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Fiscal Rules and Cyclicality of Fiscal Policy: Evidence from Indian States

Dirghau Keshao Raut and Swati Raju*

A rule-based fiscal regime, through the enactment of Fiscal Responsibility Legislations (FRLs), was adopted by state governments against the backdrop of growing debt and deficits in the early 2000s. Literature has documented the positive impact of fiscal rules in terms of fiscal discipline. However, the evidence with regard to cyclicality of fiscal policy is mixed. This paper examines the impact of fiscal rules on the cyclicality of fiscal policy of Indian states using data for the period from 1990 to 2018. The results suggest that fiscal rules have reduced pro-cyclicality of fiscal policy, particularly in terms of development expenditure. Fiscal deficit also changed its nature from pro-cyclical in the pre-FRL period to acyclical in the post-FRL period. Capital outlay displayed acyclical behaviour in both pre-and post-FRL periods.

JEL Classification: E62, C23, H62, H72

Keywords: Fiscal policy, states' expenditure, cyclicality

Introduction

Cross-country practices at national and sub-national levels suggest that fiscal rules have been adopted to discipline fiscal policy and to maintain fiscal sustainability (Grembi *et al.,* 2016; Guerguil *et al.,* 2016; IMF, 2017). In the context of Indian states, rising level of debt and deficits during the late 1990s and early 2000s necessitated the implementation of fiscal reforms at the state level and a major step in this direction was the adoption of Fiscal Responsibility Legislations (FRLs) incentivised by the Twelfth Finance

* Dirghau Keshao Raut is Assistant Adviser in the Department of Economic and Policy Research (DEPR), Reserve Bank of India. Swati Raju is Associate Professor at Mumbai School of Economics and Public Policy, University of Mumbai.

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Commission (Finance Commission, 2004). Several studies in the cross-country as well as in the Indian context have established the contribution of fiscal rules to achieve fiscal consolidation (Alesina and Bayoumi, 1996; Chakraborty and Dash, 2017; GoI, 2017; Marneffe *et al.,* 2010; Simone and Topalova 2009; Tapsoba, 2012). There have, however, been concerns about fiscal policy being pro-cyclical in a rule-based fiscal regime due to restrictions on borrowings.

Cyclicality of fiscal policy refers to the direction of change in government expenditure and taxes relative to economic/output conditions. The fiscal policy is considered pro-cyclical, if it is expansionary during economic booms and contractionary during recessions. On the other hand, if fiscal policy is expansionary during recessions and contractionary during booms, it is considered to be counter-cyclical. Keynes advocated a counter-cyclical fiscal policy – running a budgetary deficit during slowdown. In contrast, balanced budget rules generally produce a pro-cyclical fiscal policy. Decline in revenues during an economic slowdown enforces reduction in expenditure, while buoyant revenues during a high economic growth phase allow for increase in expenditure leading to a pro-cyclical fiscal policy. Clemens and Miran (2012) argue that balanced budget requirements lead to compressed government expenditures due to contraction in tax base during recession periods. Fatas and Mihov (2006) observe that restrictions on fiscal policy impair a government's ability to run a counter-cyclical fiscal policy. Bova *et al*. (2014) find fiscal policy under fiscal rules to be pro-cyclical and argue that cyclically adjusted targets and escape clauses may reduce pro-cyclicality.

There are, however, studies arguing that fiscal rules help in generating fiscal space which leads to lesser pro-cyclical or a counter-cyclical fiscal policy. For example, Nerlich and Reuter (2015) find an evidence of fiscal rules linked with higher fiscal space. They argue that fiscal discipline reduces deficits and debt, thus, widening the gap between debt limit and actual debt leading to increase in fiscal space. They also find evidence of higher fiscal space contributing to higher discretionary expenditure. Aizenman *et al.* (2019) observe that public expenditure by a government with lower fiscal space (high debt level) tends to be more pro-cyclical than that by a government having more fiscal space (low debt level). Simone and Topalova (2009) argue that fiscal consolidation creates fiscal space for following a counter-cyclical fiscal policy. Manasse (2005) finds that the impact of fiscal rules on cyclicality varies during different economic conditions. The restrictions on deficits are found to be associated with counter-cyclical policies during ‘very good’ or ‘very bad’ economic conditions, and with pro-cyclical policies during the intermediate state of the economy. The design of fiscal rules is also documented to have an impact on cyclicality. For example, cyclically adjusted budget balance rules are associated with counter-cyclical public spending (Guerguil *et al.,* 2016; Misra and Ranjan, 2019). Guerguil *et al.* (2016) observe a reduction in pro-cyclicality of investment spending when rules are investment-friendly.

In the case of Indian states, there is limited literature on the impact of fiscal rules on the cyclicality of fiscal policy. This paper thus seeks to fill this gap and examines the role of fiscal rules in influencing the nature of cyclicality of states’ fiscal policy in terms of development expenditure, capital outlay and fiscal deficit. Section II presents a review of relevant literature. Section III describes major features of the FRLs of states and the progress with respect to fiscal consolidation. Methodology is discussed in Section IV and empirical results are presented in Section V. Section VI concludes the paper.

Section II
Review of the Literature

While several country-specific as well as cross-country studies examined the various aspects of fiscal rules, this section focuses on studies analysing the impact of fiscal rules on cyclicality of revenues/expenditure and fiscal consolidation. Most of the studies have found fiscal rules contributing to fiscal consolidation, though the evidence on cyclicality of fiscal policy is mixed, *i.e.,* pro-cyclical, counter-cyclical and acyclical.

Alesina and Bayoumi (1996), using data for the period from 1965 to 1992 for 48 mainland states in the United States (US), found a positive impact of fiscal controls on budget surplus as well as higher primary surplus. Further, cyclical variability of surplus was found to be lower in states with more stringent fiscal controls. They, however, pointed out that fiscal controls did not result in any cost in terms of output variability. Based on state level data of the US from 1963 to 2000, Fatas and Mihov (2006) found that fiscal policy restrictions helped to reduce budget deficits but impaired the government’s ability to run a counter-cyclical fiscal policy. Clemens and Miran (2012) used data for 27 US states for the period 1988 to 2004 and found that balanced budget requirements caused compression in capital and other expenditures. Mcgranahan and Mattoon (2012), using quarterly data of 50 US states from 1980 to 2011, found evidence of pro-cyclical revenues, *i.e.,* a 1 percentage point increase in the growth of coincident indicator of economic conditions leading to a 0.9 percentage point increase in revenues.

Cross-country studies generally found evidence of pro-cyclical fiscal policy. Using data on 13 Latin American countries, Gavin and Perotti (1997) observed that economic downturns restricted the increase in government expenditure (due to higher borrowing cost) leading to a pro-cyclical fiscal policy. Estimating a weighted least square model based on annual data from 1960 to 1998 for 22 OECD countries, Lane (2003) found varying cyclicality across countries and expenditure categories. While current expenditure was found to be counter-cyclical, its consumption components were pro-cyclical. Similarly, government investment expenditure was found to be most pro-cyclical, while interest payments were found to be acyclical. Cross-country coefficients of cyclicality were, however, observed to differ across countries, *i.e.,* the US and the United Kingdom (UK) showed counter-cyclical fiscal behaviour, whereas Ireland and Portugal showed above average pro-cyclical fiscal behaviour. In a study based on panel data for 1995-2008 pertaining to 16 countries in the euro area, Marneffe *et al.* (2010) found a positive association between the fiscal rule index and total and primary fiscal balance, and a negative impact of fiscal rules on government expenditure. Using data for 62 developing and industrial countries for the period 1960-2009, Vegh and Vuletin (2011) found tax policy to be pro-cyclical in developing countries and acyclical in industrial countries. They also observed government spending to be pro-cyclical in developing countries and counter-cyclical in industrial countries. However, Ilzetzki and Vegh (2008), using quarterly data of 49 countries from 1960 to 2006, observed pro-cyclical government consumption spending in developing as well as high-income countries. Using panel data of 72 countries, Cicek and Elgin (2011) found evidence of more pronounced pro-cyclicality of fiscal policy in countries with a larger size of shadow economy. They suggested strengthening of tax enforcement and improving legal and administrative processes to reduce the shadow economy and pro-cyclicality of fiscal policy. Aghion and Marinescu (2008) provided evidence of a more counter-cyclical budgetary policy with higher level of financial development, adoption of inflation targeting and lower openness of the economy.

The design of fiscal rules in terms of balanced budget rule (BBR) and cyclically adjusted balance (CAB) was found to influence the cyclicality of fiscal policy. Misra and Ranjan (2019), using a correlation approach for data on 61 countries from 2001 to 2016, found a positive correlation between expenditure and gross domestic product (GDP) in 75 per cent of the sample countries. In the panel system GMM estimation, results showed higher pro-cyclicality coefficient (0.92) for a sub-sample of 25 countries with BBR *vis-à-vis* that for overall sample (0.66) and for sub-sample of countries with fiscal rule in terms of CAB (-0.08).

Studies on fiscal rules in the context of Indian states have looked into aspects such as fiscal discipline; causes of slower/faster adoption of FRL; impact of fiscal rules on development expenditure, guarantees given by states, borrowings by state utilities; and forecasting of revenues. Simone and Topalova (2009) observed that higher transfer dependent states were slower in adopting FRLs. They also observed that the enactment of FRLs coincided with fiscal consolidation. Further, the impact on fiscal discipline was stronger when FRLs included debt target and expenditure rules. Buiter and Patel (2010), based on a review of seven major states, observed 'discretionary counter-cyclical' fiscal policy at the state level in India. Using data pertaining to 14 states for the period from 2000-01 to 2013-14, Chakraborty and Dash (2017) estimated the panel GMM model and found evidence of reduction in gross fiscal deficit (GFD)-gross state domestic product (GSDP) ratio and revenue deficit (RD)-GSDP ratio after the introduction of fiscal rules. The study also found that states have reduced their discretionary development expenditure to maintain the deficit targets as per their fiscal rules. The *Economic Survey 2016–17* (GoI, 2017), observed that revenue deficit of states declined by 2.5 percentage points of GSDP in the post-FRL period. The survey pointed out that several factors contributed to this improvement such as increase in states' own tax revenue due to acceleration in nominal GDP growth; increased central transfers; decline in interest payments due to debt restructuring; and the Centre's contribution in social sector expenditure under Centrally Sponsored Schemes. The regression results showed that FRLs contributed to the decline in RD and GFD but not primary deficit. The survey also observed a decline in guarantees in the three year period post-FRLs, and a decrease in borrowings by states' utilities and an improvement in forecasting of own tax revenues in the post-FRL years.

Though not in the context of fiscal rules, studies have examined the cyclicality of expenditure by Indian states. The results are mixed and vary across expenditure components. For example, based on data for 17 non-special category states and estimating panel least square (LS), instrument variables (IV) and 2SLS estimation, Kaur *et al.* (2013) observed acyclical social sector expenditure (SSE) on account of downward rigidity of SSE in the revenue account, and pro-cyclical education expenditure with pro-cyclicality being more pronounced during upturns, defined as positive output gap. Using correlation analysis, pooled least square technique and 2SLS method on data for 14 states, the RBI (2014) observed the capital outlay of states to be pro-cyclical and primary revenue expenditure to be acyclical.

Section III
Fiscal Rules and Fiscal Consolidation at the State Level

Fiscal rules are generally implemented through legislative provisions for the conduct of fiscal policy in terms of operational targets including escape clauses for deviation from such targets. While the adoption of fiscal rules began in advanced countries, some emerging market economies and underdeveloped countries have also adopted fiscal rules regimes successfully (IMF, 2017). Though the nature of fiscal rules varies across countries, they usually include ceilings on deficit-GDP ratio, revenue balance, primary balance and debt. Revenue and expenditure targets are also sometimes used as operating targets in a rule-based fiscal policy. In some countries, implementation of fiscal rules has been advocated as a pre-condition to implement certain macroeconomic policies. In India, the Committee on Capital Account Convertibility 1997 (Chairman: Shri S. S. Tarapore) recommended the fiscal deficit of the central government at 3.5 per cent of GDP along with reduction in states' deficit and quasi-fiscal deficit as a precondition for capital account convertibility (RBI, 1997).

The fiscal rules at the state level in India were adopted in the backdrop of a prolonged deterioration in state finances and the consequent fiscal reforms.

The fiscal position of states witnessed deterioration beginning late 1980s due to increased expenditure on salaries and pensions after the implementation of the Fourth Pay Commission. The deficits of states widened further during the 1990s accentuating with the implementation of the Fifth Pay Commission award in 1998. In 2003-04, the consolidated GFD-GDP ratio and debt-GDP ratio of states reached peaks of 4.2 per cent and 31.8 per cent, respectively. Consequently, measures were adopted to stabilise state finances through multi-pronged reforms – strengthening revenues and compressing expenditure. First, the debt swap scheme was implemented during 2002-03 to 2004-05, which allowed states to repay high-cost central government loans through relatively low-cost market loans and small savings, that helped states to reduce their interest burden. Second, the Twelfth Finance Commission recommended the adoption of a recruitment and wage policy by states to limit their salary expenditure to 35 per cent of revenue expenditure net of interest payments and pension. Third, the state governments implemented value added tax (VAT) which helped them raising higher own tax revenue. Fourth, the introduction of an incentive structure by the Twelfth Finance Commission in terms of debt consolidation and relief facility, and linking of grants to enactment and adherence of fiscal rules encouraged states to enact their FRLs.

The states in India adopted rule-based fiscal policy by enacting FRLs beginning 2002 when Karnataka implemented it even before the enactment of the Fiscal Responsibility and Budget Management Act by the central government in 2003 (see Appendix). Most of the states enacted their FRLs during 2004-05 to 2006-07 and the process was completed in 2010 with the enactment of FRLs by Sikkim and West Bengal. In line with cross-country practices and the fiscal rules implemented by the central government in India, the state governments also adopted fiscal rules in terms of quantitative ceilings mainly on deficits. While the targets under FRLs for elimination of revenue deficit/achievement of revenue surplus and reduction in GFD-GSDP ratio to 3.0 per cent were broadly uniform across states, few states also incorporated other targets such as limiting debt as well as guarantees, rationalisation of committed/revenue expenditures, review of the compliance to fiscal targets, greater fiscal transparency and medium term fiscal plan (MTFP) for the fiscal indicators. There was, however, variation across states in terms of timeline for achieving these targets. Further, the ceiling on RD and GFD adopted by states under their respective FRLs was broadly consistent with the recommendations of the Twelfth Finance Commission.

The enactment of the FRLs, brought about considerable progress in fiscal consolidation at the state level. Most states achieved revenue surplus and brought down their GFD-GSDP ratio to below 3.0 per cent before 2008-09. Table 1 shows that the consolidated revenue account of states turned from a deficit of 2.6 per cent of GDP in 2001-02 (the pre-FRL year) to a surplus of 0.9 per cent of GDP in 2007-08, the year by which most states had adopted FRLs.

Revenue receipts, comprising states' own revenues (own tax and own non-tax revenue) and central transfers (share in central taxes and grants) contributed 56.1 per cent improvement in the revenue account. In fact, the contribution of central transfers at 34.7 per cent was higher than own revenues (21.3 per cent). The period 2001-08 also witnessed tax reforms such

Table 1: Fiscal Consolidation and the Quality of Adjustment

(Per cent of GDP)

Variable	2001-02	2007-08	Variation*	Contribution to Fiscal Consolidation** (Per cent)
1	2	3	4=(3-2)	5
1. Revenue Deficit (3-2)	**2.6**	**-0.9#**	**-3.4**	–
2. Revenue Receipts (2.1+2.2)	**10.6**	**12.5**	**1.9**	**56.1**
2.1 Own Revenues	6.6	7.3	0.7	21.3
2.1.1 Own Tax Revenues	5.2	5.7	0.5	15.1
2.1.2 Own Non-tax Revenues	1.3	1.5	0.2	6.3
2.2 Central Transfers	4.0	5.2	1.2	34.7
2.2.1 Share in Central Taxes	2.2	3.0	0.8	23.9
2.2.2 Grants	1.8	2.2	0.4	10.8
3. Revenue Expenditure	**13.2**	**11.6**	**-1.5**	**43.9**
Of Which:				
Development Revenue Expenditure	7.2	6.8	-0.5	13.2
Non-development Revenue Expenditure	5.7	4.6	-1.2	34.8

*: Variation in percentage points of GDP.

**: Contribution in variation of revenue deficit-GDP ratio.

#: Minus (-) indicates surplus.

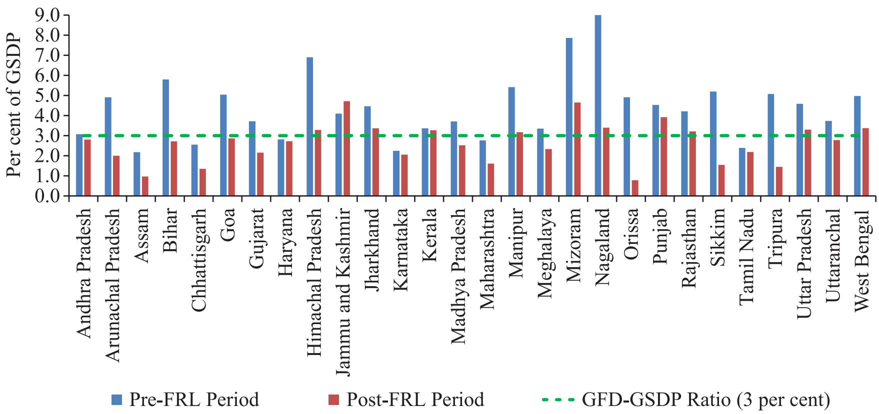
Note : Signs of contributions of revenues in column 5 have been changed from minus (-) to plus (+) as the increase in revenue is a positive contribution to fiscal consolidation.

Source : Authors' calculations based on data from the Reserve Bank of India (RBI) and National Statistical Office (NSO).

as implementation of VAT that coincided with higher own tax revenue-GDP ratio, and higher tax buoyancy of central taxes leading to increase in transfers. From the expenditure side, reduction in non-development revenue expenditure contributed around 35 per cent to the improvement, indicating mainly the decline in interest payments owing to the debt swap scheme, decline in debt level and shift in GFD financing to relatively low-cost market loans.

The fiscal consolidation was also discernible in terms of GFD of states in the post-FRL period (Chart 1). The GFD-GSDP ratios of 27 out of 28 states were lower in the post-FRL period compared to the pre-FRL period.[1] There were 22 states (12 non-special category states and 10 special category states) with a GFD-GSDP ratio above 3.0 per cent in the pre-FRL period while in post-FRL period there were only 11 such states. Among the states which reduced their GFD-GSDP ratio to below 3.0 per cent in the post-FRL period, 6 were non-special category states and 5 were special category states. Overall, the trend in GFD-GSDP ratio indicates that the gains in terms of fiscal consolidation in the post-FRL period were visible across both non-special and special category states.

Chart 1: Average GFD-GSDP Ratio in Pre- and Post-FRL Periods



Source: Authors' calculations based on data from RBI and NSO.

[1] Pre- and post-FRL periods are defined based on year of enactment of FRL by a state. For example, Andhra Pradesh enacted its FRL in June 2005, hence the period from1990-91 to 2004-05 is taken as its pre-FRL period and 2005-06 to 2017-18 as the post-FRL period. State-wise month and year of the enactment of FRLs are provided in the Appendix.

Section IV
Methodology

The literature suggests that there are two main approaches that can be used to examine the cyclicality of fiscal policy. The first approach is based on the correlation between the cyclical component of output and a fiscal policy variable (Goyal and Sharma, 2015; Misra and Ranjan, 2019; RBI, 2014; Vegh and Vuletin, 2011 and 2012). In this method, the cyclical components of output and the fiscal policy variable are estimated and then the correlation between the two is computed. A positive correlation coefficient suggests pro-cyclicality of fiscal policy, while negative correlation indicates counter-cyclicality.

The second approach is regression based, wherein a fiscal policy variable is regressed on the output variable along with some control variables. A positive coefficient of output variable suggests pro-cyclicality of fiscal policy, whereas a negative coefficient indicates a counter-cyclical fiscal policy (Gavin and Perotti, 1997; Ilzetzki and Vegh, 2008; Lane, 2003; Mcgranahan and Mattoon, 2012; Misra and Ranjan, 2019). The absence of statistical significance of the coefficient of output variable indicates that the fiscal policy is acyclical. Both correlation and regression methods have been used in this paper. In the regression method, a panel system GMM model was estimated to examine the effect of fiscal rules on cyclicality of fiscal policy represented by development expenditure, capital outlay and fiscal deficit. The development expenditure/capital outlay was regressed on GSDP, first lag of GFD and gross transfers from the Centre (*i.e.,* share in central taxes, grants and loans) (equations 2 and 3). The cyclicality of the fiscal deficit was examined by regressing the GFD-GSDP ratio on GSDP and gross transfers from the Centre (equation 4).

The stationarity of variables was checked using panel unit root test, conducted for development expenditure, capital outlay, GSDP, gross transfers and GFD-GSDP ratio after converting all these variables (except GFD-GSDP ratio) into first differences of their natural logarithm.

Panel unit root tests are based on the following standard Dickey-Fuller-type regression:

$$\Delta y_{it} = \alpha_i x_{it} + \rho_i y_{i,t-1} + \sum_{j=1}^{ki} \beta_{ij}\, \Delta y_{i,t-j} + \varepsilon_{it} \qquad \text{.........(1)}$$

Where i represents state, t represents time period (year) and x_{it} represents exogenous variables which *inter alia* includes fixed effects. ρ_i indicates autoregressive coefficients and ε_{it} represents errors. The specific tests used to check stationarity include the Levin-Lin-Chu (2002); Im-Pesaran-Shin (2003); and Fisher-type Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests as proposed by Maddala and Wu (1999), and Choi (2001). The null hypothesis in Levin-Lin-Chu (LLC) test assumes common unit root process, whereas in the other three tests, the null hypothesis assumes individual unit root process.

In the next step, a panel GMM model proposed by Arellano and Bover (1995) and Blundell and Bond (1998) was estimated. Following Gavin and Perotti (1997), Kaur *et al.* (2013) and RBI (2014), the equations used to examine cyclicality of development expenditure, capital outlay and GFD are as follows.

$$dlog\ devexp_{i,t} = \beta_{0i} + \beta_1 * dlog\ devexp_{i,t-1} + \beta_2 * dlogRGSDP_{i,t} + \beta_3 * GFD\text{–}GSDP_{i,t-1} + \beta_4 * dlogRGT_{i,t} + u_{1i,t} \quad \text{.........(2)}$$

$$dlogCO_{i,t} = \alpha_{0i} + \alpha_1 * dlogCO_{i,t-1} + \alpha_2 * dlogRGSDP_{i,t} + \alpha_3 * GFD\text{–}GSDP_{i,t-1} + \alpha_4 * dlogRGT_{i,t} + u_{2i,t} \quad \text{.........(3)}$$

$$GFD\text{–}GSDP_{i,t} = \gamma_{0i} + \gamma_1 * GFD\text{–}GSDP_{i,t-1} + \gamma_2 * dlogRGSDP_{i,t} + \gamma_3 * dlogRGT_{i,t} + u_{3i,t} \quad \text{.........(4)}$$

Where i and t stands for state and year, respectively. β_0, α_0 and γ_0 represents state fixed effect, *devexp* stands for real development expenditure, CO is real capital outlay, *RGSDP* indicates real gross state domestic product, *GFD - GSDP* denotes gross fiscal deficit as a per cent of GSDP, *RGT* stands for real gross transfers and $u_{1i,t}$, $u_{2i,t}$ and $u_{3i,t}$ are error terms. The GSDP deflator has been used to convert nominal variables into real values.

The preference for panel system GMM estimation over other methods was motivated by the following reasons. There is a strong possibility of path dependence in fiscal policy variables such as development expenditure due to factors such as (i) larger proportion of expenditure on operations and maintenance, and (ii) implementation of developmental schemes relating to education and health. The projects related to irrigation and construction of highways typically take longer than a year to complete. Therefore, lagged dependent variable was included to capture the path dependence in fiscal policy variables. In this situation, the OLS model may provide inconsistent results due to correlation between lagged dependent variable and error term. Thus, the system GMM estimator, which uses internal instruments based on lagged values of independent variables and makes correlation of lagged dependent variable with error term insignificant, is employed. Further, there could be endogeneity between GFD, GSDP growth and gross transfers which can be addressed by using GMM. The Sargan test is used to check the validity of instruments. The null hypothesis in this test is: over-identifying restrictions are valid. The Arellano-Bond test is used to provide a robustness check with regard to autocorrelation. The null hypothesis in this test is: the error term is serially uncorrelated.

Section V
Empirical Evidence

The analysis of cyclicality of fiscal policy was undertaken using both methods, namely, the correlation-based approach and the system GMM estimator for the period 1990-91 to 2017-18 for 28 states[2]. Data on fiscal policy variables were sourced from various issues of RBI's publication *State Finances: A Study of Budgets* and data on GSDP at current and constant prices were sourced from the NSO, Ministry of Statistics and Programme Implementation, Government of India. Data on GSDP for earlier years were adjusted to the latest 2011-12 base. All the variables were considered in real terms and were log transformed (except GFD-GSDP ratio). In order to estimate the impact of FRLs separately from other factors affecting cyclicality, the time period from 1990 to 2018 was categorised into pre- and post-FRL periods for each state depending on the year of enactment of FRL (see Appendix). Accordingly, the data set used for empirical estimation consists of unbalanced panels of 369 observations of the pre-FRL period and 356 observations of the post-FRL period.

The nature of cyclicality of fiscal policy was examined in terms of select expenditure components and fiscal deficit. The expenditure components

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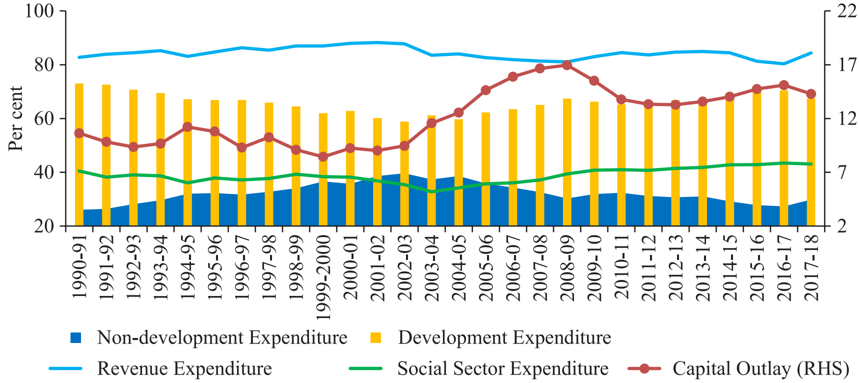
2 Data for Telangana from 2014-15 to 2017-18 was included in the data for Andhra Pradesh.

were chosen in view of their discretionary nature and multiplier effect on output – an important aspect when undertaking a counter-cyclical fiscal policy. Development expenditure was chosen for the following reasons. First, development expenditure includes investment and maintenance expenditure on social and economic services such as education, health, agriculture, transport and communications, rural and urban development, irrigation *etc.* It does not include committed expenditures such as interest payments and pension, and thus it is relatively discretionary in nature. Second, it accounts for more than two-thirds of the total expenditure (Chart 2). Third, it captures the compositional change in the expenditure pattern of states in the wake of fiscal reforms undertaken in the 2000s. For instance, the decline in non-development revenue expenditure on interest payments allowed states to spend more on social and economic services. Fourth, as observed by Jain and Kumar (2013), the size of impact multiplier for development expenditure is higher than that of other expenditures. Fifth, there is evidence of fiscal rule sharing a negative association with development expenditure (Chakraborty and Dash, 2017).

Besides development expenditure, we have also examined the cyclicality of capital outlay as it appears to be the most discretionary component of public expenditure and easy to curtail when states face fiscal constraints. For example, as evident from Chart 2 and 3, the share of capital outlay in total

Chart 2: Share of Major Expenditure Categories in Total Expenditure



Source: Reserve Bank of India and authors' calculations.

expenditure witnessed a declining trend when fiscal deficit was higher during 1994-2002 (averaged 3.5 per cent of GDP) and an increasing trend when it was lower during 2003-09 (averaged 2.8 per cent of GDP). The capital outlay also has the highest cumulative multiplier, implying its implications for long-term growth (Jain and Kumar, 2013). Further, the share of capital outlay of states in general government capital outlay has increased over the years (from around 45 per cent in the early 1990s to above 60 per cent in 2016-17 and 2017-18).

Finally, in view of the targets set by states under fiscal rules in terms of fiscal deficit, the cyclicality of GFD-GSDP ratio is also examined in the paper. Under the fiscal rules, the limits on GFD-GSDP ratio are likely to produce a pro-cyclical fiscal policy as the reduction in tax collection during slowdown would necessitate government to curtail expenditure to adhere to the targets. However, if the government borrows and prevents expenditure cutback despite lower taxes during slowdown, it would lead to a counter-cyclical policy. This would be reflected in an increase in GFD-GSDP ratio during the slowdown. Also, if fiscal space is available with a state (for example, if the GFD-GSDP ratio is less than the target), then it can go for higher expenditure and higher deficit even in the case of shortfall in revenue. It is, therefore, useful to examine the cyclicality of fiscal policy based on GFD-GSDP ratio.

Correlation-based Approach

This approach uses the cyclical components of fiscal variables and real GSDP. The cyclical components of real GSDP, real development expenditure, real capital outlay and GFD-GSDP ratio were obtained using the Hodrick-Prescott filter. Correlation coefficients of cyclical real GSDP with cyclical components of fiscal variables for each state for both the pre-FRL and post-FRL periods are given in Table 2.

Table 2: Correlation Coefficients of Cyclical Real GSDP with Cyclical Components of Fiscal Variables

State	Development Expenditure		Capital Outlay		GFD-GSDP Ratio	
	Pre-FRL	Post-FRL	Pre-FRL	Post-FRL	Pre-FRL	Post-FRL
Andhra Pradesh	0.69*** (0.00)	0.16 (0.58)	0.19 (0.50)	0.35 (0.24)	0.30 (0.27)	-0.02 (0.95)
Arunachal Pradesh	0.33 (0.23)	0.43 (0.17)	0.24 (0.38)	0.13 (0.68)	0.17 (0.53)	-0.15 (0.65)
Assam	-0.01 (0.98)	-0.32 (0.28)	-0.26 (0.37)	-0.31 (0.30)	0.02 (0.95)	-0.21 (0.48)
Bihar	0.01 (0.95)	-0.26 (0.41)	0.06 (0.82)	-0.57** (0.05)	-0.26 (0.32)	-0.35 (0.26)
Chhattisgarh	0.59 (0.29)	-0.34 (0.24)	-0.35 (0.57)	-0.09 (0.75)	0.82* (0.09)	-0.09 (0.76)
Goa	0.43* (0.09)	0.61** (0.03)	0.11 (0.66)	0.54* (0.07)	0.24 (0.38)	-0.49* (0.10)
Gujarat	-0.21 (0.45)	0.22 (0.47)	0.25 (0.37)	-0.21 (0.49)	-0.07 (0.82)	0.08 (0.80)
Haryana	0.27 (0.32)	0.46 (0.11)	0.23 (0.40)	0.39 (0.19)	-0.04 (0.89)	0.27 (0.38)
Himachal Pradesh	0.26 (0.34)	0.36 (0.23)	0.07 (0.80)	0.25 (0.41)	-0.02 (0.94)	-0.30 (0.33)
Jammu and Kashmir	0.57** (0.02)	0.63** (0.03)	-0.27 (0.32)	0.33 (0.30)	0.68*** (0.00)	0.03 (0.92)
Jharkhand	-0.26 (0.63)	-0.44 (0.17)	0.15 (0.77)	-0.33 (0.31)	-0.08 (0.88)	-0.06 (0.85)
Karnataka	0.39 (0.21)	0.42* (0.10)	0.39 (0.21)	0.32 (0.22)	0.27 (0.39)	0.05 (0.85)
Kerala	0.31 (0.29)	0.27 (0.33)	0.13 (0.67)	0.45* (0.09)	0.40 (0.17)	-0.06 (0.82)
Madhya Pradesh	0.50* (0.06)	0.27 (0.37)	-0.17 (0.55)	0.65** (0.02)	0.36 (0.19)	0.55** (0.05)
Maharashtra	-0.10 (0.71)	-0.52* (0.07)	0.03 (0.91)	-0.34 (0.25)	0.02 (0.95)	-0.39 (0.18)
Manipur	0.78*** (0.00)	-0.06 (0.85)	0.73*** (0.00)	-0.20 (0.50)	0.66*** (0.01)	0.38 (0.20)
Meghalaya	0.46* (0.08)	0.27 (0.40)	0.13 (0.63)	0.11 (0.74)	0.02 (0.94)	0.08 (0.83)
Mizoram	0.47* (0.07)	0.32 (0.31)	0.13 (0.61)	0.17 (0.58)	0.35 (0.18)	0.16 (0.62)

State	Development Expenditure		Capital Outlay		GFD-GSDP Ratio	
	Pre-FRL	Post-FRL	Pre-FRL	Post-FRL	Pre-FRL	Post-FRL
Nagaland	0.43 (0.11)	0.23 (0.44)	0.49* (0.07)	0.24 (0.44)	-0.07 (0.82)	-0.40 (0.17)
Odisha	0.02 (0.95)	0.06 (0.84)	-0.40 (0.14)	-0.00 (0.99)	0.04 (0.88)	0.10 (0.73)
Punjab	0.14 (0.65)	-0.03 (0.92)	0.12 (0.69)	0.00 (0.99)	-0.17 (0.59)	0.04 (0.88)
Rajasthan	0.63*** (0.01)	0.05 (0.86)	0.34 (0.22)	-0.17 (0.59)	-0.10 (0.74)	-0.17 (0.58)
Sikkim	0.27 (0.24)	-0.14 (0.73)	-0.01 (0.97)	-0.43 (0.29)	-0.10 (0.67)	0.13 (0.75)
Tamil Nadu	-0.05 (0.86)	-0.43 (0.11)	0.29 (0.33)	0.04 (0.89)	-0.30 (0.31)	-0.46* (0.09)
Tripura	0.28 (0.31)	0.61** (0.03)	0.39 (0.15)	0.24 (0.43)	0.34 (0.20)	0.15 (0.63)
Uttar Pradesh	0.08 (0.79)	0.46* (0.09)	0.08 (0.80)	0.35 (0.22)	0.01 (0.96)	0.36 (0.21)
Uttarakhand	-0.27 (0.66)	-0.41 (0.16)	-0.43 (0.46)	-0.41 (0.17)	-0.90** (0.04)	-0.01 (0.96)
West Bengal	-0.10 (0.65)	-0.11 (0.79)	-0.07 (0.78)	-0.03 (0.94)	0.43** (0.05)	-0.36 (0.39)

***,**,*: Indicate statistical significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.

Note: Figures in parentheses are p-values.

Source: Authors' estimation/calculations based on data from RBI and NSO.

In the pre-FRL period, the correlation coefficients of the cyclical component of GSDP and cyclical development expenditure were positive and statistically significant for eight states, indicating pro-cyclical development expenditure (Table 3). For the remaining 20 states, the positive/negative correlation coefficients were statistically not significant implying the acyclical nature of development expenditure. In the post-FRL period, the number of states with positive and statistically significant correlation coefficients decreased to five and there was one state (Maharashtra) with negative and statistically significant correlation coefficient. With regard to capital outlay, in the pre-FRL period, the correlation coefficients were positive and statistically significant for two states indicating pro-cyclical nature of capital outlay. For the other 26 states, correlation coefficients (negative/positive) were statistically insignificant. In the post-FRL period, capital outlay was pro-cyclical in three

Table 3: Cyclicality of Fiscal Policy in Pre- and Post-FRL Period

(Number of states)

Period	Pro-cyclical	Counter-cyclical
Development Expenditure		
Pre-FRL period	8	0
Post-FRL period	5	1
Capital Outlay		
Pre-FRL period	2	0
Post-FRL period	3	1
GFD-GDSP ratio		
Pre-FRL period	4	1
Post-FRL period	1	2

Source: Authors' calculations.

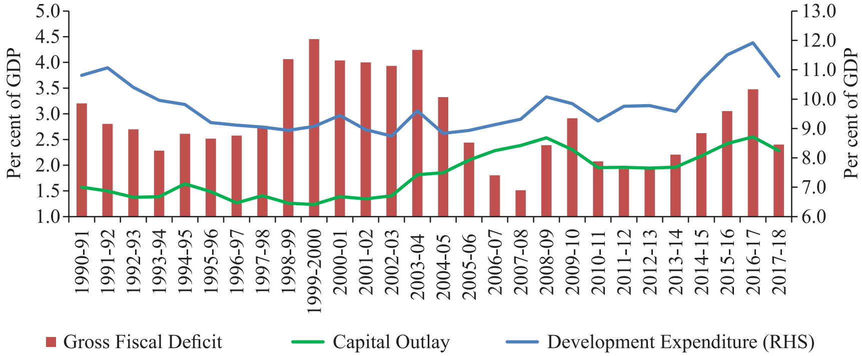
states, counter-cyclical in one state (Bihar), and acyclical in the remaining 24 states. These results were broadly in line with the findings of an earlier study (RBI, 2014) which observed a mix of positive and negative correlation between cyclical GSDP and cyclical expenditures (total expenditure, primary revenue expenditure and capital outlay) across states. With respect to the GFD-GSDP ratio, the number of states showing pro-cyclical GFD declined from four in the pre-FRL period to one in the post-FRL period, while the number of states indicating counter-cyclical GFD increased to two in the post-FRL period from one in the pre-FRL period.

Overall, the correlation analysis suggests that the development expenditure and GFD-GSDP ratio were less pro-cyclical during the post-FRL period compared with the pre-FRL period. However, literature suggests that the cyclicality analysis based on correlation approach may not give correct assessment as the magnitude of volatility in variables could be different and, therefore, the regression approach is a preferred approach to examine the cyclicality (Forbes and Rigobon, 1998; Lane, 2003; Misra and Ranjan, 2019; RBI, 2014).

Regression Approach: System GMM Estimator

The regression-based approach allows to control for variables other than GSDP, *viz.,* gross transfers and fiscal space. The first lag of the GFD-GSDP ratio is expected to have an inverse relationship with development

Chart 3: Consolidated Development Expenditure, Capital Outlay and the GFD of States



Source: Authors' calculations based on data from RBI and NSO.

expenditure and capital outlay. The GFD in the previous year could serve as a proxy of the fiscal space available to a state. An increase in GFD would lead to an increase in expenditure on interest payments in the following year, which in turn could crowd out development expenditure and capital outlay. Chart 3 shows negative association of development expenditure-GDP ratio and capital outlay-GDP ratio with GFD-GDP ratio of the previous year. The correlation coefficients of the first lag of the GFD-GDP ratio with capital outlay-GDP ratio and development expenditure-GDP ratio for the period 1990-2018 were negative (-0.43[3] and -0.21, respectively).

Before proceeding with system GMM estimation, the panel unit root tests were undertaken to check stationarity of the variables (Table 4). The results of all the tests employed, *viz.,* LLC, IPS, ADF and PP indicated stationarity of the GFD-GSDP ratio and the first differences of natural logarithm of GSDP, development expenditure, capital outlay and gross transfers.[4]

The results of the system GMM estimator are provided in Tables 5 to 7.

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[3] The correlation coefficient of GFD-GDP ratio with capital outlay-GDP ratio was statistically significant at 5 per cent level.

[4] Null hypothesis 'panels contain unit roots' rejected.

Table 4: Results of Panel Unit Root Tests

(sample period: 1990-2018)

Variable	LLC t-statistics	IPS W-statistics	Fisher-ADF Chi square	Fisher-PP Chi square
GFD-GSDP ratio	-6.18 (0.00)	-7.87 (0.00)	165.49 (0.00)	168.47 (0.00)
D(log RGSDP)	-258.16 (0.00)	-91.65 (0.00)	492.35 (0.00)	527.92 (0.00)
D(log devexp)	-24.14 (0.00)	-25.64 (0.00)	546.39 (0.00)	863.66 (0.00)
D(log CO)	-20.74 (0.00)	-22.10 (0.00)	475.14 (0.00)	555.36 (0.00)
D(log RGT)	-25.08 (0.00)	-26.10 (0.00)	560.97 (0.00)	853.95 (0.00)

LLC: Levin-Lin-Chu; IPS: Im-Pesaran-Shin; ADF: Augmented Dickey-Fuller; PP: Phillips-Perron.

Note: 1. For the LLC test, the null hypothesis is ‘panels contain unit roots’; for the IPS, ADF and PP test, it is ‘all panels contain unit roots’.
2. Figures in parentheses are p-values for the relevant null hypothesis.
3. Automatic lag length selection based on SIC.

Development Expenditure

The results of panel system GMM model estimated for assessing development expenditure cyclicality are given in Table 5. The log difference of real development expenditure (devexp) was regressed on log difference of real GSDP (RGSDP), first lag of GFD-GSDP ratio and log difference of real gross transfers (RGT). In view of the persistence in development expenditure growth in the post-FRL period (Chart 4), the second lag of the dependent variable was added as a regressor which was found to be statistically significant.

The results suggest that development expenditure of states was pro-cyclical in both pre-FRL and post-FRL periods, as the coefficient of output variable (RGSDP) was positive and statistically significant. These results were similar to the findings of RBI (2014) and Kaur *et al.* (2013) in respect of education expenditure but differ from the finding in respect of social sector expenditure which was found to be acyclical by Kaur *et al.* (2013). However, these results were not strictly comparable with earlier studies due to differences in categories of expenditure, number of states and time period covered.

Table 5: Empirical Results – Cyclicality of Development Expenditure

(Dependent Variable: Log difference of real development expenditure)

Variable	Pre-FRL period	Post-FRL period
1	2	3
d(log devexp $_{i, t-1}$)	-0.171*** (-6.40)	-0.293*** (-5.24)
d(log devexp $_{i, t-2}$)		-0.120*** (-2.54)
d(log RGSDP$_{i, t}$)	0.428*** (10.96)	0.364*** (7.12)
GFD-GSDP$_{i, t-1}$	-0.016*** (-7.08)	-0.021*** (-8.83)
d(log RGT$_{i, t}$)	0.140*** (6.49)	0.278*** (4.41)
Constant	0.097*** (7.70)	0.121*** (16.79)
No. of states included	28	28
No. of Observations	341	356
Sargan test statistics Prob>Chi^2	22.86 (1.00)	23.68 (1.00)
AR (1) Test (P-value)	0.00	0.00
AR (2) Test (P-value)	0.32	0.41

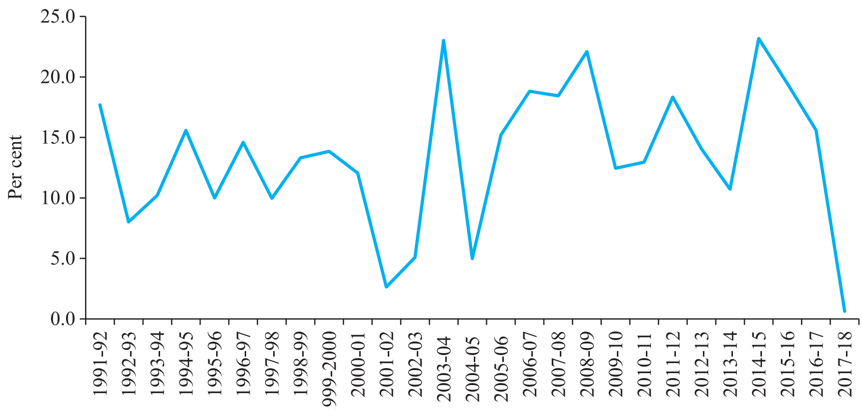
***: Indicates statistical significance at 1 per cent level.

Note: 1. Figures in parentheses are z-statistics.

2. AR (1) and AR (2) are Arellano–Bond tests (Arellano and Bond, 1991) for first order and second order serial correlation, respectively.

The results indicate that a 1 percentage point increase in output was associated with a 0.43 percentage point increase in development expenditure

Chart 4: Growth in Development Expenditure



Source: Authors' calculations based on data from RBI.

in the pre-FRL period and 0.36 percentage point in the post-FRL period suggesting that development expenditure was less pro-cyclical during the post-FRL period. The results of the system GMM model corroborate the findings of the correlation analysis where fewer states showed a pro-cyclical development expenditure in the post-FRL period. Fiscal space created by states through a compression of non-development revenue expenditure might have provided headroom to avoid cutback in discretionary development expenditure during times of economic slowdown in the post-FRL period.

The negative and statistically significant coefficient of the lagged GFD-GSDP ratio, which is observed for both the pre- and post-FRL periods, implies that an increase in the GFD-GSDP ratio was followed by a decline in growth rate of development expenditure in the next year. Gross transfers from the Centre led to increased development expenditure of states in both the pre- and post-FRL periods. However, the impact was stronger in the post-FRL period compared to that in the pre-FRL period, which could be due to increased contribution of centrally sponsored schemes during the 2000s.[5] The negative and significant coefficient of lagged dependent variable suggests discretionary nature of development expenditure. The results of Sargan test, which verifies the validity of the instruments for over-identifying restrictions, were found to be satisfactory. Further, AR (1) and AR (2) tests (used to check first order and second order serial correlation, respectively) satisfy an important assumption for the consistency of system GMM estimator.

Capital Outlay

Capital outlay, which forms a small proportion of the total expenditure of states (average 12.2 per cent during 1990-2018), showed a volatile pattern of growth (Chart 5). Further, the growth of capital outlay also exhibited persistence. Therefore, the second lag of dependent variable was added as a regressor which was found to be statistically significant (Table 6).

The coefficient of GSDP was statistically insignificant in both pre- and post-FRL periods suggesting acyclical nature of capital outlay in both

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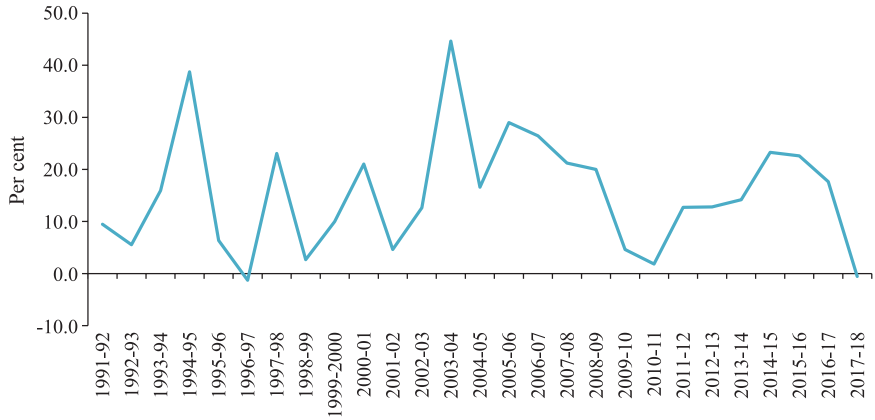
[5] The *Economic Survey 2016-17* (GoI, 2017) estimated that the need for spending by states reduced by around 1.2 per cent of GDP due to an increase in the Centre's contribution to centrally sponsored schemes, which contributed to a reduction in states' deficit in the post-FRL period.

Chart 5: Growth in Capital Outlay



Source: Authors' calculations based on data from RBI.

the periods. The results differ from RBI (2014) that showed pro-cyclical behaviour of capital outlay which could be due to different sample size (both

Table 6: Empirical Results – Cyclicality of Capital Outlay

(Dependent Variable: Log difference of real capital outlay)

Variable	Pre-FRL period	Post-FRL period
1	2	3
d(log CO $_{i, t-1}$)	-0.348*** (-15.40)	-0.325*** (-3.17)
d(log CO $_{i, t-2}$)	-0.315*** (-24.67)	-0.255*** (-3.10)
d(log RGSDP$_{i, t}$)	0.106 (0.34)	-0.217 (-0.44)
GFD-GSDP$_{i, t-1}$	-0.035*** (-7.46)	-0.029*** (-5.84)
d(log RGT$_{i, t}$)	0.307*** (8.35)	0.354*** (3.71)
Constant	0.200*** (7.49)	0.205*** (5.73)
No. of states included	28	28
No. of Observations	341	356
Sargan test statistics Prob>Chi^2	21.25 (1.00)	20.67 (1.00)
AR (1) Test (P-value)	0.05	0.01
AR (2) Test (P-value)	0.59	0.28

***: Indicates statistical significance at 1 per cent level.

Note: 1. Figures in parentheses are z-statistics.

2. AR (1) and AR (2) are Arellano–Bond tests (Arellano and Bond, 1991) for first order and second order serial correlation, respectively.

in terms of number of states and time period). Among other variables, the first lag of GFD-GSDP ratio was found to be negatively associated with capital outlay. Further, as expected, the GFD-GSDP ratio seems to have stronger impact on the capital outlay than on the development expenditure. Similar to development expenditure, the coefficient of gross transfers was found to be higher in the post-FRL period compared with that in the pre-FRL period. However, the coefficient of gross transfers in the case of capital outlay was higher than that for development expenditure in both pre- and post-FRL periods.

Gross Fiscal Deficit

Table 7 reports the estimation results for GFD cyclicality. Following Gavin and Perotti (1997)[6], the GFD-GSDP ratio was regressed on log difference of RGSDP and the log difference of RGT. The coefficient of RGSDP was positive and statistically significant in the pre-FRL period.[7] In the post-FRL

Table 7: Empirical Results – Cyclicality of Gross Fiscal Deficit

(Dependent Variable: GFD-GSDP ratio)

Variable	Pre-FRL period	Post-FRL period
1	2	3
$GFD\text{-}GSDP_{i,t-1}$	0.305***	0.217***
	(35.69)	(7.72)
$d(\log RGSDP_{i,t})$	2.73***	0.090
	(2.85)	(0.14)
$d(\log RGT_{i,t})$	-3.51***	-3.01***
	(-13.76)	(-10.21)
Constant	3.12***	2.49***
	(21.20)	(31.94)
No. of states included	28	28
No. of Observations	369	356
Sargan test statistics	22.87	25.66
Prob>Chi^2	(1.00)	(1.00)
AR (1) Test (P-value)	0.00	0.05
AR (2) Test (P-value)	0.58	0.29

***: Indicates statistical significance at 1 per cent level.

Note: 1. Figures in parentheses are z-statistics.
2. AR (1) and AR (2) are Arellano–Bond tests (Arellano and Bond 1991) for first order and second order serial correlation, respectively.

[6] Gavin and Perotti regressed fiscal balance-GDP ratio on real GDP growth, controlling for other factors such as GDP growth in good and bad times, terms of trade and lagged fiscal balance.

[7] One unit change in log difference of real GSDP was associated with an increase in GFD-GSDP ratio by 0.03 unit [the coefficient 2.73 of d(log RGSDP) in Table 7 multiplied by 0.01].

period, the coefficient of RGSDP was positive but statistically insignificant. This suggests that the GFD was pro-cyclical in the pre-FRL period and acyclical in the post-FRL period. The negative and statistically significant coefficient of RGT in pre- and post-FRL periods was along expected lines as most of the gross transfers are in the form of revenue account transfers, *i.e.,* share in central taxes and grants (accounting for 85 per cent of gross transfers during 1990-2018), which help in reducing GFD. The coefficient of lagged dependent variable was positive and significant in both the periods, but the smaller size of the coefficient in the post-FRL period indicates that the introduction of fiscal rules helped in lowering the persistence of fiscal deficit.

Section VI
Conclusion

The fiscal position of states in India witnessed a significant improvement after the enactment of FRLs by them. The paper found that the implementation of fiscal rules by the states has had an impact on cyclicality of their fiscal policies. The assessment of cyclicality in terms of different fiscal policy variables suggested that the development expenditure turned less pro-cyclical in the post-FRL period. Capital outlay, however, showed acyclical behaviour in both pre- and post-FRL periods. The GFD of states turned acyclical in the post-FRL period from being pro-cyclical in the pre-FRL period. The findings of the paper, therefore, indicates that the adoption of fiscal rules reduces the pro-cyclicality of fiscal policy. The fiscal rules regime also assisted in enforcing fiscal discipline at the state level in India. Therefore, it may be concluded that the pursuance of a rule-based fiscal policy can play an effective role in macroeconomic management by allowing to follow counter-cyclical/ less pro-cyclical fiscal policy.

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Appendix

Fiscal Responsibility Legislations at State Level: Major Features

State	Month and year of enactment of FRL	GFD-GDSP ratio of 3 per cent	Revenue deficit elimination/ revenue surplus	Target for liabilities	Expenditure target	Ceiling on guarantees
Andhra Pradesh	June 2005	√	√	35 per cent of GSDP	–	Risk weighted guarantees at 90 per cent of RR.
Arunachal Pradesh	March 2006	√	√	–	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Expenditure management consistent with revenue generation. Protecting 'high priority development expenditure'.	–
Assam	September 2005	√	√	45 per cent of GSDP including guarantees	Ceiling on revenue expenditure under annual state plan.	50 per cent of own revenues or 5 per cent of GSDP.
Bihar	April 2006	√	√	–	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Norms for prioritisation of capital expenditure.	–
Chhattisgarh	September 2005	√	√	–	–	–

(Contd...)

State	Month and year of enactment of FRL	GFD-GDSP ratio of 3 per cent	Revenue deficit elimination/ revenue surplus	Target for liabilities	Expenditure target	Ceiling on guarantees
Goa	May 2006	√	√	30 per cent of GSDP	–	Ceiling as per Goa Guarantees Act.
Gujarat	March 2005	√	√	30 per cent of GSDP	–	Cap as per Gujarat Guarantees Act.
Haryana	July 2005	√	√	28 per cent of GSDP	–	–
Himachal Pradesh	April 2005		√	–	–	80 per cent of RR.
Jammu and Kashmir	August 2006	√	√	55 per cent of GSDP	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Norms for prioritisation of capital expenditure.	Risk weighted guarantees at 75 per cent of RR.
Jharkhand	May 2007	√	√	300 per cent of RR by 2007-08	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Expenditure management consistent with revenue generation.	–
Karnataka	September 2002	√	√	–	–	–
Kerala	August 2003	3.5 per cent by 2005-06 and 2.0 per cent by 2006-07	√	–	–	–

(Contd...)

State	Month and year of enactment of FRL	GFD-GDSP ratio of 3 per cent	Revenue deficit elimination/ revenue surplus	Target for liabilities	Expenditure target	Ceiling on guarantees
Madhya Pradesh	May 2005	√	√	40 per cent of GSDP	–	80 per cent of RR.
Maharashtra	April 2005	Shall specify by rule, target reduction	√	–	–	
Manipur	August 2005	√	√	–	Salary bill not to exceed 35 per cent of RE (excluding interest payment and pension). Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare.	As per Manipur Guarantees Act.
Meghalaya	March 2006	√	√	28 per cent of GSDP	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Expenditure management in relation to receipts potential. Efforts to contain non-plan expenditure. Reduce expenditure on wages and salaries.	–
Mizoram	October 2006	√	√	–	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Norms for prioritisation of capital expenditure.	Risk weighted guarantees not to exceed twice of consolidated fund receipts.

(Contd...)

State	Month and year of enactment of FRL	GFD-GDSP ratio of 3 per cent	Revenue deficit elimination/ revenue surplus	Target for liabilities	Expenditure target	Ceiling on guarantees
Nagaland	August 2005	√	√	40 per cent of GSDP	Salary bill not to exceed 61 per cent of RE (excluding interest payment and pension). Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare.	Risk weighted guarantees at 1 per cent of RR/ GSDP.
Odisha	June 2005	√	√	300 per cent of RR by 2007-08	–	–
Punjab	October 2003	√	√	40 per cent by 2006-07	–	80 per cent of RR.
Rajasthan	May 2005	√	√	Debt (excluding public account) not to exceed twice of consolidated fund receipts.	–	–
Sikkim	September 2010	√	√	–	–	–
Tamil Nadu	May 2003	√	√	–	–	100 per cent of RR or 10 per cent of GSDP.
Tripura	June 2005	√	√	40 per cent of GSDP	–	Risk weighted guarantees to 1 per cent of GSDP.

(Contd...)

State	Month and year of enactment of FRL	GFD-GDSP ratio of 3 per cent	Revenue deficit elimination/ revenue surplus	Target for liabilities	Expenditure target	Ceiling on guarantees
Uttarakhand	October 2005	√	√	25 per cent of GSDP by March 2015	Expenditure policies to provide impetus to economic growth, poverty reduction and improvement in human welfare. Expenditure management consistent with revenue generation. Protecting 'high priority development expenditure'.	No guarantee beyond state stipulated limit.
Uttar Pradesh	February 2004	√	√	25 per cent of GSDP by March 2018	As per the target in MTFP.	No guarantee beyond state stipulated limit.
West Bengal	July 2010	√	√	–	–	–

Note: RE: Revenue Expenditure, RR: Revenue Receipts, MTFP: Medium Term Fiscal Policy Plan
Source: *State Finances: A Study of Budgets* (various issues), RBI.

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Payment Systems Innovation and Currency Demand in India: Some Applied Perspectives

Dipak R. Chaudhari, Sarat Dhal and Sonali M. Adki*

In this study, we postulate currency demand for transaction purposes driven by income effect, and a payment technology induced substitution effect working through velocity of currency. Innovations in payment systems have shown a statistically significant long-run inverse relationship with currency demand in India. However, the magnitude of its coefficient indicates that the substitution effect on currency demand could be smaller than the dominant income effect. In the presence of payment indicators and financial variables, the income effect coefficient on currency demand has come closer to unity, in line with the standard quantity theory of money but different from the inventory theoretic transaction demand model prediction (0.5). The impact of 1 per cent growth in digital retail transactions volume was estimated to be one tenth of the income effect. Thus, to neutralise the dominant income effect, the payment systems need rapid growth to the extent of 100 per cent in digital retail transactions volume.

JEL Classification: E41, E47, E51, C22

Keywords: Money demand, monetary policy, payment system, error correction and cointegration, ARDL model

Introduction

India's payment systems have witnessed significant growth in digital transactions, supported by policy thrust, sustained efforts from banking and financial sectors to provide technology enabled services and consumers' adoption of various non-cash payment instruments. At the same time, the demand for currency also exhibits growth momentum. Illustratively, currency in circulation to GDP ratio, after declining from 12.1 per cent in 2015-16 to

* Sarat Dhal and Sonali M. Adki are Directors and Dipak R. Chaudhari is an Assistant Adviser in the Reserve Bank of India (RBI). The authors thank the anonymous referee, Dr. Jay Chander, Editor, RBI Occasional Papers and internal discussants of the paper for their valuable comments and suggestions. The usual disclaimer applies: the views expressed in this paper are those of the authors and do not represent the views of the RBI. Please direct all correspondence to: scdhal@rbi.org.in.

8.7 per cent in 2016-17 in the wake of demonetisation[1], recovered to 10.7 per cent in 2017-18 and 11.2 per cent in 2018-19. In this context, a question arises on the impact of payments technology innovation on currency demand. The empirical studies for a cross-section of countries do not offer unique answers. A common perspective is that the relationship of payment systems with currency demand can be country specific. Therefore, we examine this relationship in the Indian context. We analyse currency demand as a function of payment indicators along with other proximate determinants such as income and financial variables (interest rate on deposits and stock return). We are specifically interested in assessing whether payment indicators could impinge on long-run currency demand, for which we use the autoregressive distributed lag (ARDL) model based on quarterly data. The rest of the study is organised into seven sections. Section II provides details of the policy approach to payment systems development in India. Section III reviews the existing literature on payment systems. Section IV gives details of the analytical framework used in this study. Section V discusses data and empirical modelling. Section VI explains stylised facts, Section VII explains empirical findings, and Section VIII concludes the study.

Section II
Payment Systems Development: India's Policy Approach

The central bank of a country is usually the driving force behind the development of national payment systems. India's central bank, the Reserve Bank of India (RBI), has been playing this developmental role and has taken several initiatives for safe, secure, sound, efficient, accessible and authorised payment systems in the country (Gupta and Gupta, 2013). A chronology of major initiatives since the late 1980s in the Indian payment systems is given in the Appendix (Table A.1).

The initial steps towards establishing modern payment systems were taken in the early 1980s, when the RBI introduced the magnetic ink-character recognition (MICR) technology for cheque processing, which sowed the seeds for digital payment systems in the country. Migration to

[1] The Government of India, on November 8, 2016, announced that ₹500 and ₹1,000 denomination bank notes issued by the RBI shall cease to be legal tender.

the cheque truncation system (CTS) happened in 2008, when the RBI first implemented it in New Delhi, on February 1, 2008 with 10 pilot banks. Soon thereafter the deadline was set to April 30, 2008 for all banks to migrate to the CTS. Further, to handle bulk payments and receipts, the electronic clearing system (ECS) was introduced, which has undergone many changes from being local to regional and then national. For a pan-India system for processing bulk and repetitive payments, the ECS has been subsumed into the National Automated Clearing House (NACH). The next step towards electronic products was the introduction of interoperable ATMs, wherein the National Financial Switch (NFS) had proved that in a large country like India, networked ATMs can function very well.

Payment systems have evolved over time to meet the requirement of remittances using non-cash and non-paper payment methods. The popularly known retail system is the National Electronic Funds Transfer (NEFT). Besides NEFT, the Immediate Payment Service (IMPS) and Real-time Gross Settlement (RTGS) also meet users' funds transfer requirements. Recently, the NEFT has been made operational on a 24x7 basis from December 16, 2019 to ensure availability of digital payments at any time. The IMPS is also a 24x7 immediate funds transfer system. The RTGS is meant for processing large value transactions of above ₹200,000, apart from interbank transactions. The modernisation of the information technology (IT) systems of banks and their core banking solutions has made possible the integration of various delivery channels. The large number of mobile phone users and the availability of cost-effective internet data have led to an increase in the number of mobile internet users. Taking advantage of this, an increasing number of payment facilities are being integrated through the mobile channel. Further, the introduction of a unified payment interface (UPI) has revolutionised the mobile payment system.

A wide range of reforms have been introduced to promote digital payments, covering customer-initiated transactions and government payments. From the perspective of financial inclusion and digitisation of government payments, the use of Aadhaar[2] for beneficiary identification and authentication in payments has played an important role, enhancing

[2] Aadhaar is a 12-digit number issued by the Unique Identification Authority of India (UIDAI) to the residents of India based on their demographic and biometric information.

efficiency and transparency in transactions. Accordingly, the Aadhaar Payment Bridge System (APBS) has been put in place to facilitate bulk and repetitive government payments to Aadhaar-seeded bank accounts of identified beneficiaries. Similarly, the Aadhaar Enabled Payment System (AePS) facilitates operations from Aadhaar-seeded bank accounts using biometric authentication of customers. Today, AePS is increasingly being used for Business Correspondent (BC) operations in an interoperable manner. Another significant segment of retail electronic payments is the RuPay cards issued under the Pradhan Mantri Jan Dhan Yojana, with its associated benefits dependent upon usage of the card.

The entry of non-bank players in payment systems has made an important contribution in terms of innovations and convenience to customers. Besides setting up White Label ATMs (WLAs) to bridge the gap in ATM infrastructure in rural and semi-urban areas in the country, non-banks are actively involved in issuance of Pre-paid Payment Instruments (PPIs). There are many payment systems with significant potential to influence the payment habits of different individuals. The Bharat Bill Payment System (BBPS) provides facility of anytime, anywhere, anyhow bill payments in the country and supports all forms of electronic payments. Also, the Trade Receivables Discounting System (TReDS) caters to the financing needs of the micro, small and medium enterprises (MSMEs) for faster financing and liquidity requirements. Thus, the retail payments ecosystem has made revolutionary progress over the years. The standards of all the payment channels and systems along with their security features in India are comparable with the best in the world. Compared with other countries, the changes in India's payments ecosystem have been fast-forwarded to reach its present stage in the shortest possible time. User trust in the payments system is being strengthened through policy initiatives over the years with implementation of certain policies relating to cyber security, fraud, customer awareness, and customer protection. Finally, the RBI has released its payment vision documents in the public domain. According to the latest document, 'Payment and Settlement Systems in India: Vision

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[3] On May 15, 2019 the RBI announced a vision document titled 'Payment and Settlement Systems in India: Vision 2019–2021', with its core theme of 'Empowering Exceptional (E) payment Experience'. The document aims to empower every Indian with access to a bouquet of e-payment options that are safe, secure, convenient, quick and affordable.

2019-2021'[3], digital transactions through UPI/IMPS are likely to register average annualised growth of over 100 per cent, which would help in the reduction of currency demand over the vision period.

Section III
The Literature

Economics literature on payment systems has evolved in various dimensions, broadly through macroeconomic and microeconomic perspectives (Kahn and Roberds, 2009). The macroeconomic perspective focuses on the impact of payment technology on currency and money demand (Amromin and Chakravorti, 2007; Bech *et al.*, 2018; Columba, 2009; Duca and VanHoose, 2004; Durgun and Timur, 2015; Fischer, 2007; Humphrey, 2004 and 2010; Lippi and Secchi, 2009; Oyelami and Yinusa, 2013). Some studies address the liquidity effects of payment systems (Li and Carroll, 2011), while some others consider the substitution effect of mode of payments (Schuh and Stavins, 2010). On the other hand, microeconomic studies offer perspective on the various determinants affecting the behaviour of people towards the adoption of modern payment instruments and alternate money such as the availability of technology, internet facility and education (Basnet and Donou-Adonsou, 2016; Lippi and Secchi, 2009), card prices (Hazra, 2017; Scholnick *et al.*, 2008), switching and search costs (Ausubel, 1991; Calem and Mester, 1995; Calem *et al.*, 2006; Stango, 2002), interest cost impact on card debt (Brito and Hartley, 1995; Lee, 2014), transaction cost and opportunity cost (Klee, 2008), impact of rewards, discounts and incentives on the use of credit and debit cards (Arango *et al.,* 2015; Arango-Arango *et al.,* 2018; Simon *et al.,* 2010; Stavins, 2018; Valverde and Zegarra, 2011), impact of safety and security aspects (Eze *et al.*, 2008; Kosse, 2013), usefulness of record-keeping of electronic payment data (Galbraith and Tkacz, 2018; Lotz and Zhang, 2016), consumer preference for a specific payment instrument and the impact of price elasticity on instrument choice (Stavins, 2018) and the evidence of beta convergence in the European countries' payment system (Martikainen *et al.,* 2015).

The literature provides mixed evidence on the role of payment systems innovation on money and currency demand. The differential impact is largely due to differences in payment instruments. Illustratively, using disaggregated provincial data in Italy, Columba (2009) shows that innovations in transaction technology through diffusion of ATMs and POS have a negative effect on the demand for currency in circulation but a positive effect on narrow money demand due to the positive effect of technology on bank deposits. Bouhdaoui *et al.* (2014) analyse the relationship between convenient prices[4] and cash usage by French nationals and find that individuals' shares of cash payments increased with convenient prices. Clearly, price rigidity can, in part, be explained by the use of cash to pay convenient prices. For Japan, Fujiki and Tanaka (2014), using household-level survey data and a quantile regression model, provide evidence that users of electronic money held more currency than non-users. Bech *et al.* (2018), using a cross-country (advanced and emerging market economies) panel data model, suggest that despite the increasing use of digital payments across the world, cash continues to be the more preferred mode of payment due to store of value motive and lower opportunity cost rather than payment needs. Some studies also find modern payment instruments to have a positive effect on tax collection – cashless payments reduce tax evasion as the transactions can be tracked easily by the authorities (Hondroyiannis and Papaoikonomou, 2017; Immordino and Russo, 2018).

In the case of developing nations, Oyelami and Yinusa (2013), using data on the Nigerian economy, provide evidence that internet payments and mobile money substituted currency while credit cards, Automated Teller Machine (ATM) and Point of Sale (POS) complimented it. Moreover, barring ATM debit cards and internet payments, all payment channels showed an inverse relationship with shocks to the interest rate and currency demand. This finding may have serious implications for how monetary policy is implemented, especially in developing countries. For India, Nachane *et al.* (2013) find that despite the emergence of various alternatives to cash-based transactions, currency retained its predominance. There exists a cointegrating relationship between currency in circulation, gross domestic product (GDP), wholesale price index (WPI) and deposit rates. The RBI report on the macroeconomic impact of demonetisation (RBI, 2017) analyses growth rates

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[4] Convenient prices are round prices that usually match monetary denominations. Firms set convenient price to avoid cash payments when the cost of handling cash is high or risky (e.g. theft) compared to the costs of other payment instruments. The same reasoning applies to consumers who also face transaction and holding costs when they use cash or other payment instruments (Bouhdaoui *et al.*, 2014).

in various payment channels, observing that an important consequence of demonetisation has been the sharp increase in the use of digital transactions. Maiti (2017) finds that post demonetisation cash transactions have moved in a sustained manner to non-cash modes of payment. Reddy and Kumarasamy (2017) examine the impact of credit and debit cards usage on currency demand in India by employing the ARDL approach. Their results show that the usage of credit cards is negatively associated with currency demand, whereas the usage of debit cards shows a positive association with currency demand in India.

Some studies find that payment technology innovation can also affect income effect on transaction demand for currency and money. In the case of Switzerland, Fischer (2007) re-examines the estimates for income elasticity of money demand based on cross-regional (cantonal) data. The study estimates that income elasticity can range between 0.4 and 0.6. On the contrary, Kumar (2011) analyses data on 20 developing Asian and African countries and finds that the magnitude of income elasticity did not change significantly with the increase in the use of modern payment systems. In the case of India, the income elasticity of currency demand is somewhat higher in comparison to the long-term elasticity observed in similar studies for advanced countries (Nachane *et.al.*, 2013).

Section IV
Analytical Approach

From a theoretical perspective, the role of payment systems in currency demand derives from its impact on the velocity of money (Meltzer, 1978). Let us consider the standard quantity theory of money or Fisher's version of the transaction demand for money M (currency with public), driven by velocity of money in circulation (V), economic activity (Y) and general price level (P):

$$MV = PY \tag{1}$$

which can be written in log-linearised statistically estimable form as,

$$LnM_t = \mu + LnY_t + LnP_t + e_t \tag{2}$$

According to this approach, velocity of money V is a constant, thus $\mu = Ln(V)$, for it is driven by technological progress which could be slow moving. Relaxing this assumption, velocity can change due to rapid progress in payments technology (S) and S_t^j representing different payment indicators, we can rewrite equation (1) as:

$$M\,V(\mu^v, S_t^j) = PY \tag{3}$$

Taking log-linearised form,

$$LnM_t = \mu^v + \theta LnS_t^j + LnY_t + LnP_t + e_t^v \tag{4}$$

where $LnV(\mu^v, S_t^j) = \mu^v + \theta LnS_t^j$. Thus, in line with the quantity theory of money, it can be shown that

$$LnV(\mu^v, S) = LnM_t - LnP_t - LnY_t = \mu^v + \theta LnS_t^j + e_t^v \tag{5}$$

Empirical studies, however, follow generalised versions of money demand while allowing income elasticity of demand for money deviating from unity (since national income or GDP may not be exactly equal to Fischer's definition of economic transaction) but suppressing technological progress induced change in velocity,

$$LnM_t = \mu + \alpha LnY_t + LnP_t + e_t \tag{6}$$

Or

$$LnM_t - LnP_t = \mu + \alpha LnY_t + e_t \tag{7}$$

It is also evident that some studies estimate nominal demand for money such as

$$LnM_t = \mu + \alpha^n LnY_t^n + e_t \tag{8}$$

Studies considering payments system indicator induced technological progress in velocity would consider

$$LnM_t = \mu^v + \theta LnS_t^j + \alpha^v LnY_t + LnP_t + e_t^v \tag{9}$$

Or

$$LnM_t - LnP_t = \mu^v + \theta LnS_t^j + \alpha^v LnY_t + e_t^v \tag{10}$$

Alternatively, for nominal demand for cash,

$$LnM_t = \mu^{v,n} + \theta^n LnS_t^j + \alpha^{v,n} LnY_t^n + e_t^{v,n} \tag{11}$$

Specific payment indicator S can either increase or decrease money demand depending upon the sign of its coefficient θ. Also, it can induce a differential income elasticity of demand for money, when $\alpha \neq \alpha^{v}$. Similarly, we can have different intercepts $\mu \neq \mu^{v}$, reflecting on the scale effect. Furthermore, deriving from Baumol's inventory model of cash demand and Tobin's portfolio and liquidity preference model of money demand, studies incorporate interest rate and asset prices in empirical models of currency and money demand. Finally, a payment indicator can be considered in either volume terms (real transactions) or value (nominal) terms. Both will have different implications on the estimated demand for cash and income elasticity of demand for money.

Section V
Data and Empirical Modelling

For the econometric estimation of currency demand in line with the current literature and analytical insights, we use an autoregressive distributed lag (ARDL) model owing to Pesaran and Shin (Pesaran *et al.*, 2001). The choice of the model is partly determined by the sample period for which the data is available. Illustratively, data on currency with the public, part of money demand are available for a very long period from 1950-1951. However, quarterly data on its main determinant, the aggregate income or GDP, are available only from 1996-1997. On the other hand, payments indicators data are available on a monthly basis from April 2004, allowing us to generate quarterly series data for the sample period 2004:2 to 2019:1. Thus, we have a common sample period 2004:2 to 2019:1, *i.e.*, about 60 quarters data, which is not sufficiently large to allow time series models such as vector autoregression (VAR) and vector error correction (VEC) models. Moreover, the advantage of the ARDL model is that it can encompass a mix of stationary and non-stationary variables and allows the estimation of short-run error correction and long-run cointegration relationships among the variables. Since the ARDL model is quite popular, we have avoided offering its technical details.

The ARDL is preferred to other cointegration methods by Engle and Granger (1987), Johansen (1991), and Johansen and Juselius (1990) for various reasons: (i) it provides unbiased estimates of long-run model and valid t-statistics, even when some of the explanatory variables are endogenous (Ali *et al.*, 2016); (ii) it also facilitates short-run analysis: the dynamic error correction model is derived from a simple linear transformation in the ARDL model; and (iii) being a single equation approach, it can be suitable to a smaller sample. However, the model is not applicable if the order of integration of any of the variables is greater than one, for example, I(2) variable (Menegaki, 2019). In this case, the critical bounds provided by Pesaran *et al.* (2001) and Narayan (2005) are not valid. The ARDL procedure involves two stages. The first stage is to establish the existence of a long-run relationship. Once such a relationship is established, a two-step procedure is used to estimate the long-run and short-run coefficients of the same equation in the error correction framework. The existence of the long-run relationship is confirmed with the help of an F-test to determine that the coefficients of all explanatory variables are jointly different from zero (Menegaki, 2019). A notable aspect of our empirical exercise is that the payment indicators data exhibit large shifts, reflecting the introduction of new instruments. Large outliers could give rise to biased estimates. In order to overcome this problem, we use the TRAMO/SEATS approach developed by Gómez and Maravall (1995) to derive smooth linearised series for the payment indicators.

Section VI
Stylised Facts

Table 1 provides summary statistics (sample mean, median, standard deviation, *etc.*) of growth rates of currency in circulation, real GDP growth, CPI inflation, and growth of payment indicators in volume and value terms for the period 2004:Q2-2019:Q1. The average growth in payment indicators, both in value and volume terms was two to three times larger than currency growth and four to five times larger than the GDP growth and inflation rate over the sample period.

Table 2 provides summary statistics of nominal and real interest rates and asset returns (equity and gold) which denote the opportunity cost of holding money. During the sample period, real interest rates on bank deposits and medium-term government bond yield (5-year maturity) show a mean of 0.6 percentage points, while assets like equity and gold show higher real returns.

Table 1: Summary Statistics: Currency, GDP, Inflation and Payment Indicators (Growth Rates)

Statistic	GCURP	GY	CPINF	GX50VL	GX53VL	GX54VL	GX55VL	GX50VA	GX53VA	GX54VA	GX55VA
Mean	13.8	7.5	7.2	34.8	34.5	25.7	32.7	23.1	41.9	26.1	28.1
Median	14.9	7.7	6.7	17.9	30.6	24.7	29.1	14.0	37.7	24.4	19.4
Maximum	54.6	13.5	15.1	195.5	81.9	86.5	71.7	122.2	85.1	87.1	219.5
Minimum	-29.1	0.0	2.2	-2.4	3.9	-27.6	-7.3	0.5	20.2	-16.6	0.9
Std. Dev.	11.2	2.5	3.0	52.9	16.1	23.2	19.2	25.6	13.9	21.7	34.0
Skewness	-0.8	-0.6	0.5	2.2	1.0	0.5	0.3	2.6	1.4	0.9	3.9
Kurtosis	9.5	4.0	2.6	6.5	3.8	4.0	2.6	9.3	4.7	4.3	20.4
Jarque-Bera	103.1	5.5	2.4	71.9	10.3	4.8	1.2	153.4	23.5	10.7	831.6
Probability	0.0	0.1	0.3	0.0	0.0	0.1	0.5	0.0	0.0	0.0	0.0

Note: GCURP is growth rate of currency in circulation; GY is real GDP growth; CPINF is inflation indicator of consumer price index; while GX50VL to GX55VL represent growth of payment indicators in volume terms; and GX50VA to GX55VA represent growth rates of payment indicators in value terms.

Table 2: Summary Statistics of Interest Rate and Asset Returns

Statistic	CPINF	CMR	DRT	GB5	BSER	GGOLD	CMRR	BSERR	DRTR	GB5R	GGOLDR
Mean	6.9	6.5	7.5	7.5	18.2	13.1	-0.4	11.2	0.6	0.6	6.1
Median	6.5	6.5	7.5	7.7	15.6	10.4	0.5	9.9	0.9	1.2	5.4
Maximum	15.1	9.8	9.5	9.0	85.0	52.4	4.1	69.9	4.5	5.0	46.1
Minimum	2.2	3.2	5.2	4.9	-48.5	-12.6	-11.8	-58.7	-8.3	-7.8	-16.7
Std. Dev.	3.0	1.6	1.1	0.8	25.6	15.3	3.4	25.9	2.7	2.8	14.4
Skewness	0.5	-0.2	-0.3	-0.6	0.1	0.5	-1.5	-0.1	-1.2	-0.9	0.6
Kurtosis	2.6	2.6	1.9	3.4	3.8	2.6	5.2	3.6	4.7	3.4	3.0
Jarque-Bera	3.2	1.0	3.9	3.6	1.6	3.0	34.4	1.1	21.3	8.0	3.2
Probability	0.2	0.6	0.1	0.2	0.4	0.2	0.0	0.6	0.0	0.0	0.2

Note: CMR: call money rate; DRT: deposit interest rate; GBS: 5 years Government bond yield; BSER: return on equity; GGOLD: Gold price inflation; CMRR, BSERR, DRTR, GBSR, GGOLDR are indicated real returns of the above variables.

Section VII
Empirical Findings

Since the ARDL method is not applicable when the variables are I(2), we conducted the standard augmented Dickey-Fuller test (ADF) method of unit root test for currency, income and payment system indicators. The unit root test results (Appendix Table A.2) suggest that none of the variables considered in the paper could be characterised with the I(2) process. Hence, the ARDL model could be used for empirical estimation. Since our objective is to examine the long-run impact of payment indicators on currency demand, we begin with the baseline model (M1) that does not include payment indicators and then include alternative payment indicators measured in volume terms in the other models. The different models include different payment indicators, such as retail electronic clearing (REC) including ECS and NEFT (M2), card transactions at POS (M3), retail transactions such as ECS, NEFT, card transactions at POS (M4) and all-digital transactions including BHIM and IMPS (M5). Table 3 provides a summary of the estimated results of the long-run demand function for currency measured in real terms. We derive some interesting perspectives from the estimated cointegrating equations.

First, across the models M2 to M5, coefficients associated with payment indicators have plausible negative sign. Except retail clearing, all other payment indicators have statistically significant coefficients. Thus, in general, we find that the volume growth of non-cash digital payments has a moderating effect on currency demand. Second, the impact differs across payment indicators, as evident from the magnitude of coefficients; illustratively, the coefficient of a narrow measure like POS transactions is twice the coefficient of a broader measure like an all-digital transactions. Third, a crucial finding pertains to the income effect on currency demand, when we compare models with payment indicators (M2 to M5) to models without it (M1). The coefficient of income variable (real GDP) increases when payment indicators are included in the regression, while the intercept term, which captures the deterministic component of velocity, or the scale effect, becomes much smaller. Here, our findings are consistent with the literature (Columba, 2009; Nachane *et al.*, 2013). Fourth, the coefficient of error correction (EC) term associated with the ARDL model, which indicates the speed of adjustment to a long-run path following a short-run deviation, also indicates the role of technology. The EC coefficient is negative and statistically significant, and larger in absolute

Table 3: ARDL Model Estimate of Long-run Real Currency Demand Function
(Dependent Variable: Natural Log of Currency in Circulation Deflated by CPI)

Variable	M1	M2 (REC)	M3 (POS)	M4 (retail)	M5 (all-digital)
Real GDP (LY)	0.64 (0.00)	1.36 (0.00)	1.68 (0.00)	1.17 (0.00)	1.35 (0.00)
Payment Indicator (LP)-Volume		-0.17 (0.13)	-0.33 (0.00)	-0.25 (0.00)	-0.18 (0.00)
Intercept	-1.79 (0.03)	-8.32 (0.04)	-10.87 (0.00)	-6.15 (0.00)	-8.08 (0.00)
R-squared	0.94	0.94	0.95	0.96	0.95
SE / SSQ	0.0479 0.1146	0.0479 0.1124	0.0452 0.1000	0.0409 0.0803	0.0464 0.1054
Log Likelihood	93.91	94.46	95.04	103.87	96.26
AIC / SIC	-3.1397 -2.9227	-3.1235 -2.8703	-3.2400 -2.9868	-3.4239 -3.1435	-3.1878 -2.9346
DW-statistic	1.91	1.90	1.93	1.95	1.90
EC	-0.28 (0.00)	-0.30 (0.00)	-0.43 (0.00)	-0.53 (0.00)	-0.45 (0.00)
Null: No residual autocorrelation: AR(2) Test: F-stats (probability) Chi-sq (probability)	1.34(0.27) 2.97(0.23)	1.32(0.28) 2.98(0.22)	1.53(0.22) 3.45(0.18)	0.82(0.44) 1.94(0.38)	1.42(0.24) 3.30(0.19)
F-Bound Test:					
Null: I(0): F stat / 10%, 5% , 1%, critical values	4.71 3.13 3.80 5.38	3.77 2.74 3.29 4.56	5.75 2.74 3.29 4.56	9.48 2.74 3.28 4.56	4.84 2.74 3.29 4.56
Null: I(1): 10%, 5% , 1%, critical values	3.65 4.36 6.03	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59

Note: Figures in parentheses indicate the significance/probability 't' statistic associated with the coefficient.

size for the currency demand equation including payment indicator, than for the equation without it. This implies that payment indicators foster currency demand's adjustment to long-run path through its impact on velocity induced effect.

Table 4 shows the estimates of the long-run demand function for currency in nominal terms. The explanatory variables are nominal GDP and alternative payment indicators measured in volume terms. The results are comparable with the equation estimated for real currency demand, and they provide some notable insights. First, we obtain a statistically significant inverse relationship of payment indicators with currency demand as was the case in the equation for currency demand in real terms. Second, the income

Table 4: ARDL Model Estimate of Long-run Nominal Currency Demand Function
(Dependent Variable: Natural Log of Currency in Circulation)

Variable	M1	M2 (REC)	M3 (POS)	M4 (retail)	M5 (all-digital)
Nominal GDP (LYN)	0.92 (0.00)	1.34 (0.00)	1.34 (0.00)	1.14 (0.00)	1.22 (0.00)
Payment Indicator (LP)-volume		-0.18 (0.01)	-0.24 (0.00)	-0.19 (0.13)	-0.15 (0.00)
Intercept	0.05 (0.87)	-3.47 (0.01)	-3.22 (0.00)	-1.52 (0.00)	-2.40 (0.00)
R-squared	0.99	0.99	0.99	0.99	0.99
SE / SSQ	0.0482 0.1163	0.0474 0.1104	0.0454 0.1008	0.0418 0.0838	0.0461 0.1043
Log Likelihood	93.49	94.95	97.49	102.68	96.54
AIC / SIC	-3.1248 -2.9078	-3.1409 -2.8877	-3.2317 -2.9785	-3.3816 -3.0923	-3.1980 -2.9448
DW-statistic	1.93	1.93	1.99	1.90	1.96
EC	-0.30 (0.00)	-0.31 (0.00)	-0.43 (0.00)	-0.43 (0.00)	-0.48 (0.00)
Null: No residual autocorrelation: AR(2) Test: F-stats (probability) Chi-sq (probability)	1.27 (0.29) 2.79 (0.25)	1.21 (0.31) 2.74 (0.25)	2.34(0.11) 5.07(0.08)	0.73(0.49) 1.71(0.42)	1.98(0.15) 4.35(0.11)
F-Bound Test:					
Null: I(0): F stat / 10%, 5% , 1%, critical values	7.24 3.13 3.80 5.38	6.26 2.74 3.29 4.56	8.02 2.74 3.28 4.56	11.64 2.74 3.29 4.56	7.35 2.74 3.29 4.56
Null: I(1): 10%, 5% , 1%, critical values	3.65 4.36 6.03	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59

Note: Figures in parentheses indicate the significance/probability 't' statistic associated with the coefficient.

elasticity of demand for money without payment indicators is closer to unity but remains above unity when payment indicators are included. Compared with the real currency demand function, nominal income elasticity shows some moderation. Third, the absolute size of the coefficient of payment indicators shows some moderation. Fourth, the size of the intercept term in absolute terms is substantially lower in a nominal demand function.

Next, we examine the impact of payment indicators taken in value terms on currency demand. We estimate both nominal and real currency demand functions. The estimates of nominal currency demand equation are given in Table 5. The retail electronic clearing and POS indicators show a statistically significant inverse relationship with currency demand. On the contrary, the

Table 5: ARDL Model Estimate of Long-run Nominal Currency Demand Function with Payment Indicators in Value Terms
(Dependent variable: Natural Log of Currency in Circulation)

Variable	M1	M2 (REC) 53	M3 (POS) 54	M4 (retail) 50	M5 (all-digital) 55
Nominal GDP (LYN)	0.92 (0.00)	1.36 (0.00)	1.34 (0.00)	1.23 (0.00)	0.91 (0.00)
Payment Indicator (LP): Value		-0.13 (0.09)	-0.23 (0.00)	-0.35 (0.11)	-0.05 (0.42)
Intercept	0.05 (0.87)	-3.41 (0.10)	-3.02 (0.00)	0.85 (0.03)	0.65 (0.03)
R-squared	0.99	0.99	0.99	0.99	0.99
SE / SSQ	0.04 0.11	0.04 0.11	0.04 0.10	0.04 0.08	0.04 0.09
Log Likelihood	93.49	93.66	95.83	101.99	99.93
AIC / SIC	-3.1248 -2.9078	-3.095 -2.8420	-3.1724 -2.9192	-3.2497 -2.8518	-3.1764 -2.7785
DW-statistic	1.93	1.92	1.95	2.03	1.97
F-Bound Test:					
Null: I(0): F stat / 10%, 5% , 1%, critical values (Finite sample)	7.24 3.13 3.80 5.38	5.43 2.74 3.29 4.56	6.85 2.74 3.28 4.56	8.73 2.74 3.29 4.56	6.11 2.74 3.29 4.56
Null: I(1): 10%, 5% , 1%, critical values	3.65 4.36 6.03	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59

Note: Figures in parentheses indicate the significance/probability 't' statistic associated with the coefficient.

coefficient of broader measures of payments indicator (all-digital) is negative but statistically not significant.

Results for the real currency demand seem implausible barring the card transactions indicator (Table 6). In the regression equations incorporating all other payment indicators, the coefficient of income is statistically not significant, which seems counter-intuitive. Thus, it is evident that the impact of payments technological innovation on currency demand could be better explained when payment indicators are taken in volume terms rather than in value terms.

Next, to assess the impact of financial variables on currency demand, we estimate the equation by incorporating deposit interest rate and asset

Table 6: ARDL Model Estimate of Long-run Real Currency Demand Function with Payment Indicators in Value Terms

(Dependent Variable: Natural Log of Currency in Circulation Deflated by CPI)

Variable	M1	M2 (REC)	M3 (POS)	M4 (retail)	M5 (all-digital)
Real GDP (LY)	0.64 (0.00)	0.48 (0.47)	1.43 (0.00)	0.29 (0.34)	0.15 (0.55)
Payment Indicator (LP)-Value measure		0.03 (0.78)	-0.24 (0.06)	0.16 (0.18)	0.18 (0.02)
Intercept	-1.79 (0.03)	-0.35 (0.95)	-8.46 (0.00)	-0.06 (0.97)	-8.08 (0.00)
R-squared	0.94	0.94	0.95	0.94	0.95
SE / SSQ	0.04 0.11	0.04 0.11	0.04 0.11	0.04 0.11	0.04 0.10
Log Likelihood	93.91	93.93	94.90	94.13	95.41
AIC / SIC	-3.1397 -2.9227	-3.1047 -2.8515	-3.1393 -2.8861	-3.1119 -2.8588	-3.1573 -2.9042
DW- statistic	1.91	1.92	1.90	1.95	1.95
F-Bound Test:					
Null: I(0): F stat / 10%, 5% , 1%, critical values	4.71 3.13 3.80 5.38	3.48 2.74 3.29 4.56	4.03 2.74 3.29 4.56	3.59 2.74 3.28 4.56	4.33 2.74 3.29 4.56
Null: I(1): 10%, 5% , 1%, critical values	3.65 4.36 6.03	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59	3.47 4.07 5.59

Note: Figures in parentheses indicate the significance/probability 't' statistic associated with the coefficient.

(stock) return. The equation for nominal currency demand function did not provide plausible results. The results for the equation of real currency demand function are given in Table 7. Real deposit interest rate and stock

Table 7: ARDL Model Estimate of Long-run Real Currency Demand Function
(Dependent Variable: Natural Log of Currency in Circulation Deflated by CPI)

Variable	**M1**	**M2 (REC)**	**M3 (POS)**	**M4 (retail)**	**M5 (all-digital)**
Real Income/GDP (LY)	0.64 (0.00	1.10 (0.00)	1.53 (0.00)	1.12 (0.00)	1.16 (0.00)
Payment Indicator (LP)-volume		-0.10 (0.08)	-0.23 (0.00)	-0.23 (0.01)	-0.13 (0.01)
DRTR*		-0.93 (0.03)	-0.12 (0.74)	-0.20 (0.37)	-0.45 (0.17)
BSER*		-0.09 (.00)	-0.07 (0.00)	-0.03 (0.12)	-0.06 (0.00)
Intercept	-1.79 (0.03)	-5.94 (0.00)	-9.54 (0.00)	-5.76 (0.00)	-5.84 (0.00)
EC		-0.43 (0.00)	-0.51 (0.00)	-0.58 (0.00)	-0.52 (0.00)
R-squared	0.94	0.94	0.95	0.96	0.95
SE / SSQ	0.0479 0.1146	0.0474 0.1058	0.0454 0.0967	0.0415 0.0793	0.0467 0.1024
Log Likelihood	93.91	96.14	98.66	104.22	97.07
AIC / SIC	-3.1397 -2.9227	-3.1122 -2.7867	-3.2021 -2.8766	-3.3650 -3.0033	-3.1454 -2.8199
DW-statistic	1.91	1.89	1.92	1.92	1.89
Null: No residual autocorrelation test: AR(2) Test: F-stats (probability) Chi-sq (probability)	1.34(0.27) 2.97(0.23)	0.79(0.46) 1.90(0.39)	0.96 (0.39) 2.28 (0.32)	0.53 (0.59) 1.31 (0.52)	0.89 (0.42) 2.14 (0.34)
F-Bound Test:					
Null: I(0): F stat / 10%, 5% , 1%, critical values	4.71 3.13 3.80 5.38	3.05 2.32 2.74 3.71	4.07 2.32 2.74 3.71	6.24 2.32 2.74 3.71	3.42 2.32 2.74 3.71
Null: I(1): 10%, 5% , 1%, critical values	3.65 4.36 6.03	3.27 3.79 4.97	3.27 3.79 4.97	3.27 3.79 4.97	3.27 3.79 4.97

Note: Figures in parentheses indicate the significance/probability 't' statistic associated with the coefficient.
*: Coefficients multiplied by 100.

return show negative impact on currency demand, though the interest rate is statistically not significant. Overall, we can say that interest rate and asset returns can marginally influence currency demand. However, the crucial finding here is that with the presence of real interest rate and asset returns, and volume-based payment indicators, barring POS, income effect come closer to unity. Moreover, payment indicators have a statistically significant inverse relationship with currency demand. But the impact is somewhat lower than that found in the equation without financial variable (Table 3), highlighting the role of financial innovation (interest rate and stock return).

For robustness of empirical findings, it is important to reflect on the role of policy to withdraw high denomination specified bank notes (SBNs). Here, we re-estimate two of the equations M1 and M5 from Table 7 for the truncated period up to 2016:Q2; we exclude the period after November 2016 when SBNs were withdrawn from circulation (Table 8). It is crucial to note that we are omitting a small period of 11 quarters, 2016:Q3 to 2019:Q1, which may not be fully adequate to reflect on the policy regime. Nevertheless, this could provide some early reflection. Compared with counterpart equations for the full sample period in Table 7, we find that the income effect is comparable but there is a marginal improvement in the substitution effect of payment indicators on the currency demand. However, the difference in the long-run intercept term, which could reflect upon the scale effect, is somewhat noticeable. Thus, the impact of demonetisation could have impinged in moderating the scale effect on currency demand.

Furthermore, for the stability analysis, we consider the model (M5) of Table 7 and carry out CUSUM and CUSUM square test. The model passed the stability test based on CUSUM test but failed the CUSUM square test, which could be attributed to the period 2016:Q4 for which the model had a relatively larger residual. However, the model could pass the Breusch–Godfrey serial correlation LM test as shown in the estimation tables. In this context, we conclude that since the income effect could be closer to unity, the impact of technology on currency demand could be explored through its impact on velocity of currency in line with equation 5 in Section 4. The suitable ARDL model for velocity of currency, satisfying the stability consideration and no residual serial correlation, could be the one with a structural dummy variable

Table 8: ARDL Model Estimate of Long-run Real Currency Demand Function
(Dependent Variable: Natural Log of Currency in Circulation Deflated by CPI; Sample period 2004:Q2 to 2016:Q2)

Variable	**M1**	**M5**
Real Income/GDP (LY)	0.76 (0.00)	1.13 (0.00)
Payment Indicator (LP)-volume (all-Digital)		-0.10 (0.01)
DRTR*		-0.27 (0.11)
BSER*		-0.04 (0.00)
Intercept	-2.88 (0.00)	-6.19 (0.00)
R-squared	1.00	1.00
SE / SSQ	0.0075 0.2231	0.0066 0.0016
Log Likelihood	159.17	167.00
AIC / SIC	-6.8074 -6.5665	-7.0222 -6.6610
DW-statistic	1.82	2.18
EC	-0.11 (0.00)	-0.33 (0.00)
Null: No residual autocorrelation test: AR(2) Test: F-stats (probability) Chi-sq (probability)	1.13 (0.33) 2.51 (0.28)	2.18 (0.11) 7.04 (0.06)
F-Bound Test:		
Null: I(0): F stat / 10%, 5% , 1%, critical values	**5.30** 3.02 3.62 4.94	**5.97** 2.20 2.56 3.29
Null: I(1): 10%, 5% , 1%, critical values	3.51 4.16 5.58	3.09 3.49 4.37

Note: Figures in parentheses indicate the significance/probability 't' statistic associated with the coefficient.

*: Coefficients multiplied by 100.

for the period since the 2016:Q4 (Table 9 and Appendix Chart A.1). The long-run impact of broader measure of technology on velocity turned out to be statistically significant, though the coefficient size was somewhat lower than the model M5 in Table 7.

Table 9: ARDL Model Estimate of Long-run Velocity of Currency in Circulation
(Dependent Variable: Velocity)

Variables	M1	M5
Payment Indicator (LP)-volume	-0.07 (0.00)	-0.08 (0.00)
DRTR*		-0.05 (0.87)
BSER*		-0.06 (0.07)
Structural dummy	0.09 (0.14)	0.10 (0.01)
Intercept	-6.42 (0.00)	-6.39 (0.00)
R-squared	0.99	0.99
SE / SSQ	0.0130 0.0084	0.1221 0.0067
Log Likelihood	170.41	176.92
AIC / SIC	-5.7336 -5.4827	-5.9624 -5.7115
DW-statistic	1.79	1.64
EC	-0.18 (0.00)	-0.27 (0.00)
Null: No residual autocorrelation test: AR(2) Test: F-stats (probability) Chi-sq (probability)	0.37 (0.69) 0.86 (0.65)	0.96 (0.39) 2.44 (0.30)
F-Bound Test:		
Null: I(0): F stat / 10%, 5% , 1%, critical values	**11.29** 2.63 3.10 4.13	**27.67** 2.20 2.56 3.29
Null: I(1): 10%, 5% , 1%, critical values	3.35 3.87 5.00	3.09 3.49 4.37

Note: 1. Figures in parentheses indicate the significance/probability ‘t’ statistic associated with the coefficient.

2. Since velocity is defined as the inverse function, V=-(lnM-LP-LY), where LM, LP, and LY refer to natural logarithm of currency in circulation, consumer price index, and real GDP, respectively, the negative coefficient sign in this table may be interpreted with positive impact; increased payment innovations can accentuate velocity and thus, reduce the currency demand.

*: Coefficients multiplied by 100.

Summing up, we found payment technology innovations, as measured in terms of digital volume transactions, having a statistically significant inverse relation with India's currency demand in the long run. However, the substitution effect of digital transactions on currency demand was lower than the strong positive income effect, which suggests that the digital transactions need to increase rapidly if the income effect on currency demand were to be neutralised.

Section VIII
Conclusion

The findings of the paper suggest that real income is the major driver of currency demand in India. The income effect of currency demand is closer to unity even when payment indicators, interest rate and asset returns are included as explanatory variables. Payment systems innovation, especially digital transactions in volume terms, showed statistically significant negative effect on currency demand. However, the coefficient of payment indicators was only about one tenth of the income coefficient. Thus, in order to neutralise the real income and inflation induced positive effect on currency demand, digital payments need to increase at a faster pace. Nevertheless, payment systems indicators with growth of around 35 per cent in volume terms during the sample period could have sizeable potential impact of around 3 per cent reduction in currency demand. Digital payments need to grow at a pace of about 100 per cent per annum in order to neutralise the income effect on currency demand. The empirical findings of the study could serve useful for policy purposes. As the payment system grows, and the sample period accumulates with more quarterly data, future studies could exploit the advanced econometric methodology and reassess the impact of technology innovations on currency demand.

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Appendix

Table A.1: Major Milestones in India's Payments and Settlements System'

Year	Major milestone in India's Payment and Settlement Systems
1987	The first ATM machine was introduced by HSBC in Mumbai.
1996	The Institute for Development and Research in Banking Technology (IDRBT) was established by the RBI as an autonomous centre for development and research in banking technology. IDRBT's purpose is to implement a variety of payment applications and foster the development of a reliable communications network. The Governing Council of the IDRBT includes the Deputy Governor and an Executive Director of the RBI, in addition to members from the Indian Banks' Association (IBA) and leading academic institutions (in the areas of science and technology).
1998	The RBI set out its objectives on payment systems in India.
2001	Clearing Corporation of India Limited (CCIL) was setup for clearing & settlement of traders in money, Gsec & foreign exchange markets.
2002	To facilitate faster settlement of trades in government securities in dematerialised form, the RBI introduced an electronic negotiation-based trading and reporting platform called the Negotiated Dealing System (NDS).
_	The subsequent Payment System Vision Document for 2001–04 provided a roadmap for the consolidation, development and integration of the country's payment systems.
2003	The Special Electronic Fund Transfer (SEFT) system was introduced in April 2003 (subsequently discontinued in March 2006 after the introduction of the NEFT).
2004	The Real-time Gross Settlement (RTGS) system introduced to settle interbank and customer transaction above ₹2 lakhs.
2005	National Electronic Funds Transfer (NEFT) system was introduced in November 2005 to facilitate one to one funds transfer of individuals/ businesses.
_	To enhance trading infrastructure in the government securities market, the RBI introduced an electronic order-matching system called the RBI-NDS-GILTS-Order Matching or NDS-OM in short.
_	The Payment and Settlement Systems was detailed in the Vision Document for 2005-08.
_	The RBI constituted the Board for Regulation and Supervision of Payment and Settlement Systems (BPSS) as a committee of its Central Board.

(Contd...)

Table A.1 (contd.)

Year	Major milestone in India's Payment and Settlement Systems
2008	The Payment and Settlement Systems Act, 2007 was enacted empowering the RBI to regulate and oversee all payment and settlement systems in the country and also provide settlement finality and a sound legal basis for netting.
–	The National Electronic Clearing Services (NECS) system, which aims to centralise the Electronic Clearing Service (ECS) operation and bring uniformity and efficiency to the system, was implemented.
–	The National Payments Corporation of India (NPCI), a 'Not for Profit' company, was set up as an umbrella organisation for retail payment systems in India with the guidance and support of the Reserve Bank and the IBA. With initial shareholding of 10 promoter banks, the ownership has since been diversified to 56 banks. The RBI approves the appointment of the Chairman, and the Managing Director and Chief Executive Officer (MD & CEO) of NPCI; it also has placed a nominee director on NPCI's Board. Over the years, NPCI has developed various retail payment products. Taking into account the public sector characteristic of NPCI, the shareholding comprises at least 51 per cent stake by the public sector banks.
–	The Negotiable Instruments Act, 1881 was amended to allow scanned cheque images, paving the way for the cheque truncation initiative that went live in February 2008 in the New Delhi region.
2010	The Vision Document 2009-2012 released on February 16, 2010 reflect the changes after the enactment of the Payment and Settlement Systems Act, 2007, and sets out the objective of ensuring 'that all the payment and settlement systems operating in the country are safe, secure, sound, efficient, accessible and authorised'.
2012	'Payment Systems in India: Vision 2012-15' was announced to proactively encourage electronic payment systems – to ultimately usher in a less-cash society in India – and to ensure that payment and settlement systems in the country are safe, efficient, interoperable, authorised, accessible, inclusive and compliant with international standards.
2016	The 'Payment and Settlement Systems in India: Vision 2018' was announced with the aim of building best in class payment and settlement systems for a 'less-cash' India through responsive regulation, robust infrastructure, effective supervision and customer centricity.
–	In order to achieve the twin objectives of promoting debit card acceptance by a wider set of merchants (especially the small merchants) and ensuring sustainability of the business for the entities involved, the RBI rationalised the Merchant Discount Rate (MDR) framework with effect from January 1, 2018.

(Contd...)

Table A.1 (contd.)

Year	Major milestone in India's Payment and Settlement Systems
2019	The RBI on January 8, 2019 released guidelines on tokenisation for debit/credit/prepaid card transactions as a part of its continuous endeavour to enhance the safety and security of the payment systems in the country. Tokenisation involves a process in which a unique token masks sensitive card details. Thereafter, in lieu of actual card details, this token is used to perform card transactions in contactless mode at Point of Sale (POS) terminals, Quick Response (QR) code payments, *etc*.
–	The RBI released the draft 'Enabling Framework for Regulatory Sandbox' on April 18, 2019. Comments on the draft guidelines were invited from stakeholders.
–	Aiming for a 'cash-lite' society, on May 15, 2019 the RBI announced the 'Payment Systems in India: Vision 2021' to ensure a safe, secure, convenient, quick and affordable e-payment system as it expects the number of digital transactions to increase more than four times to ₹8,707 crore in December 2021.
–	On October 15, 2019 the RBI allowed on-tap authorisation for Bharat Bill Payment Operating Unit, Trade Receivables Discounting System (TReDS) and White Label ATMs.
–	On September 17, 2019 the RBI released a discussion paper on 'Guidelines for Payment Gateways and Payment Aggregators' and invited feedback from the public.
–	On September 20, 2019 the RBI announced the harmonisation of turnaround time and customer compensation for failed transactions using authorised payment systems.
–	On December 16, 2019 the RBI made NEFT available round-the-clock on all days including weekends and holidays.
–	The RBI introduced a semi-closed Prepaid Payment Instrument up to ₹10,000/- with loading only from a bank account on December 24, 2019.
2020	On January 1, 2020 the Government of India announced no MDR charges for transactions through RuPay cards and UPI platforms.
–	The RBI mandated banks not to charge savings bank account customers for online transactions in the NEFT system.
–	The RBI on January 15, 2020 announced to provide additional security features to card payments by allowing switch on/off and set/modify transaction limits on domestic and international transactions.

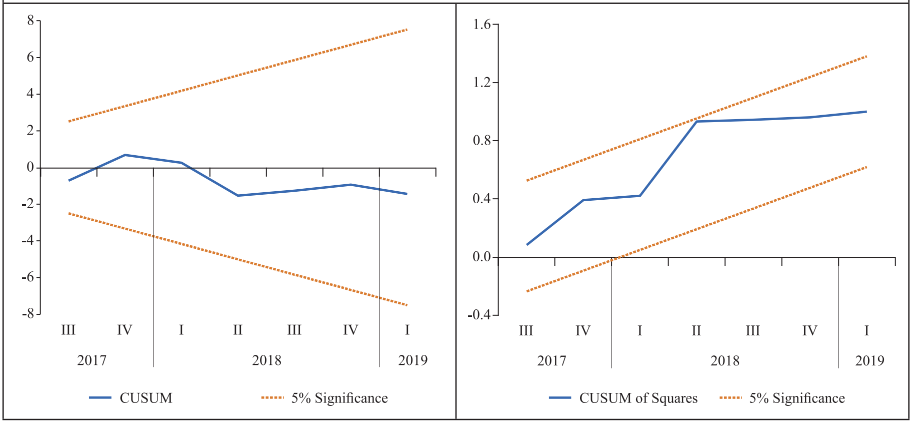
Table A.2: Unit Root Test

Sr. No	Variable	Test	Lag Criteria (lags selected)	Test Statistics
1	LCURSA	ADF	AIC (4)	-1.38*
2	LCURRSA	ADF	AIC (4)	-1.30*
3	LYNSA	ADF	AIC (2)	-2.23*
4.	LYS	ADF	AIC (0)	-1.17*
5	LX50VL	ADF	AIC (0)	1.80*
6	LX50VA	ADF	AIC (4)	-1.28*
7	LX53VL	ADF	AIC (4)	-1.31*
8	LX53VA	ADF	AIC (2)	-1.55*
9	LX53VL	ADF	AIC (4)	-1.31*
10	LX53VA	ADF	AIC (2)	-1.55*
11	LX54VL	ADF	AIC (2)	1.09*
12	LX54VA	ADF	AIC (4)	-0.47*
13	LX55VL	ADF	AIC (2)	1.51*
14	LX55VA	ADF	AIC (4)	-0.92*
15	D(LCURPSA)	ADF	AIC (3)	-4.97
16	D(LCURPRSA)	ADF	AIC (3)	-4.96
17	D(LX50VL)	ADF	SIC (0)	-6.69
18	D(LX50VA)	ADF	AIC (3)	-4.35
19	D(LX53VA)	ADF	AIC (1)	-6.93
20	D(LX53VL)	ADF	SIC (0)	-7.81
21	D(LX54VA)	ADF	SIC (2)	-5.20
22	D(LX54VL)	ADF	SIC (1)	-6.68
23	D(LX55VA)	ADF	AIC (4)	-5.19
24	D(LX55VL)	ADF	SIC (0)	-6.50
25	D(LYNSA)	ADF	SIC (0)	-5.56
26	D(LYS)	ADF	SIC (0)	-7.63

Note: *: indicates not significant at 5 per cent (critical value 2.9); thus, cannot reject the null hypothesis that the series has unit root, *i.e.* non-stationary in levels.

Definition:
L: natural log, SA: seasonally adjusted; D: first difference; VA: value, VL: volume, CUR: currency in circulation, CURR: currency in circulation deflated by CPI, YN: nominal GDP, Y: real GDP, X50: retail transactions; X53: retail electronic clearing; X54: card transactions at point-of-sales; X55: all-digital transactions.

Chart A.1: Stability Test: ARDL Model of Velocity of Currency
(Table 9: Model M5)



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Can Financial Markets Predict Banking Distress? Evidence from India

Snehal S. Herwadkar and Bhanu Pratap*

In this paper, we test whether the efficient market hypothesis works in the context of Indian banking sector. In particular, using a panel dataset of 39 publicly listed banks in India for 2009–2017, we test whether equity markets provide any lead information about stress in the banking system before quarterly data becomes available to the supervisors. We find that markets are able to price-in the banking stress concurrently but not much in advance. As the supervisory data are available with a lag, there is some merit in incorporating market-based information to track banking distress. Use of a machine learning technique to reaffirm the results is a novelty of this paper. Interestingly, our findings suggest that markets are relatively less efficient in the case of public sector banks *vis-à-vis* private sector banks.

JEL Classification Codes: C14, C33, C51, G21, G14

Keywords: Banking sector, banking distress, equity markets, financial stability

Introduction

The face of banking has changed dramatically in the last couple of decades. As the range of banking activities expanded from simple borrowing and lending to more complex operations, supervisors have also tried to proactively keep pace by constantly fine-tuning their supervisory frameworks and updating the underlying models. Besides their own bank inspection data, which is the outcome of both on-site and off-site surveillance, supervisors

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* Dr. Snehal S. Herwadkar (snehal@rbi.org.in) is Director and Bhanu Pratap (bhanupratap@rbi.org.in) is Manager in the Department of Economic and Policy Research, Reserve Bank of India (RBI), Mumbai. The authors are thankful to Sitikantha Pattanaik for motivating them and for numerous insightful discussions and to Jibin Jose for excellent data support. The authors are also grateful to Dr. Pallavi Chavan and an anonymous referee for their insightful suggestions. The views expressed in the paper are of the authors and do not necessarily reflect the views of the Reserve Bank of India. The authors take responsibility for errors, if any, that may have remained.

also employ market information to assess and ensure financial stability. Since market investors require a risk premium unlike secured depositors, they incorporate all available information relating to potential risks while pricing bank stocks and forming their expectations on its likely performance in the future (Distinguin *et al.,* 2006). For example, in the debt market, the market could penalise a bank for excessive risk-taking by demanding higher returns as compensation for higher risk. Similarly, equity prices of banks perceived to have weak financial health could decline as markets expect lower future flow of returns from investing in such scrips. If debt and equity markets are indeed efficient, market prices should accurately reflect the level of risk faced by banks and, therefore, should indicate the likelihood of emerging stress in a given bank (Krainer and Lopez, 2004b).

This line of thinking is not without its share of critics. It is often argued that not all the banking equity shares are traded on a stock exchange. Even when they are, the implicit or explicit state guarantees in the form of eventual, unavoidable bailout or even in the form of lender of last resort, inhibit market prices to reflect financial position of a bank realistically.

Notwithstanding these scepticisms, the academic appeal of the hypothesis has not waned. This paper attempts to evaluate whether market-based indicators help in predicting banking distress in the Indian context ahead of hard information either through quarterly accounts or through supervisory returns. While we have used stressed asset ratio as an indicator of banking distress, market-based indicators like equity returns, price-to-book value ratio and volatility, are evaluated to assess if financial markets can predict impending stress in banks. The findings suggest that in India, market variables can foretell banking distress in the same quarter, if not well in advance. As the supervisory data are available with a lag, supervisors may benefit by looking at financial market price movements while assessing banking distress. The robustness of these results was confirmed by employing the random forest algorithm from the machine learning genre.

We aim to add to the literature in the following ways: first, although the usefulness of market indicators to supervisors has been extensively researched for developed countries, there is limited literature on this topic in the context of developing or emerging market economies like India. It would be a useful exercise to see how far the Indian experience is in conformity with the international evidence. Second, while research in the international arena has used non-performing assets (NPAs) as an indicator of banking stress, we have used the stressed assets ratio – which combines gross NPAs with restructured assets – as a more realistic depiction of stress in the Indian banking sector. Third, in recognition of the peculiar structure of the Indian banking sector – where public sector banks have implicit state guarantees and have also borne larger part of the recent stress – this paper extends the analysis by dividing banks on the basis of their ownership. The aim of this exercise is to examine whether markets differentiate public sector banks from their private counterparts while pricing risk. Fourth, while we present a panel fixed effect model using several alternative specifications, the analysis is complemented with a random forest model which serves as an effective cross-validation without any *a priori* specification.

The rest of the article is organised as follows: Section II presents the review of the literature, while Section III elaborates on the data, the empirical analysis and the results. Section IV concludes the paper and evaluates policy implications.

Section II
Review of Literature

Literature suggests a wide range of market-based predictors, including movements in insured and uninsured deposits, debt instruments and bank equity returns, as potential candidates to supplement the supervisory efforts. Banking stress is reflected in the financial markets through several channels, which can be classified into direct and indirect impact, as well as into quantity and price-based impact. In direct quantity impact, the bank perceived as risk-prone experiences gradual or sudden withdrawal of deposits. In contrast, in the indirect quantity impact, bank creditors restructure their holdings, thereby signalling their concerns to the bank. Another layer could also be involved in this channel, whereby supervisors or private agents make it mandatory for the bank to reduce its risks. Thus, both the direct as well as indirect channels imply movement of funds from ‘risky’ to ‘safer’ banks, converting uninsured funds to insured funds, obtaining collateral, and cancelling existing banking relationships (Bennett *et al.,* 2015).

The direct price mechanism manifests itself when a bank is forced to pay higher risk premiums on at-risk liabilities (*e.g.,* uninsured deposits) or suffer other risk-based cost increases (*e.g.,* higher credit default swap spreads) when its risk increases.

Finally, indirect price discipline occurs when the equity prices of a risk-prone bank decline more than the market thereby sending signals to investors as well as to the bank management. These adverse wealth effects may be expected to prompt the majority stakeholders or bank supervisors to force the bank to take corrective action.

This paper is focussed on India where, partly due to an implicit government guarantee, banking activity is largely perceived to be low risk, and major quantity impact, such as a bank run, has been largely absent. Taking a cue from the literature, which suggests that at low levels of risk the price mechanism dominates the quantity mechanism in disciplining the banks, we focus on price mechanism, particularly in equity markets, and prepare the ground through a detailed survey of the literature on this aspect. Moreover, by focusing on equity market-based predictors for banking stress, we derive motivation from Caldwell (2007), who compared three market instruments, *viz*., equity, subordinated debentures and uninsured deposits for their effectiveness in disciplining banks' risk choice and found that equity weakly dominates the other two instruments.

Elmer and Fissel (2001) and Krainer and Lopez (2004a, 2004b) found evidence of equity markets providing information that can help in predicting bank distress, thus advocating use of this information in the supervisory review process. Earlier, Flannery (1998), González-Hermosillo (1999) and Jagtiani and Lemieux (2001) also emphasised the importance of combining market-based indicators with macroeconomic data for prior information on banking stress. Curry *et al.* (2003) documented evidence that stock prices incorporate banking distress as much as two years ahead of the supervisory rating downgrade. In addition, their findings suggested that adding market variables to standard models with bank financial data improved the predictive power of these models, *albeit* marginally. Based on empirical evidence for banks in the Eurozone, Distinguin *et al.,* (2006) and Gropp *et al.,* (2006) suggested creation of early-warning systems based on market information.

Borio and Lowe (2002), who examined three sets of possible predictors of a banking crisis – credit gap, real equity gap and real exchange rate gap, each measured in terms of deviation from Hodrick-Prescott filtered trend – found that while the credit and exchange rate gaps tend to rise one year before the crisis and peak during the crisis year, the equity prices tend to fall in the year immediately preceding the crisis. Their findings also suggest that a composite indicator consisting of credit and asset prices is a superior predictor of banking crises compared with other alternatives because of its high predictive power and lower noise-to-signal ratio, especially at longer horizons.

Taking a slightly different stance, some researchers found that bank-specific characteristics such as reliance on short-term funding, more leverage and hunger for quick growth make some banks more sensitive to crisis than others. Analysing a sample of 347 banking firms in the US between 1998 and 2006, Fahlenbrach *et al.,* (2012) showed that a bank's stock return performance during the 1998 crisis helped in predicting both its stock return performance and probability of failure during the recent global financial crisis. The authors concluded that persistence in a bank's risk culture and business model make their performance sensitive to crisis.

Along with studies that recommend the use of market variables to aid supervisory process, contradictory line of thinking also exists in the literature, making the debate inconclusive. For example, Berger *et al.* (2000) examined the relationship between supervisory information and several market indicators such as rating changes, and abnormal stock returns. Their results suggested that the supervisory assessments and bond ratings complement each other, partly because both agencies are concerned with bankruptcy risk. In contrast, supervisory assessments and equity indicators are not strongly related reflecting the fact that the latter concentrate more on wealth creation which is essentially a non-default risk feature.

In the Indian context, Mishra and Sreeramulu (2017) constructed three separate indices to gauge banking stress, *viz.,* index of speculative pressures, index of macroeconomic vulnerability and index of banking sector vulnerability, using several macro-financial indicators. The present paper takes this strand of literature further by empirically testing the predictive power of equity market variables in predicting banking stress.

Section III
Data, Methodology and Results

We estimate a panel fixed effect model using quarterly accounting and supervisory data of 39 publicly listed, scheduled commercial banks[1] (SCBs). The equity market performance of each bank, including excess return on bank scrip compared to the banking sector as a whole, market capitalisation, price-to-book value ratio and 90-day realised volatility of each bank stock, represent the equity market variables.

The NPA ratios are widely used in the literature as proxies for banking distress (*e.g.,* Beck *et al.,* 2015). We have, however, used the stressed assets ratio as a proxy, which takes into account not only the NPAs but also the restructured assets, in recognition of the fact that before the asset quality review (AQR) in 2015, the NPA ratio of Indian banks did not portray a realistic picture of the defaults.

Lastly, we also use a machine learning method, namely random forest algorithm to reinforce the findings of the panel fixed effects model (Appendix A). Like any other machine learning method, the random forest algorithm makes almost no *a priori* assumptions on the underlying relationship between the target and predictor variables. Additionally, the algorithm is designed to use bootstrapped method to learn from the data to make predictions. Such features of the random forest approach make it robust even in the presence of a large number of highly collinear variables. In particular, we use the *variable importance*, computed using the random forest algorithm, to assess the predictive ability of financial market variables. However, unlike econometric techniques, this method does not provide the level of significance or direction of causality for such estimates.

Considering factors like availability of data, the time period for the analysis was set from 2009:Q1 to 2017:Q4 (Appendix B and C). Incidentally, this period is crucial for the Indian banking sector as the health of the banking system was considered robust at the beginning of this period but observed

[1] The data consists of 24 public sector banks and 15 private sector banks. One publicly listed foreign bank, *i.e.,* Standard Chartered PLC, was excluded from the sample to focus only on public sector and private sector banks.

sharp deterioration midway through. Thus, this period provides the right window to test the hypothesis whether market indicators are better predictors of banking distress.

Bank-wise Stressed Assets and Market Information: Fixed Effects Panel Model

A fixed effect model, in line with Beck *et al.,* (2015), is estimated with stressed assets ratio (*SAR*) as the dependent variable. The basic objective was to test whether financial market variables are able to anticipate banking stress over and above the supervisory data, and if so, then how much in advance. In order to test whether markets anticipate stress in advance, we also introduce up to two lags in the financial market explanatory variables. Thus, *ceteris paribus*, if the coefficients of the one (two) quarter lagged financial market variables turn out to be significant, we deduce that the financial markets anticipate stress one (two) quarter ahead and that the financial markets are strongly efficient in anticipating the stress in banks.

We estimate a baseline model for bank distress that includes one quarter lagged supervisory variables controlling for size (*assets*), profitability (return on equity *i.e., RoE*), and capital (capital to risk-weighted assets *i.e., CRAR*):

$$SAR_{it} = \alpha_i + \beta Assets_{it-1} + \gamma RoE_{it-1} + \delta CRAR_{it-1} + \varepsilon_{it} \quad (1)$$

The motivation behind the usage of the one-period lagged independent variables is that supervisory returns data for the current quarter are available with a time lag of close to one to three months after the end of a given quarter. Therefore, an assessment of bank-level stress at any given point of time is possible on the basis of one quarter old information, which might be an outdated information from the point of view of financial stability. In addition to cross-section fixed effects to control bank-level heterogeneity, we also allow for time fixed effects[2] in the model to control for macroeconomic and regulatory policies that uniformly impact all banks. Finally, to control for cross-sectional dependence[3] arising from several factors like sample selection,

[2] Corroborated by the joint Wald test of significance for inclusion of time fixed effects in equation 1 (Appendix D).

[3] Standard diagnostic tests for panel models (Torres-Reyna, 2007) confirm the presence of cross-sectional dependence, serial autocorrelation and heteroscedasticity (Appendix D).

unobserved shocks and policies, we estimate the model with *Driscoll-Kraay* robust standard errors (Driscoll and Kraay, 1998) using the algorithmic routine provided by Hoechle (2007). Such standard errors are also robust to heteroscedastic and autocorrelated disturbances.

Building on this baseline specification, we then introduce one by one contemporaneous, one- and two-period lagged values of equity market variables in the model to ascertain the predictive power of equity markets. Equation (2) represents weak efficiency of the financial markets, where they anticipate the stress in the same period such that $j = 0$.

$$\begin{aligned} SAR_{it} = \; & \alpha_i + \beta Assets_{it-1} + \gamma RoE_{it-1} + \delta CRAR_{it-1} + \\ & \mu Ret.Niftybank_{it-j} + \varphi PB\ Ratio_{it-j} + \\ & \rho Volatility_{it-j} + \varepsilon_{i,} \end{aligned} \qquad (2)$$

In particular, we test a variety of signals provided by the equity markets, *viz.,* stock returns adjusted to NSE Nifty Bank Index (*Ret. Niftybank*); price-to-book value ratio (*PB Ratio*) of a bank stock which reflects the value that market participants attach to the bank's equity relative to its book value; and observed volatility (*Volatility*) in the bank's stock[4]. As mentioned earlier, if financial markets are indeed forward-looking, lagged values of market variables should return statistical significance (for $j = 1$ or 2). The estimation results for the full sample are provided in Appendix Table D5.

The results suggest that financial markets pick up signals of banking distress in the same quarter but not much in advance, and thus are at best, weakly efficient in predicting the same. The results suggest a contemporaneous statistical relationship between market variables and stressed assets ratio; with the coefficients of the lagged values of equity market variables lacking statistical significance except in the case of one-period lagged price-to-book value ratio and two-period lagged volatility. Compared to the baseline, only a

[4] To reiterate, the aim of the study is to assess whether financial market information adds any predictive power to the supervisory data. As such the estimation here is not aimed at assessing whether stock market variables 'cause' banking stress or *vice versa*. Nonetheless, we conducted causality tests in panel framework and found no evidence to support that SAR granger causes excess equity returns and *vice versa*.

marginal improvement in the overall R^2 of the models after incorporating market information, also suggests weak statistical power of market information[5].

Given the heterogeneous nature of the Indian banking system, we also examine whether the ownership pattern of banks makes a difference to equity markets reaction. Thus, we split our sample into public sector bank and private sector banks subsamples and estimate the same model as in equation (2) for both the subsamples. The estimation results are provided in Appendix Tables D6 and D7.

For the public sector banks, asset base and CRAR showed inverse association with SAR as expected. However, the coefficient of return on equity (RoE) was not statistically significant. Regarding the predictive power of equity markets, none of the equity market variables were found to have a statistically significant relationship with SAR, even at 10 per cent level of significance. The only exception to this was the two quarter lagged observed volatility in the bank stock price, which might signal trading activity on a bank stock on account of policy announcements such as recapitalisation.

On the other hand, results for the private sector banks depict a more sanguine story. Specifically, the price-to-book value ratio was found to contain more meaningful information to predict bank-level distress. Price-to-book value ratio is simply the market price per share divided by the book value per share. Thus, it can be argued that price-to-book value ratio contains information from the balance sheet of a bank as well as the market's expectations in the form of its share price. In the case of private sector banks, therefore, it seems that equity markets do make their own assessment of impending stress on the balance sheet of a bank. Model 11 in Table D7 incorporates stock returns, price-to-book-value and volatility *albeit* leading to only a slight improvement in the R^2 with respect to the baseline model.

The results of the public and private sector banks indicate that the markets differentiate their anticipation of stress based on ownership pattern. Acquisition, verification and pricing of information is costly. For public sector

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[5] In the results of some specifications, the constant gets omitted due to collinearity between one or more than one time dummies and explanatory variables in the regression model.

banks, which have implicit state guarantees, these costs seem to outweigh the benefits. In particular, if the investors are confident that the stress on a public sector bank – however grave it may be – would be relieved by the government through various means such as recapitalisation, then the market has little incentive to price-in the stress. Stressed assets affect bank's balance sheet because they involve higher provisioning and reduce the lendable resources available with banks. However, if the government stands ready to recapitalise the banks then the stress on their balance sheet is relieved automatically. Factoring in these considerations, markets may be providing meaningful information about the impending stress in case of private sector banks but not in the case of public sector banks.

Machine Learning-based Assessment

The random forest (RF) algorithm[6], a popular technique from the machine learning paradigm, is a useful alternative method that can be used to confirm the findings of the econometric model. The RF algorithm allows the computation of *variable importance* to assess the relative importance of a variable in a regression (when the dependent/target variable is continuous) or classification (when the dependent/target variable is binary) problem.

The basic building block of the RF algorithm is a decision tree, which can be depicted in the form of a flowchart-like graph to illustrate all possible outcomes of a decision or a series of decisions. A decision tree splits the input parameter space into non-overlapping subsamples, such that the predicted value of the target variable in each subsample is a constant value contingent on minimisation of overall residual sum of squares (RSS). Decision trees, however, are prone to an overfitting problem. In contrast, as a non-parametric, *supervised* machine learning model, the RF algorithm avoids this problem by way of bagging or bootstrapped aggregation. First, it grows a collection or ensemble of decision trees. Second, it uses a random, bootstrapped sample of input data as well as a random subset of input variables to grow each tree. This simple modification of using a random subset of input variable for growing

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[6] See Appendix A for a technical summary of regression trees, random forest algorithm and variable importance. Readers may also refer to Liaw and Wiener (2002) for an excellent exposition of the RF algorithm.

each tree, de-correlates individual trees to reduce the variance in the overall prediction. Third, for each tree, it calculates a prediction error using *out-of-bag (OOB)* data, *i.e.,* data left out from the initial sample for that tree. Lastly, with the aim to minimise prediction error, it averages out the predictions from all individual trees to arrive at a final prediction. Thus, random forests can efficiently deal with very large numbers of correlated explanatory variables, and the predicted model is highly non-linear.

As mentioned earlier, while training the model, the algorithm calculates the prediction error on OOB data that was not used during its training. This step allows the computation of variable importance that can be used to select the most important predictors amongst a large batch of potential predictor variables. The algorithm can be trained to solve the following regression task to predict bank-level distress:

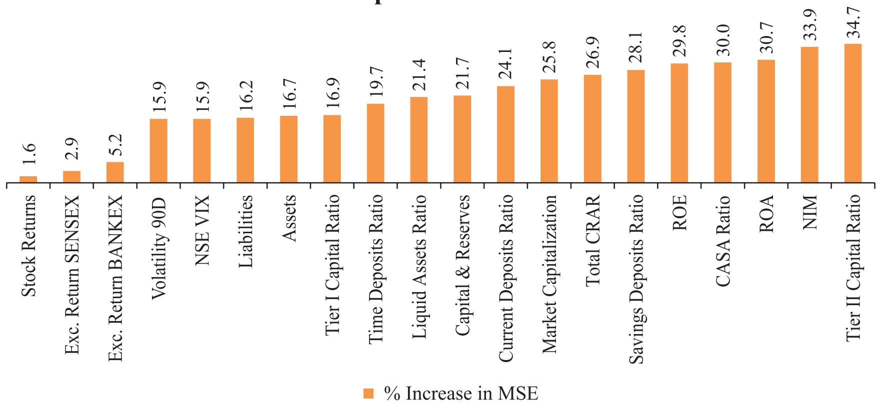
$$SAR_{i,t} = F\left(supervisory\ information_i; equity\ market\ information_i\right) + \varepsilon_{i,t} \mid j = 0,1,2 \quad (3)$$

We note that while implementing the panel fixed effect model, only a limited number of dependent variables[7] – whether supervisory or market-based – were used in order to achieve a best fit while avoiding the multicollinearity problem. Since the RF algorithm can efficiently deal with correlated variables, the entire set of independent variables (including those on bank size, capital, profitability, deposit ratios, *etc.*) available at our disposal were utilised as a set of potential predictors. Like the fixed-effect regression approach, we control for bank and time fixed effects by introducing bank-specific dummies and some macroeconomic variables in the set of input variables, respectively. Full sample data is used for training the model since our primary interest is in assessing the importance of a given variable as a predictor of the target variable.

The rankings of important predictor variables, in terms of increase in mean squared error (MSE), are provided in Chart 1. The higher the increase in MSE of any given predictor variable, higher the importance

[7] The issue is further complicated when faced with a choice between several indicators which can be used as a potential proxy for the same economic variable. In the case of banks, for instance, return on assets (RoA), return on equity (RoE) and net interest margin (NIM) can all be potentially used as a proxy for bank profitability.

Chart 1: Variable Importance: Stressed Assets Ratio (%) as Dependent Variable



of that variable. Clearly, bank regulatory capital and profitability are the strongest predictors of banking distress. Indicators such as Tier-2 capital ratio, total CRAR, return on assets (RoA), net interest margin (NIM) occupy top ranking in the variable importance measure. Similarly, short-term liquidity, proxied by savings deposits ratio and liquid assets ratio, also emerge as important predictors. In line with the findings of the fixed effect panel model, the random forest approach also ranked market variables as the least important predictors of banking distress. Moreover, in a relative sense, most of the market indicators show very low percentage increase in MSE which underlines the low predictive power contained in equity market information. Lagged values of market variables do not even appear in the top predictors. To further analyse the impact of market variables on predicting bank distress, we retrain the model without including market variables in the training data set. We find no meaningful impact of the exclusion of financial market information on the overall predictive accuracy of the model. The findings[8] are also robust to changes in the hyper-parameters of the model – number of trees grown, number of nodes on each tree and number of variables used in each iteration.

[8] Our findings are also corroborated by a penalized linear regression model, namely the least absolute shrinkage and selection operator (LASSO) model, on the same data set (James *et al.*, 2013). See Appendix D.

Section V
Conclusion

The primary aim of this analysis is to determine the incremental predictive value of market information over and above that provided by the supervisory information. The paper finds evidence that the market variables incorporate information about banks' stress in the same quarter, though not much in advance and thus markets are weakly efficient. Considering, however, that the supervisory data are available with a lag, the paper suggests that there is some merit in using market variables to identify stress in the banking sector. The random forest model – which ranks variables in terms of their importance in predicting stress – also confirms the findings of the fixed effect panel model by allotting lower ranks to market variables as compared with the supervisory variables.

More significantly, our results suggest that the markets differentiate between banks on the basis of their ownership while incorporating information about stress in stock prices. This may be because public sector banks are perceived to have an implicit sovereign guarantee against failure, thereby reducing incentives to monitor them, which may be weakening the market discipline channel.

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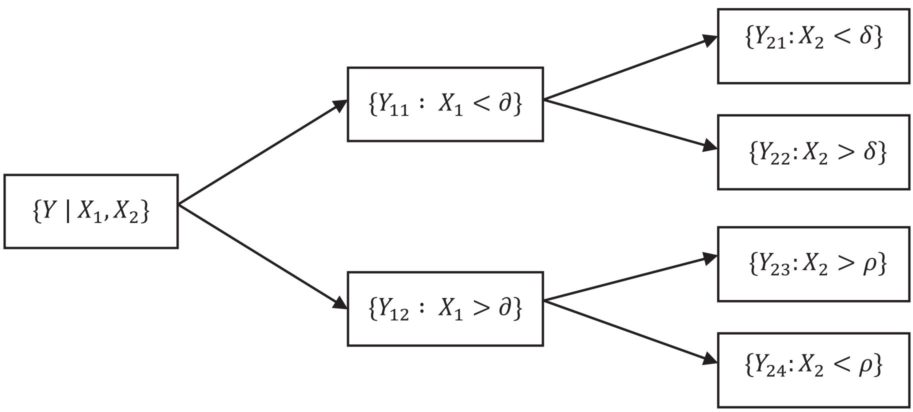
APPENDIX A

Random Forest Algorithm: A Summary

Decision Tree

In *supervised* machine learning, tree-based methods are popular for solving both regression (when target variable is continuous) and classification (when target variable is binary) problems. Such methods generate prediction through rules derived from recursive binary partitioning of the covariate space. In other words, a regression tree method splits the predictor space into a number of smaller regions, wherein the mean or mode of all observations falling in that region is used as a prediction for any given observation in the same region. A typical *decision tree* model to predict a target variable, say Y, given two predictors, say X_1, X_2, can be represented as shown in Figure A.1.

Figure A.1: Decision Tree



More formally, the covariate space *i.e.,* the set of possible values of $X_1, X_2 \ldots \ldots X_N$ is divided into J distinct and non-overlapping regions, $R_1, R_2 \ldots \ldots R_J$. For each observation in region R_J, the prediction is simply $\hat{Y}_{R\,j}$ *i.e.,* the mean of all observations falling within the same region. Given predictor X_N and a cut-off point S_{Ni} for each such predictor, the optimal division of the covariate space is achieved by recursively minimising the following residual sum of squares (RSS):

$$\sum_{j=1}^{J} \sum_{i \in R_j} \{Y_i - \hat{Y}_{R_j}\}^2$$

Random Forest Algorithm

Decision trees discussed above suffer from the issue of high variance or overfitting. To overcome this issue, several strategies have been highlighted in the literature. Bootstrapped aggregation or bagging is one such procedure, which when applied to decision trees is popularly known as the random forest algorithm. Proposed by Breiman (2001), the algorithm includes the construction of T decision trees using distinct bootstrapped subsamples of input data. While constructing each tree, the algorithm uses $n < N$ predictor variables chosen at random. This small tweak over conventional bagging results in a decorrelation of regression trees. After all the trees are constructed, the algorithm generates a final prediction by averaging the prediction of all T regression trees. Formally, each tree in a random forest is built using the following steps where T represents the entire forest and t represents a single tree. For $t = 1$ *to* T:

i. Create a bootstrap sample B with replacement from the training set comprising X, Y and label these X_t, Y_t;

ii. Train the tree F_t on X_t, Y_t; and,

iii. Average the predictions to arrive at a final prediction given by $\hat{Y}_i = \frac{1}{T}\sum_{t=1}^{T} F\{X_t\}_t$.

Out-of-bag Error Estimation and Variable Importance

Recall that the random forest algorithm uses a bootstrapped input sample data for training each regression tree. In Breiman's proposed algorithm, each bagged regression tree uses two-thirds of the input data for construction. The input data that is left out from such a sample is termed out-of-bag (OOB) data. A straightforward way to estimate the test error of a random forest model is to use the OOB data. A mean prediction for each i^{th} observation can be obtained by averaging the prediction of each tree in which the observation was OOB. This way an OOB mean squared error (MSE) can be computed for the random forest model:

$$MSE^{OOB} = \frac{1}{T'}\sum_{i=t}^{T'}\{Y_i - \hat{Y}_i^{OOB}\}^2$$

which is considered a valid estimate of the test error for the model since the response for each observation is predicted using the trees that were not fit using the same observation.

The random forest model, by obtaining an MSE^{ooB}, allows the computation of *variable importance* which can be used to select most important predictors amongst a large batch of potential predictor variables. Variable importance is said to describe the dependence of a model's prediction accuracy on the information contained in each covariate used by the model (Fisher *et al.*, 2019). The importance of a variable say X_N , is estimated by computing the increase in mean prediction error when the *OOB* data, with the n^{th} input variable randomly permuted, is again passed down the tree(s) to make predictions. Intuitively, the random shuffling of the n^{th} variable would mean that the shuffled variable has no predictive power. The mean increase in prediction error is computed for all variables – the larger the increase in prediction error for any given variable, higher is the predictive power of that variable. The variable importance (VI_N) for each variable is computed as follows:

i. OOB data for input variable X_N is shuffled at random, leaving the target and all other input variables unchanged;

ii. Using the new OOB data with shuffled X_N, new predictions are generated for $\hat{Y}_i$ to arrive at $MSE^{OOB}_{shuffled,X_n}$;

iii. Finally, VI_N is computed as follows: $VI_N = \left(\frac{MSE^{OOB}_{shuffled,X_n} - MSE^{OOB}}{MSE^{OOB}}\right) * 100$

.

Appendix B
Data Description and Sources

Variable	Description	Frequency	Source
Stressed Assets Ratio (%)	(Restructured Standard Advances + Gross Non-Performing Advances) / Total Gross Advances	Quarterly	Supervisory Returns, RBI
Assets (INR billions)	Total Assets of the Bank	Quarterly	Supervisory Returns, RBI
Current Deposits Ratio (%)	Total Current Deposits / Total Assets	Quarterly	Supervisory Returns, RBI
Time Deposits Ratio (%)	Total Term Deposits / Total Assets	Quarterly	Supervisory Returns, RBI
Savings Deposits Ratio (%)	Total Savings Deposits / Total Assets	Quarterly	Supervisory Returns, RBI
CASA Ratio (%)	(Total Current Deposits + Total Savings Deposits) / Total Assets	Quarterly	Supervisory Returns, RBI
Capital & Reserves	Total Capital & Reserves / Total Assets	Quarterly	Supervisory Returns, RBI
Liquid Assets Ratio (%)	Total Liquid Assets / Total Assets	Quarterly	Supervisory Returns, RBI
Total CRAR (%)	Total Regulatory Capital / Risk-Weighted Total Assets of the Bank	Quarterly	Supervisory Returns, RBI
Tier 1-Capital Ratio (%)	Total Tier 1 Regulatory Capital / Risk-Weighted Total Assets of the Bank	Quarterly	Supervisory Returns, RBI
Tier 2-Capital Ratio (%)	Total Tier 2 Regulatory Capital / Risk-Weighted Total Assets of the Bank	Quarterly	Supervisory Returns, RBI
Return on Assets (%)	Total Net Profits / Average Total Assets	Quarterly	Supervisory Returns, RBI
Return on Equity (%)	Total Net Profits / Average Total Shareholders' Equity for the Bank	Quarterly	Supervisory Returns, RBI
Net Interest Margin (%)	Net Interest Income / Average Total Assets	Quarterly	Supervisory Returns, RBI
VIX	NSE VIX Index	Quarterly	Bloomberg
Excess Return over NSE Bank (%)	Δ%Q-o-Q($Price_{i,q}$) - Δ%Q-o-Q($Price_{,niftybank,q}$); where $Price_{i,q}$ is the stock price value of i^{th} Bank in quarter 'q' and $Price_{niftybank,q}$ is the stock price value of NSE Bank Index in quarter 'q'	Quarterly	Bloomberg; Authors' calculation

(Contd...)

Variable	Description	Frequency	Source
Excess Return over NSE Bank (%)	Δ%Q-o-Q(Price$_{i,q}$) - Δ%Q-o-Q(Price$_{NIFTY,q}$); where Price$_{i,q}$ is the stock price value of ith Bank in quarter 'q' and Price$_{NIFTY,q}$ is the stock value of NSE NIFTY Index in quarter 'q'	Quarterly	Bloomberg; Authors' calculation
Price-to-Book Ratio	Market price per share / Book value per share; where book value per share is equal to (total assets – total liabilities) / number of shares outstanding	Quarterly	Bloomberg
Market Capitalisation	(Current market price per share) x (Total number of shares outstanding);	Quarterly	Bloomberg
90-d Price Volatility	Standard deviation of daily logarithmic price changes for the 90 most recent trading days closing price	Quarterly	Bloomberg

Appendix C
Summary Statistics

Table C1: All Scheduled Commercial Banks

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Stressed Assets Ratio (%)	1,404	8.65	5.85	0.00	29.49
Assets (INR billions)	1,404	2.068	2.771	0.00	2.883
Total CRAR (%)	1,404	12.86	2.36	0.00	20.61
Return on Equity (%)	1,404	9.59	10.51	-46.97	41.48
Return over NSE Bank (%)	1,404	-0.97	6.67	-25.92	41.17
Price-to-Book Ratio	1,404	1.14	1.14	0.00	7.17
Market Capitalisation (INR billions)	1,404	2.404	5.067	0.00	4.845
90-d Stock Volatility	1,404	36.37	11.62	0.00	88.40

Table C2: Public Sector Banks

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Stressed Assets Ratio (%)	864	11.00	5.83	0.00	29.49
Assets (INR billions)	864	2.565	3.155	0.00	2.883
Total CRAR (%)	864	11.91	1.78	0.00	18.18
Return on Equity (%)	864	7.76	11.33	-46.97	41.48
Return over NSE Bank (%)	864	-1.74	6.76	-25.92	37.44
Price-to-Book Ratio	864	0.63	0.42	0.00	2.85
Market Capitalisation (INR billions)	864	1.515	3.361	0.00	2.675
90-d Stock Volatility	864	37.33	11.32	0.00	88.40

Table C3: Private Sector Banks

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Stressed Assets Ratio (%)	540	4.89	3.43	0.00	21.54
Assets (INR billions)	540	1.273	1.739	0.00	9.246
Total CRAR (%)	540	14.37	2.37	7.44	20.61
Return on Equity (%)	540	12.53	8.23	-33.96	29.68
Return over NSE Bank (%)	540	0.27	6.34	-25.15	41.17
Price-to-Book Ratio	540	1.95	1.42	0.00	7.17
Market Capitalisation (INR billions)	540	3.826	6.743	0.00	4.850
90-d Stock Volatility	540	34.82	11.93	12.65	86.17

Appendix D
Diagnostic Tests and Estimation Results

Table D1: Joint Wald Test of Significance for Inclusion of Time-Fixed Effects (Null: $\alpha_t = 0$ for all t)

F (34, 38)	39.20
Prob. > F	0.000

Table D2: Modified Wald Test for Group-wise Heteroscedasticity in Fixed Effect Regression Model (Null: sigma(i)^2 = sigma^2 for all i)

chi^2 (39)	3294.78
Prob. > chi^2	0.000

Table D3: Wooldridge Test for Autocorrelation in Panel Data (Null: No First Order Autocorrelation)

F (1, 38)	5.721
Prob. > F	0.0218

Table D4: Pesaran's Test of Cross-sectional Independence (Null: No Cross-sectional Dependence)

test-stat	-2.687
Prob.	0.0072

Table D5: Estimation Results for Fixed Effect Panel Model (Sample – Full Sample)

Independent Variable ↓ / Dependent Variable →	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	SAR	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**
Assets (-1) (in Logs)	-0.087^{***} (0.0055)	-0.089^{***} (0.0053)	-0.088^{***} (0.0055)	-0.090^{***} (0.0051)	-0.084^{***} (0.0049)	-0.083^{***} (0.0055)	-0.085^{***} (0.0059)	-0.083^{***} (0.0065)	-0.083^{***} (0.0066)	-0.081^{***} (0.0050)	-0.067^{***} (0.0061)
RoE(-1)	-0.19^{***} (0.028)	-0.18^{***} (0.028)	-0.18^{***} (0.028)	-0.18^{***} (0.030)	-0.18^{***} (0.029)	-0.18^{***} (0.029)	-0.18^{***} (0.031)	-0.19^{***} (0.027)	-0.18^{***} (0.027)	-0.18^{***} (0.029)	-0.16^{***} (0.028)
CRAR (-1)	-0.38^{***} (0.078)	-0.38^{***} (0.080)	-0.38^{***} (0.079)	-0.38^{***} (0.081)	-0.37^{***} (0.075)	-0.38^{***} (0.076)	-0.38^{***} (0.079)	-0.37^{***} (0.079)	-0.36^{***} (0.081)	-0.37^{***} (0.084)	-0.32^{***} (0.086)
Adj.Ret		-0.041^{*} (0.018)									-0.043^{*} (0.020)
Adj.Ret(-1)			-0.020 (0.014)								-0.043^{*} (0.019)
Adj.Ret(-2)				-0.034 (0.020)							
PB Ratio					-0.0087^{*} (0.0034)						-0.0064^{**} (0.0018)
PB Ratio(-1)						-0.0066^{*} (0.0029)					
PB Ratio(-2)							-0.0054 (0.0036)				
Vol.90d								0.00030 (0.00016)			
Vol.90d(-1)									0.00033 (0.00018)		
Vol.90d(-2)										0.00050^{***} (0.00011)	0.00034^{**} (0.000099)
Constant	1.23^{***} (0.069)	1.25^{***} (0.066)	1.24^{***} (0.069)	0 (.)	1.20^{***} (0.061)	1.19^{***} (0.068)	0 (.)	1.18^{***} (0.087)	1.17^{***} (0.088)	0 (.)	0 (.)
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1358	1358	1358	1319	1358	1358	1319	1358	1358	1319	1303
R^2(within)	0.6508	0.6538	0.6516	0.6547	0.6550	0.6534	0.6542	0.6537	0.6544	0.6607	0.6589

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D6: Estimation Results for Fixed Effect Panel Model (Sample – Public Sector Banks)

Independent Variable ↓ / Dependent Variable →	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	SAR	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**
Assets (-1) (in Logs)	-0.13*** (0.021)	-0.13*** (0.021)	-0.13*** (0.021)	-0.14*** (0.016)	-0.13*** (0.023)	-0.13*** (0.022)	-0.14*** (0.018)	-0.13*** (0.022)	-0.13*** (0.022)	-0.14*** (0.017)	-0.14*** (0.018)
RoE (-1)	-0.067 (0.037)	-0.061 (0.038)	-0.065 (0.037)	-0.069 (0.038)	-0.067 (0.036)	-0.067 (0.037)	-0.072 (0.038)	-0.069 (0.037)	-0.067 (0.036)	-0.075 (0.037)	-0.065 (0.039)
CRAR (-1)	-0.84*** (0.21)	-0.83*** (0.20)	-0.84*** (0.21)	-0.85*** (0.20)	-0.84*** (0.22)	-0.84*** (0.23)	-0.85*** (0.23)	-0.84*** (0.22)	-0.84*** (0.22)	-0.84*** (0.22)	-0.82*** (0.21)
Adj.Ret.		-0.051 (0.028)									-0.052 (0.029)
Adj.Ret.(-1)			-0.024 (0.016)								-0.040 (0.023)
Adj.Ret.(-2)				-0.045 (0.027)							
PB Ratio					0.00023 (0.0064)						-0.0017 (0.0041)
PB Ratio(-1)						0.0023 (0.0058)					
PB Ratio(-2)							0.00089 (0.0068)				
Vol.90d								0.00018 (0.00018)			
Vol.90d(-1)									0.00018 (0.00022)		
Vol.90d(-2)										0.00041*** (0.00011)	0.00030** (0.000098)
Constant	0 (.)	0 (.)	0 (.)	2.01*** (0.22)	0 (.)	0 (.)	2.00*** (0.25)	0 (.)	0 (.)	1.95*** (0.24)	0 (.)
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	834	834	834	810	834	834	810	834	834	810	798
R^2(within)	0.7408	0.7436	0.7415	0.7436	0.7408	0.7410	0.7412	0.7416	0.7416	0.7455	0.7374

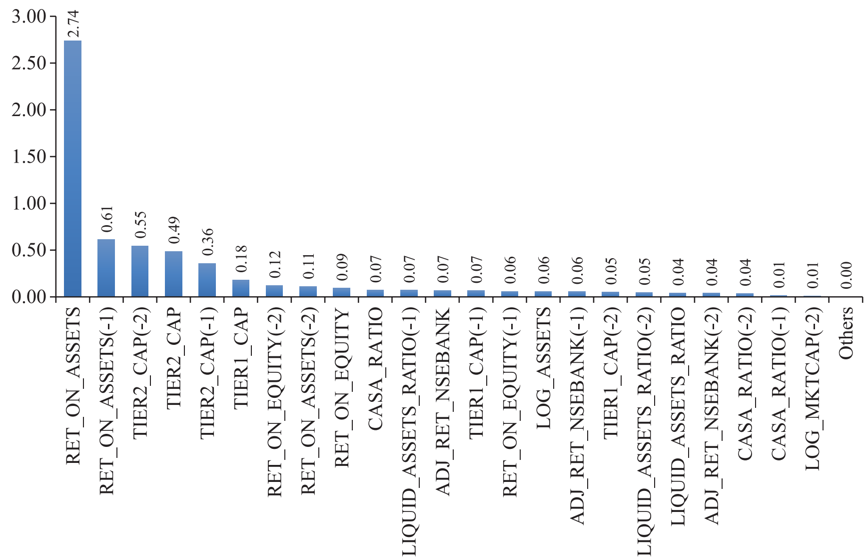
Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D7: Estimation Results for Fixed Effect Panel Model (Sample – Private Sector Banks)

Independent Variable ↓ / Dependent Variable →	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	SAR	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**	**SAR**
Asset (-1) (In Logs)	-0.036*** (0.0061)	-0.037*** (0.0059)	-0.036*** (0.0062)	-0.038*** (0.0061)	-0.034*** (0.0056)	-0.033*** (0.0057)	-0.034*** (0.0059)	-0.036*** (0.0067)	-0.035*** (0.0066)	-0.037*** (0.0059)	-0.028** (0.0091)
RoE (-1)	-0.23*** (0.026)	-0.23*** (0.026)	-0.23*** (0.026)	-0.22*** (0.027)	-0.21*** (0.028)	-0.22*** (0.028)	-0.22*** (0.029)	-0.23*** (0.026)	-0.22*** (0.026)	-0.22*** (0.028)	-0.20*** (0.029)
CRAR (-1)	-0.21** (0.070)	-0.21** (0.069)	-0.21** (0.070)	-0.22** (0.075)	-0.20** (0.073)	-0.22** (0.076)	-0.22* (0.082)	-0.21** (0.072)	-0.20** (0.067)	-0.22** (0.077)	-0.20* (0.097)
Adj.Ret.		-0.031** (0.0090)									-0.030** (0.0096)
Adj.Ret. (-1)			-0.0042 (0.014)								-0.027* (0.012)
Adj.Ret. (-2)				-0.015 (0.013)							
PB Ratio					-0.0071** (0.0025)						-0.0065*** (0.0017)
PB Ratio(-1)						-0.0057* (0.0024)					
PB Ratio(-2)							-0.0053* (0.0024)				
Vol.90d								-0.000016 (0.00013)			
Vol.90d (-1)									0.00014 (0.00010)		
Vol.90d (-2)										0.00006 (0.0001)	0.00004 (0.0001)
Constant	0.53*** (0.072)	0.54*** (0.069)	0.53*** (0.073)	0.55*** (0.071)	0.51*** (0.065)	0.51*** (0.067)	0.52*** (0.067)	0.52*** (0.081)	0.50*** (0.077)	0.54*** (0.067)	0.51*** (0.074)
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	524	524	524	509	524	524	509	524	524	509	505
R^2(within)	0.5158	0.5216	0.5160	0.5173	0.5291	0.5246	0.5233	0.5159	0.5174	0.5159	0.5396

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chart D8: LASSO-based Regression Coefficients



Note:

1. Penalty = LASSO; Alpha = 1.
2. K-fold Cross Validation based on MSE has been adopted for selection of optimal hyper-parameters measures.
3. Above results control for bank-specific effect and time-trend by introduction of appropriate dummies.

Source: Authors' calculations.

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Narrative Economics: How Stories Go Viral and Drive Major Economic Events by Robert J. Shiller, 377 pp., Princeton University Press (2019), US$27.95

Behavioural economics is one of the recent dimensions of mainstream economics that combines psychological, emotional and social factors to explain economic decision making by individuals. This field of economics contests the traditionally held economic premise and argues that economic decisions are driven by emotions rather than rational calculation. The Nobel Prize-winning economist Robert J. Shiller is known for his pioneering research in the field of financial markets and accurately predicting the dot-com bubble in the year 2000 and the financial crisis of 2008-09. He observes that the fluctuations in asset prices over long periods occur in predictable patterns and that the markets are in fact irrational. His new book *Narrative Economics: How Stories Go Viral and Drive Major Economic Events* explains the role of popular narratives in driving economic behaviour of agents and their implications for the real world. The book expands on earlier works on the subject such as Daniel Kahneman's *Thinking, Fast and Slow* (2011), Richard Thaler's *Nudge* (2008) and *Misbehaving* (2015), Dan Ariely's *Predictably Irrational* (2008) and *Upside of Irrationality* (2010), Robert Shiller and Roger Akerlof's *Animal Spirits* (2009) and the former's *Irrational Exuberance* (2000).

The impact of narratives on people's behaviour is shown through controlled experiments in the field of marketing, journalism, education, health, and philanthropy. However, Shiller expands the analysis of narratives into the field of economics and argues that sometimes the most dominant reason behind economic fluctuations happens to be the spread of certain powerful stories that evoke human interest and emotion, which cannot be explained by mainstream economics. Using historical examples extensively, the book explains the impact of these 'viral' stories on individuals' economic decision-making and their contagious impact on aggregate economic variables. A careful study of these narratives can help economists perform economic forecasts better and predict major economic events like recessions or depressions rather than relying solely on the mathematical tools and data.

The term ‘narrative’ means simple stories or explanations of events that goes viral and drives economic events. Economic decisions are often influenced more strongly by the manner in which information is presented to people, rather than by the underlying facts. The presentation of such information before the public forms popular narratives like ‘stock prices can only go up’, ‘real estate prices never fall’, *etc.* A common influence of these narratives across individuals affects economic behaviour at an aggregate level in the form of changes in macroeconomic variables such as investment and savings, thus making such narratives self-fulfilling prophecies. These narratives spread through word of mouth, news media and, more recently, through social media. Understanding the impact of these narratives can help us improve our ability to predict and prepare ourselves for major economic events.

Shiller’s book consists of four parts. Part one elaborates on the concept of narratives, the beginning of narrative economics and the occurrence of contagion. The author begins with one of the most viral narratives of the decade, that of bitcoins, and tries to explore the reason behind the popularity of the currency that has no underlying value. He compares the rise of bitcoins to the seventeenth-century tulip mania, when the prices of tulip bulbs exceeded the prices of real estate. He argues that the rise in the value of bitcoin can be attributed to the fact that people are interested in believing the bitcoin story and they do not want to miss out on the technological advances and the possible profits they might gain, even without understanding the idea behind the creation of the cryptocurrency. The complicated and costly technology behind the bitcoin generates a perception that it has an intrinsic value. The popularity of bitcoin is also associated with anarchism as it challenges the monopoly of government over financial structure through fiat currencies.

Part two of the book explains the causality between the popular narratives and economic events and provides different propositions to help the reader identify and understand the evolution of important narratives. Shiller draws a comparison between narratives and contagious epidemics that recur after a mutation changes its contagiousness. He argues that some narratives are like viruses that die out on their own, while others mutate and recur in new generations. Some of the perennial narratives that find themselves being repeated through time after mutation relate to the advent of industrialisation or mechanisation, automation and artificial intelligence – replacing human capital and ultimately resulting in mass unemployment. Similarly, there are many other economic theories and events that find space in the form of popular narratives, repeatedly, in slightly different formats.

In part three of the book, the author examines nine perennial narratives and their role in the occurrence of various economic phenomena. Shiller begins with a major class of narratives about confidence that has influenced economic outcomes: people's confidence in banks, in business, in one another, and in the economy. The author has linked the periods of boom and bust to a state of confidence and a state of panic in general public. A recession or depression is an outcome of confidence erosion in the future trajectory of the economy and associated unwillingness to invest in business or to hire more labour. Similarly, a bank run occurs when people lose confidence in the bank's ability to repay along with the belief that other consumers may also try to withdraw their money at once. Most of the economic theories are based on the assumption that human beings are rational agents who make well-informed decisions. However, in reality, human mind is suggestible and can be guided by irrational suggestions to display herd-like behaviour.

Another major narrative is related to the gold standard of the mid-twentieth century. Since 1971, countries around the world have abandoned the gold standard and replaced it by fiat currency. The central banks, however, still hold gold though not for backing their currency. One of the reasons why central banks still hold gold is because of the public perception that the end of the gold standard means the end of 'something traditional and honest'. This narrative is not so prominent today, but its mutations can be found in the form of the bitcoin narrative or in other forms in future.

The author uses 'Google Ngram' to understand the popularity of different narratives at any point in history. The use of the term 'technological unemployment' started in 1917 but it began its contagious swing in 1928 and reached a peak around the worst years of the Great Depression. The period preceding the Great Depression was a period of prosperity. Still, we see an upswing in the popularity of the technological unemployment narrative. This happened after official data in the United States showed an unemployment rate of 7.4 per cent, which led people to speculate about the reasons behind such a high rate of unemployment. The Google Ngram reveals that such narratives usually become popular around the period of economic downturn and have the potential to amplify the impact of economic crisis by causing instability in expenditure and investment patterns. Shiller cites examples of viral stories about electronic brain (computers), artificial intelligence, machine learning, *etc.*, which contributed to raising the fear of unemployment. The labour-saving machines narrative has recurred several times in economic history, usually during phases of economic crisis. Under the influence of these narratives, temporary economic downturns are mistaken for technological unemployment which generate pessimistic sentiments.

The author also adumbrates speculation-based narratives where people speculated on real estate and stock prices which led to the formation of asset price bubbles. The dot-com bubble of the early 2000s was characterised by a pattern similar to that of the tulip mania of the 1630s that showed a rise in prices, without underlying financials, followed by a sharp correction. One could observe similarities between the narratives related to real estate and the stock market – both are driven by social comparison, are contagious, and are linked to investor greed and irrationality. The stock market crash story of 1929 may not have a contagious effect today but it still remains as a part of public thinking and can recur with a mutation in a changing economic environment. Such stories and legends from the past have the potential to influence people's behaviour and economic outcomes.

Shiller also talks about the narratives and perceptions that were generated during the period of the Great Depression. An environment of collective sympathy was created wherein people postponed their consumption and maintained a simple lifestyle in deference to the suffering of those who lost their jobs, thereby contributing to the prolonging of the Depression. The 'American dream' narrative, which has recurred several times in the twentieth century, originally involved the idea of a higher standard of living and prosperity for all. One aspect of this narrative was the ownership of a house which led to the housing bubble that collapsed in 2007-08.

In part four of the book, the author discusses the scope of analytical research in the area of narrative economics that can help in understanding the link between narratives and real economic variables. He argues that traditional research methods like focus groups – interviews conducted on a group of people from diverse backgrounds to elicit actual conversation on economic narratives and new technological tools like textual analysis – involving counting of words and phrases in digitised texts can be used to supplement macroeconomic models. The author emphasises the importance of collecting such data and adding it to the major economic databases for further analysis on what people are talking about during economic downturns.

Shiller challenges the basic assumption of economics that people are 'consistent optimisers of a sensible utility function' and that they are rational agents who make best choices for themselves using all the available information. He argues that human behaviour is susceptible to popular narratives or stories and people often tend to collectively make irrational decisions. He has, however, emphasised only the macroeconomic impact of these narratives, leaving microeconomic aspects untouched. The book is silent on modelling this irrational behaviour into microeconomic theories that are based on the assumption of rationality. The author has also missed the challenges that researchers may face while tracking and quantifying a set of narratives as they are sometimes conflicting in nature, largely driven by emotions and their study involves a great degree of human judgement. The practical utility of the premises advocated in the book could have been increased had the author provided some guidance on incorporating the impact of narratives into mainstream economic theories. The book gives a sense that assumption of rationality is redundant in explaining economic behaviour of agents, which may not really be the intention of the author. Also, the assertions made in the book are not backed by analytical research or empirical evidence. Nevertheless, in the era of social media where stories go viral at a click, the book offers interesting insights that may help to better understand major economic outcomes, complementing traditional mathematical models.

Palak Godara*

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* Palak Godara is a Manager in the Department of Economic and Policy Research, Reserve Bank of India.

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How to Combat Recession: Stimulus without Debt, Laurence S. Seidman, 239 pp., Oxford University Press (2018), INR ₹1595.

There has been an inconclusive debate on the effectiveness of different macroeconomic policies to deal with recessionary conditions. The monetary and fiscal policies have remained at the core of the debate. The rising level of debt and associated concerns over sustainability of government finances often constrain the authorities to undertake the required level of fiscal stimulus. With rising concerns about economic slowdown in the global pretext, Professor Laurence Seidman, in his book, 'How to combat recession: Stimulus without debt', provides a seemingly new idea whereby government can undertake large fiscal stimulus without an increase in its debt. This book is an elaboration of the idea advocated in his paper – 'Stimulus without debt'- undertaking fiscal stimulus without creating debt to combat demand induced recession.

Laurence Seidman is Chaplin Tyler Professor of Economics at University of Delaware, USA. He has authored 12 books and published many articles in economics and public policy journals. On the lines of Keynesian approach, the author – in this book – proposes implementation of fiscal stimulus to tackle any future recession. However, policymakers and public at large are generally averse to fiscal support due to its implication on budget deficit and government debt, as was evident during the previous recessionary situations. The author argues that economies are not prepared for another recession and there is need to have a clear strategy to deal with any such recession. In this book, the author addresses several questions pertaining to the suggested policy tool to tackle another recession. The book consists of 14 chapters, each answering a question pertaining to the proposed idea.

The author believes that severe recession caused by a fall in aggregate demand can be dealt with large temporary fiscal stimulus. During the great recession of 2008, the United States government adopted fiscal stimulus of US$150 billion in 2008 and of approximately US$ 750 billion in 2009 which was around 6 per cent of GDP. The author considers this size of stimulus to be insufficient to move the US economy out of recession. With estimated tax rebate to GDP multiplier at 1 and GDP to unemployment ratio of 2:1, the approved fiscal package reduced unemployment by 1 per cent each year, from what it would have been without any fiscal boost. However, his own calculation suggests that if fiscal package of 6 per cent of GDP was allotted each year from 2008 to 2010, unemployment rate would have been reduced by 3 per cent points in 2010 from its level without any fiscal stimulus. Experience from 2008 crisis shows that even if fiscal stimulus works, large scale stimulus is resisted by policymakers, economists and public due to concerns about huge government borrowings. Also, monetary stimulus being largely perceived to be ineffective in reviving the economy, the author suggests non-debt creating fiscal stimulus.

In standard fiscal and monetary stimulus, government finances its expenditure through issue of bonds which are then purchased by the central bank from market resulting in rise in the government debt and central bank's holding of treasury bonds. The author suggests that paper money held by public remains the liability of central bank and is not included in the government debt. Therefore, transfer equivalent to fiscal deficit unlike bonds, does not lead to increase in public debt.

Stimulus without debt has two components. The first comprises fiscal stimulus through a temporary increase in tax rebates to households, federal grants to state and local governments, tax credit to firms for the purchase of capital goods and government spending on infrastructure maintenance projects. The second consists of a monetary stimulus wherein the central bank transfers money to the government. Regarding the fiscal stimulus, the author argues that tax rebates should be a major component of this stimulus, in view of the consumers' response to tax rebates extended by the US government in 2001 and 2008. The studies show that an average household spends about one-third of its rebate within three months and about two-third within six months of receiving the rebate.

Further, the author analyses the American Recovery and Reinvestment Act (ARRA), enacted by the US government in 2009, which proposes making large fiscal stimulus through tax incentives to individuals. The stimulus is given as reduction in withholding from paycheck, thus, increasing take-home salary of individuals. According to the author, widely publicised rebates have greater impact on demand. Issuance of work pay tax credits in the same manner would have been more effective. It is generally believed that a one-time transfer is not spent immediately, rather it is saved for the future by households. Nevertheless, the aforementioned studies show that during recession households tend to spend tax rebates on consumption. The author argues that apart from tax rebate as the major component of fiscal package, fiscal stimulus should be supplemented by tools like temporary increase in federal aid to state governments, temporary tax incentives for business investment and infrastructure repairs and maintenance. As sub-national spending plummets during recessions, the author recommends federal aid based on an objective numerical formula to maintain the level of spending. The author argues that only temporary tax incentive may be considered for business investment promotion as permanent tax incentive is not likely to yield the desired result. Infrastructure repairs and maintenance can complement tax rebate by increasing state spending despite their impact on demand being limited to specific industries. The author also gives reasons for not recommending temporary cut in income tax withholding, a temporary cut in payroll taxes, a cut in income taxes and an increase in spending on long-term programmes. Unlike tax rebates, small cut in income tax withholding and payroll taxes, results in small increase in monthly pay-checks which are less noticeable and, thus, have lesser impact on household expenditure. The author advocates that cut in income taxes and increase in spending in long term programmes should be agenda for long term policy decisions and should not be part of temporary fiscal stimulus package.

Regarding the impact of stimulus without debt on inflation, the author uses basic aggregate demand (AD) and aggregate supply (AS) framework to show that during recession, AS curve is elastic when output gap is negative. Any increase in demand would result in greater rise in output and relatively less increase in inflation. As the economy approaches normality, central bank can reduce the growth of money supply to restore it to normal level.

As per the standard accounting framework, when central bank increases money supply through purchase of bonds, assets side of balance sheet increases but this does not happen in case of transfer to government. Thus, the central bank's net worth worsens if central bank finances government deficit through transfer instead of buying bonds. The author recommends the central bank to print notes equivalent to transfer and then store the same in its vault. The cash would increase the assets side of balance sheet just as when bonds are purchased. Central banks with power to increase assets can always keep its net worth positive. Further, the author highlights the problems in the current reporting system of central banks' balance sheet and proposes its reformation.

The author argues that the stimulus without debt does not sabotage the independence of a central bank. The powers can be clearly defined between the central bank and government. Central bank may have the sole power to decide the amount of transfer and government may decide the size of fiscal stimulus which could be less, equal or greater than the transfer the central bank provides. Government can finance stimulus by issue of bonds, if transfer amount falls short.

The author sees limited role of monetary policy during recessions. He emphasises that relying only upon monetary policy during severe recession would not be effective in reviving economy to the desired growth trajectory. During recession, customers' and investors' confidence is low, thus, any reduction in interest rate would not induce them to increase spending. As elaborated by Paul Samuelson, "you can lead a horse to water, but you can't make him drink." Similarly, when central bank purchases government bonds, their yield diminishes, resultantly investors shift towards high return providing assets, *viz.*, corporate stocks and bonds. This enhances consumers' and businesses' confidence but this is not sufficient to boost demand. Moreover, concerns about rise in debt limits the size of fiscal stimulus.

The book revolves around the US economy and implications of stimulus without debt, if implemented by the US government during recession. According to the author, any economically advanced country with its own independent central bank would be successful in executing the idea. Also, the idea of transfer from central bank is not new and some resembling ideas have been proposed previously. For instance, Milton Friedman's helicopter money parable suggested dropping of money in a full employment economy. But this act will result into only rise in prices with no increase in real income. Therefore, Ben Bernanke in his 2016 blog also proposed money-financed Fiscal Program for next severe recession, wherein the Federal Reserve can directly credit account of the US government with the amount of fiscal stimulus instead of financing though purchase of government bonds from the public. Similarly, author has mentioned various articles, proposing serious thought to helicopter money and transfers from central bank as policy tool and, thus, showing that idea is getting attention.

The author argues that secular stagnation, characterised by chronically insufficient demand and slow growth in potential output, can also be tackled by transferring money from central bank till actual output reaches its potential level. Stimulus without debt can solve the problem of insufficient demand by providing money into the hands of consumers. This policy would not be useful in case of stagnant potential output caused by slow pace of technological progress.

The author develops a macroeconomic model to study the impact of stimulus without debt in severe recession. He analyses and compares four alternative policy scenarios in terms of their impact upon inflation, output gap, government debt, budget deficit, interest rates, money supply and nominal income over a period of 16 years. Each variable takes different growth path when four different policies are undertaken. First path shows a growth trajectory when no recession hits the economy and other three present response of a recession hit economy when different policy tools are adopted. The second path shows 'no fiscal stimulus' path wherein central bank adjusts interest rate based on Taylor's rule in recession hit economy, third path shows the response when fiscal stimulus is financed by borrowing and fourth path shows growth trajectory when fiscal stimulus is financed by central bank transfer. Post-recession, all the three paths show that inflation rate never exceeds the targeted inflation rate and in long run it converges to target inflation rate. Also in long run, all the paths show convergence to pre-recession deficit and debt level, but in short-run, 'stimulus without debt' achieves lower deficit and debt compared to other paths. In 'no fiscal stimulus' path, economy takes seven years to reach zero output gap, while it takes only one year in case of large fiscal stimulus with debt or without debt. The negative demand shock increases debt and deficit as per cent of nominal income due to drop in tax revenue, but stimulus with bonds issuance further increases the debt and deficit. However, stimulus without debt does not worsen the debt and deficit as per cent of nominal income. Another observation is that the money injected in stimulus with or without debt is the same keeping in line with Taylor's rule. The author, through the model, proves that large temporary fiscal stimulus can eliminate the output gap in one year. It is better than relying solely on monetary stimulus and also better than stimulus with debt in terms of keeping debt and deficit in control.

The author has lucidly presented his arguments on economic policy of stimulus without debt. With each chapter comprehensively answering the next question that can arise in the reader's mind, he has made the book an interesting read for a wide range of audience. In theory, the proposal appears to be uncomplicated and straight. However, it is not clear how the proposal is really different in practice than the traditional idea of printing money to finance the government deficit. The book seems to have ignored several major macro-economic issues which can hardly be resolved by merely changing the accounting framework. The change in accounting can only superficially address the concerns regarding rising debt and 'aversions' to undertake fiscal stimulus. The more substantial issues such as effectiveness of such stimulus in raising the output and employment; and impact on inflation need answers. The proposal to transfer money without raising any liability can make government complacent and lead to its misuse to implement populist schemes. Further research is needed to seriously consider the proposed idea as a policy alternative.

Deepika Rawat*

* Deepika Rawat is a Manager in Department of Economic Policy and Research, Reserve Bank of India.

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