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Economic Benefit of Decentralized System: Blockchain Technology Company Analysis by Using Linear Regression Model and Neural Network Model

Xing Yin

University of Mississippi, Oxford, MS 38655, USA

Abstract: *Blockchain technology is a popular area in technology innovations. There are several companies using blockchain techniques to build their business service. In this paper, we use LBRY's data to analyze LBRY's quantity demand and sales. We created our quantity demand and sales function, and we predicted that in the future, the quantity demand and sales will continue to grow. We also use a linear regression model and a neural network model for our prediction. We compared the results of these two models and their prediction efficiency.*

Keywords: *Economic, Blockchain, Linear regression, Neural network, LBRY, Technology innovation*

1. Introduction and Purpose

The purpose of this article is to analyze the quantity demand and sales of a blockchain company by using a linear regression model and neural network model. We create our quantity demand function with the quantity of purchased service, price of service, LBRY's[1] users' income, price of related service, and several LBRY's[1] users. We also create our sales function based on the sales related to time series. We have the following two hypotheses: Hypothesis I: The sales (number of claims) of LBRY[1] will keep growing linearly. Based on the growth trend of the past five years, we assume that the sales growth rate will keep the increase in the following five years as well. Hypothesis II: The demand (number of claims) of LBRY[1] will keep growing linearly. Based on the demand trend of the past five years, we assume that the demand growth rate will keep the increase in the following five years as well. Based on our analysis, we have the following findings: The quantity of demand is positively related to the consumer's income and the number of buyers. We also use the linear regression model and neural network model to predict the sales of LBRY[1] in time series. We found out that the coefficient between time and sales is positively related. Following the trend, we predict that in the future the sales will increase as time increases. After we compared the results of the linear regression model and neural network model, we found out that for the sales prediction function, the linear regression model has less mean average error than the neural network model. However, for the demand quantity function, the neural network model has less mean average error than the linear regression model.

2. Literature Review

Blockchain techniques have been largely used nowadays. Innovation in technology helps businesses to have competitive advantages so they would be able to generate bigger markets and higher profits. The research showed that for those organizations, their success comes from their large quantity of innovations and these innovations helped the companies in many different ways. For example, the research showed that when there are new products, the market shares usually increase. There is a correlation between the maintenance and increase of market shares and new products offering[2]. Blockchain technology is a newly developing innovation. Blockchain technology has been largely used by companies all over the world. According to recent research, a survey of applying blockchain technology in Norwegian Companies, with these new blockchain techniques, the digitally-enabled distributions are increased and marketing cost has been reduced down to 10% with well-defined and more efficient pricing models and supply chains[3]. This decentralized crypto-economy is privately managed by entrepreneurs, not by governments, which could explain the diversity of blockchain innovations. Meanwhile, blockchain entrepreneurs can develop more market opportunities[4]. Blockchain is a hot area in recent market and research, and it is time to start thinking about the security, scalability, and efficiency of service provided by blockchain[5]. Blockchain is also a new information technology that will lead a commercial revolution

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in the future[6].

3. Methodology

In this paper, we use a company called LBRY[1]. LBRY[1] is an open-source protocol blockchain company. We use LBRY's[1] database as an example to apply the economic models and make this statistical analysis to testify our hypothesis of blockchain technology companies. LBRY[1] is an open-source protocol, which provides users with a decentralized digital content marketplace. Users could post, download or buy the content. Decentralized platforms have a lot of advantages compared to a centralized platforms. Only the creators who posted the content to the platform would be able to edit or remove the content. Anyone else would not be able to edit or remove the content unilaterally. When creators posted content on a centralized host like YouTube, the creators have to follow the enforced rules governed by the centralized host, However, at LBRY's[1] protocol, creators have free speech, which they would be able to post or remove any content they are interested in and do not need to follow the opaque rules (lbry. tech). The blockchain could also record and track every content that has been posted to LBRY[1]. For example, each block has information on multiple transactions which are hashed together. The block would be able to store the data such as user id, new coin created in the block, etc. Therefore, LBRY[1] would be able to provide users with a list of content that is available on the LBRY[1] network. Users would be easy to find the content that they are interested in. Access to the data is free and the cost is transparent. LBRY[1] would be able to provide more services to the client than YouTube. For example, LBRY[1] sells tokens and distributed tokens and creators would be able to earn 100% of the price they set up on LBRY[1]. Creators post content and also would be able to name it using the claim system provided by LBRY[1]. Our research is based on the analysis of the claim data provided. The claim is a stake that contains metadata about a stream or channel. The claim which contains metadata about a stream or channel could be created, updated, or abandoned. URLs are memorable references to claims. Each URL should be able to refer to the distinguishable claim for that name. The URL should be able to be resolved by other users if the content posted on that URL is interesting to the users and they would like to buy these memorable URLs.

Because blockchain techniques are most popular until recently. It is difficult for us to create more accurate forecasting models over a long period. Because LBRY[1] is an open-source protocol company, we mining the raw data from the company's website. The data we have is from December 2016 to August 2020. We program the data and create an SQL database. We have done data mining to understand the blockchain system and how it helps users to claim and bid for the URLs they liked. We believe there is still more work for us to understand how blockchain innovation technology could help us build our companies and how efficient they are. The number of claims that the users create would satisfy the users' activity using the company's website and service. Therefore, based on the data we had so far, we considered the number of claims would be assumed as the sales volume the company made. The database is huge for a simple time-series forecasting model. Therefore, we chose a sample with a time series of each month's first-day sales (number of claims) starting from December 1st, 2016 to August 1st, 2020. The total number of claims made between December 1st, 2016, and August 1st, 2020 are around 4.74 million. Because of the complexity of the dataset and the limitation of the linear trend time-series forecasting method, our result might not be as accurate as we expected. However, since the linear trend forecasting model is one of the simplest time-series forecasting methods. By using a linear trend forecasting model, we would have a more visualized vision of the future sales of the company. LBRY[1] is one of the successful blockchain companies and we use LBRY's[1] database to help us better understand how blockchain innovative technology has been used in business and forecast its future economy of it. Based on the data analysis, we made our first hypothesis as follows:

Hypothesis I: The sales (number of claims) of LBRY[1] will keep growing linearly. Based on the growth trend of the past five years, we assume that the sales growth rate will keep the increase in the following five years as well.

From the increasing sales (number of claims) we saw in our database, we assume that the demand for LBRY[1] is increasing and we estimate the demand function for LBRY[1]. To simplify our models, we will apply the general demand relation among five variables for our function. They are:

$Q = f(P, M, PR, N)$

Where

Q = quantity purchased of a good or service (number of claims in our scenario)

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P = price of good or service (cyber currency LBC/LBRY[1] users put to bid for each claim)

M = consumers' income (users' income)

PR= price(s) of related good(s) (average price for a URL sold in market)

N = number of buyers (number of users in the LBRY[1])

While this function is created based on the methodology to simplify the scenario and generate a more visualized result. We believe, to have more accurate results still required more data mining and research. Based on the data analysis of previous years starting from December 1st, 2016 to August 1st, we made our first hypothesis as follows:

Hypothesis II: The demand (number of claims) of LBRY[1] will keep growing linearly. Based on the demand trend of the past years year, we assume that the demand growth rate will keep increasing in the following five years as well.

4. Data Analysis and Results

For the first hypothesis of the linear trend forecasting model, we chose a sample with a time series of each month's first-day sales (number of claims) starting from December 1st, 2016 to August 1st, 2020. The total number of claims made between December 1st, 2016, and August 1st, 2020 are around 4.74 million. The number of sales will be our target variable (y-axis), and the date and time will be another input variable (x-axis). The correlation between sales and time is changing and unstable. The sales increase dramatically since July. 1st, 2019. The correlation of the sales and time on average is +0.756. The linear regression model could be seen more clearly in Figure 1:

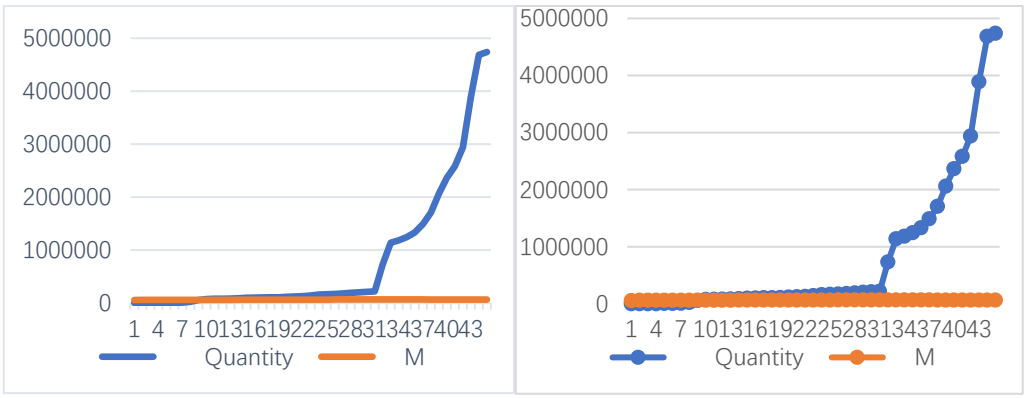

Figure 1: The Change of Sales from December 1st, 2016 to August 1st, 2020

The number of Dates (x-axis) is sequenced with a digit from 1 to 43. The number from 1-43, each digit represents each month starting from December 1st, 2016 to August 1st, 2020 (Figure 1). The scatter plot is as Figure 2:

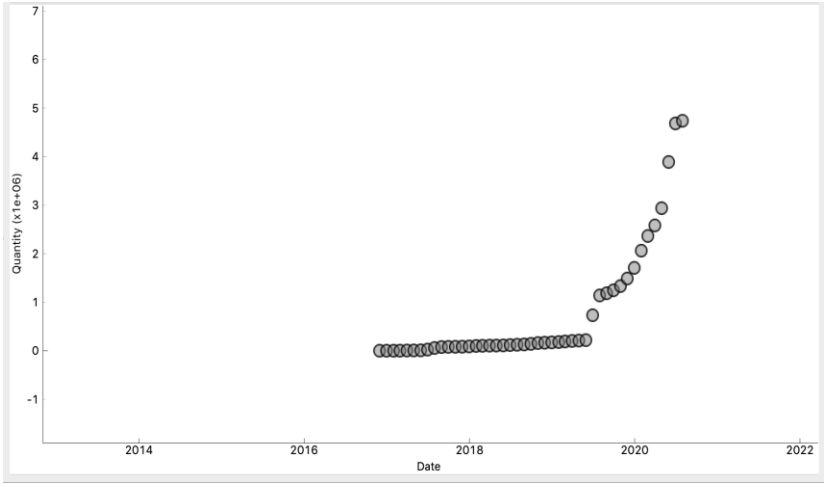

Figure 2: Scatter Plot of the Change of Sales from December 1st, 2016 to August 1st, 2020

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From Figure 2, we could see that sales increase dramatically in May 2019. From this linear trend regression forecasting model we could assume that in the future the sales will keep growing along the linear trend. However, because of the complexity of our database and the limitation of the research at this point, our model's accuracy is not up to expectations. The Mean Average Error is very high with R2= 0.571. There is still more work to do to make our model more accurate. The results are shown in Figure 3:

Descriptive Statistics

	Mean	Std. Deviation	N
Quantity	781254.978	1255860.42	45
Time	04/29/18 409 17:22...		45

Correlations

		Quantity	Time
Pearson Correlation	Quantity	1.000	.756
	Time	.756	1.000
Sig. (1-tailed)	Quantity	.	.000
	Time	.000	.
N	Quantity	45	45
	Time	45	45

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time[b]	.	Enter

a. Dependent Variable: Quantity
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	.756[a]	.571	.561	831749.924	.571	57.311

Model Summary[b]

Model	Change Statistics			Durbin-Watson
	df1	df2	Sig. F Change	
1	1	43	.000	.159

a. Predictors: (Constant), Time
b. Dependent Variable: Quantity

Figure 3: Statistics Description and Model Summary

Because of the complexity of our database, we also tried to use Neural Network Model to predict our future sales. However, with Neural Network Model the Mean Average Error is even higher than the linear regression model, and the R2 of the Neural Network Model is -1162.610 which is not up to our expectations as well.

Our second hypothesis is our simplified demand function. The LBRY's[1] cyber currency called LBC is valued as 1USD equals 5.09882LBC from the market. To post and update content on LBRY's[1] website and claim an URL is free. The amount of money spent to bid for a favorable URL depends on many elements. It is hard for us to get the exact amount of the bid from our dataset. It could be a question to work on in future research. Since most URL is free to get from LBRY[1], we decide our coefficient for P, the price of a good or service (cyber currency LBC/LBRY[1] users put to bid for each claim), is set to be zero. We use the US Census Bureau's data[7] of median household income for our M, consumers' income (users' income). In 2016, the median household income is $57,617. In 2017, it is $61372. In 2018, it is $64324. In 2019, it is $68703. In 2020, it is $66280 (census.gov). For the related product price, we are looking for the price of paying for a new regular URL in the market is $15 on average, which is 76LBC. The coefficient of the related product price to the quantity of demand is 0. We have our N, the number of buyers (number of users in the LBRY[1]) from the dataset we had. The coefficient of the number of users in the LBRY[1] to the quantity of demand is +0.984. The coefficient of median household income to the quantity of demand is +0.384. The coefficient of the number of users in the LBRY to the quantity of demand is +0.494. The demand function would be as the following:

Q = 0*P+ 0.384M + 0*PR +0.984N

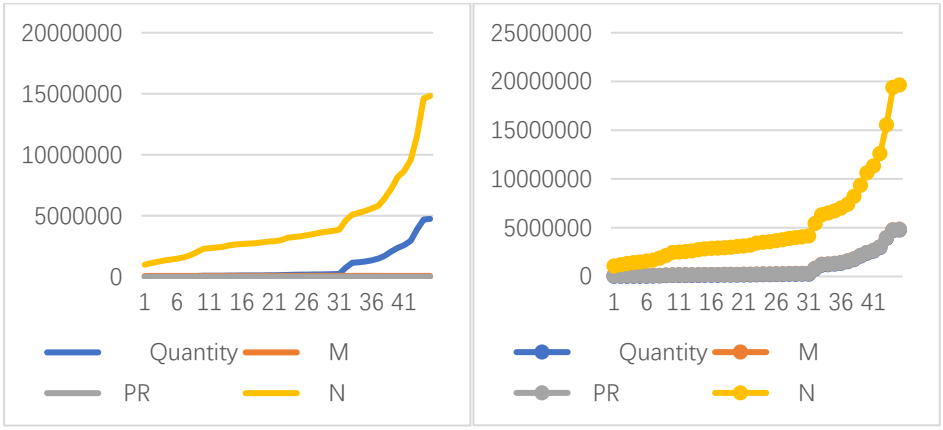

Figure 4: The Relations of Quantity, Median Household Income, Related Product Price and Number of Buyers to Demand

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However, our model is for us to simplify the complexity of the database and use the basic economic theory to analyze the demand function. The model is not perfect. It still requires more research to generate more accurate predictions. Since the coefficient of price related to the quantity of the demand is 0. We analyze the other four variables and their relations to the quantity of the demand. Figure 4. illustrates the result of our analysis:

From the three coefficients that are related to the quantity of demand, we could assume that the quantity of demand will increase in the future as all the variables: related to product price, median household income, and the number of users are all directly related to the quantity of demand and indicated a positive relationship. As each of the related product prices, median household income, and the number of users increases, the quantity of demand will also increase. From the trend the graphs showed, the quantity of demand will keep growing in the future as well. We used the linear regression model to testify our perditions. From the data computation, we have the following results: the linear regression model's mean average error is high, and the R2 value is 0.982. We also applied the neural network model, the mean average error is much lower than the linear regression model, and the R2 value is 0.991. For the demand function predictions, we suggested that the neural network model predicted more accurate results than the linear regression model.

Because the quantity of demand for LBRY's[1] claims is irrelated to the price of the create and update the claims because users could create and update their claims mostly for free. The average price for claiming a URL in the market is also stable and costs $15 on average. We considered the claim services offered by LBRY[1] to be perfectly inelastic demand with a coefficient equal to zero. The detailed data information is shown in Figure 5, Figure 6 and Figure 7:

Descriptive Statistics

	Mean	Std. Deviation	N
Quantity	781254.978	1255860.42	45
M	64903.2222	2996.86673	45
PR	76.0000	.00000	45
N	4257236.40	3262857.54	45

Correlations

		Quantity	M	PR	N
Pearson Correlation	Quantity	1.000	.384	.	.984
	M	.384	1.000	.	.494
	PR	.	.	1.000	.
	N	.984	.494	.	1.000
Sig. (1-tailed)	Quantity	.	.005	.000	.000
	M	.005	.	.000	.000
	PR	.000	.000	.	.000
	N	.000	.000	.000	.
N	Quantity	45	45	45	45
	M	45	45	45	45
	PR	45	45	45	45
	N	45	45	45	45

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	N, M[b]	.	Enter

a. Dependent Variable: Quantity
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	.991[a]	.982	.981	173298.622	.982	1134.354

Model Summary[b]

Model	Change Statistics			Durbin-Watson
	df1	df2	Sig. F Change	
1	2	42	.000	.371

a. Predictors: (Constant), N, M
b. Dependent Variable: Quantity

Figure 5: Statistics Description and Model Summary

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-289574.88	4972645.00	781254.978	1244394.67	45
Residual	-266073.19	295160.406	.00000	169314.213	45
Std. Predicted Value	-.861	3.368	.000	1.000	45
Std. Residual	-1.535	1.703	.000	.977	45

a. Dependent Variable: Quantity

Figure 6: Residuals Statistics

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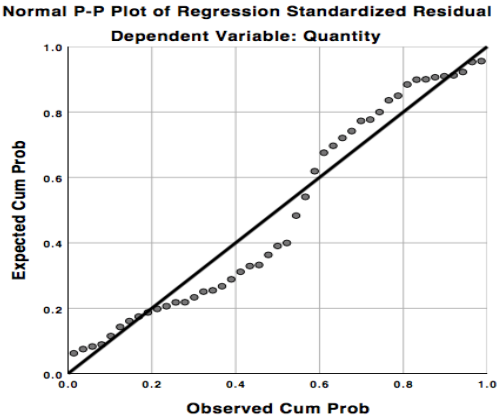

Figure 7: Normal P-P Plot of Regression Standardized Residual Dependent Variable: Quantity

5. Discussion and Implications

For this paper, we use the linear regression model and neural network model to predict the demand quantity function related to the price, consumers' income, price of related goods, and the number of buyers. LBRY's[1] service is free to users so it is inelastic to the price and the related product price. The quantity of demand is positively related to the consumer's income and the number of buyers. We also use the linear regression model and neural network model to predict the sales of LBRY[1] in time series. We found out that the coefficient between time and sales is positively related. Following the trend, we predict that in the future the sales will increase as time increases. For both the demand quantity function and sales prediction function, we use the linear regression model and neural network model. After we compared these two models, we found out that for the sales prediction function, the linear regression model has less mean average error than the neural network model. However, for the demand quantity function, the neural network model has less mean average error than the linear regression model.

6. Conclusion

LBRY[1] is an open-source protocol blockchain company. We download the raw database from LBRY's[1] library online. We create our database. In our research, we used LBRY's[1] data as an example to understand how is the quantity demand and sales in a blockchain company. We found that by using the linear regression model and neural network model. The quantity demand and sales are positively related to the variables and will continue to grow in the following years. However, our research also has several limitations. For example, to have a more accurate prediction we need to have more data. In the future, we could build more complicated models to have more accurate results. Innovation helps the company to grow and there is a great need for innovations in the market as well. The technology of blockchain will continue to develop to provide better business services in the future.

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