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Driving Marketing Efficiency in the Age of Big Data: Analysis of Subprime Automotive Borrowers

Edwin Baidoo
Tennessee Tech University, ebaidoo@tntech.edu

Ryan Matthews
Tennessee Technological University, rlmatthews@tntech.edu

Frances Ann Stott
Ohio University, fstott@ohio.edu

F. Stuart Wells
Tennessee Tech University, swells@tntech.edu

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Edwin Baidoo, Tennessee Tech University
Ryan Matthews, Tennessee Tech University rlmatthews@tntech.edu
F. Stuart Wells, Tennessee Tech University
Francis Ann Stott, Ohio University

Abstract **-** Big Data methodologies are applied to understand subprime borrowers in the U.S. automobile space. The focus on the automobile market is essential as this subsegment is responsible for directly and indirectly employing over one million people and creating payrolls in excess of $100 billion annually in the U.S. It is found in this article that if a subprime borrower is a homeowner, the probability of repaying their auto loan increases by almost 4%. However, if the borrower is renting, the likelihood of repaying their auto loan increases by nearly 1.4%. Applying Big Data in making subprime auto loans can add 1000's of jobs and improve security of millions of dollars in payroll.

Keywords **-** Marketing, Auto Industry, Subprime, Borrowers

Relevance to Marketing Educators, Researchers, and Practitioners **–** This study profiles subprime borrowers in the automobile industry by investigating their default behavior so that organizational leadership can better understand these groups. Additionally, it may appeal to individuals who are at the intersection of marketing and policy.

Introduction

The automotive industry is significant to the American economy. In 2010, over 1.7 million people were directly employed by the automotive industry. The automotive industry was also indirectly responsible for over 8 million jobs (consumer goods and services from other sectors). People in these lines of employment earn over $500 billion in annual wages and generate more than $70 billion in tax revenues (Hill K.et al., 2010). In 2010, US auto sales were 11.5 million units increasing to 17 million units in 2019 (Good Car Bad Car, 2021). The numbers provided above have grown significantly over the last 10 years.

In 2021, an industry report revealed that Americans spend $463 billion annually on auto loans amounting to an average monthly payment of $412 or $4,944 per year. Roughly 73% of households pay auto loans with an average household paying on average of $3,605 per year (DoxoInsights, 2021). The American auto loan consumer is broken into multiple categories dependent on their credit score. Experian, a major credit rating company, divides auto loan customers as follows: Super prime (credit score 781 – 850), prime (credit score 661 – 780), nonprime (601 – 660), subprime (501 – 600), and deep subprime (300 – 500) (Business Insider, 2019). Roughly 19% of all borrowers are subprime and deep subprime (Business Insider, 2019).

Developing efficiencies in the subprime markets is impactful because this subsegment employs well over a million people creating in excess of $100 billion in salaries (ISIB World, 2021).

Delving deeper into understanding the subprime market is beneficial. Subprime lending occurs when lenders originate loans to risky borrowers. Here, risky is defined in terms of the credit score. Specifically, subprime borrowers have lower credit scores, resulting in them not meeting standard underwriting criteria. Two significant implications arise from this. The first is that subprime borrowers may not receive favorable loan characteristics, i.e., interest rate or loan duration. The second is that subprime borrowers may turn to largely unregulated alternative financial products such as payday loans, check-cashing, etc. Combining these implications, it is no wonder that Aitken (2017) suggests that the current credit system overlooks subprime borrowers.

However, like all consumers, subprime borrowers also need access to credit. The demand for credit has allowed some lenders to properly recognize and offer credit to borrowers who are subprime and creditworthy. However, there is some uncertainty among lenders on whether lending to subprime borrowers is profitable. From that perspective, a potential solution is to combine marketing efforts with Big Data analytics. Using Big Data analytics, lenders may be able to identify profitable subprime borrowers. Using marketing techniques, lenders can get a tailored message to these targeted groups.

This research seeks to make the following contribution. First, current literature on subprime lending has been focused disproportionally on the housing market (Apgar & Herbert, 2006, Temkin et al., 2002, Amromin & McGranahan, 2015). This is expected and even justified, given that one of the reasons offered as a cause for the Great Recession is the gradual increase of subprime loans in the mortgage industry. As a result, minimal energy has been spent on other forms of subprime lending, much less the auto industry.

The second contribution this paper makes is to better understand subprime borrowers in the auto industry for marketing purposes. More specifically, mapping out drivers of default, which has not been done. It is believed that this article is the first to respond to this challenge. For marketing purposes, it is crucial to know how to respond to such groups of consumers. What treatment should be handed down? Are subprime groups homogenous? What is the best approach to help subprime consumers?

The third contribution is to facilitate a policy discussion. Research has shown that there are multiple factors behind subprime consumers, ranging from low income to race (Apgar & Herbert, 2006). Therefore, a holistic view – combining marketing efforts and policy discussion – may be fruitful for subprime borrowers who wish to become prime or super-prime.

This article is outline in the following manner: first, the impact of Big Data on marketing is discussed in section 2. Sections 3 and 4 describe the data and the variable reduction process. Sections 5 and 6 present the summary statistics, model description, and results. Sections 7 and 8 discuss model robustness and conclusion.

Impact of Big Data on Marketing

The term Big Data describes datasets that are too large to be stored, managed, and analyzed using traditional database methodology. The driving force behind Big Data are the five "Vs": volume, velocity,variety, value and veracity, (Cao & Manrai, 2014, Onay & Öztürk, 2018). Volume refers to the influx of data produced. Velocity refers to the rapid pace at which data is being generated, while variety denotes the different kinds of data[1] that is being generated. Value represents the monetrary and organizational contributions of Big Data to a firm's strategy. Veracity refers to the extent to which a data – being generated and stored – can be trusted objectively to produce insights.

According to Court et al. (2015), the age of Big Data has provided marketing opportunities not yet seen since the onset of the internet almost 20 years ago. For example (Manyika et al., 2011) reports that retailers could increase their operating margin by as much as 60% and that the healthcare industry could experience $300 billion in annual value using Big Data. This presents clear marketing opportunities for many business industries.

Court et al. (2015) point out three marketing strategies that are useful in the age of Big Data. First, managers and practitioners can use Big Data technologies to improve marketing return on investment through insight generation. The second is that these insights should be turned into products that help and delight customers. The third is to use marketing efforts to deliver the products into the marketplace.

Through marketing efforts, companies can use Big Data to develop a deeper understanding of their customer base. Perhaps significantly, companies can rely on Big Data to form a competitive advantage through innovation. While it is evident that using Big Data can dramatically impact marketing opportunities, there are challenges as well. For example, the increase in velocity makes it difficult to store and maintain data from different sources (Rejeb et al., 2020).

In this research, we seek to use Big Data to understand subprime borrowers in the automobile space. The focus on the automobile market is vital because transportation allows consumers to seek employment, which in turn allows them the opportunity to climb the economic ladder. We find that we find that if a subprime borrower is a homeowner, the probability of repaying their auto loan increases by almost 4%. However, if the borrower is renting, the likelihood of repaying their auto loan increases by nearly 1.4%. Suppose a borrower increases the number of telecom-related inquiries within 12 months, the probability of repayment of the auto loan decreases by almost 2%.

Data Description

The data for this research pertains to automobile loans given from 2013 to 2014. It is proprietary and provided for the sole purpose of this study. The breakdown of credit classification is shown in Table 1. Additionally, we used the credit range of Experian's State of the Automotive Finance Market[2] reports to generate Table 1. For the purpose of this study, we refer to borrowers who are

[1] Example structured, unstructured, or semi-structured data

[2] See (Zabritski, 2014), (Zabritski, 2013), (Zabritski, 2015a), (Zabritski, 2015b), (Zabritski, 2015c)

not prime or super-prime as subprime. Note: the mix of categories is heavily weighted toward subprime segments and is not equally weighted to the overall U.S automotive market.

Table 1: Risk Classification for Data Set

Classification	Percentage
Super prime	0.14%
Prime	1.50%
Nonprime	4.75%
Subprime	44.09%
Deep Subprime	49.52%

The presence of super-prime and prime borrowers indicates that the dataset is not entirely made up of subprime borrowers. However, it also suggests that approximately 98.36% of the population under study represent subprime borrowers. Therefore, the subsequent analysis will hold true for subprime borrowers.

Variable Preprocessing and Reduction

Our proprietary dataset has 591 variables impacting credit worthiness and 23,981 automotive transactions. To begin the analysis, the following types of variables are deleted: date, IDs, and those with unclear or no meaning. This reduced the number of variables to 579.

Variables with more than 25% missing values are excluded for this study, resulting in 167 variables and 23,981 observations. This threshold is selected because the algorithm to impute missing values - proposed by Stekhoven & Bühlmann (2012) - was tested on datasets with missing values ranging from 10% to 30%. In this regard, the choice of 25% falls within the range.

An advantage of the imputation method is that it is non-parametric and considers non-linear interactions between mixed-type data. Additionally, Shah et al. (2014) show that it is computationally efficient for high dimensional data.

According to Dormann et al. (2013), multicollinearity exists if variables have a correlation coefficient greater than 0.7. Therefore, highly correlated variables are excluded. Doing so resulted in 44 variables and 23,981 observations.

Summary Statistics

The summary statistics of the resulting variables are shown in the table below. Their meanings are in Table 5 of the Appendix.

Table 2: Descriptive Statistics of Resulting Variables

Variable	Obs	Mean	Std.Dev	Median	Min	Max
depVar	23,981	0.778	0.416	1	0	1
act6m	23,981	2.134	2.632	2	0	37
st6mLn	23,981	1.504	1.774	1	0	27
crdTot	23,981	19,037.30	41,965.04	10,565.00	0	1,149,000.00
clTrd	23,981	3.412	4.398	3	0	69
tradeAge	23,981	95.275	59.525	93	0	615
trdMnt	23,981	45.789	51.014	34	0	540
Trd30	23,981	0.738	1.405	0.1	0	23
st90Trd	23,981	0.153	0.458	0	0	14
op6mTd	23,981	0.250	0.657	0	0	8
mYgRt	23,981	32.004	34.585	18.95	0	433
icApp	23,981	2,903.26	3,035.12	2,513.00	-	288,025.00
bkRevLim	23,981	314.47	3,138.59	-	-	240,914.00
blRev6m	23,981	24.425	210.389	0	0	16,301.00
blRev12m	23,981	48.908	366.196	0	0	19,986.00
blRev24m	23,981	92.953	886.538	0	0	95,945.00
nsCol	23,981	6.826	5.698	6	1	63
col6m	23,981	1.056	1.406	1	0	25
amCol	23,981	6,248.17	10,180.22	3,940.00	0	350,554.00
am6Col	23,981	905.80	3,508.40	269.00	-	269,349.00
nmdCols	23,981	3.211	3.274	2	0	42
nmd6Cols	23,981	0.501	0.879	0	0	17
nmdYT	23,981	12.927	13.960	9	0	265
oColsYT	23,981	48.699	22.957	52	1	369
recCollAge	23,981	10.075	12.421	5	0	265
mtEyT	23,981	52.317	67.114	26	0	601
fCr0e	23,981	528.280	50.067	520.48	412	812
nQr	23,981	8.219	7.321	6	1	62
n1mQr	23,981	2.558	3.096	2	0	54
colInq12m	23,981	0.050	0.267	0	0	5
tel12mQr	23,981	0.179	0.518	0	0	11
inQ1m	23,981	1.081	1.294	1	0	37
inQ30m	23,981	0.771	0.420	1	0	1
cols3m	23,981	0.014	0.121	0	0	2
tel3mQr	23,981	0.044	0.228	0	0	5
crdMt	23,981	181.214	105.979	171	0	783
nbRevBalLim	23,981	127.366	1,563.57	0	0	151,315.00
nbRevBalLim12	23,981	46.756	215.157	0	0	10,824.00
aCdur	23,981	72.693	89.202	36	0	1,008.00
trdRvv	23,981	1.420	2.408	1	0	36

Variable	Obs	Mean	Std.Dev	Median	Min	Max
trdVc	23,981	0.944	1.127	1	0	15
otRes	23,981	0.051	0.220	0	0	1
onRes	23,981	0.109	0.311	0	0	1
rentRes	23,981	0.521	0.500	1	0	1

Modeling and Results

This article seeks to understand some aspects of subprime borrowers. Without question, one of the features that have remained unexplored is their default behavior. While there is research that explores their demographics[3], it is important to take an objective look at their default behavior.

Once correctly done, it provides a window for marketing purposes. It provides an avenue to understand this population and better understand their needs. To this end, logistic regression is used to model subprime default behavior. In so doing, it is targeted to draw insights from factors that contribute to their default. Logistic regression is used because it is the most common model used for default prediction (Lessmann et al., 2015). Additionally, it is a parametric model that will allow us to interpret and make inferences about the results.

Logistic regression is constructed with variables in Table 2 [above]. However, the results in Table 3 [below] only show variables that are statistically significant at the 5% level. The results, shown in Table 3, are sorted by marginal effects.

Table 3: Logistic Regression Results

Variables	**Estimates**	**Std. Err**	**Z-stat**	**P>|z|**	**Marg. Effect (%)**
Intercept	-1.541200	0.206000	-7.486000	<0.0001	-
onRes	0.226200	0.062000	3.650000	<0.0001	3.58
st90Trd	-0.154100	0.033000	-4.633000	<0.0001	-2.57
tel12mQr	-0.112100	0.028000	-3.950000	<0.0001	-1.87
op6mTd	-0.109400	0.027000	-4.080000	<0.0001	-1.83
rentRes	0.081500	0.034000	2.414000	0.016000	1.36
trdRvv	0.064400	0.010000	6.240000	<0.0001	1.07
n1mQr	0.059200	0.007000	8.939000	<0.0001	0.99
trdVc	0.057600	0.017000	3.307000	0.001000	0.96
nmdCols	-0.038700	0.005000	-8.124000	<0.0001	-0.65
nQr	-0.021900	0.003000	-8.555000	<0.0001	-0.37
fCr0e	0.004900	0.000000	12.927000	<0.0001	0.08
mYgRt	0.002400	0.001000	4.402000	<0.0001	0.04
crdMt	0.000800	0.000000	4.942000	<0.0001	0.01
crdTot	0.000002	0.000001	3.026000	0.002000	0.00

[3] See (Apgar and Herbert, 2006)

The following interpretations are gleaned from the results of the logistic regression:

- For each non-student loan account that is 90 days past due, the probability of repayment decreases by almost 3%
- If an individual is a homeowner, the probability of repayment increases by almost 4%
- If an individual is renting, the probability of repayment increases by almost 1.4%
- An increase in the number of telecom related inquiries within 12 months decreases the probability of repayment by almost 2%
- Increasing the number of accounts opened within six (6) months decreases the probability of repayment by almost 2%
- Each increase in the credit score increases the probability of repayment by almost 0.1%
- For each non-medical account sent to collections, the probability of repayment decreases by almost 0.7%
- The increase in the number of inquiries decreases the probability of repayment by almost 0.4%

Model Robustness

Although researchers and practitioners place great emphasis on data in an era of Big Data, it is equally important to measure the robustness of the techniques that rely on Big Data. This is even more important when the goal is to draw conclusions that will inform organizational leaders.To this end, we use a 10-fold cross-validation[4] to reinforce the results of Table 4. It is also reported that the following model diagnostics: accuracy, precision, recall, and AUC. The average of the model diagnostics is shown in Table 4, along with their bootstrapped confidence interval. The bootstrapping process was done using 2,000 iterations and a sample size of 10,000. Additionally, the ROC curve showing the AUC metric for each of the 10-fold cross-validation is shown below.

Table 4: Model Diagnostics

Metric	**Value**	**Conf. Int**
Accuracy	0.777	(0.7770, 0.7774)
Precision	0.778	(0.7781, 0.7785)
Recall	0.997	(0.9976, 0.9977)
AUC	0.620	(0.6201, 0.6207)

A brief overview of the metrics used in Table 4 are provided below:

- **Accuracy**: The fraction of labels that the model correctly predicted. It is mathematically analogous to:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

[4] See (Khandani et al., 2010)

Where

- TP is True Positive, TN is True Negative, FP False Negative, and FN is False Negative.

- **Precision**: Of the true positives predicted by the model, the proportion of actual positives. It is mathematically analogous to:

$$Precision = \frac{TP}{TP + FN}$$

- **Recall**: The fraction of true positives correctly predicted by the model. It is mathematically analogous to:

$$Recall = \frac{TP}{TP + FP}$$

- **AUC**: The area under the ROC Curve[5]. It ranges from 0.5 to 1, with higher values being preferred.

The higher level of the model's accuracy reinforces confidence in the model. It indicates that logistic regression can be used to draw inferences from subprime borrowers. However, the moderate AUC may suggest that more research is necessary to appreciate these borrowers' groups fully.

Conclusion

In marketing, it is important to understand a population to better service the market. In the era of Big Data, understanding a customer base is done through the use of data and algorithms. In this analysis, it was an intention to understand subprime borrowers. Specifically, using proprietary data to map out default profile for marketing purposes.

The subprime automotive market is ~19% of a $643 billion automotive financing maket within the United States. The automotive industry directly employs over 1.7 million people while indirectly creating over 8 million jobs. This industry creates over $500 billion in annual wages and generates more that $70 billion in tax revenues (Hill K. et al., 2010). Driving efficiency with Big Data creates significant savings and assists in securing future employment.

In the automobile space, is was found that if a subprime borrower is a homeowner, the probability of repaying their auto loan increases by almost 4%. However, if the borrower is renting, the likelihood of repaying their auto loan increases by nearly 1.4%. Suppose a borrower increases the number of telecom-related inquiries within 12 months, the probability of repayment of the auto loan decreases by almost 2%.

Future research could focus on subprime borrowers in other industries in order to determine if similar relationships exist. It remains open whether the insights discovered within the subprime

[5] See (Verbraken et al., 2014)

automotive business can also hold true for different industries and sectors. Future research could also include comparisions of different buy segments, age demographics, credit scores, and regional impacts of automotive buyers.

Limitations of this research exist in that the data set spans 2013 and 2014. It is unknown if current events like COVID-19 pandemic would have positive or negative impacts on the model used for this study. This study does help explain the ~19% of the subprime automotive market, however, it is unknown about the default behavior of the other loan quality segments.

Appendix

Table 5: Variables and Their Meaning

Variables	Meaning
act6m	Number of active accounts in six months
st6mLn	Number of active accounts within six months excluding student loans
clTrd	Number of accounts that are closed
crdTot	Total credit amount on all accounts
trdMnt	Months since oldest active account opened
tradeAge	Months since oldest trade opened
Trd30	Number of accounts that are 30 days past due
st90Trd	Number of accounts that are 90 days past due, excluding student loans
op6mTd	Number of accounts opened within 6 months
mYgRt	Months since most recent accounts was opened
depVar	Repayment indicator
icApp	Income of applicant
bkRevLim	Balance on a revolving account with a limit
blRev6m	Balance on a revolving account with limit opened within six months
blRev12m	Balance on a revolving account with limit opened within 12 months
blRev24m	Balance on a revolving account with limit opened within six months
nsCol	Number of accounts in collections
col6m	Number of accounts taken to collections within six months
amCol	Amount sent to collections
am6Col	Amount sent to collections within six months
nmdCols	Number of non-medical accounts sent to collections
nmd6Cols	Number of non-medical accounts sent to collections within six months
nmdYT	Time since most recent non-med collection assigned
oColsYT	Months since oldest collection was recorded
recCollAge	Months since recent collection was recorded
mtEyT	Number of month since employed
fCr0e	Credit score
nQr	Number of inquiries
n1mQr	Number of inquiries within a month
inQ1m	Number of inquiries within 14 days

Variables	Meaning
inQ30m	Number of inquiries within 30 days
colInq12m	Number of collection related inquiries within 12 months
tel12mQr	Number of telecommunication related inquiries within 12 months
cols3m	Number of collection related inquiries within three months
tel3mQr	Number of inquiries related to telecommunications
crdMt	Months since credit file was opened
nbRevBalLim	Revolving balance on a non-bank account with limit
nbRevBalLim12	Revolving balance on a non-bank account with limit opened within 12 months
aCdur	Months at current address
otRes	Description of having other residential accommodation
onRes	Description of owning resident
rentRes	Description of renting resident
trdRvv	Number of revolving accounts
trdVc	Number of auto related accounts

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