Analysing the Impact of Demonetisation on Digital Payments in India

MSc Research Project
FinTech

Sneha Sadaye
Student ID: x19107692

School of Computing
National College of Ireland

Supervisor: Noel Cosgrave

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Sneha Sadaye
Student ID:	X19107692
Programme:	MSc in FinTech **Year:** 2020
Module:	MSc Research Project
Supervisor:	Noel Cosgrave
Submission Due Date:	17th August 2020
Project Title:	Analysing the Impact of Demonetisation on Digital Payments in India
Word Count:	9620 **Page Count** 26

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: ……………………………………………

Date: 17th August 2020

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Analysing the Impact of Demonetisation on Digital Payments in India

Sneha Sadaye
x19107692

Abstract

Demonetisation is defined as an act of invalidating the legal tender status of a currency and it renders the currency worthless for exchange. The Government of India announced the demonetisation of two of the country's highest denomination notes, INR 500 and INR 1000, in November 2016. The announcement was very sudden and was implemented immediately, leaving the entire country in a state of shock. India being majorly cash-dependent economy, the sudden change led to a severe disruption in most of the economic sectors including payments. Various studies have analysed the impact of demonetisation on digital payments. While most existing studies show that demonetisation led to a drastic improvement in the usage of digital payment services, the findings are mostly based on the immediate impact. This research presents a thorough analysis to determine the impact of demonetisation on digital payments in India. The methods such as segmented regression, dynamic regression models and ARIMA-intervention analysis using transfer function models are used. The findings of this research indicate that while there was an instantaneous growth in the number of digital payment transactions after demonetisation, the growth was only about 10% and has not been extremely high. There was no significant change in the amount of transactions done via digital payments. This research, therefore, concludes that demonetisation has not been very effective in driving the nation towards digitalisation.

1 Introduction

On 8th November 2016, the Prime Minister of India announced via a television speech that two of the country's highest denomination currency notes, INR 500 and INR 1000 would be demonetised with effect from midnight, 9th November. This meant that the banknotes would be stripped off their legal currency status overnight. According to a report by the Reserve Bank of India, these banknotes together constituted about 86% of the total value of Indian currency circulation at the time[1]. India being predominantly a cash-based economy, this news came as a shock to the citizens and businesses alike. The demonetisation was implemented by the Government of India with a view to curb corruption and prevent terrorism by attempting to eliminate black money or unaccounted and untaxed money from the Indian economy. For few weeks following the event, the country faced an intense cash crunch until new banknotes became available to the general public. This period also witnessed economic uncertainty and chaos among the people. The Government announced this event as a move towards

[1] https://rbidocs.rbi.org.in/rdocs/AnnualReport/PDFs/0RBIAR2016CD93589EC2C4467793892C79FD05555D.PDF

digitalisation by encouraging people and businesses to use digital payment systems for monetary transactions. Due to the unavailability of new banknotes for a considerable time, the citizens were forced to use alternative modes of payment to perform financial transactions. A huge portion of the population owning mobile phones and other factors such as access to internet and availability of digital payment systems offered by banks and financial institutions led to a significant rise in digital payments. The usage of digital modes of payments saw a drastic increase in terms of both volume and value of transactions in the few months after demonetisation (Bansal and Jain, 2018; Hindocha and Pandya, 2019). While most of the digital transactions show an upward trend, their proportion of the total transactions do not show a great improvement as would be expected after a demonetisation drive (Nithin et al., 2018).

This study aims to analyse the medium- to long-term effect of demonetisation on the payments sector in India and to determine whether the push towards digitalisation was permanent or merely a short-lived effect due to unavailability of cash. Time series analysis is performed to observe the trend of digital payments over the period of study and to determine if there are any significant breaks in the data during the demonetisation period. Time series analysis using Autoregressive Integrated Moving Average (ARIMA) models is performed in this project. The effects of demonetisation are accounted for by using dynamic regression models and transfer function models. The performance of the models is evaluated in terms of various error measures and, finally, the best model is used to measure the level of impact of demonetisation on the digital payments.

1.1 Research Question

Has there been a significant and long-lasting impact of demonetisation on the growth of digital payments in India?

1.2 Objectives

- To analyse the impact of demonetisation on digital payments.
- To analyse if there was a significant growth in the usage of digital payment platforms as a result of demonetisation.
- To determine whether the increase in digital payments was a temporary effect caused by cash crunch during demonetisation or has it been persistent post demonetisation.

The organisation of this paper is as follows:

Section 2 presents a review of literature and demonstrates a critical analysis of the existing studies performed in the research area. It also describes the different approaches used to perform analysis of data in the presence of an external event. This provides a base for the research work done in this project. Section 3 presents the research methodology and describes the steps to be followed in the project. Section 4 demonstrates the implementation of the project, which is followed by evaluation of all the applied methods and a detailed discussion of the results in Section 5. Finally, section 6 concludes the project and states the limitations of the work and proposes the future research directions.

2 Related Work

Section 2.1 presents a critical review of the approaches used in existing studies to analyse the impact of demonetisation on the payments sector in India. Section 2.2 presents the time series analysis techniques used in the presence of external incidents or interventions on time dependent data and describes its applications in various impact analysis problems.

2.1 The impact of demonetisation

Following the Government of India's demonetisation drive of November 2016, substantial research has been done to analyse its impact on various sectors of the Indian economy.

Bansal and Jain (2018) present evidence showing that in the year following demonetisation, the usage of digital banking services offered by the Indian banks such as Real Time Gross Settlement (RTGS), National Electronic Fund Transfer (NEFT), Electronic Clearing System (ECS) and Mobile Banking have increased as compared to that in the previous year. The study has used data consisting of transactions in different modes of payment during a period of two years, a year prior to and a year post demonetisation. The research was performed by using a paired sample t-test to find any significant difference in the usage of digital payments in the pre and post demonetisation periods. The results of the t-test show that there has been an increase in the utilisation of digital banking services in India immediately after demonetisation. While the results of the t-test do indicate a difference in the statistical properties of the two samples, the analysis does not prove that it satisfies the underlying assumption of the t-test that the observations must be independent of one another. Since the data consists of the observations over a period of time, it is time dependent data which might have serial dependence and the results of t-test on such data might not be accurate. Testing for the presence of autocorrelation before performing a paired t-test could be beneficial to validate the results.

Hindocha and Pandya (2019) analysed the usage of digital transactions by comparing the pre and post demonetisation data. They used a one-tailed paired t-test and found that there was a significant increase in the usage of electronic fund transfers (EFT), specifically RTGS and NEFT. The study shows that mobile banking transactions also increased significantly in terms of both volume and value of transactions. It analyses the percentage change in the average of transaction amount and volume in the two samples rather than simply using the raw data in the t-test. Calculating the difference in values might imply that the autocorrelation might have been removed, thus satisfying the assumption for the t-test analysis. However, the paper does not clarify this and hence, the results of this research also may not be considered accurate.

The investigation by Khatik (2018) shows that a few months after the demonetisation incident, the payment activity on electronic payment systems like NEFT, National Automated Clearinghouse (NACH) and Immediate Payment Service (IMPS) grew drastically. The year-on-year growth of IMPS alone during December 2016 and January 2017 was 157.2% and 177.7% respectively. However, following this spike, the growth rate was moderate in the next month. A thorough statistical analysis of the payment data of the next few months can give a better insight into the actual impact of demonetisation on electronic payments.

Nithin et al. (2018) have investigated the effect of demonetisation on digital payments like mobile transactions, Point of Sale (POS) transactions, card transactions etc. They have used time series analysis and the results show that while there was an increase in the use of cards for transactions after demonetisation, the percentage of POS and mobile transactions have shown a declining trend. Majority of the card transactions were done at ATM to withdraw cash rather than at POS, thus, indicating the preference of cash over cashless systems. The paper uses an intervention analysis in time series approach using ARIMA with the intervention point set as the date of demonetisation. It presents the changes in the mean and the differences in the slopes of the pre and post intervention time series data. Although this analysis provides an insight into the trend of some of the digital payment systems in terms of transaction amount, it does not provide a holistic view as it is not certain whether digital payments grew in terms of volume.

Tiwari et al. (2019) surveyed the citizens of National Capital Region (NCR) of India to study the adoption of digital wallets after demonetisation. The research is descriptive in nature and analyses the primary data collected from questionnaires using techniques like ANOVA test, regression analysis and correlation to find the relationship between demographic factors like age, occupation, marital status, annual income, gender and qualification and the questions pertaining to the adoption of digital wallets like awareness, frequency of use, eagerness to learn more about digital wallets, preference of digital wallets over cash or cards etc. It shows the impact of all such factors on the adoption of digital wallets. While this study shows that the adoption of e-wallets has increased, this change cannot be attributed to demonetisation alone. Also, the study only focuses on a limited region and sample size which might not represent the entire population.

Krishnan et al. (2019) have analysed the impact of demonetisation on residents in both rural and urban locations in the Indian state of Tamil Nadu. The data was collected by conducting interviews and surveys and included demographic factors, livelihood details, individual attributes like income, financial literacy, technology access etc. The impact of behaviour change components like awareness (information on digital payment instruments), access (infrastructure and service availability) and action (practice of using payment services) on perceived change in income and perceived change in volume of transactions was analysed by using linear regression. The study showed how different segments of society reacted to the sudden change and adopted digital systems for payment and found that those with more dependence on bank accounts without the knowledge of alternate modes of payment were the most affected. The rural poor who neither had access nor awareness were less vulnerable and least impacted. This study shows that events like demonetisation to be successful as a driver of digitalisation, there needs to be proper access and awareness among people about the existing alternatives to cash.

Megha et al. (2018) have presented the impact of demonetisation on the use of plastic money. They have surveyed 50 respondents in the Indian district of Ernakulam. They have analysed the collected data by using SPSS with statistical attributes like mean and percentage. The results of the study indicate that most of the respondents prefer cards or plastic money. While the results show a preference of cards over cash, it is important to note that the respondents in the research mainly constitute of students in the age group of 18-25. Based on the demographics of the respondents, it cannot be said with certainty that the entire population has shifted to the use of cards over cash.

The technology adoption models provide a means of studying the use of technology within a sample. Sivathanu (2019) has used the unified theory of acceptance and use of technology (UTAUT) and innovation resistance (IR) theory for investigating the usage of digital payment systems during the demonetisation period. The research is based on the data collected from a sample of respondents who were surveyed using a questionnaire from 9th November 2016 to 30th December 2016. The research determines the adoption, resistance and actual usage (AU) of digital payments in India and shows that innovation resistance affects the usage of digital payments while the relation between the behavioural intention to use digital payment systems and the actual usage is restricted by people's preference for cash based payments. The results show that the adoption of digital payment systems increased during the demonetisation period due to various reasons like unavailability of cash, access to digital modes, incentives to use them etc. The study suggests that post demonetisation, factors such as higher availability of cash and lack of incentives to use cashless payments might lead to cash stickiness among people. This research presents an immediate impact of demonetisation; however, it remains to be seen whether the adoption was on a temporary basis or permanent. Moreover, the research sample consisted of limited consumers in Pune city and the findings may not be generalised to other population.

Sobti (2019) has presented the application of an extended UTAUT model for investigating the adoption of mobile payment services like mobile wallets and mobile banking during the demonetisation period in India. The research was based on data collected from surveying people online regarding their intention to use mobile payment services. The data was analysed to determine the impact of several variables like facilitating conditions, perceived risk, perceived cost, behavioural intention, usage and demonetisation effect on mobile payment adoption. The research found that demonetisation had a significant impact on the adoption of mobile payment services. It must be noted that the description of data suggests a concentration of young people in the age group of 20-25 years, thus indicating that majority of the respondents were tech-savvy urban youth. While the results show a positive impact on mobile payment adoption, it can be attributed to the sample used in the study which was biased with respect to the demographics and was not representative of the entire population.

The use of mobile payments in the post-demonetisation period was studied by Sinha *et al.* (2019) by examining the factors like the consumer's adoption readiness, technology readiness and privacy concerns. They found out that although mobile payment adoption has grown in India after the recent demonetisation, the usage and retention is very low. The main reason for this is the privacy concerns associated with using mobile phones for financial transactions. The findings of this research may also be biased as the sample mainly consists of males in the age group of 18 to 35 years.

The analysis by Chopra (2017) shows the impact of demonetisation on various sectors of the Indian economy. It presents the growth in electronic modes of payment as Year-on-Year increase in percentage terms and shows that the growth in IMPS transaction value was as high as 196.7% in January 2017. Other system like NACH saw a growth of 116.7% in December 2016. This study shows that demonetisation caused an immediate upward trend in digital payments, but it does not present the long-term impact.

2.2 Interrupted time series analysis techniques

Analysis of interrupted time series to determine the intervention effects using segmented regression was proposed by Wagner, Soumerai, Zhang et al. (2002). The paper describes an intervention as a change point which breaks an underlying series into multiple segments which might exhibit different levels and trends. Segmented regression models perform a linear regression between time and the output variable within each segment by fitting least squares lines to each segment. The linear regression model can be specified in a way so that it can estimate the level and trend as mean of the pre-intervention segment and the changes in level and trend in the post-intervention segment. This model was applied to an interrupted time series to evaluate the effects of a health policy on medication use and cost. While the study shows that segmented regression detects changes in the level and trend in interrupted time series, the results might not be accurate in the presence of autocorrelation in the data. Thus, autocorrelation in data has to be addressed before applying segmented regression. Segmented regression has also been used by Bernal *et al.* (2017) in their research to perform an interrupted time series analysis to determine the impact of interventions in public health systems. They suggest that in order to perform segmented regression, the intervention point should be clearly identifiable. Again, the results of this approach may not be considered accurate when data is serially correlated.

Determining structural breaks in a time series data can help in identifying major historical, political or economic events that might have occurred. This is shown in the study by Zeileis *et al.* (2003) in which linear regression is used to identify changes in the mean level of the time series. In order to do this, a constant is fitted to the data. R tools to identify breaks in time series data using the strucchange package are discussed. The study shows that the breakpoints() function is useful in identifying multiple structural breaks in data. It also provides significance tests and computes breakpoint estimates by minimising the residual sum of squares.

Box and Tiao (1975) introduced the intervention analysis modelling in time series to investigate whether a known intervention causes an expected change in the time series and if so, to determine the nature and magnitude of change. The paper shows how an exogenous variable can be modelled within a time series to understand its impact. The exogenous variable is represented by a series of 0 and 1 values denoting the absence and presence of intervention. An appropriate transfer function model which represents the intervention can be used to determine a change in a given series. Two types of functions, step function and pulse function, are discussed; the former indicating that a change caused by an intervention is permanent and the latter indicating that the change is temporary.

An impact analysis using the ARIMA-intervention model is presented by Chung et al. (2009) in their paper which studies the impact of the financial crisis of 2008 on the manufacturing industry in China. The results of the analysis indicate that although the impact was temporary, it was abrupt and significant. The study analyses and compares the results of ARIMA and ARIMA intervention models and shows that the effects of an intervention can be explained in a detailed and precise manner by using the ARIMA intervention technique. The intervention modelling helped in quantifying the percentage change in China's manufacturing market which could not be done easily with other time series models.

Another implementation of the ARIMA intervention analysis is presented by Lai and Lu (2005) to analyse the impact of the September 2001 terrorist attack on the air travel passenger demand in the USA. The results of the study show that the impact was temporary but significant. The authors present a comparison of a seasonal ARIMA model and an ARIMA intervention model and conclude that the intervention model better predicts the changes of an interruption than the seasonal ARIMA. The impact of an intervention has been studied in yet another research where the Government of India's introduction of a new policy to impose an import duty on gold affected the domestic prices of gold in the country (Unnikrishnan and Suresh, 2016). The study used the ARIMA intervention model for analysing the impact of the policy on gold prices. It compares the results of the ARIMA intervention model with Holt's Linear Trend method and finds that the performance of the former model is better in determining the significance of impact.

Ahmar *et al.* (2018) show that detecting outliers in time series data and accounting for their effects during model estimation greatly reduces the errors of the model and enhances the model fit. The paper describes the model estimation using ARIMA and detects the additive outliers in the series by using an iterative process. These detected outliers are then included in model estimation. The results show that the ARIMA model with outliers gave an improvement in model fit and reduced the forecast errors.

This research builds on the previous studies to analyse the impact of demonetisation on digital payments by investigating its effect on the time series by using interrupted time series analysis techniques. This study aims at determining and quantifying the impact by using proven statistical techniques.

3 Research Methodology

This section provides a detailed description of the data used and the methodology followed in this study and the motivation for its selection.

3.1 Data Selection and Preparation

The first step involves identifying the data sources and collecting data. The data for this research was collected from the Reserve Bank of India's (RBI) Database on Indian Economy[2]. The data consists of the monthly value and volume of financial transactions performed through various payment platforms during the period of April 2004 to October 2019. This data was selected as it spans a significant time frame before demonetisation and a considerable time period after it, which would help analyse not only the immediate, but also the medium- and long-term impact of the incident. The variables considered for this research include the transactions performed using digital payment systems like Real Time Gross Settlement (RTGS), Retail Electronic Clearing (REC), debit and credit card usage at POS, m-wallets and mobile banking, all in terms of volume and value and the grand total of all transactions, including cash-based and cashless.

[2] https://dbie.rbi.org.in/DBIE/dbie.rbi?site=home

This section also includes pre-processing and transformation of data. The first step is calculating digital transactions as a percentage of total. This is done in order to normalise the data. The data is then converted into time series and split into two parts – data before November 2018 is considered as training set and the data from November 2018 onwards is considered as the test set. Thus, there are two univariate time series data, one representing digital transaction volume as percentage of total volume and the other representing digital transaction value as percentage of total value.

3.2 Exploratory Data Analysis

Exploratory data analysis (EDA) is performed on the data obtained in the previous step in order to visualise the data over the period of study. This helps in visualising the trend of digital payment transactions until the occurrence of the demonetisation incident and in determining whether there is an abrupt change on or after demonetisation.

3.3 Model Estimation

This section begins with a preliminary analysis of the data by performing segmented regression. The segmented regression model is given by equation (1).

$$Y_t = \beta_0 + \beta_1 \times time_t + \beta_1 \times intervention_t + \beta_2 \times time\ after\ intervention_t + e_t \quad (1)$$

Where Y_t= mean of the output variable at time t, $time_t$= continuous numeric variable denoting time period t, starting with 1 and increasing serially, $intervention_t$ = indicator for intervention at time t, coded as 0 before and 1 after intervention, $time\ after\ intervention_t$= continuous numeric variable denoting time period t after the intervention, coded as 0 before intervention and increasing serially, starting from 1 after intervention.

The next step is to estimate dynamic regression models so as to include the effect of external variables representing the demonetisation effect in addition to regular ARIMA components that take into consideration the lagged values of data (autoregressive process) and historical error terms (moving average process). This is known as regression with ARIMA errors and is given by equation (2).

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \eta_t \quad (2)$$

where $x_{1,t}\ldots,\ x_{k,t}$ are k external predictor variables and η_t represents an ARIMA(p, d, q) process, given by equation (3).

$$\Phi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t \quad (3)$$

where,

$\Phi(B)$ represents the autoregressive parameter of order p and is given by,

$\Phi(B) = 1 - \boldsymbol{\Phi_1} B - \boldsymbol{\Phi_2} B^2 - \cdots - \boldsymbol{\Phi_p} B^p$

$\theta(B)$ represents the moving average parameter of order q and is given by,

$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$

ε_t represents the noise term and B is the backshift operator and represents the d^{th} order difference of y_t.

The external regressors are selected in two ways: (i) a simple numeric vector with 0 and 1 values for pre-demonetisation and post-demonetisation time periods respectively, and (ii) a matrix of variables determined by detecting level shifts and additive outliers in the time series.

The next step is to apply intervention analysis using transfer function in ARIMA models to find if there is a significant difference in the mean function or trend of the time series. The change in mean level is determined by applying a step function which is 0 during pre-intervention and 1 throughout the post-intervention period. A pulse function indicates a temporary change at the intervention point and is equal to 1 at the time of intervention and 0 otherwise (Cryer and Chan, 2010). These models also provide a way to incorporate the lagged effects of covariates on the time series.

3.4 Diagnostic measures

After estimating the models, the next important step is to perform residual diagnostics to ensure that the models fit correctly to the data and the residuals of the models are white noise and contain no autocorrelation. If there exists autocorrelation among the residuals of the model, the model order is changed and tested again iteratively until the residuals are found to be random errors. This is done by examining the autocorrelation plots in addition to diagnostic tests like the Ljung-Box test (Hyndman and Athanasopoulos, 2018).

3.5 Forecasting and Interpreting results

The fitted models that pass the diagnostic checks are used to forecast the values for the test data. The forecasted values are compared against the actual values and the accuracy of the models is computed. The coefficients of the ARIMA-intervention model are used to quantify the percent change caused due to the impact. The results help in determining the changes to the time series data and whether demonetisation had a significant impact on digital payments.

4 Implementation

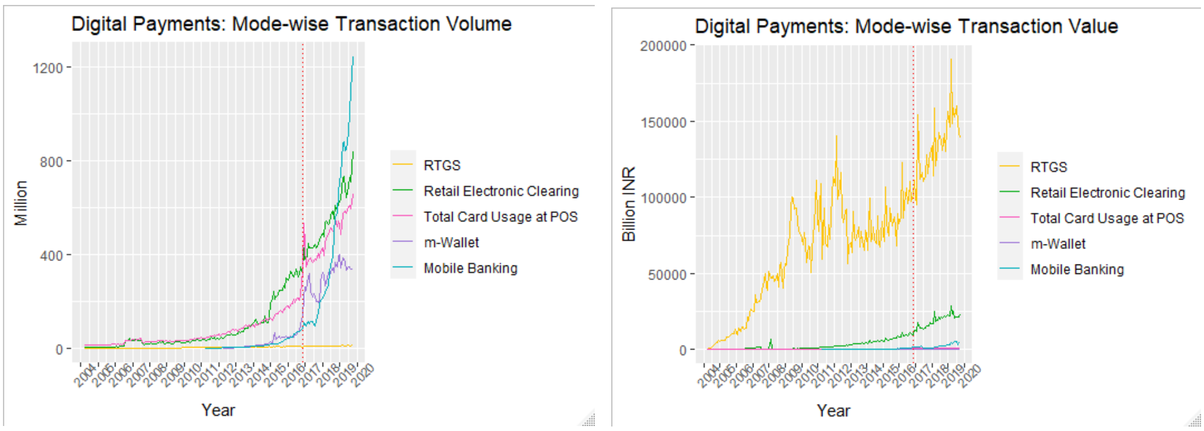
This quantitative research follows the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology and includes five major steps as described in detail in the following subsections.

4.1 Data extraction and pre-processing

The dataset acquired from the RBI website is analysed using R language. The first step in the analysis includes loading the data and performing the necessary cleaning in order to make the data usable for analysis. The dataset includes the number (volume) and amount (value) of transactions performed through several payment systems, both cash-based and digital; and also, the data on number of ATMs and POS terminals. For the purpose of this study, only the transactions done via digital modes of payment are of interest. The other columns are hence, not considered in this study. The updated dataset now includes the variables of interest like Real Time Gross Settlement (RTGS), Retail Electronic Clearing (REC), Card (Debit + Credit) usage at POS, Mobile wallets and Mobile banking, all in terms of volume and value of transactions. Data cleaning tasks like date formatting, type conversion and sorting the data according to date are included in this step. The data are converted to percentage terms by dividing each column by the grand total of transactions. This conversion is done so as to normalise the data and present a real view on the trend of payments as the raw data in a payment mode might show a growing trend in terms of numbers, but as a share of the total transactions, it might not be the case. The sum of all these digital transactions in terms of volume and value is calculated and converted to percentage terms by dividing by the total number and amount of transactions respectively.

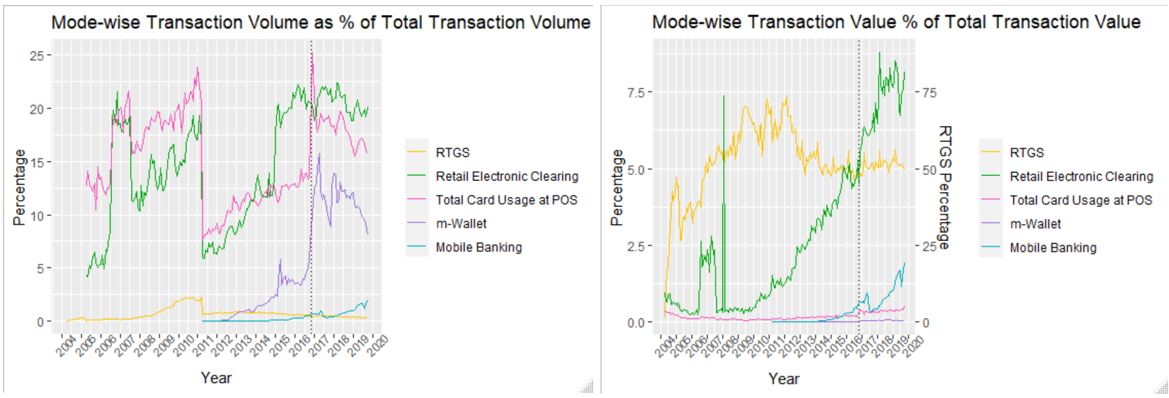
4.2 Exploratory data analysis to visualise the data

After pre-processing the data, the next step is to perform Exploratory Data Analysis (EDA) to gather data understanding such as trend, seasonality and any visible abrupt change in the series. It includes generating plots of the time series data. Figure 1(a) shows the volume of transactions and Figure 1(b) shows the value of transactions in individual digital payment modes from April 2004 to October 2019, with the red dashed line denoting the date of demonetisation. It can be seen that the volume of digital transactions grew exponentially post demonetisation, however, the change in transaction value is not visibly clear for all payment modes.



(a) **(b)**

Figure 1: (a) Mode-wise transaction volumes (b) Mode-wise transaction values over time.



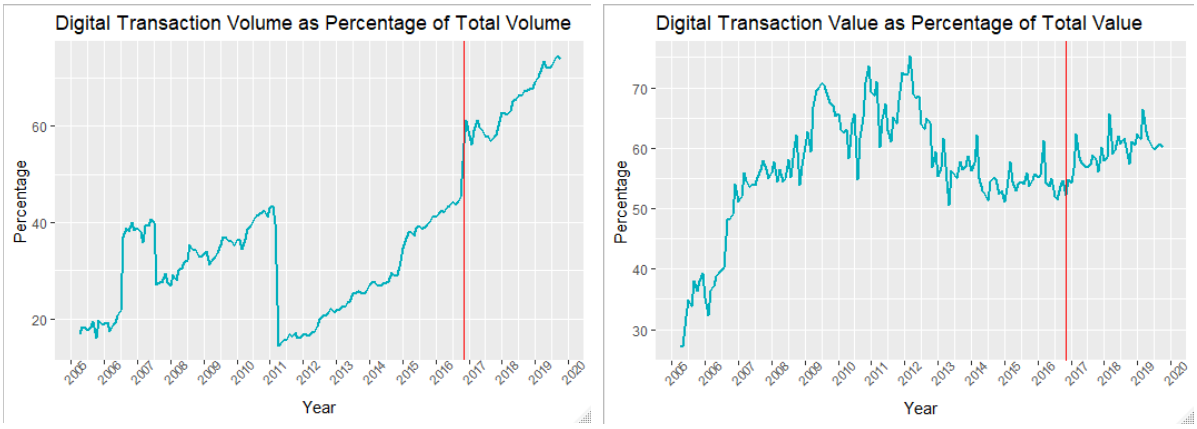
(a) **(b)**

Figure 2: (a) Mode-wise volume of transactions as percentage of total volume; (b) Mode-wise value of transactions as percentage of total value.

Figure 2(a) shows the transaction volume and Figure 2(b) shows transaction value in individual digital modes as percentage of total volume and value respectively, with the dashed line denoting the date of demonetisation. It is observed that only total card usage at POS and m-wallet transaction volumes see a large growth post demonetisation, the other modes do not show any significant growth in volume after the incident.

The plot of value shows that while RTGS makes up the major percentage of the total value (indicated by the y-axis scale at right side in Figure 2(b)), it shows no significant increase post demonetisation. Of the other modes, Retail electronic clearing and mobile banking values show an upward trend after demonetisation (indicated by y-axis scale on the left side in Figure 2(b)).

For the purpose of this study, the sum total of digital transactions is considered as a percentage of the grand total of transactions. This is done in order to examine the trend of total digital transactions as opposed to individual payment modes with an aim to find if digitalisation has increased post demonetisation. Figure 3(a) shows the digital volume and Figure 3(b) shows the digital value of transactions as percentage of total transactions. This data will be used for all further analysis.



(a) (b)

Figure 3: (a) Volume of digital transactions as percentage of total volume; (b) Value of digital transactions as percentage of total value.

4.3 Model Estimation

A preliminary analysis is performed using segmented regression on the data. For this, three predictor variables are added to the dataset, a variable coding for time t which starts at 1 and increases by 1 successively until the number of time points in the data, the binary intervention variable X which is 0 pre-intervention and 1 post-intervention and the time after intervention t_i, coded 0 before intervention and increases by 1 successively for the time points in the post intervention period. The model fits regression lines through the data and the coefficients represent the intercept, the slope of the pre-intervention data, the level change due to intervention and the slope of the post intervention data.

Next, the data is converted to time series and analysed using time series models. To estimate the model and to calculate the accuracy of the models, the data is split into two samples for training and testing purpose. Data before November 2018 is the training set and the data from November 2018 onwards is the test set. The point of intervention is kept as part of the training data to account for its effect while model estimation. Next, the training data is modelled using dynamic regression models and transfer function models using ARIMA.

The dynamic regression model is implemented by using the auto.arima() function in R and providing the value of xreg parameter as the external regressor variable. To determine the value of external regressor, the series is first tested using break point analysis. For this purpose, the strucchange package is used. The breakpoint determined by the breakpoints() method is used to create the external regressor with value 0 before the breakpoint index and 1 after it. Another variation of this model is analysed, where the external regressors are determined using the outliers detected by the tso() function from the tsoutliers package. The Level Shift and Additive Outliers are used to form a matrix of external regressors and passed as xreg.

Another model estimated is the ARIMA-intervention model by using transfer functions. The ARIMA order is first determined from the pre-intervention series. This order is used on the train set along with transfer functions like step function and pulse function to account for intervention. This is performed by using the arimax() function from the TSA package. The models are estimated by using several transfer functions.

5 Evaluation

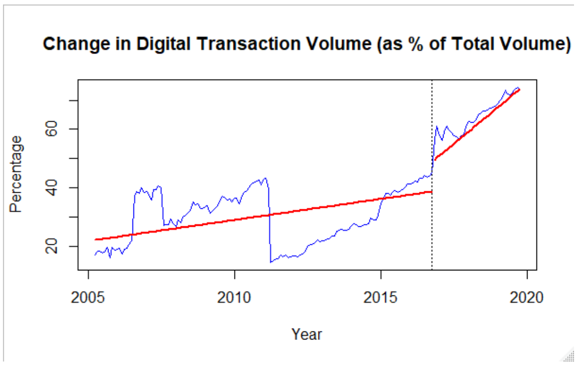
This section focuses on evaluating all the estimated models. The segmented regression models are evaluated by checking the residuals of the fit. If significant autocorrelation is present in the residuals, then the model is not used for forecasting. The dynamic regression and transfer function models are subjected to residual diagnostics. The ACF plots of the residuals are checked for the presence of autocorrelation between the lagged values of residuals and Ljung-Box test is used to determine whether the residuals follow a random white noise pattern. The models that pass the diagnostic tests are evaluated based on criteria such as Akaike Information Criterion (AIC), Akaike Information Criterion – corrected (AICc) and Bayesian Information Criterion (BIC). The model with the least values of these three criteria is selected as the best model. The models are then used to forecast the values for the test period and the difference between actual and predicted values is calculated to find the forecast errors. The forecast errors are measured by different error metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Scaled Error (MASE). The best model is the one with the lowest values of RMSE, MAE, MAPE and MASE (Hyndman and Athanasopoulos, 2018). The error metrics are calculated as shown in Table 1.

Table 1: Formulae of Error measures

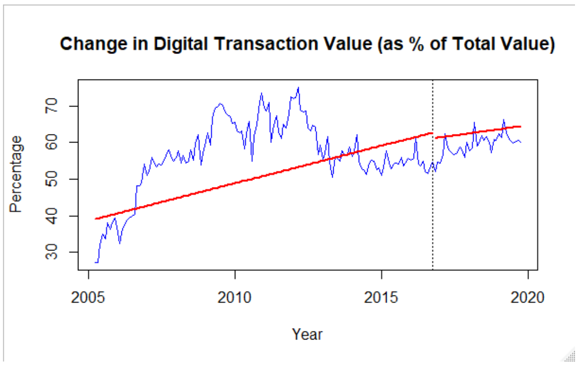
Error Measure	**Formula**
Mean absolute error	MAE = $mean(\|e_t\|)$
Root mean squared error	RMSE = $\sqrt{mean(e_t^2)}$
Mean absolute percentage error	MAPE = $mean(\|p_t\|)$ where $p_t = 100\frac{e_t}{y_t}$
Mean absolute scaled error	MASE = $mean(\|q_j\|)$ where $q_j = \frac{e_j}{\frac{1}{T-m}\sum_{t=m+1}^{T} y_t - y_{t-m}}$

5.1 Experiment 1 – Preliminary analysis with Segmented Regression

The first experiment is executed by fitting segmented regression to each dataset to determine the change in level and slope of the series due to demonetisation. Figure 4(a) and (b) shows the changes in the digital volume and value data respectively.



(a)



(b)

Figure 4: Level and slope change in (a) digital transaction volume; (b) digital transaction value.

The coefficients of the segmented regression model for volume data are shown in Table 2.

Table 2: Segmented Regression coefficients for digital volume data

	Estimate	Std. Error	p-value
Intercept	21.91	5.92	0.0002147 ***
T	0.12	0.097	0.0809093 .
X	10.24	2.998	0.0002808 ***
Ti	0.57	0.343	0.0715945 .

The fitted model equation for volume data can be written as

$$\mathrm{Y} = 21.91 + 0.12\mathrm{T} + 10.24\mathrm{X} + 0.57\mathrm{Ti} + \mathrm{e}$$

The coefficients of the variables for the volume data show that the intercept value pre-demonetisation is 21.9, the trend is 0.12 which suggests that the growth was 0.12 per month before demonetisation. The change in level is 10.24 and the change in trend is 0.57 post-demonetisation. The level change is significant but the change in trend is not very significant as indicated by the p-value in Table 2.

The coefficients of the segmented regression model for value data are shown in Table 3.

Table 3: Segmented Regression coefficients for digital value data

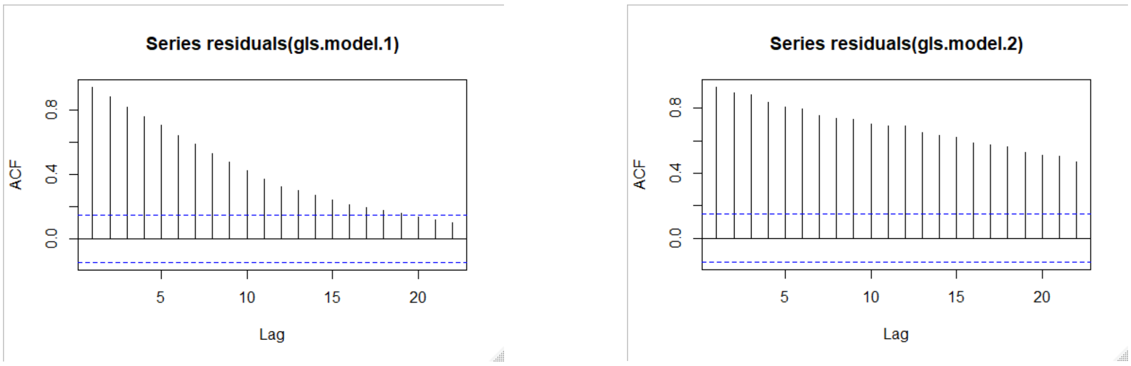
	Estimate	Std. Error	p-value
Intercept	38.88	9.136	2.079e-05 ***
T	0.17	0.097	0.07809 .
X	-1.60	2.998	0.59344
Ti	-0.079	0.343	0.81602

For the value data, the model equation can be written as

$$\mathrm{Y} = 38.9 + 0.17\mathrm{T} - 1.6\mathrm{X} - 0.07\mathrm{Ti} + \mathrm{e}$$

The coefficients of the variables for the value data show that the intercept value pre-demonetisation was 38.9, the trend was 0.17 which decreased by 0.07 post-demonetisation. The level dropped by around 1.6% after demonetisation. However, the coefficients X and Ti are not significant at the 5% or 1% confidence interval as indicated by the p-value.

Although the change in level and trend is visible, the residuals of the segmented regression model are not completely random noise, there is autocorrelation present within lags of residuals, as seen from the ACF plots of the residuals in Figure 5. Therefore, the estimates of the model are not used for further forecasting.



(a) **(b)**

Figure 5: ACF plots of residuals of segmented regression models on (a) digital transaction volume and (b) digital transaction value.

5.2 Experiment 2 – Dynamic regression using simple level shift external regressors

This experiment determines an external regressor variable to account for a level shift in the series. The series is first checked for breakpoints and based on the breakpoint index which is closest to the demonetisation date, the external variable is created as 0 before the breakpoint index and 1 after it. This simple numerical variable is used as xreg parameter in the auto.arima() function. The residuals of the model are evaluated using Ljung-Box test and by the ACF plot of residuals. The model estimation is done iteratively until the residuals of the model represent white noise. The best model is selected based on AIC, BIC and AICc values. The Information Criteria(IC) values for different models fitted on digital volume data are shown in Table 4.

Table 4: IC values for dynamic regression models (simple level shift) for digital volume

Model	**AIC**	**AICc**	**BIC**
Regression with ARIMA(1,0,0)(0,0,1)[12] errors	809.7489	810.1311	825.2177
Regression with ARIMA(1,1,1)(0,0,1)[12] errors	799.2964	799.6811	814.7344
Regression with ARIMA(1,1,1)(1,0,1)[12] errors	796.5080	797.0500	815.0336

For the digital volume series, the best dynamic regression model using simple level shift regressor is found to be Regression with ARIMA(1,1,1)(1,0,1)[12] errors model. However, the forecast errors were found to be minimum with Regression with ARIMA(1,1,1)(0,0,1)[12] errors model as shown in Table 5.

Table 5: Error measures for dynamic regression models (simple level shift) for digital volume

Model	MAE	RMSE	MAPE	MASE
Regression with ARIMA(1,0,0)(0,0,1)[12] errors	7.3012318	8.2977336	10.045950	0.80196405
Regression with ARIMA(1,1,1)(0,0,1)[12] errors	4.938596	5.797655	6.749465	0.5424532
Regression with ARIMA(1,1,1)(1,0,1)[12] errors	7.1611471	8.3145786	9.799449	0.78657722

The coefficients of Regression with ARIMA(1,1,1)(0,0,1)[12] errors model are shown in Table 6.

Table 6: Coefficients of Regression with ARIMA(1,1,1)(0,0,1)[12] errors model

Coefficient	Estimate	Std. Error	P value
ar1	-0.943903	0.029338	< 2.2e-16 ***
ma1	0.999998	0.024423	< 2.2e-16 ***
sma1	-0.155568	0.080341	0.0528253 .
xreg	9.872048	2.629386	0.0001737 ***

The p-value indicates that ar1, ma1 and xreg are significant in determining the digital volume time series. The model equation can be written as follows

$$y_t = 9.872xreg + n_t$$
$$n_t = -0.943n_{t-1} + e_t + 0.999e_{t-1} - 0.155e_{t-12}$$
$$e_t \sim NID(0,7.736)$$

The Information Criteria(IC) values for different models fitted on digital value data are shown in Table 7.

Table 7: IC values for dynamic regression models (simple level shift) for digital value

Model	AIC	AICc	BIC
Regression with ARIMA(2,1,2)(0,0,1)[12] errors	786.3759	787.1031	807.9890
Regression with ARIMA(2,1,3)(0,0,1)[12] errors	784.7726	785.7138	809.4734
Regression with ARIMA(3,1,3)(1,0,1)[12] errors	786.6065	787.7907	814.3948

For the digital value series, the best dynamic regression model using simple level shift regressor is found to be Regression with ARIMA(2,1,3)(0,0,1)[12] errors model. The forecast errors were also found to be minimum with this model, as shown in Table 8.

Table 8: Error measures for dynamic regression models (simple level shift) for digital value

Model	MAE	RMSE	MAPE	MASE
Regression with ARIMA(2,1,2)(0,0,1)[12] errors	3.383761	3.622419	5.466334	0.6111288
Regression with ARIMA(2,1,3)(0,0,1)[12] errors	2.904750	3.203975	4.684918	0.5246164
Regression with ARIMA(3,1,3)(1,0,1)[12] errors	2.963473	3.262067	4.780371	0.5352221

The Regression with ARIMA(2,1,3)(0,0,1)[12] errors model coefficients are shown in Table 9.

Table 9: Coefficients of Regression with ARIMA(2,1,3)(0,0,1)[12] errors model

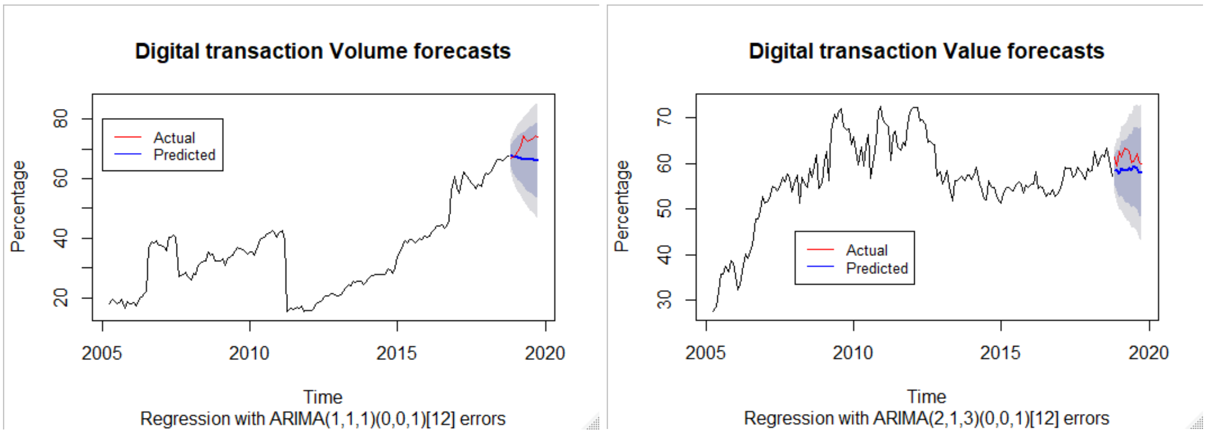
Coefficient	Estimate	Std. Error	P value
ar1	-1.392627	0.055560	< 2.2e-16 ***
ar2	-0.929739	0.042750	< 2.2e-16 ***
ma1	1.271800	0.096086	< 2.2e-16 ***
ma2	0.634027	0.125566	4.434e-07 ***
ma3	-0.164758	0.086093	0.05566 .
sma1	0.257573	0.083899	0.00214 **
xreg	-2.563419	2.489299	0.30312

The p-value indicates that ar1, ar2, ma1, ma2 and sma1 are significant in determining the digital value time series while xreg is not significant at the 5% or 1% confidence interval. This model is therefore a pure ARIMA model, without any significant external regressor. The model equation can be written as follows

$$y_t = -1.39y_{t-1} - 0.929y_{t-2} + e_t + 1.27e_{t-1} + 0.63e_{t-2} + 0.257e_{t-12}$$

$$e_t \sim NID(0{,}6.983)$$

Figures 6 (a) and (b) show the forecasts from the best models selected for the digital volume and digital value series respectively.



(a) **(b)**

Figure 6: Forecasts for (a) digital transaction volume and (b) value.

5.3 Experiment 3 – Level shifts and Additive outliers as external regressors

The tso() function is used to determine the outliers in the time series data. This function determines different types of outliers such as level shift, additive outliers, temporary change, innovative outliers and seasonal level shift and reports their index in the series. The level shift and additive outlier effects on the data are used to create a matrix and passed as external regressors to the ARIMA model. Table 10 shows the comparison of AIC, AICc and BIC values of the models. The best model is the one having the least values of these criteria. Thus, Regression with ARIMA(0,1,1)(1,0,1)[12] errors is the best for digital volume series.

Table 10: IC values for dynamic regression models (level shift and additive outliers) for digital volume series

Model	AIC	AICc	BIC
Regression with ARIMA(0,1,1)(1,0,1)[12] errors	493.8592	496.3187	533.9980
Regression with ARIMA(0,1,2)(1,0,1)[12] errors	498.0515	500.5110	538.1903

The forecast errors from both the fitted models are shown in Table 11. Regression with ARIMA(0,1,1)(1,0,1)[12] errors model gives the lowest forecast errors.

Table 11: Error measures for dynamic regression models (level shift and additive outliers) for digital volume series

Model	MAE	RMSE	MAPE	MASE
Regression with ARIMA(0,1,1)(1,0,1)[12] errors	1.2351794	1.407283	1.715891	0.13567156
Regression with ARIMA(0,1,2)(1,0,1)[12] errors	1.7044069	1.974414	2.343808	0.18721129

The coefficients of the Regression with ARIMA(0,1,1)(1,0,1)[12] errors model are shown in Table 12.

Table 12: Coefficients of Regression with ARIMA(0,1,1)(1,0,1)[12] errors model

Coefficient	Estimate	Std. Error	P value
ar1	-0.252175	0.096533	0.0089932 **
sar1	0.813988	0.078020	< 2.2e-16 ***
sma1	-0.416985	0.116528	0.0003457 ***
drift	0.365464	0.151045	0.0155386 *
LS17	14.738537	0.989654	< 2.2e-16 ***
LS29	-14.562174	0.939874	< 2.2e-16 ***
LS73	-27.075831	0.940315	< 2.2e-16 ***
LS118	4.003101	0.932150	1.751e-05 ***
LS128	0.392341	0.938912	0.6760440
LS140	10.516389	0.961700	< 2.2e-16 ***
LS158	2.319996	0.985028	0.0185098 *
AO141	3.878453	0.756645	2.962e-07 ***

The p-value indicates that almost all external regressors except LS128 are significant. The model equation can be written as follows

$$y_t = 14.73LS17 - 14.56LS2 - 27.07LS73 + 4.0LS118 + 10.51LS140 + 2.31LS158 + 3.87AO141 + n_t$$

$$n_t = 0.819n_{t-1} + 0.81n_{t-12} + e_t - 0.41e_{t-12}$$

$$e_t \sim NID(0,1.098)$$

The Information Criteria(IC) values for different models fitted on digital value data are shown in Table 13. The best model is Regression with ARIMA(2,1,1)(1,0,0)[12] errors.

Table 13: IC values for dynamic regression models (level shift and additive outliers) for digital value series

Model	AIC	AICc	BIC
Regression with ARIMA(2,1,1)(1,0,0)[12] errors	766.2971	767.0244	787.9103
Regression with ARIMA(2,1,2)(1,0,0)[12] errors	767.1125	768.0536	791.8132
Regression with ARIMA(1,1,2)(1,0,0)[12] errors	768.6470	769.3743	790.2602

Table 14 shows the forecast error metrics of the models. The lowest errors are found by Regression with ARIMA(1,1,2)(1,0,0)[12] errors model.

Table 14: Error metrics for dynamic regression models (level shift and additive outliers) for digital value series

Model	MAE	RMSE	MAPE	MASE
Regression with ARIMA(2,1,1)(1,0,0)[12] errors	2.839037	3.114573	4.580907	0.5127480
Regression with ARIMA(2,1,2)(1,0,0)[12] errors	3.028368	3.281719	4.889605	0.5469424
Regression with ARIMA(1,1,2)(1,0,0)[12] errors	2.799999	3.079904	4.517720	0.5056976

The coefficients of the Regression with ARIMA(1,1,2)(1,0,0)[12] errors model are shown in Table 15.

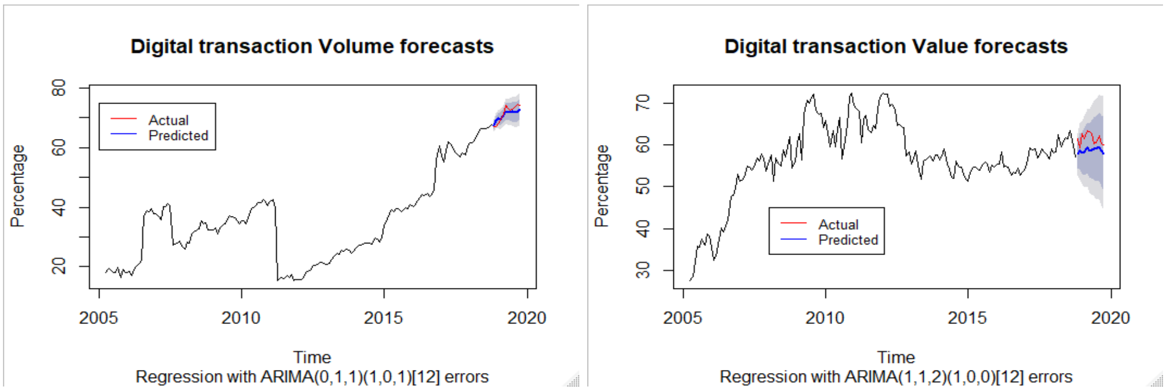
Table 15: Coefficients of Regression with ARIMA(1,1,2)(1,0,0)[12] errors model

Coefficient	Estimate	Std. Error	P value
ar1	-0.594978	0.202310	0.0032723 **
ma1	0.470870	0.195823	0.0161916 *
ma2	-0.247123	0.070743	0.0004772 ***
sar1	0.247747	0.079456	0.0018207 **
LS92	-8.918307	2.390792	0.0001913 ***
AO73	-6.856590	1.802027	0.0001418 ***

The p-value indicates that all the external regressors are significant. The model equation can be written as follows

$$y_t = -8.91LS92 - 6.85AO73 + n_t$$
$$n_t = -0.59n_{t-1} + 0.247n_{t-12} + e_t + 0.47e_{t-1} - 0.247e_{t-2}$$
$$e_t \sim NID(0{,}6.377)$$

Figure 7 shows the forecasts from the dynamic regression models.



(a) **(b)**

Figure 7: Forecasts from dynamic regression models with LS and AO for (a) digital volume and (b) digital value.

5.4 Experiment 4 – ARIMA with transfer function models

This experiment is performed by estimating ARIMA models with transfer functions. The best ARIMA order is determined from the pre-intervention series using auto.arima() function. This model is then used on the training data along with covariates. The covariates are determined based on the month of demonetisation and passed to the xtransf parameter of the arimax() function. The covariates are set as (1) pulse indicator, having value 1 only at the intervention point and 0 elsewhere; and (2) step indicator, having value 0 before intervention point and 1 after it. The lag values of both the pulse and step indicator are also accounted for in the model estimation by setting the AR order as 1 in the transfer parameter of the arimax() function. The estimated models are compared based on AIC as shown in Table 16 and the model with the least AIC is selected. For the digital volume series, the AIC is lowest for ARIMA(0,1,0)(0,0,1)[12] with Step function with AR(1) model and it is used for forecasting.

Table 16: AIC for ARIMA-transfer function models for digital volume series

Model	AIC
ARIMA(0,1,0)(0,0,1)[12] with Pulse	807.6309
ARIMA(0,1,0)(0,0,1)[12] with Step	796.4407
ARIMA(0,1,0)(0,0,1)[12] with Pulse AR(1)	800.2668
ARIMA(0,1,0)(0,0,1)[12] with Step AR(1)	795.9984
ARIMA(0,1,0)(0,0,1)[12] with Pulse + Step AR(1)	796.0294

The forecast errors are shown in Table 17.

Table 17: Error metrics for ARIMA-transfer function model for digital volume series

Model	MAE	RMSE	MAPE	MASE
ARIMA(0,1,0)(0,0,1)[12] with transfer function	1.438329	2.856531	4.920629	0.1579854

The coefficients of ARIMA-transfer function model for the digital volume series are shown in Table 18.

Table 18: Coefficients of ARIMA(0,1,0)(0,0,1)[12] with transfer function for digital volume

Coefficient	Estimate	Std. Error	P value
sma1	-0.190898	0.081535	0.0192168 *
Nov16-AR1	0.309462	0.194828	0.1121987
Nov16-MA0	10.173352	2.671667	0.0001402 ***

The p-values of the coefficients indicate that the Nov16-MA0 covariate, which represents the instantaneous impact of the intervention is significant, whereas the impact of the lagged covariate is not very significant.

The model equation for the digital volume data can be written as follows

$$y_t = 10.1734(x_t + 0.3095x_{t-1}) + n_t$$
$$n_t = e_t - 0.1909e_{t-12}$$
$$e_t \sim NID(0, 7.659)$$

The Information Criteria(IC) values for different models fitted on digital value data are shown in Table 19. The best model is ARIMA(3,1,0)(0,0,1)[12] with Step function.

Table 19: AIC for ARIMA-transfer function models for digital value series

Model	AIC
ARIMA(3,1,0)(0,0,1)[12] with Pulse	785.3022
ARIMA(3,1,0)(0,0,1)[12] with Step	785.2635
ARIMA(3,1,0)(0,0,1)[12] with Pulse with AR(1)	788.5412
ARIMA(3,1,0)(0,0,1)[12] with Step with AR(1)	789.1930
ARIMA(3,1,0)(0,0,1)[12] with Pulse + Step AR(1)	789.1739

Table 20 shows the error metrics of the transfer function model for the digital value series.

Table 20: Error metrics for ARIMA-transfer function model for digital value series

Model	MAE	RMSE	MAPE	MASE
ARIMA(3,1,0)(0,0,1)[12] with transfer function	1.438329	2.856531	4.920629	0.1579854

The coefficients of ARIMA-transfer function model for the digital value series are shown in Table 21.

Table 21: Coefficients of ARIMA(3,1,0)(0,0,1)[12] with transfer function for digital volume

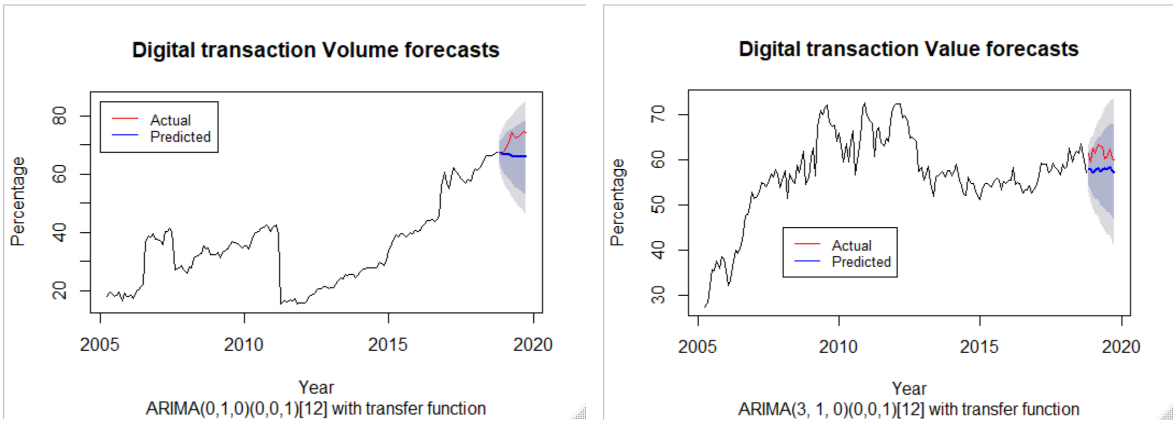
Coefficient	Estimate	Std. Error	P value
ar1	-0.174399	0.077877	0.02513 *
ar2	-0.110065	0.079510	0.16627
ar3	0.182189	0.079607	0.02210 *
sma1	0.174982	0.079351	0.02744 *
Nov16-MA0	-1.850245	2.532162	0.46496

The p-values of the coefficients indicate that the Nov16-MA0 covariate, which represents the instantaneous impact of the intervention is not very significant.

The model equation for the digital volume data can be written as follows

$$y_t = -1.8502x_t + n_t$$
$$n_t = -0.1744n_{t-1} - 0.1101n_{t-2} + 0.1822n_{t-3} + e_t + 0.1750e_{t-12}$$
$$e_t \sim NID(0, 6.989)$$

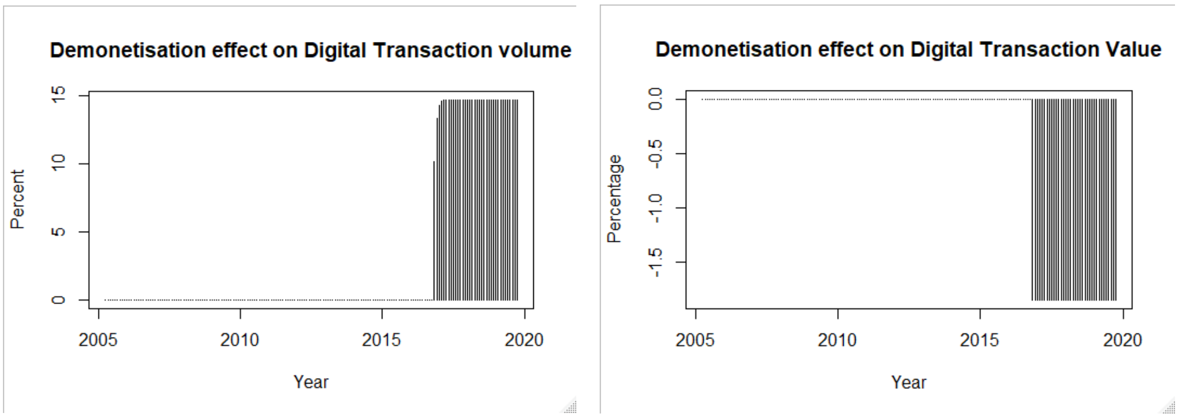
Figure 8 shows the forecasts from ARIMA-transfer function models for the digital volume and value data.



(a) (b)

Figure 8: Forecasts from ARIMA–transfer function models for (a) digital volume and (b) digital value.

The magnitude of the impact of demonetisation can be calculated from the coefficients of the ARIMA-transfer function models. For the digital volume data, the model indicates that the immediate impact was an instantaneous growth of 10.17% as presented in Table 18. Figure 9(a) shows the effect of demonetisation on digital transaction volume. The impact is seen to rise to about 15% and is constant in the subsequent months. Figure 9(b) shows the impact of demonetisation on digital transaction value, which is seen as an instantaneous drop of around 1.85% as presented in Table 21. The impact is a step change, which is constant over the following months.



(a) (b)

Figure 9: Effect of demonetisation on (a) digital transaction volume and (b) digital transaction value.

5.5 Discussion

A review of the experiments is presented in this section. The segmented regression is used as a preliminary analysis tool as it presents a visualisation of the impact of demonetisation on the digital volume and value data by showing the change in the level and trend before and after the incident. The dynamic regression models allow to model the time series as a function of external regressors. The simple level shift regressors indicated by 0 before and 1 after the intervention show that the external regressors have a significant effect on the underlying time series of digital transaction volume data whereas for the digital transaction value data, the level shift is not very significant indicating that while the number of digital transactions increased post demonetisation, the transaction amounts did not increase substantially.

The ARIMA-intervention analysis using transfer function models helps in estimating the magnitude of change caused by demonetisation on the digital transaction volume and value. The results of transfer function models show that digital transactions saw an instantaneous growth of 10.17% in terms of volume, while the amount of digital transactions dropped by about 1.85% as an immediate result of demonetisation. The rise in volume of digital transactions gradually increased until it reached about 15% in November 2017 and has remained constant thereafter as shown in Figure 9(a). The drop in value is permanent as shown in Figure 9(b). Thus, the results of all the models suggest that there was an instantaneous impact of demonetisation on the digital payments and it caused a permanent shift in the level of the series. While the impact was positive on the volume of digital payments, it was negative on the value.

6 Conclusion and Future Work

This research performed a thorough analysis to determine the impact of the November 2016 demonetisation of the Indian currencies on the digital payments in the country. The study is performed on the monthly digital transaction data in terms of volume and value over a period of 15 years to determine if there was a change in the mean level or the trend of the time series data after the implementation of demonetisation. The proven techniques such as segmented regression, dynamic regression models and intervention analysis using transfer function models are used. The steps followed in the research include model estimation, diagnostic testing and forecasting. The estimates of the model fit, and the significance of the model coefficients are used to determine the magnitude of change in the underlying time series caused due to the sudden occurrence of an external event. The results of the research indicate that demonetisation caused an immediate change in the amount of digital transactions as well as in the number of transactions. The impact on digital transaction volume was significant with an instantaneous growth of over 10%, while the impact on digital transaction value was not very significant with a small decrease of 1.85%. These changes in the trend of digital transactions were permanent. While most of the existing research in this area shows that demonetisation led to a drastic growth of digital payments, this study demonstrates that when the digital payments are studied as a percentage of total payments, the results are different. On an individual level, the digital payment systems might indicate an upward trend as suggested by existing papers, but as a share of the total payments, digital payments have only grown very little over the years, even after demonetisation. Thus, it can be concluded that demonetisation caused a sudden upward push on the numbers of digital payments, but the impact was not very drastic and there has been no major change in the amounts of digital payment transactions that can be attributed to demonetisation.

This paper presents the analysis of only the major digital payment systems operated by the Reserve Bank of India. The Government of India has introduced additional payment systems in the recent years which are not included in this study. These include Aadhar Enabled Payment Services (AEPS) and Unified Payments Interface (UPI)[3]. The major future research directions for this project are to perform a holistic study by including all available payment services. In terms of analysis, this paper uses a limited number of tools and modelling techniques. It can be worth trying other time series analysis techniques using regression models and neural networks like Long Short-Term Memory (LSTM), Prophet etc.

References

Ahmar, A.S. *et al.* (2018) 'Modeling Data Containing Outliers Using ARIMA Additive Outlier (ARIMA-AO)'. *Journal of Physics: Conference Series*, 954(1). DOI: 10.1088/1742-6596/954/1/012010.

Bansal, N. and Jain, M. (2018) 'Progress in Digital Banking After Demonetization: Some Evidence.' *IUP Journal of Bank Management*, 17(2), pp. 50–59.

Bernal, J.L., Cummins, S. and Gasparrini, A. (2017) 'Interrupted Time Series Regression for the Evaluation of Public Health Interventions: A Tutorial'. *International Journal of Epidemiology*, 46(1), pp. 348–355. DOI: 10.1093/ije/dyw098.

Box, G.E.P. and Tiao, G.C. (1975) 'Intervention Analysis with Applications to Economic and Environmental Problems'. *Journal of the American Statistical Association*, 70(349), p. 70. DOI: 10.2307/2285379.

Chopra, R. (2017) 'Impact of Demonetization on Indian Economy'. *Global Journal of Enterprise Information System*, 9(2), p. 100. DOI: 10.18311/gjeis/2017/15857.

Chung, R.C.P., Ip, W.H. and Chan, S.L. (2009) 'An ARIMA-Intervention Analysis Model for the Financial Crisis in China's Manufacturing Industry'. *International Journal of Engineering Business Management*, 1(1), pp. 15–18. DOI: 10.5772/6785.

Cryer, J.D. and Chan, K.-S. (2010) *Time Series Analysis With Applications in R*. 2nd ed. DOI: 10.1016/0377-2217(85)90052-9.

Hindocha, M. and Pandya, J.K. (2019) 'The Impact of Demonetization on Electronic Fund Transfers.' *IUP Journal of Bank Management*, 18(2), pp. 7–18.

Hyndman, R.J. and Athanasopoulos, G. (2018) *Forecasting: Principles and Practice*. 2nd

[3] http://cashlessindia.gov.in/digital_payment_methods.html

editio. OTexts: Melbourne, Australia Available at: OTexts.com/fpp2 (Accessed: 4 July 2020).

Khatik, S.K. (2018) ‘A Study on Pre- and Post-Analysis of Demonetization Period : Issues and Challenges’. *International Journal of Business Analytics & Intelligence*, 6(2), pp. 56–65.

Krishnan, N.K. *et al.* (2019) ‘Cashing out: Digital Payments and Resilience Post-Demonetization’. *ACM International Conference Proceeding Series*. DOI: 10.1145/3287098.3287103.

Lai, S.L. and Lu, W.L. (2005) ‘Impact Analysis of September 11 on Air Travel Demand in the USA’. *Journal of Air Transport Management*, 11(6), pp. 455–458. DOI: 10.1016/j.jairtraman.2005.06.001.

Megha, E., Prathap, S. and Krishna, M.B. (2018) ‘Study on Impact of Demonetization on Increased Use of Plastic Money-with Special Reference to Ernakulam District’. *International Journal of Pure and Applied Mathematics.*, 119(10), pp. 29–37.

Nithin, M., Jijin, P. and Baiju, P. (2018) ‘Has Demonetisation Pushed Digitalisation in India? Some Counter Evidences’. *Journal of Business Thought*, 9(March), pp. 58–69. DOI: 10.18311/jbt/2018/21170.

Sinha, M. *et al.* (2019) ‘Mobile Payments in India: The Privacy Factor’. *International Journal of Bank Marketing*, 37(1), pp. 192–209. DOI: 10.1108/IJBM-05-2017-0099.

Sivathanu, B. (2019) ‘Adoption of Digital Payment Systems in the Era of Demonetization in India: An Empirical Study’. *Journal of Science and Technology Policy Management*, 10(1), pp. 143–171. DOI: 10.1108/JSTPM-07-2017-0033.

Sobti, N. (2019) ‘Impact of Demonetization on Diffusion of Mobile Payment Service in India: Antecedents of Behavioral Intention and Adoption Using Extended UTAUT Model’. *Journal of Advances in Management Research*, 16(4), pp. 472–497. DOI: 10.1108/JAMR-09-2018-0086.

Tiwari, P., Garg, V. and Singhal, A. (2019) ‘A Study of Consumer Adoption of Digital Wallet Special Reference to NCR’. *Proceedings of the 9th International Conference On Cloud Computing, Data Science and Engineering, Confluence 2019*, pp. 664–669. DOI: 10.1109/CONFLUENCE.2019.8776939.

Unnikrishnan, J. and Suresh, K.K. (2016) ‘Modelling the Impact of Government Policies on Import on Domestic Price of Indian Gold Using ARIMA Intervention Method’. *International Journal of Mathematics and Mathematical Sciences*, 2016. DOI: 10.1155/2016/6382926.

Wagner, A.K. *et al.* (2002) ‘Segmented Regression Analysis of Interrupted Time Series Studies in Medication Use Research’. *Journal of Clinical Pharmacy and Therapeutics*, 27(4), pp. 299–309. DOI: 10.1046/j.1365-2710.2002.00430.x.

Zeileis, A. *et al.* (2003) ‘Testing and Dating of Structural Changes in Practice’. *Computational Statistics and Data Analysis*, 44(1–2), pp. 109–123. DOI: 10.1016/S0167-9473(03)00030-6.