primary predictor of loan repayment, it risks selecting a poor customer base in addition to losing some potential borrowers. The underwriting process, which determines what customers are issued loans, is the most important factor for the success of a BHPH dealership. As down payment and payment ratio were significant predictors of loan repayment for the subprime population that Auto Capital primarily lends to, incorporating them into Auto Capital's underwriting model would aid in the selection of customers with the highest likelihood for repayment. This would help Auto Capital to create a customer base with less delinquency and default, which would increase profitability and allow Auto Capital to stay competitive in a changing market.

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