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FORECASTING DIGITAL TRANSACTIONS (NEFT AND RTGS) IN INDIA: ANALYZING COMPOUND ANNUAL GROWTH RATE AND EVALUATING THE INFLUENCE OF DEMONETIZATION AND COVID-19 USING R STUDIO AND PYTHON

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ABSTRACT

This paper discusses the availability of digital transaction methods introduced by the government and banking sectors in India as steps toward achieving a cashless society. The data for this study is sourced from the Reserve Bank of India's website, covering the period from 2011 to 2022. The study focuses on the growth rate of digital transactions through NEFT and RTGS, analyzing the impact of demonetization and COVID-19 using dummy variable regression. Additionally, it provides predictions for the number and value of transactions in future years. The Compound Annual Growth Rate (CAGR) analysis is conducted using the inverse semi-logarithmic regression model. The study finds that NEFT and RTGS transactions experienced a significant annual growth rate of 31.46% and 8.93% respectively during the study period. Holt-Winters forecasting is utilized to predict the value of cashless transactions, estimating the values for NEFT in January and February 2023 to be approximately 27086 and 27353 billion rupees respectively. The forecast method demonstrates 97% and 98% accuracy for digital transactions via NEFT and RTGS respectively. The paper provides recommendations to stakeholders in India's cashless transaction ecosystem, including network providers collaborating with the government to expand coverage in remote and rural areas, enhancing network reliability through infrastructure upgrades, introducing specialized data packages for digital payment apps, partnering with payment service providers for bundled services, and ensuring secure transactions through encryption. Banks are also encouraged to promote digital payment adoption by offering incentives such as cashback rewards, reduced costs, and user benefits.

Keywords: Digital Transactions, NEFT, RTGS, Cashless Transactions, CAGR, Inverse-Semi Logarithmic Regression, Dummy Variable, Holt-Winter

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1.0 INTRODUCTION

The use of digital payments has been increasing rapidly in recent years, with a significant shift towards cashless transactions. This shift has been fueled by technological advancements, increasing internet penetration, and government policies promoting digital payments.The widespread adoption of digital payments have the potential to bring about significant benefits to the Indian economy, such as increased efficiency, convenience, and transparency in financial transactions. However, it also raises concerns about security, privacy, and financial inclusion, particularly for those who are not well-versed in digital transactions.

In India, National Electronic Funds Transfer (NEFT) and Real-Time Gross Settlement (RTGS) are two popular methods for cashless transactions. NEFT is a payment system that enables the electronic transfer of funds from one bank account to another, while RTGS is a payment system that facilitates the real-time transfer of funds between banks.

This research paper aims to examine the trends, growth, impact of demonetization, forecasting, opportunities, and challenges associated with cashless transactions in India, with a focus on NEFT and RTGS. We will explore the factors driving the growth of digital payments, the impact of government policies and initiatives, and the challenges faced by various stakeholders in adopting digital payments.

Currency demonetization is a governmental measure to discontinue the use of specific physical money such as banknotes and coins, rendering it no longer valid as legal tender. Consequently, individuals are unable to utilize the currency for purchasing goods and services. The withdrawn currency is then replaced by new notes and coins, and in certain instances, an entirely new currency may be introduced. The primary objectives of demonetization are to address issues such as corruption, the existence of illicit funds, and the financing of terrorism. This transformative event holds significant implications for a nation's economic history, permeating its entire economy and society. As exemplified by Priyanka Sharma (2018), the Indian government, under the leadership of Prime Minister Narendra Modi, implemented demonetization in 2016, removing the circulation of the old Rs 500 and Rs 1000 notes. The motive behind this action was to combat corruption, the circulation of counterfeit currency within the Indian economy, and black income; see Aggarwal (2017) forthe types, sources, and government intervention to control black income in India. This policy in the long run contributed to the rise of digital transactions in India, thus the transaction of money is in digital form other than cash (Kotishwar, 2018).

1.1 Objectives

The study objectives are:

1. Analyzing the growth rate of cashless transactions in India with a focus on NEFT and RTGS.
2. Revealing the impact of demonetization and COVID-19 on cashless transactions by NEFT and RTGS in India.
3. Forecast the value and number of transactions (beyond the study period) of NEFT and RTGS in India using the Holt-Winters forecasting technique.

1.2 Significance of the Study

The significance of this research paper lies in its contribution to creating awareness and providing valuable insights to the government and the banking sector regarding the shifting landscape of cashless transactions in India, specifically focusing on NEFT and RTGS methods. The major findings of this study will enable stakeholders to proactively adapt to the changing transaction patterns and take necessary measures in advance.

The forecasting values generated through this study will play an integral role in helping the government and banking institutions prepare and allocate resources effectively. By considering aspects such as infrastructure, security, and human resources, stakeholders can adequately address the upcoming changes in transaction preferences. This proactive approach will ensure a seamless transition and enhance the overall efficiency of the cashless transaction ecosystem in India.

Further, policymakers can utilize the results from this study to reform regulatory frameworks and policies that support and encourage the growth of cashless transactions.

Overall, this research paper will contribute to the ongoing dialogue on cashless transactions in India and provide insights into the growth rate, opportunities, and challenges associated with digital payments, particularly with respect to NEFT and RTGS. These cashless transaction methods area simple, safe, and secure ways to transfer money electronically between bank accounts, with transactions processed in batches.

1.3 NEFT and RTGS

National Electronic Funds Transfer is the full form of NEFT. The Reserve Bank of India created and oversees this method of transaction, which was launched in November 2005 to facilitate one-to-one fund-secured transfer requirements of individuals and corporate organizations. Only banks that provide NEFT-enabled services can conduct transfers using this method. This method of transaction is not real-time and they take a few days to be completed. According to RBI norms, NEFT payments are processed and cashed in batches every half-hour and the number of NEFT transactions is unrestricted.

Real Time Gross Settlement, abbreviated as RTGS, is a system that allows for the continuous and real-time settlement of fund transfers on a transaction-by-transaction basis (without netting or bunching). "Real Time" refers to processing instructions as soon as they are received; "Gross Settlement" refers to the individual settlement of each funds transfer order.

NEFT is an electronic fund transfer system that processes batches of transactions that have been received up to a certain point in time. This is in contrast to RTGS, where transactions are continuously processed one at a time throughout the day.

The RTGS system is mainly designed for transactions with large amounts. There is no maximum amount that can be transferred but the minimum amount is 200,000 rupees.

NEFT transactions can be initiated through various channels, such as Internet banking, mobile banking, or by visiting the bank branch. Both NEFT and RTGS are secure, reliable, and convenient methods for cashless transactions in India. While NEFT is suitable for low-value transactions, RTGS is preferred for high-value transactions that require immediate settlement. The adoption of NEFT and RTGS has contributed to the growth of digital payments in India, promoting financial inclusion, and reducing cash usage.

2.0 RELATED LITERATURE

Kotecha (2019) conducted a comparative analysis of three prominent cashless transaction systems in India: National Electronic Funds Transfer (NEFT), Real Time Gross Settlement (RTGS), and Immediate Payment Service (IMPS). The study aims to provide insights into the features, usage, and effectiveness of these payment systems in facilitating cashless transactions.The research conducted by this author provides a comprehensive comparative analysis of NEFT, RTGS, and IMPS as cashless transaction systems in India. By focusing on these three prominent methods, the study highlights their features, transaction speed, convenience, and adoption rates. The findings contribute to a better understanding of the effectiveness and suitability of NEFT, RTGS, and IMPS in facilitating cashless transactions, aiding policymakers and stakeholders in making informed decisions in the Indian context.

Vasan and Senthil (2018) in their paper titled "A Study on Payment and Settlement System in Indian Banking Sector"investigate the usage and impact of National Electronic Funds Transfer (NEFT) and Real-Time Gross Settlement (RTGS) systems in facilitating cashless transactions in India.Firstly, the paper emphasizes that NEFT has become one of the most widely used electronic payment systems, enabling individuals and businesses to transfer funds securely and conveniently. The authors note the steady growth of NEFT transactions, attributing it to factors such as improved digital literacy, demonetization, enhanced banking infrastructure, and the widespread availability of smartphones.Furthermore, the study identifies the benefits of NEFT for customers, including cost-effectiveness, accessibility, and the ability to schedule transactions according to their convenience. The authors also discuss the challenges faced by NEFT users, such as transaction delays due to batch processing and limitations in transaction timings. They suggest potential improvements to address these challenges and enhance the efficiency of NEFT transactions.

In addition to NEFT, the research paper examines the utilization of Real-Time Gross Settlement (RTGS) in India. It highlights the unique features of RTGS, such as instantaneous settlement and the ability to process high-value transactions. The authors emphasize the significance of RTGS for businesses and financial institutions involved in time-critical and large-value transactions.

The study discusses the advantages of RTGS, including reduced settlement risk and enhanced operational efficiency. However, it also acknowledges the challenges associated with RTGS adoption, such as higher transaction costs and the requirement for robust technological infrastructure. The authors suggest measures to mitigate these challenges and promote the wider use of RTGS in cashless transactions.The research paper provide valuable insights into the utilization of NEFT and RTGS in cashless transactions in India. The findings highlight the growing popularity of NEFT and its benefits in terms of accessibility and cost-effectiveness. The study also underscores the significance of RTGS for time-sensitive and high-value transactions, while acknowledging the challenges in its adoption.It serves as a valuable resource for policymakers, financial institutions, and researchers seeking to enhance the efficiency and effectiveness of cashless payment systems.

Chandravathi (2022) examines the transaction volumes of NEFT and RTGS in Indian private-sector banks. The study analyzes the growth patterns, trends, and variations in the usage of these payment systems. By understanding the transaction volume, the research provides insights into the importance and scale of NEFT and RTGS in the private banking sector. Her study contributes valuable insights into the usage and prominence of NEFT and RTGS transactions within Indian private sector banks. By focusing on these specific electronic payment systems, the study provides a detailed analysis of their transaction volumes, enabling a better understanding of the role and significance of NEFT and RTGS in facilitating cashless transactions in the private banking sector

CAGR stands for compound annual growth rate. It is a metric in finance used to measure the average annual growth rate of an investment over a specific period of time. It is expressed as a percentage to understand the growth potential of an investment or a specific sector. By calculating the CAGR, researchers can determine the rate at which cashless transactions are growing or declining in India over a specific time period. This metric allows for a more accurate assessment of the overall trend in cashless transactions, rather than simply looking at individual year-by-year changes. This metric helps to identify the consistent annual growth rate, making it a valuable tool for understanding and predicting the future performance of cashless transactions in India. It is traditionally defined as,

$$CAGR = \left[\left(\frac{initial\ observation}{final\ observation}\right)^{\frac{1}{n}} - 1\right] \times 100\% \tag{1}$$

The initial observation is the beginning value of the study period and the final observation is the final value of the study period, and $n$denotes the total number of periods However, many researchers opine that the use of regression technique in finding the CAGR is more efficient. In regression models, the estimate of the regression coefficientgives the amount of change in the dependent variable for a unit change in the independent variable. Therefore, multiplying one less than the regression coefficient, by 100 gives the percentage change or growth rate in the dependent for an absolute change in the independent variable (Sharma *et al.*, 2017). In this study, we employed the regression technique of CAGR calculation by fitting an inverse semi-logarithmic regression model.

Dummy variable regression analysis is a statistical technique used to estimate the relationship between independent and dependent variables in a regression model in which the independent variables include a qualitative variable of two or more categories.

The paper by Sahoo and Das (2010) uses the CAGR technique to analyze the growth rate of NEFT transactions over time. The authors calculate the CAGR for the NEFT transaction volume and find that the growth rate of NEFT transactions has been significant over the years, indicating the increasing popularity of the NEFT system among Indian banks.

The paper also employs a dummy variable regression analysis to investigate the factors that affect the adoption of NEFT by Indian banks. The paper uses dummy variables to capture the effect of various factors, such as bank size, geographical location, and ownership type, on the adoption of NEFT.

The results of the dummy variable regression analysis show that bank size and geographical location significantly affect the adoption of NEFT by Indian banks. The study finds that larger banks are more likely to adopt the NEFT system compared to smaller banks, and banks located in urban areas are more likely to adopt the NEFT system compared to rural banks. The study also finds that the ownership type of the bank has no significant effect on the adoption of NEFT.

The use of statistical techniques such as CAGR and dummy variable regression analysis in this paper provides a rigorous analysis of the factors that affect the adoption of NEFT by Indian banks. The results of the analysis provide valuable insights into the factors that influence the adoption of electronic payment systems by banks, which can be used by policymakers and regulators to promote the adoption of electronic payment systems in India.

The study by Dinnesh, Reddy, and Suhasini (2018) utilizes the CAGR in drawing insights into digital transactions. The study indicated that debit card users in India increased by 414% followed by NEFT which increased by 155%, and RTGS by 122%. They revealed that mobile transactionsrecorded the highest CAGR of 3.40%. They also showed the growth rate in the case of the value of transactions and the highest growth rate was found in the debit card transactions with 205% followed by mobile and NEFT at 193% and 178% respectively. Their study also concluded that there was a significant effect of demonetization on digital payments.

The Holt-Winters method is a popular exponential smoothing technique used to forecast time series data that has trend and seasonal components. These components together with the average and the random part of the series are assumed to be multiplied or added together. i.e., data = average × trend × seasonality × random or data = average + trend + season + random. The method estimates the average values (level), the increasing or decreasing values (trend), and the repeating short-term cycle (seasonality)in the series using three different smoothing factors. The method has been widely used in various fields, including economics, finance, and marketing, for forecasting and trend analysis.

In their endeavor to analyze time series data for tax income forecasting, Wahyu, Rahmawati, and Umam (2022) concluded that the most effective method among Single Exponential Smoothing, Double Exponential Smoothing, and Holt-Winters Multiplicative method was the Holt-winters exponential smoothing with an additive seasonal component. The Holt-Winters Additive method exhibited the lowest Mean Absolute Percentage Error, measuring at 14% with a level of 0.1, a trend of 0.2, and a seasonal of 0.1. These findings led the researchers to propose recommendations for policymakers to shape the economic development planning of Java Province.

In a research conducted by Taylor (2003), the utilization of the Holt-Winters forecasting technique was employed to anticipate the electricity demand by considering both trend and seasonal fluctuations.

3.0 METHODOLOGY

The data for this study is secondary data obtained from the website of the Reserve Bank of India (RBI) which is published every month. We considered the data from the period 2011 to 2022 for NEFT and RTGS. The data were cleaned and structured to suit the purpose of our analysis.The NEFT and RTGS data contain two main columns i.e., total outward debits and total inward credits (only one of these columns is considered in our study since both have the same value). The number of transactions is given in millions while the value of transactions is given in billion rupees.

After restructuring the data, the main statistical techniques that were used are the inverse semi-logarithmic regression model for the CAGR analysis and the Holt-Wintersmethod for the forecasting. Further, to assess the impact of demonetization on these cashless transaction methods, the dummy variable regression technique was used.

3.1 Compound Annual Growth Rate (CAGR)

The CAGR takes into account the compounding effect of investment returns, which means it considers how the investment's value grows or declines each year and factors into the overall growth rate. In the context of this study, CAGR is used to analyze the growth rate of NEFT and RTGS transaction methods over the study period (2011 – 2022). It provides a standardized way to measure the average annual growth rate of these cashless transaction methods, taking into consideration the fluctuations in transaction volumes and values year over year. The inverse semi-logarithmic regression model of the form,

$$\log Y_t = \alpha + \beta t + u_t, \tag{2}$$

$u_t \sim \mathrm{N}\,(0, \sigma^2)$, $u_t$is the disturbance term which is homoscedastic, independent, and uncorrelated,$Y_t$takes values of the cashless transaction methods (NEFT and RTGS), and t denotes the study period in years, is used in the CAGR calculation in this study. Thus,

$$\text{CAGR}= \left[antilog(\hat{\beta}) - 1\right] \times 100\%, \tag{3}$$

$\hat{\beta}$ is the Ordinary Least Square (OLS) estimate of the regression coefficient in equation **(2).** Future predictions on NEFT and RTGS number and value of transactions were also made using the model in equation **(2).**

3.2 Dummy Variable Regression Model

Artificial variables constructed to represent the categories of a qualitative variable are called ***dummy variables***and it is used to quantify the categories.A regression model containing a dummy variable is referred to as a dummy variable regression model. A dummy variable takes values 0's and 1's. The impact of demonetization on the value of transactions using NEFT and RTGS was statistically revealed by the dummy variable regression technique. The model is of

the form,

$$Y_t = \alpha_1 + \alpha_2 D + \beta_1 X_t + \beta_2 X_t D + u_t, \text{ t} = 1, 2 \ldots . n_1 + n_2, \quad \textbf{(4)}$$

where the disturbance term$u_t \sim$ N $(0, \sigma^2)$ and uncorrelated (Damodar and Porter, 2009). In the setup of this study,

$D = 1$, before demonetization (2011-2016)

$= 0$, after demonetization (2017-2022),

$n_1$and $n_2$are the number of years before and after demonetization respectively, $Y_t$takes the value of the cashless transactions (NEFT and RTGS)and$X_t$denotes the periods in years. The constantsα_1 and $\beta_1$denote the intercept parameters before and after demonetization respectively, whereas α_2 and β_2 denote the slope parameters before and after demonetization respectively.

The average change in the value of transactions pre- and post-demonetization isobtained as,

$$E(Y_t \mid D = 0) = \alpha_1 + \beta_1 X_t \quad \textbf{(5)}$$

and

$$E(Y_t \mid D = 1) = (\alpha_1 + \alpha_2) + (\beta_1 + \beta_2) X_t \quad \textbf{(6)}$$

respectively, where $\alpha_2$represents the difference in intercepts and $\beta_2$represents the differencein the slope coefficients in the two periods (before and after demonetization).

3.3 Holt-Winters Forecasting Method

The forecasting method employed in this study is the Triple Exponential Smoothing also known as the Holt-Winters forecasting method.The equations for this method, considering additive components are given by, Level equation: $L_t = \alpha(Y_t - S_{t-L}) + (1-\alpha)(L_{t-1} + T_{t-1})$

Trend equation: $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$

Season equation: $S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-L}$, and

Forecasting equation: $Y_{t+m} = L_t + T_t m + S_{t-L+m}$ **(7)**

Where L is the seasonality length, $L_t$is the overall smoothing, $T_t$is trend smoothing, $S_t$is seasonal smoothing, $Y_t$refers to the real data at time period t, Y_{t+m}isthe forecast for $m$future period and $\alpha, \beta, \gamma$are the smoothing parameters, (Cowpertwait and Metcalfe, 2009).

4.0 ANALYSIS AND DISCUSSIONS

In this section, the data analysis, outcomes, and understanding derived from the study are presented. Additionally, the complete expansions of certain abbreviations utilized during the analysis are provided below.

neft_nt: NEFT Number of Transactions
neft_vt: NEFT Value of Transactions (billion rupees)
rtgs_nt: RTGS Number of Transactions
rtgs_vt: RTGS Value of Transactions (billion rupees)

The **descriptive analysis** for the methods of cashless transactions considered in this study is presented below. Table 1 provides an overview of the data structure utilized.

Table 1: Structure of Data of Cashless Transactions by NEFT and RTGS Used in Python

Year	rtgs_nt	rtgs_vt	neft_nt	neft_vt
2011	51.1104	519375	199.48	15377.4
2012	65.4662	644714	339.688	25887.7
2013	78.0894	725983	571.854	39919.8
2014	90	743994	873.026	55339.5
2015	97.2684	794161	1162.62	75985.8
2016	103.167	943728	1480.42	106104
2017	120.937	1116611	1897.65	157997
2018	134.567	1296190	2218.06	216348
2019	148.228	1388670	2621.68	232966

2020	146.46	1053160	2946.34	238495
2021	198.752	1235048	3800.89	276782
2022	236.454	1444560	4948.03	327951

The graph in Figure 1 below shows the patterns in the value of transactions by NEFT and RTGS in India.

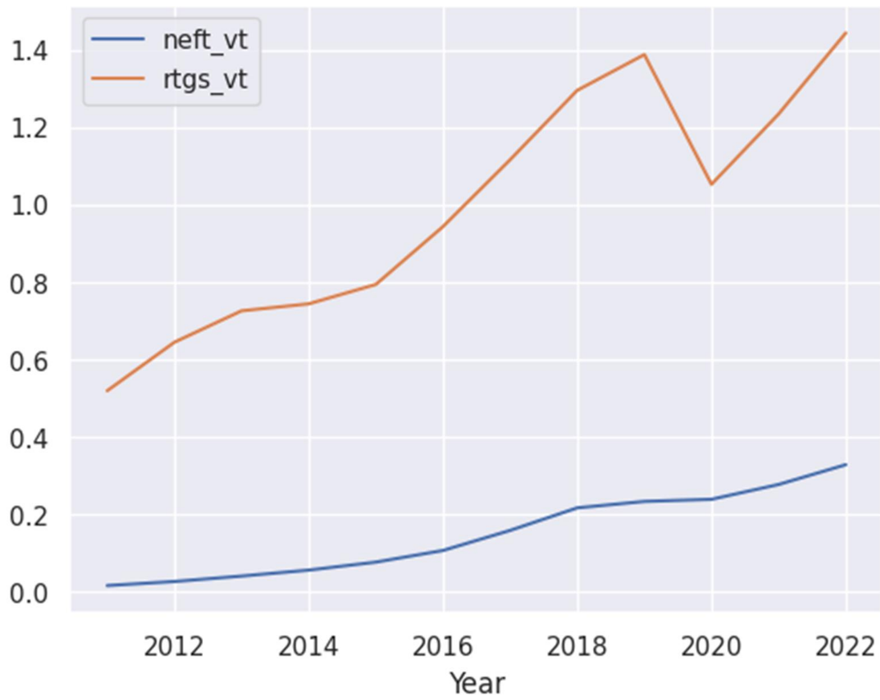

Figure 1: Graph of Pattern in the Value of Transactions

From 2016 onwards, there is a consistent upward trend, followed by a notable structural change leading to a higher growth rate. This shift can be attributed to the implementation of demonetization by the Indian government. However, there was a decline in 2020, likely due to the impact of the Covid pandemic on NEFT and RTGS transactions. These same patterns were observed in terms of transaction volume (refer to Appendix A, Figure A-1).

The graphs depicted in Figure 2 offer valuable insights into the logical connection between transaction volume and the value of NEFT and RTGS transactions. It is evident that there is a strong positive linear correlation between the number of transactions and their corresponding values across different methods. This indicates that as the number of transactions increases, so does the overall transaction amount. Pearson's product-moment correlation test further confirms this finding, revealing significant positive correlation coefficients of 0.981 and 0.872 for NEFT and RTGS, respectively. These statistical results substantiate the observations made in the graph.

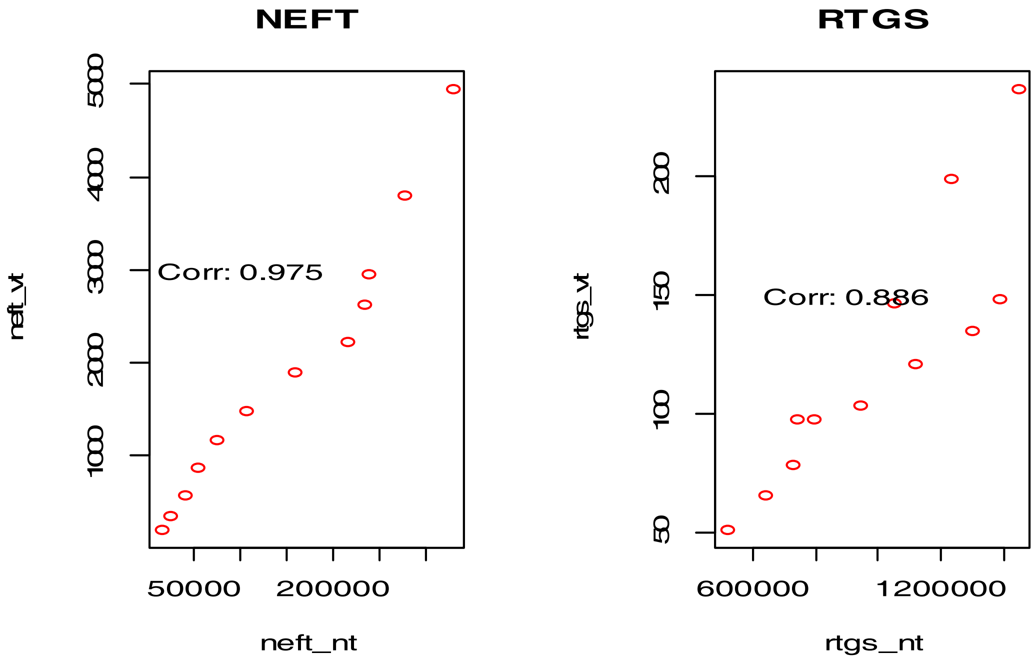

Figure 2: Graphical Relationship Between Value and Number of Transactions

Table 2 presents the summary statistics computed in Python for the different methods analyzed in this study. It includes the mean (average), standard deviation (std), minimum, and maximum values of transactions observed during the study period (2011-2022). Notably, the year 2011 recorded the lowest transaction value for NEFT, amounting to 15377.4 billion rupees, while the highest value of 327951.4 billion rupees was observed in 2022. These findings indicate a substantial increase in transaction values across the study period. The summary statistics align with the graph depicted in Figure 1, supporting the claim that demonetization contributed to the rise in transaction values across different methods. The mean transaction value post-demonetization surpasses the pre-demonetization period. For example, the mean annual transaction value for NEFT was 53102.3 billion rupees before demonetization, whereas it increased to 241756.6 billion rupees after demonetization. These results imply a higher average transaction amount per year following the implementation of demonetization.

Table 2: Summary Statistics of Transaction Methods

Summary	neft_nt	neft_vt	rtgs_nt	rtgs_vt
		Total (2011-2022)		
Mean	1921.645	147429.483	122.542	992182.8
Std	1461.003	108230.458	54.416	309068.1
Min	199.480	15377.439	51.110	519375.2
Max	4948.030	327951.425	236.454	1444560
		Pre-demonetization		
Mean	771.181	53102.342	80.850	728659.1
Std	493.837	33690.929	19.900	142572.0
Min	199.480	15377.439	51.110	519375.2
Max	1480.420	106103.790	103.167	943727.9
		Post-demonetization		
Mean	3072.108	241756.6	164.233	1255706
Std	1129.394	57280.8	44.123	152173.0
Min	1897.650	157997.3	120.937	1053160
Max	4948.030	327951.4	236.454	1444560

neft_vt, rtgs_vt are in billion rupees, neft_nt&rtgs_nt in millions

4.1 Discussion Pertaining to the Compound Annual Growth Rate (CAGR)

The CAGR calculation with regards to NEFT and RTGS using the inverse semi-logarithmic model approach involved testing several key assumptions (normality, independent errors, autocorrelation, and homoscedasticity) on the residuals, as indicated in the highlighted section.

4.1.1 Normality of the Residuals

The w statistic value obtained from the Shapiro-Wilks normality test for the model in (2) with Y_t as the neft_vt was 0.9572, and its corresponding p-value was 0.7432, which is greater than the significance level of 0.05. Therefore, based on these results, we accept the null hypothesis that the data follows a normal distribution. Consequently, we can conclude that the residuals from the neft_vt model in (2) exhibit a normal distribution.

Similarly, for the model in (2) with Y_t as the rtgs_vt, the w statistic was calculated as 0.9636, and its associated p-value was 0.8338, also exceeding the significance level of 0.05. Thus, we accept the null hypothesis and infer that the residuals from the rtgs_vt model in (2) are normally distributed.

4.1.2 Homoscedasticity Check on the Residuals

This assumption suggests that the residuals' variance in the regression model remains relatively constant across all predicted variable values. After conducting the studentized Breusch-Pagan-Godfrey test, we obtained p-values of 0.7202 and 0.142 for the neft_vt and rtgs_vt models, respectively. Both p-values exceed the significance level of 0.05. As a result, we are unable to reject the null hypothesis, leading us to conclude that our model in (2) exhibits homoscedasticity when using Y_t as the neft_vt and rtgs_vt variables.

4.1.3 Autocorrelation Assessment on the Residuals

This assumption is based on the idea that the regression model should not exhibit autocorrelation, meaning that the residuals should not be dependent on each other. To assess the independence of the residuals, the runs test was utilized for separate analysis. The obtained standardized runs test statistic for the fitted model yielded a value of -1.2111, accompanied by a p-value of 0.2259, which is greater than the significance level of 0.05. Consequently, we can infer that the residuals, when Y_t is considered as the rtgs_vt, demonstrate independence.

Furthermore, to examine this assumption for the rtgs_vt, the Breusch-Godfrey test was employed to assess serial correlation up to order 1. The p-value resulting from this test was determined to be 0.224, which is also greater than the significance level of 0.05. As a result, we conclude that the residuals exhibit no correlation up to order 1. Similarly, these assumptions hold true when $Y_t$is chosen as the neft_nt, rtgs_vt, and rtgs_nt variables. Refer to Appendix C.1 for the algorithms used to conduct the aforementioned tests.

The absence of serial correlation can be deduced from the graphical examination using the autocorrelation function. This observation is supported by the fact that all the lagged values associated with the cashless transaction methods under consideration fall within the control limits, as depicted inFigure 3.

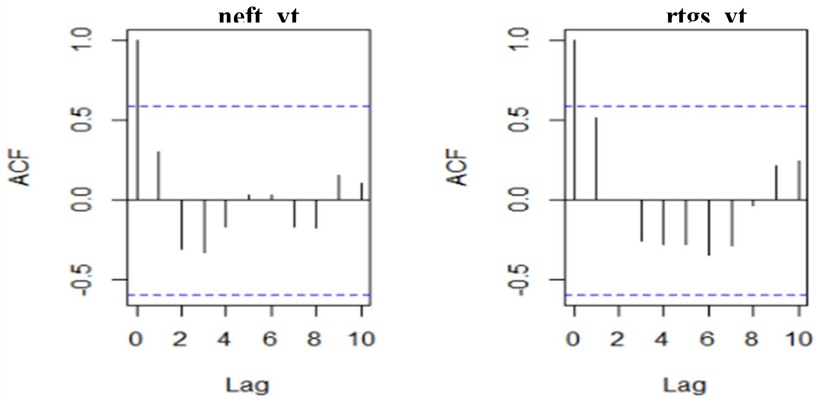

Figure 3: Plot for Autocorrelation Assessment (ACF Plot)

In Table 3, we present the Compound Annual Growth Rate (CAGR) for the value of transactions using equations (1) and (2). The significance test[1]was conducted on the OLS estimate of the regression coefficient($\hat{\beta}$= 0.2735), obtained by fitting our model with Y_t as the neft_vt. As a result, we determined that the CAGR for neft_vt is 31.46% based on equation (2).

[1]The regression analysis indicates the significance of time t on both neft_vt and rtgs_vt. When Y_t is neft_vt, the estimated coefficient, $\hat{\beta}$ = 0.2735, accompanied by a standard error of 0.021. The t-value of 13.07 and Pr (>|t|) = $1.31e-07$ further validate the significance of $\hat{\beta}$ at a significance level of 0.001. Consequently, it can be concluded that time t has a significant impact on neft_vt. Similarly, when Y_t represents rtgs_vt, the estimated coefficient $\hat{\beta}$ = 0.0855, with a standard error of 0.0104. The t-value of 8.23 and Pr (>|t|) = $9.15e-06$ also affirm the significance of $\hat{\beta}$ at a significance level of 0.001, thereby indicating that time t has a significant influence on rtgs_vt.

Table3: CAGR of Value of Transactions by NEFT and RTGS (2011-2022)

CAGR =	$[antilog(\beta) - 1] \times 100\%$	$\left[\left(\frac{ending\ value}{beginning\ value}\right)^{\frac{1}{n}} - 1\right] \times 100\%$
neft_vt	31.46%	29.05%
rtgs_vt	8.93%	8.89%
neft_nt	30.54%	30.68%
rtgs_nt	12.81%	13.61%

The CAGR analysis reveals noteworthy growth patterns within our study period. In particular, neft_vt experienced a significant annual increase of 31.46% using equation (2), while it grew by 29.05% per annum using equation (1). Similarly, rtgs_vt showed substantial growth rates of 8.93% and 8.89% annually using equations (2) and (1) respectively. These findings indicate that digital transaction methods in India exhibit an upward trend over time. The utilization of inverse semi-logarithmic regression in equation (2) better captures this growth compared to the traditional method in equation (1). The NEFT transactions' value exhibited a much higher growth rate compared to RTGS due to the absence of a minimum cap per transaction, unlike RTGS where a minimum value of 200,000 rupees is required. This distinction leads to a larger volume of transactions using NEFT, resulting in a substantial increase in its transaction value compared to RTGS. A similar observation can be made regarding the number of transactions for both cashless methods, neft_nt and rtgs_nt. Consequently, it is anticipated that customers in India will frequently opt for cashless transactions through NEFT rather than RTGS.

4.2 Utilizing the Dummy Variable Regression Method to Analyze the Impact of Demonetization

The obtained model coefficients were derived by fitting the model using equation (4) and considering Y_t as the transaction value through RTGS:

$\widehat{\alpha_1} = 13.119, \widehat{\alpha_2} = 0.683, \widehat{\beta_1} = 0.104$ and $\widehat{\beta_2} = -0.079$, therefore the fitted model becomes;

$$\widehat{Y_t} = 13.119 + 0.683D + 0.104X_t - 0.079(X_tD). \qquad \textbf{(8)}$$

The expected values of transactions during the periods before demonetization (2011-2016) and after demonetization (2017-2022) were derived from equation (8) as follows:

$E(Y_t \mid D = 0) = 13.119 + 0.104X_t$ **(9)**

$E(Y_t \mid D = 1) = (13.119 + 0.683) + (0.104 - 0.079)X_t = 13.802 - 0.069X_t$ **(10)**

For NEFT,

$\widehat{\alpha_1} = 9.367, \widehat{\alpha_2} = 1.807, \widehat{\beta_1} = 0.378$ and $\widehat{\beta_2} = -0.251$ therefore the fitted model becomes;

$\widehat{Y_t} = 9.367 + 1.807D + 0.378X_t - 0.251(X_t D)$.

The expected values of transactions during the periods before demonetization (2011-2016) and after demonetization (2017-202) were respectively derived as:

$E(Y_t \mid D = 0) = 9.367 + 0.378X_t$ **(11)**

and

$E(Y_t \mid D = 1) = (9.367 + 1.807) + (0.378 - 0.251)X_t = 11.174 + 0.629X_t$ **(12)**

It is important to note that the estimated coefficients were found to be significant[2] in all the aforementioned cases.

The change in rtgs_vt before and after demonetization, indicated by equations (9) and (10), demonstrates that for every unit increase in time (X_t), the average increase in rtgs_vt is 13.223 billion rupees pre-demonetization and 13.733 billion rupees post-demonetization. Similarly, equations (11) and (12) reveal that for one unit increase in time (X_t), the average change in neft_vt before and after demonetization is 9.745 billion rupees and 11.803 billion rupees, respectively. These results suggest that the impact of demonetization was greater on rtgs_vt compared to neft_vt.

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[2]The parameter Y_t representing rtgs_vt exhibits a statistically significant impact of time t, indicated by the estimated coefficient $\widehat{\beta_1} = 0.104$ (SE = 0.0237, t-value = 4.382, Pr (>|t|) = 0.00234) at a significance level of 0.001. Consequently, the variable rtgs_vt is influenced significantly by time t. Additionally, the coefficient $\widehat{\alpha_2} = 0.683$ (SE = 0.247, t-value = 2.77, Pr (>|t|) = 0.0244) suggests that the dummy variable D has a significant effect on rtgs_vt at a significance level of 0.05. Likewise, the intercept (representing the general mean of rtgs_vt) denoted by $\widehat{\alpha_1} = 13.119$ and the interaction term (involving the dummy D and time t) expressed by $\widehat{\beta_2} = -0.081$ are both statistically significant, implying their impact on rtgs_vt.

Similarly, when considering Y_t as neft_vt, the estimated coefficient $\widehat{\beta_1} = 0.378$ (SE = 0.019, t-value = 19.70, Pr (>|t|) = 4.57e-08) signifies a significant effect of time t, on neft_vt at a significance level of 0.001. Furthermore, the coefficient $\widehat{\alpha_2} = 1.807$ (SE = 0.199, t-value = 9.060, Pr (>|t|) = 1.76e-05) suggests a significant impact of the dummy variable D on neft_vt at a significance level of 0.001. Additionally, the intercept $\widehat{\alpha_1} = 9.367$ and the interaction term $\widehat{\beta_2} = -0.251$ both display statistical significance, indicating their influence on neft_vt, the general mean of neft_vt, and the interaction of the dummy D and time t, on neft_vt, respectively.

The impact of demonetization on cashless transactions, as evident from the above findings, can be attributed to the Indian government's decision to withdraw banknotes under the demonetization policy, resulting in a decrease in the amount of cash circulating in the country. This scarcity of cash led individuals to realize the convenience and time-saving benefits of digital transactions, while businesses incentivized the adoption of digital payments by offering cashbacks and discounts. The government also actively promoted digital transactions through various initiatives, leading to increased awareness and usage. Ultimately, demonetization facilitated the widespread adoption of digital payment systems, as most citizens shifted away from cash transactions It is also understood from the analysis that the demonetization had more impact on rtgs_vtthan neft_vt. This may be due to the following reasons:

Transaction Size: RTGS transactions generally involve larger amounts of money compared to NEFT transactions. During demonetization, when there was a sudden shortage of cash in circulation, individuals and businesses had a greater need to transfer larger sums of money securely. RTGS, being a real-time gross settlement system, is specifically designed for high-value transactions, making it the preferred choice for such transfers.

Urgency and Immediacy: RTGS transactions offer a real-time settlement, ensuring immediate transfer of funds from the sender's account to the recipient's account. This feature became crucial during demonetization when individuals and businesses needed to swiftly transfer significant amounts of money to ensure business continuity and meet financial obligations. NEFT transactions, on the other hand, are processed in batches at set intervals throughout the day, which may not provide the same level of urgency and immediacy as RTGS.

Business Transactions: RTGS transactions are commonly used for large-value business transactions, such as interbank transfers, corporate payments, and high-value purchases. During demonetization, businesses needed to carry out such transactions to maintain operations and manage financial transactions. This increased the demand for RTGS as a reliable and efficient payment method.

Regulatory Support: The regulatory framework and guidelines during demonetization encouraged the use of digital payment methods, especially for high-value transactions. The government and financial institutions promoted the adoption of RTGS as a secure and transparent payment mechanism, providing incentives and support for businesses and individuals to utilize this mode of transaction.

Considering these factors, the impact of demonetization on transaction values was more pronounced in RTGS transactions compared to NEFT transactions due to the larger transaction sizes, the need for immediate transfers, the importance of business transactions, and the regulatory support favoring the use of RTGS during that period.

4.3 Holt-Winter's Exponential Smoothing

Table 4 illustrates the data structure employed for Holt-Winters forecasting, while a comprehensive overview of the complete dataset can be found in Appendix A Table A.2.

Table 4: DataforHolt-Winter'sForecasting

Months	No. of transactions	RTGS (billionrs)	No. of transactions	NEFT (billionrs)
Jan 2011	3.832583	38238.54563	12.9600	938.8800
Feb 2011	3.805814	38080.88615	13.4300	905.8800
Mar 2011	4.79526	59915.92759	16.3600	1503.8100
April 2011	3.295927	38184.71256	14.8600	1302.9400
May 2011	4.27525	41900.85317	15.7700	1145.3200
June 2011	4.251614	47690.05094	15.9400	1319.9500
July 2011	4.125403	40563.8953	16.6300	1283.5400
…………	………..	…………..	………	………...

The Holt-Winters forecasting method relies on the fundamental assumption that the time series data contains both trend and seasonal components. If these components are present, it implies that the mean and variance of the data for different cashless transaction methods throughout the study period are not constant, indicating non-stationarity. To assess the non-stationarity of our data, we employed the Augmented Dickey-Fuller test.

4.3.1 AugmentedDickey-FullerTest(ADFtest)

Table 5 displays the outcomes of utilizing the ADF test to examine the stationarity of the data for the different transaction methods examined. The hypothesis tested can be summarized as follows:

Null hypothesis: The data is non-stationary.

Alternative hypothesis: The data is stationary.

Table5: AugmentedDickey-FullerTest

	Dickey-Fuller	Lagorder	p-value	Result
neft_nt	0.5959	5	0.99**	Non-stationary
neft_vt	-2.7116	5	0.2802**	Non-stationary
rtgs_nt	-1.733	5	0.6876**	Non-stationary
rtgs_vt	-1.9568	5	0.5944**	Non-stationary

***Impliesat5% levelofsignificance*

For all the aforementioned cases, the p-values obtained are higher than the significance level (0.05), leading us to reject the null hypothesis. Consequently, we can deduce that the data, with the specified lag order, is non-stationary for all the methods. This suggests that the mean and variance exhibit variability throughout the study period, indicating the possible presence of trend and seasonal patterns in our time series data for the different cashless transaction methods.

The trend in the transaction method data is visually depicted in Figure 4.

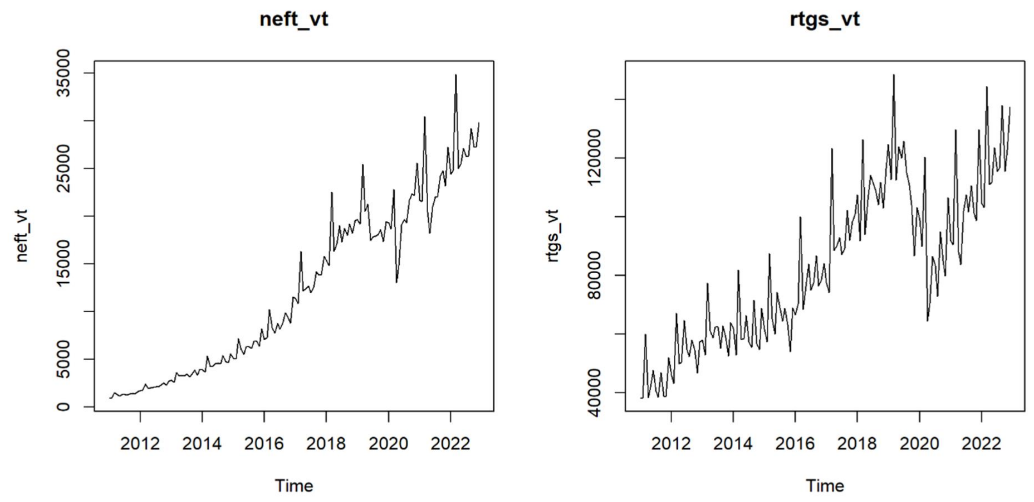

Figure 4: GraphforTrendinValue ofTransactions

By examining Figure 4, specifically the plots illustrating the relationship between time and neft_vt as well as time and rtgs_vt, it becomes evident that there is a noticeable upward trend in the transaction values. However, in the year 2020, a sudden decline is observed, which can be attributed to the impact of the COVID-19 pandemic. As the pandemic gradually subsides, the increasing trend in transaction values reemerges. The implementation of lockdown measures and social distancing practices during the pandemic has significantly contributed to the surge in digital payments. The public's increased familiarity with digital payment methods, driven by concerns about virus transmission through physical currency, has propelled this growth.

Furthermore, it is noteworthy that there has been an upward surge in transaction values since 2016, primarily attributed to the influence of demonetization. This effect is more pronounced in the case of rtgs_vt compared to neft_vt, which aligns with the conclusions drawn from the dummy variable regression technique.

For similar graphs depicting the number of transactions, please refer to Appendix A, Figure A-2.

4.3.2 Additive Time Series Decomposition Pertaining to The Cashless Transaction Methods

In accordance with the assumptions required for Holt-Winters forecasting, the presence of both trend and seasonality components is expected. The charts presented in Figure 5 depict these components within the data concerning the transaction values for the different methods.Considering the assumption of additive components for both transaction methods, a noticeable linear upward trend can be observed from the second panel (Trend) of Figure 5 for both methods. The sharp increase around 2016 and the subsequent decline near 2020 are attributed to the effects of demonetization and the COVID-19 pandemic, respectively.

Moving to the third panel (Seasonal), a repeating short-term cycle is evident in the series of both transaction methods, characterized by consistent frequency (width of cycles) and amplitude (height of cycles). This indicates a linear seasonality within the series for both transaction methods. For similar charts illustrating the number of transactions, please refer to Appendix A, Figure A-3.

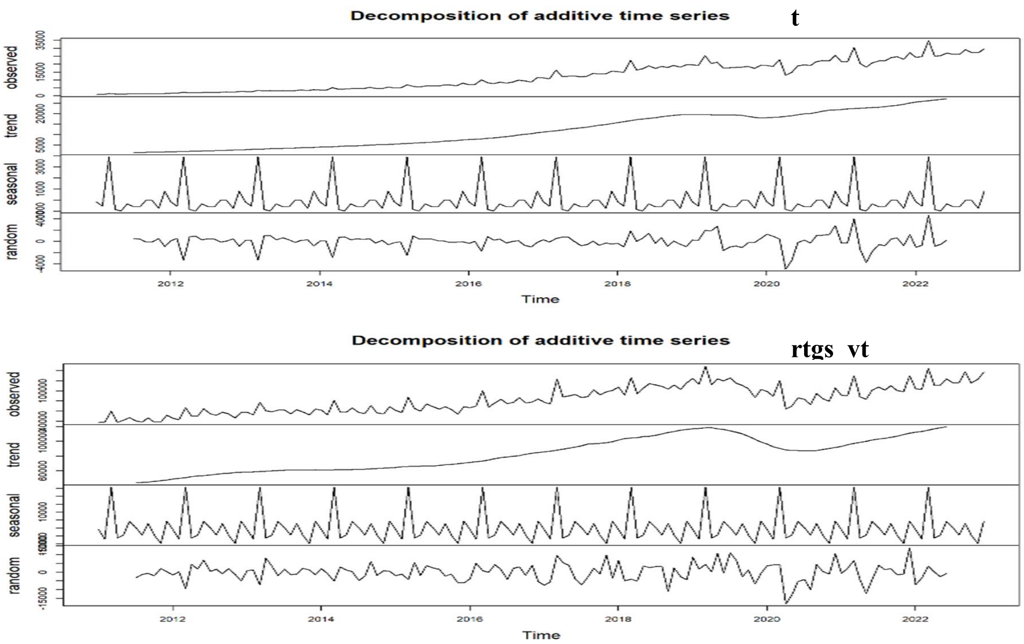

Figure 5: APlotofAdditiveDecompositionforthe DataoftheCashlessTransaction Methods

Since the presence of trend and seasonality in the data of all the digital transaction methods considered are evident, the Holt Winters method of forecasting can be used.

The performance of Holt-Winters forecasting was evaluated, considering trend and additive seasonal components. The estimation of smoothing parameters can be found in Table 6.

Table 6: SmoothingParameters

Smoothing parameters	Alpha	Beta	Gamma
Neft_nt	0.472883	0.05580982	0.6419326
Neft_vt	0.5844687	0.01043234	0.9939879
Rtgs_nt	0.6291859	0	0.2145479
Rtgs_vt	0.534934	0	0.5381466

The adaptation of level and seasonal variations in the case of rtgs_nt is excellent, but the trend does not adapt well.Similar observations can be made for rtgs_vt, where level and seasonal variations are adapted effectively, but the trend is not.For neft_nt, it is evident that the level and seasonal variation adapt quickly, while the trend is slower in doing so. In neft_vt, the seasonal variation adapts rapidly, followed by the level, but the trend does not adapt as much.

The coefficients (level, trend, and season) used for forecasting the various cashless transaction methods are available in Appendix A, Table A.6. Figure 6 displays graphs of Time vs Observed/Fitted values for neft_vt and rtgs_vt, demonstrating a good fit that accurately captures the trend and seasonality components. The fitted values closely resemble the observed values (represented by the red and black lines, respectively). Please refer to Appendix A, Figure A-4for similar charts depicting the number of transactions.

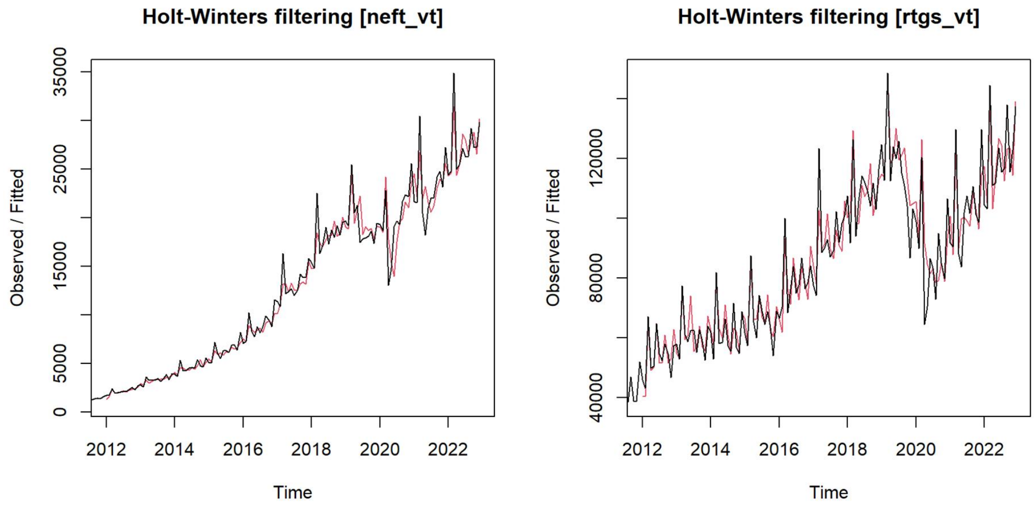

Figure 6: TheHolt-Winters FilteringGraph

4.3.3 Forecasting

Forecasting was conducted on neft_vt and rtgs_vt to determine the projected values for the years beyond the study period. A comparison was made between these predicted values and the actual values of 2023, allowing for the computation of the forecast error. This analysis aimed to assess the accuracy of the Holt-Winters method on our data. The results, including point-forecasts and corresponding confidence intervals (at 80% and 95% confidence levels), can be found in Table 7. The column labeled "Point.Forecast" presents the forecasted values for neft_vt from January to December 2023. Notably, our forecasted values remain within the 95% confidence interval. For further details, the Holt-Winters point forecast values for neft_nt and rtgs_nt are available in Appendix A, specifically Tables A.3 and A.4, respectively.

Table7: Holt-WintersPointForecast

neft_vt	"Point.Forecast"	"Lo.80"	"Hi.80"	"Lo.95"	"Hi.95"
"Jan 2023"	27086.30871	25422.09443	28750.52299	24541.11261	29631.50482
"Feb 2023"	27353.64407	25420.88413	29286.40402	24397.74282	30309.54533
"Mar 2023"	35490.72274	33317.80718	37663.63829	32167.53517	38813.91031
"Apr 2023"	25195.77017	22802.48412	27589.05621	21535.55501	28855.98532
"May 2023"	25654.03364	23055.08476	28252.98251	21679.28433	29628.78294
"Jun 2023"	28200.93984	25407.74823	30994.13146	23929.12191	32472.75778
"Jul 2023"	28329.49635	25351.21221	31307.78049	23774.60382	32884.38888
"Aug 2023"	28527.272	25371.4025	31683.14151	23700.7861	33353.75791
"Sep 2023"	30651.89323	27324.71229	33979.07417	25563.4091	35740.37737
"Oct 2023"	29589.91606	26096.74495	33083.08717	24247.57186	34932.26026
"Nov 2023"	29199.69363	25545.10029	32854.28697	23610.47543	34788.91182
"Dec 2023"	31909.45473	28097.39975	35721.50971	26079.41974	37739.48971
"Jan 2024"	29178.09168	24970.1631	33386.02025	22742.62027	35613.56308
"Feb 2024"	29445.42704	25094.93321	33795.92087	22791.92089	36098.93319
"Mar 2024"	37582.5057	33091.46454	42073.54686	30714.05096	44450.96044
"Apr 2024"	27287.55313	22657.77655	31917.3297	20206.92088	34368.18538
"May 2024"	27745.8166	22978.93671	32512.69649	20455.50293	35036.13027
"Jun 2024"	30292.72281	25390.21377	35195.23184	22794.98226	37790.46336
"Jul 2024"	30421.27931	25384.47577	35458.08286	22718.15303	38124.4056
"Aug 2024"	30619.05496	25449.16762	35788.94231	22712.39457	38525.71536
"Sep 2024"	32743.6762	27441.80516	38045.54723	24635.16418	40852.18822
"Oct 2024"	31681.69902	26248.84529	37114.55275	23372.86625	39990.53179
"Nov 2024"	31291.47659	25728.55193	36854.40125	22783.71749	39799.23569
"Dec 2024"	34001.23769	28309.07327	39693.40211	25295.82344	42706.65194

rtgs_vt	"Point.Forecast"	"Lo.80"	"Hi.80"	"Lo.95"	"Hi.95"
"Jan 2023"	125948.2289	117114.9989	134781.4589	112438.9694	139457.4884
"Feb 2023"	123498.8496	113481.194	133516.5052	108178.1675	138819.5317
"Mar 2023"	160544.1914	149468.0507	171620.3322	143604.696	177483.6869
"Apr 2023"	122215.8052	110173.8633	134257.747	103799.2443	140632.366
"May 2023"	126858.5457	113922.7104	139794.381	107074.8928	146642.1986
"Jun 2023"	140397.3954	126625.5653	154169.2256	119335.1988	161459.5921

"Jul 2023"	138423.1237	123863.2207	152983.0268	116155.6736	160690.5739
"Aug 2023"	134506.8863	119199.4291	149814.3435	111096.1507	157917.6219
"Sep 2023"	145656.5366	129636.3707	161676.7026	121155.8071	170157.2662
"Oct 2023"	132489.2284	115786.738	149191.7189	106944.9736	158033.4833
"Nov 2023"	131820.9275	114462.9132	149178.9418	105274.1355	158367.7195
"Dec 2023"	149430.5029	131440.8356	167420.1702	121917.681	176943.3249
"Jan 2024"	137630.8819	118350.4483	156911.3154	108144.0033	167117.7604
"Feb 2024"	135181.5026	115330.4928	155032.5124	104822.003	165541.0022
"Mar 2024"	172226.8444	151821.2065	192632.4824	141019.1143	203434.5746
"Apr 2024"	133898.4581	112952.8732	154844.0431	101864.9503	165931.966
"May 2024"	138541.1987	117069.2402	160013.1571	105702.672	171379.7254
"Jun 2024"	152080.0484	130094.3151	174065.7818	118455.7709	185704.326
"Jul 2024"	150105.7767	127618.0036	172593.5499	115713.6955	184497.8579
"Aug 2024"	146189.5393	123210.6922	169168.3863	111046.4254	181332.6532
"Sep 2024"	157339.1896	133879.5459	180798.8333	121460.7607	193217.6186
"Oct 2024"	144171.8814	120241.0989	168102.664	107572.9078	180770.8551
"Nov 2024"	143503.5805	119110.7573	167896.4037	106197.9767	180809.1843
"Dec 2024"	161113.1559	136266.8827	185959.4292	123114.0601	199112.2518

Lo:LowerLimitConfidenceInterval,Hi:HigherLimitofConfidenceInterval

Figure 7 visually displays the graphical representation of the forecasts generated by the Holt-Winters method. In the graph, the predicted values are represented by the blue line. It is notable

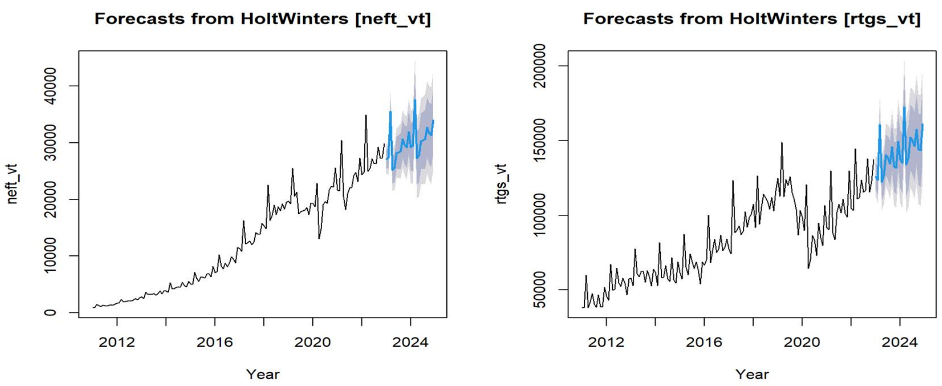

Figure 7: PlotforForecastsfrom Holt-Winter

that these predicted values lie within two confidence intervals: the dark gray area corresponds to the 95% interval, while the light gray area corresponds to the 80% interval. For additional illustrations of similar graphs for neft_nt and rtgs_nt, please refer to Appendix A, specifically Figure A-5.The code for implementing the Holt-Winters method in R Studio can be found in Appendix B.3.

The provided statement describes the residual plots generated by the Holt-Winter's forecast for the cashless transaction methods, neft_vt and rtgs_vt in Figure 8. The left graph represents the residual plot for neft_vt, while the right graph corresponds to rtgs_vt. The Appendix A Figure A-6contains similar charts for the transaction numbers of NEFT and RTGS.

Examining the residual plot for rtgs_vt (on the right), we observe that the majority of points cluster around the zero-horizontal line in the first graph, which represents the mean of the residuals. However, there is a significant drop around the year 2020, indicating the impact of COVID-19, and a peak around 2016-2017, attributed to demonetization. Both neft_vt and rtgs_vt exhibit residuals that are potentially normally distributed, with a mean of zero and relatively constant variance. Nevertheless, it is important to note that fitting or generating point forecasts from an exponential smoothing model does not assume normality.

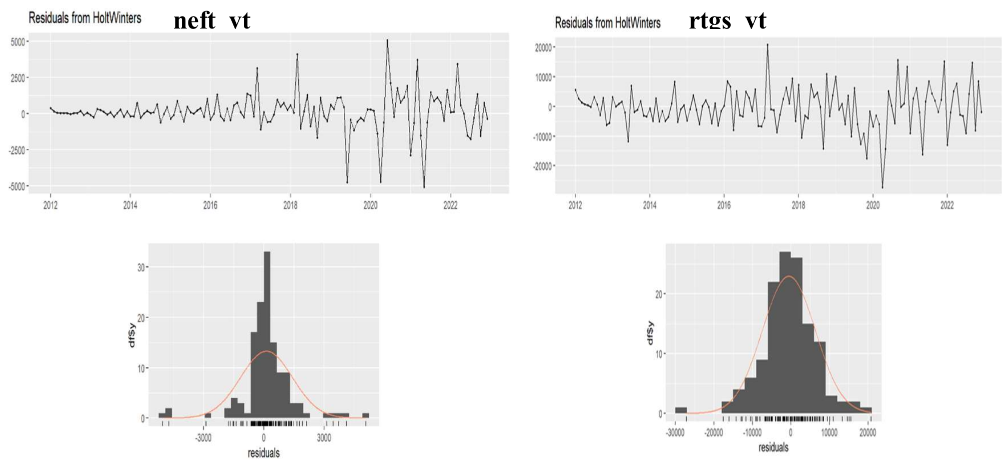

Figure 8: ResidualPlotfrom Holt-WintersForecastfor neft_vtand rtgs_vt

4.3.4 Measurement of Prediction Discrepancy Using the Mean Absolute Percentage Error

The precision of the forecasting method employed in this analysis was evaluated using the Mean Absolute Percentage Error (**MAPE**). The Table 8 illustrates the Absolute Percentage Error (**APE**) and MAPE in our forecast for NEFT and RTGS transactions during the initial two months of 2023, specifically January and February. The calculation for the Mean Absolute Percentage Error (MAPE) is as follows:

$$\textbf{APE} = \frac{|(Predicted\ Value - Actual\ Value)|}{(Actual\ Value)} \text{ x } 100$$

$$\therefore \textbf{MAPE} = \frac{\sum APE}{n}$$

The average absolute percentage deviation for the months of January and February is 2.53% for neft_vt and 1.41% for rtgs_vt. In summary, we can conclude that the Holt-Wintersforecasting technique exhibits a high level of accuracy, approximately 97.47% for neft_vt and 98.59% for rtgs_vt, when used for forecasting.

Likewise, the percentage deviation for neft_nt and rtgs_nt is 1.21% and 3.58% respectively, indicating a favorable forecast accuracy of 98.79% for neft_nt and 96.42% for rtgs_nt. Therefore, we can infer that the Holt-Winters Exponential Smoothing method is an exceptionally reliable forecasting approach for neft_nt, neft_vt, rtgs_nt, and rtgs_vt.

Additionally, we employed equation (2) with a monthly structure (and the appropriate algorithm[3]) to predict the future transaction values for various cashless transaction methods, in order to compare its effectiveness with the Holt-Winters forecasting method. Table 8 reveals that the Holt-Winters method yields the lowest MAPE across all cashless transaction methods when compared to the Inverse Semi-Log Regression Model. Hence, the Holt-Winters forecasting method is considered more efficient for the cashless transaction methods examined. For forecast values generated by the Inverse Semi-Log Regression Model,

[3]Fit the inverse semi-log regression model $\log Y_t = \alpha + \beta t + u_t, u_t \sim \mathrm{N}(0, \sigma^2)$, $u_t$is the disturbance term which is independent and uncorrelated,$Y_t$takes values of various cashless transaction methods, and t is the study period (in month-wise form).
Obtain the OLS estimates of the parameters α and β, and form a vector of these estimates.
Form a matrix containing the time periods (month-wise in our setup) ahead of the study periods.
Find the product of the vector in step 2 and step 3.
Exponentiate the product in step 4 to obtain the predicted values. (Refer Appendix B.4 for the R Studio codes).

please refer to Appendix A, Table A.5.

Table 8: ForecastError(MAPE)ForNEFT and RTGSTransactions

Holt-Winters Forecasting							
	January 2023			February 2023			**Mean Absolute Percent Error**
	Actual	Predicted	Absolute Percent Error	Actual	Predicted	Percent Error	
neft_nt	479.830951	469.1413	2.22%	467.560818	468.5238	0.20%	1.21%
neft_vt	28101.79955	27086.30871	3.6%	27759.71895	27353.64407	1.46%	2.53%
rtgs_nt	20.4179	21.0557	3.12%	20.0497	20.8603	4.04%	3.58%
rtgs_vt	125464.6677	125948.2289	0.38%	120535.7903	123498.8496	2.45%	1.41%
Forecasting Using Inverse Semi-Log Model							
neft_vt	28101.79955	43822.03	55.9%	27759.71895	44831.77	61%	58.45%
rtgs_vt	125464.6677	130820.0	4.27%	120535.7903	131751.9	9.31%	6.79%
neft_nt	479.830951	559.4808	16.60%	467.560818	572.0682	22.35%	19.48%
rtgs_nt	20.4179	19.29385	5.51%	20.0497	19.48945	2.79%	4.15%

5.0 FINDINGS, CONCLUSION, AND RECOMMENDATION

5.1 Summary of Key Findings and Conclusion

In the comprehensive analysis conducted, it was observed that digital payment methods in India, including NEFT and RTGS, have exhibited a consistent upward trend over time. The implementation of demonetization in 2016 had a substantial influence on the growth of these digital payment methods. Additionally, a strong positive linear relationship was identified between the number of transactions and their corresponding values across different payment methods.

Key findings from the examination of digital transactions (via NEFT and RTGS)in India are as follows:

The number and value of transactions (via NEFT and RTGS) have demonstrated a consistent increase over time, with a noticeable change in trend following the implementation of demonetization in 2016.

Summary statistics and Compound Annual Growth Rate (CAGR) analysis indicate a substantial rise in the transaction values for the various methods throughout the study period, with demonetization playing a significant role in this increase, indicating a likely continued increase in the adoption of these payment methods going forward.

A positive linear correlation exists between the number and value of transactions, suggesting that as transaction volume rises, the transaction value also tends to increase.

The growth rate of transaction values for NEFT surpasses that of RTGS due to the absence of a minimum cap per transaction. This distinction leads to a larger volume of transactions using NEFT, resulting in a substantial increase in its transaction value compared to RTGS.Therefore, it is anticipated that customers in India will frequently opt for cashless transactions through NEFT rather than RTGS which is demonstrated by the future point forecast values.

The pandemic-induced restrictions in 2020 led to a sudden decline in transaction values. However, digital payments experienced notable growth as a consequence of lockdown measures and social distancing practices. Subsequently, significant growth was observed again post-pandemic.

The forecasting method utilized in the study (Holt-Winters) exhibited a relatively low Absolute Percentage Error (APE) and outperformed the Inverse Semi-Log Regression Model, indicating its accuracy in predicting transaction values for transactions viaNEFT and RTGS.The Holt-Winters forecasting method predicted that the value of transactions NEFT in January and February 2023 would be about 27086 and 27353 billion rupees respectively, which was found to be 97.5% accurate.

5.2 Recommendation

Based on the findings of this study, it is advisable for policymakers to take deliberate steps towards increasing transaction volume through cashless methods. To achieve this, they should tackle obstacles faced by the cashless economy in India, such as the digital divide, poor network system, and low digital literacy among certain groups. Policymakers should also promote the use of digital payment methods by offering incentives to both merchants and consumers, lowering transaction costs, and enhancing the security and dependability of digital payment systems.

Network providers in collaboration with government should expand network coverage to remote and rural areas, improve network reliability through infrastructure upgrades introduce special data packages for digital payment apps, collaborate with payment service providers for bundled services, and ensure secure transactions with encryption.

Banks should prioritize robust digital payment infrastructure by investing in new technologies, upgrading existing systems, and ensuring security and reliability. They should also collaborate to promote digital payment adoption, offering incentives like cashback rewards, reduced costs, and benefits to users.

Finally, we suggest to customers to embrace digital payment methods, educate themselves on options, prioritize security, and be adaptable to emerging technologies

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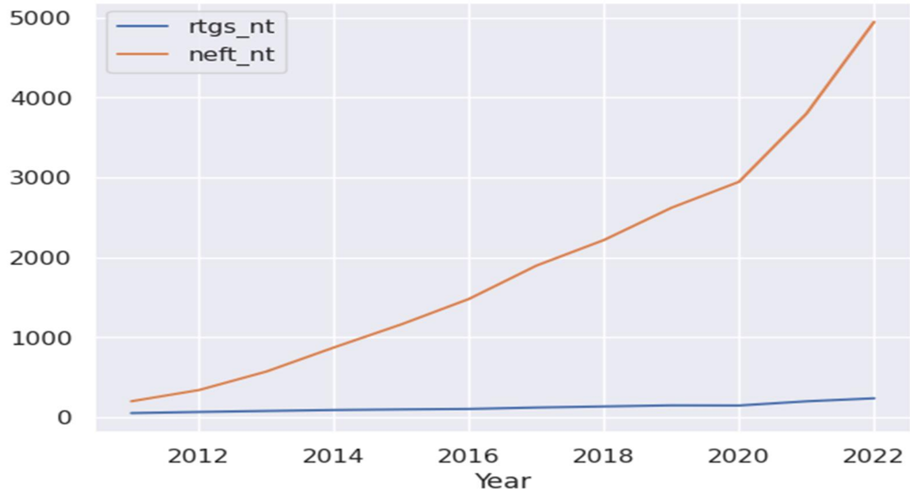
Figure A-1: Graph of Pattern in the Number of Transactions



Notes: The graph reveals a consistent upward trend in the number of transactions for NEFT and RTGS, except for a decline in 2020 due to the influence of Covid. Both NEFT and RTGS experienced a temporary decrease in transactions during that year. Furthermore, it is worth noting that RTGS transactions exhibited greater growth compared to Credit Card transactions.

APPENDIX A

Table A. 1: Structure of Data of Cashless Transactions Used in R Studio for CAGR and Dummy Variable Regression

Year	X1	X2	X3	X4
2011	199.48	15377.4	51.1104	519375
2012	339.688	25887.7	65.4662	644714
2013	571.854	39919.8	78.0894	725983
2014	873.026	55339.5	97.2684	743994
2015	1162.62	75985.8	97.2684	794161
2016	1480.42	106104	103.167	943728
2017	1897.65	157997	120.937	1116611
2018	2218.06	216348	134.567	1296190
2019	2621.68	232966	148.228	1388670
2020	2946.34	238495	146.46	1053160
2021	3800.89	276782	198.752	1235048

X1: neft_nt X2: neft_vt X3: rtgs_nt X4: rtgs_vt

Table A. 2: Data for Holt-Winters Forecasting

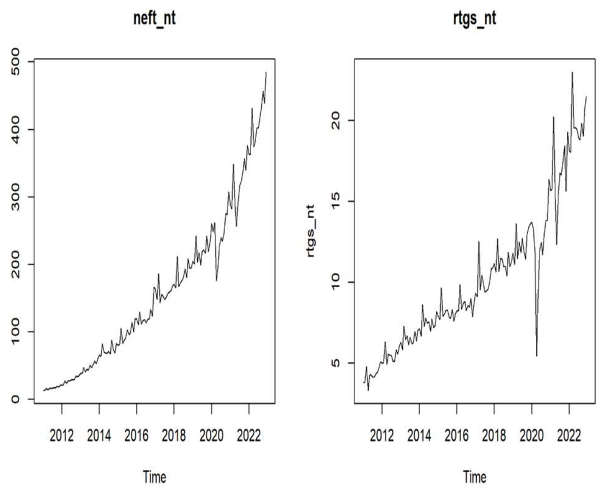
Year	Months	No. of transactions	RTGS (billion)	No. of transactions	NEFT (billiion)
2011	**Jan**	3.832583	38238.54563	12.9600	938.8800
	Feb	3.805814	38080.88615	13.4300	905.8800
	March	4.79526	59915.92759	16.3600	1503.8100
	April	3.295927	38184.71256	14.8600	1302.9400
	May	4.27525	41900.85317	15.7700	1145.3200
	June	4.251614	47690.05094	15.9400	1319.9500
	July	4.125403	40563.8953	16.6300	1283.5400
	August	4.130165	38446.45619	17.3300	1225.6790
	Sept	4.340623	46838.67849	17.5500	1365.5100
	Oct	4.461522	38884.88405	19.2500	1420.3300
	Nov	4.698557	38709.96425	18.7900	1362.1500
	Dec	5.097667	51920.32809	20.6100	1603.4500
2012	**Jan**	4.996935	45882.90927	20.6300	1705.7000
	Feb	5.020473	43110.34734	21.6300	1765.0300
	March	6.339614	67174.06666	27.1100	2403.8900
	April	4.92853	49945.35867	23.7700	1954.9600
	May	5.562933	50407.70919	27.3000	1994.7700
	June	5.502721	64583.56333	27.1930	2070.2617
	July	5.475349	54735.27529	29.2547	2108.9974
	August	5.125939	52366.54337	29.2800	2107.7553
	Sept	5.097981	57997.01129	29.4304	2272.9389
	Oct	5.833365	54458.82681	34.8400	2534.2100
	Nov	5.549751	46774.56811	33.7100	2301.5500
	Dec	6.0326	57277.90423	35.5400	2667.6800
2013	**Jan**	6.284692	58002.05313	38.3600	2814.8800
	Feb	5.821396	52882.70793	38.2900	2560.3500
	March	7.294396	77409.55275	47.0896	3602.4757
	April	6.463274	61061.11999	40.6591	3247.9599
	May	6.693509	58723.10682	45.0557	3289.5000
	June	6.143437	62383.42925	43.1900	3253.0700
	July	6.579571	62422.86614	50.4200	3444.3900
	August	6.206023	55083.36574	47.6200	3150.5800
	Sept	6.256432	62835.22286	51.2500	3434.4500
	Oct	6.952413	58824.07096	56.9100	3860.1900
	Nov	6.376494	52505.25692	52.6500	3332.6500
	Dec	7.017796	63850.3808	60.3600	3929.2800
2014	**Jan**	7.12405	61921.84	65.9100	3871.5400
	Feb	6.650225	52867.90887	64.1500	3656.0500
	March	8.635504	81773.84164	82.8300	5312.2500
	April	7.267031	58109.4127	70.6200	4219.5600

	May	7.796914	58381.6323	69.1100	4307.3800
	June	7.473492	66242.97164	67.8600	4509.5200
	July	7.545986	57378.86856	71.6700	4577.8400
	August	6.967847	55570.26561	66.9800	4520.4000
	Sept	7.718709	71529.22513	88.0000	5393.3600
	Oct	7.206852	56828.88603	73.2900	4781.5000
	Nov	7.325796	54644.75839	69.1200	4616.7500
	Dec	8.1859	68744.00844	83.4860	5573.3600
2015	**Jan**	7.889908	61648.02261	80.2200	5084.7300
	Feb	7.687796	57414.10892	81.9000	5046.4100
	March	9.672739	87421.4823	106.0000	7173.0900
	April	7.897752	65199.83485	83.5300	6043.7500
	May	8.05928	60051.45395	88.1300	5536.0300
	June	8.255629	74181.48288	91.2200	6324.5800
	July	8.255249	68891.0372	103.1100	6289.3700
	August	7.822176	64376.22335	95.9400	6153.3800
	Sept	7.767111	68791.35158	98.5400	6860.2100
	Oct	8.33515	63365.56426	114.6000	6906.8800
	Nov	7.600845	53896.02976	99.8200	6370.1600
	Dec	8.024735	68924.03951	119.6100	8197.2100
2016	**Jan**	8.220044	66517.704	118.9700	7086.7500
	Feb	8.223609	70341.89872	110.1700	7278.6000
	March	9.864091	100045.3609	129.2400	10226.3600
	April	8.325513	68411.27162	111.8400	8324.5200
	May	8.703795	76332.5826	117.1500	7732.5400
	June	8.828509	83834.94123	118.2900	8815.3100
	July	8.254641	74919.55245	113.4800	8145.3900
	August	8.557454	77588.32323	118.5600	8764.1400
	Sept	8.467531	86687.34545	120.1500	9880.1700
	Oct	9.00672	76473.29295	133.2100	9504.5000
	Nov	7.874669	78479.19011	123.0500	8807.8800
	Dec	8.840374	84096.47783	166.3100	11537.6300
2017	**Jan**	9.330505	77486.07222	164.1900	11355.0800
	Feb	9.104185	74218.81154	148.2100	10877.9100
	March	12.538081	123375.8348	186.7000	16294.5000
	April	9.54308	88512.1859	143.1700	12156.1700
	May	10.432997	90170.52454	155.8200	12410.8100
	June	9.828299	92812.58207	152.3400	12694.2000
	July	9.380015	87149.25958	148.1400	12011.6000
	August	9.455952	89163.39284	151.6100	12500.3800
	Sept	9.606041	102348.1286	157.6700	14182.1400
	Oct	9.999427	92056.09524	158.7800	13851.2800
	Nov	10.825229	98410.48808	161.9700	13884.0000
	Dec	10.892992	100907.7896	169.0500	15779.2000

2018	**Jan**	11.158876	107488.3989	170.2000	15374.1000
	Feb	10.626864	91765.63022	165.6000	14843.9000
	March	12.683495	126340.3007	212.0100	22540.7700
	April	10.658169	94045.74624	167.3500	16326.6400
	May	11.491966	105720.9333	172.9000	17152.0000
	June	11.430497	114199.0279	177.1500	19017.0800
	July	10.967555	112012.9128	180.6000	17321.4000
	August	11.009656	109214.0963	193.2000	18712.4000
	Sept	10.398144	104037.3413	181.0000	18015.5000
	Oct	11.86148	111856.7468	209.0400	19227.0300
	Nov	10.963207	103085.1042	194.2100	18246.6800
	Dec	11.317114	116423.7297	194.8000	19570.4000
2019	**Jan**	11.77896	124797.0318	205.1000	19662.6000
	Feb	11.085693	112759.8515	201.1000	19214.3000
	March	13.640534	148729.3487	242.4000	25470.0000
	April	11.472913	112453.3145	203.4000	20546.7000
	May	12.48839	123973.8204	217.7000	21277.7000
	June	11.823245	120017.4262	199.1000	17496.5000
	July	12.742096	125770.5667	219.4000	17842.6000
	August	11.87713	115236.2863	221.2600	17961.5280
	Sept	11.439729	110834.6956	216.7100	18117.8090
	Oct	12.890009	104129.824	242.3600	18607.8630
	Nov	13.38741	86798.06189	219.4600	17346.5120
	Dec	13.601582	103169.3681	233.6900	19422.3070
2020	**Jan**	13.728613	98808.21251	260.5600	19294.6350
	Feb	13.317695	89909.39914	248.3600	18704.9360
	March	11.894618	120472.2074	262.3700	22836.6460
	April	5.434644	64436.53106	175.9800	13064.0640
	May	9.003796	70418.69359	192.9400	14817.4950
	June	11.967828	86519.77721	227.4000	19065.8610
	July	12.476268	83352.79049	240.1000	19631.1340
	August	11.677166	72923.79697	234.6100	19305.5230
	Sept	13.010503	94890.65747	246.8300	21655.1450
	Oct	13.821531	84960.45698	276.1700	22353.8900
	Nov	13.779836	79876.55453	273.4100	22182.5250
	Dec	16.347917	106591.2035	307.6100	25583.0420
2021	**Jan**	15.668058	91701.62304	287.4900	21658.6950
	Feb	15.769554	90504.2545	282.1100	21528.4370
	March	20.2349	129822.146	348.1400	30463.2850
	April	15.15206	88028.67761	286.2700	20462.3460
	May	12.33439	83665.99425	256.5400	18194.5900
	June	15.413551	101969.8944	292.3300	20977.7110
	July	16.765021	107413.1411	317.0000	22043.0280
	August	16.632063	101600.9262	321.8700	22098.1790

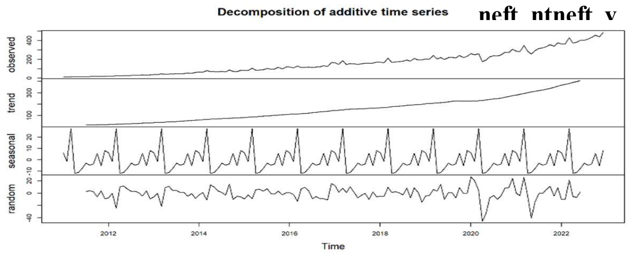
	Sept	17.45694	110696.3102	335.9500	24196.8820
	Oct	18.411308	101343.6791	357.4500	24763.9660
	Nov	15.63529	98631.13158	339.4000	23144.9040
	Dec	19.278396	129669.9079	376.3400	27249.8010
2022	**Jan**	18.129052	104491.095	362.9000	24426.8580
	Feb	18.028552	103246.1782	363.2600	24770.5860
	March	23.003813	144589.5504	431.4200	34925.7820
	April	19.53243	110975.9449	373.7600	24985.8690
	May	19.572062	111839.4697	381.3300	25469.2760
	June	19.441531	123560.5353	402.2300	27160.1290
	July	18.92627	115514.3968	401.8400	26273.5400
	August	18.80802	116655.8271	416.6800	26316.3900
	Sept	19.830016	137896.3712	433.2500	29229.1280
	Oct	19.03365	115512.7686	457.0500	27268.2710
	Nov	20.645798	122917.4949	438.8300	27308.7840
	Dec	21.50315	137360.5718	485.4800	29816.8120

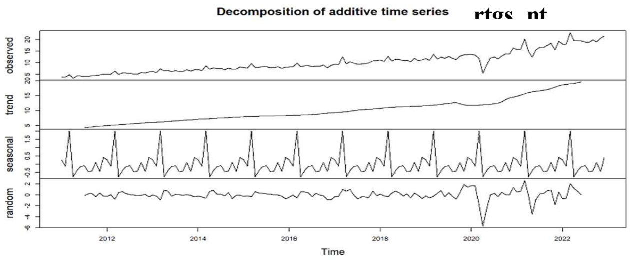
Figure A-2: Graph for Trend in the Number of Transactions



Notes: Based on the graphical data, it is evident that there is a consistent rise in transaction volumes for NEFT and RTGS. However, a notable decline occurred in 2020 due to the Covid-19 pandemic, followed by a subsequent recovery as the pandemic situation improved. Additionally, it is noteworthy that there was a significant increase in transaction numbers starting in 2016, which can be attributed to the impact of demonetization.

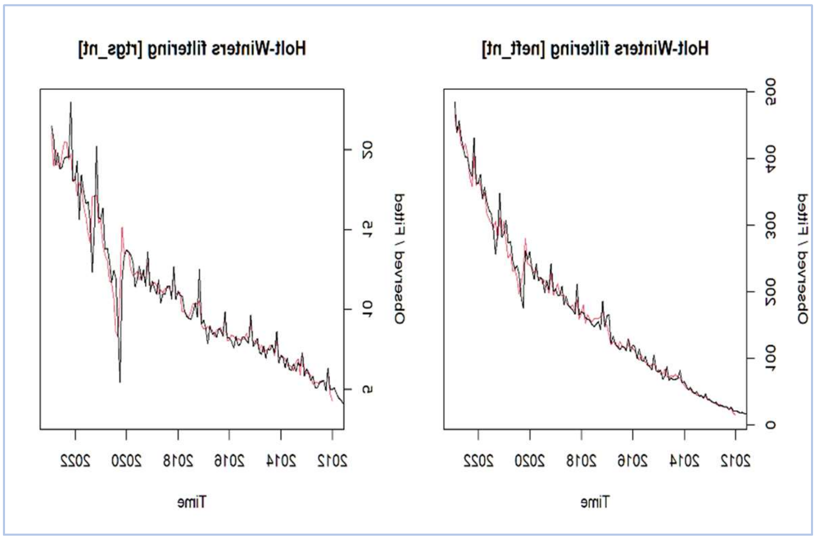
Figure A-3:A Plot of Additive Decomposition for the Data of the Cashless Transaction Methods (for Number of Transactions)





Notes: The presented charts exhibit clear patterns and recurring elements in the data concerning the number of transactions for NEFT and RTGS. Assuming the presence of additive components in both transaction methods, it is noticeable from the second panel (Trend) of the graphs that there is a steady upward trend. The decline observed around 2020 can be attributed to the impact of the Covid-19 pandemic. In the third panel (Seasonal), there is a consistent cyclic pattern in the series, characterized by cycles of uniform duration and magnitude. This indicates the presence of linear seasonality in both transaction methods, making the Holt-Winters forecasting method applicable.

Figure A-4: Holt-Winters Filtering Graph



Notes: Upon examining the graphs depicting Time versus Observed/Fitted values for neft_nt and rtgs_nt, it is evident that the fitted values closely resemble the observed values. The red and black lines represent the fitted and observed values, respectively. This indicates a strong resemblance between the two, indicating a good fit that effectively captures the trend and seasonality components.

Table A. 3: Point Forecast for neft_nt by the Holt-Winters Method

	"Point.Forecast"	"Lo.80"	"Hi.80"	"Lo.95"	"Hi.95"
"Jan 2023"	469.1413	452.7719	485.5107	444.1064	494.1761
"Feb 2023"	468.5238	450.2276	486.8201	440.5421	496.5055
"Mar 2023"	521.1028	500.8841	541.3215	490.1810	552.0247
"Apr 2023"	459.1759	437.0296	481.3223	425.3060	493.0458
"May 2023"	463.9466	439.8609	488.0323	427.1107	500.7825
"Jun 2023"	490.8880	464.8468	516.9293	451.0613	530.7147
"Jul 2023"	503.7781	475.7618	531.7945	460.9308	546.6255
"Aug 2023"	513.8284	483.8150	543.8417	467.9270	559.7298
"Sep 2023"	524.7827	492.7488	556.8166	475.7911	573.7743
"Oct 2023"	545.8423	511.7630	579.9217	493.7224	597.9622
"Nov 2023"	529.8063	493.6556	565.9569	474.5186	585.0939
"Dec 2023"	564.1490	525.9006	602.3975	505.6530	622.6450
"Jan 2024"	551.4581	508.9863	593.9300	486.5030	616.4133
"Feb 2024"	550.8407	506.3180	595.3634	482.7491	618.9323
"Mar 2024"	603.4197	556.8106	650.0288	532.1373	674.7022
"Apr 2024"	541.4928	492.7625	590.2231	466.9662	616.0194
"May 2024"	546.2635	495.3778	597.1492	468.4405	624.0865
"Jun 2024"	573.2049	520.1303	626.2795	492.0343	654.3755
"Jul 2024"	586.0950	530.7986	641.3914	501.5264	670.6636
"Aug 2024"	596.1453	538.5947	653.6958	508.1293	684.1612
"Sep 2024"	607.0996	547.2631	666.9361	515.5876	698.6116
"Oct 2024"	628.1592	566.0055	690.3129	533.1033	723.2151
"Nov 2024"	612.1231	547.6214	676.6249	513.4762	710.7701
"Dec 2024"	646.4659	579.5857	713.3461	544.1814	748.7503

Table A. 4: Point Forecast for rtgs_nt by the Holt-Winters Method

	"Point.Forecast"	"Lo.80"	"Hi.80"	"Lo.95"	"Hi.95"
"Jan 2023"	21.0557	19.6452	22.4662	18.8985	23.2128
"Feb 2023"	20.8603	19.1938	22.5268	18.3117	23.4089
"Mar 2023"	22.8644	20.9764	24.7525	19.9769	25.7519
"Apr 2023"	20.2192	18.1330	22.3054	17.0286	23.4098
"May 2023"	21.1143	18.8471	23.3814	17.6470	24.5815
"Jun 2023"	21.6551	19.2205	24.0897	17.9316	25.3786
"Jul 2023"	21.5792	18.9878	24.1705	17.6161	25.5423
"Aug 2023"	21.2773	18.5382	24.0164	17.0882	25.4664
"Sep 2023"	21.5693	18.6900	24.4485	17.1658	25.9727
"Oct 2023"	21.8958	18.8829	24.9088	17.2879	26.5037
"Nov 2023"	21.7037	18.5627	24.8446	16.9000	26.5073
"Dec 2023"	22.5883	19.3244	25.8522	17.5966	27.5800
"Jan 2024"	22.2845	18.8709	25.6980	17.0639	27.5051
"Feb 2024"	22.0891	18.5621	25.6161	16.6949	27.4832
"Mar 2024"	24.0932	20.4562	27.7302	18.5309	29.6555
"Apr 2024"	21.4480	17.7043	25.1917	15.7225	27.1735
"May 2024"	22.3430	18.4956	26.1905	16.4589	28.2272
"Jun 2024"	22.8839	18.9354	26.8324	16.8452	28.9226
"Jul 2024"	22.8080	18.7610	26.8549	16.6187	28.9973
"Aug 2024"	22.5061	18.3630	26.6492	16.1697	28.8425
"Sep 2024"	22.7981	18.5609	27.0352	16.3179	29.2782
"Oct 2024"	23.1246	18.7956	27.4537	16.5039	29.7454
"Nov 2024"	22.9325	18.5134	27.3516	16.1740	29.6909
"Dec 2024"	23.8171	19.3098	28.3245	16.9238	30.7105

Table A. 5: Forecast Values by the Inverse Semi-Log Regression Model

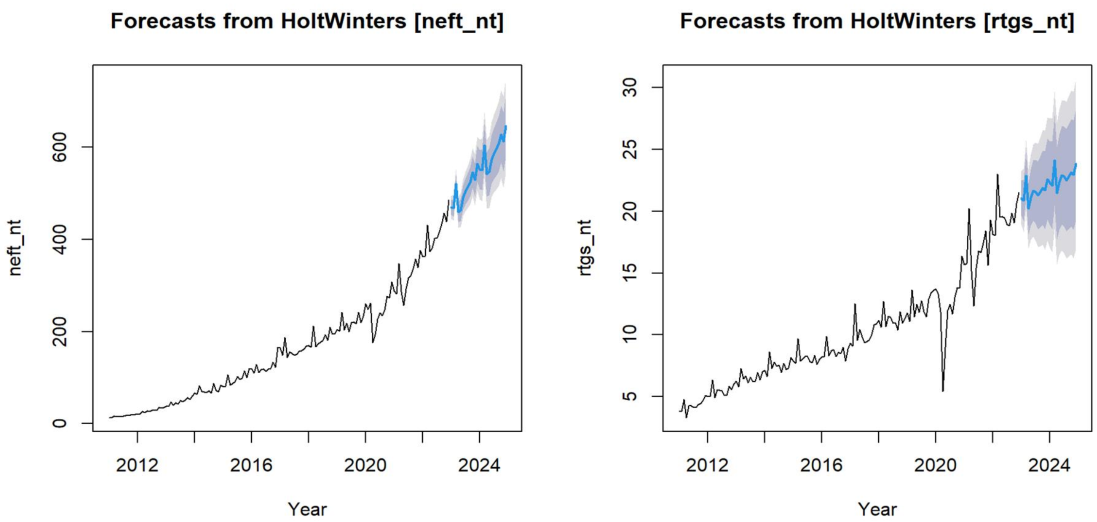
	NEFT_value	NEFT_number	RTGS_value	RTGS_number
Jan 2023	43822.03	559.4808	130820.0	19.29385
Feb 2023	44831.77	572.0682	131751.9	19.48945
Mar 2023	45864.76	584.9388	132690.4	19.68703
Apr 2023	46921.56	598.0989	133635.6	19.88661
May 2023	48002.71	611.5552	134587.6	20.08821
Jun 2023	49108.77	625.3141	135546.3	20.29186
Jul 2023	50240.32	639.3826	136511.9	20.49757
Aug 2023	51397.94	653.7677	137484.3	20.70537
Sep 2023	52582.23	668.4763	138463.7	20.91527
Oct 2023	53793.81	683.5159	139450.0	21.12731
Nov 2023	55033.31	698.8939	140443.4	21.34149
Dec 2023	56301.37	714.6178	141443.9	21.55784
Jan 2024	57598.64	730.6955	142451.4	21.77639
Feb 2024	58925.81	747.1350	143466.2	21.99715
Mar 2024	60283.55	763.9442	144488.2	22.22015
Apr 2024	61672.59	781.1317	145517.4	22.44541
May 2024	63093.62	798.7059	146554.0	22.67296
Jun 2024	64547.40	816.6754	147598.0	22.90281
Jul 2024	66034.68	835.0492	148649.4	23.13499
Aug 2024	67556.23	853.8364	149708.3	23.36952
Sep 2024	69112.83	873.0463	150774.8	23.60644
Oct 2024	70705.31	892.6884	151848.8	23.84575
Nov 2024	72334.47	912.7724	152930.5	24.08749
Dec 2024	74001.18	933.3082	154019.9	24.33168

Table A.6: Table for Estimated Coefficients (Level, Trend, and Season) for NEFT and RTGS

	neft_nt	neft_vt	rtgs_nt	rtgs_vt
"a"	453.7056	27218.7259	20.8338	131184.8531
"b"	6.8597	174.3152	0.1024	973.5544
"s1"	8.5760	-306.7324	0.1195	-6210.1786
"s2"	1.0988	-213.7123	-0.1783	-9633.1123
"s3"	46.8180	7749.0511	1.7234	26438.6751
"s4"	-21.9686	-2720.2167	-1.0242	-12863.2656
"s5"	-24.0577	-2436.2685	-0.2315	-9194.0795
"s6"	-3.9760	-63.6775	0.2069	3371.2158
"s7"	2.0544	-109.4362	0.0286	423.3897
"s8"	5.2449	-85.9758	-0.3757	-4466.4022
"s9"	9.3395	1864.3301	-0.1861	5709.6938
"s10"	23.5394	628.0377	0.0380	-8431.1688
"s11"	0.6436	63.5000	-0.2565	-10073.0242
"s12"	28.1266	2598.9459	0.5258	6562.9968

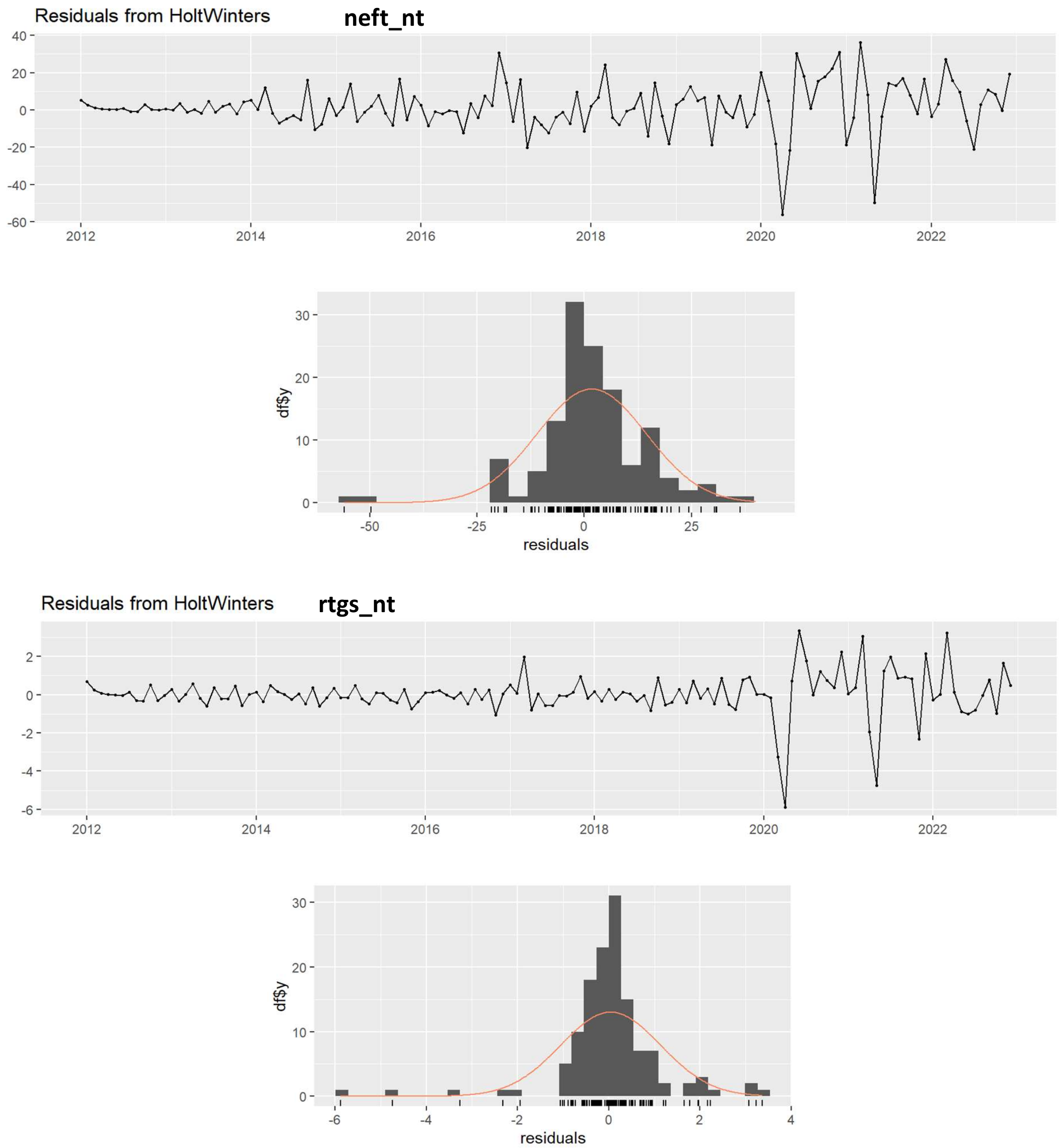
a: level, b: trend, s: season

Figure A-5: Plot for Forecasts from Holt-Winters



Notes: The provided graphs depict the forecasted values for neft_nt and rtgs_nt as represented by the blue line. Notably, these forecasted values consistently fall within the confidence intervals of 80% and 95%. The 95% confidence interval is indicated by the dark gray area, while the light gray area corresponds to the 80% confidence interval.

Figure A- 6: Residual Plots from Holt-Winters Forecasting for neft_nt and rtgs_nt



Notes: These are the residual plots obtained from Holt-Winter's forecasting for neft_nt and rtgs_nt. In the case of neft_nt, the majority of the data points in the first graph cluster around the zero-horizontal line, representing the mean of the residuals. However, there is a significant drop near the year 2020, which can be attributed to the impact of COVID-19. Similarly, the second graph for neft_nt reveals residuals that exhibit a near-normal distribution, but with a longer tail on the left side, which is also influenced by the effects of COVID-19. The same observation can be made for rtgs_nt, where the residuals follow a normal distribution, yet the impact of COVID-19 is evident.

APPENDIX B

B.1: Python-code

B.1.1: Descriptive Statistics for NEFT and RTGS

```
Import numpy as np    ## import the required libraries

Import pandas as pd

Import seaborn as sns

From matplotlib import pyplot as plt

%matplotlib inline

Import plotly.express as px

sns.set()

df= pd.read_csv( ‘ / content/neft(EDA).csv’ )

df

df.describe()

plt.figure(figsize=(20,10))

Bar_plot=sns.barplot( x=’Year’ , y=’rtgs_nt’ , data-df)

plt.figure(figsize=(20,10))

Bar_plot=sns.barplot( x=’Year’ , y=’neft_nt’ , data-df)

plt.figure(figsize=(20,10))

Bar_plot=sns.barplot( x=’Year’ , y=’rtgs_vt’ , data-df)

plt.figure(figsize=(20,10))
```

```
Bar_plot=sns.barplot( x='Year' , y='neft_vt' , data-df)

df[['rtgs_nt', 'neft_nt']].groupby(by=df ['year']).sum().plot(kind= 'line' )

df[['neft_vt', 'rtgs_vt']].groupby(by=df ['year']).sum().plot(kind= 'line' )

a=df.iloc[6:,:]  ##select all the columns and select only from 6th row

a.describe()

b=df.iloc[:6,:]

b

b.describe()
```

B.2: R-codes:

CAGR and Dummy Variable Regression

###################### NEFT and RTGS ###############

```
neft=read.csv(file.choose(), header=TRUE)

neft

neft=as.data.frame(neft)

neft

t=c(1:12)
```

B.2.1 NEFT Analysis ##########################

```
NEFT_value=neft$X2

NEFT_value

NEFT_number=neft$X1

NEFT_number
```

```
# Correlation test for NEFT_value and NEFT_number

# scatter plot

par(mfrow=c(1,2))

plot(NEFT_value,NEFT_number,main = "NEFT", xlab = "NEFT_number", ylab =
"NEFT_value",col="red")

abline(lm(NEFT_value~NEFT_number),lwd=2,col="blue")

text(paste("Corr:",round(cor(NEFT_value,NEFT_number),3)),x=100000,y=3000)

cor.test(NEFT_number,NEFT_value)

# normality test

shapiro.test(NEFT_value)

# Growth rate NEFT_value, CAGR=(antilogβ1-1)*100, Y=NEFT_value, X = time

Y=NEFT_value

Y

X=t

X

model1=lm(log(Y)~X,data=neft)

model1

summary(model1)

β1=model1$coefficients[2]

β1

library(aod)

wald.test(b=coef(model1),Sigma=vcov(model1),Terms = 1:2)

# since pvalue<0.05 we reject Ho and conclude coefficients are sig.
```

```
shapiro.test(residuals(model1))

library(car)

library(lmtest)

acf(model1$residuals,type = 'correlation')

library(tseries)

# Homoscedasticity check

library(base)

bptest(model1)

library(skedastic)

white(model1)

antilogβ1=exp(β1)

antilogβ1

CAGR=(antilogβ1-1)*100

CAGR

# ALITER  CAGR= [(ending value/beginning value)^1/n-1]*100

NEFT_value

n=length(X)

end_val=NEFT_value[12]

beg_val=NEFT_value[1]

CAGR= (((end_val/beg_val)^(1/n))-1)*100

CAGR

# neft_nt

Y=NEFT_number
```

```
Y
X=t
X
model.netftnt=lm(log(Y)~X,data=neft)
model.netftnt
summary(model.netftnt)
β1=model.netftnt$coefficients[2]
β1

antilogβ1=exp(β1)
antilogβ1
CAGR=(antilogβ1-1)*100
CAGR
# ALITER  CAGR= [(ending value/beginning value)^1/n-1]*100
NEFT_number
n=length(X)
end_val=NEFT_number[12]
beg_val=NEFT_number[1]
CAGR= (((end_val/beg_val)^(1/n))-1)*100
CAGR
```

 # fitting the dummy variable regression for demonetization

```
attach(neft)
```

```
di=rep(0,length(Year))

di

demonitization=2016

di[Year>demonitization]=1

neft$Dummy=di

neft$t=t

View(neft)


# Yt = α1 + α2Dt + β1Xt + β2(Dt Xt ) + ut


fit=lm(log(NEFT_value)~(Dummy+t+(Dummy*t)),data=neft)

summary(fit)

a1=fit$coefficients[1]

a2=fit$coefficients[2]

b1=fit$coefficients[3]

b2=fit$coefficients[4]

a_pre=a1

b_pre=b1

a_post=a1+a2

b_post=b1+b2

a_pre+b_pre

a_post+b_post

# E(yi /Di=0,   xi) =α1+ β1xi mean change b4 demonitization
```

yi=a1+b1*Xi

a1+b1*1

E(yi /Di=1, xi) =(α1+ α2) + (β1+β2)X i

#yi=a_post+b_post*Xi

#a_post+b_post*1

B.2.2 RTGS Analysis

RTGS_value=neft$X4

RTGS_value

RTGS_number=neft$X3

RTGS_number

 # correlation test for RTGS_value and RTGS_number

scatter plot

par(mfrow=c(1,2))

plot(RTGS_value,RTGS_number,main = "RTGS", xlab = "rtgs_nt", ylab = "rtgs_vt",col="red")

abline(lm(RTGS_value~RTGS_number),lwd=2,col="blue")

text(paste("Corr:",round(cor(RTGS_value,RTGS_number),3)),x=900000,y=150)

cor.test(RTGS_number,RTGS_value)

normality test

shapiro.test(RTGS_value)

independent testing

library(lawstat)

```
runs.test(RTGS_value)
```

 # Growth rate RTGS_value, CAGR=(antilogβ1-1)*100, Y=RTGS_value, X = time

```
Y=RTGS_value
Y
X=t
X
model2=lm(log(Y)~X,data=neft)
model2
summary(model2)
β1=model2$coefficients[2]
β1
library(aod)
wald.test(b=coef(model2),Sigma=vcov(model2),Terms = 1:2)
# since pvalue<0.05 we reject Ho and conclude coefficients are sig.
runs.test(residuals(model2))
shapiro.test(residuals(model2))
library(car)
```

 # autocorrelation

```
bgtest(model2)
library(lmtest)
par(mfrow=c(1,2))
acf(model2$residuals,type = 'correlation')
library(tseries)
```

```
# Homoscedasticity check
library(base)
bptest(model2)
bptest(model1)
library(skedastic)
white(model2)
antilogβ1=exp(β1)
antilogβ1
CAGR=(antilogβ1-1)*100
CAGR
```

 # ALITER CAGR= [(ending value/beginning value)^1/n-1]*100

```
RTGS_value
n=length(X)
end_val=RTGS_value[12]
beg_val=RTGS_value[1]
CAGR= (((end_val/beg_val)^(1/n))-1)*100
CAGR
View(neft)
```

 # rtgs_nt

```
Y=RTGS_number
Y
X=t
```

```
X
model.rtgsnt=lm(log(Y)~X,data=neft)
model.rtgsnt
summary(model.rtgsnt)
β1=model.rtgsnt$coefficients[2]
β1

antilogβ1=exp(β1)
antilogβ1
CAGR=(antilogβ1-1)*100
CAGR
```

 # ALITER CAGR= [(ending value/beginning value)^1/n-1]*100

```
RTGS_number
n=length(X)
end_val=RTGS_number[12]
beg_val=RTGS_number[1]
CAGR= (((end_val/beg_val)^(1/n))-1)*100
CAGR
```

 # fitting the dummy variable regression for demonetization

```
attach(neft)
di=rep(0,length(Year))
di
demonitization=2016
```

```
di[Year>demonitization]=1

neft$Dummy=di

neft$t=t

View(neft)


# Yt = α1 + α2Dt + β1Xt + β2(Dt Xt ) + ut


fit=lm(log(RTGS_value)~(Dummy+t+(Dummy*t)),data=neft)

summary(fit)

a1=fit$coefficients[1]

a2=fit$coefficients[2]

b1=fit$coefficients[3]

b2=fit$coefficients[4]

a_pre=a1

b_pre=b1

a_post=a1+a2

b_post=b1+b2

a_pre+b_pre

a_post+b_post

# E(yi /Di=0,   xi) =α1+ β1xi mean change b4 demonitization

yi=a1+b1*Xi

a1+b1*5

# E(yi /Di=1, xi) =(α1+ α2) + (β1+β2)X i
```

```
#yi=a_post+b_post*Xi

#a_post+b_post*1
```

B.3: Holt-Winter's exponential smoothing Analysis

For PoS

```
#### Import necessary libraries

install.packages("tidyverse")

install.packages("fpp2")

library(readxl)

library(tseries)

library(tidyverse)

library(fpp2)

#### Import data

data=read_excel(file.choose())                    ### import file (N_R)

data=data[,3:6]

class(data)

data=ts(data,frequency=12,start=c(2011,1))

data

class(data)                        ### to check class of the data

start(data)                        ### to check starting point of data

end(data)                          ### to check ending point of data

frequency(data)                    ### to check the frequency of data
```

B.3.1: NEFT_NT

```
### Extract only 3rd column

neft_nt=data[,3]

neft_nt

plot(neft_nt,main="neft_nt")

summary(neft_nt)

adf.test(neft_nt,alternative="stationary")

decomposed_data_1=decompose(neft_nt)

x=plot(decomposed_data_1)

HW_neft_nt=HoltWinters(neft_nt)

HW_neft_nt

plot(HW_neft_nt,main="Holt-Winters filtering [neft_nt]")

checkresiduals(HW_neft_nt)

A=forecast:::forecast.HoltWinters(HW_neft_nt,h=24)

plot(A,xlab="Year",ylab="neft_nt",main="Forecasts from HoltWinters [neft_nt]")

A
```

B.3.2: NEFT_VT

```
### Extract only 4th column

neft_vt=data[,4]

neft_vt

plot(neft_vt,main="neft_vt")
```

```
summary(neft_vt)

adf.test(neft_vt,alternative="stationary")

decomposed_data_2=decompose(neft_vt)

x=plot(decomposed_data_2)

HW_neft_vt=HoltWinters(neft_vt)

HW_neft_vt

plot(HW_neft_vt,main="Holt-Winters filtering [neft_vt]")

checkresiduals(HW_neft_vt)

B=forecast:::forecast.HoltWinters(HW_neft_vt,h=24)

plot(B,xlab="Year",ylab="neft_vt",main="Forecasts from HoltWinters [neft_vt]")

B
```

B.3.3: RTGS_NT

```
### Extract only 1st column

rtgs_nt=data[,1]

rtgs_nt

plot(rtgs_nt,main="rtgs_nt")

summary(rtgs_nt)

adf.test(rtgs_nt,alternative="stationary")

decomposed_data_3=decompose(rtgs_nt)

x=plot(decomposed_data_3)

HW_rtgs_nt=HoltWinters(rtgs_nt)
```

```
HW_rtgs_nt

plot(HW_rtgs_nt,main="Holt-Winters filtering [rtgs_nt]")

checkresiduals(HW_rtgs_nt)

C=forecast:::forecast.HoltWinters(HW_rtgs_nt,h=24)

plot(C,xlab="Year",ylab="rtgs_nt",main="Forecasts from HoltWinters [rtgs_nt]")

C
```

B.3.4: RTGS_VT

```
### Extract only 2nd column

rtgs_vt=data[,2]

rtgs_vt

plot(rtgs_vt,main="rtgs_vt")

summary(rtgs_vt)

adf.test(rtgs_vt,alternative="stationary")

decomposed_data_4=decompose(rtgs_vt)

x=plot(decomposed_data_4)

HW_rtgs_vt=HoltWinters(rtgs_vt)

HW_rtgs_vt

plot(HW_rtgs_vt,main="Holt-Winters filtering [rtgs_vt]")

checkresiduals(HW_rtgs_vt)

D=forecast:::forecast.HoltWinters(HW_rtgs_vt,h=24)

plot(D,xlab="Year",ylab="rtgs_vt",main="Forecasts from HoltWinters [rtgs_nt]")
```

D

B.4 ######## Forecasting Using the Inverse Semi-Log Regression Model ##########

```
neft=read.csv(file.choose(), header=TRUE)      ##importing data
neft
neft=as.data.frame(neft)              ##converting data to dataframe
t=c(1:144)
# NEFT ANALYSIS
NEFT_value=neft$neft_vt
NEFT_value
Y=NEFT_value
length(Y)
X=t
X
model1=lm(log(Y)~X,data=neft)
model1
summary(model1)
```

 # forecast

```
beta=s$coefficients[,1]          ##Obtaining Regression Coefficients
beta
x=c(145:168)          ##Creating of vector of future time to be predicted
x0=cbind(rep(1,length(x)),x)  ##Creating array for the future time
x0
eta=x0%*%beta           ## multiplying the coefficients by the future time
```

```
eta
pred_NEFT_value=exp(eta)      ###Obtaining the predicted values
pred_NEFT_value
```

 # number of transactions

```
NEFT_number=neft$neft_nt
NEFT_number
Y=NEFT_number
length(Y)
X=t
X
modelnt=lm(log(Y)~X,data=neft)
modelnt
# forecast
s=summary(modelnt)
beta=s$coefficients[,1]
beta

x=c(145:168)
x0=cbind(rep(1,length(x)),x)
x0
eta=x0%*%beta
eta
pred_NEFT_number=exp(eta)
```

```
pred_NEFT_number


# RTGS ANALYSIS
RTGS_value=neft$rtgs_vt
RTGS_value
Y=RTGS_value
Y
X=t
X
model2=lm(log(Y)~X,data=neft)
model2
summary(model2)
# forecast
s=summary(model2)
beta=s$coefficients[,1]
beta
x=c(145:168)
x0=cbind(rep(1,length(x)),x)
x0
eta=x0%*%beta
eta
pred_RTGS_value=exp(eta)
pred_RTGS_value
```

 # number of transactions

```
RTGS_number=neft$rtgs_nt
RTGS_number
Y=RTGS_number
length(Y)
X=t
X
modelrnt=lm(log(Y)~X,data=neft)
modelrnt
# forecast
s=summary(modelrnt)
beta=s$coefficients[,1]
beta

x=c(145:168)
x0=cbind(rep(1,length(x)),x)
x0
eta=x0%*%beta
eta
pred_RTGS_number=exp(eta)
pred_RTGS_number
```

APPENDIX C

C.1: Algorithms for the Tests for Assessing the Assumptions of the Inverse Semi-Log Regression Model

The tests described in Damodar and Porter (2009) were employed to evaluate the underlying assumptions of the model expressed as $\log Y_t = \alpha + \beta t + u_t$:

Runs Test

To assess the presence of serial correlation in the residuals, a method is employed. Initially, the regression model is fitted using the ordinary least squares (OLS) technique, resulting in residuals. The number of runs formed by the positive and negative signs within the residuals is then calculated. If there is an excessive number of runs, it indicates frequent sign changes and implies negative serial correlation. Conversely, too few runs suggest positive autocorrelation.

Let's define the following variables:

N_1: The count of positive symbols (i.e., positive residuals)

N_2: The count of negative symbols (i.e., negative residuals)

R: The number of runs

N: The total number of observations, which is equal to N_1+N_2

$\sqrt{\sigma_R{}^2}$: Standard Deviation of Run

The mean, E(R)= $\frac{2N_1N_2}{N} + 1$ and the variance: V(R)= $\frac{2N_1N_2(2N_1N_2-N)}{(N)^2(N-1)}$

Durbin Watson's d Statistic

Statisticians Durbin and Watson developed a test to identify autocorrelation in a regression model up to order 1. The null hypothesis assumes the absence of autocorrelation up to order 1. This test is commonly referred to as the Durbin-Watson d statistic, which can be defined as follows:

$$d = \frac{\sum_{t=2}^{t=n}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{t=n}\hat{u}_t^{\ 2}}$$

Simplifying the above equation, we obtain the approximation $d \approx 2(1-\rho)$, where ρ is correlation, with $-1 \leq \rho \leq 1$. The value of d falls within the range $0 \leq d \leq 4$.

The decision rules for interpreting the Durbin-Watson test results are as follows:

If the estimated correlation $\hat{\rho}$ is approximately 0 and d is around 2, it indicates no autocorrelation in the residuals.

In the case of an estimated correlation close to 1, resulting in an approximate d value of 0, it suggests perfect positive autocorrelation in the residuals.

Conversely, if the estimated correlation is approximately -1, leading to an approximate d value of 4, it implies perfect negative autocorrelation in the residuals.

Breusch Godfrey (BG) Test

Breusch and Godfrey, two statisticians, developed a test to identify autocorrelation of any order in a model. This test offers the flexibility to handle various scenarios, including non-stochastic regressors such as lagged values of the dependent variable, higher-order autoregressive schemes (e.g., AR (1), AR (2), etc.), and simple or higher-order moving averages of white noise error terms.

Consider our model, assuming that the error term u_t follows a pth-order autoregressive scheme, AR(P), represented as:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \cdots + \rho_p u_{t-p} + \varepsilon_t$$

where ε_t represents the white noise error term. The null hypothesis is:

$H_0: \rho_1 = \rho_2 = \cdots = \rho_p = 0,$

indicating no serial correlation of any order. The BG test involves the following steps:

- Estimate the model using ordinary least squares (OLS) and obtain the residuals.
- Regress $\hat{u}_t$on the original regressors as well as lagged values of the estimated residuals from step 1, namely $\hat{u}_{t-1}$, $\hat{u}_{t-2}$,.... $\hat{u}_{t-p}$.
- Calculate the coefficient of determination, R^2. For instance, if p = 4, introduce 4 lagged values of residuals as additional regressors in the model.

If the sample size is large, Breusch and Godfrey demonstrated that (n-p)R^2 follows a chi-square distribution with p degrees of freedom.

In an application, if (n-p)R^2exceeds the critical chi-square value at the chosen level of significance, the null hypothesis is rejected.

Breusch-Pagan-Godfrey (BPG) Test

Breusch and Godfrey, statisticians known for their contributions to statistical testing, developed a method called the BPG test to detect heteroscedasticity in a regression model. This test assumes that the error variance (σ_i^2) in the model is a function of a non-stochastic variable Z or a combination of independent variables. Specifically, it follows the form:

σ_i^2= f ($\alpha_1 + \alpha_2 Z_{2i}$+……. + $\alpha_{\mathrm{m}} Z_{\mathrm{m}i}$)

Alternatively, it can be simplified as:

$\sigma_i^2 = \alpha_1 + \alpha_2 Z_{2i}$+……. + $\alpha_{\mathrm{m}} Z_{\mathrm{m}i}$

If α_2 =……. = α_{m} where σ_i^2 = α_1i.e., constant

To test the hypothesis of homoscedasticity, the following steps can be followed:

Ho: $\alpha_2 = \alpha_3$ =……. = α_{m}= 0

Steps:

Step1: Estimate the model by OLS and obtain the residuals $\hat{u}_1$, $\hat{u}_2$,…… $\hat{u}_n$.

Step2: Obtain $\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} \hat{u}_i^2}{n}$

Step3: Construct variables $p_i = \frac{\hat{u}_i^2}{\hat{\sigma}^2}$

Step4: Regress p_i on Z's as

$$p_i = \alpha_1 + \alpha_2 Z_{2i} + \ldots\ldots + \alpha_{\mathrm{m}} Z_{\mathrm{m}i} + \gamma_i \textbf{(*)}$$

where γ_i is the residual term of this regression.

Step5: Obtain the explained sum of squares (ESS) from **(*)** and define $\tau = \frac{(\mathrm{ESS})}{2}$ assuming $\hat{u}_i$ are normally distributed. If the sample size n increases indefinitely, then

$\tau \sim \chi^2_{m-1}$ i.e., τ follows the chi-square distribution with (m-1) degrees of freedom.

If the computed value of τ exceeds the critical value χ^2_{df} at the chosen significance level, the null hypothesis of homoscedasticity is rejected. Otherwise, if the computed value of τ does not exceed the critical value, the null hypothesis is not rejected. The implementation of these tests can be facilitated by utilizing R Studio software (refer to Appendix B.2 for the specific codes).