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**Modelling and Forecasting Currency Demand in India: A Heterodox Approach**
*Janak Raj, Indranil Bhattacharyya, Samir Ranjan Behera, Joice John and Bhimappa Talwar*

**Pass-through of International Food Prices to Emerging Market Economies: A Revisit**
*Satyananda Sahoo, Sujeesh Kumar and Barkha Gupta*

**Trends and Dynamics of Productivity in India: Sectoral Analysis**
*Sarthak Gulati, Utsav Saksena, Avdhesh Shukla, V. Dhanya and Thangzason Sonna*

**Book Reviews**

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# *Modelling and Forecasting Currency Demand in India: A Heterodox Approach*

**Janak Raj, Indranil Bhattacharyya, Samir Ranjan Behera, Joice John and Bhimappa Arjun Talwar***

The paper uses an array of time series and econometric techniques to analyse and forecast currency demand in India. While the weekly forecasting model includes institutional and idiosyncratic factors to generate forecasts of currency in circulation which are crucial for efficient day-to-day liquidity management operations of the Reserve Bank, the monthly model incorporates both macroeconomic factors and technological innovations in the payment system to delineate the impact of digital payments on currency demand. The quarterly and annual models incorporate macroeconomic factors to understand the long-run determinants and short-run dynamics of currency demand. The key findings emerging from the study are: (i) currency in circulation shows weekly and monthly seasonality apart from exhibiting significant variations during festivals and elections; (ii) an increase in the number of digital (card) transactions dampens currency demand in the short-run; and (iii) the long-run income elasticity of currency in circulation is unity.

**JEL Classification:** E41, Q55, F62, C32, C22, C58

**Keywords:** Currency in circulation, technological innovations, macroeconomic factors, time series techniques, ARIMA, ARCH, ARDL model

## Introduction

Central banks, as the monopoly issuers of currency, calibrate the supply of currency in circulation (CiC) in the economy in sync with its demand, which is determined by the overall level of economic activity. CiC constitutes

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one of the key autonomous drivers of banking system liquidity, the others being the size of foreign exchange market operations of the central bank and movements in government cash balances. Therefore, modelling the demand for currency and forecasting its future movements accurately is one of the pre-requisites for the effective conduct of liquidity management operations by central banks (Koziński and Świst, 2015). In turn, the successful conduct of such operations plays a crucial role in aligning the operating target with the policy rate and ensuring smooth monetary transmission across the term structure by stabilising short-term interest rates.

The fundamental determinants of currency demand in the long run vary distinctly from those in the short term; nevertheless, both the short run and long run determinants display distinct similarities across countries/regions (Khatat, 2018). Cross-country evidence suggests that recurring seasonal factors such as day of the week or day of the month effects, salary dates, holidays, festivals and some idiosyncratic factors (elections), among others, exert a strong influence on currency demand in the short run, while overall economic activity represented by real gross domestic product (GDP), inflation, the opportunity cost of holding currency and payment system innovations are the principal drivers in the long run.

For the purpose of liquidity management operations across the time horizon, different models of CiC forecasts are estimated for various time periods spanning the short-run based on daily/weekly data and the longer horizon (monthly, quarterly or annual). For central banks conducting market operations on a weekly basis or even longer durations, the forecast of CiC and other autonomous drivers of liquidity for the corresponding period becomes extremely important. In such situations, CiC forecasts based on high frequency (daily) data are typically used to fine-tune the volume of central banks' regular market operations in anticipation of short-term liquidity shocks.[1]

In the Indian context, currency projections constitute a key element of liquidity management operations of the Reserve Bank. Currency projections

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[1] Central banks' liquidity forecasts improve significantly when modelled using daily CiC movements (Khatat, 2018).

are made, based on some initial conditions, to simulate the *ex ante* liquidity scenario consistent with the monetary policy stance (RBI, 2002). Currency forecasts are generated at weekly, fortnightly and monthly intervals for short- to medium-term liquidity management operations.

While there have been many studies estimating currency demand in the Indian context, this study is perhaps the most comprehensive as it analyses demand for currency for different time periods and frequencies using different techniques. It follows a heterodox approach by developing a menu of models for (a) forecasting CiC movements in India at a weekly interval and (b) analysing the determinants of CiC at monthly, quarterly and annual frequencies. For instance, the weekly model drawn from the empirical literature on time series techniques is *atheoretical* and is principally used to generate forecasts of CiC with the objective of minimising out-of-sample forecast errors. In contrast, the key determinants of currency demand are analysed through monthly, quarterly and annual models based on the theoretical foundations of transaction and precautionary demand for currency. To be precise, while the monthly model is used to understand the impact of digital transactions on CiC, the quarterly and annual models focus on estimating currency demand based on the underlying motives for holding currency.

The remaining part of the paper is structured in five sections. Section II presents a synoptic view of the theoretical underpinnings, empirical literature and cross-country experiences relating to the analysis and forecasting of the demand for cash. Section III briefly discusses currency movements in India from 1970 onwards. Section IV explains the research methodology followed. Section V sets out the findings and draws key inferences. Section VI concludes the paper by summing up the key findings and spelling out some policy implications.

## Section II
## Review of the Literature

The theoretical underpinnings of the demand for currency are based on three distinct strands in the existing literature. The first relates to the inventory-theoretic models in which the optimal amount of currency holding is derived from a cost minimisation exercise – the cost of holding currency

(Baumol, 1952; Karni, 1973; Miller and Orr, 1966; Tobin, 1956).[2] In the second category of models, economic agents with excess cash and those who are in shortage of cash search and interact in a general equilibrium framework (Li, 2007). The third approach emphasises the transaction motive of money demand in which the demand for cash is primarily determined by the level of income and interest rate in the economy (Cassino *et al.*, 1997).

In terms of empirical strategy, currency demand has been modelled in two alternative ways. The first type of models involves a standard currency demand equation which could be estimated either as a single equation or as part of a larger macroeconometric model (Dotsey, 1988; Jadhav, 1994; Palanivel and Klein, 1999). These models are basically used to understand the impact of the various determinants of demand for currency and identify structural or policy-induced shifts in currency movements. The second set of models is *atheoretical*, usually based on standard linear time series techniques such as autoregressive integrated moving average (ARIMA) that are typically used to generate out-of-sample forecasts of currency holdings. Some empirical studies have specified and compared performances of both types of models without arriving at any definitive conclusion about their relative performance (Cassino *et al.*, 1997).

Some studies have used sophisticated non-linear time series techniques, such as the neural network model for forecasting daily CiC of the Czech Republic (Hlaváček *et al.*, 2005) or the structural time series model (Harvey *et al.*, 1997) to address problems arising from (i) seasonal coefficients exhibiting stochasticity; and (ii) changes in seasonality due to continuous structural changes. Although these models provide working solutions and good forecasts, economic interpretations of the results are vague.

A recent study using the vector autoregression (VAR) framework and quarterly data for Brazil, Kazakhstan, Morocco and New Zealand reveals that the level of income (measured by GDP) and changes in price (inflation)

2 The optimal size of cash withdrawal is directly proportional to the size of transaction (expenditure) requirements and the cost of withdrawal but inversely proportional to the opportunity cost of holding currency, *i.e.*, interest rate (Baumol, 1952).

influence CiC demand in the long run, but interest rates do not have any significant impact. Furthermore, dummy variables-based ARIMA modelling using daily data of Brazil, Kazakhstan, Morocco, New Zealand and Sudan indicates that weekdays, payroll dates, holidays and calendar effects are the main determinants of short-run currency demand (Khatat, 2018). Based on both monthly and quarterly data for the period 2001 to 2016 and using a vector error correction model (VECM), a study on Sri Lanka suggested that GDP, inflation and deposit rate along with events like elections, Christmas and New Year largely explained the changes in CiC (Kulatunge, 2019).

In the Indian context, a study by Bhattacharya and Joshi (2000) examined the intra-month variation of CiC by deploying the ordinary least squares (OLS) method using weekly data from April 1992 to March 2000. The model, which incorporates dummy variables keeping in view the seasonal pattern of intra-month currency demand, suggests that CiC growth is impacted by the day of the month effect, with holidays and festivals having a strong influence. This study was subsequently augmented by incorporating a group of index dummy variables (as against the earlier study which used dependent or independent variables with various lags) but showed only marginal improvement in explanatory powers and forecasting abilities (Bhattacharya and Joshi, 2002). A subsequent study found a cointegrating relationship between currency (CiC), economic activity (GDP), inflation (measured by the changes in the Wholesale Price Index) and interest rate (deposit rates) based on annual Indian data. The positive signs of the elasticities associated with growth and inflation and the negative sign with interest rate were along expected lines; however, the income elasticity of currency (elasticity of currency demand with respect to GDP) at 1.38 was found to be somewhat higher while the elasticity with respect to interest rate at -0.01 was much lower compared with those in advanced economies (Nachane *et al.*, 2013).

The evolving literature on the macroeconomic and microeconomic perspectives of payment systems has encompassed various dimensions (Kahn and Roberds, 2009). While the macroeconomic perspective concentrates on the impact of payment technology on currency and money demand (Bech *et al.*, 2018; Durgun and Timur, 2015; Oyelami and Yinusa, 2013), microeconomic studies focus on behavioural aspects relating to innovations in payment instruments and alternate money (Arango *et al*., 2015; Arango-Arango *et al.*, 2018; Basnet and Donou-Adonsou, 2016; Galbraith and Tkacz, 2018; Hazra, 2017; Lee, 2014; Lotz and Zhang, 2016; Stavins, 2018).

Innovations in payment technology can impact income elasticity of demand for currency, though the results are not conclusive. While estimates for income elasticity ranged between 0.4 and 0.6 based on cross-regional (cantonal) data of Switzerland (Fischer, 2007), evidence from 20 developing Asian and African countries reveals no significant change in income elasticity with the increased use of modern payment systems (Kumar, 2011). While examining the impact of technology on the seasonality of CiC for the United States (US) and India, a study by Bhattacharya and Singh (2016) extends the standard inventory-theoretic framework by incorporating the changing currency holding patterns due to technological advancement in the banking sector. In this study, total transactions in a period are assumed to follow a Gompertz distribution which leads to a non-linear model of currency growth.[3] Apart from providing theoretical justification, a comparison of the non-linear model with the standard dummy variable linear model reveals that the former is better in terms of goodness of fit and model selection criteria for both the countries.

The received literature suggests a differential impact of innovations in payment systems on currency demand largely due to differences in payment instruments. A cross-country panel data (comprising advanced and emerging market economies) model suggests that cash is the more preferred mode of payment due to (i) store of value motive and (ii) lower opportunity cost despite the increasing use of digital payments across the world (Bech *et al.*, 2018). Disaggregated provincial data for Italy, however, indicate that payment system innovations through diffusion of automated teller machines (ATMs) and point of sale (POS) had a negative effect on currency demand (Columba, 2009). Evidence from Nigeria suggests that internet payments

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[3] The Gompertz distribution, named after British mathematician and actuary Benjamin Gompertz (1779–1865), is an exponentially increasing, continuous probability distribution. It is basically a truncated extreme value distribution, also called an EVD Type I (Johnson *et al.*, 1994).

and mobile money substituted currency, while credit cards, ATMs and POS complemented it. Moreover, all payment channels, barring ATM debit cards and internet payments, showed an inverse relationship with interest rate and currency demand (Oyelami and Yinusa, 2013). Using household-level survey data and an instrumental quantile regression (IQR) framework, a study on Japan modelled currency demand conditional on electronic money adoption and reported the counter-intuitive result that users of electronic money held more currency (Fujiki and Tanaka, 2014).

There has been a sharp increase in digital transactions in India post demonetisation (November 8, 2016), with cash transactions steadily migrating to non-cash modes of payment (Maiti, 2017; RBI, 2017). The impact of credit and debit cards usage on currency demand, analysed through an autoregressive distributed lag (ARDL) model, suggests that while the usage of credit cards is inversely proportional to currency demand in India, that of debit cards has a positive impact (Reddy and Kumarasamy, 2017). Estimating transaction demand by incorporating payment indicators (growth in volume of digital retail transactions) through an ARDL model and using quarterly data for the period Q2:2004 to Q1:2019, a more recent study found the level of real income to be the main driver, while volume of digital transactions had a dampening effect on currency demand in India (Chaudhari *et al.*, 2020).

## Section III
## Currency Demand in India: Stylised Facts

As outlined in the previous section, the demand for currency in any country/region is primarily determined by (i) the relative composition of the volume of transactions in the formal and informal sectors; (ii) the extent of precautionary motive in cash holdings relative to speculative demand; (iii) the rate of change and deepening of financial innovations in the economy which have an impact on transaction habits; and (iv) the demand for home currency beyond its national jurisdiction (for instance, Nepal and Bhutan in the case of Indian currency). This section briefly analyses how the demand for currency has evolved over the past five decades in light of the changing macroeconomic, financial and technological landscape. The analysis has been restricted to the period 1970-71 to 2019-20 as the data on some variables were not available for the period prior to nationalisation of banks.

The transaction motive for holding cash relative to output or private final consumption expenditure is likely to decline with (i) sophistication in payment systems; (ii) relatively higher contribution of the tertiary sector (services) in GDP *vis-à-vis* the primary sector (agriculture); and (iii) greater financial deepening through wider bank branch networking and ATM services, which reduce transaction costs of holding cash. At the same time, increasing monetisation of the economy, higher inflation (a reason for holding a greater amount of cash to protect the real value of consumption), higher rates of taxation, large informal sector and increase in illegal (unaccounted cash) transactions are some of the factors that increase the propensity to use/hoard cash.

Over the last five decades (1970-71 to 2019-20), annual growth of CiC has been highly volatile (coefficient of variation at 0.5), although decadal average growth during this period was relatively stable. In the decade immediately after bank nationalisation, currency growth was low, but picked up over the next three decades due to a wider reach of currency with the proliferation of bank branches to every nook and corner of the country (Table 1). Higher nominal GDP caused by higher inflation was also a contributing factor for higher currency demand during the 1980s and the 1990s. CiC, however, continued to surge in the first decade of this century despite considerable moderation in nominal GDP growth due to lower inflation (although average real GDP growth was high). In the last decade (2011-20), CiC growth reduced significantly reflecting *inter alia* a sharp increase in innovations in digital payments and electronic funds transfer. As average inflation declined from over 9 per cent during the 1990s to just above 7 per cent in the 2010s, the

**Table 1: Decadal Average Growth Rates**

(Per cent)

| Variable | 1971-80 | 1981-90 | 1991-2000 | 2001-10 | 2011-20 | 1971-2020 |
|---|---|---|---|---|---|---|
| CiC | 11.6 | 14.6 | 15.2 | 15.1 | 12.6 | 13.8 |
| Nominal GDP | 11.0 | 14.9 | 14.9 | 12.5 | 12.4 | 13.1 |
| Nominal PFCE | 10.5 | 13.7 | 14.3 | 10.9 | 13.2 | 12.5 |
| CPI-Industrial Workers | 7.7 | 9.1 | 9.5 | 5.9 | 7.1 | 7.8 |
| Deposit rates (1-3 years) | 6.7 | 8.8 | 10.7 | 7.0 | 7.9 | 8.2 |

**Source**: Database on Indian Economy (DBIE), RBI; authors' calculations.

opportunity cost of holding currency declined with the fall in the real deposit rate (from 1.2 per cent in the 1990s to 0.8 per cent in the 2010s).

There were four occasions during the last fifty years when currency growth was higher than 17 per cent for three to four consecutive years. On three occasions, *i.e.*, during 1987-90, 1993-96 and 2005-09, higher currency demand was caused by relatively high nominal GDP growth (Table 2).[4] The higher currency demand during the period 2017 to 2020 was largely on account of remonetisation of the economy after the withdrawal of high value banknotes (demonetisation) on November 8, 2016. The high growth in CiC during the last three years was despite low nominal GDP growth.

During the first three decades of the sample period (1970s to 1990s), the decadal average CiC/GDP ratio was broadly stable in the range of 9.3 and 9.9 per cent (Table 3). It, however, increased to about 12 per cent in the first decade of this century, partly reflecting lower nominal GDP growth (facilitated by lower inflation) and stable currency demand. In addition, several factors might have contributed to this shift, *viz*., (i) lower opportunity cost of holding currency on account of lower real rate of return on bank deposits during the 2000s (a sharper fall in nominal deposit rates *vis-à-vis* the inflation rate); (ii) higher currency holding among the poorer sections of society on account of higher levels of consumption expenditure in rural and urban areas; (iii) improved supply of currency reflecting the Reserve Bank's proactive currency management policy; and (iv) relatively easier access to currency

**Table 2: High Phases of CiC Growth During 1971-2020**

(Per cent)

| Phase | CiC growth | | Average Nominal GDP Growth | Inflation | Interest Rate |
|---|---|---|---|---|---|
| | Average | Range | | (CPI-IW) | Deposit Rates |
| 1987-88 to 1989-90 | 17.3 | 14.2-20.4 | 15.7 | 8.2 | 9.5 |
| 1993-94 to 1995-96 | 19.8 | 17.1-22.6 | 16.6 | 9.2 | 11.0 |
| 2005-06 to 2008-09 | 17.0 | 16.5-17.4 | 14.7 | 6.6 | 7.7 |
| 2017-18 to 2019-20 | 22.7 | 14.2-37.0 | 9.8 | 5.3 | 6.7 |

**Source**: DBIE, RBI; authors' calculations.

[4] High deposit rates failed to deter sharp rise in CiC during 1987-90 and 1993-96.

**Table 3: Currency in Circulation – Key Ratios**

(Per cent)

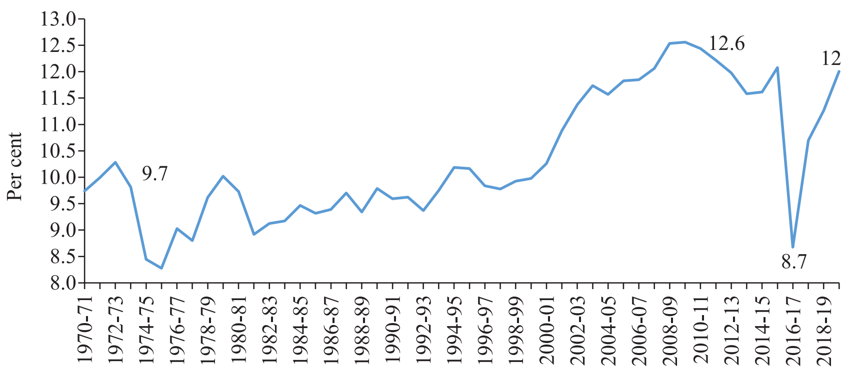
| Ratio | 1971-80 | 1981-90 | 1991-2000 | 2001-10 | 2011-20 | 1971-2020 |
|---|---|---|---|---|---|---|
| CiC/GDP | 9.3 | 9.4 | 9.9 | 11.9 | 11.3 | 11.3 |
| CiC /PFCE | 14.2 | 19.4 | 23.2 | 28.7 | 25.6 | 19.1 |
| CiC /M0 | 84.4 | 67.2 | 65.9 | 71.0 | 75.8 | 74.0 |
| CiC /M1 | 58.8 | 60.1 | 56.8 | 54.4 | 63.2 | 63.9 |
| CiC /M3 | 30.9 | 22.1 | 19.0 | 15.3 | 14.4 | 15.7 |

**Source**: DBIE, RBI; authors' calculations.

through a wide network of ATMs, which could have provided an impetus to demand similar to many countries in Europe (Nachane *et al*., 2013). CiC growth has moderated somewhat over the last decade reflecting innovations in digital payments technology. While the share of currency in broad money (CiC/M3) has steadily declined across the five decades reflecting the increase in the share of time deposits (which are interest bearing), the increasing share of currency in reserve (base) money (CiC/M0)[5] over the last two decades is indicative of the reduction in cash reserve ratio (CRR) requirements of the banking system during this period.

Annually, the CiC/GDP ratio has increased gradually since the second half of the 1990s (Chart 1). At the same time, there has been (i) a steady

**Chart 1: CiC/Nominal GDP Ratio**




**Source:** DBIE, RBI.

[5] CiC, the single largest liability of the central bank, constitutes more than 80 per cent of the monetary base.

increase in the share of the services sector in overall GDP and (ii) lower transaction costs of holding cash (rise in the number of ATMs). After reaching a peak of 12.6 per cent in 2009-10, the CiC/GDP ratio plummeted to 8.7 per cent in 2016-17 after demonetisation. As mentioned earlier, a gradual increase in CiC over the last three years led to an increase in the ratio to 12.0 per cent in 2019-20 (partially facilitated by lower nominal GDP) *albeit* lower than the peak of 2009-10.

III.i *Demonetisation*

As mentioned before, high value currency notes of ₹500 and ₹1,000 denomination amounting to ₹15.4 lakh crore, constituting 86.9 per cent of the then total value of CiC, were demonetised on November 8, 2016 (RBI, 2017). This decision was taken to eliminate corruption, black money, counterfeit currency and terror funding and was guided by the motive of reaping potential benefits. Perceived medium-term gains from demonetisation included (i) greater digitisation; and (ii) greater formalisation of the economy through increased flow of financial savings, which would lead to higher GDP growth, augment tax revenues and improve the overall business environment (*ibid.*).

The decline in CiC after demonetisation was sharp as high value notes were withdrawn while new notes were gradually injected into the system. Between November 4, 2016 and January 6, 2017 (*i.e.*, in the weeks immediately prior to the lowest level of CiC witnessed after demonetisation), total CiC declined by about ₹9 lakh crore.

On the first anniversary of demonetisation, a study undertaken by Singh *et al.* (2017) for the sample period Q3:1998 to Q2:2017 used rolling regressions and found that the income elasticity of currency demand experienced a significant drop to 0.91 in Q2:2017 (post-demonetisation period) from 1.07 in Q2:2014; furthermore, the demonetisation impact was found to be statistically significant.

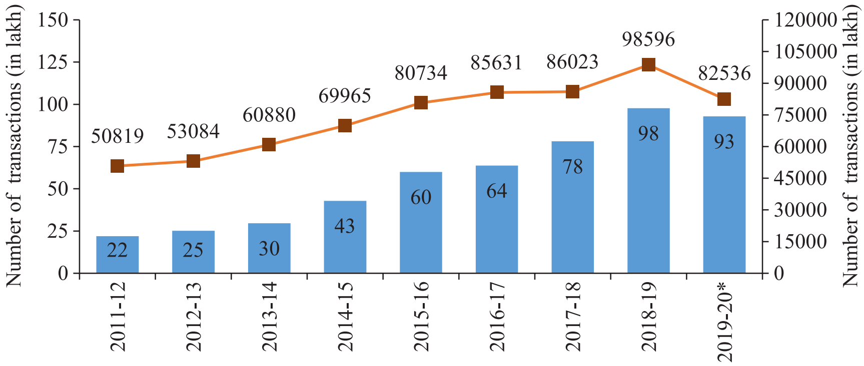
Remonetisation occurred at a rapid pace during 2017-18, wherein CiC reached its pre-demonetisation level by March 9, 2018. As on May 22, 2020, CiC growth at 18.4 per cent (y-o-y) was higher than 14.2 per cent a year ago. As on May 22, 2020, CiC was about 45.2 per cent higher than its pre-demonetisation level. As a proportion of broad money (M3), CiC at 15.2 per cent on May 22, 2020 was also higher than 14.4 per cent immediately prior to demonetisation (on October 28, 2016).

III.ii *ATMs and Digital Payments*

The number of cash withdrawal transactions from ATMs has increased significantly since 2014-15 – both through debit and credit cards (Chart 2). Although India is next only to China in terms of cash withdrawals from ATMs, the percentage of cash withdrawals to GDP has remained broadly unchanged at around 17 per cent over the last five years (RBI, 2020). Nevertheless, in terms of both volume and value of cash withdrawals through ATMs, the growth has been slow when compared with digital payment transactions, indicating a shift towards digitisation. This is possibly because the infrastructure for cash withdrawal, *i.e.*, ATMs, has grown at a slow pace of about 4 per cent over the last five years.

Monthly data from April 2011 on the number of credit and debit cards issued suggest a significant spurt in debit card issuance from October 2014 through November 2018. In contrast, credit card issuance has increased at a steady pace, especially after demonetisation (Chart 3). The increase in card issuances has facilitated the growth in both online and physical POS terminals-based card payments, resulting in an increase in digital transactions.

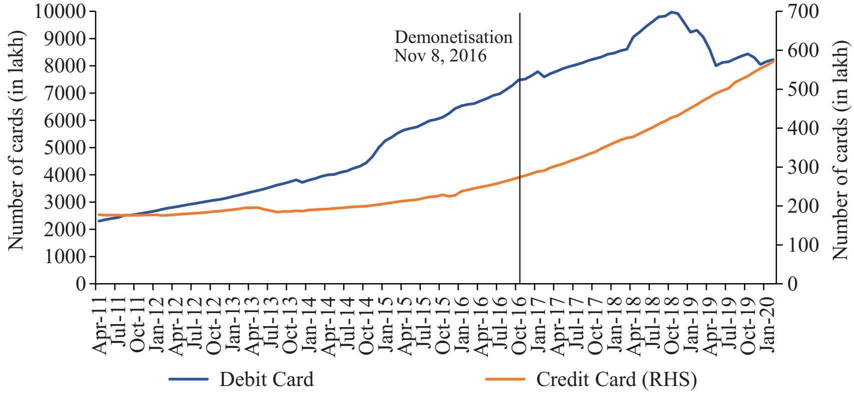
**Chart 2: Cash Withdrawal Transactions at ATMs**




* Up to Feb, 2020

**Source:** DBIE, RBI.

**Chart 3: Issuances of Credit and Debit Cards**




**Source:** DBIE, RBI.

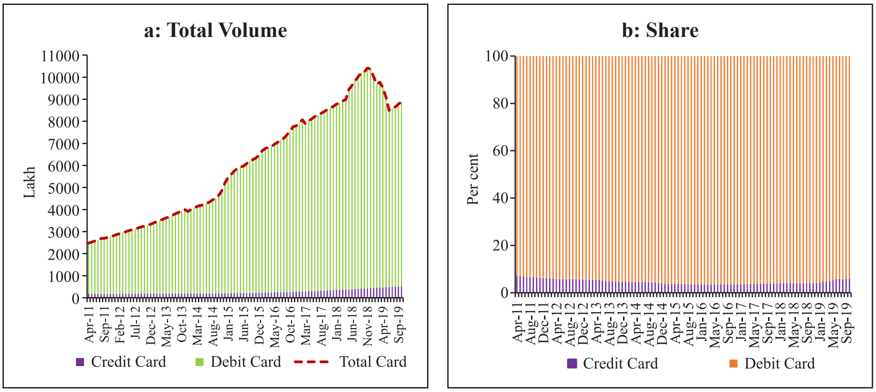
Commercial banks also issued new cards to comply with the requirement to convert all existing magnetic stripe (magstripe) cards to Europay, Mastercard, and Visa (EMV) chip and Personal Identification Number (PIN) compliant cards by December 31, 2018 and subsequently removed deactivated cards from the system resulting in a drop in the number of active debit cards after November 2018, as mentioned before. This reduction was partly also due to the consolidation of public sector banks.

The volume of total card issuance, which registered a secular increase from October 2014 to a peak of about 10,413 lakh in November 2018, dipped to 8,494 lakh in May 2019 because of the deactivation of some debit cards (Chart 4a). The share of credit cards in total card issuances, however, was less than 10 per cent (ranging from 3.4 to 7.2 per cent) during April 2011 to October 2019. The share of debit cards reached its peak of 96.6 per cent in January 2016 (Chart 4b).

Both in terms of value and volume (number of transactions), digital payments have grown rapidly in the last five years (Chart 5).

Digital payments comprise both wholesale and retail payments. Wholesale transactions, in the form of real-time gross settlement system (RTGS), are of high value and cannot substitute cash. They are, therefore, not considered in our analysis. For the purpose of this study, retail payments comprising prepaid payment instruments (PPIs), credit cards, debit cards and

**Chart 4: Credit and Debit Cards**

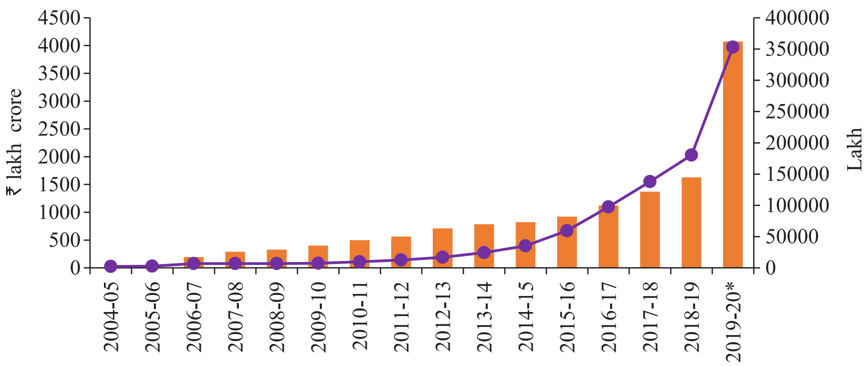



**Source:** DBIE, RBI.

retail electronic clearing (REC) are more appropriate. REC consists of (i) National Electronic Funds Transfer (NEFT); (ii) Immediate Payment Service (IMPS); and (iii) National Automated Clearing House (NACH). In volume terms, PPI, credit cards, debit cards and REC are broadly of the same size.

There has been a considerable increase in the number of PPIs comprising mainly mobile wallets and PPI cards with credit and debit cards also reflecting a sharp increase in usage after demonetisation (Chart 6a). The usage remained higher even during the remonetisation phase, although card usage somewhat

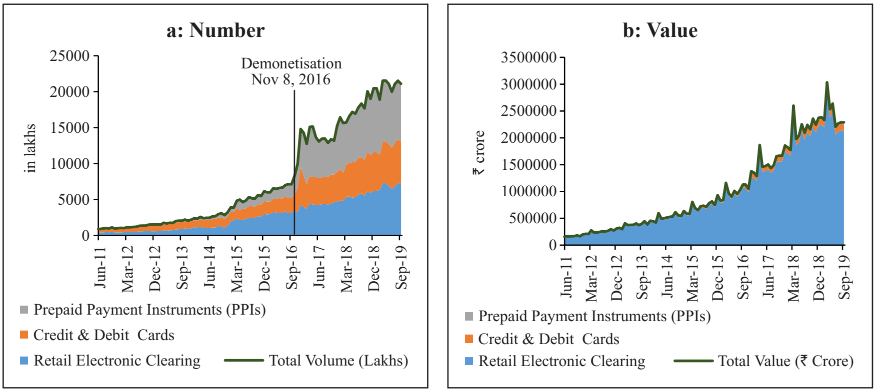
**Chart 5: Digital Payments**




* Up to Oct, 2019

**Source:** DBIE, RBI.

**Chart 6: Digital Transactions**




**Source:** DBIE, RBI.

shrank as cash got replenished in the system. In value terms, REC constitutes 94.1 per cent of digital transactions (Chart 6b).

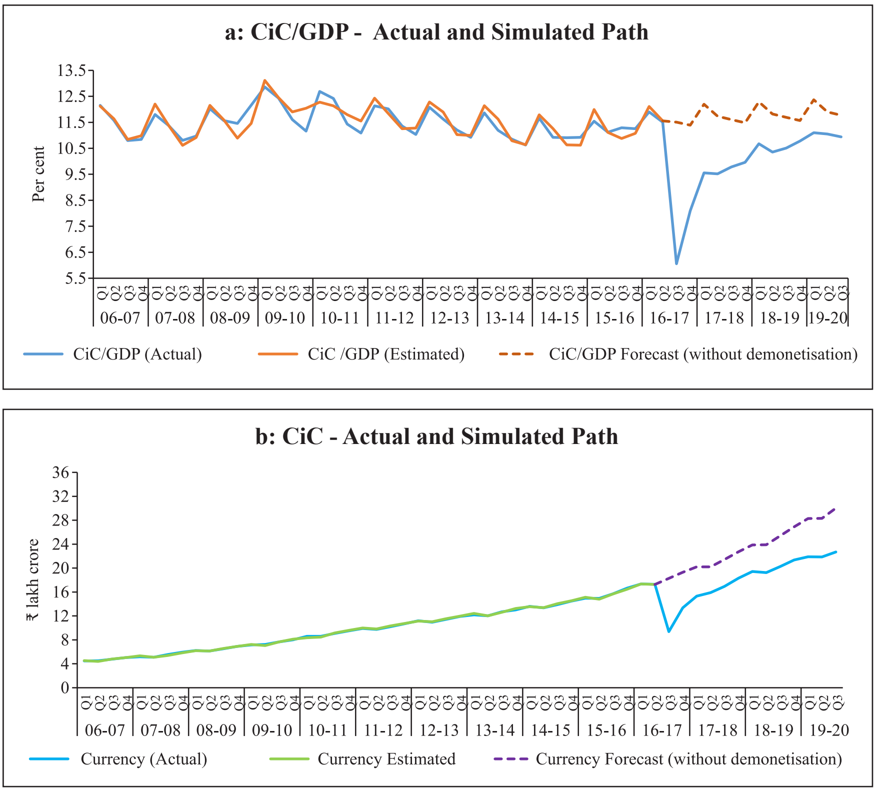
Technological innovation is making digital payments increasingly convenient, instantaneous and ubiquitous. Systems that offer near instant person-to-person retail payments are becoming increasingly available globally. Many payment systems in the country now operate 24 hours a day, seven days a week, thereby alluring customers. The fast payment systems in India such as IMPS and the Unified Payments Interface (UPI) are driving the volume in retail payments. In addition, the availability of NEFT on a 24x7x365 basis (with half-hourly settlements) since December 16, 2019 is likely to propel digital payments in India to a higher growth trajectory.

Greater digitalisation of retail transactions and the sharp increase in electronic modes of payments might have resulted in a downward shift in currency demand. Time series forecasts of quarterly CiC movements, both in relation to GDP (CiC/GDP) and in level form, were generated separately using a univariate unobserved components model (UCM)[6] based on data from Q1:2001-02 to Q2:2016-17. The forecast of CiC/GDP for the remonetisation period (Q3:2016-17 and beyond) is represented by the dotted line representing the path of CiC/GDP in the absence of demonetisation whereas the thick

[6] Univariate UCM carries out the decomposition of a time series into various components, *viz.,* trend, seasonal, cycle, and irregular.

blue line represents the actual value of CiC/GDP (Chart 7a). This model's performance was robust for the period prior to demonetisation, tracking the path of actual CiC/GDP ratio fairly accurately (represented by the thick orange line). Based on the model forecast, it is noted that the CiC/GDP ratio could have been higher by 0.9 percentage points in Q3:2018-19 (11.8 per cent instead of the actual 10.9 per cent) in the absence of demonetisation. Thus, the forecast path beyond the demonetisation period can be treated as a counterfactual scenario of the expected path of CiC/GDP in the absence of demonetisation. A similar analysis using the level of CiC (in logarithm) also suggests that CiC would have been significantly higher at the end of Q3:2019-20 than its actual level in the absence of demonetisation (Chart 7b).

**Chart 7: Quarterly CiC Movements**




**Note:** The simulated path shows the the currency forecast generated from UCM had there been no demonetisation.
**Source:** DBIE, RBI; authors' estimates.

## Section IV
## Methodology and Data

IV.i *Weekly Model*

As mentioned before, forecasting banking system liquidity on a weekly basis is of paramount importance for the effective conduct of liquidity management operations. Accurate forward-looking liquidity assessment is contingent on accurate forecasts of CiC. Consequently, the forecast performance often outweighs the consideration for strong theoretical underpinnings in the weekly model. Moreover, data on variables which are proximate determinants of currency demand in the medium term – *viz*., income and opportunity cost of holding cash or any of their suitable proxies – are not available at a weekly frequency. Hence, the weekly model for forecasting CiC is based on an *atheoretic* framework, focusing on time series properties, idiosyncratic factors and other short-term determinants following the available literature (Khatat, 2018).

Since CiC is a trending variable exhibiting non-stationarity, the dependent variable in the model is represented as the weekly change in the logarithm of CiC (ΔLCiC). The model controls for (i) persistence; (ii) volatility clustering; (iii) seasonality; (iv) Indian festivals; (v) national and state elections; and (vi) demonetisation as discussed below.

(a) *Persistence*: The dynamic nature of ΔLCiC is modelled by incorporating the lag terms, autoregressive (AR) terms and moving average (MA) terms.

(b) *Volatility Clustering*: In view of high frequency of data on CiC, the possibility of volatility clustering cannot be ruled out; hence, statistical tests are conducted to identify the presence/absence of volatility clustering. Accordingly, we first estimate an ARIMA model for the sample period and test for the heteroscedasticity in residuals using the Breusch-Pagan-Godfrey test. On being found significant, the variance equation is required to be augmented with the ARIMA equation so as to control for the residual heteroscedasticity. Thus, we estimate an autoregressive conditional heteroscedastic (ARCH) model for ΔLCiC.

(c) *Seasonality*: The seasonality is captured using monthly and weekly dummies; eleven dummies have been used to represent the monthly seasonality, with September (middle of the financial year) being the reference period. One month is dropped to avoid the dummy variable trap.[7] The weekly seasonality is controlled by using three weekly dummies representing the 2nd, 3rd, and 4th weeks in a month where the 1st week is taken as the reference period.

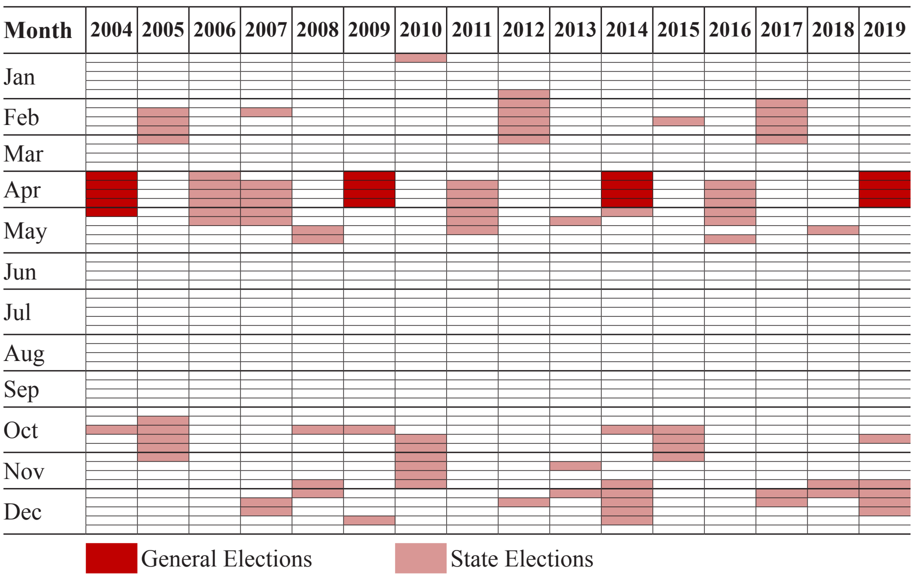
(d) *Indian Festivals*: In India, consumption usually increases during the festive season which, in turn, leads to an increased demand for currency. Since most of the festivals follow a lunar calendar, these changes are not captured in the seasonal dummies and need to be separately incorporated. The main festivals considered are *Diwali*, *Dussehra*, *Eid* and *Ganesha Chaturthi*. Usually, currency demand starts rising days before the festival and continues during the festive period; however, subsequently, currency returns (flows back) to the banking system. Accordingly, three dummies are considered separately for each of these festivals to capture the impact of the festive season: pre-festive week, festive week and post-festive week, respectively.

(e) *Elections*: During the sample period (2004-19), four general elections were conducted in India (2004, 2009, 2014 and 2019). Apart from these elections, state elections were also conducted every year in some states as per their respective electoral cycle. Although the national elections have pan-India coverage, the impact of state elections on CiC depends on the number of days on which elections are held and the population size of the states conducting the elections each time. Accordingly, the model covers the general elections of 2004, 2009, 2014 and 2019 and the state elections in 22 major states comprising 95.1 per cent of India's

[7] The dummy variable trap is a scenario in which the independent variables suffer from multicollinearity, a scenario in which two or more variables are highly correlated, *i.e.*, one variable can be predicted from the others. So, regression models should be ideally designed excluding one dummy variable.

total population (as per the 2011 Census), *viz*., Andhra Pradesh, Assam, Bihar, Chhattisgarh, Delhi, Goa, Gujarat, Haryana, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Punjab, Puducherry, Rajasthan, Sikkim, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal. Furthermore, elections are conducted in several phases in each state. The dates of all phases of national and state elections between 2004 and 2019 are presented in Table 4.

**Table 4: Phase-wise National and State-level Elections in India, 2004–19**




**Source**: Election Commission of India (www.eci.gov.in).

All the information in Table 4 is encapsulated in one indicator of election ($E_t$).

$$
\begin{aligned}
E_t &= 1, \text{ if general election is held during week t} \\
&= P^c/P, \text{ if state election/s is/are held during week t} \\
&= 0 \text{ other wise,}
\end{aligned}
$$

where $P^c$ represents the total population covered during that phase of the election across all states and P represents pan-India electoral coverage (since electoral details are not available, it is proxied by the population).

(f) *Demonetisation*: As alluded to earlier, CiC fell sharply in November and December of 2016 following demonetisation of high value currency notes, which gradually began to rise subsequently (remonetisation). Accordingly, 20 separate dummy variables are used to represent the demonetisation and remonetisation periods, starting from the second week of November 2016 till end-March 2017. These dummy variables are single period dummies. When single period dummies are used in the regression equation, it is equivalent to removing that particular period from the analysis while estimating the other parameters. Thus, by using single period dummies we have removed the demonetisation and remonetisation periods while estimating the other parameters. These, in addition, will produce zero residuals in those periods, which should not be considered as model accuracy, rather as a technical approach to remove an extraordinarily volatile period from the analysis. The parameters of these dummies, however, can be used to estimate the size of the impact of demonetisation and remonetisation on CiC.

Incorporating all these factors, equations (1) and (2) represent the specification of the ARCH model, which is used to forecast CiC at a weekly frequency. The mean equation (1) has 11 dummies for months $M^1$ to $M^{12}$, except $M^9$, which is the reference month; three weekly dummies ($W^2$ to $W^4$); one dummy each for pre-*Dussehra* week ($Dussehra^{pre}$), *Dussehra* week (*Dussehra*) and post-*Dussehra* week ($Dussehra^{post}$); one dummy each for pre-*Diwali* week ($Diwali^{pre}$), *Diwali* week (*Diwali*) and post-*Diwali* week ($Diwali^{post}$); one dummy each for pre-*Eid* week ($Eid^{pre}$), *Eid* week (*Eid*), and post-*Eid* week($Eid^{post}$); one dummy each for pre-*Ganesha Chaturthi* week ($Ganesha^{pre}$), *Ganesha Chaturthi* week (*Ganesha*), and post-*Ganesha Chaturthi* week($Ganesha^{post}$). We include the variable ($E$) to capture the impact of both general and state elections. We also include dummy variables for both the demonetisation and remonetisation periods ($D^1$ to $D^{20}$). In addition, we control for autoregressive and moving average terms.

$$\Delta LCiC_t = \alpha_0 + \sum_{i=1}^{n} \beta_i * \Delta LCiC_{t-i} + \sum_{i=1}^{11} \gamma_i * M^i + \sum_{i=2}^{4} \delta_i * W^i + \eta_1 * Dussehra^{pre} + \eta_2 * Dussehra + \eta_3 * Dussehra^{post} + \theta_{11} * Diwali^{pre} + \theta_{12} * Diwali + \theta_{13} * Diwali^{post} + \theta_{21} * Eid^{pre} + \theta_{22} * Eid + \theta_{23} * Eid^{post} + \theta_{31} * Ganesha^{pre} + \theta_{32} * Ganesha + \theta_{33} * Ganesha^{post} + \psi * E_t + \sum_{i=0}^{20} \phi_i * D^i + \varepsilon_t \qquad ......(1)$$

The variance equation is:

$$\varepsilon_t^2 = \omega_0 + \omega_1 * \varepsilon_{t-1}^2 \qquad ......(2)$$

We use weekly data from January 2004 till September 2019, sourced from RBI's Database on Indian Economy (DBIE).[8]

IV.ii *Monthly Model Incorporating Digital Payments*

For the monthly CiC model, we use the standard cointegration approach under the time series econometric framework since it has been the conventional workhorse model in estimating short- and long-run relationships among economic variables (Johansen and Juselius, 1990). VECM approach, however, has a shortcoming in that all variables used should be strictly of the same order of integration. The bound testing and ARDL cointegration approaches do not require every variable in the model to necessarily have the same order of integration (Pesaran *et al.*, 2001). The relative merit of this approach is its applicability, irrespective of whether the underlying regressors are purely I(0), purely I(1), or a mixture of both with the condition that none of the series is I(2). Consequently, we formulate a monthly model primarily focusing on the impact of digital payments on CiC following an ARDL bound testing approach. A brief description of the ARDL methodology is given in Appendix D.

Following the specification of the demand for currency, long-run cointegration was tested for CiC, nominal income (Y)[9] and average deposit

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

[9] Quarterly nominal GDP has been interpolated using Denton method (Baum and Hristakeva, 2001).

rate (ADR), the latter representing the opportunity cost of holding cash. Both Y and CiC are seasonally adjusted and represented in logarithmic form (represented by LY and LCiC). The change in digital transactions in terms of transaction value and number of transactions is alternately used as an explanatory variable in the short-run dynamics along with the error correction term and the other short-run variables.

One of the distinctive features of the monthly model is the use of the data on digital payments (component-wise disaggregated data) to forecast CiC. As disaggregated data on digital payments, sourced from DBIE, are available from 2011 onwards (although aggregate data are available from 2004), we restricted the sample period from April 2011 to September 2019 given the surge in digital payments network and infrastructure during the last decade which helps in assessing the impact of its penetration on currency demand.

### IV.iii *Quarterly and Annual Models*

Similar to the monthly model, the ARDL cointegration approach (Pesaran and Shin 1995, 1999; Pesaran *et al.*, 1996) is used to model the relationship between CiC and other variables for the quarterly and annual models as well.

For the quarterly model, data from Q2:1998-99 to Q3:2019-20 encompassing 86 observations have been used, while the annual model is based on data from 1970-71 to 2018-19. The variables used both in the quarterly and annual models are CiC, nominal GDP and average deposit rates of 1-3 years tenor, which are sourced from RBI's DBIE, National Statistical Office (NSO), Government of India, and State Bank of India.

## Section V
## Results

### V.i *Weekly Model*

The regression coefficients estimated from equations (1) and (2) are presented in Table 5. The diagnostics of the model are found to be satisfactory. The errors are free from autocorrelation and heteroscedasticity as evident from correlograms of standardised residuals and standardised residual squares

## Table 5: Estimated Regression Coefficients

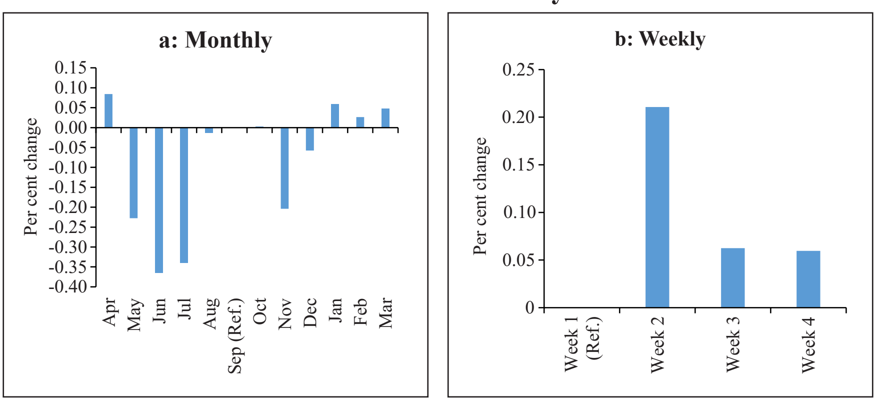
| Regressor | Coeff. | SE | z | Prob. |
|---|---|---|---|---|
| **Mean Equation** | | | | |
| C1 | 0.001 | 0.001 | 1.143 | 0.253 |
| ΔLCiC(-1) | 0.152 | 0.076 | 1.982 | 0.047 |
| ΔLCiC(-2) | -0.019 | 0.047 | -0.409 | 0.682 |
| ΔLCiC(-3) | -0.018 | 0.042 | -0.425 | 0.671 |
| ΔLCiC(-4) | 0.341 | 0.041 | 8.314 | 0.000 |
| ΔLCiC(-5) | 0.038 | 0.039 | 0.992 | 0.321 |
| ΔLCiC(-6) | 0.046 | 0.035 | 1.301 | 0.193 |
| $M^1$ | 0.001 | 0.001 | 0.965 | 0.335 |
| $M^2$ | 0.000 | 0.001 | 0.373 | 0.709 |
| $M^3$ | 0.000 | 0.001 | 0.806 | 0.420 |
| M4 | 0.001 | 0.000 | 6.224 | 0.000 |
| $M^5$ | -0.002 | 0.001 | -2.945 | 0.003 |
| $M^6$ | -0.004 | 0.001 | -5.282 | 0.000 |
| $M^7$ | -0.003 | 0.001 | -4.313 | 0.000 |
| $M_8$ | 0.000 | 0.001 | -0.174 | 0.862 |
| $M^{10}$ | 0.000 | 0.001 | 0.039 | 0.969 |
| $M^{11}$ | -0.002 | 0.001 | -2.696 | 0.007 |
| $M^{12}$ | -0.001 | 0.001 | -0.847 | 0.397 |
| $W^2$ | 0.002 | 0.001 | 2.362 | 0.018 |
| $W^3$ | 0.001 | 0.001 | 0.605 | 0.545 |
| $W^4$ | 0.001 | 0.001 | 0.691 | 0.489 |
| $Dussehra^{pre}$ | 0.005 | 0.001 | 4.586 | 0.000 |
| Dussehra | 0.006 | 0.001 | 5.869 | 0.000 |
| $Dussehra^{post}$ | -0.003 | 0.001 | -2.270 | 0.023 |
| $Diwali^{pre}$ | 0.009 | 0.001 | 11.811 | 0.000 |
| Diwali | 0.014 | 0.001 | 12.101 | 0.000 |
| $Diwali^{post}$ | -0.007 | 0.002 | -4.380 | 0.000 |
| $Eid^{pre}$ | 0.001 | 0.001 | 0.749 | 0.454 |
| Eid | 0.001 | 0.001 | 1.211 | 0.226 |
| $Eid^{post}$ | -0.002 | 0.001 | -2.040 | 0.041 |
| E | 0.002 | 0.001 | 2.322 | 0.020 |
| $D^2$ | -0.225 | 0.007 | -30.67 | 0.000 |
| $D^3$ | -0.140 | 0.017 | -8.015 | 0.000 |
| $D^4$ | -0.108 | 0.017 | -6.500 | 0.000 |
| $D^5$ | -0.076 | 0.018 | -4.211 | 0.000 |
| $D^6$ | 0.060 | 0.021 | 2.810 | 0.005 |
| $D^7$ | 0.059 | 0.027 | 2.227 | 0.026 |
| $D^8$ | 0.055 | 0.014 | 3.859 | 0.000 |
| $D^9$ | -0.008 | 0.009 | -0.942 | 0.346 |
| $D^{10}$ | 0.082 | 0.008 | 10.491 | 0.000 |
| $D^{11}$ | 0.034 | 0.009 | 3.671 | 0.000 |
| $D^{12}$ | 0.027 | 0.008 | 3.224 | 0.001 |
| $D^{13}$ | 0.041 | 0.009 | 4.638 | 0.000 |
| $D^{14}$ | 0.018 | 0.007 | 2.513 | 0.012 |
| $D^{15}$ | 0.011 | 0.018 | 0.605 | 0.545 |
| $D^{16}$ | 0.016 | 0.014 | 1.154 | 0.248 |
| $D^{17}$ | 0.010 | 0.016 | 0.631 | 0.528 |
| $D^{18}$ | 0.005 | 0.012 | 0.441 | 0.659 |
| $D^{19}$ | 0.009 | 0.013 | 0.705 | 0.481 |
| $D^{20}$ | 0.010 | 0.012 | 0.883 | 0.377 |
| AR(13) | 0.485 | 0.073 | 6.606 | 0.000 |
| AR(9) | 0.166 | 0.037 | 4.534 | 0.000 |
| AR(4) | 0.106 | 0.090 | 1.180 | 0.238 |
| AR(3) | -0.185 | 0.099 | -1.874 | 0.061 |
| AR(23) | -0.126 | 0.060 | -2.102 | 0.036 |
| AR(1) | 0.002 | 0.110 | 0.018 | 0.986 |
| AR(2) | -0.178 | 0.085 | -2.092 | 0.036 |
| MA(13) | -0.299 | 0.067 | -4.435 | 0.000 |
| MA(3) | 0.344 | 0.118 | 2.913 | 0.004 |
| MA(4) | -0.314 | 0.116 | -2.710 | 0.007 |
| MA(23) | 0.012 | 0.063 | 0.189 | 0.850 |
| MA(1) | -0.061 | 0.146 | -0.421 | 0.674 |
| MA(2) | 0.192 | 0.098 | 1.954 | 0.051 |
| **Variance Equation** | | | | |
| C2 | 0.000 | 0.000 | 13.334 | 0.000 |
| $\varepsilon_t^2(1)$ | 0.143 | 0.053 | 2.693 | 0.007 |
| **Diagnostics** | | | | |
| Adjusted R-squared = 0.93 | | | | |
| Sum squared residuals = 0.01 | | | | |
| Heteroscedasticity Test ARCH-LM p-value = 0.41 | | | | |

**Note:** Coeff. : Coefficient value; SE: Standard Error; z: z-Statistics; Prob.: Probability.

along with the ARCH-LM test. The main findings of the model are analysed below.

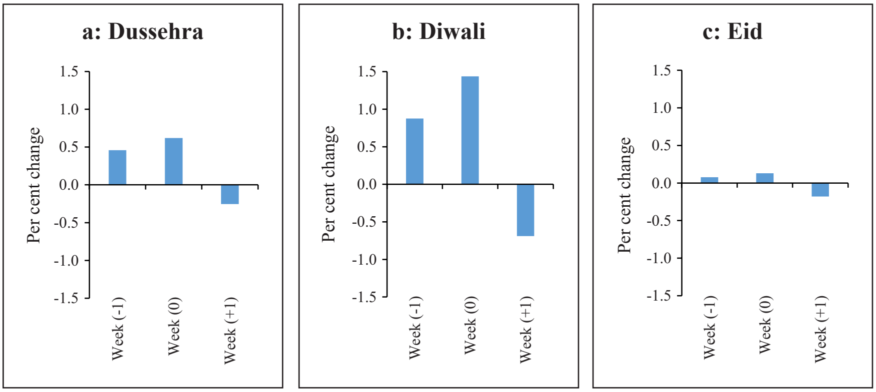
(a) *Seasonality:* CiC increases in March and April compared to September (reference month), while it declines during May, June and July (Chart 8a). The increase in CiC in March and April can be attributed to the *rabi* harvest, rice and wheat procurement, marriage season and celebration of *Hindu* New Year festivals (*e.g.*, *Gudhi Padwa, Pongal, Baisakhi, Ugadi*) across India. The decline in CiC during May, June and July roughly coincides with the monsoon season. *A priori,* it is expected that CiC would be higher during the festive season (October to December) compared with other months. As we have explicitly modelled the impact of several festivals separately through festival dummies, the partial regression coefficients of seasonal dummies corresponding to those months are not statistically significant and positive. In fact, these effects were reflected in the weekly dummies corresponding to those festivals. Thus, the seasonal dummies for the festive period (October to December) do not show any significant uptick compared with September after controlling for those effects. While considering intra-month movements, the largest increase in CiC occurs in the second week (Chart 8b).

**Chart 8: Seasonality**




**Source:** Authors' estimates.

**Chart 9: Festival Impact on CiC**



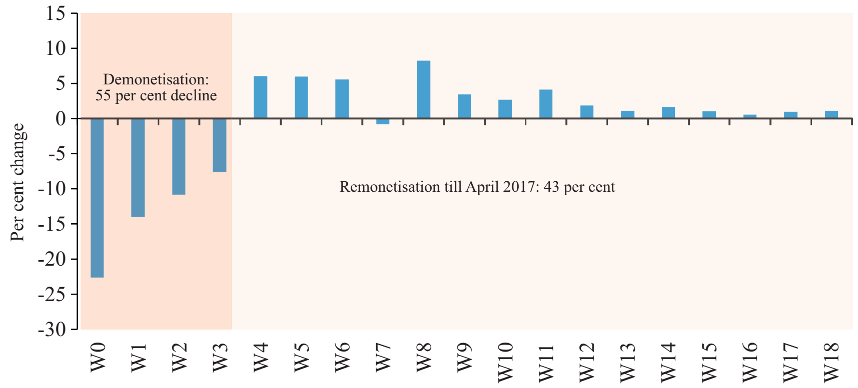

**Source:** Authors' estimates.

(b) *Festivals*: *Ganesha Chaturthi* did not have statistically significant impact on CiC at the national level; hence, this festival was dropped from the final regression equation. CiC increases before and during the festive weeks, part of which returns to the banking system a week later (Chart 9 and Table 5). Among the festivals, *Diwali* has the largest impact on CiC (Chart 9b). Cumulatively, CiC increases by around 2.2 per cent during *Diwali* followed by *Dussehra* (1.1 per cent) and *Eid* (0.2 per cent).

(c) *Elections*: The regression coefficient corresponding to the election variable was found to be positive and statistically significant. CiC increases by 0.2 per cent in each week (on average) during the period in which general elections are held; thus, CiC is expected to increase cumulatively by 1 per cent if the general election phase is held over a five-week period.[10] The estimates also suggest that the impact is larger if there is (i) a larger size of the electorate (general or bigger state elections) and (ii) if the duration of the electoral process is longer.

[10] The intra-month movements, however, are difficult to estimate because of the complexities of the Indian electoral process.

**Chart 10: Impact of Demonetisation**




**Source:** Authors' estimates.

(d) *Demonetisation*: The estimated regression coefficients of the demonetisation dummies suggest that CiC did fall significantly by about 55 per cent[11] during the first four weeks after demonetisation (Chart 10). After remonetisation began, the increase in CiC stock (statistically significant) was from week 4 (W4) to week 12 (W12) when nearly 36.8 per cent CiC got replenished, which increased further to 43 per cent by April 2017.

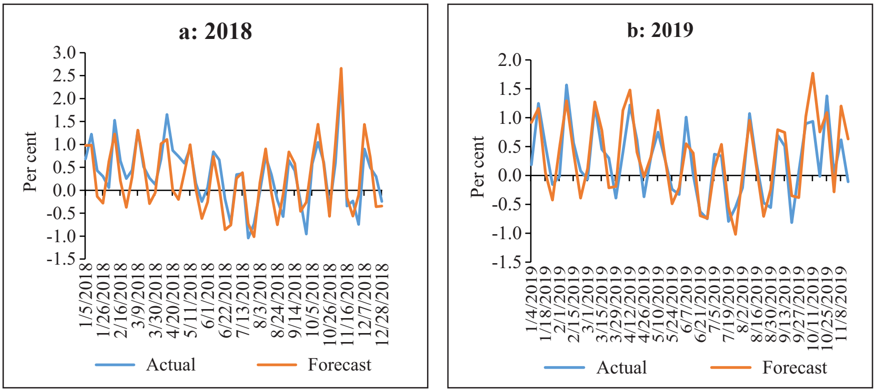
(e) *Forecast Performance*: The model is used to produce *pseudo* out-of-sample one week ahead forecasts for 2018 and 2019. A comparison of the fitted and actual values of the percentage changes in CiC suggests that the model can reasonably predict currency movements (Chart 11). The average out-of-sample root mean square error (RMSE) for 2018 and 2019 was found to be 0.33 per cent.

V.ii *Monthly Model Incorporating Digital Payments*

The bound testing cointegration test with alternate specifications suggests that LY, LCiC and ADR are not cointegrated, unlike in the quarterly

[11] These are estimates based on regression coefficients after controlling for all the factors that affect CiC.

**Chart 11: Forecast Performance**




**Source:** Authors' estimates.

model discussed below (Table 6). After removing ADR, however, LY and LCiC were found to be cointegrated. This is different from the results obtained from the quarterly model on account of the difference in the sample period – a shorter sample for the monthly model (2011-19) and a longer sample for the quarterly model (1997-2019). This could be attributed to the fact that the bank deposit rate may no longer represent the opportunity cost of money with the proliferation of several new financial market products in the more recent period.

To understand the short-run dynamics, the value and the number of digital transactions are used alternately as additional explanatory variables along with the other short-term variables. The regression results suggest that the long-run coefficient of nominal income is statistically significant and close to unity (Table 7). In the short run, the error correction term is negative and significant. The change in the value of transactions is found to be statistically insignificant; however, the number of transactions is found to be statistically

**Table 6: Test for Cointegration**

| Model with variables | LY, LCiC and ADR | LY and LCiC |
|---|---|---|
| Bound Test | F = 2.486 | F = 5.933 |
| Critical Values (5 per cent) | [3.79 4.85 ] | [4.94 5.73] |
| Inference | Not Cointegrated | Cointegrated |

**Table 7: Regression Coefficients – Long-run and Short-run**

| Regressor | Regression 1 | Regression 2 |
|---|---|---|
| Long-run coefficient of LY | 0.936<br>(0.00) | 0.909<br>(0.00) |
| **Short-run coefficients** | | |
| Error correction | -0.067<br>(0.00) | -0.070<br>(0.00) |
| ΔLog of value of digital transactions | 0.009<br>(0.75) | -- |
| ΔLog of value of digital transactions (-1) | 0.023<br>(0.40) | -- |
| ΔLog of number of digital transactions | -- | -0.027<br>(0.36) |
| ΔLog of number of digital transactions (-1) | -- | -0.052<br>(0.07) |
| **Diagnostics** | | |
| LM test for autocorrelation (p-value) | 0.02 | 0.06 |
| BP test for heteroscedasticity (p-value) | 0.02 | 0.06 |

**Note:** Figures in parentheses are probability values.

significant and negative (with one period lag) indicating that an increase in the number of digital transactions helps in reducing CiC (Table 7, Regression 2). This suggests that the penetration/coverage of digital transactions can significantly impact CiC demand.

A disaggregated analysis with number of transactions in REC, Cards and PPI was undertaken to measure the impact of each instrument on CiC. The findings suggest that the long-run coefficients of nominal income are statistically significant and close to unity in all specifications (Table 8). Short-run dynamics indicate that the number of card transactions significantly moderates CiC expansion.

V.iii *Quarterly Model*

The correlation matrix reveals that there is a strong and statistically significant positive correlation between LY and LCiC, as expected (Table 9). Furthermore, in accordance with the theory, there is a negative and statistically significant correlation between ADR and LCiC.

**Table 8: Regression Coefficients – Long-run and Short-run Coefficients**
(Alternative modes of payment)

| Regressor | Regression 1 | Regression 2 | Regression 3 |
|---|---|---|---|
| Long-run coefficient of LY | 0.922<br>(0.00) | 0.916<br>(0.00) | 0.922<br>(0.00) |
| **Short-run coefficients** | | | |
| Error correction | -0.068<br>(0.00) | -0.060<br>(0.00) | -0.068<br>(0.00) |
| ΔLog of number of PPI transactions | 0.000<br>(0.99) | -- | -- |
| ΔLog of number of PPI transactions (-1) | 0.001<br>(0.86) | -- | -- |
| ΔLog of number of card transactions | -- | -0.072<br>(0.07) | -- |
| ΔLog of number of card transactions (-1) | -- | -0.131<br>(0.00) | -- |
| ΔLog of number of REC transactions | -- | -- | 0.008<br>(0.68) |
| ΔLog of number of REC transactions (-1) | -- | -- | -0.004<br>(0.83) |
| **Diagnostics** | | | |
| LM test for autocorrelation (p-value) | 0.01 | 0.25 | 0.04 |
| BP test for heteroscedasticity (p-value) | 0.02 | 0.05 | 0.02 |

**Note:** Figures in parentheses are probability values.

As mentioned before, the ARDL technique (Pesaran and Shin, 1995, 1999; Pesaran *et al.*, 1996) is used to model the relationship between LCiC and other variables for the quarterly and annual model. The augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are employed to test the stationarity properties of the variables under consideration. The unit root tests in the form of ADF and PP indicate that the variables under consideration

**Table 9: Correlation Matrix**

| Correlation | LCiC |
|---|---|
| LY | 0.99* |
| ADR | -0.23* |

**Note:** * significant at 1 per cent level.

**Table 10: ADF and PP Unit Root Tests**

| Variable | Level | | First Difference | |
|---|---|---|---|---|
| | ADF | PP | ADF | PP |
| LCiC | -0.673 | -0.997 | -9.9293* | -18.280* |
| LY | -0.022 | -0.869 | -3.103* | -13.847* |
| ADR | -2.980* | -2.195 | - | -8.030* |

**Note:** * denotes significance at 1 per cent. The constant and time trends are included in level, but the time trend is removed in the first difference equation. The optimal lag order is selected based on SIC in the ADF test equation.
- = Not applicable.

are either I(1) or I(0), but not I(2), as is appropriate for estimating an ARDL model[12] (Table 10).

The F-statistic and critical values under the bounds test are presented in Table 11. The cointegration test applied on the unrestricted model is an F-test on the hypothesis that the coefficients of the lagged level variables are jointly equal to zero. The F-statistic for the joint significance of the parameters of the lagged level variables is found to be 22.90, which exceeds the upper bound critical value. The results, therefore, reveal statistically significant evidence in favour of the existence of a long-run cointegrating relationship between the variables under consideration.

The long-run ARDL cointegration test shows statistically significant unitary income elasticity of currency demand (Table 12). The expected inverse relationship between average deposit rate and CiC, however, is statistically insignificant.

The error correction model (ECM) under the ARDL approach is estimated to examine the short-run dynamics of the relationship between dependent and independent variables to estimate the persistence of short-

**Table 11: Bounds Test for Cointegration**

| F-statistic | 99% lower bound | 99% upper bound | Outcome |
|---|---|---|---|
| 22.90 | 4.13 | 5.00 | cointegration |

[12] The ARDL model fails to hold good when the variables under study are I(2).

**Table 12: Long-run ARDL Cointegration Model (2, 1, 2)[#]**

| Dependent variable: LCiC | | |
|---|---|---|
| **Regressor** | **Coefficient** | ***t*-Statistics** |
| LY | 1.048 | 17.87* |
| ADR | -5.845 | -1.29 |
| C | 0.625 | 0.45 |

[#] Lag length is selected using Akaike Information Criteria (AIC).
**Note:** * denotes significance at 1 per cent.

run shocks and the speed of adjustment for the return to equilibrium. The estimated error correction term is negative and significant, thereby indicating that the system reverts to equilibrium regardless of any short-run shock to the system (Table 13). The adjustment to the short-run shock, however, is quite slow – only 4 per cent of deviation because of any short-run shock gets corrected in a quarter.

We infer from the estimated short-run relationship that the change in nominal GDP influences change in CiC positively and the change in average deposit rate has a negative impact on the change in CiC – both these relationships being statistically significant. In the short run, the impact of the average deposit rate is higher: (i) one percentage point increase in deposit rate leads to a 0.34 per cent decline in CiC over a period of two quarters, while (ii) one percentage point increase in nominal GDP leads to a 0.13 per cent increase in CiC in the same quarter. Furthermore, the model is robust on the basis of all diagnostic tests – no residual serial autocorrelation and heteroscedasticity, and parameter stability – as depicted in the lower panel of Table 13.

We also conducted the same empirical exercise using ARDL methodology with annual data, the details of which are given in Appendix A. The results are broadly in line with the findings obtained in the case of the quarterly model. In terms of the degree of impact, CiC has the same unitary elasticity with respect to nominal GDP in the long run as in the quarterly model (Appendix A, Table A.4). The impact of the deposit rate, however, is qualitatively different – it is statistically significant in the annual model, while not so in the quarterly

**Table 13: ARDL Cointegration Short-run Error Correction Model**[13]

| Dependent variable: ΔLCiC | | |
|---|---|---|
| **Regressor** | **Coefficient** | ***t*-Statistics** |
| ΔLCiC(-1) | -0.164 | -1.53 |
| ΔLY | 0.130 | 2.50* |
| ΔADR | -1.202 | -2.49** |
| ΔADR(-1) | 0.861 | 1.80*** |
| Q2DUM | -0.062 | -10.25* |
| Q3DUM | -0.018 | -1.79*** |
| Q4DUM | -0.010 | -1.44 |
| Q32017DUM | -0.662 | -40.70* |
| Q42017DUM | 0.174 | 2.32* |
| Q12018DUM | 0.122 | 3.39* |
| Q22008DUM | 0.050 | 2.75** |
| Error Correction (-1) | -0.040 | -9.77* |
| *Diagnostic tests* | | |
| Adjusted $R^2$: | | 0.98 |
| DW statistics: | | 1.83 |
| LM serial correlation F-test (*p*-value): | | 0.49 |
| Breusch-Pagan-Godfrey heteroscedasticity Test F-test (*p*-value): | | 0.34 |
| CUSUM test: | | Stable |
| CUSUM of squares test: | | Stable |

**Note:** *, ** and *** denote significance at 1 per cent, 5 per cent and 10 per cent, respectively.

model. The longer time horizon of the annual model may have contributed to this divergence in results. The quarterly data represent the recent one-and-a-half decades when the economy witnessed proliferation of several alternative financial instruments, while the annual data represent a longer time period, the earlier half of which was characterised by limited avenues for financial

[13] Q2DUM, Q3DUM and Q4DUM are dummies for the second, third and fourth quarters, respectively, to account for seasonal variations in CiC among quarters. The quarterly dummies suggest that, on average, CiC declines in the second, third and fourth quarters in comparison to the first quarter (which is the reference quarter). The dummy variable Q32017DUM is for the third quarter of 2016-17 and captures the impact of demonetisation – the dummy variable captures the return of currency to the banking system during the period of demonetisation. CiC, however, increased in the fourth quarter of 2016-17, with remonetisation as captured through the dummy variable (Q42017DUM). Q12018DUM represents the dummy for the first quarter of 2018-19 during which CiC increased on account of state elections. The dummy variable Q22008DUM captures the effect of the global financial crisis, indicating that the demand for currency increased during the period on account of the stimulus measures undertaken to revive the economy.

savings other than bank deposits. Financial market development and other avenues for savings available in the more recent period might have reduced the role of bank deposit rates as a proxy for the opportunity cost of currency in the quarterly model compared to the annual model. Short-run results, as expected, are stronger in the annual model with income elasticity being higher than in the quarterly model (Appendix A, Table A.5).

## Section VI
## Concluding Observations

In view of the importance of currency movements for implementation of monetary policy, this study draws on the existing literature to construct a menu of models for analysing and forecasting currency demand using a variety of time series and econometric techniques. The objective of the study was to develop a weekly currency forecasting model and analyse the determinants of currency demand with lower frequency data.

Several important findings emerge from the study. Digital payments are playing an increasingly important role in changing the payment habits of economic agents. The increased use of digital payments in the recent period has reduced the demand for currency, which has important ramifications for currency demand in the future. Moreover, policy-induced measures such as demonetisation have also brought about a downward shift in the trend component of currency which would have been much higher in the absence of demonetisation.

The key findings of the study from the weekly model are: (i) currency demand is higher in March and April and lower during the monsoon season; (ii) intra-month movements indicate a surge in currency demand in the second week of the month; (iii) demand for currency is also high during the festive season, especially during *Diwali;* and (iv) currency demand increases cumulatively by about 1 per cent during general elections when the election phase spans five weeks; the impact of elections on currency is higher if there are national or bigger state elections and if the duration of the electoral process is longer.

The monthly model incorporating digital payments suggests that (i) long-run income elasticity of currency demand is close to unity; and (ii) an increase in the number of digital (credit and debit card) transactions dampens currency demand in the short run. Findings from the quarterly model indicate that (i) in the long-run, income elasticity of currency demand is unity while the interest rate is not found to have any significant impact; and (ii) in the short run, however, both impact currency demand. Finally, the annual model suggests that: (i) currency has unitary income elasticity and the interest rate also impacts currency demand in the long run; and (ii) income elasticity in the annual model is higher than that in the quarterly model in the short-run.

There are several important policy implications that emerge from the findings. First, income continues to be a key determinant of currency demand and income elasticity of currency demand is unity in all the models across the time horizon. Therefore, currency demand in the foreseeable future is expected to grow broadly at the same rate as nominal income, which serves as an important guide for policy making. Second, it is found that currency will expand relatively at a faster (slower) pace in a low (high) interest rate environment when the opportunity cost of holding money is low (high), given the inverse relationship between currency demand and the interest rate. Third, since digital transactions (especially credit and debit cards) have a dampening impact on currency demand, there is a need to sustain the current thrust on digital transactions if currency growth is to be further moderated.

Going ahead, there is a scope to further extend the study in many dimensions. The availability of more granular-level data on digital payments over a longer time horizon would enable improved modelling of currency demand at the quarterly and annual frequencies. Increasing sophistication of financial markets would imply the availability of several alternative investment avenues for economic agents instead of relying solely on bank deposits. As a result, financial market returns from several alternative instruments can also be tested as proxies for the opportunity cost of holding cash rather than just deposit interest rates. Survey-based data on the public's preferences with regard to payment habits could also be a proxy for any behavioural shift in currency demand. Furthermore, purely statistical techniques such as a neural network model can be used for currency forecasting at higher frequency (daily data) for comparison with model-based forecasts. All of these issues, however, merit an in-depth analysis and could be the agenda for future research.

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## Appendix A: Annual Model

### Table A.1: Correlation Matrix

| Correlation | LCiC |
|---|---|
| LY | 0.99* |
| ADR | -0.07 |

**Note:** * denotes significance at 1 per cent.

### Table A.2: ADF and PP Unit Root Tests

| Regressor | Level | | First Difference | |
|---|---|---|---|---|
| | ADF | PP | ADF | PP |
| LCiC | -0.078 | -0.059 | -8.699* | -8.699* |
| LY | -0.694 | -0.134 | -4.712* | -4.781* |
| ADR | -2.022* | -2.156 | - | -5.689* |

**Note:** * denotes significance at 1 per cent. The constant and time trends are included in level, but the time trend is removed in first difference equations. The optimal lag order is selected based on SIC in the ADF test equation.
- = Not applicable.

### Table A.3: Bounds Test for Cointegration

| F-statistic | 99% lower bound | 99% upper bound | Outcome |
|---|---|---|---|
| 21.16 | 4.13 | 5.00 | Cointegration |

### Table A.4: The Long-run ARDL Cointegration Model (2, 1, 1)[#]

| Dependent variable: LCiC | | |
|---|---|---|
| **Regressor** | **Coefficient** | ***t*-Statistics** |
| LY | 1.066 | 238.04* |
| ADR | -2.465 | -6.044* |
| C | -2.690 | -45.49* |

[#] Lag length is selected using Akaike Information Criteria (AIC).
**Note:** * denotes significance at 1 per cent.

**Table A.5: ARDL Cointegration Short-run Error-correction Model**[14]

| Dependent variable: ΔLCiC | | |
|---|---|---|
| **Regressor** | **Coefficient** | ***t*-Statistics** |
| ΔLiC(-1) | -0.433 | -4.661* |
| ΔLY | 1.571 | 15.01* |
| ΔADR | -0.765 | -1.62 |
| DEMONDUM | -0.307 | -9.18* |
| 1972DUM | 0.110 | 3.04* |
| 1975DUM | -0.104 | -2.86* |
| 2008DUM | 0.084 | 2.23* |
| Error Correction (-1) | -0.826 | -9.58* |

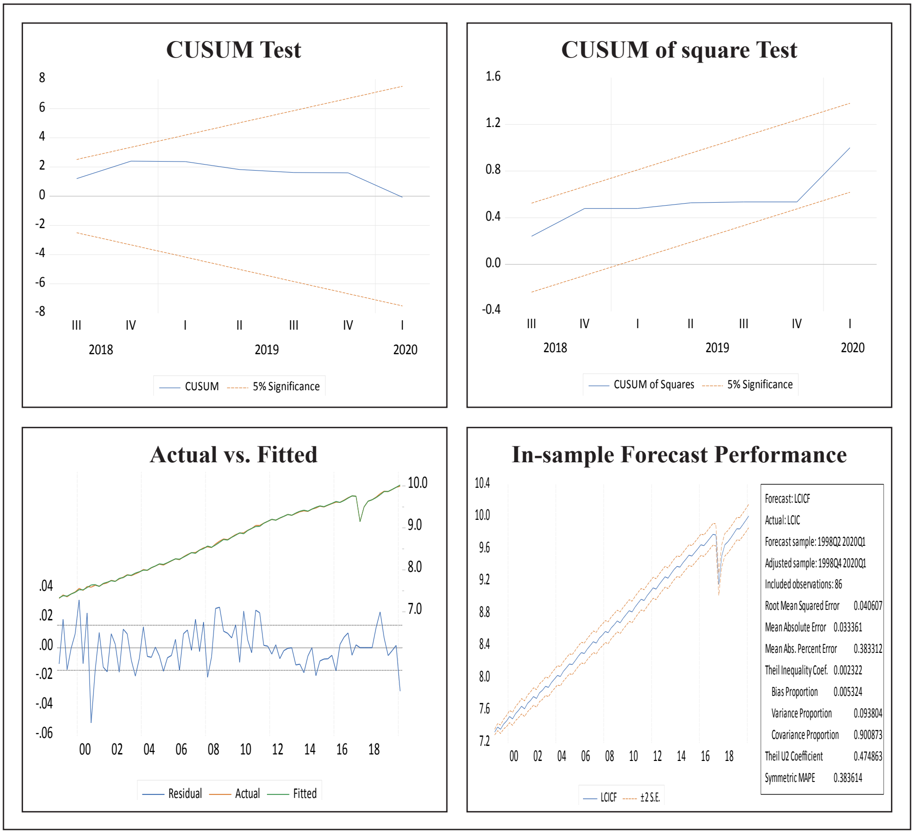
| *Diagnostic tests* | |
|---|---|
| Adjusted $R^2$: | 0.76 |
| DW statistics: | 1.89 |
| LM serial correlation F-test (*p*-value): | 0.84 |
| Breusch-Pagan-Godfrey heteroscedasticity Test F-test (*p*-value): | 0.24 |
| CUSUM test: | Stable |
| CUSUM of squares test: | Stable |

**Note:** * denotes significance at 1 per cent.

[14] DEMONDUM is the dummy variable which captures the impact of demonetisation in the year 2017. The coefficient of the dummy variable suggests that a large amount of money returned to the system during that year compared to other years, as expected. The dummy variable (2008DUM), capturing the effect of the global financial crisis, indicates that the demand for currency increased during the year on account of the stimulus measures undertaken to revive the economy. The dummy for the year 1972 (1972DUM) indicates that currency demand increased due to high inflation during that year. The dummy variable capturing the event during 1975 reveals that there was decline in currency demand because of the introduction of ₹20 denomination notes in 1972–73 and ₹50 denomination notes in 1975–76 which led to people migrating to these denominations from smaller denominations.

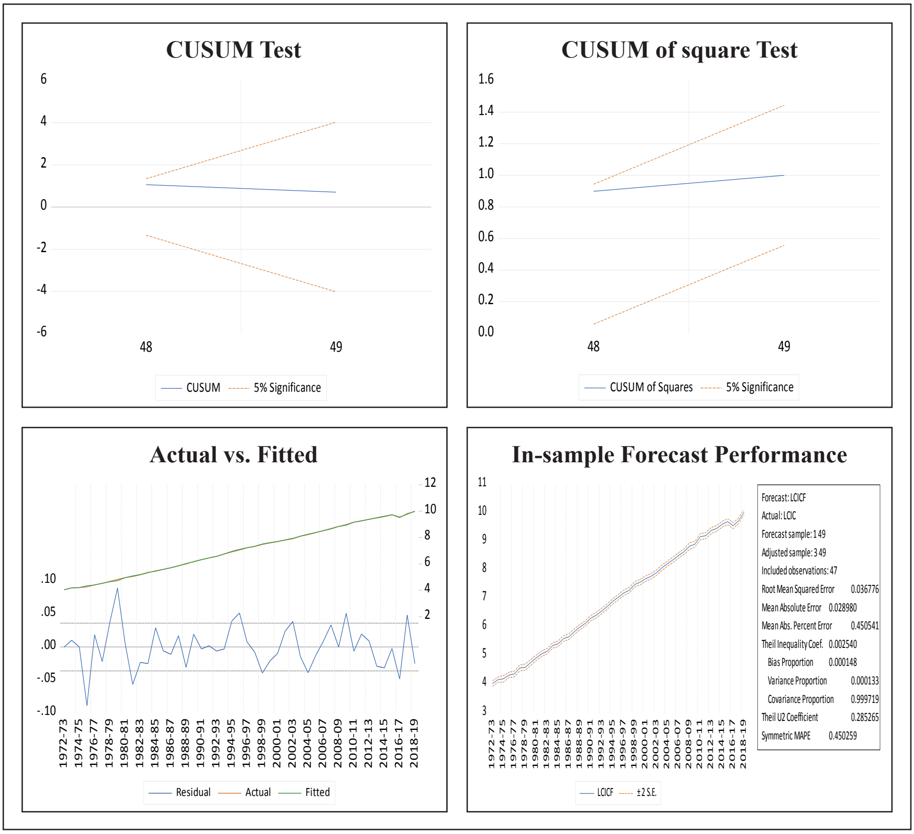
# Appendix B

## Chart B.1: Plot of CUSUM and the CUSUM of Squares of Quarterly Model



# Appendix C

## Chart C.1: Plot of CUSUM and the CUSUM of square of Annual Model



## Appendix D: Multivariate ARDL Method

The ARDL approach in this paper consists of estimating the following equation:

$$\Delta LCiC_t = \alpha_0 + \sum_{i=1}^{n} \beta_i \Delta LCiC_{t-i} + \sum_{i=0}^{n} \delta_i \Delta LNGDP_{t-i} + \sum_{i=0}^{n} \lambda_i \Delta ADR_{t-i} + \theta_1 LCiC_{t-1} + \theta_2 LNGDP_{t-1} + \theta_3 ADR_{t-1} + \varepsilon_t \qquad \text{.............(1)}$$

The first part of the equation with $\beta_i$, $\delta_i$ and $\lambda_i$ represent the short-run dynamics of the model, whereas the parameters $\theta_1$, $\theta_2$ and $\theta_3$ represent the long-run relationship. The null hypothesis of the model is

H0: $\theta_1 = \theta_2 = \theta_3$ (there is no long-run relationship)

H1: $\theta_1 \neq \theta_2 \neq \theta_3$

We start by conducting a bounds test for the null hypothesis of no cointegration. The calculated F-statistic is compared with the critical value tabulated by Pesaran and Pesaran (1997), and Pesaran *et al.* (2001). If the test statistic exceeds the upper critical value, the null hypothesis of a no long-run relationship can be rejected regardless of whether the underlying order of integration of the variables is 0 or 1. Similarly, if the test statistic falls below a lower critical value, the null hypothesis is not rejected. However, if the test statistic falls between these two bounds, the result is inconclusive. When the order of integration of the variables is known and all the variables are I(1), the decision is made based on the upper bound. Similarly, if all the variables are I(0), then the decision is made based on the lower bound.

The ARDL method estimates (p+1)k number of regressions in order to obtain the optimal lag length for each variable, where p is the maximum number of lags to be used and k is the number of variables in the equation. The orders of lags in the ARDL model are selected by the Akaike Information Criterion (AIC), before the selected model is estimated by ordinary least squares (OLS). In the second step, if there is evidence of a long-run relationship (cointegration) among the variables, the following long-run model is estimated:

$$LCiC_t = \varphi_0 + \varphi_1 LNGDP_{1t} + \varphi_2 ADR_{2t} + \nu_t \qquad \text{.............(2)}$$

After ascertaining the evidence of a long-run relationship, the next step involves the estimation of the ECM, which indicates the speed of adjustment back to long-run equilibrium after a short-term disturbance. The standard ECM involves estimating the following equation.

$$\Delta \mathrm{LCiC}_t = \alpha_0 + \sum_{i=1}^{n} \beta_i \,\Delta \mathrm{LCiC}_{t-i} + \sum_{i=0}^{n} \delta_i \,\Delta \mathrm{LNGDP}_{t-i} + \sum_{i=0}^{n} \lambda_i \,\Delta \mathrm{ADR}_{t-i} + \psi Z_{t-1} + \varepsilon_t \quad \text{.............(3)}$$

where $Z_{t-1}$ = ($\mathrm{LCiC}_{t-1}$ - $\varphi_0 - \varphi_1 \mathrm{LNGDP}_{1t-1} - \varphi_2 \mathrm{ADR}_{2t-1}$), and the $\varphi$'s are the ordinary least squares (OLS) estimates of the $\varphi$'s in equation 3.

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# *Pass-through of International Food Prices to Emerging Market Economies: A Revisit*

**Satyananda Sahoo, Sujeesh Kumar and Barkha Gupta***

Sharp upturns in international food prices in 2007-08 and 2010-11 have motivated a close scrutiny of their volatility, transmission and supply chains. While global food prices have remained tame since 2012, the uptick in prices of major food groups in the second half of 2019 is expected to add to the upside risks of domestic food prices across emerging market economies (EMEs), which are already witnessing high food inflation pressures due to internal supply shock conditions. Against this backdrop, this study intends to re-examine whether global food prices hold any implications for domestic prices in EMEs which have higher shares of food in their overall consumption baskets. Using data from January 2007 to July 2019, the study finds that short-term elasticities, in the range of 0.02-0.16, are lower than long-term elasticities. Moreover, there are large cross-country divergences in long-term transmission elasticities.

**JEL Classification:** F14, C22

**Keywords:** Food price transmission, law of one price, vector error correction model

## Introduction

Headline consumer price index (CPI) inflation in India exhibited sharp rise in the second half of 2019, breaching monetary policy's upper band level of 6.0 per cent in December 2019. This episode of high inflation is attributed to a spike in domestic food prices resulting from supply shocks across major food items. As India has transitioned along an inflation glide path[1] since 2014-15 – a precursor to the explicit Inflation Targeting (IT) framework –

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[1] The Reserve Bank followed a glide path to bring down inflation in a phased manner – 8.0 per cent by January 2015; 6.0 per cent by January 2016 and 5.0 per cent by Q4:2016-17.

such an uptrend in domestic inflation has caused resurfacing of concerns over food price volatility, raising questions on the role of the monetary authority in containing the same. While domestic supply conditions largely drive food inflation, shocks in international food prices are also among the important sources of domestic inflation in EMEs (Furceria *et al.,* 2016). Although global food prices have remained tame since 2012, an uptick in the prices of major food groups in the second half of 2019 is expected to add further upside risks to already rising domestic food prices, not just in India but also across other major EMEs.

The transmission of food price changes from international to domestic markets strengthened for EMEs due to the increased participation of these economies in global food markets and stronger market integration. Large increases in international food prices in 2007-08 and 2010-11[2] led to close scrutiny of food prices, their volatility, transmission and supply chain. Both advanced economies (AEs) and EMEs witnessed transmission of food price pressures although with different magnitudes. While a high transmission could promote comparative advantage and higher agricultural production, highly volatile prices could undermine the incentives for farmers to increase production in response to high prices, therefore undermining the scope to reduce domestic prices.

The World Bank's nominal food price index rose sharply in 2007-08 and 2010-11 registering an increase of 23.8 per cent on year-on-year (y-o-y) basis in 2007, 33.5 per cent in 2008 and 22.5 per cent in 2011. Such unanticipated increases in world food prices during these two episodes *i.e.,* 2007-08 and 2010-11 were seen across all food groups and the effect was particularly serious across EMEs as the average household in many EMEs spends a substantial part of its income on food. While the share of disposable income spent on food is around 10-15 per cent for many AEs, it is more than 20 per cent for most EMEs. As a result, the weight of food in the CPI basket remains at high levels in EMEs. Moreover, inflation expectations in AEs are relatively better anchored than in EMEs, which has further helped limit global food price pass-through across the former (*ibid*). Though the major EMEs

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[2] Refers to as the two episodes of unprecedented global food price spike.

have adopted inflation targeting to limit the pass-through of supply shocks to inflation through better anchoring of inflation expectations, high weightage of food in the overall CPI basket still remains a challenge, and thus, keeps EMEs vulnerable to such shocks.

Against this backdrop, this paper attempts to address the following issues: Are high and volatile global food prices a cause of concern for domestic inflation? If yes, to what extent do changes in world food prices get transmitted to domestic prices? While a few studies have been conducted to examine the degree of transmission at both individual and cross-country levels, no such study has been conducted in the recent past possibly because food prices have been relatively stable since 2012 until the second half of 2019, when they started showing signs of pickup again. Therefore, the present study is an attempt to re-examine whether the degree of pass-through is significant to EMEs and if any long-run relationship between world food prices and domestic food prices still holds.

The pass-through of fluctuations in world food prices to domestic food prices was examined for six EMEs, *viz*. China, Brazil, Sri Lanka, Thailand, Turkey and India as food products hold higher weightage in the CPIs of these countries. Based on monthly data from January 2007 to July 2019, the study finds that while all the transmission elasticities are positive, they differ across countries. The short-term pass-through coefficients are limited to a range of 0.02-0.16. While the findings of this paper reaffirm that transmission from global food prices to domestic food prices is incomplete in case of EMEs, it finds that there has been a large cross-country divergence in transmission elasticities in the long term. Moreover, the paper contributes to the literature by examining whether the nature of pass-through from international to domestic food prices has changed over time with evolving global and domestic trade dynamics.

The remaining of the paper is structured as follows. Section II briefly reviews the literature, while some stylised facts on global food prices are discussed in Section III. The methodology used in the paper is explained in Section IV. Empirical findings are presented in Section V. The concluding observations are set out in Section VI.

## Section II
## Review of the Literature

Global food price volatility has always been a matter of concern as it holds implications for domestic food inflation across economies and, therefore, poses a significant challenge in designing appropriate policy responses. Such concerns are specifically serious for EMEs than those for AEs since food forms a larger part of their consumption basket and their monetary policy may lack credibility to anchor inflation expectations and find it difficult to contain pass-through effects effectively (Furceria *et al.*, 2016). A vast pool of studies could be found in the literature which analysed the transmission of global food price shocks to domestic food price inflation and volatility, both individual and cross-country experiences (Appendix Table A.1).

Some of the earlier studies have examined the pass-through of global food price shocks to both AEs and EMEs and suggested that such pass-through could be incomplete across economies (Ianchovichina *et al*., 2012; IMF, 2011a; Sharma, 2003). Moreover, such transmission has also been found to be asymmetric across AEs and EMEs, with pass-through tending to be higher for the latter (IMF, 2011a). Dawe (2008), Imai *et al.* (2008) and Minot (2011) even found evidence of heterogeneity in transmission across different varieties of crops.

While assessing the impact of various internal and external factors on domestic food price inflation, Lee and Park (2013) found evidence of transmission of global food price inflation and volatility to domestic economies. According to their findings, domestic food inflation, specifically in Asia, was found to be strongly related to past values of global food inflation, while volatility spillovers from global to domestic food prices were found to be contemporaneous. Moreover, the study suggested that the degree of pass-through of global food prices to domestic food prices differs across regions and internal factors play an important role in determining national food price inflation and volatility. While examining the implications of high international food prices for inflation in select Central Asian economies, *viz.* Tajikistan, Kazakhstan, Uzbekistan, and the Kyrgyz Republic, Al-Eyd *et al.* (2012) concluded that global food prices have significant short-run effects on headline inflation in these economies. Based on a simulation experiment, they found that administrative measures are ineffective in controlling domestic inflation in these economies. Similarly, Minot (2011) in his study based on 11 Sub-Saharan African countries for eight food items during 2007 and 2008 found evidence of transmission of global food prices to domestic prices of rice and, to some extent, maize. Imai *et al.* (2008) found a faster transmission of prices for crops like rice, maize and wheat than for fruits and vegetables in India and China.

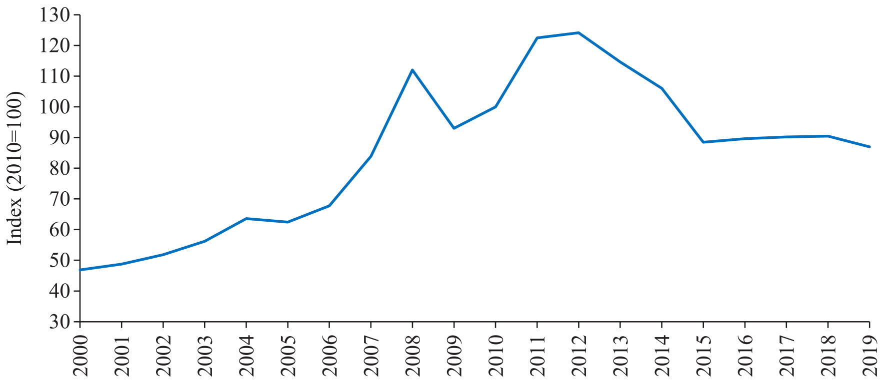
Among country-specific studies, the study by Barahona and Chulaphan (2017) examined the extent to which changes in global food price indices get transmitted to consumer price indices for diverse groups of consumers in Thailand in order to understand if the welfare of different types of consumers was equally affected by variations in world food prices. Their findings suggested that food inflation faced by the rural household was more responsive to changes in world food prices as their food basket consisted more of fresh agricultural commodities and essential food items which in turn were found to be highly sensitive to world price fluctuations. Selliah *et al.* (2015) empirically assessed the impact of the global food price surge on domestic inflation using monthly price series between 2003 and 2012 for Sri Lanka. Their results suggested a strong co-movement between global and domestic food prices. A similar study by Gomez Lopez and Gallardo (2013) on Mexican markets suggested that global food price pass-through exists in the long run and not in the short run for these markets. Shittu *et al.* (2017) examined the patterns, drivers and policy responses to food price spikes and volatility in Nigeria. They found that international food prices and crude oil prices, along with other domestic macroeconomic factors, *viz.* real exchange rate, monetary policy rate and narrow money, contributed to food price instability in Nigeria.

In the Indian context, we found very few studies that particularly examined the pass-through of global food prices to Indian food prices. In most studies, the variations in global food prices have either been included as one of the factors affecting Indian food inflation (Bhattacharya and Sen Gupta, 2017; Mishra and Roy, 2012) or India has been considered as one of the EMEs in the cross-country analysis (Dawe, 2008; Imai *et al.*, 2008; Sivabalasingam, 2018). Rajmal and Misra (2009) have, however, particularly looked into the pass-through of global food prices to the Indian food prices. In their analytical review, they suggested that domestic food price levels and volatility remained lower than that of international prices and were driven mainly by domestic factors which led to limited pass-through during the price hike episode of 2007-08. The findings of the above-mentioned studies have, however, been quite unanimous, showing limited pass-through from international food prices to domestic prices as local factors play a dominant role in driving food prices in India. With this background, the present study attempts to revisit the phenomenon of international food price pass-through to domestic prices in some of the major EMEs and to empirically examine whether international food prices, which have been relatively stable yet high over the past couple of years but have shown signs of firming up in the second half of 2019, drive domestic food prices.

## Section III
## International Food Prices: Stylised Facts

Global food prices have eased since 2012 after witnessing a sharp increase in 2007-08 and 2010-11 and remained relatively stable since 2015, until recently when global food prices showed signs of pickup in second half of 2019. The rise was particularly significant between 2000 and 2008, as reflected in an increase of more than 80 per cent in real terms in the World Bank's food price index (Chart 1). During the first episode of 2007-08, world food prices firmed up by 24 per cent in 2007. This increase accelerated further

**Chart 1: World Bank Global Food Prices**




**Source:** World Bank Commodity Price Data (The Pink Sheet).

in the first half of 2008 on demand-supply imbalances in the global market, resulting in an overall increase of around 34 per cent in 2008. Besides, the rise in demand for biofuels, increased agricultural input prices due to high oil prices, adverse weather conditions in some major producing countries and speculative transactions in commodity markets further added to the upward pressure on food prices during that period. The upturn in international food prices resulted in increased food price inflation around the world, thereby raising concerns over food security and its impact on health and nutrition, specifically for countries with a larger proportion of low-income consumers who spend a substantial portion of their income on food commodities (Table 1). Although food prices declined in the second half of 2008, the uptrend resumed in mid-2010, marking a second consecutive spike within a decade, thus reviving concerns over high prices and the associated volatility.

In both the episodes (2007-08 and 2010-11), movements in the world and domestic food prices were in line with earlier episodes of high prices seen in 1970s, where domestic prices adjusted gradually to rapidly rising world prices. However, the major difference between these two episodes of 2007-08 and 2010-11 was that the food price increase in 2007-08 followed a long period of stability in prices, while in 2010-11, the food price spike episode occurred when world markets and domestic polices were still in the phase of

**Table 1: Food Weightage in Consumer Price Index**

(In per cent)

| Country | Food Share | Does Target Inflation? |
|---|---|---|
| Bangladesh | 58.84 | No |
| Brazil | 22.90 | Yes (4.0 ± 1.5) |
| China | 30.20 | No |
| India | 45.86 | Yes (4.0 ± 2.0) |
| Indonesia | 36.20 | Yes (3.0 ± 1.0) |
| Pakistan | 40.34 | No |
| Philippines | 46.58 | Yes (3.0 ± 1.0) |
| Russia | 37.30 | Yes (4.0) |
| South Africa | 17.24 | Yes (3.0-6.0) |
| Sri Lanka | 45.50 | No |
| Thailand | 33.01 | Yes (1.0 - 3.0) |
| Turkey | 34.78 | Yes (5.0) |

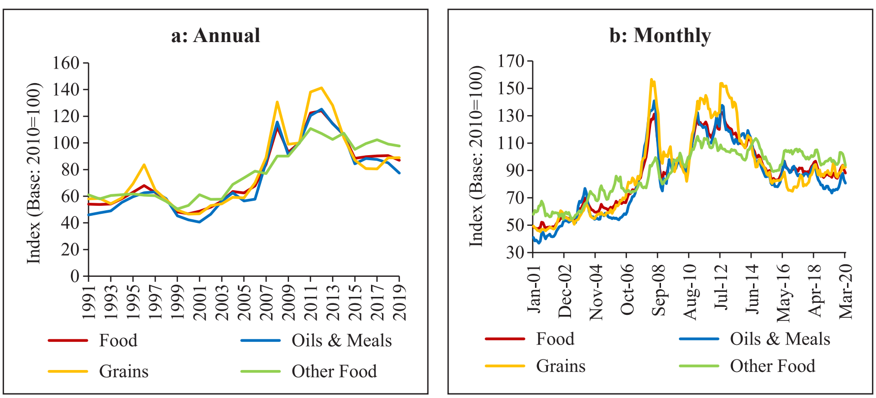
**Source:** Websites of respective central banks and statistics authorities.

recovery from the 2007-08 price shock (Laborde *et al.*, 2019; World Bank, 2019).

The unanticipated spikes were witnessed across all food groups with grains contributing to the highest increase in price followed by oils and meals (Chart 2). While the extent of price hike in both episodes was more or less the same, the affected commodities were not the same. During 2007-08, while sugar prices remained low, prices of rice, wheat, oil and other cereals remained elevated.

World rice prices increased by almost 100 per cent in 2008 (y-o-y) following export restrictions by major producers amid concerns over food security, while a weak dollar and rising oil prices added further upward pressures (World Bank, 2019). During 2010-11, however, rice prices increased merely by around 15 per cent - much less than that during the first episode (Chart 3a). Rice prices were particularly high in Asia, while the rise in wheat and maize prices was much more prominent in Central and South America (Rajmal and Misra, 2009). World wheat prices increased sharply by around 70 per cent between 2006 and 2008 on supply disruptions caused by drought in major exporting countries, while in 2011 it increased by 41 per cent (y-o-y), driven by supply-demand imbalances (Chart 3b). Similarly, world maize prices increased by around 57 per cent in 2011 compared to 36 per cent increase in 2008 (Chart 3f), largely driven by adverse weather conditions in

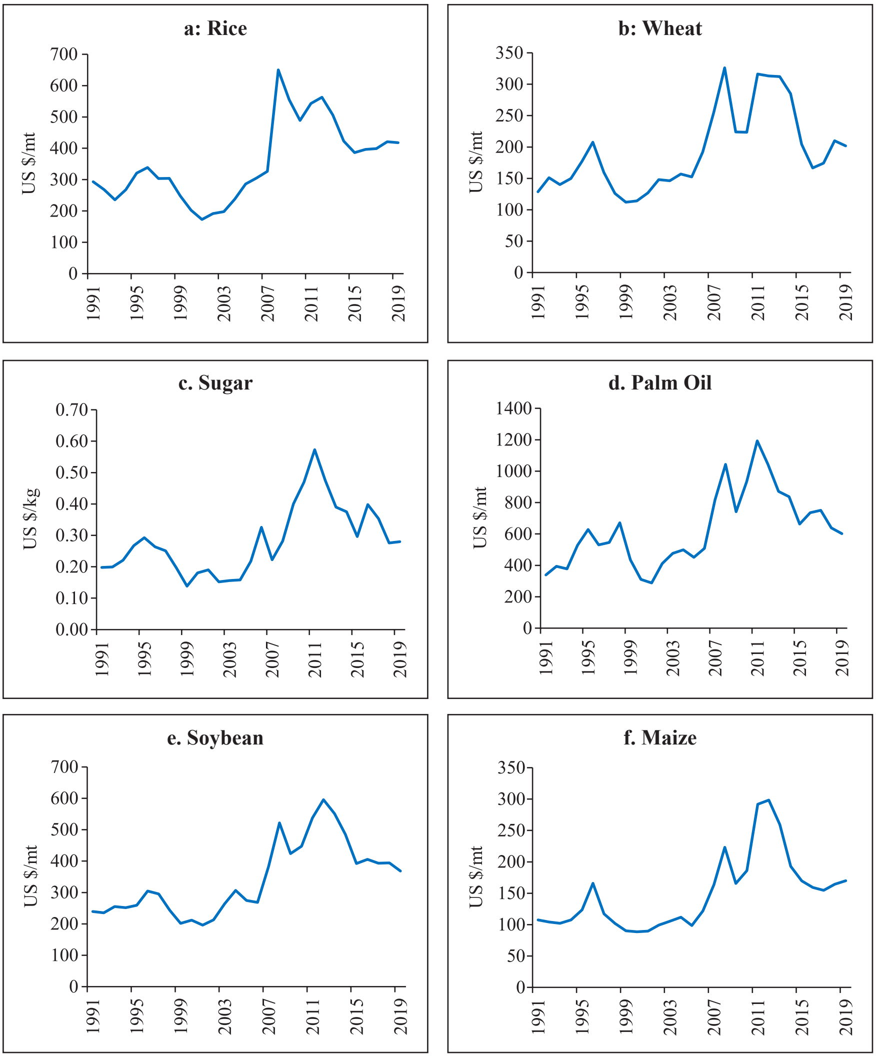
**Chart 2: Global Food Prices – Major Components**




**Source:** World Bank Commodity Price Data (The Pink Sheet).

major maize exporting countries and increased demand from the United States (US) to meet mandatory targets of ethanol production (World Bank, 2019). In contrast to cereals, sugar prices remained relatively stable during the first episode, picking up gradually to register a sharp rise in 2011 due to demand pressures emerging out of rising biofuel production (Chart 3c). A similar trend was witnessed for palm oil and soybean (Charts 3d and 3e).

**Chart 3: World Prices of Major Food Items**



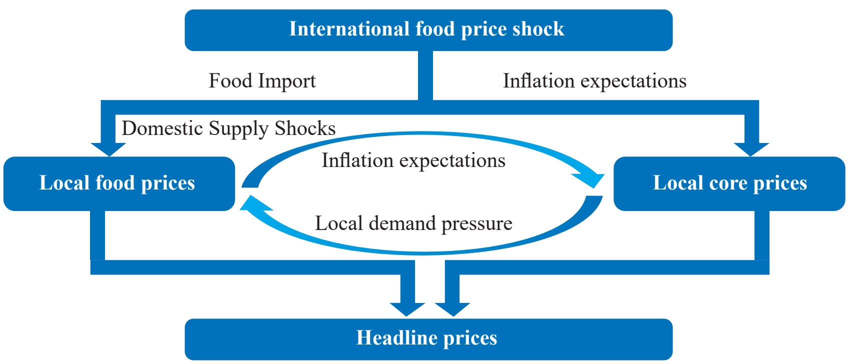

**Source:** World Bank Commodity Price Data (The Pink Sheet).

### *III.1 Transmission of Global to Domestic Food Prices*

International food prices can get transmitted to domestic prices through different channels. First, and the most direct, is the import channel which operates (a) when economies are either highly dependent on imported food items to meet their domestic demand or (b) in situations of internal supply shocks where economies attempt to contain the price rise through imports. In such situations, the possibility of pass-through from elevated global prices to domestic prices increases. Second, an increase in prices of imported food items encourages import substitution with locally produced goods, thereby adding upward pressure to the local prices of those goods (Jalil and Tamayo Zea, 2011). Furthermore, high global prices incentivise local producers to increase their share of exports in total production to earn higher profits, which in turn pushes domestic prices upwards on the back of internal supply shortages (Chart 4).

While there are various channels through which changes in international prices get transmitted to domestic prices, country-specific factors play an important role in determining the effectiveness and magnitude of these pass-through channels, thereby explaining the differential impact of international food price shocks on different economies. Moreover, the extent of pass-through also varies across countries, depending on the strength of the policy framework and other structural factors (IMF, 2011b). For instance, a country's

**Chart 4: International Food Price Shocks to Domestic Prices – Transmission Channels**




**Source:** Reproduced from Jalil and Tamayo Zea, 2011.

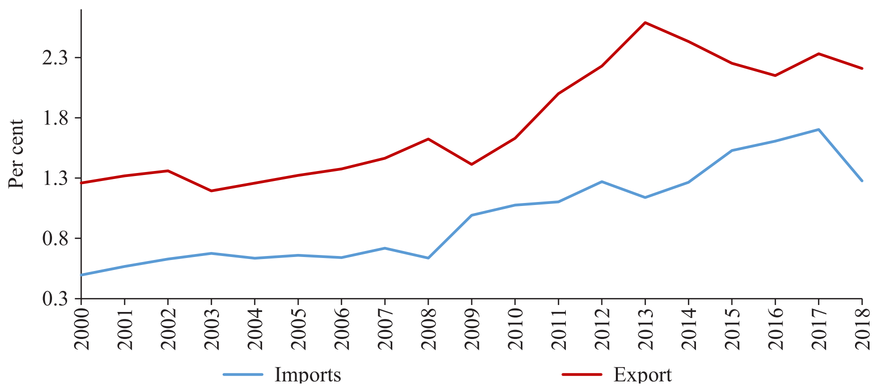
prevailing market structure and design for distribution chains determine the market power of the sellers and their ability to transmit price shocks to the consumers. Other country-specific factors, *viz*. policy interventions, transport facility, transaction cost and exchange rate regime, also determine the magnitude and intensity of the transmission process (Cachia, 2014).

### *III.2 India's Experience*

In the Indian context, the share of food exports in world food exports has remained higher than the share of food imports in world food imports, implying the dominance of the export channel. However, as India's share in world food trade in terms of both exports and imports has remained very low, the pass-through might have been weak (Chart 5).

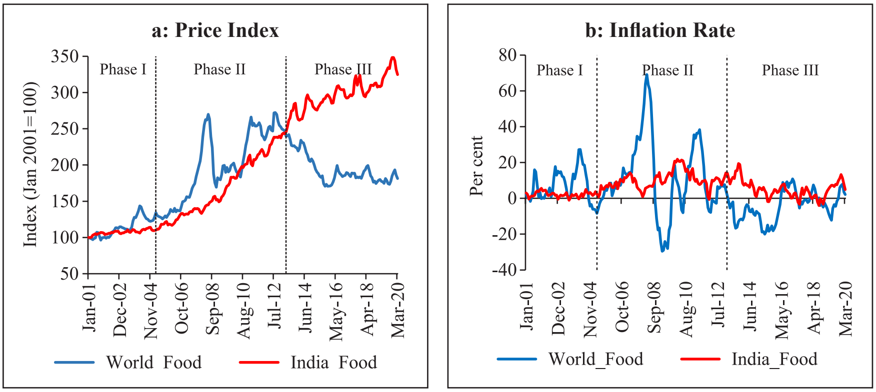
The movement of Indian food prices *versus* global food prices during the last two decades could broadly be classified into three distinct phases. Generally, Indian food prices moved in tandem with international food prices in the first two phases, between 2001 and 2013. In the first phase between 2001 and 2005, while international and domestic prices moved in close sync, they exhibited intermittent divergent movements in the second phase, *i.e*., between 2006 and early 2013 as the rise in world food prices was much sharper than the rise in Indian food prices (Chart 6a). Global food prices spiked sharply twice, *i.e.* in 2007-08 and 2010-11, while Indian food prices registered a steady increase, rising by almost 90 per cent between July 2006 and December 2012

**Chart 5: India's Share in World Food Trade**




**Source:** World Trade Organization and authors' estimates.

**Chart 6: World vs Indian Food Prices**

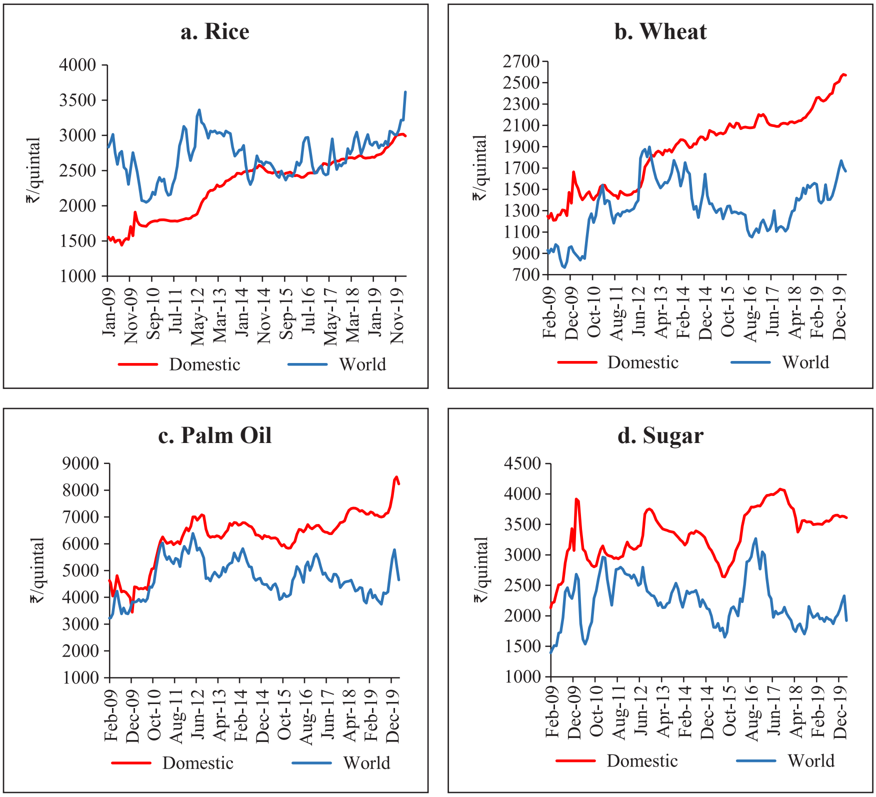



**Source:** World Bank Commodity Price Data (The Pink Sheet), RBI, and authors' estimates.

– much higher than that in the first phase. Therefore, the upward pressure on Indian food prices that started building up in early 2006 on domestic factors was further accentuated by episodes of global food price shocks. Such shocks in global food prices led to a sharp rise in global food inflation by around 70 per cent in early 2008 and 35 per cent in early 2011 (Chart 6b). Domestic food inflation also picked up during this period, reaching to almost 20 per cent in early 2010 – much higher than the level which prevailed between 2001 and 2005. In the third phase, beginning 2013, however, global and domestic food prices showed signs of divergence as global prices fell sharply on the back of excess supply leading to deflation, while domestic prices remained slightly elevated. Although Indian food prices also moderated during this period, leading to disinflation in Indian food prices, the extent of the decline was not as sharp as in global food prices. During this phase, Indian food prices were supported by an administered price policy and low import content which delinked domestic prices from global prices to some extent.

At the commodity level, significant variations could be found across different commodity prices (Chart 7). Palm oil and sugar prices – both being tradeable goods in world markets – co-moved with international prices. As a net importer of palm oil, India is a price-taker in the world market and thus domestic prices are highly influenced by global prices. In the case of sugar, while Indian prices are highly administered, a certain degree of co-movement in international and domestic sugar prices is visible due to the possibility of

**Chart 7: India vs World Food Prices**




**Source:** World Bank Commodity Price Data (The Pink Sheet), Department of Consumer Affairs, Government of India and authors' estimates.

global sugar prices being taken as the benchmark while deciding on domestic sugar prices. However, in the case of rice and wheat, such co-movement could not be traced as the prices of these commodities are highly influenced by domestic factors and the policies of the government at different points of time to limit the fluctuations in their prices, *viz.* public distribution system, minimum support price and interventions through different trade policy instruments.

In sum, while world food prices have decreased since 2012, they continue to remain higher than the levels observed before 2007-08. Also, as mentioned earlier, world food prices showed signs of uptick in last few months of 2019. Moreover, domestic food prices across some major EMEs have also edged up in recent months on supply-demand imbalances. Therefore, if global food prices continue to rise, they may add upside risks to the domestic food prices, which will in turn pose challenges in containing inflation. Thus, with this background, we examine whether global food prices still have implications for domestic prices of EMEs which have a higher share of food in their overall consumption basket.

## Section IV
## Methodology

The pass-through effect of global food prices on domestic prices could be drawn from the principle of the Law of One Price (LOP) (Ardeni, 1989; Selliah *et al*., 2015). According to the LOP principle, in efficient markets, assuming there is no transport cost or hindrances to trade, prices for a single homogenous commodity, when expressed in a common currency, are defined as follows[3] (RBI, 2019):

$$P_d = EP_w \tag{1}$$

where,

$P_d$ : domestic food price;

$E$ : exchange rate [unit(s) of domestic currency per unit of foreign currency]; and

$P_w$: world (foreign) food price.

Equation (1) can be modified to its estimable form after expressing in natural logarithm form as:

$$lnP_{d_t} = \alpha + \beta lnP_{w_t} + \gamma lnE_t + \varepsilon_t \tag{2}$$

In equation (2), $lnP_w$ is assumed to be exogenous as EMEs are usually price-takers. The coefficient β is expressed as the long-term price transmission elasticity when the long-term relationship is empirically established through cointegration test. It may be noted that LOP expressed in equation (1) is in its strict form based on the theory of purchasing power parity (PPP) which states that the exchange rate is proportional to the ratio of price levels in two

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[3] The methodology used in this paper is from the authors' earlier work (RBI, 2019).

countries. Equation (2) is an estimable version of equation (1) or a weak form of LOP under the belief that PPP holds in the long run.

Short-term price elasticity is derived from the estimated error correction model (ECM) of the following form:

$$\Delta lnP_{d_t} = \delta + \sum_{i=1}^{k} \rho_i \, \Delta lnP_{d_{t-i}} + \sum_{i=1}^{l} \varphi_i \, \Delta lnP_{w_{t-i}} + \sum_{i=1}^{m} \gamma_i \, \Delta lnE_{t-i} + \theta ECT_{t-1} + \epsilon_t \quad (3)$$

In the above equation, ECT is defined as the error correction term and Δ is the first difference operator. The parameters φ and γ are the short-term transmission elasticities and ρ is the persistence parameter.

## Section V
## Empirical Findings

To estimate the degree of pass-through from international food prices to domestic food prices, this study uses the data on six EMEs which have higher shares of food products in their respective consumer price indices, *viz.* China, Brazil, India, Sri Lanka, Turkey and Thailand. The estimated model also included the share of each country's food imports (barring Sri Lanka and Thailand) to world merchandise import and share of food exports to world merchandise exports as control variables. Data are sourced from the Food and Agriculture Organization (FAO), CEIC, the Bloomberg database and official websites of individual countries. The monthly data from January 2007 to July 2019 were used for the analysis. Further, in order to make a common base, the data were spliced wherever required. For estimation purposes, all variables were transformed to the natural logarithm.

The descriptive statistics of CPI-food and exchange rates of all six countries (Appendix Tables A.2 and A.3) indicate that the statistical properties of the series were not the same across countries. While volatility in the CPI-food measured by standard deviation was highest for Brazil, it was the lowest for Thailand. The Sri Lankan rupee exhibited the highest volatility, while volatility in the Chinese yuan was the least.

Before estimating the transmission elasticity through the ECM model, the stationarity property of the time series variables was tested by conducting unit root tests. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP)

**Table 2: ADF Unit Root Test**

| Country | ADF (level) | | ADF (first difference) | |
|---|---|---|---|---|
| | CPI Food | Exchange rate | CPI Food | Exchange rate |
| Brazil | -1.7253 | -2.5080 | -6.2446 | -11.5531 |
| China | -1.7855 | -2.5080 | -6.1810 | -8.73680 |
| India | 0.2334 | -2.6024 | -8.4563 | -11.3840 |
| Sri Lanka | -3.8280 | -2.1749 | -8.9570 | -9.61650 |
| Thailand | -1.8469 | -2.0644 | -9.9883 | -10.6706 |
| Turkey | -3.0233 | -2.4584 | -7.6827 | -10.8894 |
| World | -2.9592 | | -7.4802 | |

**Note:** ADF statistics are calculated at level and first difference. All differenced series statistics are significant at 5 per cent level.
**Source:** Authors' estimates.

tests were used to test the stationarity of the series. All variables of interest were found to be stationary in the first difference, *i.e*. I (1) (Tables 2 and 3).

Given that all the variables were I(1), Johansen's cointegration test was performed which confirmed the presence of one cointegrating relationship between the international food prices and domestic food prices of individual countries based on maximum eigen value and trace tests. Subsequently, vector error correction models (VECM), with optimal lag lengths based on Akaike Information Criteria (AIC), were used to examine if any relationship exists in the long run and the short run. The estimated VECM model for each country satisfies the condition that there is no serial correlation in the residuals.

**Table 3: PP Unit Root Test**

| Country | PP (level) | | PP (first difference) | |
|---|---|---|---|---|
| | CPI Food | Exchange rate | CPI Food | Exchange rate |
| Brazil | -1.0977 | -2.6947 | -5.9184 | -11.6374 |
| China | -1.5034 | -1.7892 | -6.1488 | -8.70770 |
| India | -1.3297 | -2.6024 | -6.4200 | -11.3660 |
| Sri Lanka | -3.7662 | -2.3750 | -10.213 | -9.84850 |
| Thailand | -1.3600 | -2.1747 | -9.9883 | -10.6137 |
| Turkey | -2.2787 | -2.5602 | -9.9818 | -10.8510 |
| World | -2.8891 | | -7.5344 | |

**Note:** PP statistics are calculated at level and first difference. All differenced series statistics are significant at 5 per cent level.
**Source:** Authors' estimates.

### *V.1. Food Price Pass-through*

The dynamics of food price pass-through were analysed by estimating long-term coefficients and short-term coefficients using the VECM framework. The short-term and long-term coefficients were obtained from the error correction models and cointegration equations, respectively. The estimated error correction term for each country was found to be negative and statistically significant, implying that the system was not explosive and thus ensured long-run equilibrium (Appendix Table A.4). The pass-through coefficient of world food prices was positive and statistically significant for all six countries, *viz.* China, Brazil, India, Sri Lanka, Turkey and Thailand (Table 4). The estimated price transmission elasticities from the VECM confirm the heterogeneity of price transmission across countries but at a lower magnitude. The pass-through coefficient ranged from 0.02 to 0.16 and the largest value 0.16 was found for Turkey. The results of the study are in line with the empirical findings of Selliah *et al.* (2015) and Sivabalasingam (2018).

In the case of India, the short-term price transmission elasticity for food price is 0.07, which implies that a 10 per cent increase in world food prices could lead to an increase of 0.7 per cent in Indian food CPI.

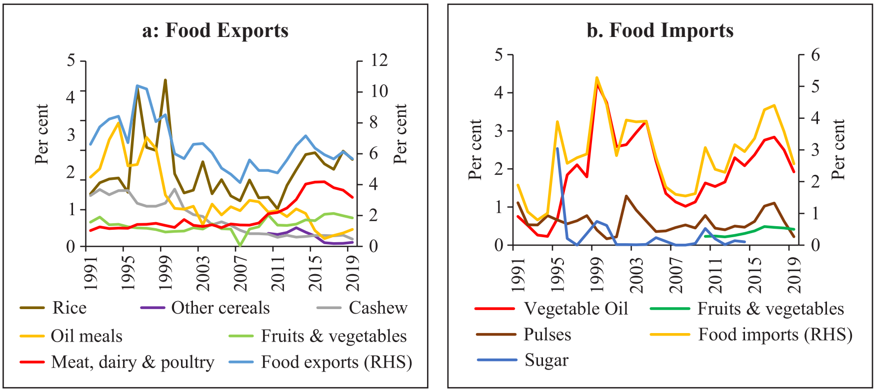
The long-term transmission elasticities were obtained from the estimated cointegrating equations. There was a high degree of heterogeneity in the pass-through of world food prices to domestic food prices. The long-term transmission elasticity of world food price ranged from a low of 0.25 for China to a high of 1.97 for Brazil (Appendix Table A.5).

**Table 4: Estimated Pass-through Parameters – World Food Prices**

| Country | Short Run | | Long Run | |
|---|---|---|---|---|
| | Coefficient | t-Statistics | Coefficient | t-Statistics |
| Brazil | 0.028* | 1.612 | 1.971*** | 23.44 |
| China | 0.024* | 1.690 | 0.247* | 1.625 |
| India | 0.077*** | 2.251 | 0.298** | 2.104 |
| Thailand | 0.036** | 1.784 | 0.396*** | 2.039 |
| Sri Lanka | 0.127*** | 2.754 | 0.426* | 1.85 |
| Turkey | 0.162*** | 2.937 | 1.030*** | 14.65 |

**Note:** ****, ***, ** and * denote 1 per cent, 5 per cent and 10 per cent and 15 per cent level of significance, respectively.
**Source:** Authors' estimates.

**Chart 8: Share of Different Food Items in Total Export and Import in India**




**Source:** Reserve Bank of India and authors' estimates.

The heterogeneity in the degree of pass-through of international food prices to domestic prices could be due to divergences in the import of food items across countries. For example, a muted pass-through for India could be reflective of a very low share of food imports to total imports (Chart 8). The share of import of three major food items, *viz*. vegetable oil, pulses, and fruits and vegetables, was very low at 2.6 per cent of total imports in 2018-19. India's export of major food items was 5.0 per cent of total exports in 2018-19. However, during periods of a very sharp increase in international food prices of more than 20 per cent or so, as witnessed during 2007-08 and 2010-11, the transmission elasticity of 0.07 could lead to an increase in domestic food prices by over 1.0 per cent. This, therefore, signifies the need for examination of the extent of the pass-through from international to domestic prices for it might have serious implications for domestic inflation in EMEs when global prices witness sudden shocks. Such an examination would help these economies to respond with appropriate policies.

## Section VI
## Concluding Remarks

The main objective of this paper was to examine, in a cross-country context, the following: (i) the degree of pass-through of global food price variations to domestic food prices; and (ii) whether a long-run relationship exists between global food prices and domestic food prices. Using cointegration tests, the paper found that while there exists a significant degree of global food price transmission to domestic prices in the long-run, such pass-through is relatively weak in the short-run. The short-run price transmission elasticities are of lower magnitude, ranging from 0.02 to 0.16, and differ across countries. The long-run transmission elasticities of world food prices range from 0.25 to 1.97.

As the weight of food is substantial in the CPI baskets of many EMEs, it is crucial that authorities design appropriate policy measures to limit the impact of high and volatile international food prices on domestic markets. Moreover, countries with a high degree of transmission need to shift policy attention towards ensuring food security by increasing food production, investing in agricultural research, facilitating grain trade, and promoting diversification. While the study signifies the importance of monitoring the impact of global food prices on domestic prices at an aggregate level, it may be useful to examine pass-through at the commodity level as well to further explore the cross-country variations in pass-through.

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# Appendix

## Table A.1: Pass-through of International Food Prices – Empirical Evidence from Select Studies

| Author(s) and Year | Period of Study/Data | Objective | Methodology | Key findings |
|---|---|---|---|---|
| Al-Eyd *et al.* 2012 | Monthly data from December 2003 to October 2010 | The paper examined the implications of elevated global food prices for inflation in select Central Asian economies – Kazakhstan, the Kyrgyz Republic, Tajikistan, and Uzbekistan – by analysing the drivers of inflation in these countries. | A simple model of inflation was estimated using panel data techniques. The transmission of monetary policy through policy interest rates was examined for which inflation outcomes were simulated under alternative scenarios for global wheat prices for each of the CA-4 using simple AR models. | The major findings of the paper suggested that global food prices have significant short-run effects on headline inflations of domestic economies of Kazakhstan, the Kyrgyz Republic, Tajikistan, and Uzbekistan, where headline inflations, driven by rising international food prices, have been found to be larger than other regions of the world. Moreover, based on a simulation experiment, the results indicated that administrative measures were ineffective in controlling domestic inflation. |
| Dawe 2008 | Monthly data for the period 2003-07 | The paper analysed the extent to which domestic food prices in seven large Asian countries have increased since 2003, specifically cereal prices, following an increase in world cereal prices | The paper conducted comparative analysis between international and domestic cereal prices to analyse the extent of pass-through. The core of the analysis was to perform a very | Major findings of the study showed that increase in world cereal prices were accompanied by real depreciation of the US dollar, which in turn neutralised, to some extent, the impact of high world |

*(Contd...)*

| Author(s) and Year | Period of Study/Data | Objective | Methodology | Key findings |
|---|---|---|---|---|
| | | from 2003. Furthermore, it examined changes in both consumer and producer prices to see if these groups were affected differently. | basic calculation of cumulative changes in international and domestic prices in real (inflation-adjusted) terms between the fourth quarter of 2003 and the fourth quarter of 2007. | prices for many countries. Additionally, the domestic commodity-specific policies further helped to stabilise domestic prices, especially for rice and wheat, relative to world prices in these Asian countries. Also, no significant difference was found in terms of the impact of world price shock on farmgate prices and consumer prices, thus reflecting that price changes were transmitting rather efficiently between farmers and consumers in the domestic markets of these Asian countries. |
| Furceria *et al.* 2016 | Two data sets were used. The first data set consists of annual data from 1960 to 2012 for 44 countries, including both AEs and EMEs. The second data set consists of monthly data on CPI | The paper analysed the impact of fluctuations in global food prices on domestic inflation of various AEs and EMEs. | To estimate the impact of global food prices on domestic inflation, the study estimated impulse response functions directly from local projections. | The study found that the fluctuations in global food prices played a significant role in driving the domestic inflation of AEs since 1960. This considerable impact, however, declined and became less persistent over time. The study also suggested that |

*(Contd...)*

| Author(s) and Year | Period of Study/Data | Objective | Methodology | Key findings |
|---|---|---|---|---|
| | and food prices for 34 AEs and 50 EMEs for the period 2000-2013. | | | global food price shocks of 2007-08 and 2010-11 had a bigger impact on EMEs than AEs as the former have a larger share of food in their consumption baskets and relatively less anchored inflation expectations than the latter. |
| Lee and Park 2013 | Panel data for the period 2000-2011 (yearly) for 72 countries. | This paper conducted a comprehensive assessment of the transmission of global food prices and their volatilities to national food prices and their volatilities. It also assessed the effects of the various internal and external factors on domestic food price inflation and volatility. | In order to assess the global transmission of food price inflation and volatilities to individual countries, the study used fixed effects model with inflation and volatility measures as two different dependent variables. | The paper found evidence in support of international transmission of food price inflation and volatility specifically in Asia, where domestic food price inflation is strongly associated with the lagged value of global food price inflation, while volatility spillovers from global to domestic food prices were rather contemporaneous. Also, the paper found that national food price inflation and volatilities were affected by both intra- and extra-regional food price inflation and volatilities, respectively. |

*(Contd...)*

| Author(s) and Year | Period of Study/Data | Objective | Methodology | Key findings |
|---|---|---|---|---|
| Bara hona and Chulaphan 2017 | Monthly data from January 1995 to November 2015. | The paper studied the extent and degree to which changes in world prices were transmitted to the consumer prices of different types of consumers in Thailand. | Cointegration between world and domestic food prices was investigated using Engle-Granger's cointegration test. | The study found that world prices were cointegrated with domestic prices and the speeds of adjustment were found to be similar across different consumer price indices, *i.e.* consumer food price indices for average consumers and low-income consumers were found to be equally sensitive to changes in world prices. |
| Minot 2011 | More than 60 price series from 11 African countries for 2007-08. | This paper examined the degree to which variations in world food markets influence the price of staple foods in Sub-Saharan Africa. | The study examined the price trend over 2007-08 and used an error correction model to estimate the degree of price transmission. | Key findings suggested that the food prices in Sub-Saharan African countries rose between 2007 and 2008, ¾ times the proportional increase in world prices. Empirical results indicate that a long-term relationship exists between world prices and 13 out of 62 Sub-Saharan African countries which were examined. Furthermore, policy responses and local factors further exacerbated the impact of the global food crisis in some cases. |

*(Contd...)*

| **Author(s) and Year** | **Period of Study/Data** | **Objective** | **Methodology** | **Key findings** |
|---|---|---|---|---|
| Ardeni 1989 | Monthly series for seven commodities across four countries, mostly between January 1964 and January 1986. | In this paper, the author tried to refute the assumption of perfect arbitrage of commodity prices and provided empirical evidence to support it. Moreover, the paper proposed an alternative methodology, *i.e.* cointegration to test the long-run relationship between non-stationary series, which allows the testing without imposing any restrictions on short-run dynamics. | A unit root test for non-stationarity and cointegration tests were conducted for a group of commodities for four countries. | The results of the study show quite uniformly that the 'law of one price' doesn't hold as a long-run relationship, and that the deviations from the pattern are permanent. |
| Rajmal and Mishra 2009 | 1995-2008 | This paper examined the trends in international and domestic food prices and attempted to analyse the nature and extent of transmission from international food prices to domestic food prices in India. | The paper used comparative analysis of international prices vis-à-vis domestic prices to explore evidence on the nature of the pass-through. | The paper found that domestic and international food prices moved in the same direction. Food prices in India, however, remained lower than international prices in terms of absolute levels, percentage variations as well as volatility. The paper also pointed out that food prices in India were predominantly driven by domestic factors, which explained the limited pass- |

*(Contd...)*

| Author(s) and Year | Period of Study/Data | Objective | Methodology | Key findings |
|---|---|---|---|---|
| | | | | through from international food prices to domestic food prices in India during the period under consideration. |
| Bhattacharya and Sen Gupta 2017 | Monthly data from April 1998 to September 2014 | This paper analysed the behaviour and determinants of food inflation in India. | The study used the SVAR framework and estimated the models for aggregate food inflation as well as inflation in individual commodities using fuel inflation, agricultural wage inflation and demand for food from the industrial sector as common factors along with global prices for the respective food components. | Major findings of the study indicated that the surge in food inflation in India between 2006 and 2013 was primarily driven by agricultural wage inflation which increased significantly in the post-MGNREGA era. Also, fuel inflation and international prices had a limited role except for tradeable goods. Finally, results suggested significant pass-through effects from food to non-food and to headline inflation. |
| Selliah *et al*. 2015 | Monthly series from 2003 to 2012. | The objective of the study was to assess how the global food price surge affects the domestic inflation process in Sri Lanka. | Parametric and non-parametric econometric techniques were used along with cointegration analysis. | Based on the empirical results, the study confirmed that domestic prices in Sri Lanka were cointegrated with global food prices. |

**Table A.2: Descriptive Statistics – CPI-Food**

| | Brazil | China | India | Sri Lanka | Thailand | Turkey | World |
|---|---|---|---|---|---|---|---|
| Mean | 3781.185 | 104.974 | 105.996 | 101.977 | 4.495 | 255.141 | 4.600 |
| Median | 3777.240 | 104.100 | 107.500 | 100.899 | 4.551 | 231.380 | 4.546 |
| Maximum | 5368.250 | 115.600 | 143.400 | 137.000 | 4.656 | 507.120 | 4.886 |
| Minimum | 2184.960 | 100.200 | 57.983 | 68.090 | 4.165 | 133.180 | 4.298 |
| Std. Dev. | 1012.816 | 3.896 | 27.243 | 19.691 | 0.143 | 95.380 | 0.149 |
| Skewness | 0.115 | 0.906 | -0.290 | 0.147 | -0.832 | 0.879 | 0.331 |
| Kurtosis | 1.570 | 3.075 | 1.659 | 1.810 | 2.422 | 3.052 | 1.936 |
| Jarque-Bera | 13.198 | 20.683 | 13.436 | 8.702 | 19.533 | 19.452 | 9.882 |
| Probability | 0.001 | 0.000 | 0.001 | 0.013 | 0.000 | 0.000 | 0.007 |
| Samples | 151 | 151 | 151 | 139 | 151 | 151 | 151 |

**Source:** Food and Agriculture Organization and authors' estimates.

**Table A.3: Descriptive Statistics - Exchange Rates (domestic currency/US$)**

| | Brazil | China | India | Sri Lanka | Thailand | Turkey |
|---|---|---|---|---|---|---|
| Mean | 2.516 | 6.630 | 56.052 | 132.867 | 32.807 | 2.449 |
| Median | 2.232 | 6.630 | 56.385 | 130.730 | 32.692 | 1.875 |
| Maximum | 4.053 | 7.774 | 74.066 | 182.900 | 36.370 | 6.543 |
| Minimum | 1.550 | 6.056 | 39.350 | 107.600 | 29.265 | 1.160 |
| Std. Dev. | 0.793 | 0.397 | 10.055 | 20.164 | 1.779 | 1.268 |
| Skewness | 0.570 | 0.862 | -0.120 | 0.648 | 0.086 | 1.376 |
| Kurtosis | 1.844 | 3.605 | 1.563 | 2.587 | 2.038 | 4.125 |
| Jarque-Bera | 16.593 | 20.992 | 13.356 | 10.718 | 6.004 | 55.603 |
| Probability | 0.000 | 0.000 | 0.001 | 0.005 | 0.050 | 0.000 |
| Sample size | 151 | 151 | 151 | 139 | 151 | 151 |

**Source:** Food and Agriculture Organization and authors' estimates.

**Table A.4: Estimated Pass-through Parameters (short-run)**

| Country | Error correction term | | World food price | | Exchange rate | | Import | | Export | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | t-Statistics | Coefficient | t-Statistics | Coefficient | t-Statistics | Coefficient | t-Statistics | Coefficient | t-Statistics |
| Brazil | -0.004*** | -4.139 | 0.028* | 1.612 | 0.030*** | 2.578 | -0.002* | -1.887 | 0.0007* | 1.842 |
| China | -0.008** | -1.932 | 0.024* | 1.690 | 0.026 | 1.358 | 0.000 | 0.193 | -0.009*** | -2.09 |
| India | -0.025*** | -4.96 | 0.077*** | 2.251 | 0.031 | 0.753 | -0.014*** | -3.185 | -0.023*** | 2.75 |
| Thailand | -0.012*** | -3.145 | 0.036** | 1.784 | 0.060* | 1.685 | - | - | 0.006*** | 2.191 |
| Sri Lanka | -0.0321*** | -3.382 | 0.127*** | 2.754 | 0.172* | 1.650 | - | - | 0.085* | 1.84 |
| Turkey | -0.075*** | -4.718 | 0.162*** | 2.937 | 0.035 | 0.900 | -0.001*** | -2.91 | 0.019*** | 2.33 |

**Note:** ***, ** and * denote 1 per cent, 5 per cent and 10 per cent level of significance, respectively.
**Source:** Authors' estimates.

**Table A.5: Estimated Pass-through Parameters (long-run)**

| Country | World food price | | Exchange rate | | Import | | Export | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | t-Statistics | Coefficient | t-Statistics | Coefficient | t-Statistics | Coefficient | t-Statistics |
| Brazil | 1.971*** | 23.44 | 1.482*** | 7.380 | 0.187*** | 2.409 | -0.262*** | 7.44 |
| China | 0.247* | 1.625 | 1.479** | 4.534 | -0.018*** | 4.143 | 0.097*** | 4.453 |
| India | 0.298** | 2.104 | 0.873*** | 5.432 | 0.096 | 1.43 | -0.037 | 0.168 |
| Sri Lanka | 0.396*** | 2.039 | 0.930*** | 6.282 | - | - | -4.70*** | 3.47 |
| Thailand | 0.426* | 1.85 | 0.633*** | 2.566 | - | - | 0.140 | 0.912 |
| Turkey | 1.030*** | 14.65 | 0.947*** | 20.985 | -0.006*** | 4.68 | 0.076 | 0.863 |

**Note:** ***, ** and * denote 1 per cent, 5 per cent and 10 per cent level of significance, respectively.
**Source:** Authors' estimates.

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# *Trends and Dynamics of Productivity in India: Sectoral Analysis*

**Sarthak Gulati, Utsav Saksena, Avdhesh Kumar Shukla, V. Dhanya and Thangzason Sonna***

Using the India KLEMS database, this paper undertakes a detailed sectoral analysis of total factor productivity (TFP). It examines the suitability of aggregation methodologies, inter-sectoral growth and their contributions to aggregate TFP growth in India from 1981-82 to 2016-17. The paper finds Information and Communications Technology (ICT) using industries like business services and financial services having emerged as drivers of productivity during the period 2008-09 to 2016-17. On the other hand, trade and construction industry remained as laggards during this period. Furthermore, this paper finds empirical evidence of convergence and spillover of TFP from the leading industries to the laggards at a faster pace during 2008-09 to 2016-17 than in earlier years.

**JEL Classification:** D24, E24, O47

**Keywords:** Total factor productivity, Domar aggregation, Harberger plot, convergence and spillover

## Introduction

"Productivity isn't everything, but in the long-run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker" (Krugman, 1997). Cross-country differences in income growth and levels are often attributed to the differences in productivity (Easterly and Levine, 2000).

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Productivity has re-emerged at the forefront of economic debate post the global financial crisis of 2008. There has been a broad-based slowdown in productivity growth in the post-crisis period across advanced economies, emerging market economies and low-income countries (Adler *et al*., 2017). While India's economic growth largely remained resilient amidst a fiscal stimulus provided after the crisis, there have been concerns about productivity slowdown in the Indian economy (Kumar and Soumya, 2010).

The literature in this area mostly focuses on single-factor productivity (primarily labour or capital productivity) and multi-factor/total factor productivity (TFP) while analysing country-specific productivity. Single-factor productivity measures provide ease of measurement and comparability (OECD, 2001). For example, labour productivity is a better measure for examining trends in an economy over a short period or making cross country comparisons, as methodologies to construct measures of productivity of capital and labour differ significantly across countries (Sargent and Rodriguez, 2000). However, single-factor productivity measures provide only a partial assessment of productivity (capital or labour) and also reflect the joint influence of multiple factors, leading to interpretation problems. On the other hand, TFP, though difficult to measure, provides a more comprehensive representation. The availability of a productivity database like KLEMS[1] (The India KLEMS Database, 2019) has made cross-country comparison possible. India KLEMS, which follows the methodology of EU KLEMS, allows detailed sectoral analysis of productivity. In a growth accounting framework like that of KLEMS, TFP is measured as a residual (ECB, 2007; Jorgenson *et al*., 2007), after adjusting for growth in labour and capital (and if appropriate, intermediate inputs). The theoretical foundation of TFP dates back to Robert Solow who described it as arising from exogenous technological shock (Solow, 1956).

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[1] Details of the KLEMS data set are given in Section III of this paper. For a detailed analysis of methodology, see the India KLEMS manual *Measuring productivity at the industry level: The India KLEMS database* available at https://www.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=&ID=936

Against this backdrop, this study explores sectoral productivity trends based on the methods and tools used in the India KLEMS database. In order to examine the dynamics of TFP growth, the Schumpeterian growth framework is used following Aghion and Howitt (2006) and Aghion *et al.* (2014). The Schumpeterian growth theory is based on Joseph Schumpeter's theory of creative destruction wherein productivity growth is an outcome of innovations. According to this, TFP growth is a catching-up phenomenon and involves the gradual adoption of new technologies by laggards from the leading sectors (Morrow *et al.*, 2010). The paper examines productivity spillover across industries in the Indian economy to see if there is any evidence of convergence and the potential for catching-up.

The rest of the paper is organised as follows. Section II provides a brief on the theory behind measuring productivity. Section III gives an overview of the India KLEMS database used in the paper and presents stylised facts on recent trends. Section IV discusses the relevant literature. Section V focuses on aggregation methodology. Section VI presents a disaggregated sectoral and industry-level analysis, while Section VII checks for convergence in TFP in India. Section VIII concludes the paper.

## Section II
## Theory

Productivity, in general terms, may be defined as a ratio of a volume measure of output to a volume measure of inputs (OECD, 2001). Among different measures of productivity, labour and capital productivity are the most commonly used measures of single-factor productivity to understand the efficiency of inputs used. Labour productivity is defined as output/ value-added per labour hour. It gives an estimate of the efficiency of labour to generate output with the available stock of capital. According to neoclassical theory, which assumes that returns to factors of production equal to their productivity – higher labour productivity is associated with higher returns to labour in the form of higher real wages (Dearden *et al.*, 2006).

Improvement in labour productivity may occur due to: (a) capital deepening (measured as capital stock per worker); (b) rise in efficiency of the existing capital stock; (c) improvement in quality of labour supply; and

(d) TFP (RBI, 2019). While capital deepening refers to an increase in capital stock per unit of labour, efficiency in utilisation of capital may improve due to better procedures or technological developments which may, in turn, increase labour productivity. In addition, improvement in the quality of labour in the form of better education, adequate skill sets and better health outcomes also contributes to labour productivity.

The residual component TFP, is often considered similar to the Hicksian 'technology' parameter used in the neoclassical production function. Increases in TFP are considered to be equivalent to shifts in isoquants of production function (Syverson, 2011). TFP contribution to growth represents an increased efficiency in use of inputs, rather than an increased use of input themselves (Solow, 1956). Solow explained TFP as arising from disembodied, and exogenous technological shock. The subsequent theoretical development treated it as arising endogenously from improvement in human capital and productive public spending (Barro, 1990; Lucas, 1988; Romer, 1987). In addition to technological progress, TFP also includes the impact of various other changes in the economy such as government policy decisions, political shocks, the impact of technology on wage efficiency and even weather-related shocks (Bosworth and Collins, 2008).

In contrast to the above, Schumpeterian growth theory relies on the notion of creative destruction in explaining the determinants of productivity growth. It emphasises the distance from technological frontier as a key driver of productivity growth (Aghion and Howitt, 2006). According to Aghion *et al.* (2014), economic growth in the Schumpeterian model, is generated by (i) innovations, (ii) entrepreneurial investments, motivated by the possibilities of monopoly rents, leading to innovations, and (iii) new innovations replacing the older ones through the process of creative destruction. The Schumpeterian production function is specified at the industry level, and the aggregate output is a simple sum of industry-specific outputs. In this model, innovations can interact with each other across sectors; innovations made in one industry could be implemented across other industries and laggard industries will try to fill the gap from frontier industries. With a suitable policy framework, the Schumpeterian model envisages the role of spillovers of innovations and catch-up by laggards in increasing aggregate productivity in the economy.

## Section III
## Data and Stylised Facts

The India KLEMS database is part of a global initiative to promote and facilitate analysis of growth and productivity patterns, based on a growth accounting framework. The India KLEMS project provides value-added based TFP growth and gross output based TFP growth for the period 1981-82 to 2016-17 at a disaggregated level across 27 industry groups.

In line with the National Industrial Classification (NIC)[2], the 27 industry groups include 'agriculture, hunting, forestry and fishing', 'mining and quarrying', the manufacturing sector comprising 13 industry groups, 'electricity, gas and water supply', 'construction' and the services sector comprising 10 industry groups. The KLEMS database was used to analyse productivity at the sectoral level – manufacturing and services – as well as at the level of 27 industry groups.

Labour productivity measured as output of goods and services per worker, has increased sharply in India post-economic reforms in the last decade of the twentieth century. From an average growth of 2.0 per cent during the period 1981-82 to 1992-93, average labour productivity growth increased sharply to 3.9 per cent during 1993-94 to 2007-08[3]. Chart 1 shows that the faster growth in labour productivity post-economic reforms was driven by higher contributions of capital deepening and TFP. Capital deepening is inclusive of the contribution from improvement in efficiency of the existing capital stock.

During the period 2008-09 to 2016-17, average labour productivity growth further accelerated to 4.5 per cent from 3.9 per cent during 1993-94 to 2007-08, with higher contributions from capital deepening even as TFP

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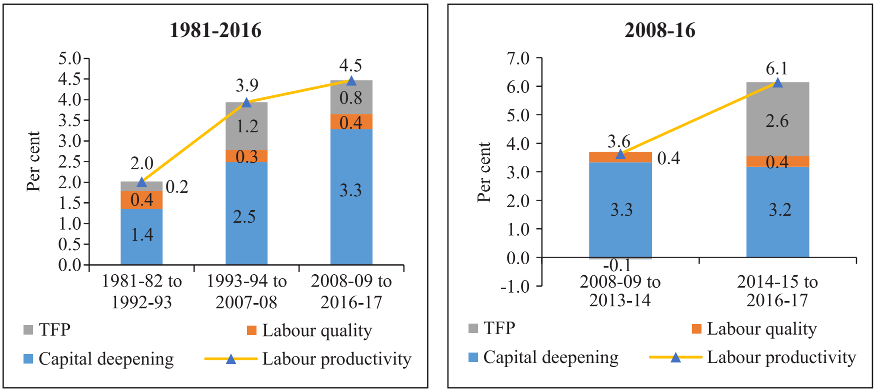
[2] The National Industrial (Activity) Classification released by the National Statistical Office (NSO) Ministry of Statistics and Programme Implementation is used in all types of censuses and sample surveys conducted in India. The first classification was NIC-62 followed by NIC-70, NIC-87, NIC-98 and NIC-2004. The latest and sixth Industrial Classification namely NIC-2008 has been developed and released by NSO.

[3] The total sample has been divided into three periods based on structural breaks in the growth of labour productivity checked using the Chow breakpoint test.

**Chart 1: Components-wise Labour Productivity Growth**




**Source:** India KLEMS, RBI.

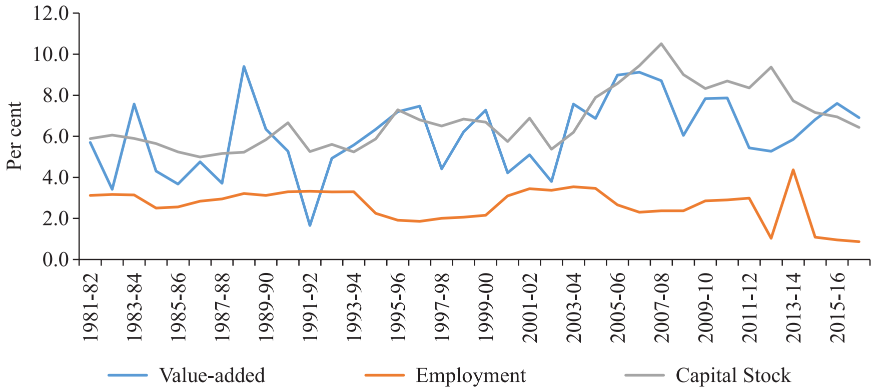
growth decelerated. The deceleration in TFP was mainly due to a contraction in TFP in the post-financial crisis period 2008-09 to 2013-14 when TFP growth[4] declined to -0.1 per cent. It rebounded to 2.6 per cent during 2014-15 to 2016-17.

From 2008-09 to 2016-17, the contribution of capital deepening increased by 3.3 percentage points per annum compared with 2.5 percentage points per annum during 1993-94 to 2007-08. During this period, the growth of capital stock in the Indian economy has been faster than that in the 15-year period before the crisis while employment growth has slowed down. The contribution of labour quality has remained subdued throughout the period indicating that labour quality has not kept pace with the changing needs of the growing economy.

Investment measured in terms of changes in capital stock showed a structural shift from 2002-03 onwards, when it started growing consistently, reaching its peak in 2007-08 and gross value added (GVA) growth also improved during this period (Chart 2). However, growth in capital stock during the period 2006-07 to 2014-15 was higher than that of GVA growth, reflecting a decline in capital efficiency. At the same time, employment growth

[4] TFP growth and contribution are used interchangeably due to the neoclassical production function.

**Chart 2: Movements in Capital Stock and Employment**




**Source:** India KLEMS.

decelerated, resulting in an improvement in capital deepening. Both capital stock and employment growth decelerated after 2014-15. With employment growth declining sharply and capital accumulation slowing down, TFP drove economic growth during 2015-16 and 2016-17. Improvement in TFP growth was visible across all the sectors.

## Section IV
## Review of the Literature

The empirical literature on productivity is vast encompassing methodology and sectoral analysis. Jorgenson and Griliches (1967) first distinguished between the different types of capital and labour inputs, thereby extending the interpretation of the Solow residual to 'non-embodied' technological change. Kuznets (1978) interpreted the Solow residual as exogenous technological innovation – a factor that would increase the marginal product of both labour and capital in the production process.

Jorgenson *et al.* (2007) presented three alternative methods to construct economy-wide estimates of sources of growth. They asserted that the production possibility frontier, which recognises differences in output prices across industries, remains the most appropriate methodology for aggregating industry data.

The studies in India have mostly focussed on aggregate productivity dynamics or looked at specific examples of firms, sectors or regions. Sector-specific studies include productivity in manufacturing (Kathuria, 2000), agriculture (Ghatak and Roy, 2007), banking (Fujii *et al.*, 2014) and trade (Topolova and Khandelwal, 2011).

Krishna *et al*. (2018) compared TFP rates for both informal and formal sectors in the Indian manufacturing sector (13 industries) using the India KLEMS database from 1980 to 2011. They found that within the formal manufacturing, 'Coke and Refined Petroleum products', 'Food, Beverages and Tobacco products', 'Chemicals and Chemical products' industries are large contributors to total TFP growth, while within informal manufacturing, increases in TFP are driven by 'Textiles and Leather products' and 'Wood and Wood products'. Their results showed that TFP rates are much lower in informal manufacturing. Comparing the Domar aggregation method with the production possibility frontier (PPF) framework, they found that Domar aggregation results in lower levels of TFP growth for both the formal and informal manufacturing sectors.

Das *et al.* (2014) analysed productivity growth in India during three periods: 1980-1989, 1992-1999, 2000-2011, classifying the traditional sectors (manufacturing, non-manufacturing and services) into high, medium and low intensity (manufacturing), market and non-market (services). They showed that market services have seen an improvement in TFP growth in the 2000s over that in 1990s with Post and Telecom, Textiles and Transport Equipment industries emerging as the best performers during the 2000s.

Das *et al.* (2019) and Krishna *et al.* (2016a) found that capital deepening has been the major contributor to gains in labour productivity in India since 1980-81. Gains in overall labour productivity have largely accrued through market services. They also found the labour reallocation effect in India to be positive; and it has increased in the 2000s, suggesting a structural transformation which is growth-enhancing.

Krishna *et al*. (2016b) compared the TFP growth rates for India and China from 1991 to 2012. Their results indicated that the services sector has registered a negative contribution to overall TFP, whereas manufacturing and construction sectors have seen positive contributions (except for the period 2004-2012) in the case of China. In contrast, aggregate TFP growth in India has seen a higher contribution from the services sector, while the manufacturing and construction sectors have exhibited lower TFP growth during multiple periods. Manufacturing TFP growth has been more stable compared to services TFP growth for China, while the opposite is true for India. They also noted that China's service sector TFP growth was impacted more in the immediate aftermath of the global financial crisis than that of the service sector in India.

## Section V
## Aggregation of TFP

This section examines the various methodologies for aggregating industry-level TFP growth and the suitability of these methodologies for Indian productivity data. Aggregation of TFP for the entire economy as well as for the manufacturing and services sectors is critical for further analysis.

The literature discusses three methods to aggregate TFP across industries based on Jorgenson *et al.* (2007): aggregate production function (PF) approach, aggregate production possibility frontier (PPF) approach and the Domar/direct approach. Of these three approaches, the PF approach is the most restrictive, imposing restrictions on both output and input aggregation. This approach assumes:

1) There exists a value-added function for each industry which is a function of capital, labour and technology.

2) This value-added function is identical across industries and hence it can be aggregated across industries.

3) The functions that aggregate heterogeneous types of capital (tractors, computers, *etc*.) and labour (factory workers, bankers, *etc*.) are the same across industries.

4) Each specific type of capital and labour receives the same price in each industry.

Aggregate value added using aggregate PF approach is given as:

$$V^{PF} = \sum \mathrm{V}_i$$

where,

$V^{PF}$ = aggregate value added using aggregate PF approach

$V_i$ = value added in industry i

Aggregate TFP growth rate for the economy (The India KLEMS Database, 2019) is then calculated as:

$$TFP^{PF} = \Delta\ln(V^{PF}) - \bar{v}_K \Delta \ln(K) - \bar{v}_L \Delta \ln(L)$$

where,

$K$ = aggregate capital stock in the economy[5]

$L$ = quality adjusted employment in the economy[6]

$\bar{v}_K$, $\bar{v}_L$ = two-year averages of the income share of capital and labour, respectively

Here, TFP is calculated as a residual after accounting for changes in labour and capital inputs from aggregate value-added.

The aggregate PPF approach relaxes the second assumption of identical value-added functions across industries. By weighing each industry's growth in value added by nominal price component, this approach captures the variability in output price for each industry. Growth in aggregate value added using PPF approach is given as:

$$\Delta\ln(V^{PPF}) = \sum \bar{w}_i \Delta ln V_i$$

Where,

$\bar{w}_i$ is the proportion of industry i's nominal value added in total nominal value added

Aggregate TFP growth, in this case, is given as:

$$TFP^{PPF} = \Delta\ln(V^{PPF}) - \bar{v}_K \Delta \ln(K) - \bar{v}_L \Delta \ln(L)$$

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[5] For the purpose of simplicity and clarity we have made use of growth rate of capital stocks. However, growth rate of capital services can also be used. For more details, see Erumban and Das (2014).

[6] Quality adjusted employment includes changes in labour quality.

Domar/direct aggregation relaxes assumptions 2, 3 and 4, and only assumes the existence of a value-added function for each industry. This approach is a 'bottom-up' methodology – individual industry TFP growth rates are weighted by Domar weights[7] to arrive at an aggregate TFP growth rate. Domar weights usually sum up to more than one, implying that aggregate productivity growth will be more than a simple average of industry TFP. TFP increase in intermediate industries has a double effect on aggregate TFP: a direct increase and an indirect increase in TFP of downstream industries through forward linkages and *vice versa*.

TFP growth level for industry i and time t is given by the Translog production function:

$$TFP_{i,t}^{direct} = \left(\ln(Y_{i,t}) - \ln(Y_{i,t-1})\right) - 1/2\sum(S_{i,t} + S_{i,t-1})(\ln(X_{i,t}) - \ln(X_{i,t-1}))$$

$Y_{i,t}$ = *Gross output or value added*

$S_{i,t}$ = *Factor share of input X in output*

$X_{i,t}$ = *Input (capital, labour, intermediate goods, etc.)*

The weighted TFP for the economy is calculated as:

$$TFP^{Direct} = \sum \frac{\overline{w}_i}{\bar{v}_{V,i}} TFP_i$$

This weighted TFP term, however, assumes same marginal productivity in all industries, something that is unlikely to hold in the case of developing economies (Wu and Liang, 2018). To counter this fact, 'labour reallocation' and 'capital reallocation' effects are also calculated and reported along with the Domar weighted TFP measure to provide a more comprehensive measure of aggregate TFP. These terms capture the impact of movement of labour and capital from a relatively low productive to high productive industry (or *vice versa*) on aggregate productivity growth in the economy.

Capital reallocation = $\sum \overline{w}_i \frac{\bar{v}^K{}_i}{\bar{v}_i^V} \Delta lnK_i - \bar{v}_k \Delta lnK$

---

7 Domar weights - $\frac{\overline{w}_i}{\bar{v}_{V,i}}$
*where,*

$\overline{w}_i$ *is the proportion of industry i's value added in total value added*

$\bar{v}_{V,i}$ *is the proportion of industry i's value added in its gross output*

Labour reallocation = $\sum \overline{w}_i \frac{\bar{v}^{L}{}_{i}}{\bar{v}_i^V} \Delta lnL_i - \bar{v}_k \Delta lnL$

In the Domar/direct aggregation method, TFP is calculated as a sum of Domar-weighted industry TFP plus capital and labour reallocation terms. By relaxing assumption 4, direct aggregation opens up the possibility of stickiness in movements of factor inputs.

Using the three approaches, the TFP growth for manufacturing and services were aggregated. First, we focus on the PF and PPF approaches (where only assumption 2 is relaxed). PF and PPF approach provide almost identical measures for TFP growth for the manufacturing sector, while there is divergence[8] in the aggregated TFP calculated for the services sector using these two approaches (Charts 3a and 3c). This suggests that assumption 2 of identical value added functions might be binding for services but not for manufacturing in India. By allowing for different value-added functions across different service industries, we get a higher estimate of aggregate services TFP.

Further, comparing aggregate TFP for manufacturing and services using PPF and Domar approaches – where Domar involves relaxing assumptions 3 and 4 – which require that the functions to aggregate heterogeneous capital and labour are same and each specific type of capital and labour receives the same price in each industry, divergence was observed in the TFP growth estimates for manufacturing sector and minimal or no divergence for services. This divergence in PPF and Domar estimates for manufacturing is statistically significant[9]. This might suggest that input types and input markets are more heterogeneous for manufacturing than services and factor movements are relatively smoother in services.

Analysing TFP growth estimates using these three approaches for the disaggregated services sector, we find divergence in PF and PPF estimates

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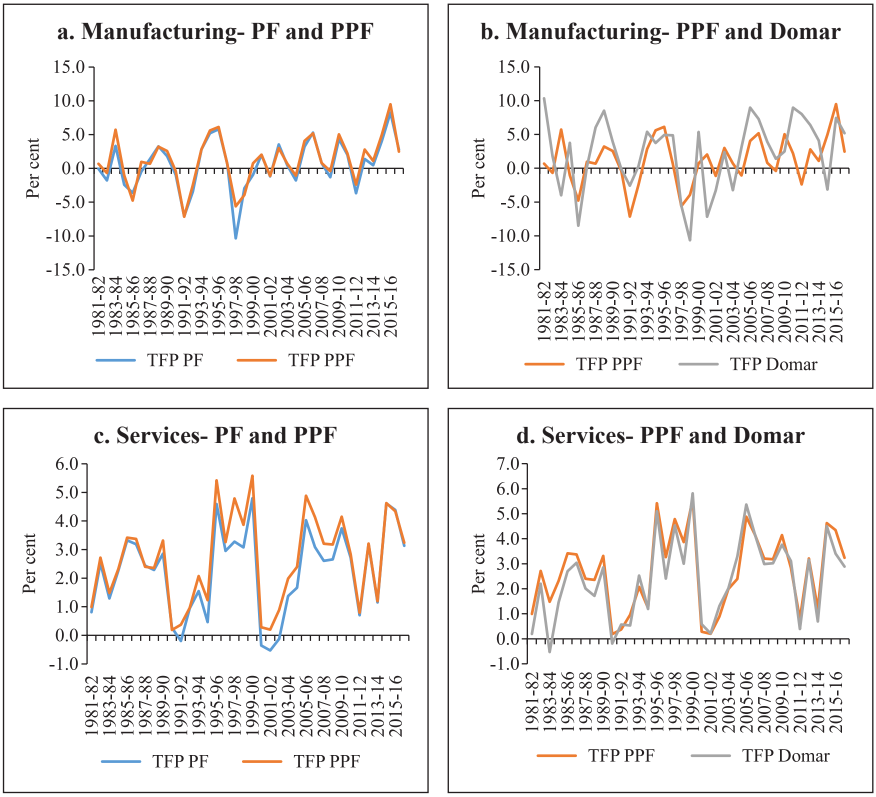
[8] However, this divergence is not statistically significant when checked using equality of means of absolute growth rates.

[9] t-test and ANOVA F-test for equality of means of absolute growth rates is rejected at 1 per cent level of significance.

**Chart 3: Aggregated TFP Growth in Manufacturing and Services Sectors**




**Source:** India KLEMS, authors' calculations.

for market services[10] (not statistically significant) but no divergence for non-market services. Further relaxing input market restrictions, we find divergence in TFP growth estimates for PPF and Domar approaches for both market (statistically significant at 5 per cent level) and non-market services (statistically significant at 1 per cent level) (Chart 4). This might suggest that while there is some evidence of homogeneity in value-added functions, assuming identical functions to aggregate heterogeneous inputs and same prices for heterogeneous inputs across industries is restrictive for all service industries – market and non-market.

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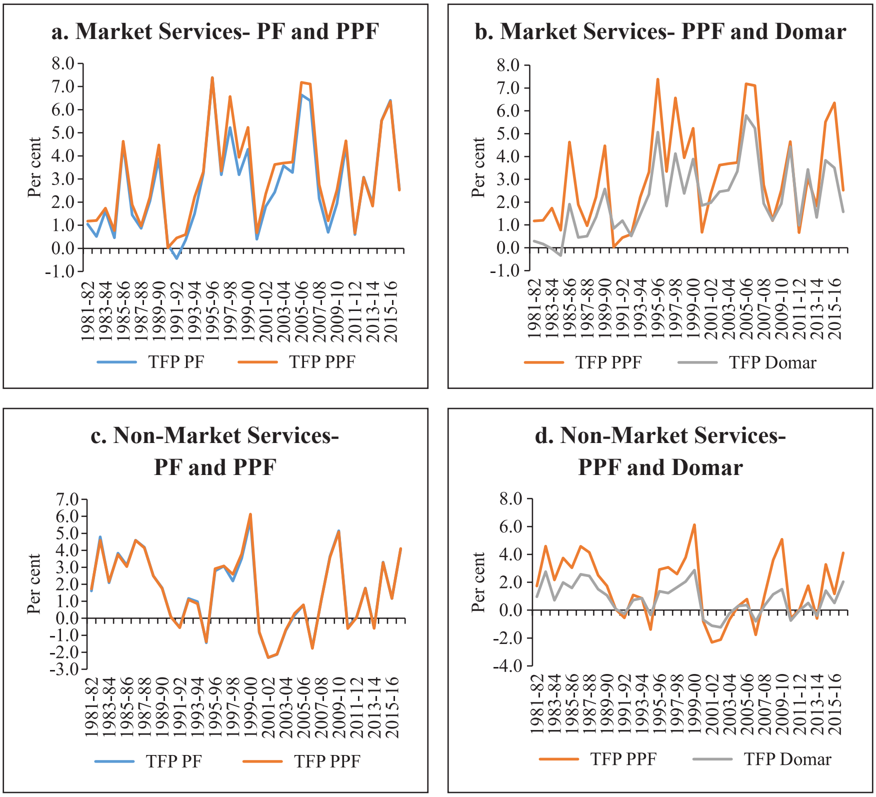
[10] Market Services include Trade, Hotels & Restaurants, Transport & Storage, Post & Telecommunication, Financial Services and Business Services. Non-Market Services include Public Administration & Defense, Education, Health and Other Services. This classification is based on Krishna *et al.* (2017)

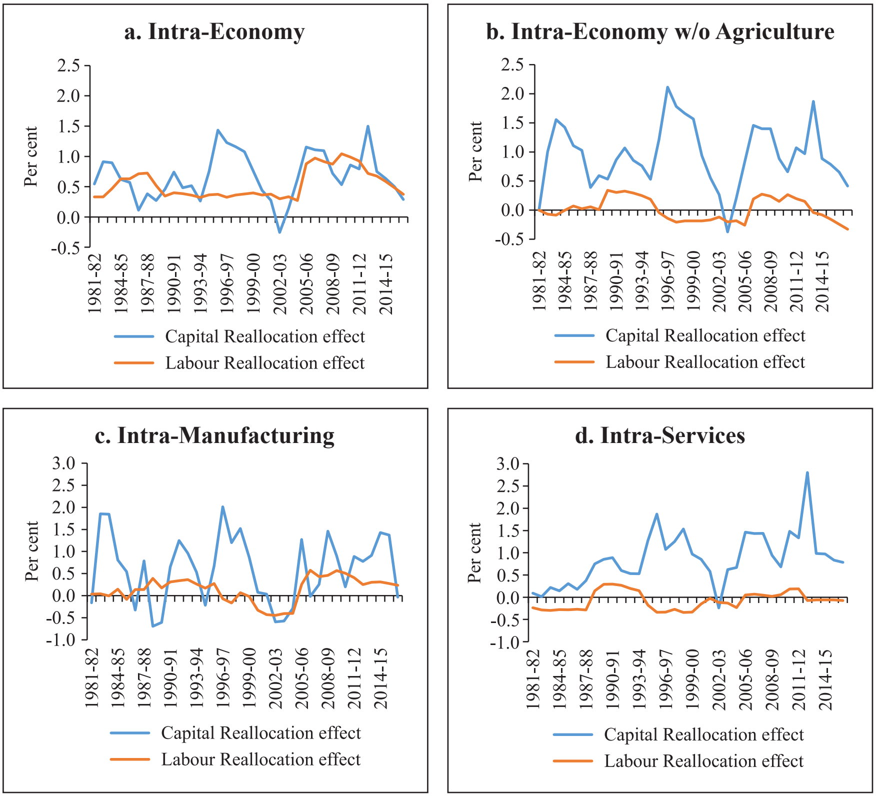
**Chart 4: Aggregated TFP Growth in Market and Non-market Based Services**




**Source:** India KLEMS, authors' calculations.

An analysis of labour and capital reallocation effects calculated using the Domar aggregation approach provides some interesting insights into the Indian economy. Charts 5a and 5b indicate that while there is a positive labour reallocation effect for the economy as a whole, such effect is negligible for the economy without agriculture. This may be explained by productivity boost due to labour moving out of agriculture to manufacturing and services, somewhat offset by the assimilation of labour into the construction sector, which remains negative contributor to aggregate productivity throughout the sample period. Also, while the capital reallocation effect is positive for both the economy as a whole and economy without agriculture, it is higher in case of the latter (Charts 5a and 5b).

**Chart 5: Intra-Sectoral Effect of Labour and Capital Reallocation**




**Source:** India KLEMS, authors' calculations.

Comparing intra-sectoral reallocation effects within manufacturing and services, we find that productivity boost from reallocation of capital is higher in both manufacturing and services industries. While the capital reallocation effect is volatile within manufacturing, it was positive and growing at a robust pace within the services sector during 2002-03 to 2016-17. Charts 5c and 5d suggest that despite indication of heterogeneous inputs and inputs markets for manufacturing, labour reallocation was positive in this sector. On the other hand, there was a very limited labour reallocation effect in services, possibly reflecting the distinct nature of activities within the services sector.

## Section VI
## Disaggregated Analysis

### Agriculture, Manufacturing and Services

This section analyses the contribution of TFP to GVA growth for the three broad sectors of the economy - agriculture, manufacturing and services. Growth in value-added in the agricultural sector has largely been driven by TFP growth, reflecting the lower contribution of factor inputs in shaping agricultural performance. This also reflects the residual nature of TFP and hence may be reflective of role of factors like the monsoon, policy interventions and other shocks in the performance of Indian agriculture.

Compared to agriculture, the gap in value-added growth and TFP contribution is marked for both manufacturing and services, reflecting the higher contribution of labour and capital inputs to valued-added in these two sectors. The gap between value-added growth and TFP growth has come down for manufacturing but increased marginally for services in the recent period 2008-09 to 2016-17. During this period, GVA growth slowed down for manufacturing, while TFP contribution grew at a faster pace than the earlier period. In the case of the services sector, both value-added growth and TFP growth for services increased in the recent period but increase in the growth of GVA was higher reflecting the higher contribution of factor inputs (Chart 6).

### Industry Groups

Examining further the productivity growth across industry groups, an analytical exercise to understand both the leaders and draggers of aggregate TFP growth in the economy among the 27 industry groups is carried out. Harberger plots (first called as 'sunrise diagrams' by Harberger, 1997) which give a visual representation of the contribution of various sectors in overall TFP growth is used for the analysis. These plots visually demonstrate the difference in industry contributions to TFP growth in comparison to their share in overall GVA. This approach has been used by Krishna *et al*. (2017) to understand how widespread or localised productivity growth and changes in growth within the Indian economy are. Our results are broadly in line with their analysis for different time

**Chart 6: Contribution of TFP to GVA Growth**

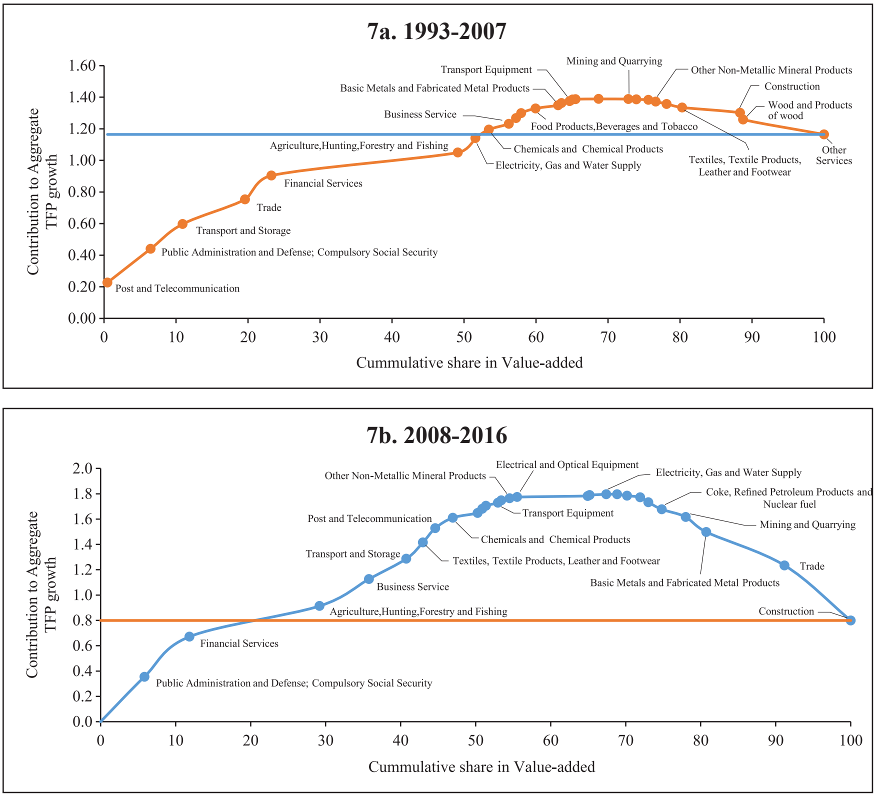

**Source:** India KLEMS, authors' calculations.

periods. We plot Harberger diagrams[10] for two periods, *i.e.,* 1993-94 to 2007-08 (Chart 7a) and 2008-09 to 2016-17 (Chart 7b).

In the first period (Chart 7a), post and telecommunication, public administration and defence, transport and storage, and trade and financial services emerge as the leading industries in terms of their contribution to TFP growth. These industries, with 23.3 per cent share in GVA, contributed 90 basis points (bps) to the total TFP growth of 1.16 percentage points during this period. Telecom, financial services and public administration were among the

[10] Industries are ordered according to their contributions to aggregate TFP growth. Accordingly, industries closer to the origin represent those with the highest TFP contributions to overall TFP growth. The blue line represents the average aggregate TFP growth during the period.

**Chart 7: Contribution to Aggregate TFP Growth (Harberger Plot)**




**Source:** Authors' calculations.

first adopters of Information and Communications Technology (ICT) in the country, and these industries account for the majority of productivity gains in the period immediately after the economic reforms.

Industries, according to their ICT adoption, are usually classified in the literature into ICT-using and ICT-producing industries (Ark *et al.*, 2003). In industrialised nations, ICT-producing sectors contribute higher to output, and also to productivity (both directly and as intermediate input to other industries). On the other hand, for developing countries, ICT-using (usually concentrated in services sector) have a higher contribution, given that most ICT-production occurs in advanced countries (Erumban and Das, 2016).

In India, ICT adoption has occurred primarily in the services (*i.e.*, ICT-using sectors), led by the financial services industry (Erumban and Das, 2016). Post and telecommunication, one of the earliest to produce and adopt IT/ICT technology contributed the highest to TFP growth in the initial part of the sample period of this paper. However, in the latter period, their share declined due to faster increase in other ICT using industries like business and financial services which adopted new technologies - with high levels of human capital and positive network externalities being the primary factors (Hall and Khan, 2003).

Explaining productivity in public administration is relatively difficult since wages in this industry are administered and are not driven by the market. Hence, the ratio of output to input does not necessarily reflect productivity (Das *et al.*, 2019).

During the second period (Chart 7b), business services, among the second adopters of ICT, emerged as one of the new leaders in driving TFP growth and the contribution of financial services and public administration further increased. Agriculture with the largest share in value-added individually contributed relatively lesser to total TFP growth in both periods. Other than the leading industries mentioned above, there are some industries that consistently contributed to TFP growth like chemical and chemical products and transport and storage. On the other hand, the contribution of some industries like 'basic metals and fabricated metal products' and 'electricity, gas and water supply' have declined in the recent period (Table 1).

The most noticeable decline in TFP contribution during the period 2008-09 to 2016-17 is seen in the trade and construction industries. These two industries have assimilated a large labour force that has moved out of agriculture, with construction emerging as more labour absorbing than trade in the recent years. Trade and construction together accounted for 43 per cent (17 per cent and 26 per cent, respectively) of total non-agricultural employment in 2016-17 (Chart 8).

**Table 1: Industry Contribution to Aggregate TFP Growth**

(Percentage points)

| Industry | 1993-94 to 2007-08 | 2008-09 to 2016-17 | Difference in Contribution |
|---|---|---|---|
| Business Service | 0.04 | 0.21 | 0.18 |
| Financial Services | 0.15 | 0.32 | 0.17 |
| Textiles, Textile Products, Leather and Footwear | -0.02 | 0.13 | 0.15 |
| Public Administration and Defense; Compulsory Social Security | 0.21 | 0.36 | 0.14 |
| Other services | -0.09 | 0.01 | 0.10 |
| Agriculture, Hunting, Forestry and Fishing | 0.15 | 0.24 | 0.10 |
| Wood and Products of wood | -0.04 | 0.01 | 0.05 |
| Education | 0.00 | 0.04 | 0.04 |
| Rubber and Plastic Products | 0.00 | 0.03 | 0.03 |
| Chemicals and Chemical Products | 0.05 | 0.08 | 0.03 |
| Other Non-Metallic Mineral Products | -0.01 | 0.02 | 0.03 |
| Manufacturing, nec; recycling | 0.01 | 0.02 | 0.01 |
| Health and Social Work | -0.01 | 0.00 | 0.01 |
| Transport Equipment | 0.01 | 0.02 | 0.01 |
| Pulp, Paper, Paper products, Printing and Publishing | 0.01 | 0.02 | 0.00 |
| Transport and Storage | 0.16 | 0.16 | 0.00 |
| Machinery, nec | 0.00 | -0.01 | -0.01 |
| Electrical and Optical Equipment | 0.03 | 0.01 | -0.02 |
| Food Products,Beverages and Tobacco | 0.03 | -0.01 | -0.04 |
| Coke, Refined Petroleum Products and Nuclear fuel | 0.00 | -0.06 | -0.05 |
| Mining and Quarrying | 0.00 | -0.06 | -0.06 |
| Hotels and Restaurants | 0.04 | -0.04 | -0.07 |
| Electricity, Gas and Water Supply | 0.09 | 0.01 | -0.09 |
| Post and Telecommunication | 0.23 | 0.11 | -0.11 |
| Basic Metals and Fabricated Metal Products | 0.02 | -0.12 | -0.14 |
| Construction | -0.03 | -0.44 | -0.40 |
| Trade | 0.16 | -0.26 | -0.42 |

**Source:** India KLEMS, authors' calculations.

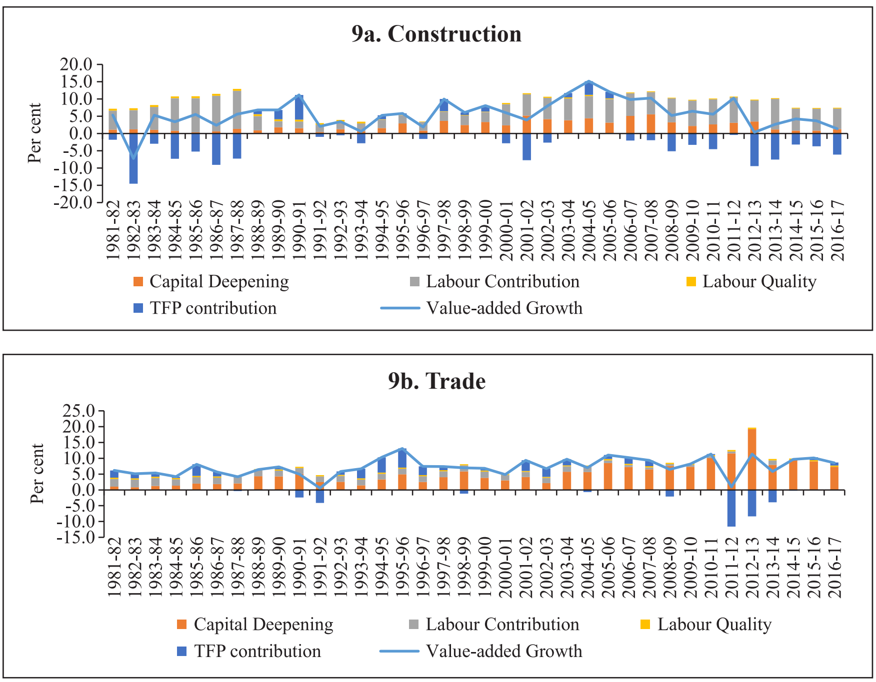
However, Chart 9 shows that, in the recent years, trade has witnessed substantial accumulation of capital and a significant reduction in labour force. Accordingly, the growth witnessed in the trade industry is attributed more to capital deepening than to contributions from labour or TFP. On the other hand, capital deepening in the construction industry has come to a complete

**Chart 8: Share in Non-Agricultural Employment**


**Source:** India KLEMS, authors' calculations.

standstill during 2008-09 to 2016-17 compared to the previous period. Also, without a commensurate increase in the contribution of labour, GVA growth has fallen in the construction industry during this period.

**Chart 9: Contribution to Value-added Growth**




**Source:** India KLEMS, authors' calculations.

## Section VII
## TFP Convergence and Spillover

After analysing the dynamics of productivity in the three major sectors and 27 industry groups in the Indian economy, we check for convergence and spillover of TFP among industries. As discussed in the section on theory, this analysis draws from the Schumpeterian growth theory (Aghion and Howitt, 2006; Aghion *et al.*, 2014). The methodology used to test convergence is similar to Morrow *et al.* (2010) and Inklaar (2016). The Schumpeterian model provides the theoretical foundation for analysing multisectoral convergence and spillover of TFP whereby innovations in one sector are built on the knowledge of the other sectors (Aghion *et al.*, 2014). The knowledge spillover from the ICT industry to other industries is one such example of productivity spillover. Biatour *et al.* (2011), in the context of Belgium, found positive domestic inter- industry research and development (R&D) spillovers on TFP growth.

With a view to look at convergence across industries, two methods are followed: i) k-means clustering[11] and ii) panel regression. While the former checks only for convergence, the latter looks into convergence and spillover across industries.

Under k-means clustering, 27 industry groups are divided into four clusters minimising total intra-cluster variance (Appendix Chart A.1), based on their average productivity growth in the two time periods 1993-94 to 2007-08 and 2008-09 to 2016-17. Post and telecommunication was an outlier with very high TFP growth in both the periods (not shown in Chart 10 as it is placed out of scale on the right top corner) and represented a cluster by itself. All the other industries were divided into three clusters shown in yellow, green and red colours in Chart 10. The horizontal axis measures average productivity growth in the period 1993-94 to 2007-08 while the vertical axis measures average productivity growth in the period 2008-09 to 2016-17.

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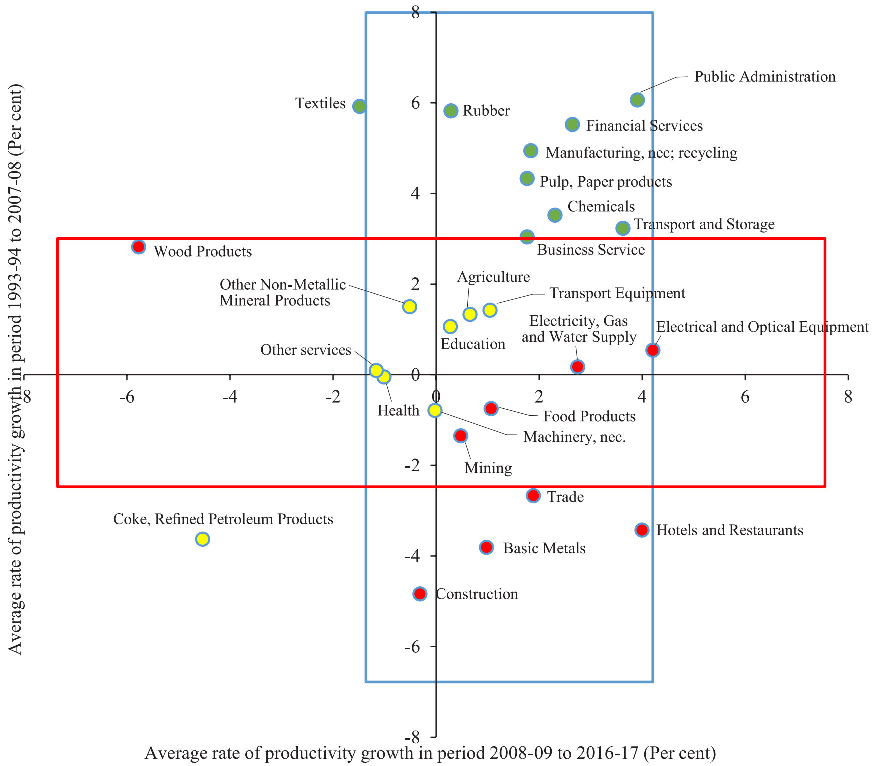
[11] K-means clustering is an unsupervised machine learning technique that works iteratively to assign each data point to one of *K* groups based on feature similarity.

**Chart 10: Cluster Analysis for Average Productivity Growth in the Two Periods (1993-94 to 2007-08 and 2008-09 to 2016-17)**




**Source:** India KLEMS, authors' calculations.

Among the three clusters, the yellow cluster represents those industries whose average TFP growth was low in both the time periods. Industries whose average TFP growth has fallen significantly in the second period compared with the first period are represented by the red cluster, while the green cluster indicates those industries where TFP growth has risen significantly in the later period. It must be noted that both green and red clusters had almost equal average TFP growth in the first period. While the green cluster has taken off in the second period, the red cluster's TFP growth has been depressed.

ICT-using industries like financial services and business services form part of the green cluster. Further, out of 10 industries with lowest TFP levels in 2008-09, five form part of the green cluster while three belong to the yellow cluster. This provides the initial motivation for examining convergence as industries lagging behind with low levels of productivity in the first period experienced faster TFP growth in the second period. This convergence is later tested empirically with a panel regression.

To calculate TFP levels, we make use of the concept of 'relative TFP' as mentioned in Inklaar (2016). TFP for a given industry is calculated relative to the overall economy, treating it as a benchmark. For a given year, the TFP level for industry *i* is given as follows –

$$\ln\left(\frac{TFP_i}{TFP_{economy}}\right) = \ln\left(\frac{Y_i}{Y_{economy}}\right) - a_i * \ln\left(\frac{K_i}{K_{economy}}\right) - (1 - a_i) * \ln\left(\frac{L_i}{L_{economy}}\right)$$

Where,

$(\frac{TFP_i}{TFP_{economy}})$ *is the TFP level of industry i, relative to the benchmark (the Indian economy)*

$(\frac{Y_i}{Y_{economy}})$ is the relative level of value added

$(\frac{K_i}{K_{economy}})$ is relative level of capital stock

$\left(\frac{L_i}{L_{economy}}\right)$ is the relative level of employment

$a_i$ is industry *i*'s share of capital in output, while $(1 – a_i)$ is the share of labour in output.

In order to empirically check the convergence and spillover hypothesis, a panel regression across industries is estimated in the form of following specification given by European Commission (2014). The methodology to test convergence is similar to Morrow *et al.* (2010) and Inklaar (2016).

$$TFP_{i,t} = \beta_0 + \beta_1 TFPgap_{i,t-1} + \beta_2 \text{TFPmax}_{i,t} + \gamma Year + \theta Ind + \epsilon_{i,t} \quad .......(1)$$

where,

*$TFP_{i,t}$ = TFP growth of industry i at time t*

*$TFPgap_{i,t-1}$ = log difference between TFP levels for the given industry and TFP levels for industry with highest productivity in the year t – 1*

*$TFPmax_{i,t}$ = TFP growth of the industry with highest productivity level for a given year t*

In this specification, TFPgap captures the impact of the convergence channel between the leading industry and other industries. A larger negative value of $TFPgap_i$ implies a wider gap between the industry i and the frontier and hence larger potential gain for laggard industry by adopting enhanced technology and advanced managerial practices. On the other hand, TFPmax captures spillover effects from the leading industry. Our results show that the channels of convergence and spillover are contributing to total factor productivity growth in India. The negative sign of TFPgap coefficient suggests that industries far away from the frontier are growing faster which also supports the results of cluster analysis. A positive sign of TFPmax coefficient suggests the existence of spillover of TFP from leading industry to others (Table 2). Further, coefficient of TFPgap has the highest value in the last period which supports the potential of higher TFP growth by assimilating improved technologies and managerial practices by the laggard industries. The spillover effect was significant all through the sample period, with fastest spillover witnessed in the period (2009-10 to 2016-17)[12], when financial services emerged as the industry with the highest level of TFP.

**Table 2: Industrial Convergence and Spillover of TFP**

| **Variable** | **1981-2016** | **1981-1992** | **1993-2007** | **2009-2016** |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| TFPGap | -0.05* | -0.27*** | -0.07* | -0.43*** |
| | (0.023) | (0.063) | (0.038) | (0.107) |
| TFPmax | 0.14** | 0.37*** | -0.85* | 2.76*** |
| | (0.619) | (0.111) | (0.492) | (0.577) |
| Constant | -0.07** | -0.39*** | -0.10** | -0.57*** |
| | (0.282) | (0.091) | (0.046) | (0.136) |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 972 | 324 | 405 | 216 |
| R-squared | 0.08 | 0.24 | 0.07 | 0.29 |
| Number of Industry | 27 | 27 | 27 | 27 |

**Note:** Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Source:** Authors' calculations.

[12] 2008-09 is excluded from the analysis due to abrupt TFP changes amidst the global financial shock.

A similar analysis is done separately for the manufacturing and services sectors. Both manufacturing and services shows presence of convergence and spillover channels (Appendix Table A.1).

## Section VII
## Conclusion

This paper analysed the trends and dynamics of productivity in India during the period 1981-82 to 2016-17. After examining the usefulness and suitability of three aggregation approaches for manufacturing and services in the Indian context, we identify the industries that have been driving productivity growth in India during the last three decades. The findings of the paper suggest that the industries which have adopted ICT were the key drivers of overall aggregate productivity. The paper also found evidence that the channels of convergence and spillover are contributing to the TFP growth in India.

Furthermore, the convergence and spillover analysis showed that productivity in India has a high potential to grow at faster rates as there is a wide gap in TFP across industries. The industries lagging behind can benefit from other industries by adopting better technologies and managerial strategies. This is particularly important for the services sector, which has emerged as the growth driver of the Indian economy. At the same time, the contribution of TFP to services sector growth is lower than other sectors, reflecting that the sector is yet to reach its potential. Analysis of factor reallocations calls for an enabling environment for free movement of labour and capital across sectors. The government can boost productivity through pro-active regulations that can facilitate labour and capital reallocation and enable spillover effects from leading industries to the laggards.

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## Appendix

Average productivity growth in the two time periods- 1993-2007 and 2008-16 is used to cluster 27 industries. Elbow chart to select value of k while minimising WCSS (within-cluster sum of squares) is shown below.

**Chart A.1: The Elbow Method**

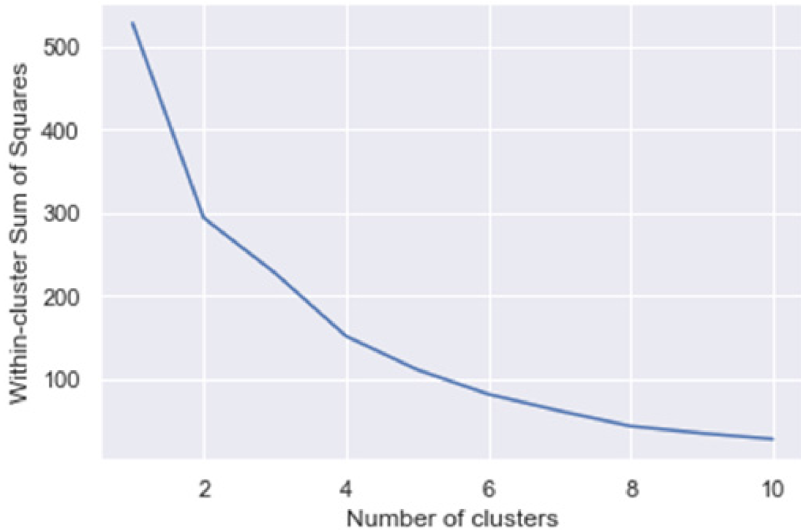

**Table A.1: Convergence Regressions**

1) Manufacturing

| **Variable** | **1981-2016** | **1981-1992** | **1993-2007** | **2008-2016** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| TFPGap | -0.105*** | -0.339*** | 0.133*** | -0.593*** |
| | (0.021) | (0.103) | (0.030) | (0.090) |
| TFPmax | 0.370** | 0.375** | 1.274*** | 5.375*** |
| | (0.124) | (0.169) | (0.272) | (1.374) |
| Constant | -0.075*** | -0.519*** | 0.227*** | -0.315*** |
| | (0.017) | (0.160) | (0.060) | (0.063) |
| Observations | 468 | 156 | 195 | 117 |
| R-squared | 0.177 | 0.305 | 0.187 | 0.370 |
| Number of Industry | 13 | 13 | 13 | 13 |
| Year FE | YES | YES | YES | YES |

**Note:** Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2) Services Sector

| **Variable** | **1981-2016** | **1981-1992** | **1993-2007** | **2008-2016** |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| TFPGap | 0.021*** | -0.103 | 0.090*** | -0.285*** |
| | (0.005) | (0.084) | (0.027) | (0.056) |
| TFPmax | 2.405** | 1.924 | 0.487 | 2.198*** |
| | (0.969) | (1.241) | (0.483) | (0.484) |
| Constant | -0.008 | -0.088 | 0.018 | -0.331*** |
| | (0.013) | (0.054) | (0.031) | (0.071) |
| Observations | 360 | 120 | 150 | 90 |
| R-squared | 0.203 | 0.406 | 0.283 | 0.525 |
| Number of Industry | 10 | 10 | 10 | 10 |
| Year FE | YES | YES | YES | YES |

**Note:** Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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*Vol. 41, No. 1: 2020*

**Good Economics for Hard Times by Abhijit V. Banerjee & Esther Duflo, 402 pp., Juggernaut Books (2019), ₹699**

The views of economists often differ from the views of the public on many core issues leading to a trust deficit towards economists. Abhijit V. Banerjee and Esther Duflo, in their book *Good Economics for Hard Times*, address this issue by stressing the need for economists to understand the true nature of the facts at hand, to acknowledge the assumptions made to interpret those facts, to be modest about the path of deductive reasoning followed, to refine the 'conclusions' through repeated trials with data and finally, to respect the existence of opposing views. The authors are winners of the 2019 Nobel Memorial Prize in Economics. Abhijit Banerjee is Ford Foundation International Professor of Economics and Esther Duflo is Abdul Latif Jameel Professor of Poverty Alleviation and Development Economics at the Massachusetts Institute of Technology, United States. An earlier work of the authors titled *Poor Economics: Rethinking Poverty and the Ways to End It* won the Financial Times and Goldman Sachs Business Book of the Year Award 2011.

In eight core chapters, the book addresses different themes encompassing migration, trade, the nature of preferences and beliefs, economic growth versus quality of life, effects of growth on climate change, labour displacement and inequality, challenges in governance and policymaking and the role of dignity in cash transfer programmes. The debates in the book draw information from different domains of economics – political, sociological, anthropological, experimental, observational, and statistical. What makes the book different from an extensive literature review is its narrative style which takes the form of an intriguing and piquant discourse rather than a stark academic piece. The book gives a strong message that economics as a subject is much more than just a collection of research papers.

Contrary to a widely held political belief on ever-increasing migration, Banerjee and Duflo reveal that the fraction of international migrants among the world's population in 2017 was more or less at the same level as it was in 1960 or 1990, most of them being legal migrants. Based on the review of robust literature, they assert that most people who migrate come from politically disturbed countries rather than economically poor countries. Furthermore, even after moving to a new location or country, they find it difficult to get jobs without prior connections and are often offered jobs that are not preferred by the native population. The uncertainty associated with migration to a far-off country or state often discourages them from leaving home. Regarding the impact of migration of low-skilled labour on the labour market of the host country, there is conclusive evidence – beginning with David Card's seminal study of the impact of Cuban immigrants on wages in Miami – which shows that such migration enables the creation of more jobs as migrants spend their earnings in the host economy. This allows the native workers to move up the rung or try better jobs and brings spirited entrepreneurship into the economy. The authors offer some policy solutions to encourage migration which include, *inter alia*, offering rent subsidies, pre-migration job-matching, and childcare help.

Antithetic to propositions of trade theory, Banerjee and Duflo observe that inequality in developing countries has increased post-trade liberalisation. Among other things, competition among labour-abundant countries seems to have driven the wages of low-skilled workers down when compared with their higher-skilled counterparts. Rigidities in labour markets, stickiness in the movement of both labour and capital towards newer prospects in the face of competition, and the additional cost incurred on marketing of products have mostly rendered trade liberalisation ineffective, at least in the short run. The authors provide examples of industry clusters and e-commerce platforms that have helped producers from developing countries to compete in the international markets with the required brand image and cost-efficiency. The authors, however, argue that the victims of trade, instead of being compensated by the beneficiaries, are often left to suffer further. The problem of subjective identification of the victims gets compounded by an unwillingness to admit the downsides of trade.

Economic policies are mostly driven by public preferences. Banerjee and Duflo, however, question if policymakers correctly ascertain these preferences and give them due importance in the decision-making process. For instance, the choice of providing food stamps over cash transfers is based on the assumption that poor people cannot make the right choice between necessary and unnecessary consumption. The literature, however, provides enough evidence suggesting that if given cash under government programmes, the poor would actually spend a very large portion of it on food. Similarly, a better understanding of radical communalism will be facilitated by a better appreciation of social norms and their impact in terms of conformist preferences in a community. This, in turn, can help in designing more effective policies to counter communalism. Public preferences in a society, which are considered to be 'rational' and 'stable', however, change with the changing circumstances and perceptions of identity. This changeability of preferences of people gives rise to the scope of polarisation in society. At one extreme, this can fuel a separatist culture and, at the other, it can stifle democracy. The authors advocate Gordon Allport's contact hypothesis – increased interpersonal contact between diverse groups in a setting where the groups enjoy equal situational status, common goals, legal support, and lack of competition – as a way to deal with such situations. This integration may be promoted through affordable public housing for the disadvantaged, made available in all neighbourhoods and allotted randomly, thereby creating mixed neighbourhoods.

Against the backdrop of slowing growth in developed countries since the mid-1970s, Banerjee and Duflo discuss two challenging issues – sustainability and measurement of growth from the perspective of improvement in quality of life. They argue that one should focus more on improving the quality of life of the average citizen rather than emphasising a generalised increase in growth. There are well-known limitations of gross domestic product (GDP) growth as an indicator of economic development performance. For instance, some of the very poor countries have shown remarkable improvement in mortality rate in recent years. Also, GDP growth does not count the happiness or satisfaction that a better quality of life brings. Thus, single-minded focus on growth might, the authors predict, lead to policies that unproductively sacrifice the poor in favour of the rich.

The authors discuss climate change, labour-displacing automation, and anti-welfare policies as some of the banes of economic growth. Several studies, conducted across the world, show that increases in temperature have the most debilitating effects on agricultural production, efficiency, and health of workers in developing countries. Through randomised controlled trials (RCTs), the authors also find evidence that simply adopting energy-efficient technologies in the pursuit of economic growth, without constraining consumption, does not lead to emission gains. By delaying their commitment to reducing $CO_2$ emissions in the quest for future growth, the authors fear that developing countries would simply threaten the health and life expectancy of their poor population today.

Similarly, the book argues, based on the literature, that if automation is not productive enough to be able to generate other businesses and new jobs, it reduces employment and depresses wages, especially for the manufacturing sector and for workers with low education. Banerjee and Duflo believe that while inventing new hardware to assist patients in post-surgery recovery at home saves money and creates jobs, searching for algorithms that automate approval of insurance claims destroys jobs. Even the most polarised partisans in the United States agree in a poll that automation should veer more towards 'dangerous and dirty' jobs. Perhaps, in recognition of these concerns, South Korea announced the world's first tax on robots in 2017.

Banerjee and Duflo identify inequality as the most immediate damaging effect of anti-welfare economic policies aimed at accelerating economic growth. They argue that high marginal income tax rates, applied to very high-income groups, are a 'perfectly sensible' solution to curb income inequality. Their assertion in this matter is, however, based mostly on evidence that only 'hints' at the possibility that tax cuts for top income brackets may increase pre-tax income inequality The authors also observe that while technological progress may have depressed the wages of low-skilled workers and made way for increasing inequality between average salaries at corporate giants and other companies, it is the astronomical salaries of financial sector managers and CEOs, linked to commissions and stock options rather than a salary scale and with no 'productivity' to justify such high salaries, that has made inequality in finance-dominated United States and United Kingdom much more pronounced than it has been in the primarily bank-based continental Europe.

The authors do not restrict the suggestion of taxation to the top income brackets. They acknowledge that if the government has to get a 'sticky' economy going, it has to adopt social policies which require funds and for which the average taxpayer has to step up his/her contribution. Tax increases can be a politically plausible policy, if the government delivers credibly on their social policies. The authors believe that the faith of citizenry in good governance can make a government behave credibly. However, they note that the political class considers the policies aimed at redistribution of income to be sloth-abetting and to be indicative of the fact that growth can actually make some people worse off.

In the realm of public programmes, Banerjee and Duflo make a strong philosophical case against conditional cash transfers (CCTs) and in favour of unconditional and specifically universal cash transfers. The stigma of being identified as poor and the possibility of not meeting the 'conditions' even if someone is actually poor are some of the issues that haunt the dignity of the possible beneficiaries of CCTs. This may reduce participation in these programmes even though empirical evidence ratifies gains in human development achieved by participants in such programmes. In developing countries, cash transfers also encourage the needy to overcome the fear of subsistence and work harder or try new things. Banerjee and Duflo make a case for Universal Ultra Basic Income (UUBI) along with CCTs with softer enforcement of 'conditions' in such countries. In developed countries, as the findings of several surveys suggest, people attach a sense of purpose and identification to their jobs and an unconditional universal basic income may not compensate for the loss of this identity when they are displaced from work. In contrast, the average low-skilled person in a developing country may not feel the same way about their job because they don't feel *entitled* to it, they do not build their lives around their work, and they are ready to switch occupations at short notice. The authors discuss some of the successful programmes in developed countries that have helped displaced workers to get suitably retrained to match the requirements of new jobs. Furthermore, these programmes have helped them to move across regions and settle with new jobs, while extending their unemployment insurance to prop them up through all of this. In the context of developing countries, an NGO programme in Bangladesh (a model found effective in seven poor economies so far) seems to have achieved long-eluded economic improvement simply by designing the programme to treat the 'very poor' with respect as human beings and recognising both their deprivation and potential.

The methodological basis for most of the assertions made by the authors in the book are RCTs. RCTs are expensive exercises and may therefore preclude the study of the impacts against a fuller picture of an economic situation with all its problems and virtues. Some statements made in the book also seem to need further explanation. For instance, the suggestions of 'streamlining the whole process and communicating it [costs and rewards of migration] more effectively [to the migrants] in Chapter 2 require elaboration, particularly from a practical standpoint. The authors discuss how the faith of its citizens in government can ensure good governance in Chapter 8, while in Chapter 9 they talk about conscious leakage in public programmes. It is difficult to see how people can develop faith in their governments when faced with these hard realities. It may help if the authors discuss the realities in the same space where they talk about faith and vice versa. Also, missing from the discussion are the programmes adapted to the needs of average middle-class people in developing countries, who struggle with their dignity too when faced with job losses.

Nevertheless, this book is very useful reading for meaningful and effective policymaking. It helps to wrap our heads around the notion that economics is a great unifier. The basic forces and laws of economics apply unanimously, across geographies and demography. People maximise their utility, given their information sets and circumstances, exhibit demand and supply behaviour based on the opportunity costs they face and respond to incentives. It is time that policymakers become better attuned to public preferences and needs and act sensitively upon it to achieve a better quality of life.

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**Advice and Dissent: Why America Suffers When Economics and Politics Collide by Alan S. Blinder, 368 pp., Basic Books (2018), ₹1005**

Economic policy is very often felt to be less than optimal and ineffective in addressing issues facing the public. This happens despite the plentiful economic advice available from eminent economists and experts in different areas. Professor Alan S. Blinder's book *Advice and Dissent: Why America Suffers When Economics and Politics Collide* explains this conundrum and offers some practical solutions to make the outcome of policymaking more effective and meaningful. The author is a professor of economics and public affairs at Princeton University and has been actively contributing to policy advisory circles. He has authored about 20 books on economic policy, drawing on his wide-ranging experience and expertise. This latest book, written primarily in the context of the United States, contains principles and practices that are applicable to other countries, including India. Its 13 chapters, though not divided into sections, follow three key themes – the reasons for dissent between economic advisers and policymakers, proposed breakthroughs or ideas to reconcile such dissent and their application in the context of certain economic challenges.

The author explains that economic advice is routinely kept in abeyance while framing public policy. As a result, public interest at large is somewhat compromised and social welfare gets eroded. It is therefore, imperative to find consonance between economic advisers and policymakers. The book begins with the assertion that policymakers often turn to economists for *post facto* validation of their policy choices rather than engaging them *ab initio* in formulating policies. Blinder cites instances where economic wisdom has been used from the word go to arrive at certain policy reforms: some popular examples include the deregulation of the trucking and airlines sectors in the United States (US) in the 1970s and 1980s, the US tax reforms in 1986 and the move towards liberalisation, privatisation and globalisation in India in the 1990s. However, instances of *post facto* validation are more ubiquitous, and there is a felt need to shift the focus to the *ab initio* kind of economic advisory process.The author argues that it is contingent upon economists to come up with policy proposals that are largely rational with minor fault lines (to accommodate the concerns and interests of the policymakers) as this will encourage policymakers to entrust economists with policy formulation to begin with. He is sanguine this will help frame policies that are 'mostly good' with insignificant stains, rather than ill-framed policies with occasional bright spots.

The second chapter focusses on understanding the basic reasons underlying the fundamental differences in the thinking of policymakers and economic advisers and their approach to an issue. The former are more concerned with general economic principles (efficacy, efficiency, costs and benefits), while the latter focus more on political aspects, face value of a policy decision, and the implementation process. Such differences often lead to a diminished role of economic principles in policy formulation. In addition, the author enumerates three impediments to annealing economic sense in framing policies – ignorance of economic principles ('economic illiteracy' among the common populace), overemphasis on ideology (instead of balanced eclecticism with a preference for 'fact and logic over ideology') and the role of interest groups (where compact and vocal groups such as industry associations are better united and more influential than dispersed groups such as consumers).

The third chapter discusses the difference in time horizons for policymakers and economic advisers. While policymakers may often have a short time horizon driven by electoral cycles, economic advisers tend to have a longer time horizon. Bridging this gap in timescale is an area that holds great promise for reconciling the views of policymakers and economic advisers. Furthermore, eminently logical and economically reasonable assumptions such as 'independence of irrelevant alternatives' and 'transitivity of preferences' may not hold water in the realm of policymaking because of the differences in the way an issue is approached in actual policymaking scenarios. As for reconciliation, the author argues that policymakers need to better appreciate the long-term consequences of their actions, thereby coming closer to the thought process of economists.

The fourth chapter deals with the skilful art and clinical science of 'messaging', that is convincing the public about the usefulness of a policy.

The author acknowledges that economists – in deference to their fairness and integrity – find it hard to express their unqualified support for any policy. He goes on to say that popular support for a policy is elusive when the verdict from economists is ambiguous or nuanced, more so in present times of shortened attention spans. The author suggests that economic advisers should extol the virtues of a proposed policy, while confining their apprehensions to fine print. The subsequent chapter elaborates on the role of the media in aiding the economist in messaging, analysed through the prism of the 'principal-agent framework' of economic theory.

After elaborating on the various avenues where policymakers and economists often differ in their diagnosis and preferred course of remedy, the author sets upon the task of suggesting reforms in the way economists make policy prescriptions. To this end, he advocates 'hard-headed but soft-hearted' policy choices that wed the virtues of free markets with compassion for those who are disadvantaged in the marketplace. While conceding that the stumbling block towards achieving such an optimal blend lies in inflexible attitudes, Blinder very persuasively establishes that such attitudinal changes are easy to accomplish, saying 'we must start thinking with our heads and feeling with our hearts, rather than the other way around'. He cites the example of negative income tax (NIT) pioneered by Milton Friedman in 1962 whereby the government would top up the income of a family whose income fell below a certain threshold as a hard-headed but soft-hearted policy that sought to alleviate poverty with only minimal disincentives to work. He then recounts that there has been bipartisan support for anti-poverty programmes in the US which are modelled on the lines of NIT, thus fortifying the case for such eclectic policies.

The author discusses the application of the foregoing discourse to three specific economic issues. On international trade, the author argues that trade always creates 'winners' and 'losers' in a country – and because the latter are mostly a starkly visible minority whereas the former are a diffused majority, there is much opposition to freer trade. However, free trade is always Kaldor-Hicks superior to restricted trade and the author therefore urges for a revamping of the income redistribution scheme in the US – the Trade Adjustment Assistance – to increase acceptability of freer trade amongst people. Nevertheless, some restrictions to free trade may be justifiable in respect of national defence, infant industry, *etc.,* and Blinder has reviewed the contextual and contemporary relevance of these grounds.

Blinder goes on to discuss the high degree, durable and comparatively elevated level of inequality in the US. Some of the factors contributing to high inequality include the dominant role of technology and relatively lower progress in education, receding unionisation, sagging minimum wage, breakdown of the implicit social contract between labour and capital, and, more remarkably, tax policies. Offering concrete remedies, he discusses the nature of redistributive policies that would be effective without the loss of efficiency (an instance of the eclectic brand of policies talked about earlier), as also other workable initiatives such as nudging corporates towards sharing profits with labour, revitalising unions, and invigorating apprenticeships. He notes that policies to reduce inequality often receive scant political support. Though the discussion pertains to the US, the key essence is universally applicable. It debunks some myths that hinder policymaking in this matter and offers sensible wisdom to economic advisers to approach this contentious policy issue with tact.

Blinder then turns to the question of tax reforms and brilliantly demonstrates the working of interest groups in holding up desirable and sensible rationalisation of tax legislation. He illustrates how economic advisers and policymakers hold divergent opinions on this question,whereby the former are concerned with adherence to certain laudable economic principles and the latter are sensitive to the interests of small but significant constituencies like industries, professions, commodities, *etc.* Nevertheless, by employing the example of the Tax Reform Act of 1986,which fared well by economic reasoning and was simultaneously politically palatable, he builds a case for improving upon what might initially appear as a stalemate between economic ‘will’ and political ‘won’t’.

In the concluding chapter, the author elaborates upon the possible way forward in terms of approaches to policy that would concurrently be good economics and also be favoured by policymakers. A key requirement of such a likelihood is that the populace should have better awareness of economics so that they can demand more of it in the policies made for them. The second principle relates to framing policies that offer upfront dividends while deferring the costs of adjustment to the future. The popular examples cited in the book relate to medical insurance, fiscal deficit and climate change. However, the author has not deliberated upon a potential threat to this approach, namely the 'time inconsistency argument', that is, a policy may turn inappropriate before it runs its projected course. Third, persuading policymakers to lengthen their time horizon for more meaningful and enduring policies – entirely in their own interest – is an urgent imperative for economic advisers. The author then explores cases where matters of policy are voluntarily abandoned by policymakers to technical experts, for instance, monetary policy and trade deal negotiations. He evaluates the relative merits of the same and undertakes a counterfactual analysis to see if this can be extended to more areas. Blinder concludes the book by suggesting ways in which economists can bridge the gap between themselves and policymakers through subtle changes in their words, thoughts and value judgment.

On balance, the book is a scholarly analysis addressing one of the longest-standing challenges to sound policymaking and strikes a commendable balance between theory and empirics in the elucidation. It deserves praise for de-jargonising precepts from the literature on political economy and conveying the essence of the same to a wider audience, as also enriching public discourse with celebrated economic principles such as independence of irrelevant alternatives, principal-agent problem, comparative advantage, to name a few.The book is peppered with easy-to-comprehend illustrations of intricate economic ideas and theories, including those that have come to form the staple of the discipline of political economy. It echoes Keynes in reiterating 'The ideas of economists… are more powerful than is commonly understood. Indeed the world is ruled by little else ...', providing germane ways in which economists can raise their contribution to policymaking that better serves public interest.

**Anshuman Kamila and Aastha***

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