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The Impact Of Macroeconomic Variables On A Vector-Autoregressive Forecast Of Small Ticket Equipment Lease And Loan Portfolio Performance

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THE IMPACT OF MACROECONOMIC VARIABLES ON A VECTOR-AUTOREGRESSIVE FORECAST OF SMALL TICKET EQUIPMENT LEASE AND LOAN PORTFOLIO PERFORMANCE.

by

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This thesis, submitted by Brian M. Schonfeld in partial fulfillment of the requirements for the Degree of Master of Science in Applied Economics from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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Title	The Impact of Macroeconomic Variables on a Vector-Autoregressive Forecast of Small Ticket Equipment Lease and Loan Portfolio Performance.
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Brian M. Schonfeld
April 16, 2015

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I wish to express my sincere appreciate to the members of my advisory committee for their guidance and support during my time in the master's program at the University of North Dakota.

To my parents Jane and Steve for showing me the way,

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I love you all!

ABSTRACT

Equipment financing is a trillion dollar industry that covers small and medium sized businesses across the entire spectrum of business categories. These transactions are typically scored utilizing the owners' personal credit, with business credit adding additional information to the credit decision. For this paper, the portfolio performance of a publically traded company that finances small ticket equipment leases and loans will be examined. Utilizing data points gathered from thousands of leases and loans over a four-year period, transactions were run through three different econometric models and forecasted for a subsequent two-month period. Macroeconomic variables were then introduced to the econometric model to determine whether or not they increase the accuracy of this prediction, and by how much they either increase or decrease said forecasts.

CHAPTER 1

INTRODUCTION

Equipment finance is a relatively unknown but nevertheless extremely important part of the US economy. Equipment leasing and financing contributes to U.S. economic growth, manufacturing, and jobs in addition to a businesses' success. According to the Equipment Financing and Leasing Association (2014) seventy-two percent of U.S. companies use some sort of financing when acquiring new collateral – including loans, leases, and lines of credit (excluding credit cards). Firms invest in nearly $1.5 trillion in plant, equipment, and software annually, and finance almost two-thirds (62%) of these equipment purchases. Equipment finance companies also finance the export of U.S. manufactured products abroad (EFLA, 2014).

In this paper we focus on so called small ticket equipment leasing and financing, generally considered to be transactions between $5,000 and $150,000. As expected, a business' commercial credit is utilized when approving or declining these transactions. However the business owners' personal credit also play an important role in the credit adjudication process. In fact, based on my fifteen plus years in the equipment finance industry as both an equipment finance broker and lender, the attributes displayed in the owners' personal credit report compose the majority of the information used in the credit decision.

It goes without saying that the performance of these transactions is of vital concern to the small ticket lenders in the U.S. As in other areas of finance, the smaller players usually have a higher cost of funds than larger ticket or captive lenders; and in fact many of these lenders were forced out of business during the last recession (Menkin, 2013). Since the majority of the businesses financed are closely held, usually only one or two owners, the personal and business credit of each transaction is used to categorize the risk of each potential lessee or borrower. This risk or pricing factor is then used to determine how the portfolio of leases and loans will be expected to perform.

But what else can be used to forecast or predict the performance of these leases and loans? What about macroeconomic data? Since the majority of these businesses are smaller "main street" business that cater to consumers (as opposed to larger B2B enterprises), how do macroeconomic factors, particularly those related to overall consumer credit profiles (mortgage delinquency, credit card debt, credit card delinquency), affect these portfolios? Will adding one or more of these variables improve the accuracy of our forecasts?

I create three different econometric models, determine which one is most accurate, and then add a set of these macroeconomic factors and determine how the addition affects our results.

CHAPTER II

LITERATURE REVIEW

A great deal of literature has been written examining loan portfolios and the impact of various economic variables on these portfolios. Periodicals such as the *Journal of Banking & Finance*, the *Journal of Applied Finance and Banking*, and the *Journal of Banking Regulation* are just a few of the publications devoting pages to this topic recently. The majority of these articles dealt the portfolio performance of various compositions from commercial and consumer mortgages, to agricultural lending, to credit cards. However, regardless of the type of portfolio being discussed, the literature usually revolved around one of two main categories: individual risk vs. portfolio list.

There was a lot of information on individual risk profiles, i.e. the initial credit-granting process, and also how to create an effective credit-scoring model. These models covered not only general personal and commercial loans, but also equipment financing scorecards. In addition, there was information covering loan portfolio risk factors, such as macroeconomic conditions and political conditions which could affect a loan portfolio's performance.

Somewhat surprising perhaps, given the aforementioned size and impact of the equipment finance industry, there was not a lot of information dealing with the performance of equipment lease and loan portfolios. Accordingly then, there was not a lot of information on how external factors, such as macroeconomic variables, will impact these portfolios – and any forecast created to predict the performance. The majority of papers discussing portfolio returns tended to address the performance of commercial bank loans, commercial real estate loans, commercial property leases, and consumer mortgages. Even though commercial equipment financing accounts for around $1trillion in new equipment annually (EFLA, 2014); this number pales in comparison to the over $9 trillion in outstanding home mortgages in the fourth quarter of 2014, and is less than one-third of the $3.3 trillion in outstanding consumer credit at the end of Q4 2014 (United States, 2015).

As mentioned previously, asset backed lending, or equipment leases and loans tied specifically to collateral, was not adequately addressed. However reviewing the literature for models and information than could be applied to equipment financing portfolios did yield positive results. Gambera (2000) in *Simple Forecasts of Bank Loan Quality* stated that there is, "Little empirical evidence about the effects of macroeconomic factors on bank assets" (p 2). Bellotti and Crook reviewed default models incorporating macroeconomic variables for credit cards (2012). They focused on modeling and forecasting using both account variables and macroeconomic variables. They stated both business conditions and macroeconomic variables at the time of default, "with possibly either a lag or lead on the date of default" can help predict the performance of the portfolio being modeled (p 172). They created four "model structures based on including different explanatory variables" (p 173) one of them being account and macroeconomic variables.

Gambera (2000) indicated that a linear model is a very easy forecasting tool. He stated that, "Vector-Autoregressive models are systems of linear equations and therefore quite easy to estimate. They have the advantage over the single-equation linear models to better consider the interactions between variables. VARs model a more complete dynamics" (p 4).

In their article Stock and Watson (1996) undertook a "forecasting comparison of 49 univariate forecasting models, plus various forecast pooling procedures" (p 1). They posed the question do "nonlinear time series models produce forecasts that improve upon linear models in real time" (p 1). They studied 49 different forecasting methods that fell into four main classes: autoregressions (AR), exponential smooth, artificial neural networks (ANN), and logistic smooth transition autoregressions (LSTAR). The end result of their work was that "Overall, AR methods have lower average loss than the LSTAR or ANN methods…" (p 30). In their opinion the best overall performance of a single method is achieved by autoregressions with unit root pretests and that, "AR models with lag lengths selected by AIC generally worked well (p 31).

The amount of information available on loan portfolios and their performance is extensive. While little of this relates specifically to business equipment leasing and financing, the treatment of information regarding portfolio performance and forecasting was generic enough to apply to the econometric model developed in this paper.

CHAPTER III

DATA AND METHODOLOGY

For this paper, I collected data from over 7,500 funded equipment lease and loan transactions funded between January 2011 and December 2014 by a small ticket equipment lease and loan company located in the Mountain Region of the United States (hereafter "the Company").

27 different monthly variables from the Company's portfolio were collected, and the data then cleaned to identify and correct incomplete and inaccurate data. These variables were both specific variables of the owners' consumer credit report, as well as matrix values created by the Company's scorecard. These matrix values are numerical values between -3 and +5 that provide both a simple score and weight to the scorecard. For example, a credit score of 650 might result in 0 matrix value, while a 750 might result in a matrix value of +5. Matrix values are calculated for each variable utilized in the Company's scorecard, and the resulting sum determines approval/decline, and if the transaction si approved where the approval will fall on the risk-based pricing spectrum. Additionally, macroeconomic variables including consumer credit card debt and mortgage delinquency were included in later models.

Table 1: List and Description of Variables Utilized

Variable Name	*Description*	*Mean*	*Standard Deviation*
Charge_Off	Dollar amount charged off portfolio per month.	$209,188	$123,244
Overall_Aging	Overall delinquency of portfolio (amount past due 1+ days / gross lease receivable)	2.4731%	0.8781%
One_To_Thirty_Aging	Percent of portfolio that is past due between one and thirty days	1.3115%	0.4636%
Thirty_One_Plus_Aging	Percent of portfolio that is past due over thirty-one days	1.1617%	0.4858%
New_Non_Accrual	Dollar amount of transactions that were put on nonaccrual list (i.e. they are not expected to accrue any more income) that month	$359,704	$186,197
Total_Non_Accural	Total amount of leases/loans on non accrual.	$838,253	$534,023
Per_Port_on_Non_Accrual	Dollar amount of portfolio on nonaccrual divided by total gross lease receivable	0.8697%	0.3780%
Total_Dollar_Approved	Total amount approved, all programs, per month	$8,434,700	$1,730,455
Total_Number_Approved	Total number of transactions approved, all programs, per month.	403.9792	74.89950
Average_Approval	Average transaction size approved per month	$20,855	$1,340
Recovery	Amount recovered from previously charged off leases	$42,477	$40,160
Avg_Funded_BNI	Average BNI (bankruptcy predictive score) of all transactions funded in a particular month.	273.3333	17.4567
Avg_Funded_Beacon	Average Beacon personal credit score of all transactions funded in a particular month.	685.4738	11.4016
Average_Matrix	Average of each transaction's overall credit score funded in a given month.	11.7938	2.2811
Total_Dollar_Funded	Total amount of equipment leases and loans funded in a given month	$3,545,690	$777,320
Total_Number_Funded	Total number of transactions funded in a given month.	169.2708	29.6589
Average_Funded	Average size of all transactions funded in a given month.	$20,862	$1,724
Fourteen_Funded	Total dollar amount of transactions with 14% buy rate funded in a given month.	$381,678	$172,603
Sixteen_Funded	Total dollar amount of transactions with 16% buy rate funded in a given month.	$399,203	$218,437
Eighteen_Funded	Total dollar amount of transactions with 18% buy rate funded in a given month.	$595,090	$260,370
Twenty_Funded	Total dollar amount of transactions with 20% buy rate funded in a given month.	$666,578	$174,316
Twentytwo_Funded	Total dollar amount of transactions with 22% buy rate funded in a given month.	$582,507	$140,483
Twentyfour_Funded	Total dollar amount of transactions with 24% buy rate funded in a given month.	$253,489	$109,511

Table 1. cont.

Twentysix_Funded	Total dollar amount of transactions with 26% buy rate funded in a given month.	$348,305	$123,677
Twentyeight_Funded	Total dollar amount of transactions with 28% buy rate funded in a given month.	$227,467	$81,114
Thirty_Funded	Total dollar amount of transactions with 30% buy rate funded in a given month.	$115,336	$65,333
TOTALNS	Total Consumer Credit Owned and Securitized, Outstanding, Billions of Dollars, in a given month.	$2,919	$203
MORTDQ	Total Conventional Single-Family Delinquency Rates, 3 or more months past due, in a given month.	3.1196%	0.8156%

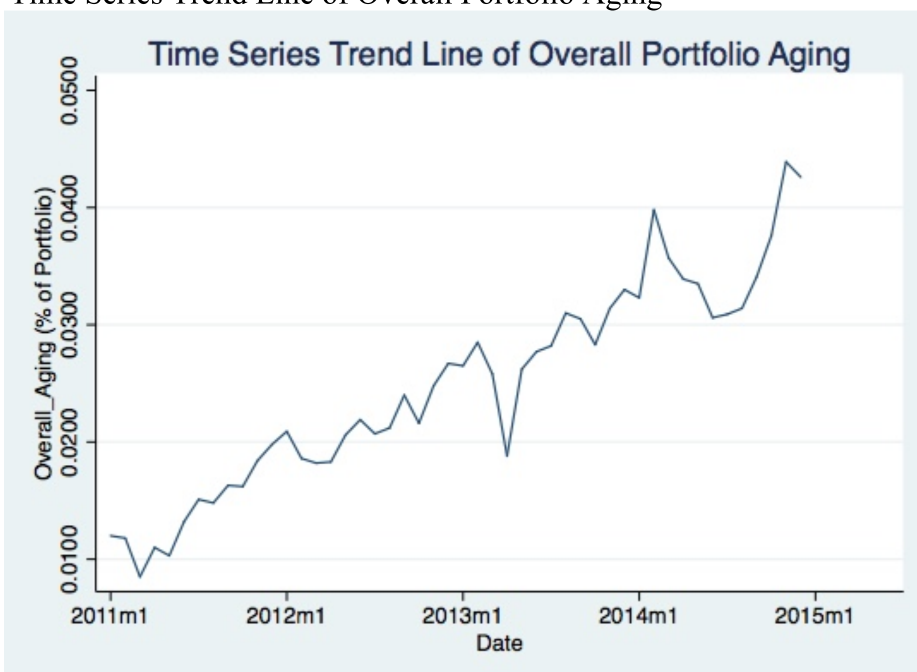
Given the success Gambera (2000) had with vector-autoregressive models in forecasting (p 4), I decided to utilize the same model for creating an econometric model and forecasting the performance of The Company's portfolio.

According to Lüetkepohl, VAR models are natural tools for forecasting (2011, p 1). The basic format of a VAR model is when past values of the involved variables partly explain the current values of a variable set. Because they describe the joint generation mechanism of the variables involved, they often are successfully used for economic analysis. Lüetkepohl (2011) commented that, "Structural VAR analysis attempts to investigate structural economic analysis with the help of VAR models. Since reduced form VAR models represent the conditional mean of a stochastic process, they lend themselves for forecasting" (p 13).

The first order of business was to test the variables for stationarity, as I had to have the data in stationary form for regression analysis. A time series is said to be stationary if its statistical properties such as mean, variance, etc. are all constant over time. Once the time series is stationary, it is easy to predict, I just make the assumption that its statistical properties will be the same in the future as they have been in the past.

Upon initial review, I noticed all of the Company's variables had a distinct upward trend, as can be seen below, displaying non-stationary properties.

Figure I: Time Series Trend Line of Overall Portfolio Aging



Simply taking the difference usually subtracts the trend from the variables, and fortunately this is the case with our variables. I confirmed this by both reviewing a trend line of the variables and ensuring no upward or downward trend over time, and in addition running a Dickey-Fuller test. As can be seen in Table 2, the test statistic for the Dickey-Fuller test for overall aging is less than the critical values, indicating no unit root is present.

Figure 2: Time Series Trend Line of 1st Difference of Overall Aging

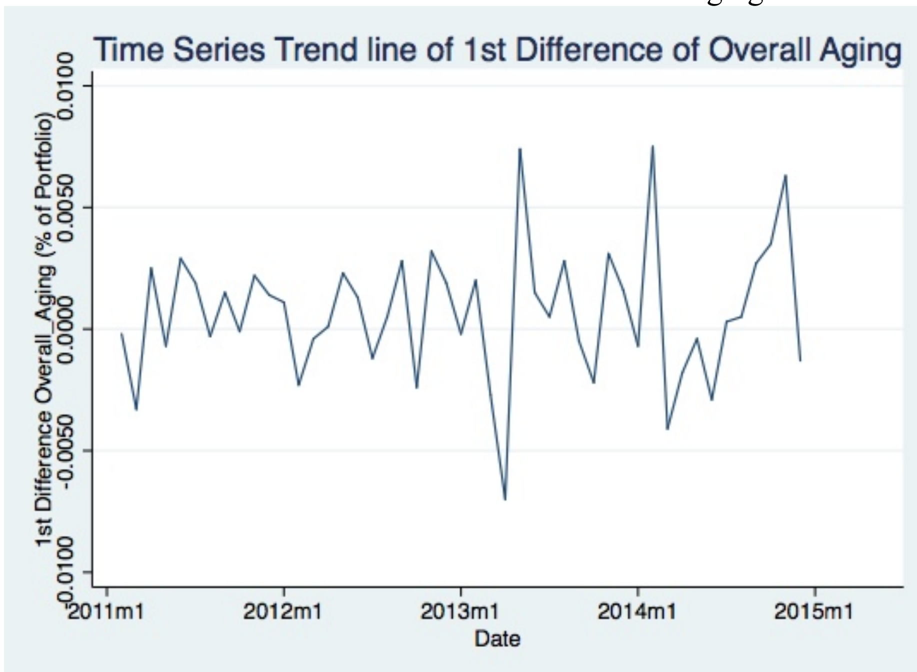


Table 2: Dickey-Fuller Test of Unit Root

Dickey-Fuller test for unit root — Number of obs = **46**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-8.708**	**-3.607**	**-2.941**	**-2.605**

MacKinnon approximate p-value for Z(t) = **0.0000**

After reviewing the Dickey-Fuller tests for all of the variables listed above, it was apparent to me that unit roots were a problem for all variables, and in an attempt to rectify this situation, the difference of each variable was taken. A revised variable list with first order differencing was created with some of the variables being the difference of the natural log of the variable and some the difference of the variable itself; depending on the value of the test statistic and the 1% critical value, with the larger the difference the better.

Given the success that Stock & Watson (1996) had with utilizing the Akaike Information Criteria to select the associated lags; I chose to run the varsoc command to determine the most predictive number of lags associated with each variable.

Table 3: Variable Lag Determination using Akaike Information Criteria

Selection-order criteria
Sample: **2011m8 - 2014m12** Number of obs = **41**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	19.0106				.001495	-.829784	-.799345	-.746195*
1	25.8241	13.627	4	0.009	.001304	-.967031	-.875716	-.716265
2	31.4068	11.165	4	0.025	.00121	-1.04423	-.892041*	-.626289
3	35.5249	8.2362	4	0.083	.001208*	-1.05*	-.836926	-.464873
4	38.0116	4.9733	4	0.290	.00131	-.976174	-.702227	-.223874
5	43.0334	10.044*	4	0.040	.001262	-1.02602	-.691195	-.106541
6	45.2684	4.4701	4	0.346	.001401	-.939923	-.544223	.146732

Endogenous: D.LNCharge_Off D.LNOverall_Aging
Exogenous: _cons

The next issue to be addressed was variable selection; a regression run with so many variables will undoubtedly run into correlation and over-fitting, due primarily due to the lack of degrees of freedom. I undertook several different approaches to select the appropriate variables, with the first being running a stepwise regression.

I chose to utilize stepwise regressions because the combination of forward and backward selection techniques allows me, based on the t-statistics of their estimated coefficients, to selectively add or remove variables. Stepwise regression is a modification of forward selection so that after each step in which a variable was added, all candidate variables in the model are checked to see if their significance has been reduced below the specified tolerance level. If a non-significant variable is found, it is removed from the model.

Stepwise regression requires two significance levels: one for adding variables and another for removing variables. The cutoff probability for adding variables should be less than the cutoff probability for removing variables so that the procedure does not get into an infinite loop. In this case, I utilized a probability of .10 for adding variables and .11 for removing variables. The results of the regression can be seen below in Table 4.

Table 4: Using Stepwise Regression

Source	SS	df	MS
Model	6.35793089	11	.577993717
Residual	1.19729726	22	.054422603
Total	7.55522815	33	.228946308

Number of obs =	34
F(11, 22) =	10.62
Prob > F =	0.0000
R-squared =	0.8415
Adj R-squared =	0.7623
Root MSE =	.23329

LNCharge_Off	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LDAvg_Funded_BEACON	.0434216	.0110256	3.94	0.001	.020556	.0662872
LDLNEIGHTEEN_FUNDED	-.3069771	.0959776	-3.20	0.004	-.5060225	-.1079317
LDLNThirty_One_Plus~g	-.7884607	.3172838	-2.49	0.021	-1.446467	-.1304544
LDLNNew_Non_Accrual	.2525183	.0930206	2.71	0.013	.0596053	.4454313
LDLNTotal_Non_Accrual	-17.93307	1.929652	-9.29	0.000	-21.93492	-13.93122
LDLNPer_Port_on_Non~l	17.84636	1.962518	9.09	0.000	13.77634	21.91637
LDTOTAL_DOLLAR_APPR~D	-1.21e-07	3.41e-08	-3.55	0.002	-1.91e-07	-5.02e-08
LDLNTWENTY_FUNDED	.4528959	.1470905	3.08	0.005	.1478489	.7579429
LDTWENTYEIGHT_FUNDED	1.20e-06	4.92e-07	2.43	0.024	1.77e-07	2.22e-06
LDLNTWENTYFOUR_FUNDED	-.4507999	.0975582	-4.62	0.000	-.6531233	-.2484765
LDAvg_Funded_BNI	-.0145155	.0079492	-1.83	0.081	-.0310012	.0019702
_cons	12.85525	.0643848	199.66	0.000	12.72172	12.98877

The next variable list was created by running a correlation analysis and utilizing all variables with a correlation coefficient better than .10. This resulted in the following variables being selected:

Table 5: Variables Selected Using Stepwise Regression

LNCharge_Off	LDLNOne_To_Thirty_Aging
LDLNNew_Non_Accrual	LDLNRecovery
LDAvg_Funded_BNI	LDAvg_Funded_BEACON
LDLNFOURTEEN_FUNDED	

Finally, a Classification And Regression Tree (CART) analysis was run to select a third variable list for testing. This methodology is known as binary recursive partitioning; binary because parent nodes are always split into exactly two child notes and recursive because the process can be repeated by treating each child node as a parent.

The three key elements of a CART analysis are the set of rules for splitting each node in a tree, deciding when each tree is complete, and assigning each terminal node to a class outcome (or predicted value for regression). The variables ultimately selected after the analysis are listed below in Table 6.

Table 6: Variable Selection Using CART Analysis

LNCharge_Off	DLNThirty_One_Plus_Aging
DAVERAGE_APPROVAL	DLNPer_Port_on_Non_Accrual

The Vector-Autoregressive model is especially useful for describing the dynamic behavior of time series and for forecasting; they are quite flexible because they can be made conditional on the future paths of specified variables in the model

A VAR model describes the evolution of a set of k endogenous variables over the same sample period (t = 1, ..., T) as a linear function of only their past values. These variables are collected in a $k \times 1$ vector y_t, which has as the i^{th} element, $y_{i,t}$, the observation at time "t" of the i^{th} variable.

A *j-th order VAR*, denoted VAR (*j*), is:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_j y_{t-j} + e_t$$

These three different VAR models were run, and the eigenvalue stability condition of the models was examined to ensure the variables are covariance stationary. All three models satisfied the stability condition, that is the Eigenvalue was less than one, and as such could be compared for accuracy.

Table 7: Eigenvalue Stability Test

Eigenvalue stability condition

Eigenvalue	Modulus
.9223402	.92234
−.4947761 + .5805096*i*	.762755
−.4947761 − .5805096*i*	.762755
.2422966 + .671892*i*	.714245
.2422966 − .671892*i*	.714245
−.6618995	.6619
−.2051058 + .5762456*i*	.61166
−.2051058 − .5762456*i*	.61166
−.3165654 + .3267152*i*	.454925
−.3165654 − .3267152*i*	.454925
.4043897	.40439
.1644959	.164496

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

After these models were run, these same models were again run with the aforementioned macroeconomic variables: the amount of consumer revolving debt and the percentage of serious consumer mortgage delinquency.

CHAPTER IV

RESULTS

Contrary to my initial belief, adding the two macroeconomic variables to our models did not clearly and significantly increase the accuracy of my forecasts. Taking a look at the first three econometric models, those without the addition of macroeconomic variables, one can see that the model utilizing variables obtained through the correlation analysis had the smallest predictive error when compared to actual charge-off values for January 2015, however it was not nearly as accurate in the second month as the model which obtained variables through the stepwise regression. Overall, the vector-autoregression run with variables selected through a stepwise regression was the most accurate over the forecast period.

However when looking at the model that incorporates the aforementioned macroeconomic variables, it is clear that there is not an across the board improvement in forecast accuracy. While incorporating the mortgage delinquency variable into the econometric model obtained from the stepwise regression increases the accuracy of the January forecast, it was one of the worst models for forecasting the subsequent month's forecast. And the model with variables obtained through a correlation analysis, while initially one of the most accurate, is almost useless in its forecasting ability due to such large forecast errors.

Table 8: Regression Results and Comparison to Actual Charge Off Values

	Jan-15	Feb-15
Actual Portfolio Charge Offs	$ 499,252.00	$ 466,824.00
	Jan-15	Feb-15
SW Regression Variables (M1)	$ 572,077.64	$ 413,453.36
Correlation Variables (M2)	$ 545,173.84	$ 294,598.89
CART Variables (M3)	$ 376,822.68	$ 396,285.42
Difference M1	$ 72,825.64	-$ 53,370.64
	14.6%	-11.4%
Difference M2	$ 45,921.84	-$ 172,225.11
	9.2%	-36.9%
Difference M3	-$ 122,429.32	-$ 70,538.58
	-24.5%	-15.1%
	Jan-15	Feb-15
SW Regression Variables & Revolving Debt (M4)	$ 567,133.50	$ 328,966.10
Correlation Variables & Revolving Debt (M5)	$ 412,408.65	$ 501,079.47
CART Variables & Revolving Debt (M6)	$ 371,182.82	$ 421,683.37
Difference M4	$ 67,881.50	$ (137,857.90)
	13.6%	-29.5%
Difference M5	$ (86,843.35)	$ 34,255.47
	-17.4%	7.3%
Difference M6	$ (128,069.18)	$ (45,140.63)
	-25.7%	-9.7%
	Jan-15	Feb-15
SW Regression Variables & Mortgage Delinquency (M7)	$ 481,297.09	$ 214,087.48
Correlation Variables & Mortgage Delinquency (M8)	$ 212,088.73	$ 284,221.74
CART Variables & Mortgage Delinquency (M9)	$ 344,862.13	$ 405,736.82
Difference M7	-$ 17,954.91	-$ 252,736.52
	-3.6%	-54.1%
Difference M8	-$ 287,163.27	-$ 182,602.26
	-157.5%	-139.1%
Difference M9	-$ 154,389.87	-$ 61,087.18
	-30.9%	-13.1%

Figure 3: Actual Values vs Initial Model Values

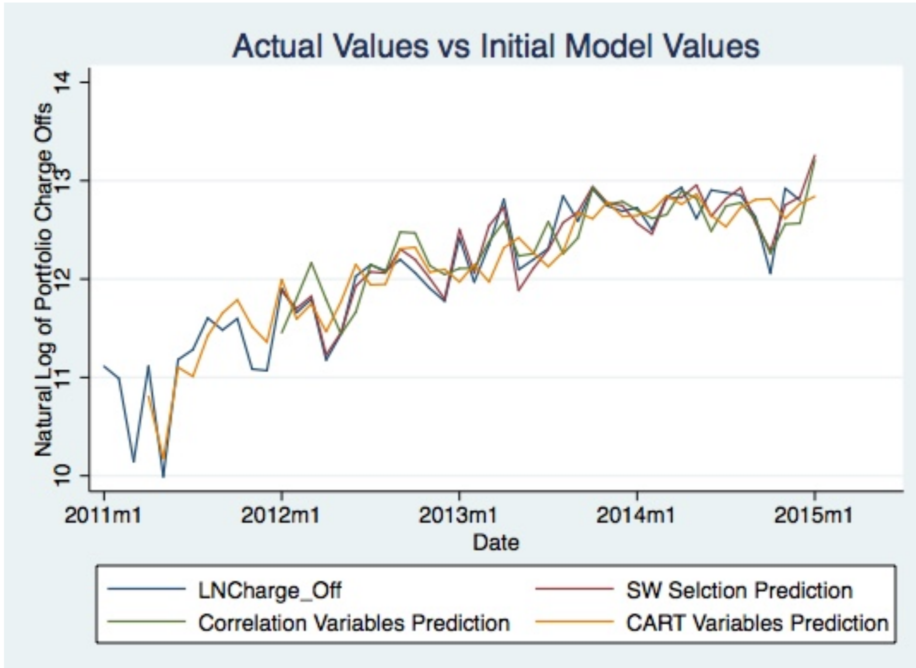


Figure 4: Actual Values vs Model with FRED Credit Card Variable

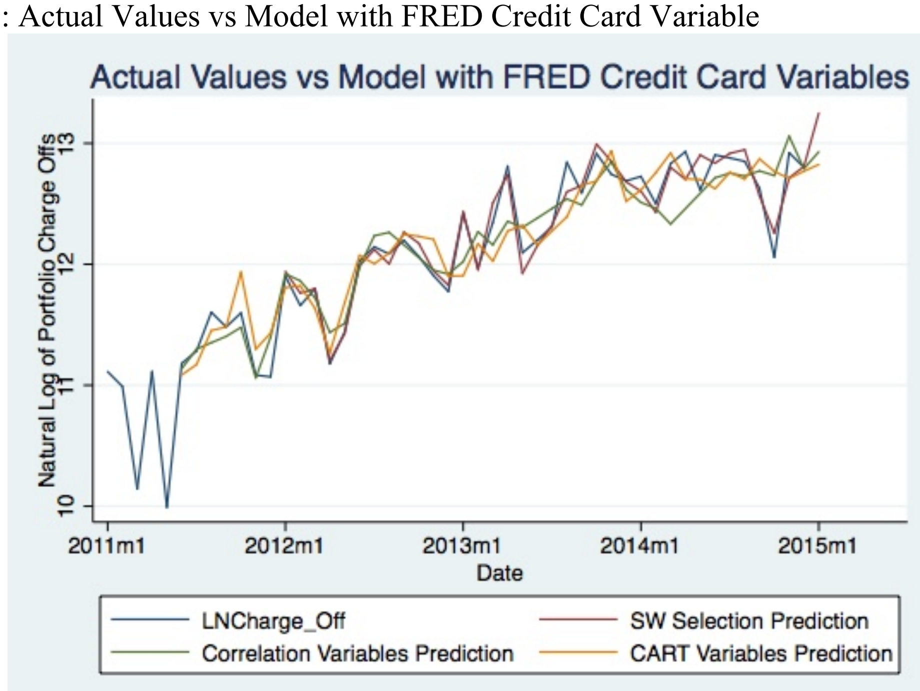
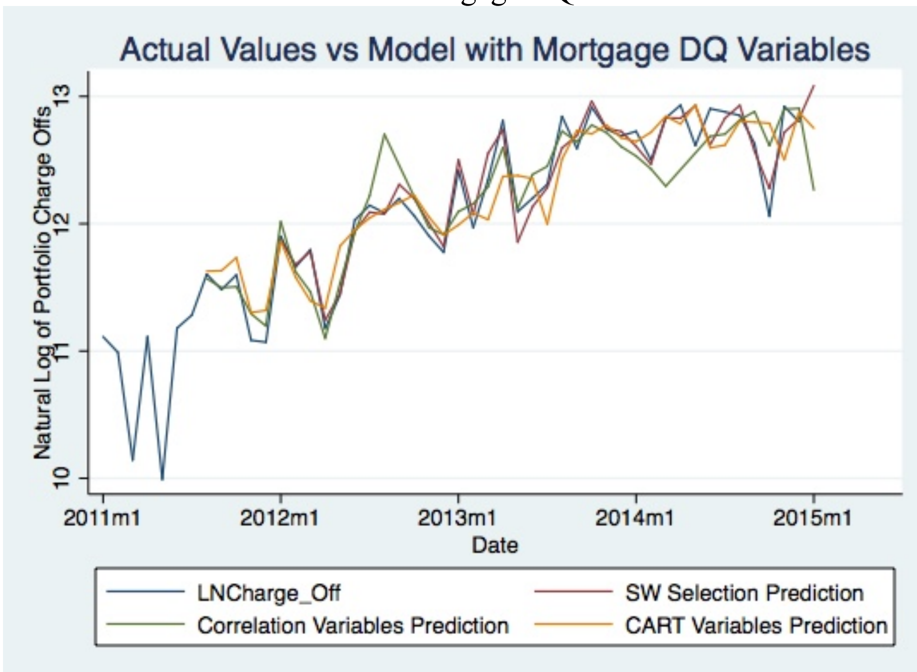


Figure 5: Actual Values vs Model with Mortgage DQ Variable



The VAR model utilizing variables obtained by a stepwise regression had the most accurate prediction over the two month time frame. A forecasting error of less than 15% for both periods is much better than the models utilizing variables obtained either through CART or correlation analysis. However, looking just one month ahead the VAR using variables selected through correlation analysis was the most accurate, only missing the predicted charge offs vales by 9.2%.

Adding the consumer revolving debt variable into the equation actually reversed the above results. Over the two month time frame the equation utilizing variables from the correlation analysis was more accurate, but the VAR using stepwise regression model selection was more accurate forecasting just one month ahead.

Finally incorporating the consumer mortgage delinquency variable into the model yield the most accurate prediction of all, the stepwise regression variable VAR was only off 3.6% of the first month's charge off values. However in general, all three econometric models incorporating consumer mortgage delinquency were not nearly as accurate as the models with consumer revolving debt and the model utilizing information from the Company's scorecard only.

CHAPTER V

FURTHER RESEARCH

Such a complicated process as forecasting portfolio performance would certainly benefit from additional research and modeling. First, while Gambera (2000) did indicate that VAR models "a more complete dynamic" (p 4); forecasting charged off values with other models would be useful for comparison. Autoregressive and Moving Average models, logistic regressions, and autoregressive conditional heteroskedasticity models might yield different results – would they be more or less accurate? Additionally, would a model utilizing simultaneous equations be more predictive?

Furthermore, there are numerous additional macroeconomic variables available that could potentially improve the accuracy of my model. For example, integrating consumer revolving credit delinquency rates (as opposed to debt levels) might be more closely correlated with portfolio delinquency levels. What about consumer confidence levels? Low consumer confidence might translate into poor sales for many of these businesses, thus probably resulting in decreased portfolio performance. Finally, utilizing geographic data to assist in modeling might yield more accurate forecasts. Landscapers in Minnesota will have a much different seasonal business model then landscape companies in California.

CHAPTER VI

SUMMARY

Equipment financing is a multiple billion-dollar industry, and being able to predict the performance of portfolios would be invaluable. Although a fair amount of research was completed on creating lending scorecards and the performance of commercial loan and consumer mortgage portfolios, I was unable to find a lot of information on equipment lease and loan portfolio performance.

27 variables from a small-ticket equipment finance company were collected; and econometric models created using stepwise regression, correlation analysis, and CART analysis for variable selection. Vector-autoregressions were run for each of the three aforementioned econometric models, and for each model I created forecasts for the next two time periods. Comparing these forecasts to the actual values indicated that the model utilizing stepwise regression for variable selection was the most accurate over the two periods forecasted, whereas the VAR utilizing variables obtained through a correlation analysis was more accurate looking ahead just one month.

Additionally two macroeconomic variables, consumer revolving debt levels and consumer mortgage delinquency were incorporated into my models with mixed results. While adding consumer revolving debt did increase the accuracy model of the VAR model that utilized correlation analysis for variable selection, I found that adding mortgage delinquency generally resulted in poorer forecast performance across all three models.

References

Bellotti, T., & Crook, J. (2012). Loss given default models incorporating macroeconomic variables for credit cards. *International Journal of Forecasting, 28*, 171-182.

Clements, M. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting & Economics, 27*, 285-303.

Clements, M., Franses, P., & Swanson, N. (2004). Forecasting economic and financial time-series with non-linear models. *International Journal of Forecasting, 20*, 169-183.

Diebold, F. (1998). The Past, Present, and Future of Macroeconomic Forecasting. *Journal of Economic Perspectives, 12*, 175-192.

EFLA. (2014). Equipment Leasing and Finance Association Industry Overview. Retrieved February 1, 2015, from https://www.elfaonline.org/About/?fa=overview

Frame, W., Srinivasan, A., & Woosley, L. (2001). The Effect of Credit Scoring on Small-Business Lending. *Journal of Money, Credit, and Banking, 33*(3), 813-825.

Gambera, M. (2000). Simple Forecasts of Bank Loan Quality in the Business Cycle. *Emerging Issues Series*.

Grenadier, S. (1996). Leasing and credit risk. *Journal of Financial Economics, 42*, 333-364.

Guerrieri, L., & Welch, M. (2012). Can Macro Variables Used in Stress Testing Forecast the Performance of Banks? *Finance and Economics Discussion Series Divisions of Research & Statistics and Monetary Affairs Federal Reserve Board,* 1-29.

Hartmann-Wendels, T., Miller, P., & Tows, E. (2014). Loss given default for leasing: Parametric and nonparametric estimations. *Journal of Banking & Finance, 40*, 364-375.

Kane, A., Kim, T., & White, H. (2010). Forecast Precision and Portfolio Performance. *Journal of Financial Econometrics, 8*(3), 265-304.

Lopez, J., & Saidenberg, M. (2000). Evaluating credit risk models. *Journal of Banking & Finance, 24*, 151-165.

Lüetkepohl, H. (2004). Vector Autoregression and Vector Error-Correction Models. In *Applied Time Series Econometrics* (pp. 86-158). Cambridge University Press.

Lüetkepohl, H. (2011). Vector Autoregressive Models. *European University Institute, 2011*(30).

Menkin, K. (2013, June 11). Update: Leasing Companies Out of Business. Retrieved April 9, 2015, from http://leasingnews.org/archives/Jun2013/6_11.htm

Minimum Payments vs. Actual Payments: A Look at Debt Service Behaviors and Credit Capacity (2013). TransUnion, LLC.

Morrison, J. (2009). Forecasting Portfolio Performance in an Uncertain Economy. *The RMA Journal,* 52-57.

Schmit, M. (2004). Credit risk in the leasing industry. *Journal of Banking & Finance, 28*, 811-833.

Smith, L., & Lawrence, E. (1995). Forecasting losses on a liquidating long-term loan portfolio. *Journal of Banking & Finance, 19*, 959-985.

Stavins, J. (2001). Credit Card Borrowing, Delinquency, and Personal Bankruptcy. *New England Economic Review,* 15-36.

Stepanova, M., & Thomas, L. (2002). Survival Analysis Methods for Personal Loan Data. *Operations Research - INFORMS, 50*(2), 277-289.

Stock, J., & Watson, M. (1996). Evidence on Structural Instability in Macroeconomic Time Series Relations. *Journal of Business and Economic Statistics, 14*(1), 11-30.

Timofeeva, G., & Timofeev, N. (2012). Forecasting Credit Portfolio Components with a Markov Chain Model. *Automation and Remote Control, 73*(4), 637-651.

United States. Federal Reserve Board. (2015, March 12). D.3(Q) Credit Market Debt Outstanding by Sector, s.a. Retrieved from the Federal Reserve Web site: http://www.federalreserve.gov/datadownload/default.htm

Ziwot, E., & Wang, J. (2006). Vector Autoregressive Models for Multivariate Time Series. In *Modeling Financial Time Series with S-PLUS* (pp. 385-429). Springer New York.