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Working Paper

The real-time impact on real economy: A multivariate bvar analysis of digital payment systems and economic growth in India

ADB Working Paper Series, No. 1128

Provided in Cooperation with:

Asian Development Bank Institute (ADBI), Tokyo

Suggested Citation: Rooj, Debasis; Sengupta, Reshmi (2020) : The real-time impact on real economy: A multivariate bvar analysis of digital payment systems and economic growth in India, ADB Working Paper Series, No. 1128, Asian Development Bank Institute (ADBI), Tokyo

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ADB Working Paper Series

**THE REAL-TIME IMPACT ON REAL ECONOMY—
A MULTIVARIATE BVAR ANALYSIS
OF DIGITAL PAYMENT SYSTEMS
AND ECONOMIC GROWTH IN INDIA**

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No. 1128
April 2020

Asian Development Bank Institute

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Suggested citation:

Rooj, D. and R. Sengupta. 2020. The Real-Time Impact on Real Economy—A Multivariate BVAR Analysis of Digital Payment Systems and Economic Growth in India. ADBI Working Paper 1128. Tokyo: Asian Development Bank Institute. Available: <https://www.adb.org/publications/real-time-impact-real-economy-india>

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The authors acknowledge the research support provided by FLAME University. We also thank Bihong Huang of the Asian Development Bank Institute (ADBI) and other participants at the Conference on Macroeconomic Stabilization in the Digital Age sponsored by ADBI and Singapore Management University held on 16–17 October 2019 for their wonderful comments and suggestions, which have significantly improved the quality of this paper.

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Abstract

Financial sector development can play a crucial role in driving economic growth. Innovation in the payment system can potentially impact output, prices, and monetary policy transmissions. However, there is a conspicuous lack of work on the role of the payment system in driving economic activity, especially for an emerging economy like India. This paper examines the dynamic linkage between a digital payment system, real-time gross settlement (RTGS), and economic growth in India, using a multivariate Bayesian vector autoregressive (BVAR) model. Using monthly observations on the value and the volume of RTGS, we show that the value of RTGS has a significant impact on both income and price level in the economy. Our results also indicate that both RTGS and economic growth positively and significantly impact each other, supporting the existence of bidirectional causality between the two. A variance decomposition analysis confirms that both RTGS and economic activity contribute significantly to each other's fluctuations. Several sensitivity analyses reinforce our main findings.

Keywords: financial innovation, RTGS, economic growth, bidirectional casualty, Bayesian vector autoregressive

JEL Classification: E32, G22, C53

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1. INTRODUCTION

A well-developed financial sector is an essential ingredient for the long-run economic growth of a country (Schumpeter 1911). In recent times, the world has witnessed a rapid increase in technological innovation, including that in the financial sector. Rapid advances in financial technology, commonly referred to as “FinTech,” are transforming the economic and financial landscape of the world economy (IMF 2018). Financial technologies are offering a wide range of services across the world. Different definitions of FinTech are possible and are in use by international as well as national authorities. It can be categorized either in the form of a new product or a new process for supplying an already existing product, or be in terms of market arrangements (Lewis and Mizen 2000). One such example of financial innovation is the digitalization of means of payment.

One of the primary functions of the financial sector is to provide efficient and fast modes of payments to facilitate the transaction process. By reducing transaction costs, the payment system can facilitate trading and thus allow for greater specialization in economic activities by economic agents (Bech and Hobijn 2007). Moreover, emerging market economies (EMEs), such as India, have a relatively less developed financial sector than advanced economies (AEs). A large section of India’s population is financially excluded. A lack of knowledge and awareness among people about the working of financial institutions is an important reason for financial exclusion. A large section of the population does not have access to banking and other financial services or even to formal credit facilities. However, people have widespread access to mobile phones and mobile data. Hence, in such a scenario, India can try to bring in infrastructural innovations and digitalization, which have enormous potential in terms of making the financial sector inclusive.

In recent years, the Government of India has made a big digital push across several sectors of the economy to bring a broad ambit of its economy under the digital umbrella. The objective is to provide an inclusive, leakage-free delivery of services to a vast majority of its population. One such mechanism is to push for digital transactions, and Indian banks are being encouraged to use technology in their banking operations and make various electronic payment modes available to their customers.

The central bank of a country is responsible for providing the medium of payment to settle small-value cash transactions as well as supporting an interbank system that settles large-value transactions and time-critical payments (Bech and Hobijn 2007). Moreover, the central bank also uses the interbank payment system to implement monetary policies. The system also serves as the platform for the interbank money market.

Payment and settlement systems are the backbone of any economy (RBI 2019). Over the last decade, India has witnessed a significant development in the use of modern technology in financial services. In India, the Reserve Bank of India (RBI) is the sole custodian of the payment system. The RBI has endeavored to ensure that India has one of the most “state-of-the-art” payment and settlement systems in the world.

One such payment and settlement system introduced by the RBI in India is RTGS. RTGS is an internet-based fund transfer system, which enables money transfers on a real-time basis. The initialism “RTGS” stands for “Real-Time Gross Settlement.” RTGS is a payment settlement system where there is a continuous and real-time settlement of fund transfers on an individual transaction basis (without netting). “Real time” refers to the processing of instructions at the time they are received, and “gross settlement”

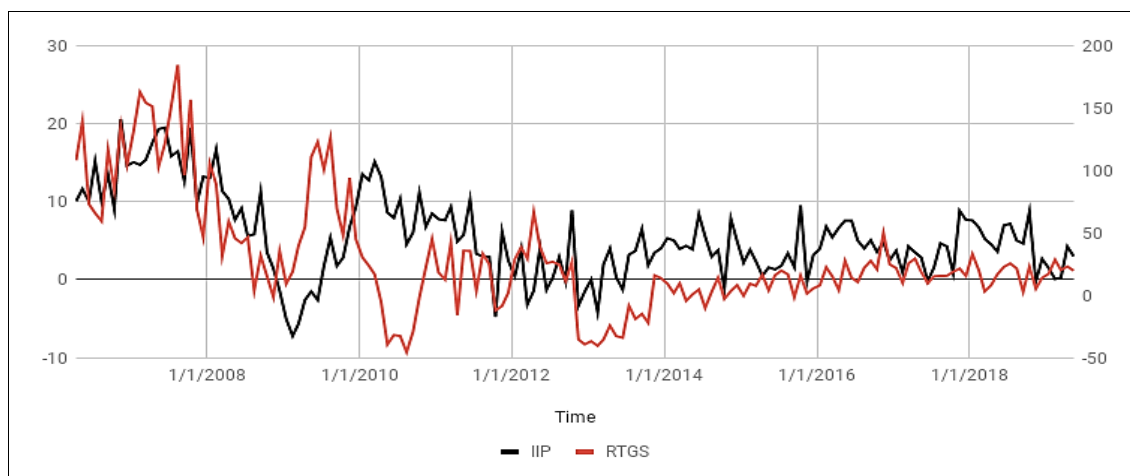
means that the settlement of funds transfer instructions occurs individually. The RTGS system adopted by the RBI in 2004 primarily deals with large-value transactions with the objective of providing not only a safe and secure but also an efficient, fast, and affordable payment system to boost the economic activity in the country. This transaction system requires a minimum transfer value of INR 2 lakh (approximately \$3,000) with no upper limit. RTGS payments are final and are not revocable by the paying bank. An RTGS system reduces settlement risk, as payments are settled individually and irrevocably on a gross basis in real time.¹

The database on the payment system from the RBI shows that electronic transactions in the total volume of retail payments increased to 95.4% in 2018–2019 from 92.6% in the previous financial year. In 2018–2019, RTGS transactions constituted less than 0.40% of the total volume of payments but were close to 46% of the transactions in terms of value. While the volume of RTGS increased by close to 10% in 2018–2019 from 2017–2018, the value increased by close to 17% during the same period.

The RBI plans the ratio of digital payment transaction turnover to nominal GDP to increase from 10.37 in 2019 to 12.29 in 2020 and consequently to 14.80 in 2021. To facilitate this process, on 6 June 2019 the RBI decided to withdraw the charges levied upon the transaction processes using RTGS and NEFT systems. The RBI also directed the banks to pass these benefits to their customers. Some commercial banks have already implemented this policy.

Using data on the indicators of the payment system as well as data on economic growth, we observe that the value and volume of RTGS are steadily growing in India. A visual analysis (see Figure 1) shows a close linkage between the value of RTGS (RTGS) and economic growth, measured by the index of industrial production in India. A similar trend is observed between the volume of RTGS (RTGSV) and economic growth (see Figure 2).

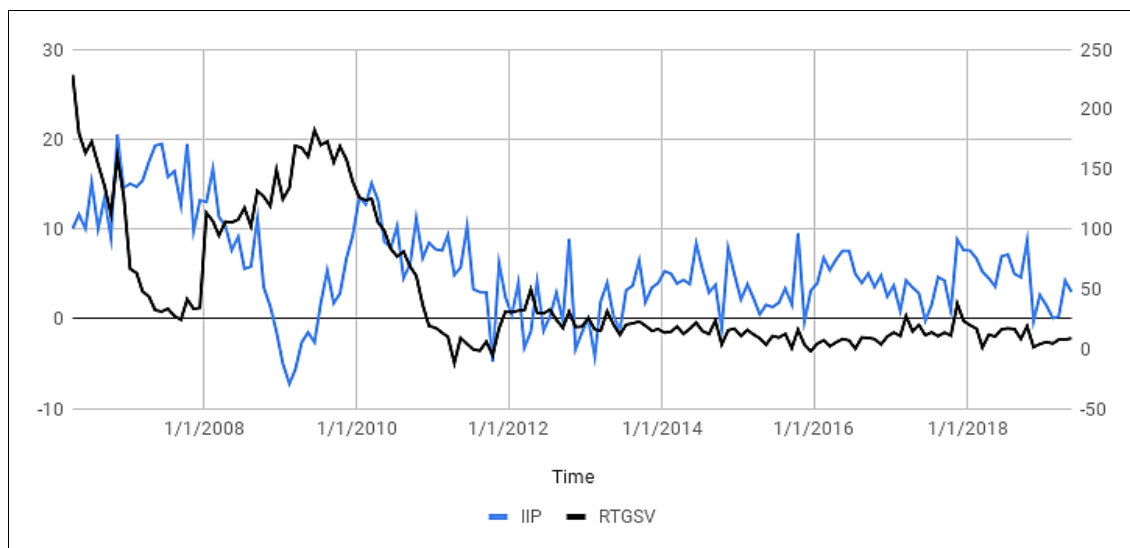
Figure 1: The Dynamics of the Value of RTGS, and the Index of Industrial Production



Note: RTGS represents the growth rate of the value of RTGS (right-hand vertical axis); IIP represents the growth rate of the index of industrial production (left-hand vertical axis). The observations are percentage changes, year on year (monthly). The sample period is from 2005 M4 to 2019 M5.

¹ More details on the Indian RTGS can be found at <https://m.rbi.org.in/Scripts/FAQView.aspx?Id=65>.

Figure 2: The Dynamics of the Volume of RTGS, and the Index of Industrial Production



Note: RTGSV represents the growth rate of the volume of RTGS; IIP represents the growth rate of the index of industrial production. The observations are percentage changes, year on year (monthly). The sample period is from 2005 M4 to 2019 M5.

Motivated by these observations, in our study, we attempt to understand the dynamic relationship between the usage of financial technology and economic activity in India. We use real-time gross settlements as a proxy for the payment system (RTGS) and the index of industrial production (IIP) as a measure of economic activity.

We use a Bayesian VAR methodology that simultaneously addresses the problem of model misspecification and the “curse of dimensionality.” We corroborate our findings through several sensitivity analyses. In this paper, we provide a detailed understanding of the empirical linkage between the development of a digital payment system and economic growth, thereby providing a strong basis for policy recommendations to promote the digital economy.

The rest of the paper is organized as follows. Section 2 briefly discusses the relevant literature. The data sets used for the study are discussed in Section 3. In Section 4, we describe the empirical methodology, and in Section 5, the empirical results are presented. Finally, in Section 6, we conclude.

2. RELATED LITERATURE

Information technology plays a vital role in driving economic activity. Jorgenson and Stiroh (1999) suggest that information technology could be a substitute for capital and labor inputs, given its significantly high contribution to the growth of total output in the United States (US). They show that although computers contributed virtually nothing to the US economic growth before 1973, from 1990 to 1996, computers contributed close to 16% of that nation’s output growth. Dedrick, Gurbaxani, and Kraemer (2003) and Jorgenson and Vu (2007) provide further evidence of the role of information technology on economic growth.

The role of information technology in the financial and banking sector is also widely accepted (Berentsen 1998; Nsouli and Fullenkamp 2014; Goodhart 2000). However, the quantitative literature on the dynamics of the payment system and the economy is limited.

Yilmazkuday (2011) examines the linkage between the usage of credit cards and monetary policy in Turkey. Using VAR, he finds that credit card usage has an increasing effect on inflation rates over time. He suggests that there is an increasing need to consider the credit channel of monetary policy transmission through credit cards.

Geanakoplos and Dubey (2010) argue that the introduction and widespread use of credit cards not only increases trading efficiency but also increases the velocity of money, which in turn causes inflation in the absence of monetary intervention. They also point out that price rises might worsen when there is any default on the part of the credit card holders. Tule and Oduh (2017) demonstrate that the increase in financial innovation has gradually dampened the effectiveness of the money multiplier. Milbourne (1986) argues that financial innovation complicates the task of monetary policy by shifting the monetary aggregates, making it difficult to understand the behavior of interest rates and using the asset demand function as the basis for the conduct of monetary policy.

Bech and Hobijn (2007) examine the diffusion of real-time gross settlement (RTGS) technology across the world's 174 central banks. They find that the probability of adoption of RTGS in a given year increases significantly with the per capita GDP of an economy. Moreover, they also show that countries with a lower relative price of capital and countries whose major trading partners have already adopted RTGS are also more likely to adopt RTGS. These determinants are similar to those that seem to drive the cross-country adoption patterns of other technologies.

Lee and Yip (2008) argue that RTGS turnover is a good indicator of the overall performance of the economy. According to these authors, faster economic growth is usually associated with higher turnover in the RTGS system.

However, to the best of our knowledge, no study so far has focused on empirically analyzing the impact of such payment systems on the economic growth in India. Given the increasing adoption of modern technology in the financial sector across the globe, it is essential to empirically analyze the role of RTGS in enhancing economic growth and also to ascertain the effect of economic growth on the use of such payment methods. The choice of RTGS is motivated by the fact that RTGS is widely used in almost all parts of the world (Bech, Shimizu, and Wong 2017). In the case of India, this is the prime form of electronic transaction.

To the best of our knowledge, this is the first study to examine the dynamic linkages between RTGS and economic growth using a multivariate framework and the Bayesian VAR methodology that simultaneously addresses the problem of model misspecification and the "curse of dimensionality." We corroborate our findings using several sensitivity analyses.

The findings from our empirical analysis show a positive and significant relationship between RTGS and economic growth in India. We demonstrate the existence of bidirectional causality between RTGS and IIP, where one affects the other. We also find that RTGS increases the general price level in the economy. Our variance decomposition analysis also shows that both RTGS and IIP explain a considerable variation in each other's fluctuations. However, we do not find any direct evidence on the effect of monetary policy on RTGS in India. Our study provides evidence-based

policy implications highlighting the importance of digitalization in facilitating economic growth in India.

3. DATA AND VARIABLE SELECTION

The objective of this paper is to examine the dynamic relationship between RTGS and economic growth. Thus, the choice of variables in our analysis translates into considering variables capturing financial transactions, economic activity, monetary policy, and a price index.

The variable representing financial transactions is real-time gross settlement (RTGS). The data on RTGS are available for both the value and the volume (number of transactions) of the transactions. We use the value of transactions in our baseline model and the volume while conducting the sensitivity analyses.

For economic activities, we use the data on the Index of Industrial Production (IIP) as a proxy for economic growth. Monthly observations are used to capture the high-frequency dynamics between RTGS and economic growth in our model. The IIP series is available from the Central Statistical Organization, Government of India. The monetary policy is represented by the yield on the 91-day T-Bill (INT). We include the CPI as a measure of price in our analysis. Finally, we use M1 as a measure of the money supply (MS) in our analysis. All the variables mentioned above are available from the Reserve Bank of India (RBI) website.

We use a sample period of 170 months from 2005-M4 to 2019-M5. All the relevant variables are seasonally adjusted using the X-13ARIMA-SEATS seasonal adjustment program by the United States Census Bureau.²

4. EMPIRICAL METHODOLOGY

4.1 BVAR

Empirical macroeconomics literature often employs a VAR model to examine the linear causal relationship between the time series variables and also to forecast their evolution (Sims 1972 1980). The model is a simple dynamic simultaneous equations system where it simultaneously estimates the equations with endogenous variables.

In this study, the dynamic link between the payment system and economic growth is simultaneously determined after controlling for several endogenous variables; therefore, we use a VAR model in our analysis. The VAR model allows us to examine the dynamic link between payment system (RTGS) and economic growth (IIP) alongside capturing the feedback mechanism that exists among the other controls, CPI, INT, and MS.

Consider the following VAR(p) model:

$$Y_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + CX_t + \epsilon_t \text{ where } t = 1, 2, \dots, T \quad (1)$$

where $Y_t = (y_{1,t}, y_{2,t}, \dots, y_{n,t})'$ is an n-dimensional vector of endogenous variables; X_t represents a vector of m exogenous regressors, including a constant; A_p are $n \times n$ matrices of coefficients; C are $n \times m$ coefficient matrices of the exogenous regressors;

² Hamilton (1994) argues that the Minnesota prior is not very suitable for seasonal data.

and ϵ_t is an n -dimensional Gaussian white noise with covariance matrix, X , $E(\epsilon_t \epsilon_t') = \Omega$. T is the size of the sample used for the regression. For n and p of modest size, the number of estimated coefficients becomes quite large leading to the problem of the “curse of dimensionality.”³ Bayesian VAR models can resolve this problem by shrinking these coefficients toward some prior belief.

The primary advantage of using Bayesian analysis is its ability to use prior information and combine it with the likelihood function as derived from the sample using Bayes' theorem. This combination helps in obtaining the posterior distribution for any parameter and deals with the over-parameterization problem (the “curse of dimensionality”) by imposing prior beliefs on the parameters. However, posterior results must be confronted with prior beliefs, and hence prior distributions must be chosen carefully to avoid any misspecifications, which may affect the posterior results. Therefore, we follow Litterman (1986) in defining the BVAR prior specifications with some modifications as proposed by Kadiyala and Karlsson (1997) and Sims and Zha (1998) to improve the model outcomes.

Following Koop and Korobilis (2010) and Dieppe and Legrand (2016), equation (1) can be rewritten as

$$Y = XB + \varepsilon \quad (2)$$

where

$$Y = \begin{bmatrix} y'_1 \\ y'_2 \\ \dots \\ y'_T \end{bmatrix}, X = \begin{bmatrix} y'_0 & y'_{-1} & \dots & y'_{(1-p)} & x'_1 \\ y'_1 & y'_0 & \dots & y'_{(2-p)} & x'_2 \\ \vdots & \vdots & \dots & \vdots & \vdots \\ y'_{(T-1)} & y'_{(T-2)} & \dots & y'_{(T-p)} & x'_T \end{bmatrix}, B = \begin{bmatrix} A'_1 \\ A'_2 \\ \dots \\ A'_p \\ C \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon'_1 \\ \varepsilon'_2 \\ \dots \\ \varepsilon'_T \end{bmatrix} \quad (3)$$

with $y = \text{vec}(Y)$, $\bar{X} = I_n \otimes X$, $\beta = \text{vec}(B)$, and $\varepsilon = \text{vec}(\varepsilon)$

$$e: N(0, \bar{S}), \bar{S} = S \ddot{A} I_T \quad (4)$$

The likelihood function $f(y|b, \bar{S})$ can then be written as

$$f(y|b, \bar{S}) \propto \exp\left[-\frac{1}{2} (y - \bar{X}b)' \bar{S}^{-1} (y - \bar{X}b)\right] \quad (5)$$

Now, for the prior distribution of β , it is assumed that β follows a multivariate normal distribution with mean β_0 and covariance matrix Ω_0 : with $p(b): N(b_0, V_0)$.

We follow Litterman (1986) to identify β_0 and Ω_0 . In a VAR setup, the explanatory variable in any equation can take several lag structures, such as the dependent variable's own lag(s) and the lags of the other dependent variables and the exogenous or the deterministic variables, including the constant.

³ The structure of the VAR implies that there are $k = np + m$ coefficients to estimate for each equation, leaving a total of $q = nk = n(np + m)$ coefficients to estimate for the full VAR model.

In the Minnesota prior, most or all of the coefficients of the parameters are set to zero, thereby ensuring shrinkage of the VAR coefficients toward zero and lessening the risk of overfitting. As most observed macroeconomic variables seem to be characterized by a unit root, our prior belief is that each endogenous variable as included in the model presents a unit root in its first own lag and coefficients equal to zero for further lags and cross-variable lags. Moreover, in the absence of any prior belief about exogenous variables, the most reasonable strategy is to assume that they are neutral with respect to the endogenous variables, and hence their coefficients are equal to zero. All these elements thus translate into β_0 being a vector of zeros, except for the entries concerning the first own lag of each endogenous variable, which are given a value of 1 each.

For the variance-covariance matrix, Ω_0 , it is assumed that no covariance exists among the elements in β , which implies that Ω_0 is diagonal.

Moreover, Litterman (1986) argues that the further the lag, the more confident one should be that coefficients linked to this lag have a value of zero. Therefore, the variance of the coefficients linked to a lag should be smaller than the initial lags the further it is from the initial lags. Also, the confidence is expected to be greater for the coefficients that relate variables to their past values. Finally, as little is known about the exogenous variables in the model, we assume that their variance is large. Thus, according to Litterman (1986), Minnesota priors are imposed by setting the following moments for the prior distribution of the coefficients:

For parameters in β that relate the endogenous variables to their own lags, the variance is given by

$$\sigma_{a_{ii}}^2 = \left(\frac{\lambda_1}{l^{\lambda_3}} \right)^2 \quad (6)$$

where λ_1 is an overall tightness parameter, l is the lag considered by the coefficient, and λ_3 is a scaling coefficient controlling the speed at which coefficients for lags greater than 1 converge to 0 with greater certainty.

For parameters related to cross-variable lag coefficients, the variance is given by:

$$\sigma_{a_{ij}}^2 = \left(\frac{\sigma_i^2}{\sigma_j^2} \right) \left(\frac{\lambda_1 \lambda_2}{l^{\lambda_3}} \right)^2 \quad (7)$$

where σ_i^2 and σ_j^2 denote the OLS residual variance of the autoregressive models estimated for variables i and j , and λ_2 represents a cross-variable specific variance parameter.

For exogenous variables, including constant terms, the variance is given by:

$$\sigma_{c_i}^2 = \sigma_i^2 (\lambda_1 \lambda_4)^2 \quad (8)$$

where σ_i^2 is again the OLS residual variance of an autoregressive model previously estimated for variable i , and λ_4 is a large (potentially infinite) variance parameter. Several combinations are possible for λ_1 , λ_2 , λ_3 , and λ_4 . Following the standard literature practice, for example in Sims and Zha (1998) and Giannone et al. (2014), we choose $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 1$, and $\lambda_4 = 100$.

4.2 Identification of the Structural Shocks in the BVAR Model

Following Bańbura, Giannone, and Lenza (2015), we identify several shocks using a simple recursive ordering, commonly known as the Cholesky decomposition of the error covariance matrix. In other words, as indicated by Forni and Gambetti (2016) and Erten (2013), this implies that the independent standard normal shocks can be identified based on the estimated reduced-form shocks, and also the ordering of the variables in equation 1. Thus the initial ordering is as follows: IIP, CPI, INT, MS, RTGS. The initial ordering of the variables in the model determines the sequence of the structural shocks and their effect on the other endogenous variables. We place the variables in order of output, prices, and monetary policy instruments. This ordering assumes that the RBI sees current output and prices when it sets the policy instrument, but that output and prices only respond to a policy shock with one lag. RTGS is ordered last, implying that the financial sector variable responds to a policy shock with no lag. This ordering mostly follows the monetary policy literature (Christiano, Eichenbaum, and Evans 1996, 2005; Thorbecke 1997), which places the VAR variables in order of macroeconomic variables, monetary policy variables, and financial variables. In our sensitivity analysis, we place RTGS before other variables and examine the implications of such identification for the other variables of our model.

All the variables in our model enter in log levels. Sims, Stock, and Watson (1990) argue that as the Bayesian approach is entirely based on the likelihood function, the associated inference does not need to take special account of nonstationarity. The likelihood function has the same Gaussian shape regardless of the presence of nonstationarity.

Moreover, estimation of a VAR model in levels will produce consistent estimates of VAR impulse responses and is robust to cointegration of an unknown order (Barsky and Sims 2011). Hamilton (1994) also indicates that when there is uncertainty regarding the nature of the common trends in the data, estimating a VAR in levels is a “conservative” approach. Brooks (2014) also favors using VAR in levels, when the objective is to purely examine the dynamic relationship among the variables and not to merely estimate the parameters of a model as opposed to differencing where we may lose important information as embedded in a series. Given this, all the variables (except for interest rate, which is levels) have been specified in log levels (Fujiwara 2006).

In macroeconomics literature, a common practice is to use a log transformation of the variables. According to Ehrlich (1977) and Layson (1983), a log transformation helps in providing better empirical results than a linear specification. Moreover, the coefficient estimates can be interpreted in terms of elasticities (i.e. a percentage change in one variable due to a percentage change in the other variable).

We include one lag of each endogenous variable and a constant term. This choice of lag structure is selected by deviance information criteria (DIC) that measure the goodness of fit and complexity of fitted Bayesian models to optimize the behavior of the residual error terms (Spiegelhalter, Best, and Carlin 2002; Saldías 2017).⁴ The stability of the VAR model is important as the impact of the shocks is calculable and finite only when VAR is stable. The stability condition requires all the eigenvalues to be less than unity, i.e., no root lies outside the unit circle (Patterson 2000). Our estimated VAR

⁴ The DIC value for our baseline model is $-2,919.39$. We provide an alternate model using classical AIC lag selection criteria in our robustness analysis.

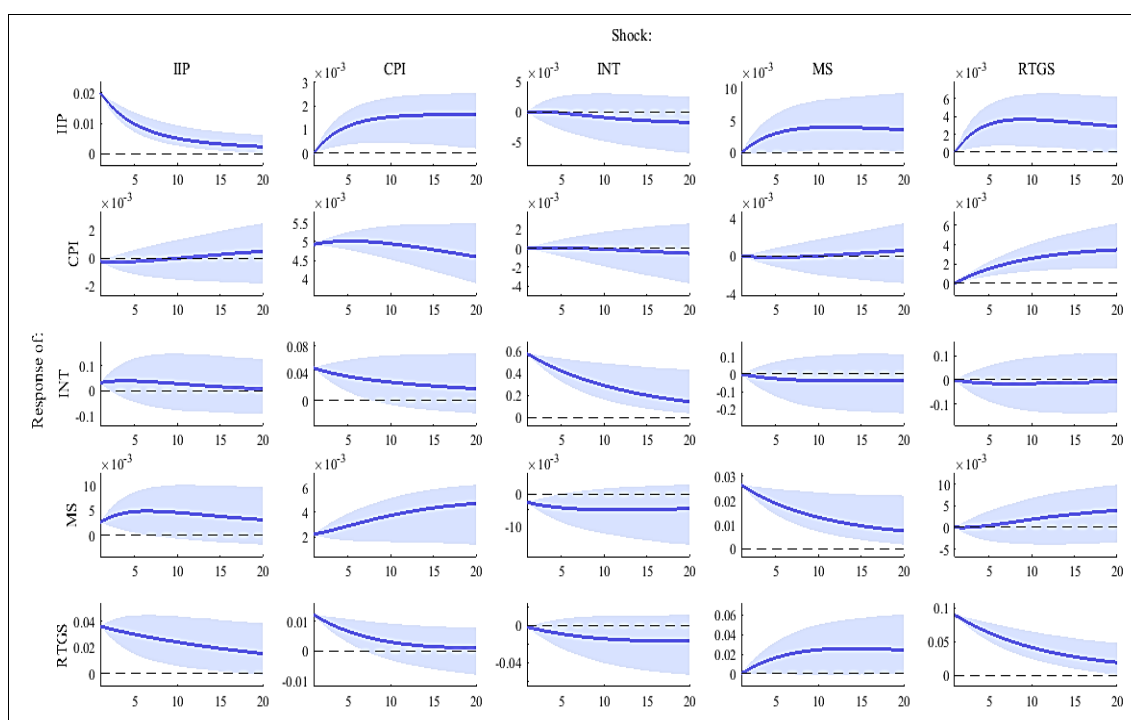
model satisfies the stability condition. We present the impulse responses based on 15,000 MCMC draws after discarding the first 10,000 draws as burn-in.⁵

5. RESULTS

5.1 Impulse Response Analysis

In this section, we present the impulse responses from our baseline BVAR, as presented in Section 4.2 of the paper. We present the impulse responses to all the shocks in Figure 3. The continuous solid line depicts the median posterior response, and the shaded area represents a 68% confidence interval. We follow Sims and Zha (1999) for the 68% interval band.⁶ The horizontal axis shows the time period or the horizon after the initial shock, while the vertical lines in impulse responses show the magnitude of the response to the shocks.

Figure 3: Impulse Responses – Baseline BVAR



Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply, RTGS is the value of real-time gross settlement. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

⁵ BVAR estimation is carried out by using the BEAR toolbox (Dieppe and Legrand 2016).

⁶ Sims and Zha (1999) argue that the conventional frequentist error bands can be misleading because they mix information about parameter location with information about model fit. They propose likelihood-based bands and suggest using 68% interval bands to provide a more precise estimate of the true coverage probability.

We present the impulse responses for a one-standard-deviation shock on IIP in the first column of Figure 3. A one-standard-deviation IIP shock leads to a close to 2% increase in IIP. This shock is persistent and remains significant almost for the entire horizon of nearly 20 months. The impact of IIP on RTGS is also positive and significant. The effect is maximum immediately on impact and declines slowly over the time horizon. On impact, the value of RTGS increases by close to 4%. This is a significant impact of economic growth on the high-value transfer of money using RTGS. We also find that IIP also increases MS, but the effect becomes insignificant after six months. Interestingly, we find no significant impact of IIP on CPI.

Next, we examine the impact of RTGS on the other variables of our model. In the fifth column of Figure 3, we show the impulse responses for a one-standard-deviation shock on RTGS. A one-standard-deviation shock on RTGS increases RTGS by close to 10%. The impact of RTG on IIP is positive and significant. This impact reaches its peak at around the seventh month with an increase in IIP of 0.4% at the peak. The effect remains significant for the entire horizon. We also find that an increase in RTGS also increases CPI; the effect is persistent and remains significant for the entire horizon.

The inflationary impact of RTGS on CPI is akin to the inflationary impact of credit cards in Turkey (Yilmazkuday 2011). In our analysis, we control for the money supply. Hence, the finding indicates that an increase in RTGS not only increases the value of output but also impacts prices through an increase in the velocity of money.

Thus our multivariate BVAR analysis to examine the dynamic link between RTGS and economic growth suggests the existence of bidirectional causality between IIP and RTGS.

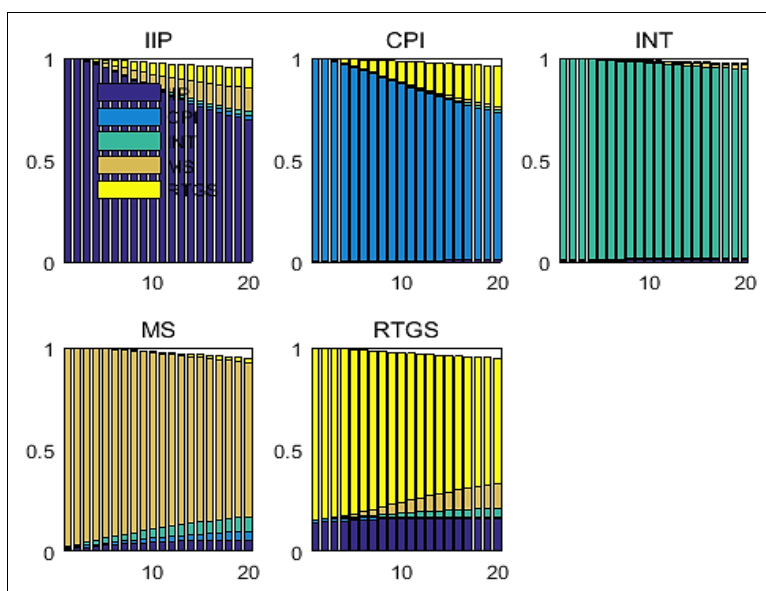
5.2 Forecast Error Variance Decomposition

In this section, we discuss the contribution of IIP and RTG shocks, respectively, in explaining each other's variations. We use forecast error variance decomposition (FEVD) to show the significance of each of the identified shocks in fluctuations of the variables. The FEVDs presented in Figure 4 show that RTGS contributes close to 10% of the fluctuations in IIP in the long run. Similarly, IIP is responsible for explaining almost 16% of the fluctuations in RTGS. Combined with the impulse responses, FEVDs also support the close link between RTGS and IIP in India. These findings suggest that high-value online transactions and economic growth are closely interlinked. RTGS also contributes to approximately 20% of the variations in the CPI.

5.3 Historical Decomposition

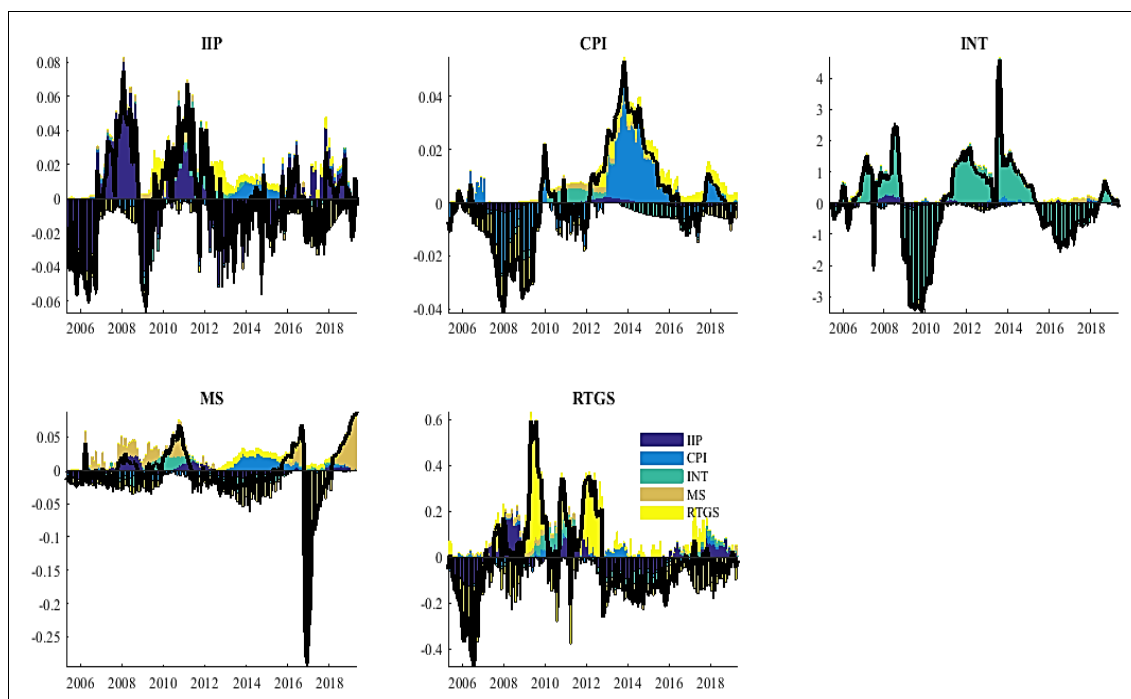
The historical decompositions are presented in Figure 5. Similarly to impulse response and FEVD, they also emphasize the impact of RTGS on IIP and CPI. The roles have clearly been stronger during the post-2012 period with the growth of the RTGS activity. The impacts have been less in the recent past given that other forms of digital payments are also growing.

Figure 4: Forecast Error Variance Decomposition – Baseline BVAR



Note: The FEVD is based on median target IRFs as suggested by Fry and Pagan (2011). The shocks are represented as follows: IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply, RTGS is the value of real-time gross settlement. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS.

Figure 5: Historical Decomposition – Baseline BVAR



Note: Shock contributions are expressed in the deviation from the unconditional model forecast. The shocks are represented as follows: IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply, RTGS is the value of real-time gross settlement. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS.

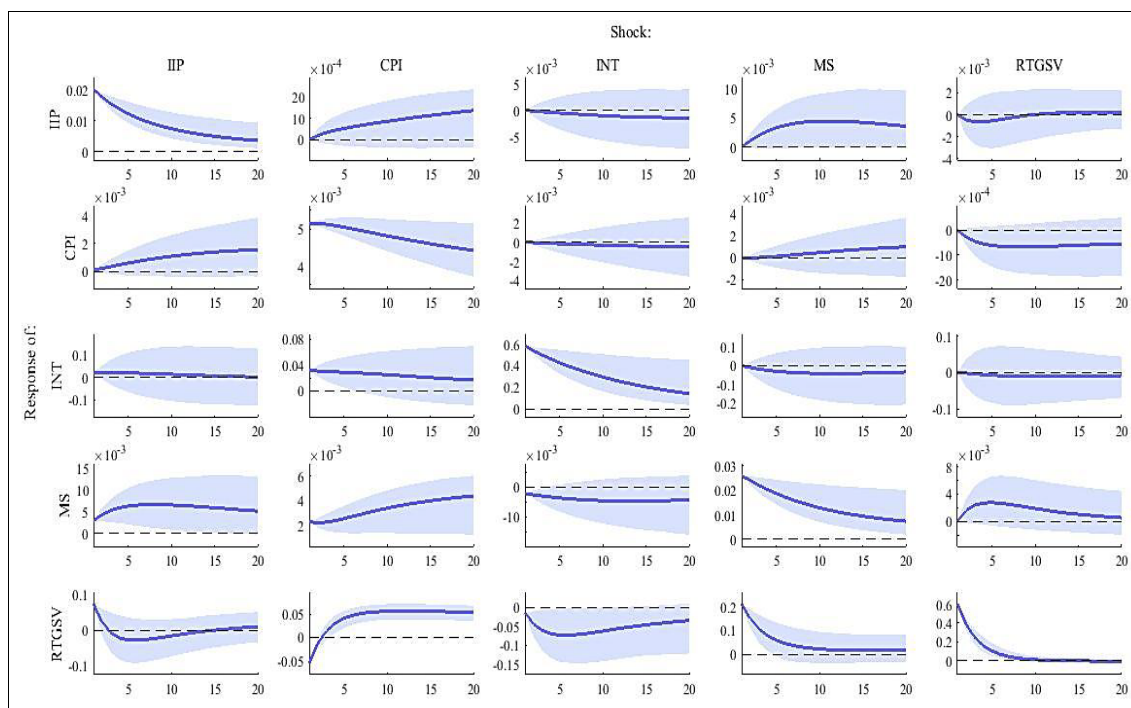
5.4 Sensitivity Analysis

In this section, we examine the sensitivity of our empirical results to several changes in the basic setup of our model. We primarily examine the robustness of our model by (i) using the volume of RTGS as a measure of the usage of a digital payment system, (ii) ordering RTGS before the other variables for identification of the shocks, (iii) using the Akaike information criterion (AIC) as an alternative lag selection criterion, (iv) including an exogenous variable capturing the change in monetary policy stance in India (inflation-targeting regime), (v) using an alternative measure of the digital payment system, and finally (vi) using interpolated real GDP as a measure of economic activity. In each case, the model is identified through the Cholesky ordering as discussed for our baseline model. We evaluate these changes by comparing the impulse responses with our baseline model.

5.4.1 Using Volume of RTGS as a Measure of Usage of Payment System

In this specification, we use the volume of RTGS (RTGSV) as a measure of the payment system in our analysis. RTGSV represents the number of monthly RTGS transactions. The ordering of the variables is the same as in the baseline model, with RTGSV coming after IIP, CPI, INT, and RMS. The impulse responses are presented in Figure 6. We find that the impact of the impulse responses is not as strong as the value of such transactions, indicating that the value of RTGS is a better measure of the payment system than the volume to capture the dynamic linkage between RTGS and economic activity.

Figure 6: Impulse Responses – BVAR with RTGS Volume

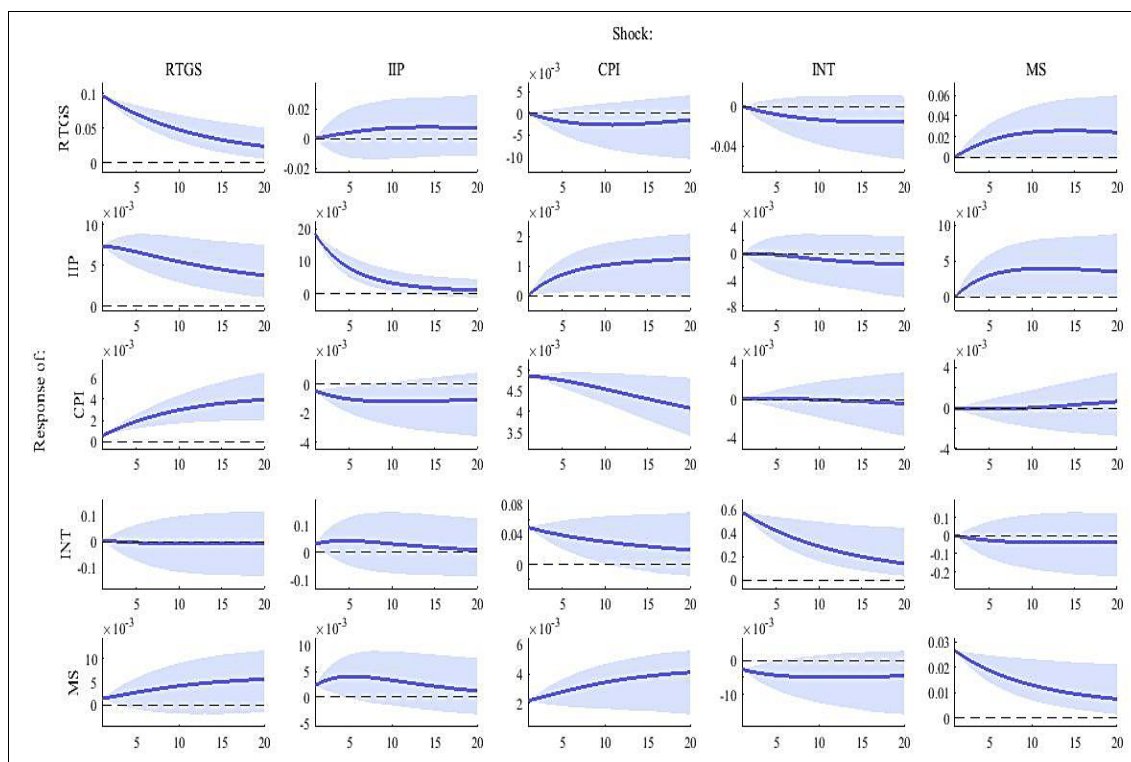


Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply, RTGSV is the volume of real-time gross settlement. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

5.4.2 Ordering RTGS before the Other Variables in Our Model

In our baseline BVAR, we identified the shocks by placing RTGS last. However, it can be argued that online payment impacts the other variables in our model (IIP, CPI, INT, and MS) contemporaneously, but itself is impacted by the other variables with a lag. Thus we provide an alternate ordering where RTGS is placed before the output, price, and monetary variables. Figure 7 represents the impulse responses with such identification. The impulse responses indicate that the impact of RTGS on IIP and CPI is similar to our baseline model, but the impact of IIP on RTGS is not significant with such identification of RTGS shock.

Figure 7: Impulse Responses – BVAR with the Alternate Ordering of RTGS

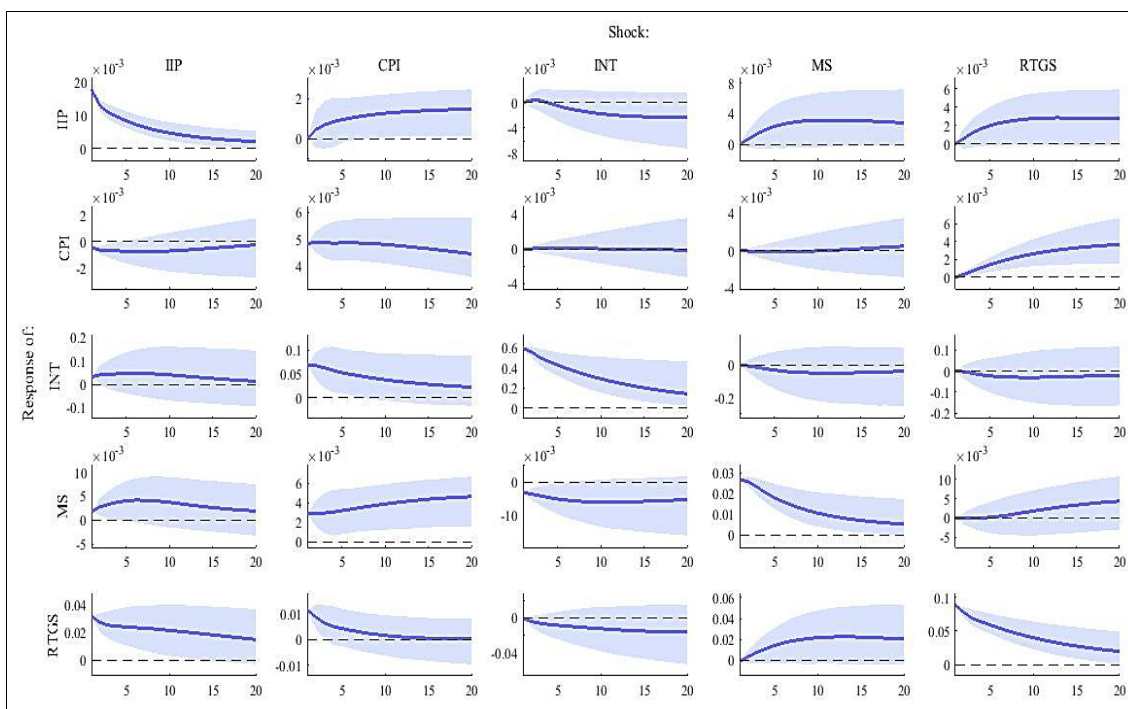


Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: RTGS is the value of real-time gross settlement, IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

5.4.3 Identification with Alternative Lag Selection Criteria

There are alternative procedures to select the number of lags for the endogenous variables in a VAR model (Bańbura, Giannone, and Lenza 2015). In our baseline model, we chose the lag length of 1 based on DIC. However, the use of other lag selection criteria based on AIC, Hannan-Quinn Information Criteria (HQIC), Bayesian Information Criteria (BIC), and similar methods is not uncommon (Chatziantoniou et al. 2013). Given our data, AIC suggests a lag length of 4. Thus we re-estimate our model with four lags. Once again, the qualitative impulse responses remain unchanged between RTGS and IIP (see Figure 8).

Figure 8: Impulse Responses – BVAR with a Lag Length of Four (AIC)



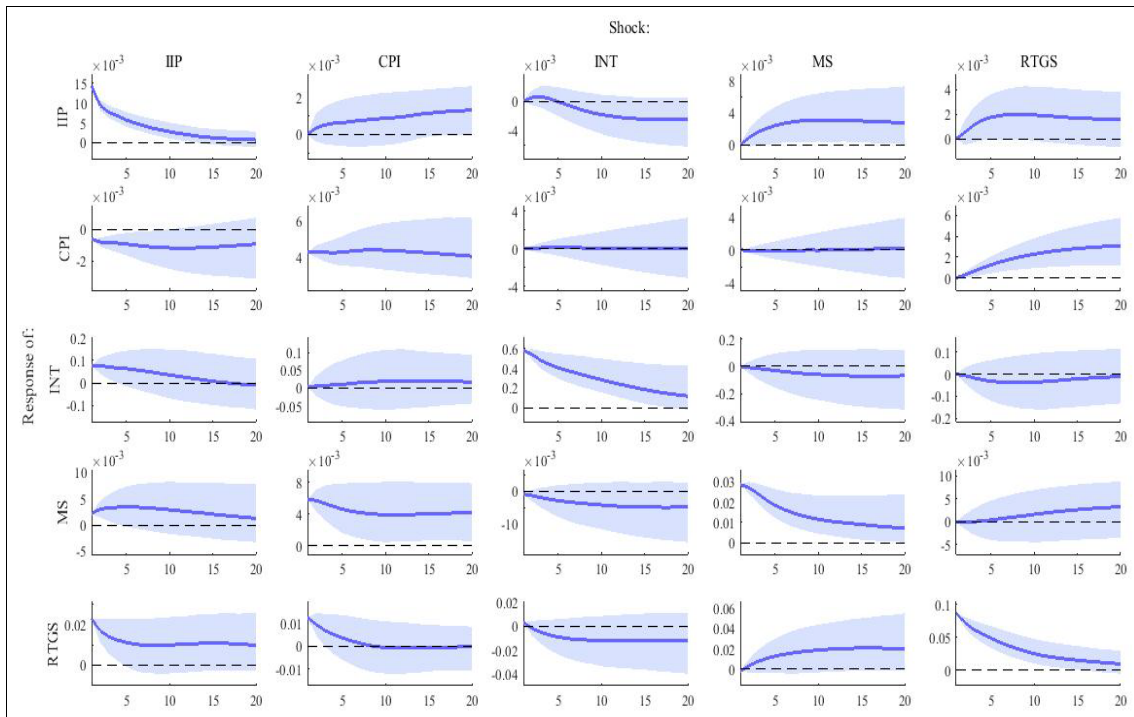
Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: RTGS is the value of real-time gross settlement, IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

Further, a few empirical studies (Ivanov and Kilian 2005; Carriero, Clark, and Marcelliano 2015) using monthly observations employ longer lag lengths to capture the long-run dynamics of the variables. Generally, the lag length is set to $p = 13$, which for any monthly data represents a year’s worth of lags +1. Figure 9 presents the impulse responses using a lag length of 13. We find that the impact of RTGS on IIP is similar to those in the baseline model.

5.4.4 Identification with an Exogenous Variable that Captures the Inflation-targeting Regime Change

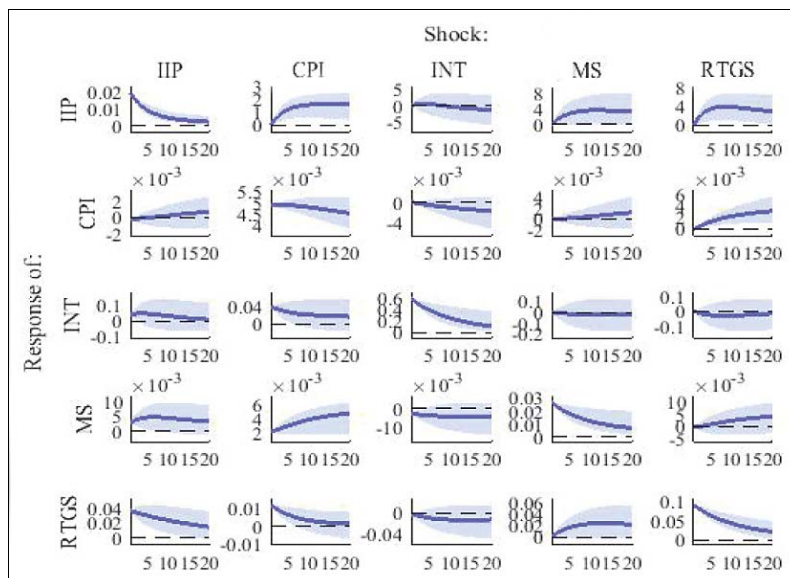
Following an agreement between the Government of India (GOI) and the Reserve Bank of India (RBI), a Monetary Policy Committee (MPC) was constituted in February 2015 with the mandate to target CPI inflation from 5 August 2016 to 31 March 2021. The objective was to keep the rate of inflation of 4%, with a band of two percentage points on either side. To capture this structural change, we use a dummy variable indicating the shift in policy change and use it as an exogenous variable in our model. In this specification, our baseline VAR includes an exogenous dummy (0 and 1) after July 2016 to account for the changes in the monetary policy stance. The impulse responses presented in Figure 10 reveal that the introduction of this exogenous variable does not affect the primary findings of our analysis.

Figure 9: Impulse Responses – BVAR with a Lag Length of 13



Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: RTGS is the value of real-time gross settlement, IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

Figure 10: Impulse Responses – BVAR with Exogenous Variable

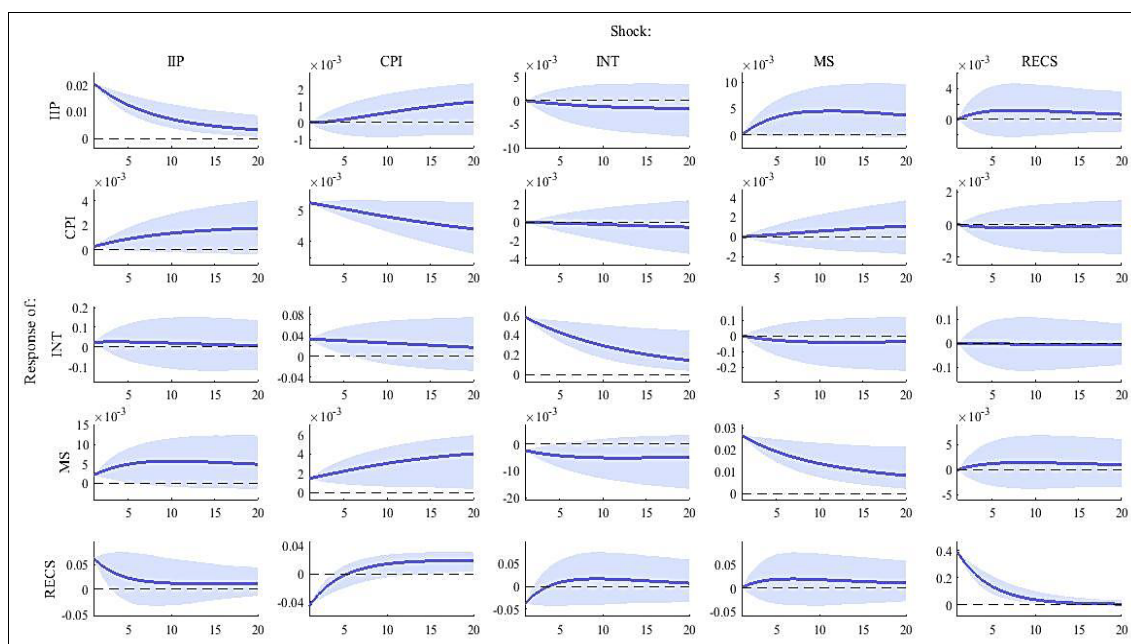


Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: RTGS is the value of real-time gross settlement, IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

5.4.5 Use of Alternate Measure of Payment System

Next, we use the other most frequently used digital mode of the payment system in our analysis. This variable captures the retail electronic clearing service (RECS), which includes Electronic Clearing Service (both credit and debit), National Electronic Funds Transfer (NEFT), Immediate Payment Services (IMPS), and National Automated Clearing House (NACH) to compare with our baseline model and we use the value of RECS in this specification. In 2018–2019, RECS constituted about 36% in volume and about 9% in the value in the transactions for all kinds of payment system indicators. Figure 11 plots the impulse responses with RECS as the measure of the payment system. We find that the impact of RECS on IIP and other variables is weaker and insignificant, indicating that the value of such a mechanism is yet to develop in India and it has not been able to create any significant impact on the other macroeconomic indicators.

Figure 11: Impulse Responses – BVAR with RECS

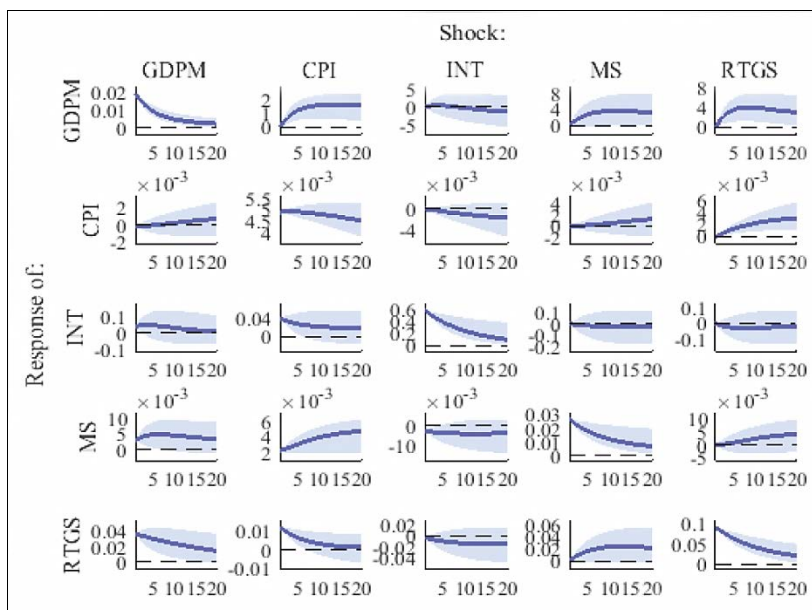


Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: IIP is an index of industrial production, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply, RECS is the value of transactions using retail electronic clearing system. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

5.4.6 Using Interpolated Real GDP as a Measure of Economic Activity

Finally, we use real monthly GDP (GDPM) as the measure of real economic activity. We use linear interpolation to convert the quarterly real GDP into monthly observations using the interpolation method based on the Chow-Lin procedure (Silva and Cardoso 2001). The other parameters remain the same as our baseline BVAR, including the lag length of 1. Figure 12 plots the impulse responses with GDP as the measure of economic activity. We find the impulse responses mimic responses similar to IIP.

Figure 12: Impulse Responses – BVAR with GDP as a Measure of Economic Activity



Note: Each column represents a shock; rows show the impulse responses due to shocks in the rows. The shocks are represented as follows: RTGS is the value of real-time gross settlement, GDPM is the interpolated monthly real GDP, CPI is consumer price index, INT is short-term interest rate, MS is nominal money supply. The impulse responses are generated from the five-variable Bayesian VAR with Minnesota prior including, in this order, IIP, CPI, INT, MS, RTGS. The shocks are identified using the Cholesky decomposition. The solid blue line is the median posterior response, and the shaded area represents 68% confidence interval.

Therefore, even after using several different specifications in our robustness analysis, we find no major shift from our initial finding of bidirectional causality between RTGS and economic growth in India. Hence, we conclude that our baseline model is robust to any changes in the specifications.

6. CONCLUSION

The world is experiencing an expanding use of digital technology. The banking sector is no different. The digital payment system is increasingly being adopted by the central banks to improve the efficiency of the financial sector, which facilitates economic growth. However, quantitative literature examining the role of the electronic payment system in driving economic growth is still underexplored. Therefore, in this study, we use a multivariate Bayesian vector autoregressive (BVAR) model to capture the relationship between the online payment system and economic growth and add several important endogenous variables, which may affect both the payment system and economic growth. The BVAR model is helpful in this setting as it simultaneously addresses the misspecification problem and the “curse of dimensionality,” which may arise due to the incorporation of multiple endogenous variables in a simultaneous equations setup. Also, this is the first study of its kind to analyze the relationship between a payment system and economic growth using uniquely available data on India in monthly frequencies.

Our results from the BVAR model after controlling for several endogenous variables (such as consumer price index, monetary policy variables, and nominal money supply) suggest that RTGS positively impacts economic growth in India. At the same time, economic growth also leads to an increase in the value and volume of RTGS, indicating the presence of bidirectional causality between RTGS and economic growth in India. The forecast error variance decomposition also suggests a strong association between RTGS and economic growth where a change in one variable (say, RTGS) causes a change in the other (say, economic growth), and vice versa. Several robustness checks using alternative measures of the online payment system, the inclusion of an exogenous variable, and a change in the lag structure not only preserve our primary findings but also provide additional support for the bidirectional causality between RTGS and economic growth, as is evident from our baseline model. We also find that an increase in RTGS leads to an increase in money supply and price level as indicated by the CPI. This finding indicates that when the economy is performing well and incomes are rising, thereby increasing demand in the economy, people tend to indulge in more electronic transactions and thus enhance economic growth.

Electronic payment modes are cost-effective, faster, and convenient. Digitalization of the economy with the increasing use of online payments thus has a potential economic effect. Promotion of online payment systems will accelerate economic growth. However, our findings also indicate that greater usage of digital payment can also lead to higher price levels in the economy. Given that monetary policy has no significant impact on inflation and online payment systems, we need to explore further the channels through which payment systems and monetary policy are linked.

We also find that agents involved in retail transactions still prefer conventional modes of payment rather than a digitalized payment system. Thus we do not find any effect of retail electronic payments on economic growth. With increasing penetration and digitalization of the banking sector, a detailed micro-level analysis could shed more light on the role of digital payment at the retail level, such as the impact of mobile banking or payment banking on a particular sector of the economy, such as agriculture or daily wage earners.

REFERENCES

- Bañbura, M., Giannone, D., and Lenza, M. (2015). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. *International Journal of Forecasting*, 31(3), 739–756. <https://doi.org/10.1016/j.ijforecast.2014.08.013>.
- Barsky, R. B., and Sims, E. R. (2011). News shocks and business cycles. *Journal of Monetary Economics*, 58(3), 273–289. <https://doi.org/10.1016/j.jmoneco.2011.03.001>.
- Bech, M. L., and Hobijn, B. (2007). Technology diffusion within central banking: The case of real-time gross settlement. *International Journal of Central Banking*, (212), 147–182. <https://doi.org/10.2139/ssrn.932596>.
- Bech, M., Shimizu, Y., and Wong, P. (2017). The quest for speed in payments. *BIS Quarterly Review*, (March), 57–68. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2931564.
- Berentsen, A. (1998). Monetary policy implications of digital money. *Kyklos*, 51(1), 89–117. <https://doi.org/10.1111/1467-6435.00039>.
- Brooks, C. (2014). *Introductory Econometrics for Finance* (3rd edition). Cambridge.
- Carriero, A., Clark, T. E., and Marcelliano, M. (2018). Measuring uncertainty and its impact on the economy. *Review of Economics and Statistics*, 100(5), 799–815.
- Chatziantoniou, I., Filis, G., Eeckels, B., and Apostolakis, A. (2013). Oil prices, tourism income and economic growth: A structural VAR approach for European Mediterranean countries. *Tourism Management*, 36, 331–341. <https://doi.org/10.1016/j.tourman.2012.10.012>.
- Christiano, L. J., Eichenbaum, M., and Evans, C. (1996). The effects of monetary policy shocks: Evidence from the flow of funds. *Review of Economics and Statistics*, 78(1), 16–34.
- Christiano, Lawrence J., Eichenbaum, M., and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1), 1–45. <https://doi.org/10.1086/426038>.
- Dedrick, J., Gurbaxani, V., and Kraemer, K. L. (2003). Information technology and economic performance. *ACM Computing Surveys*, 35(1), 1–28. <https://doi.org/10.1145/641865.641866>.
- Dieppe, A., and Legrand, R. (2016). Working Paper Series The BEAR Toolbox, (1934).
- Ehrlich, I. (1977). Capital Punishment and Deterrence: Some Further Thoughts and Additional Evidence. *Journal of Political Economy*, 85(4), 741–788.
- Erten, B. (2013). Macroeconomic transmission of Eurozone shocks to emerging economies. *International Economics*, 131(April), 43–70. [https://doi.org/10.1016/s2110-7017\(13\)60054-2](https://doi.org/10.1016/s2110-7017(13)60054-2).
- Forni, M., and Gambetti, L. (2016). Government spending shocks in open economy VARs. *Journal of International Economics*, 99, 68–84. <https://doi.org/10.1016/j.jinteco.2015.11.010>.
- Fry, R., and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49(4), 938–60.

- Fujiwara, I. (2006). Evaluating monetary policy when nominal interest rates are almost zero. *Journal of the Japanese and International Economies*, 20(3), 434–453. <https://doi.org/10.1016/j.jjie.2006.02.001>.
- Geanakoplos, J., and Dubey, P. (2010). Credit cards and inflation. *Games and Economic Behavior*, 70(2), 325–353. <https://doi.org/10.1016/j.geb.2010.02.004>.
- Giannone, D., Lenza, M., Momferatou, D., and Onorante, L. (2014). Short-term inflation projections: A Bayesian vector autoregressive approach. *International Journal of Forecasting*, 30(3), 635–644. <https://doi.org/10.1016/j.ijforecast.2013.01.012>.
- Goodhart, and E., C. A. (2000). Can central banking survive the IT revolution? *International Finance*, 3(1999), 189–209.
- Hamilton, J. D. (1994). *Time Series Analysis* (Vol. 2). New Jersey: Princeton.
- IMF. (2018). The Bali fintech agenda, 1–3. Retrieved from <https://www.imf.org/en/Publications/Policy-Papers/Issues/2018/10/11/pp101118-bali-fintech-agenda>.
- Ivanov, V., and Kilian, L. (2005). Studies in nonlinear dynamics and econometrics: A practitioner's guide to lag order selection for VAR impulse response analysis. *Studies in Nonlinear Dynamics and Econometrics Volume*, 9(1), 1–36.
- Jorgenson, D. W., and Stiroh, K. J. (1999). Information technology and growth. *American Economic Review*, 89(2), 109–115. <https://doi.org/10.1257/aer.89.2.109>.
- Jorgenson, D. W., and Vu, K. (2007). Information technology and the world economy. *German Economic Review*, 8(2), 125–145. <https://doi.org/10.1111/j.1467-9442.2005.00430.x>.
- Kadiyala, K. R., and Karlsson, S. (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics*, 12(2), 99–132.
- Koop, G., and Korobilis, D. (2010). Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends® in Econometrics*, 3(4), 267–358.
- Layson, S. (1983). Homicide and Deterrence: Another view of the Canadian Time series Evidence. *Canadian Journal of Economics*, 16, 52–73.
- Lee, E., and Yip, S. (2008). Liquidity and risk management in the RTGS system: The Hong Kong experience. *Hong Kong Monetary Authority Quarterly Bulletin*, (March), 1–4.
- Lewis, M. K., and Mizen, P. D. (2000). *Monetary economics*. Oxford: Oxford University Press.
- Litterman, R. B. (1986). Forecasting with Bayesian vector autoregressions: Five years of experience. *Journal of Business and Economic Statistics*, 4(1), 25–38. <https://doi.org/10.1080/07350015.1986.10509491>.
- Milbourne, R. (1986). Financial innovation and the demand for liquid assets: Note. *Journal of Money, Credit and Banking*, 18(4), 506–511.
- Nsouli, S. M., and Fullenkamp, C. (2014). Six puzzles in electronic money and banking. *IMF Working Papers*, 04(19), 1. <https://doi.org/10.5089/9781451843774.001>.
- Patterson, K. D. (2000). Which vintage of data to use when there are multiple vintages of data?: Cointegration, weak exogeneity and common factors. *Economics Letters*, 69(2), 115–121.

- RBI. (2019). Payment and settlement systems in India: Vision-2021 Empowering Exceptional (E)payment Experience. Reserve Bank of India.
- Saldías, M. (2017). The nonlinear interaction between monetary policy and financial stress. *IMF Working Papers, WP/17/184*. <https://doi.org/10.5089/9781484313794.001>.
- Schumpeter, J. (1911). The theory of economic development. Harvard Economic Studies. Vol. XLVI.
- Silva, J. S., and Cardoso, F. N. (2001). The Chow-Lin method using dynamic models. *Economic modelling, 18(2)*, 269-280.
- Sims, C. A. (1972). Money, income, and causality. *The American Economic Review, 62(4)*, 540–552.
- Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48(1)*, 1–48. <https://doi.org/10.2307/2223855>.
- Sims, C. A., Stock, J. H., and Watson, M. W. (1990). Inference in linear time Series Mmodels with some unit roots, *Econometrica: Journal of the Econometric Society, 58(1)*, 113–144.
- Sims, C.A., and Zha, T. (1998). Bayesian Methods for Dynamic Multivariate Models. *International Economic Review, 39(4)*, 949–968.
- . (1999). Error bands for impulse responses. *Econometrica, 67(5)*, 1113–1155. <https://doi.org/10.1111/1468-0262.00071>.
- Spiegelhalter, D. J., Best, N. G., and Carlin, B. P. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series b (statistical methodology), 64, Part 4*, 1–57. Retrieved from papers2://publication/uuid/D36F390C-E803-4A64-A6B2-EF72A6EB7B5F.
- Thorbecke, W. (1997). On stock market returns and monetary policy. *Journal of Finance, 52(2)*, 635–654. <https://doi.org/10.1111/j.1540-6261.1997.tb04816.x>.
- Tule, M. K., and Oduh, M. O. (2017). Financial innovations and the future of monetary policy in Nigeria. *Economics of Innovation and New Technology, 26(5)*, 453–476. <https://doi.org/10.1080/10438599.2016.1229854>.
- Yilmazkuday, H. (2011). Monetary policy and credit cards: Evidence from a small open economy. *Economic Modelling, 28(1–2)*, 201–210. <https://doi.org/10.1016/j.econmod.2010.09.010>.