Predicting Retail Company Bankruptcies in the Era of COVID

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Trade journals and the popular press have suggested that the COVID-19 pandemic precipitated a second "retail apocalypse." The current study tests whether pre-pandemic data can be used to predict COVID-19 retail firm bankruptcies using a chaos-based model. This study successfully uses a chaos statistic calculated from stock market time-series returns for pair-match retail firms prior to the pandemic to predict bankruptcies occurring shortly afterwards.

Keywords: retail apocalypse, COVID-19, bankruptcy prediction, chaos

INTRODUCTION

In 1996, Campbell and Lindsay published "A Chaos Approach to Bankruptcy Prediction" in the *Journal of Applied Business Research*. That study showed that firms approaching bankruptcy exhibit less chaos than pair-matched firms not approaching bankruptcy. The 1996 study was conducted using data from 1983-1992. In 2019, the authors published "The Chaos Based Bankruptcy Model – Current Status" in the *Journal of Accounting and Finance*. That study used data from 2009 through 2014 and obtained comparable results to the 1996 study.

The stock market had no way of predicting the COVID-19 pandemic. Trade journals and the popular press have suggested that the COVID-19 pandemic precipitated a "retail apocalypse." This study attempts to use the chaos-based bankruptcy model to predict COVID-19 related retail firm bankruptcies, using data from before the pandemic.

LITERATURE REVIEW

One definition of the term retail apocalypse is "the perceived decline of brick-and-mortar retail in the United States due to the meteoric rise of eCommerce" (https://www.dynamicyield.com/glossary/retail-apocalypse/). The term gained currency in 2017 when nearly 7,000 store closure announcements were made, up 200 percent from 2016 (https://www.cnbc.com/2017/12/26/store-closures-rocked-retail-in-2017-and-more-should-come-next-year.html). Many of the 2017 closures were attributed to the rise of Amazon (https://www.businessinsider.com/retail-apocalypse-amazon-accounts-for-half-of-all-retail-growth-2017-11).

On January 20, 2020, the Centers for Disease Control of the U.S. Department of Health and Human Services (CDC) disclosed the first U.S. laboratory-confirmed case of COVID-19 from samples taken in Washington state. It soon became clear that COVID-19 was spreading through the U.S. population. A second coming of the retail apocalypse was predicted due to the pandemic (https://www.businessinsider.com/coronavirus-could-trigger-retail-bankruptcies-and-mass-store-closings-2020-4).

The following is an abbreviated history of the COVID-19 pandemic. On March 13, 2020, President Trump declared a nationwide emergency. On March 15, 2020, U.S. states began to shut down to prevent the spread of COVID-19. By May 9, 2020, the U.S. unemployment rate reached 14.7%, the worst rate since the Great Depression. With 20.5 million people out of work, the hospitality, leisure, and healthcare industries took the greatest hits. In November of 2020, Moderna and Pfizer-BioNTech announced that their COVID-19 vaccines were found to be 95% effective in clinical trials. By March 13, 2021, more than 100 million COVID-19 vaccine doses were administered in the U.S. On March 8, 2022, Hawaii became the last state to announce an end to its universal indoor mask mandate (https://www.cdc.gov/museum/timeline/covid19.html). On May 11, 2023, the U.S. Department of Health and Human Services declared an end to the COVID-19 public health emergency (https://www.hhs.gov/about/news/2023/05/09/fact-sheet-end-of-the-covid-19-public-health-emergency.html).

Many different bankruptcy prediction models are availalbe in the literature. Bellovary, Giacomino and Akers (2007) examine 165 models for assessing bankruptcy. These studies show that despite the methodology used, two issues must be addressed: misclassification errors and a test for external validity.

With respect to misclassification errors, a Type 1 error misclassifies a firm which will go bankrupt as one which will not go bankrupt. A Type 2 error misclassifies a firm which will not go bankrupt as one which will. Type 1 errors have been estimated to be 35 times more costly to decision makers than Type 2 errors (Altman et al., 1977).

Jones [1987] discusses the issue of model validation. Once a model has been developed using one set of data, it should be tested using an independent set of data. Often this is accomplished by testing the model on a hold-out sample. Bootstrapping is used as an alternative in studies with a small sample size.

This study relies upon non-linear dynamics, which is also referred to as chaos. Chaotic Systems appear to be random, but they are deterministic and predictable over short periods of time (Yorke, 1976). They are extremely sensitive to initial conditions, which is often referred to as the butterfly effect. Certain endogenously determined catastrophic system failures have been predicted using chaos models. Goldberger used a chaos model to predict myocardial infarction (1990). Since stock returns have been shown to exhibit chaotic behavior, it makes sense to use a chaos model to predict corporate bankruptcy (Peters, 1991).

HYPOTHESIS DEVELOPMENT

This study uses a chaos statistic, the Lyapunov exponent, to measure chaos by measuring the rapidity with which a system becomes unpredictable. The larger the exponent, the sooner the system will become unpredictable. Any system with a positive Lyapunov exponent is chaotic. Goldberger suggests that healthy systems exhibit more chaos than unhealthy systems (1990). The hypothesis of the study is:

***H_1**: The Lyapunov exponents estimated from the stock market returns of pre-pandemic retail firms approaching bankruptcy will be lower than the Lyapunov exponents of pre-pandemic retail firms not approaching bankruptcy.*

METHODOLOGY

The goal of this study is to use the chaos-based bankruptcy model to predict COVID-19 era retail company bankruptcies using data from antedating the pandemic. The CDC disclosed the first U.S. laboratory-confirmed case of COVID-19 on January 20, 2020. It was soon clear that COVID-19 was spreading through the U.S. population. The pre-pandemic data used in this study were from the four-year period ending November 29, 2019.

Once the CDC made the announcement, the existence of COVID-19 would have been discounted into stock prices. Retail firms which filed for Chapter 11 bankruptcy protection between February 1, 2020, and April 3, 2023, were identified from CBInsights.com. These firms' daily stock returns were obtained from Thomson Reuters Eikon database. One thousand daily returns were collected to provide enough data points to calculate chaos statistics. Bankrupt firms lacking a complete set of data were removed from the sample. Each firm in the bankrupt sample was pair matched by four-digit NAICS (North American Industry Classification System) code with a non-bankrupt firm to create a control sample. Pair match firms lacking adequate data were replaced if another match was found.

The Chaos Data Analyzer software package was used to calculate Lyapunov exponents for both bankrupt firms and their pair matches (Sprott and Rowlands, 1992). The study's hypothesis is: "The Lyapunov exponent estimated from the stock market returns of pre-pandemic retail firms approaching bankruptcy will be lower than the exponents of pre-pandemic retail firms not approaching bankruptcy." If so, the Lyapunov exponent will distinguish between bankrupt firms and pair-match firms.

This study uses a binary logistic regression model. The Lyapunov exponent is the covariate (independent variable) in the model. The 0,1 categorical variable, not bankrupt/bankrupt, is the dependent variable.

RESULTS

The test sample is comprised of 21 firms that declared Chapter 11 bankruptcy between February 1, 2020, and April 30, 2023, and their NAICS code pair matches. Daily stock market returns for each of the 42 firms were obtained from Eikon for the four-year period ending November 29, 2019, providing 1,000 daily returns. The impact of COVID-19 could not have been discounted into this sample of stock returns, since the CDC was not aware that COVID-19 was spreading through the U.S. until January 20, 2020. The returns were used to calculate Lyapunov exponents for both the test firms and the pair-match firms. Table 1 presents the 21 bankrupt companies, their Chapter 11 filing dates, their NAICS codes, their pair matches, and the Lyapunov exponents.

TABLE 1
LYAPUNOV EXPONENTS OF BANKRUPT AND PAIR-MATCH FIRMS

Bankrupt Name	Filling Date	NAICS Code	Bankrupt Lyapunov	Pair-Match Name	Pair-Match Lyapunov
Pier 1	2/17/2020	442299	0.49	Ethan Allen	0.641
Bluestem Brands	3/9/2020	454110	0.555	Wayfare	0.582
Stage Stores	5 11 2020	448140	0.549	Nordstrom	0.588
J. C. Penney	5/15/2020	452210	0.608	Macy’s	0.617
Centric Brands	5/18/2020	315240	0.056	Cintas	0.608
GNC	6/23/2020	446191	0.473	Natural Grocers	0.453
RTW Retailwinds	7/13/2020	448190	0.512	Abercrombie & Fitch	0.579
Ascena	7/23/2020	448120	0.621	Express	0.609
Tailored Brands	8/02/2020	448110	0.504	American Eagle Outfitters	0.607
Stein Mart	8/12/2020	452210	0.422	Burlington Stores	0.572
Town Sports International	9/14/2020	713940	0.41	Planet Fitness	0.621
Francesca’s	12/3/2020	448120	0.415	Express	0.609
Christopher and Banks	1/14/2021	448120	0.527	Urban Outfitters	0.633
L'Occitane	1/262021	446120	0.429	Sephora	0.616
Washington Prime Group	6/14/2021	531210	0.509	Zillow	0.508
Global Brands	7/31/2021	541810	0.485	Ralph Lauren	0.517
Sequential Brands	8/31/2021	315990	0.556	Deckers Outdoor	0.568
Revlon	6/22/2022	325620	0.503	Coty	0.412
Party City	1/17/2023	459420	0.394	Build-A-Bear Workshop	0.555
Serta Simmons	1/23/2023	337910	0.640	Tempur Sealy	0.523
Bed Bath & Beyond	4/23/2023	449129	0.509	Williams-Sonoma	0.617

Table 2 reports descriptive statistics of the Lyapunov exponent variable and of the dependent variable, which is the not bankrupt/bankrupt 0,1 categorical variable.

TABLE 2
DESCRIPTIVE STATISTICS

Variable	N	Minimum	Maximum	Mean	Standard Deviation
Bankrupt or Not	42	0	1	0.50	0.506
Lyapunov Exponent	42	0.056	0.654	0.530	0.105

Table 3 presents the Pearson correlation coefficients between the two variables. The correlation between the dependent variable, not bankrupt or bankrupt, and the independent variable, the Lyapunov exponent, is -0.440, and it is significant at the 0.01 level. The negative correlation supports the hypothesis that the

Lyapunov exponent estimated from the stock market returns of pre-pandemic firms approaching bankruptcy will be lower than the exponents of pre-pandemic firms not approaching bankruptcy.

TABLE 3
PEARSON CORRELATION COEFFICIENTS

N = 4

	Bankrupt or Not	Lyapunov Exponent
Bankrupt or Not	1	-0.440*
Lyapunov Exponent		1

*Correlation is significant at the 0.01 level.

Table 4 reports the t-test of the differences between bankrupt firm Lyapunov exponents and pair-match firm Lyapunov exponents. The mean of the difference is negative and significant at the .008 level. These results support the hypothesis.

TABLE 4
t-TEST OF THE DIFFERENCES BETWEEN BANKRUPT FIRM LYAPUNOV EXPONENTS AND PAIR-MATCH FIRM LYAPUNOV EXPONENTS

N = 21

Mean	Standard Deviation	t	Two-Sided p
-0.091	0.142	-2.94	0.008

It is inappropriate to use a linear regression when the dependent variable in a model is a 0,1 categorical variable since the function is discontinuous. The correct methodology to use is a binary logistic regression. In linear regressions, R-squared is the appropriate measure of how well the model fits the data. In binary logistic regressions, a pseudo R-squared serves this function. (Field, 2013). Table 5 reports the model's Cox & Snell R-squared of 0.239 and the Nagelkerke R-squared of 0.319.

TABLE 5
PSEUDO R-SQUARED OF THE BINARY LOGISTIC REGRESSION

Cox & Snell R-squared	Nagelkerke R-squared
0.239	0.319

Table 6 reports the binary logistic regression output. In the model, the Lyapunov exponent is the sole covariant. The coefficient on the log of the Lyapunov exponent variable (B) is -15.550, which is significant at the 0.006 level. These results support the hypothesis.

TABLE 6
BINARY LOGISTIC REGRESSION OUTPUT

N=48

	B	S.E.	Wald	df	Sig.	Exp(B)
Lyapunov	-15.550.5.609	7.686	1	.006	.000	
Constant	8.390	3.080	7.419	1	.006	4404.429

The binary logistic classification table for the model is reported in Table 7. The model correctly predicts the bankruptcy status of a company 73.8 percent of the time. A naive model, such as a coin toss, would obtain a 50 percent success rate. The model successfully predicts which specific firms will go bankrupt 71.4 percent of the time, and it successfully predicts firms that will not go bankrupt 76.2 percent of the time.

TABLE 7
BINARY LOGISTIC CLASSIFICATION TABLE

N=48

Observed	Predicted		
	Not Bankrupt	**Bankrupt**	**Percent Correct**
Not Bankrupt	16	**5**	76.2
Bankrupt	6	15	71.4
Overall Percentage			73.8

Due to the limited sample size of 21 bankrupt firms and their pair matches, a set-aside sample was not created. Instead, bootstrapping was used to generate 1,000 samples. The results of bootstrapping for the model are reported in Table 8. Bootstrapping does not change the values of the estimated coefficients of the variables; it only impacts the coefficients' significance and their confidence intervals. The estimated coefficient on the Lyapunov exponent variable remained significant at 0.012 level.

TABLE 8
BOOTSTRAP* TEST TO VALIDATE MODEL

			95% Confidence Interval	
	B	**Sig.**	**Lower**	**Upper**
Lyapunov Exp.	-15.550	0.012	-39.490	-5.898
Constant	8.390	0.013	3.073	21.688

*Results are based on 1,000 bootstrap samples.

SUMMARY AND CONCLUSIONS

The goal of this study is to predict COVID-19 related retail company bankruptcies using the chaos-based bankruptcy model with data from before the pandemic. Using time series stock market return data for the four-year period ending November 29, 2019, Lyapunov exponents are calculated for 21 COVID-19 era bankrupt firms and 21 NAICS pair-matched firms. A binary logistic regression model is developed using the Lyapunov exponent as the independent variable and not bankrupt/bankrupt status as the dependent variable.

The model correctly predicts the bankruptcy status of 73.8 percent of sample firms. The independent variable is significant at .006, and the Nagelkerke R-squared is .319. To test for external validity of the model, bootstrapping 1,000 samples is used in lieu of a set aside sample.

Bootstrapping indicates that the independent variable is significant at .012. Future studies will test the chaos-based bankruptcy model on other industries.

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