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Macroeconomic Implications of Bank Capital Regulations

Ranajoy Guha Neogi and Harendra Behera*

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This paper examines the role of regulatory bank capital in influencing credit flows and GDP growth. Using a theoretical model and empirical estimates from a sign restricted vector autoregression (VAR) model, it provides evidence of a positive effect of bank capital on credit supply and output growth. Higher capital tends to lower risk premium and overall cost of liabilities of banks, while enhancing their capacity to undertake risky lending. Regulatory capital to risk weighted assets ratio (CRAR) is also found to work like a macro-prudential tool as a higher CRAR triggers loan portfolio reallocation in banks away from unsecured high risk loan towards secured and low risk loans.

JEL Classification: E43, E44, E50, E58

Keywords: Bank capital, Basel III, financial stability, leverage, CRAR, sign-restricted VAR, Bayesian estimates

Introduction

The role of regulatory bank capital gained prominence in the Indian context from the days of the Basel Accord. Research on the role of adequate bank capital in ensuring financial stability and mitigating losses from future crises has gained further traction at a global level in the post-subprime crisis period. Our focus in this paper is on the macro-financial implications of increased regulatory capital requirements.

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The net marginal benefit of bank capital can be assessed by determining the benefits of bank capital due to reduced crisis probability and the output loss because of higher capital maintenance by banks. In Cline (2016, 2017) and BCBS (2019), the positive effect of higher capital adequacy is defined in terms of reduced expected loss from crisis and the negative effect is in terms of output loss (drag). If k is capital adequacy, net marginal benefit (k) = reduced crisis probability (k) x crisis cost – output drag (lending spread (k)).

We examine the macroeconomic implications by revisiting the theory and empirics, with a focus on the output (drag) effects of regulatory capital.

Despite the potential benefits of higher bank capital, greater equity financing raises banks' weighted average cost of capital (WACC) (BCBS, 2010; 2019; Birn *et al.* 2020). This leads to a rise in the interest rate spread and therefore clogs credit supply to the non-financial firms. Due to imperfect substitutability between bank credit and other forms of credit under asymmetric information in the market, this further results in subdued investment and lowers economic growth. Heightened capital adequacy[1] supposedly entails cost in terms of loss in GDP growth due to costlier bank credit. On the other hand, going by the Modigliani-Miller (MM) theorem[2], equity financing may not increase the cost of lending as it does not matter whether the bank finances its lending by issuing equity or borrowing in the form of debt. Therefore, a rise in capital adequacy is costless to ensure a safer balance sheet (of the banks) under perfect realisation of the Modigliani-Miller theorem. This is because the rise in cost of equity, due to higher capital adequacy, exactly balances out by the fall in funding cost, leading to no additional net cost to the banks and hence no adverse impact on the economy. However, the MM theorem seldom holds (at least fully) in reality. Thus, based on the extant studies, BCBS (2010) considers zero Modigliani-Miller offset (MM offset, henceforth).[3] Also, BCBS (2019) in their updated survey, on the basis of latest findings from

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[1] As per Basel norm, capital adequacy is measured in terms of Capital to Risk (weighted) Assets Ratio (CRAR) by which central bank tries to assess the financial strength of a bank. The same definition is followed in India as well.

[2] According to Modigliani and Miller (1958) and Miller (1995), the overall financing cost of a firm is unaffected by how it is being financed whether through equity or debt.

[3] MM offset refers to the cost impact of higher capital requirements offset by lower unit cost of equity due to reduction in risk premium.

a number of recent articles, concluded that the cost of equity could fall by around fifty per cent of what MM theorem may suggest. Thus, all the existing literature covered in BCBS studies generally concludes that the funding cost of banks rises, with negative implications for economic growth of varied extent depending upon the degree of fall in the cost of equity. Gambacorta and Shin (2018) and Muduli and Behera (2020), however, showed that higher capital adequacy raises credit supply of the banks. Gambacorta and Shin (2018) found a steep fall in the cost of funds for better capitalised banks, due to their sounder balance sheets. They attributed this finding to the possibility of a larger MM offset due to falling cost of debt financing. Thus, sounder financial health along with a fall in cost of funds could lead to a rise in loan supply as against BCBS (2019)'s finding of a reduction in credit supply by banks due to rise in lending spread. Our aim in this paper is to theoretically analyse and empirically examine the impact of increased regulation-induced higher capital position of banks on credit flows under partial MM offset.

As against the perceived notion of bank equity financing to be costlier and therefore could lead to dampen the loan growth and economic output, we examine whether higher CRAR could lead to higher growth in loan supply and thereby higher economic growth. To study this hypothesis, we first theoretically show the possibility of reduction in WACC of the banks due to lower leverage, with higher CRAR, contributing to higher flow of bank credit and resultant rise in GDP growth.

In the empirical analysis, we find that a positive bank capital shock (*i.e.,* higher capital adequacy) can push the GDP growth up and reduce risky lending. We use an aggregate measure of CRAR (a weighted average of bank level CRARs) to capture the effects of regulatory change on system level bank capital as a whole. We also verify the robustness of the results by treating a different version of aggregate CRAR series, based on median of bank level CRARs. The subsequent sections are organised as follows. Section II summarises the bank capital environment in India and Section III discusses the literature review. Section IV provides a theoretical exposition, Section V explains the data and the estimation methodology while Section VI discusses empirical results, and Section VII concludes the paper.

Section II
Bank Capital Environment in India

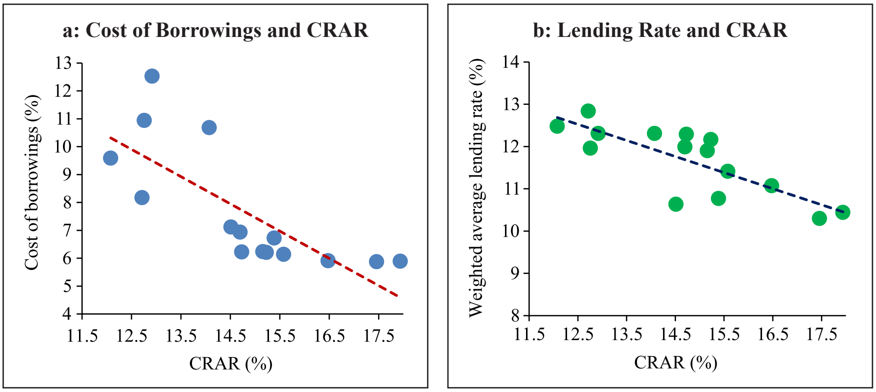
The Basel framework evolved over time since the introduction of Basel I norms in 1988 and thus necessitated banks to maintain capital as a percentage of their credit risk exposures. Subsequently, the risk coverage of the capital framework was expanded to include other risks on the banks' balance sheet such as market risk and operational risk. In the post global financial crisis (GFC) period, systemic risk as a separate category also gained traction to address the risk of financial contagion. Clearly, credit risk has drawn the highest attention as an increase in defaults can abruptly lead to illiquidity and insolvency problems. Over time, the RBI has broadly moved as per the evolving frameworks of the BCBS to ensure financial stability.

Capital regulation under Basel-III was further strengthened to increase the quantity and quality of capital, enhance the risk coverage and introduce macro prudential elements such as leverage ratio, countercyclical buffers and liquidity ratios. As against the international norms of 8 per cent CRAR, the Reserve Bank has stipulated banks in India to maintain a higher minimum CRAR of 9 per cent, in addition to capital conservation buffer (CCB) of 2.5 per cent and counter-cyclical capital buffer. Banks in India had to maintain CCB of 2.5 per cent by March 31, 2019 in tranches of 0.625 percentage points, which was deferred to March 31, 2020. Considering the potential stress on account of COVID-19, the Reserve Bank further deferred the implementation of the last tranche of 0.625 per cent of the CCB from March 31, 2020 to September 30, 2020 and subsequently to April 01, 2021. It has been further deferred to October 1, 2021.

India being a bank dominated economy, capital regulation has a major role to ensure financial stability. Due to the rise in stressed assets of banks in India, maintaining capital adequacy becomes critical.

As discussed earlier and found by Muduli and Behera (2020), an increase in CRAR is expected to raise economic growth by enhancing credit supply. It is argued that higher CRAR, by improving the financial health of banks, reduces their cost of borrowing, which in turn helps them to supply more loans at a cheaper price. The median cost of borrowings of banks are plotted against the median values of bank level CRARs for the period 2004-05

Chart 1: Relationship between Bank Capital and Costs

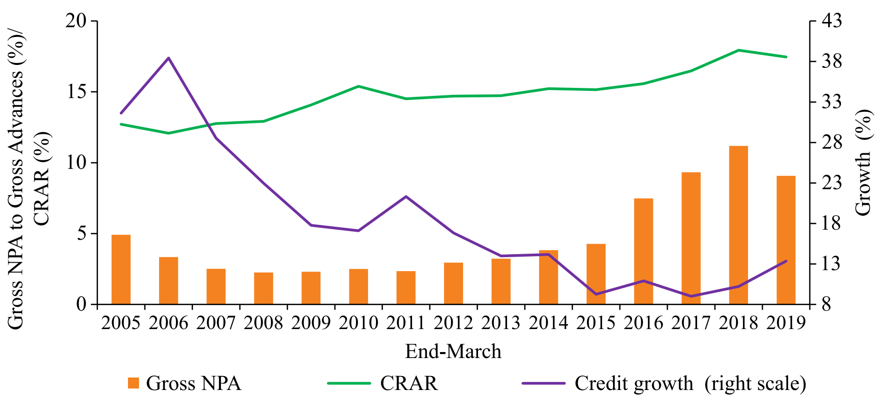


Sources: Authors' calculations and Database on Indian Economy, RBI.

to 2018-19 (Chart 1). The chart shows that the cost of borrowing declines with rise in capital of banks in India. Similarly, lending rate of banks is also found to be lower for banks with higher capital ratios. The sensitivity of borrowing cost to CRAR is found to be greater than sensitivity of lending rate to CRAR as evident from a steeper trend line for the former. Thus, an increase in the capital position of banks help them to not only access funds at cheaper costs but also increase credit as they reduce their lending rate.

At the aggregate level, non-food bank credit growth has decelerated, despite the increase in capital ratio (Chart 2). In the Indian context, Muduli

Chart 2: Asset Quality and Credit Growth



Sources: Authors' calculations and Database on Indian Economy, RBI.

and Behera (2020) reported that elevated level of gross non-performing assets (GNPA) has impacted the credit growth of banks negatively while high CRAR has contributed positively. A statistically significant and negative correlation coefficient (-0.50) between credit growth and GNPA ratio clearly indicates that credit supply of banks is constrained due to high stressed assets in recent years. As large volume of literature has documented that a rise in capital requirement could lead to lower credit growth, one may argue that the lower credit growth in India is also because of increase in regulatory capital requirements. As a counter view, it is important to explore whether the rise in CRAR has any positive effect on credit growth, as found in a few studies.

In the next section, we review the literature to provide an overview of the microeconomic as well as macroeconomic consequences of bank capital regulation, the methodological limitations in separating bank capital shock from other shocks and the empirical findings on the effects of this shock.

Section III
Review of Literature

The literature on bank capital shock posits that an exogenous rise in regulatory capital requirement causes a fall in credit supply. This is because the rise in capital requirement leads banks to rebalance their portfolio towards secured assets as they gradually increase their capital levels. On the contrary, the 'microprudential' literature dealing with bank level data finds a strong positive effect on credit supply from a rise in equity component in bank's balance sheet (Catalán *et al*. 2017; Gambacorta and Shin 2018; Cantú *et al*. 2019; Muduli and Behera, 2020). Although cost of equity is generally more than the cost of debt funding, increase in equity significantly reduces the average cost of equity due to fall in risk premium. The overall cost of debt-financing also falls due to an improvement in creditworthiness, which along with a fall in average cost of equity leads to a reduction in the overall cost of finance, as a major portion of bank liabilities are in the form of deposits or debts. The profitability of banks possibly rises from falling spread as banks' credit supply is observed to shoot up with increased CRAR (RBI, 2019). The observed CRAR induced positive credit supply shock consequently should lead to higher growth in GDP. Some studies, using both microprudential approach and macroprudential approach, find that the impact of a rise in capital requirement on bank lending is negative but short-lived (Fang *et al.* 2018; Budnik *et al.* 2019); the effect depends on the distribution of capital across banks in the financial system (Catalán *et al*. 2017); and, on the state of the business cycle (Bedayo *et al.* 2018).

The effect of change in economy-wide bank capital in the macroeconomic context is categorised in BCBS (2019) from the benefit-side (reducing probability of crisis and hence the cost of the crisis) and the cost-side (output drag due to the rise in lending spread originating from the rise in the WACC of banks due to shift towards costlier equity financing). The effect on the cost side of higher bank capital is the loss of output, grounded on the assumption of a partial MM offset. Full MM offset refers to the fall in the unit cost of equity with the rise in capitalisation (due to fall in the underlying risk of leverage causing cost of equity to fall) which exactly balances out the increase in the average cost of capital due to shift to greater equity financing. The full MM offset makes the bank capital regulation costless. BCBS (2019) and its surveyed papers point out that MM offset does not hold true, at least fully, resulting in macroeconomic costs in terms of output loss. BCBS (2019) concludes that MM offset is somewhere between 30 to 60 per cent. This wide agreement in the literature on the cost of higher capital is solely based on fall in equity prices, where the cost of debt is taken as invariant to changes in leverage. For example, Miles *et al.* (2013), Angelini *et al.* (2015) and Cline (2016, 2017) estimate the loss in GDP due to higher bank capital. We revisit this in the subsequent sections to check if WACC indeed falls due to reduction in cost of debt that depends on underlying leverage as against the perceived notion of cost of debt financing as risk-free or completely inelastic to leverage in most studies.

Bank capital itself is endogenous and it can also have effects on the macro-financial variables. Therefore, bank capital for individual banks and any aggregate measure of the same used to comprehend the role of regulatory capital requirements can be susceptible to endogeneity problem, which complicates its proper estimation and the analysis of regulatory changes. Therefore, separation of exogenous bank capital shock from other shocks is important to know the true effects of regulatory bank capitalisation.

In the literature, many researchers have isolated shocks to bank capital from losses due to bursting of the housing market bubble or stock market collapse (Bernanke and Lown, 1991; Hancock *et al.* 1995; Peek and Rosengren, 1997; Watanabe, 2007; Mora and Logan, 2012; Liu and Molise, 2019); a few researchers separated regulatory shocks to bank capital as bank-level shock from system-wide shock (Peek and Rosengren, 1995; Woo, 2003; Francis and Osborne, 2009; Aiyar *et al.* 2012; Bridges *et al*. 2014; Jimenez *et al*. 2017; Mesonnier and Monks, 2015; Maurin and Toivanen, 2012). The above literature faces the criticism of unaddressed endogeneity problem. This is because regulatory capital also responds to changes in macro-financial variables. For example, Mahakud and Dash (2013) find a counter-cyclical behaviour of capital buffer in response to a change in business cycle in the Indian context. As most of the studies in these categories use single equation framework, they are prone to the possibility of undetected endogeneity. However, several recent studies in later stage used time-series models, *viz*., structural vector autoregression (SVAR) models to addresses the endogeneity issue (Lown and Morgan, 2006; Berrospide and Edge, 2010; Noss and Toffano, 2014; Meeks, 2017; Gross *et al.* 2016; Kanngiesser *et al*. 2017). In this type of literature, the dynamic interactions across asset classes and between the macro-financial variables are captured, and the capital adequacy ratio is introduced as a variable to account for exogenous bank capital shock. Kanngiesser *et al*. (2017) aptly categorises the literature on the effect of bank capital on macro-financial variables based on the mechanism used to weed out the endogeneity issue. In a similar fashion, Gerali *et al.* (2010) develops a DSGE model with financial frictions and imperfectly competitive banks and showed that a negative credit supply shock reduces bank capital to which banks react by increasing interest rates that subsequently reduces loan demand and hence consumption and investment.

In the Indian context, there are only a few studies that examine the effects of bank capital shock. Ghosh and Das (2005) point out in the Indian context that higher capital adequacy significantly brings down the borrowing cost of the banks. Similarly, in a related study, Das and Ghosh (2006) shows that the financially sound banks are more efficient and have less non-performing loans; Ghosh (2008) and Nachane *et al.* (2006) found that the effectiveness of monetary policy to influence lending depends on the capital position of banks.

A more direct approach to study the implications of bank capital (RBI, 2019) shows that higher bank capital raises credit supply. Using bank level data for the period 2008-18, Verma and Herwardkar (2019) shows that the relationship between bank capital and credit growth is positive and non-linear. Muduli and Behera (2020) found that higher equity to total asset ratio reduces the cost of funding and thereby increases credit supply. These findings are similar to the evidences provided by Gambacorta *et al*. (2018) and Bridges *et al*. (2014) who showed that the cost of external financing of bank's borrowing reduces with increases in their capital adequacy, which in turn increases credit supply. The underlying cause of fall in average cost of borrowing by banks is the improvement in their creditworthiness, led by enhanced equity component in their liabilities. This leads to a reduction in risk premium on debt (due to fall in leverage) and stronger balance sheets provides confidence to the shareholders to subscribe to the equity even at higher prices. In addition to this, banks being largely dependent on deposits and certificate of deposits, a small fall in borrowing cost due to the fall in risk premium can substantially reduce the average borrowing costs.

To sum up the findings from the literature, the bank capital shock can have beneficial effects; however, the isolation of bank capital shock from other shocks is important to observe this effect. A CRAR shock, to the aggregate measure of CRAR, in a VAR framework can mimic an exogenous change in the regulatory capital requirements. The change in regulatory capital requirement acts through the change in credit supply that affects the real economy. Novelty lies in identifying it from the shock emanating from the change in regulatory CRAR. It helps to pinpoint the source of the shock to discover its policy implications.

Section IV
Theoretical Exposition

Gambacorta *et al.* (2018) observe the effect of falling cost of debt-financing in banks, especially due to falling cost of certificate of deposits, *etc.,* under greater capitalisation since it signals deeper financial soundness at the bank level. However, Cline (2016, 2017) found evidence of partial MM offset of about 45 per cent. Hence, greater equity-financing cannot be a free lunch for the banks under any situation as it surely raises the WACC to some extent, which dents the profitability of the bank, raises spread, chokes credit supply from banks and consequently impacts output growth adversely.

We depart from the framework of Cline (2016, 2017) by including dependence of cost of debt financing on the underlying leverage of the bank and show that even with zero MM offset, there can be a fall in the average cost of capital from increased equity financing if the sensitivity of cost of debt to leverage is very high.

Let the WACC (τ) in the banking sector be given by,

$$\tau = (1 - x)\, r_d + x\, r_e \qquad \text{... (1)}$$

where r_d is the cost of debt and r_e is the cost of equity and x is the equity to total asset ratio. The value of the firm be defined as,

$$V = D + E \qquad \text{... (2)}$$

Here, D is the total debt funding and E is the total equity holding by the bank.

The share of equity financing is defined as,

$$x = E/(D + E) \qquad \text{... (3)}$$

And the debt to equity ratio as,

$$L = D/E \qquad \text{... (4)}$$

It follows from the MM Theorem that for a given class of firms (the banking sector in our case), the return on equity is [4],

$$r_e = \tau + (\tau - r_d)\left(\frac{D}{E}\right) \qquad \text{... (5)}$$

Due to the observed partial MM offset (as concluded in Birn *et al.,* 2020; Cline, 2016; 2017), we define:

$$\frac{dr_e}{dx} = \mu * \frac{d}{dx}\left(\tau + (\tau - r_d)\left(\frac{D}{E}\right)\right) \qquad \text{... (6)}$$

---

[4] See Cline (2016, 2017) for banking sector specific results and Modigliani and Miller (1958) for greater details.

where, $\mu \epsilon [0,1]$ is the MM offset parameter and its value is unity under perfect MM offset and zero under no MM offset. The BCBS (2010) concludes that the MM offset is zero whereas Birn *et al.* (2020) points out its value is around 50 per cent.

In the extant literature on optimal bank capital, the cost of funding r_d is taken as invariant to the underlying leverage by the bank.

Gambacorta *et al.* (2018) and Muduli and Behera (2020) have shown that the fall in the leverage or higher capitalisation can significantly bring down the cost of debt financing of the banks. Indeed, Modigliani and Miller (1958) had conjectured as an extension of the benchmark model in their seminal paper that the bond yield curve for the given class of firms is likely to depend on the underlying leverage of the firm. In Birn *et al.* (2020) and the related literature this channel is not factored in the calculation of the average cost of bank capital. Miles *et al*. (2013) termed the assumption of the cost of debt-financing being invariant to leverage as the "conservative assumption" and a similar approach was also followed by Cline (2016; 2017). However, this stands in contrast to the conjecture of Modigliani and Miller (1958) about the importance of the linkage between debt-financing cost and the leverage. Thus, the role of the cost of debt financing might not be trivial. As the cost-benefit analysis of bank capital takes the effect of rising WACC of the banks due to costlier equity financing as the channel leading to fall in GDP, we should ensure if the implications hold true if the cost of debt is taken as sensitive to leverage. Therefore, we introduce cost of debt as a function of equity to total assets ratio, in line with the observations by Modigliani and Miller (1958). Hence,

$$r_d = r_d(x) \quad \text{... (7)}$$

where, $r_d'(x) < 0$.

Now, following Cline (2016; 2107) framework factoring in the cost of debt being a function of equity to total assets ratio, it follows from (6),

$$\frac{dr_e}{dx} = \mu\left(\left(\frac{dr_e}{dx}\right)_{\text{Full MM offset}}\right) = \mu\left(-\frac{1}{x}\right)\left[(\tau - r_d)\left(\frac{1}{x}\right) + (1-x)\frac{dr_d}{dx}\right] \quad \text{... (8)}$$

Clearly (8) is similar to Cline (2016; 2017) except the last term that comes due to the dependence of cost of debt on the equity to total asset ratio.

Now, the change in the weighted average cost to capital is as follows from (1),

$$\frac{d\tau}{dx} = -r_d + (1-x)\frac{dr_d}{dx} + r_e + x\frac{dr_e}{dx}$$

$$= -r_d + (1-x)\frac{dr_d}{dx} + r_e - \mu\left(\frac{1}{x}\right)[(\tau - r_d)\left(\frac{1}{x}\right) + (1-x)\frac{dr_d}{dx}]$$

$$= (1-\mu)[(\tau - r_d)\left(\frac{1}{x}\right) + (1-x)\frac{dr_d}{dx}]$$

$$= (1-\mu)[(r_e - r_d) + (1-x)\frac{dr_d}{dx}];$$

(By substituting from equation (1)) ... (9)

Considering Miles *et al*. (2013), the "conservative assumption" implies that $\frac{d}{dx}(r_d(x)) = 0$ and the same holds true for Cline (2016, 2017) and Birn *et al.* (2020) apart from the extra cost of debt financing channel. Clearly, for $\frac{d}{dx}(r_d(x)) = 0$ and with partial MM offset, it implies that a rise in bank capital will always raise WACC which in turn raises bank lending spread. Thus, under partial MM offset, this implies that with $\frac{d}{dx}(r_d(x)) = 0$, it holds always that $\frac{d\tau}{dx} > 0$, which means that higher capitalisation must raise WACC of the banks and hence they reduce credit supply or raise spread.

Substituting, (9), in the framework of CES production function as in Miles *et al*. (2013), it readily follows that[5],

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[5] Clearly, in the Cline (2016, 2017) framework, (rewriting the same in a continuous variables framework with the assumption of first order differentiability) the change in GDP growth due to a rise in equity to total asset ratio can be presented as, $\frac{dlnY}{dx} = \frac{dlnY}{dlnP_k} *, \frac{dlnP_k}{dP_k} *, \frac{dP_k}{d\tau} *, \frac{d\tau}{dx}$, where P_k is the cost of physical capital (Miles *et al.* 2013) or the WACC faced by the non-financial firms (Cline 2016, 2017) dependent on borrowing from the banks to some extent. It can be shown that, $\frac{dlnY}{dx} = A * \frac{d\tau}{dx}$, where A is independent of x, since, $\frac{dlnY}{dlnP_k} = \frac{\alpha\sigma}{\alpha-1} < 0$ (Miles *et al.* 2013) where Y is assumed to follow CES function production function and α is the factor-share of capital, and $\frac{dP_k}{d\tau}$ is a positive parameter calibrated by the extent of the dependence of the non-financial firms on the bank credit and $\frac{d\tau}{dx}$ follows from (9).

$$\frac{dlnY}{dx} = A * (1-\mu)[(r_e - r_d) + (1-x)\frac{dr_d}{dx}] \qquad ... (10)$$

where, $A < 0$, is independent of x and $\frac{dlnY}{dx}$ is the growth rate of GDP with respect to increase in equity to total asset ratio. Thus, given $\frac{d}{dx}(r_d(x)) = 0$ under partial MM offset, always $\frac{dlnY}{dx} < 0$.

Thus, it follows that:

Proposition 1: No Free Lunch

Under partial MM offset, (with cost of debt being risk free or perfectly independent of leverage)

i. Higher capitalisation raises WACC

ii. Higher capitalisation reduces GDP growth (due to higher WACC of banks affecting firms dependent on bank credit).

This implies that in a bank level study, with higher capitalisation, the WACC shall always rise and the credit supply from the banks fall. This subdued and costlier credit supply brings down the GDP as the cost of production rises for the non-financial firms.

The above finding is in sharp contrast to the bank level evidence provided by Gambacorta *et al.* (2018). They find a strong positive relationship between underlying leverage of the bank and the debt-financing cost.

Proposition 2: Hypothetical Free Lunch

Under partial MM offset, with, $\left|\frac{dr_d}{dx}\right| > \left(\frac{r_e - r_d}{1-x}\right)$, (*i.e.,* cost of debt being sufficiently elastic with respect to equity to total asset ratio)

i. Higher capitalisation reduces WACC

ii. Higher capitalisation raises GDP growth

Example 1: In the calibration study by Cline (2016, 2017) if we remove the zero restriction on $\frac{dr_d}{dx}$, we can clearly see that for, $r_e - r_d = 0.1 - 0.025 = 0.075$, $(1-x) = 0.9$, (as calibrated in Cline (2016, 2017)), $\left|\frac{dr_d}{dx}\right| > 0.083$ implies Proposition 2 to hold good. This result is indeed intriguing as it implies bank capital reduces WACC of banks and raises GDP growth rate making a free lunch situation as it not only reduces probability of crisis and the crisis contingent losses but also raises GDP for a sufficiently high magnitude of $\frac{dr_d}{dx}$.

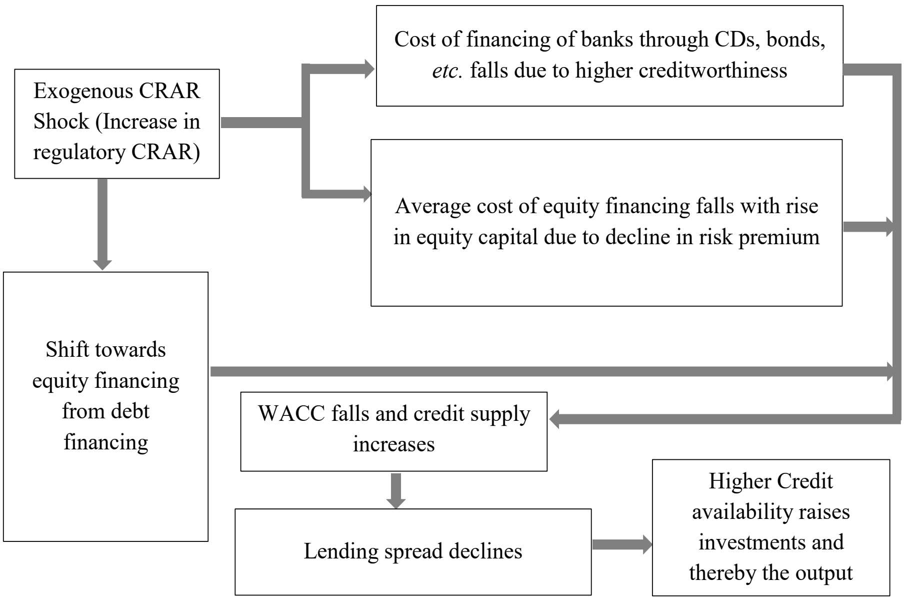
The question now lies in if such a high value of $\frac{dr_d}{dx}$ indeed makes sense in economic theory and possible in reality, then why it has been assumed to be zero in Birn *et al.* (2020) and Cline (2016; 2017). In theoretical terms, as already mentioned by Modigliani and Miller (1958), the possibility of dependence of cost of debt-financing on leverage lends support to considering a non-zero value of $\frac{dr_d}{dx}$. In empirical terms, Gambacorta *et al.* (2018), by focusing on the effect of change in leverage on the cost of debt financing, find that a unit rise in the equity to total asset ratio with one period lag reduces the cost of debt financing by 0.042. We see no reason why in the financial market, a change in equity to asset ratio will take one full year to affect the cost of debt. This is because the change in the interest rates on CDs might adjust faster with the information of possible rise in equity-financing and thus we have the hunch that actual $\left|\frac{dr_d}{dx}\right|$ might be higher than the 0.042 value as the latter only captures the lagged effect.

If we accept that the implied value of $\left|\frac{dr_d}{dx}\right|$ is sufficient for the WACC to fall, *i.e.*, $\left|\frac{dr_d}{dx}\right| > \left(\frac{r_e - r_d}{1-x}\right)$, we reach an apparent paradox as the credit supply from the bank is observed to rise with an increase in equity to total asset ratio. This rise in credit supply leads to a greater profitability of the banks; and thus, lesser spread and hence more demand for the cheaper credit from the banks. The results become clearer if we factor in a strong effect of the sharp fall in cost of debt financing with a rise in the equity to total asset ratio. Thus, based on the above theoretical and recent empirical findings, we can see that bank capital can have a free lunch effect when equity to total assets ratio is sufficiently low (*i.e.,* low x) and cost of debt is sufficiently elastic[6].

The channel of bank capital shocks is provided in the flow chart below. The chart exhibits that the overbearing presence of debt being the main component of liabilities of the bank, an increase in the equity component can have a significant fall in the cost of debt financing for the under-capitalised

[6] For empirical validation we could have directly estimated $\left|\frac{dr_d}{dx}\right|$ but we take an alternative recourse since even with some estimate of $\left|\frac{dr_d}{dx}\right|$, it will be difficult to conclude as the estimation of cost of equity can have multiple methods and multiple estimates, thus diluting the precision and implications on GDP growth.

The Flow Diagram



bank and brings down overall cost of funding and increases availability of funds, which subsequently augments the bank's profitability as the scale effect of the fall in the cost of debt outweighs the rise in cost due to increase in equity financing which possibly reduces WACC even under partial MM offset, reduces spread, and augments credit supply. Thus, hypothetically an exogenous rise in regulatory capital translates into a positive credit supply shock over a certain range.

Section V
Data and Methodology

V.1 Data

For empirical estimation, we use quarterly data of the relevant macro-financial variables for the period 2009-10:Q1 to 2017-18:Q4. The variables used are real GDP, consumer price index (CPI), policy repo rate, real non-food bank credit (RNFBC, henceforth), spread (calculated by taking the difference between weighted average lending rate and repo rate), and CRAR. The RNFBC is derived by deflating nominal non-food bank credit with CPI. Real GDP, CPI and non-food bank credit are transformed into seasonally adjusted annualised growth form while repo rate is expressed in first difference form. The aggregated CRAR is calculated by taking the weighted average of bank level CRARs wherein the weights are based on their advances. We also use median of the bank level CRARs to check the robustness of our findings. For analysing the effect of CRAR on different types of risk weighted assets, we subsequently also consider loans to housing sector and industries separately.

V.2 The Model

We follow Bayesian approach to estimate the sign-restricted VAR model. While the VAR addresses the issues related to endogeneity, the Bayesian framework is the appropriate technique to handle limitations in a short sample. In order to be agnostic, we use flat/diffuse normal inverse-Wishart priors (improper priors) in our estimation.

A structural VAR with *m* lags and *n* variables can be specified as:

$$AY_t = \sum_{p=1}^{m} A_p Y_{t-p} + e_t \ , \qquad e_t \sim i.i.d.(0, I_n)$$

where, A is a 1 x *m* vector of contemporaneous coefficients, A_p (for p = 1,2,...,*m*) is the coefficient matrix (*m* x *m*) of the variables up to *m* lags, and e_t is a *1* x *m* vector of unobserved structural shocks, which are mutually independent with variance normalised to unity. All the coefficients here are structural coefficients.

The reduced form presentation of the above VAR model is,

$$Y_t = \sum_{p=1}^{m} C_p Y_{t-p} + \epsilon_t, \quad u_t \sim i.i.d.(0, \Sigma)$$

where, $\epsilon_t = A^{-1} e_t$ are reduced-VAR shocks, and $C_i = A^{-1} A_i$ (for p = 1,2,...,*m*) are reduced form coefficients of endogenous variables in the model.

Structural shock e_t is identified by, $e_t = A\epsilon_t$. Now, A contains n^2 parameters but estimated variance-covariance matrix Σ has $n(n-1)/2$ elements. So, $n(n-1)/2$ additional restrictions are required for identifying structural shocks. In a sign-restricted VAR, the following step-by-step iterative approach is followed to identify structural shocks subject to the given sign-restrictions.

1. The reduced form coefficients are estimated using the Bayesian method with flat (diffuse) normal-inverse-Wishart priors.

2. Cholesky decomposition of $\Sigma = \mathrm{PP}'$ is computed. It is used for orthogonalisation of structural shocks and not for identification. An orthogonal Q matrix is drawn by QR decomposition. Impulse responses are derived from $A^{-1} = PQ'$.

3. It is checked whether orthogonal impulse responses satisfy full sign restrictions.

4. If yes, the orthogonal impulse responses are saved.

5. If not, drop that model and repeat steps 2 and 3. Continue till sufficient models are accepted.

We follow the QR decomposition method of Rubio-Ramirez *et al*. (2010) and Arias *et al.* (2018) for the identification[7]. This is a type of set-identification, and we restrict only to partial identification with only regulatory capital shock being identified by QR decomposition by Householder transformation approach *a la* Rubio-Ramirez *et al*. (2010) and Arias *et al.* (2018).

We augment the standard VAR method used for monetary policy analysis with the relevant banking variables to estimate the impact of bank capital shock. The effect of shock in the bank capital is tricky to estimate since capital is endogenously related to other variables. Therefore, to measure its exogenous change we address the endogeneity issue through VAR and we identify the exogenous bank capital shock using sign-restrictions. Sign-restricted identification, being less restrictive, is more aligned to economic theory as sign restrictions are imposed only to identify the theoretical linkages while remaining invariant to the order of the variables. We identify the bank capital shock based on our preliminary analysis of the data and inferring from the findings of Gambacorta and Shin (2018) and Muduli and Behera (2020).

V.3 Shock Identification

In contrast to the recursive identification scheme commonly followed in the literature to estimate the bank capital shock, we have used sign-restrictions to identify the bank capital shock as proposed by Kanngiesser *et al.* (2017).

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[7] We use the BEAR Toolbox developed by the European Central Bank as detailed in Dieppe *et al.* (2016) to implement this with MATLAB 2019b.

This is because recursive VAR models are sensitive to variable ordering and could produce mis-leading results (Mumtaz *et al.* 2015). The sign-restricted VAR has been used extensively to identify monetary policy shock, fiscal policy shock, technology shock, oil price shock, *etc.* Recently, a few studies have employed sign-restricted VAR to identify the financial shocks (Caldara *et al.* (2016); Meinen and Roehe (2018); Furlanetto *et al.* (2019)) credit supply shocks (Hristov *et al.* (2012); Duchi and Elbourne (2016)) and bank capital shocks (Kanngiesser *et al.* (2017); Kanngiesser *et al.* (2019)). As our objective is to know whether bank capitalisation has any positive effect on loan supply and thereby on economic activity, the sign-restricted VAR is the only available option to identify the effects of such shocks in macroeconomic analysis.

Shock to CRAR captures a change in regulatory CRAR that transmits to the banking sector. This ends up raising the equity (and equity to asset ratio as well) component in the liability side of the banks. We identify the effect of bank capital shock on CRAR, spread, credit and economic activity. The signs of the effect are based on the findings in the literature, our theoretical findings and the preliminary evidence as discussed in Section II. However, we remain agnostic about its effect on CPI inflation and monetary policy. While imposing restriction on impact, we also remain agnostic about its effect on the propagation of shocks over time (Table 1).

Due to a regulatory capital shock, CRAR increases. Higher CRAR, by improving creditworthiness, reduces WACC and spread, and increases credit supply and thereby output. We do not dispute the mechanism of a bank capital shock mentioned in the macro-prudential literature that higher capital requirement reduces loans with higher risk weights and increases bank capital holding (which is supposedly costlier to finance and thus dents bank's profitability). What we argue is that the positive effect of CRAR can outweigh the negative effects (on credit due to costlier equity financing and the

Table 1: Sign restrictions to identify the effects of bank capital shock

Dimensions and Shock	CRAR	Spread	RNFBC	Economic Activity	Inflation	Policy rate
Bank Capital shock (CRAR shock)	+	-	+	+		

Table 2: Alternative Sign restrictions

Dimensions and Shock	CRAR	Spread	RBCI	RBCH	Economic Activity	Inflation	Policy rate
Bank Capital shock	+	-	-	+	+		

regulatory risk weights). A net increase in credit supply would consequently let the niche firms reliant on bank credit to expand (already envisaged and established in the literature of bank lending channel).

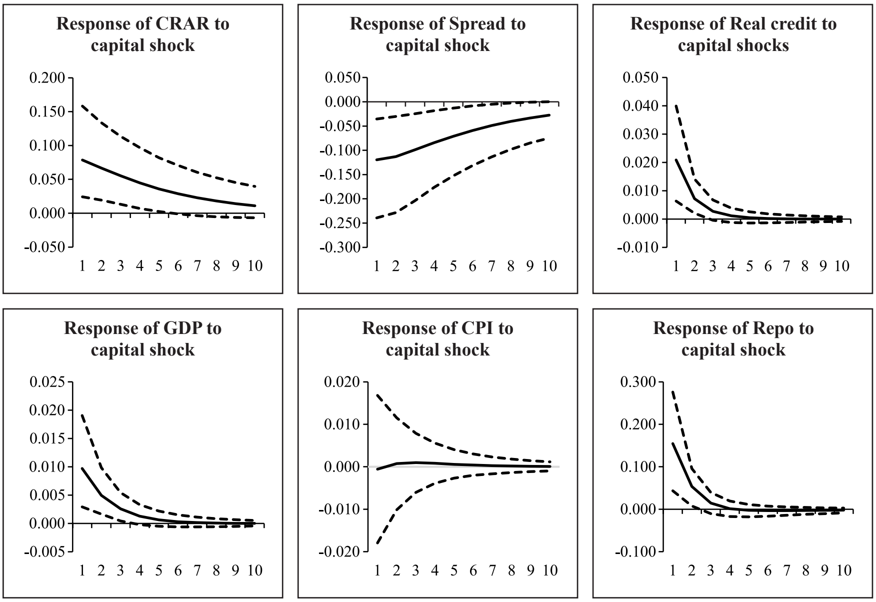
As found in the literature, the response of the credit supply could be asymmetric depending on the regulatory risk weights. Because of higher weights assigned to risky assets, banks may respond to the capital shock by reducing loan supply to the risky sectors. To examine the differential impact of bank capital shock on risky and less-risky lending, we estimate separately the VAR with loan to housing (RBCH) and industry (RBCI).We analyse the model with two credit variables with positive restriction imposed on the growth rate of credit to housing sector and negative restriction on growth rate of credit to industry, on the impact (Table 2).

Section VI
Results

VI.1 The Macroeconomic Impact of Changes in Capital

As mentioned in the previous section, we have estimated a VAR model with six variables, *viz.,* CRAR, spread, real credit growth, GDP growth, CPI inflation and change in repo rate. A shock to bank capital could lead to re-pricing of bank credit, affecting the quantity of loans provided, on top of the impact coming from the bank capital shock itself (Kanngiesser *et al.* 2019). Thus, spread is included along with policy rate in the set of variables. Under a partial identification, with only an exogenous rise in economy wide CRAR due to regulatory changes, we look out for the macroeconomic implications with a positive sign on real credit, negative sign on spread and a positive sign on GDP, all restrictions being only on the impact. The identification method followed here is robust as compared to the widely used penalty function approach as the latter has certain shortcomings that might vitiate policy inferences (Arias *et al.* 2018). The sign-restricted VAR is estimated using Bayesian methods for the period 2009-10:Q1 to 2017-18:Q4.

Chart 3: IRFs corresponding to exogenous one standard deviation bank capital shock



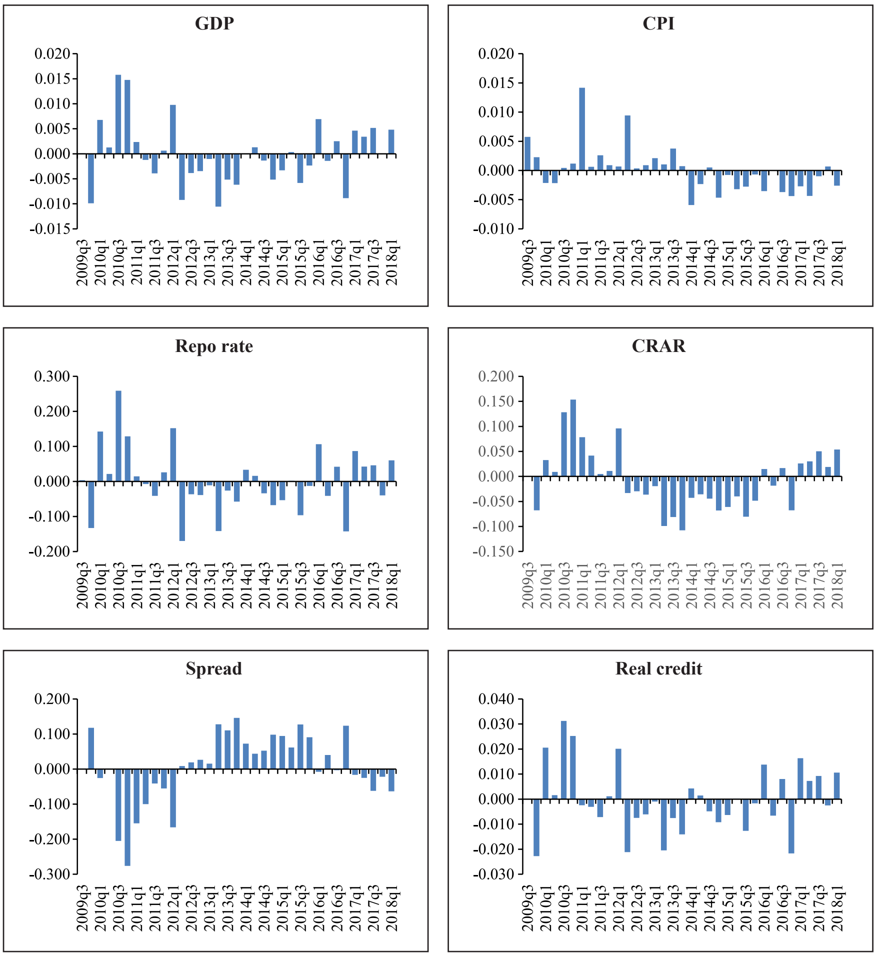
Based on the estimated VAR, the impulse responses of endogenous variables to a one standard deviation rise in bank capital is reported in Chart 3. The impulse responses are the median values (solid lines) of the accepted draws which are plotted along with their 16% and 84% Bayesian credibility bands (dotted lines).

On impact, the CRAR increases by about 9 basis points (bps) in response to one standard deviation economy-wide bank capital shock; and the effects remain for a substantial period. The bank lending spread declines noticeably and sustained over ten quarters possibly because of the increase in credibility due to improvement in their balance sheets. The reduction in risk premium provides the banks access to greater pool of funds at cheaper price. As banks adjust their lending rate downward, it leads to higher credit growth. Thus, the real credit growth rate shoots up over four quarters and consequently GDP growth rate remains buoyant over six quarters. The shock to bank capital increases credit growth by 40 bps and GDP growth by about 24 bps over a period of one year. While the response of inflation to bank capital shock remain almost nil, the policy rate increases possibly reflecting the rise in demand.

In sum, banks react to structural bank capital shock by raising their equity capital, which in turn helps them to reduce their risk premium. This results in a reduction in bank lending spread and a rise in credit growth and ultimately higher growth in the economy.

How bank capital shock has contributed to the variation in different variables over time are presented in Chart 4. Particularly, the historical decomposition allows us to evaluate the importance of structural shocks on the evolution of the variables in the VAR at a particular point in time where the historical contribution is worked out by taking the structural shocks and

Chart 4: The Historical Decomposition



the orthogonalised IRFs. The results show that CRAR had increased during 2010Q1 – 2012Q1 as banks increased their capital position to meet Basel III requirements. However, the capital shock turned adverse, possibly due to the rise in stressed assets in banking sector in the subsequent period. Starting from 2017Q1, the recapitalisation efforts by the government have contributed positively to the CRAR of the banking sector. As can be seen from the Chart 4, both credit growth and GDP growth were positive during the corresponding quarters of positive bank capital shocks. Moreover, it is clear that a rise in bank capital has contributed positively to GDP growth since 2017Q1, the period after substantial capital infusion by the government to improve the balance sheet of the public sector banks. The above results remain almost unchanged when we replace weighted average CRAR with median value of bank level CRAR (Appendix).

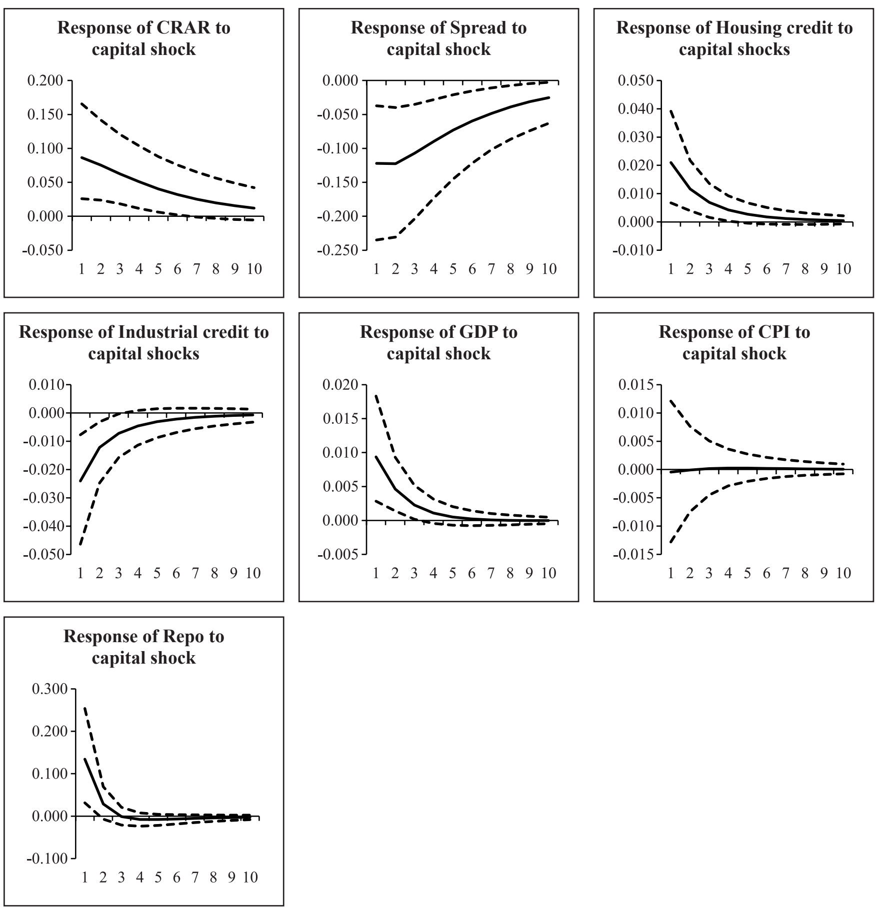
We can also observe from the historical decomposition that a decline in bank lending spreads is contributed by a positive bank capital shock during 2010Q3 – 2012Q1 and 2017Q1 -2018Q1. Hence, we conclude that an increase in bank capital has a positive effect on the economy by reducing bank lending spread and enhancing credit growth.

VI.2 The Role of CRAR as a Leverage Tax

The above findings are in line with that of Gambacorta *et al.* (2018) but it raises the question on the role of CRAR as a financial stabiliser in the economy. The rise in credit due to a positive bank capital shock does not guarantee the fall in risk weighted assets and the tuning down the financial cycle of leverage. The immediate macro-prudential goal for financial stability lies in cutting down excessive leverage. Taming unsustainable credit growth is a policy objective and as a policy tool, CRAR is supposed to be counter-cyclical to reduce the proliferation of more risky credit. However, the efficiency of CRAR as a check on leverage is augmented if it can selectively minimise unsecured loans of the banks while increasing aggregate credit. We check if a bank capital shock, without any bank-specific regulations, is also capable to operate as a leverage tax to reduce unsecured lending through the differential risk weights assigned to the assets based on their underlying risk.

To study the differential impact of bank capital shock on credit, we examine whether banks reduce their lending to industry (which is predominantly unsecured) and raise secured loans in response to a rise in bank capital requirement. We use the credit extended to the housing sector as a measure of mortgage backed lending and credit to industry as a proxy of aggregate unsecured lending by banks. Therefore, we replace the aggregate real credit growth by the growth in real credit to housing (RBCH) and to industry (RBCI) in our empirical exercise. Recent fall in the growth of bank credit to industry in India could be a result of increased stressed assets in that sector and consequent apprehension of higher default. It could also be due to higher risk weight on loans to industry, which under increased regulatory

Chart 5: De-risking happens due to differential weights in RWA



capital requirement incentivises banks to cut down on risky assets with higher weights. The VAR is re-estimated with new variables and sign-restrictions as provided in Table 2. The impulse responses show that credit growth to industry falls while loan growth of housing sector increases in response to a positive shock to bank capital (Chart 5). As banks readjust their portfolios by reducing the riskier assets due to higher capital requirements and increasing mortgage backed securities like housing loans, the overall credit may increase as found earlier. Thus, banks reduce higher risk weighted assets due to regulatory checks on leverage through CRAR. The growth rate of credit to industry falls over three quarters while growth of credit to housing sector increases over four quarters. The role of CRAR as a macro-prudential tool for financial stability thus holds true.

Section VII
Conclusion

In this paper, we examine the role of bank capital in boosting credit supply and GDP growth. We develop a theoretical model and show that the overall borrowing cost of banks falls in response to a rise in regulatory capital requirement even under a zero MM offset if the cost of debt financing is elastic to leverage. The fall in cost of capital, thus, reduces lending spread and augments credit supply. In addition to the fall in WACC, banks with higher capital ratios may feel less constrained to lend as they are less likely to reach the regulator's minimum floor. The Bayesian impulse responses and historical decomposition results also confirm the positive effect of bank capital on loan supply and GDP growth.

Regulatory bank capital shock in the Indian context renders a positive credit-led push to GDP growth by strengthening the balance sheets of banks and the consequent reduction of their overall cost of borrowings. This seems like an idealistic situation as the benefits of mitigating crisis through raised capital comes with the added fillip to GDP growth. This output-enhancing effect of greater capital holding by banks does not defeat viable macro-prudential role of capital adequacy as a leverage tax on risky lending. Under a regulatory capital shock, banks readjust their risky loans and shift towards assets that carry lesser risk weights that ultimately raises aggregate credit flows.

These empirical results should be taken with the caveat that it cannot be generalised if CRAR gets increased by a large amount and the empirical results obtained in this paper may not hold under other contexts and for other countries. At times, a statistically significant negative effect of bank capital shock on credit and GDP growth may also materialise. A future research question to explore would be to further identify the exact transmission channel(s) of a bank capital shock impacting lending spread or credit supply.

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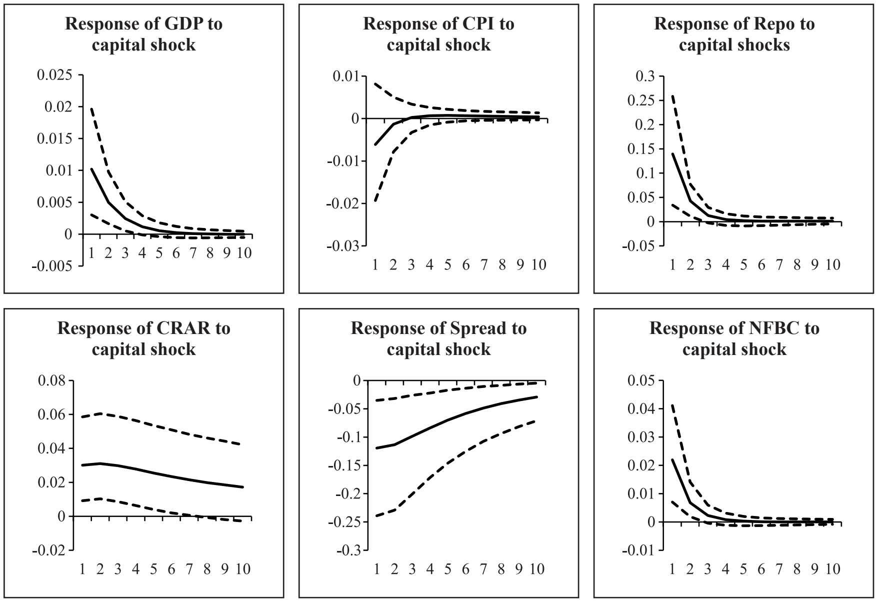
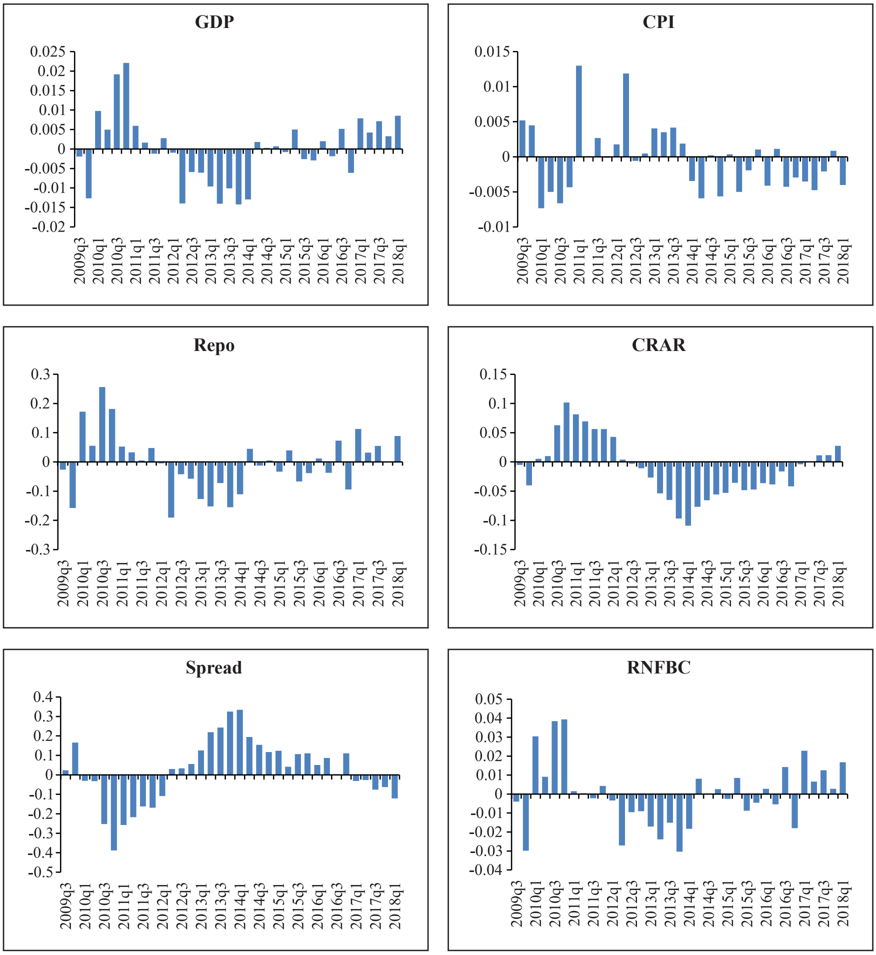
Appendix

Appendix Chart 1: Impulse responses of bank capital shock
(using median CRAR)



Appendix Chart 2: Historical Decomposition (using median CRAR)



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Education Loan NPAs of Banks in Tamil Nadu: Issues and Challenges

Shromona Ganguly and Deepa S. Raj*

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The study examines determinants of default in education loans in Tamil Nadu, a state with significant presence in education loan disbursal in the country. It uses account level data of over two lakh borrowers from two public sector banks and one private sector bank in an attempt to identify significant predictors of default. Empirical analysis suggests that loan accounts with higher interest rate and of lower duration have higher default probability while loans extended to accounts with Aadhar information, collateral backing or some subsidy element have lower risk of default.

JEL Codes: I22, I25, I28

Keywords: Education loan, non-performing assets, default risk, interest subsidy

Introduction

Education loans provide institutional funding required to harness and empower the human capital in a country, given the financial constraints faced by the public sector and individuals in meeting the rising cost of education. With governments, both at the national and sub-national levels, focused on providing universal primary education, the growing needs of a young nation

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like India in the sphere of higher education are increasingly being fulfilled by the private sector, although public sector institutions continue to play a significant role. Education loan portfolio forms only a small fraction of retail loan portfolio of all commercial banks in India (3.3 per cent) but it bears special significance in terms of skill formation required for enhancing productivity and efficiency in an economy. It is in this light that the sharp increase in non-performing assets (NPA) in education loans extended by commercial banks in India in recent years is a matter of concern, as it could hamper the growth of bank credit for higher education in the country.

Though economic theory focuses more on managing common pool resources (Ostrom, 2010), a special feature of higher education is that it suffers from the problem of "reverse tragedy of commons" (Piirainen *et al*., 2018; Mor, 2019) where the benefit that accrues to the society for imparting skill and knowledge surpasses the private cost associated with acquiring such skill and thereby results in underproduction of higher education in relation to the socially optimal or desirable level. Surmounting this problem requires huge investment in the education sector, which is challenging for developing economies, given their relatively low per capita income and high public debt.

According to the United Nation's human development data[1], gross enrolment ratio in tertiary education[2] during 2014-19 was 28 per cent for India, which was lower than the average of 33 per cent for developing countries and the world average of 39 per cent. Given that higher education helps in attaining sustainable livelihoods, it is important to bridge the resource gap for meritorious students with limited means, particularly in countries where private market for education loans is underdeveloped.

Worldwide, countries adopt various policies to address the issue of missing markets in the context of financing education which can be broadly divided into two types - government aid-based measures and private loans (Wegmann *et al*., 2003; Barr, 2004; Field 2009). India had initially envisaged a policy of state-led development of higher education, and the Education Commission (1964-66) chaired by D. S. Kothari was emphatic in its

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[1] 2020 Human Development Data: http://hdr.undp.org/en/data.

[2] As proportion to the corresponding population age.

recommendations that most of the responsibility for the support of education should be from government funds and not from the private sector. However, the same has undergone a change overtime, with the number of private institutions growing rapidly since the mid-eighties (Tilak, 2007).

Nevertheless, several policy measures taken over the years by the Government of India include provision of interest rate subsidies for education loans, inclusion of education loans up to certain prescribed limit within priority sector definition and establishment of credit guarantee fund for provision of guarantee cover against education loan default. Despite these measures, the number of accounts under priority sector education loan category has been declining since 2017-18.

The vast literature on issues associated with student loan market mainly focus on advanced economies, especially the US (Wilms *et al*., 1987; Volkwein and Szelest, 1995; Knapp and Seaks, 1992; Flint 1994), where the outstanding student loan is almost 7.5 per cent of the country's GDP in 2019 and the rising default rate in student loan remains a cause for concern for lenders as well as policymakers (Ben, 2018; Forbes, 2019). Studies on student loan default in these advanced economies often lack consensus on the common factors responsible for default, though it is generally found that borrowers' income level, gender, ethnic group, student performance and choice of education courses are significant predictors of default probability (Stockham and Hesseldenz,1979; Herr and Burt, 2005), along with spatial and macro-economic factors such as growth and employment scenario (Dynarski, 1994; Monteverde, 2000; Hillman, 2014). In contrast, studies which discuss problems associated with student loan market in developing countries are sparse. Further, so far there have been very few attempts to empirically analyse issues pertaining to education loan in India, particularly those relating to default in these loans, mainly due to lack of availability of detailed data.

In this context, this study seeks to augment the existing literature on education loan default in developing countries. It analyses the nature of education loan NPAs in Tamil Nadu, which not only features amongst the states with high education loans as well as NPAs in the same but is also a state with a significant presence of private institutions, especially in professional and technical education.[3] In the absence of sufficient studies on student loan default in developing economies, this paper does not propose a testable hypothesis. Instead, the study explores the rich account level data on education loan extended by two large public sector banks (PSBs) and one private sector bank (PVB) headquartered in the southern region to borrowers in the state in an attempt to understand the major determinants of default in the education loan segment. The data pertain to the education loan portfolio of the selected banks as at end-March 2019 and are sourced from their respective management information systems. The study also presents the main results of a survey conducted among banks in the state to obtain the lender's perspective of the problems of education loan default. Thus, to the best of our knowledge, this is the first state specific study in the Indian context, which analyses education loan default with the help of a large dataset representing both public sector and private sector banks.

The rest of the paper is structured as follows: Section II provides an overview of education loan schemes in India as well as other countries and the recent trends in education loan in India and Tamil Nadu, including NPAs in this segment. Section III discusses the theoretical underpinning as well as empirical findings related to education loan default as documented in literature. Section IV provides a descriptive analysis of the data obtained from select banks in the state, followed by empirical framework adopted in the paper. Section V presents the main results of the empirical exercise and implications thereof. Section VI sets out the findings of a questionnaire-based survey relating to the education loan portfolio of lending banks in Tamil Nadu conducted in July 2020. Section VII concludes the study by summarising the major findings, policy implications, some limitations of the present study and scope for future research.

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[3] As at end-March 2020, Tamil-Nadu accounted for almost 19 per cent of total education loans extended by scheduled commercial banks in India, which is the highest among states. Latest available data shows that its share in total NPAs in the education loan segment stood at 50 per cent as at end-September 2017, which provides the context and justification for this study.

Section II
Overview of Education Loans

II.1 Types of Education Loans: Cross Country Comparison

Worldwide, there are various types of education loans available to the students which can be broadly classified into three categories (Jayadev, 2017). In the conventional mortgage type loans (CMLs), the loan repayment period, monthly schedule of repayments and the interest rate are determined by the loan agreement, irrespective of the income of the borrower at the completion of the course. CML is popular in China and Japan. On the contrary, income contingent loans (ICLs) link the amount to be repaid in each installment with the earning capacity of the borrower. Such schemes are popular in Australia and United Kingdom. A third category of educational loans, popularly known as fixed schedule income contingent loans (FSICs), fix the minimum amount of repayment per installment, and additional amount to be repaid depends on the earning ability of the graduate. FSIC is popular in the US, South Korea and Norway.

Each of these schemes has its own advantages as well as disadvantages. In the case of CML, both the debt burden and the repayment period are known to the borrower as well as to the banks, irrespective of any contingency. However, this often results in banks not tracking the employment and income of the borrowers after the completion of the course. In many cases, since the initial income of the borrower after the completion of the course would be substantially low, this may often lead to high debt repayment burden in the initial years and high delinquency rate.

Under the ICL, the installment amount is a proportion of total income earned by the borrower. It is a better mechanism of consumption smoothening as it allows the graduates to accelerate their repayment if their incomes are high or repay a lower amount if their initial incomes are low. ICL is implemented by directly deducting the required amount from the borrowers' salary by the tax authorities in many countries. ICLs are explicitly designed to reduce the repayment burden of the borrowers and in countries with efficient tax collection offices, this method is proven to be more cost efficient than any other instrument of financing higher education. Further, education loans are often subject to market failure as in most cases such loans are not backed by collaterals. As a result, there is under-allocation of such loans as compared with the social optimal level. Presence of government guarantee could solve this problem although the same comes with other issues and problems. ICL is often proposed as an alternative to the government guarantee in education loans. Initially adopted in Sweden as an alternative to government subsidised loan programme, ICL later became popular in New Zealand, Chile, South Africa, the UK and the US. ICL varies across these countries in terms of its structure, design and implementation. The most common forms of these loans are ICL with risk pooling, ICL with risk sharing, graduate taxes and human capital contracts.

II.2 Types of Education Loan in India

The education loan schemes offered by banks in India are in the nature of CMLs, which can be further classified into the different categories on the basis of student borrower characteristics and institutions they seek admissions to/study in. Most banks offer a scheme for education loan as per the Indian Banks' Association (IBA) model education loan scheme to students pursuing higher studies in India and abroad. As per this model loan scheme, education loans up to ₹4 lakh do not require any collateral to be provided by the borrower, education loans up to ₹7.5 lakh can be obtained with collateral in the form of suitable third-party guarantee, while education loans above ₹7.5 lakh require tangible collateral. In all the above cases, co-obligation of parents is necessary. The second category of education loans are sanctioned to those students who obtain admissions to colleges/universities through management quota, provided they satisfy the minimum marks criteria in the preceding examination. The third category of education loans includes schemes for needy students for pursuing vocation education courses run by industrial training institutes (ITIs), polytechnics, training partners affiliated to National Skill Development Corporation (NSDC)/sector skill councils, state skill mission/corporation, preferably leading to a certificate/diploma/degree issued by such organisation as per National Skill Qualification Framework (NSQF) and any other institutions recognized by either the central or state education boards or university. The fourth category of scheme specifically caters to the requirement of students studying in premier institutions like IITs/IIMs/NITs/IISc or courses abroad, with demand for a higher quantum of loan amount. All education loans of up to ₹10 lakh (enhanced to ₹20 lakh in September 2020) have been included within the priority sector definition by the Reserve Bank of India.

Under most of these schemes, moratorium period consists of the course period plus six months to one year, and there are nil/negligible processing fees for schemes with high value education loans. The interest rate under the various schemes consists of a markup of 2-3 per cent above the marginal cost of funds based lending rate (MCLR)/external benchmark[4], based on the reputation of the course/institutions. The repayment period is in the range of 10-15 years.

II.3 Education Loan in Tamil Nadu: State Profile and Institutional Setup

In India, around 90 per cent of education loans are disbursed by the PSBs, while PVBs and regional rural banks (RRBs) account for around 7 per cent and 3 per cent of total education loan outstanding, respectively, as at end-March 2020[5]. During the same year, PSBs accounted around 94 per cent of total education loan disbursement in Tamil Nadu while PVBs accounted for 6 per cent. Out of total education loan outstanding in the state as at end-March 2020, semi-urban area accounted for 38 per cent, followed by rural area (26 per cent), metropolitan region (21 per cent) and urban area (15 per cent). Bank-wise data available for Tamil Nadu[6] shows that education loan sanctioned during 2019-20 was the highest for State Bank of India (SBI) among all scheduled commercial banks (18.4 per cent), followed by Canara Bank (17.0 per cent) and Indian Bank (11.4 per cent). Among the PVBs, education loan sanctioned by Axis Bank was the highest (4.2 per cent), followed by Tamil Nadu Mercantile Bank (3.2 per cent). In terms of number of education loan accounts, Canara Bank topped the list, indicating smaller loan size than SBI (Appendix Table 1).

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[4] Education loans availed from October 2019 onwards are linked to external benchmark.

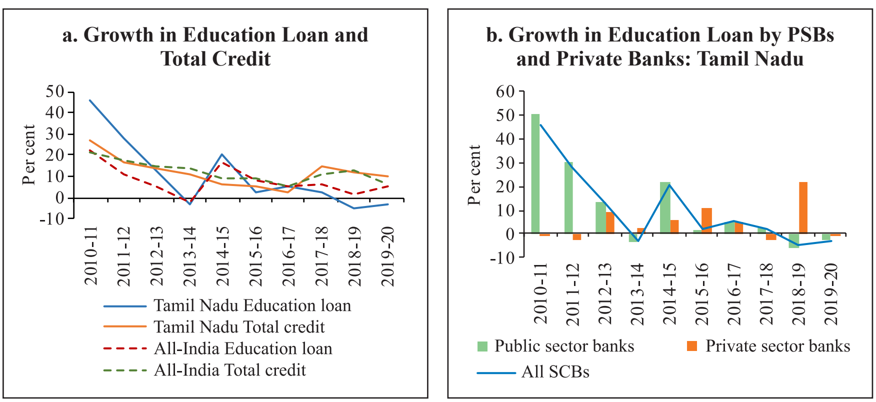
[5] **Source:** Basic Statistical Return of Scheduled Commercial Banks in India.

[6] **Source:** Agenda papers, State Level Bankers' Committee (SLBC), Tamil Nadu. Available at www.slbctn.com.

During this decade, growth in education loan portfolio was on a decelerating trend till 2013-14, both in Tamil Nadu and at all-India level, before reviving to double digits in 2014-15, only to moderate in the subsequent years. Education loan growth for Tamil Nadu turned negative in 2018-19 although the rate of decline moderated in 2019-20 (Chart 1a). While the growth in PSB advances mirrored that in overall education loans by all commercial banks, growth in advances by PVBs increased sharply in 2018-19 but turned negative in 2019-20 (Chart 1b). The number of applications received by banks in the state for education loan has also declined since 2018-19, indicating reduced demand for the same. This could be ascribed to technical courses losing their sheen in the face of declining absorptive capacity of the job market, on the one hand and remunerations incommensurate with the high cost of such education, on the other. Further, uncertainty stemming from the prevailing COVID-19 pandemic situation has also led to a sharp fall in applications for education loan in the state by 54.3 per cent in H1:2020-21 over the comparable period of the previous year[7].

Tamil Nadu's predominance in education loans extended by banks can be partly attributed to the large presence of private educational institutions in the state. As per All India Higher Education Report 2018-19, Tamil Nadu's

Chart 1: Education Loan Outstanding of Scheduled Commercial Banks



Source: Basic Statistical Return of Scheduled Commercial Banks in India, RBI.

[7] **Source:** Same as footnote 6.

Table 1: Student Enrolment in Standalone Institutions in Tamil Nadu – 2018-19

	Poly-technic	Post Graduate Diploma in Manage-ment	Nursing	Teacher's training	Paramedical	Hotel Manage-ment and Catering	Total
Number of Institutions							
Tamil Nadu	496	9	111	292	-	2	910
All-India	3,440	291	3,039	3,759	70	26	10,625
Student Enrolment							
Tamil Nadu	3,34,180	483	9,003	7,863	-	3,53,716	7,05,245
All-India	15,13,684	50,368	2,81,868	2,72,599	6,801	21,47,584	42,72,904

Source: All-India Survey on Higher Education, 2018-19, Ministry of Human Resource Development, Government of India.

gross enrolment ratio at 49 per cent was one of the highest among Indian states. Private unaided institutions in Tamil Nadu accounted for 76.5 per cent of the total number of colleges and 60 per cent of total college enrolment in the state as compared to an all-India average of 64 per cent and 45.2 per cent, respectively. The share of Tamil Nadu in terms of student enrolment in various standalone professional institutions such as polytechnic, hotel management, primary teachers training, nursing and paramedical in the country was around 17 per cent, with the state housing the highest number of polytechnic institutions in India (Table 1).

II.4 Subsidy for Education Loans

To the students availing education loan, Government of India extends support in the form of a central sector interest subsidy (CSIS) scheme, whereby full interest subsidy is provided during the moratorium period[8] on model education loans up to ₹7.5 lakh without collateral security and third-party guarantee, for pursuing technical/professional courses in India. Students whose annual gross parental/family income is up to ₹4.5 lakh are eligible for benefits under the scheme. Under the *Padho Pardesh* scheme, Government of India also provides interest subsidy on education loan availed by meritorious

[8] Moratorium period refers to course period plus one year.

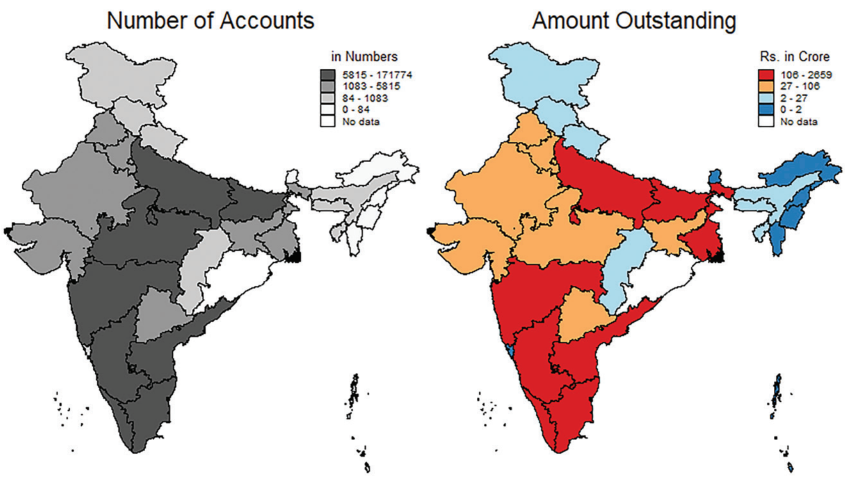
students belonging to economically weaker sections of minority communities for approved post-graduation/doctoral courses offered abroad.

Additionally, Government of India, through the National Credit Guarantee Trustee Company (NCGTC), has established a Credit Guarantee Fund for Educational loans (CGFEL) in 2015 to provide guarantee cover of up to 75 per cent against default in uncollateralised educational loan of up to ₹7.5 lakh extended by a registered lender at a rate of interest which is not higher than 2 per cent above the base rate/marginal cost of funds based lending rate (MCLR). Cumulative sanction amount covered under CGFEL was ₹12,121.45 crore as at end-March 2019, with the southern region accounting for 50 per cent of the guarantees to 3.65 lakh accounts given by NCGTC.[9]

II.5 NPAs in Education Loan

While southern states account for the largest proportion of education loans by PSBs, they also dominate in terms of number of accounts turning into NPAs as well as NPA amount outstanding (Chart 2). As at end

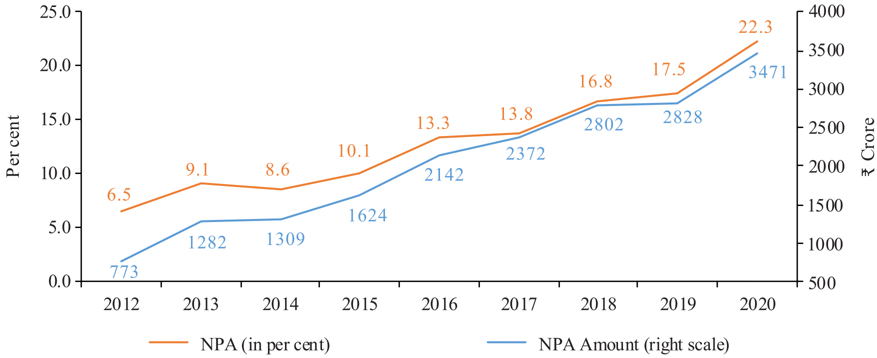
Chart 2: Spatial Distribution of Education Loan NPAs in Public Sector Banks as at End-September 2017



Note: Demarcation of States is as per prevailing situation in 2017.
Source: Lok Sabha Unstarred Question No. 676, dated July 20, 2018.

[9] **Source:** 5th Annual Report (2018-19) of National Credit Guarantee Trust Company Limited (NCGTCL)

Chart 3: Education Loan NPAs in Tamil Nadu under Priority Sector Lending (as at End-March)



Source: Agenda Papers, State Level Bankers' Committee (SLBC), Tamil Nadu.

September 2017, the share of Tamil Nadu in total NPAs in the education loan segment in India was the highest among the Indian states both in terms of number of accounts (50 per cent), and in terms of amount outstanding (42 per cent).

NPA ratio in education loan under the priority sector increased sharply from 9.1 per cent at end-March 2013 to 13.3 per cent at end-March 2016 in Tamil Nadu. The one-time settlement scheme of education loan introduced during 2016-17 led to some moderation, but it rose sharply in the following year and stood at 22.3 per cent as of end-March 2020 (Chart 3).

Section III
Education Loan: Theories and Empirics from Literature

A vast body of literature deals with the problems associated with designing education loan schemes, in particular, and student debt burden as well as loan default, in general. Most of these studies relate to developed economies, with very few focusing on developing economies, possibly because student loan segment in these countries is still very small in comparison to the burgeoning student loan market of some advanced economies. In the US, the total size of student loan market had surpassed total credit card outstanding for the first time in 2010 and has been growing rapidly since then (Avery and

Turner, 2012). Latest data place the outstanding student loan debt in the US at US $1.56 trillion from around 45 million borrowers.[10]

The empirical literature on education loan deals with several associated issues such as cross country comparison across various higher education loan schemes, cohort analysis, optimal indebtedness and loan repayment burdens of students (Chapman and Lounkaew, 2015; Andruska *et al.,* 2014; Hillman, 2015a, 2015b; Looney and Yannelis, 2015). There is a well-established literature on the subject matter dealt in the present paper *i.e.,* borrower level characteristics and default rate, most of which is in the context of the US (Wilms *et al*., 1987; Volkwein and Szelest, 1995; Knapp and Seaks, 1992). Flint (1994) analyses students' pre-college characteristics associated with loan default rate, using data of borrowers who obtained the Stafford loan[11] in the US in 1990. The empirical analysis of the paper finds that though students' grade point average is statistically significant, enrolment choices, amount borrowed, number of loans and reasons for leaving the college are not statistically significant in the context of default. Using data from the National Postsecondary Student Aid Study, Dynarski (1994) finds that low socioeconomic status of borrowers, incomplete or poor educational attainment and low earnings after completion of school were the major determinants of default in education loan. The paper, thus, concludes that efforts to reduce default rates are likely to be felt most significantly by students from disadvantaged backgrounds who were the major recipients of student aid.

In the context of developing countries, the magnitude of government spending on education, especially higher education, remains a crucial public policy debate (Birdsall, 1996; Mor, 2019), along with the social implications of subsidy and the resulting adverse selection in the student loan market (Ionescu and Simpson, 2016). In the Indian context, Chandrasekhar *et al.* (2016) use NSSO's Survey data on Social Consumption in India (2014) and find that there is binding credit constraint among poorer households in India

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[10] **Source:** Student Loan Debt Statistics 2020 available at https://educationdata.org/student-loan-debt-statistics/

[11] A Stafford Loan is a student loan offered to eligible students enrolled in accredited American institutions of higher education to help finance their education.

in availing higher education. However, there are very few studies that focus on the relationship between borrower level characteristics and loan default rate in developing countries. One such study for India which is pertinent for the present paper is Bandyopadhyay (2016). This study empirically investigates the granular level risk of education loan using a cross section of data from 5000 borrowers obtained from four major PSBs in India. The findings suggest that education loan defaults are mainly influenced by security, borrower margin, and repayment periods. The presence of guarantor or co-borrower and collateral significantly reduce default loss rates. The socioeconomic characteristics of borrowers and their regional locations also act as important factors associated with education loan defaults. The results suggest that banks can adopt better risk mitigation and pricing strategies to resolve the issue of bad debt in the education loan portfolio by segmenting borrowers on the basis of probability of default and loss given default in a multidimensional scale.

Extending the research in the Indian context, the present study explores the crucial factors associated with education loan default in Tamil Nadu. This study uses a detailed account-level lending data of over two lakh borrowers in the state from three commercial banks headquartered in the southern region as compared to a smaller sample of 5000 borrowers by Bandyopadhyay (2016). Since the southern region, particularly Tamil Nadu, has a dominant presence in education loan market in India, focusing only on the NPAs in education loans in the state throws up some interesting insights which may not have been discovered with the use of diverse all-India data. Further, unlike the study by Bandyopadhyay (2016) which was confined only to PSBs, this study covers two PSBs and one PVB, thereby facilitating a comparison between the two categories of banks by ownership. More specifically, use of micro level data allows us to investigate the spatial, borrower, scheme and course specific attributes associated with higher default probability in education loan segment. Findings of the paper have important policy implications in terms of risk identification in education loan segment. With a view to capture the lenders' perspective in extending education loan, the paper also includes the results of a questionnaire-based survey of banks in Tamil Nadu.

Section IV
Data and Methodology

IV.1 Data

The paper uses detailed account level information pertaining to March 2019 on socioeconomic characteristics of borrowers along with spatial and other relevant facts obtained from two large PSBs and one PVB operating in Tamil Nadu. Account level information is available for location (branch, district and population group indicating whether the branch is located in urban/semi-urban/rural/metropolitan area of the state), borrowers' identity (gender, income group, course of study, institution name) and lending parameters (scheme name, interest rate, amount, repayment period, availability of collateral, subsidy status, amount outstanding and NPA status), along with education loan scheme details for each account. Though the same set of information was sought from the three banks, each bank reported the information as per its own format. This is particularly true for fields like education course details, institution details and income group of the borrower. Due to differences in data format, regression results are reported separately for each bank in the following sections. Further, each bank is treated as a separate entity of analysis as it varies significantly from the others in the sample in terms of spatial presence, products offered, clientele and lending practices. For the sake of maintaining anonymity, the analysis in the paper does not name the selected banks.

IV.2 Descriptive Statistics

Table 2 provides some important statistics related to education loan portfolio of banks in the sample as well as highlights some differences between education loan portfolio of the selected PSBs and PVB. It is found that in all three banks, male borrowers accounted for around two-thirds of the total education loan portfolio, on an average. In terms of spatial dimension, while all three banks had a sizeable share of semi-urban area in the education loan portfolio, the two PSBs had a significantly higher proportion of education loan from rural area and a fairly low proportion of education loan from metropolitan area as compared to the PVB. Significant difference is also observed in the proportion of education loan accounts eligible for subsidy, with the two PSBs having a significantly higher ratio of 61 per cent (Bank A) and 76 per cent

Table 2: Education Loan Portfolio of Banks in Sample: Borrowers' Profile

Serial No.	Characteristics	Bank A	Bank B	Bank C
1	**Gender of borrower (Per cent)**			
1.1	Male	63.36	64.03	66.78
1.2	Female	36.64	35.97	33.22
2	**Spatial Distribution (Per cent)**			
2.1	Rural	29.67	40.61	12.63
2.2	Semi-urban	48.94	38.91	47.77
2.3	Urban	13.48	15.01	26.98
2.4	Metropolitan	7.92	5.47	12.63
3	**Eligibility for subsidy (Per cent)**			
3.1	Yes	61.34	76.38	31.12
3.2	No	31.21	23.62	68.88
4	**Annual income of co-borrowers (Rupees)**			
4.1	Mean	85,746	91,563	1,61,117
4.2	Median	50,000	48,000	50,000

(Bank B) as against the PVB's share of 31 per cent. This also indicates a higher presence of smaller accounts in the education loan portfolio of PSBs. We also find the mean income of co-borrowers to be higher in the case of the PVB as compared to the other two banks although in terms of median income, the difference between the two category of banks was not marked. This indicates positively skewed income distribution for all three banks.

A comparison of the NPA statistics across various categories of education loan for the three banks as set out in Table 3 unravels the following[12]: The PVB had the highest average NPA ratios for its rural, semi-urban and urban education loan portfolio whereas one of the PSB (Bank B) had the highest average NPA ratio for education loan extended in the metropolitan region. While the proportion of education loan accounts eligible for subsidy was lower for the PVB, the average NPA ratio in terms of total loan amount in this segment was substantially higher for the bank as compared to the two PSBs. However, all three banks reported higher average NPA ratio among

[12] Table 3 provides key NPA statistics (in terms of amount outstanding) while Appendix Table 4 provides default rates (in terms of frequency).

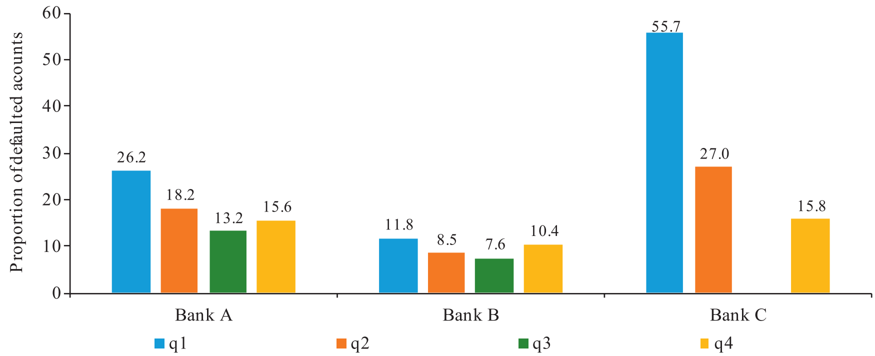
Table 3: Education Loan Portfolio of Banks in Sample: Key NPA Statistics

(in per cent to total loan amount)

Proportion of NPA	Bank A	Bank B	Bank C
Overall	12.86	11.7	22.83
Subsidy eligible loans	11.63	11.37	40.23
Non-subsidised loans	12.02	12.73	14.96
Rural	15.89	11.66	36.87
Semi-urban	12.58	11.54	20.81
Urban	10.18	9.79	25.06
Metropolitan	7.81	18.31	11.64
Male	12.86	12.40	25.11
Female	12.22	10.44	18.23
Above median income	7.84	11.42	9.70
Below median income	13.20	12.35	37.70
No. of observations	1,08,354	1,39,216	4,731

male borrowers as compared to female borrowers. For all the three banks, it was found that NPA ratio is lower for education loan borrowers having above median annual family income in the bank's education loan portfolio. In terms of number of accounts, it was found that on an average, proportion of accounts in default reduces with rise in income, though for Bank A and Bank B, the proportion of default in the highest income category is slightly higher as compared to the next income category/class (Chart 4). Appendix Table 2 provides a detailed description of various schemes offered by these three banks.

Chart 4: Share of Defaulted Accounts in Selected Banks Based on Family Income



Source: Calculations are based on income quartiles of data obtained from the three banks in the study.

IV.3 Empirical Framework

The empirical literature on credit score modelling/determinants of default can be broadly divided into three segments based on the methodology used. These are i) logistic regression model, ii) neural network and iii) genetic algorithm (Gouvêa and Gonçalves, 2007). There is no consensus in the literature, however, on the relative efficiency of these three methods as in most cases it depends on the data and the context. Most past studies attempting to understand determinants of default use either discriminant analysis (Dyl and Mcgann, 1977; Myers and Siera, 1980; Khemais *et al.,* 2016) or a broader range of limited dependent variable models. In this context, a summarised review of application of limited dependent models in the context of education loan study is presented in Appendix Table 3. Logistic regression model, which is a specific form within the family of limited dependent variable model, is also used extensively in the broad literature dealing with higher education choices, impact of student loan programme and related policy questions, a detailed review of which can be found in Cabrera (1994). Logit model is widely used not only in studies of student loan default but also in studies on credit default estimation for corporate and retail loans as well (Johnsen and Melicher, 1994; Westgaard and van der Wijst, 2001; Ballkoci and Gremi, 2016).

The present paper deploys the logistic regression model, mainly because the data available do not have sufficiently large set of predictors, thereby requiring the relatively important ones to be determined using the discriminant analysis. The choice between a binary or an ordered logistic regression model is made for individual banks in the sample based on whether the default accounts of these banks are denoted as a binary variable or are indicated through an ordered variable which captures the duration that an account remains in the default category. In our sample, Bank A classifies borrower accounts into four categories, *i.e.,* standard, substandard, doubtful and loss, depending on their repayment status, whereas the other two banks classify accounts into two broad categories of standard and NPA. While a logistic model would be a natural candidate when the dependent variable is dichotomous, we also deploy a generalized ordered logistic model in the case of Bank A, which provides further interesting insights.

In a logistic model, a non-linear specification is deployed which resembles a sigmoid or elongated S shaped curve. This solves the problem of impossible outcomes since in a logistic model, the estimated value of the dependent variable is the probability of occurrence of the event. Since probability takes the value between zero and one, a non-linear specification is more suited, especially the sigmoid curve, the tails of which level off before reaching zero or one. The logit model is specified as

$$P_i = P(Y_i = 1) = F(Z_i) = \frac{1}{1 + e^{-z_i}}$$

Where Z_i is the linear function of the predictor variable. The above expression can be rewritten in terms of the log odds ratio as follows:

$$Ln\left(\frac{P_i}{1 - P_i}\right) = Z_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon_i$$

A widely used estimation procedure for logistic regression is maximum likelihood method which involves maximizing the following log likelihood function with respect to the parameters

$$LnL = \sum_{i=1}^{n_1} Y_i LnP_i + \sum_{i=n_1+1}^{n} (1 - Y_i) Ln(1 - P_i)$$

$$= \sum_{i=1}^{n_1} Y_i Ln\left(\frac{1}{1 + e^{-z_i}}\right) + \sum_{i=n_1+1}^{n} (1 - Y_i) Ln\left(\frac{1}{1 + e^{-Z_i}}\right)$$

Where the first n_1 observations are associated with the first outcome.

An alternative specification used in the literature in the case of dichotomous dependent variable is the Probit model. In most cases, there are only few differences between estimated coefficients of the logit and probit models[13]. In the present paper, we apply a logit model for estimating the probability of default in education loan portfolio. As illustrated in the previous section, various borrower level, spatial and loan characteristics are used as predictors, detailed description of which are given in Table 4.

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[13] Amemiya (1981) shows that by multiplying the logit estimates by 0.625, one may obtain the corresponding probit estimations.

Table 4: Description of Variables

Sl No.	Variable name	Unit	Description
		Categorical/dummy variables	
1	NPA_ dummy (dependent variable)	Binary/ Categorical variable	A dummy variable takes value 1 for defaulted loan accounts/ categorical variable with values 1 (standard), 2 (substandard), 3 (doubtful), and 4 (loss)
2	Population group dummies	-	Dummy variables named rural, urban, semi-urban and metropolitan which takes values 1 for rural, urban, semi-urban and metropolitan areas, respectively, and 0 otherwise.
3	Gender dummy	-	Dummy variables named male and female to indicate the respective gender.
4	Course dummies	-	Dummy variables used to define courses for which education loan was availed by the borrower.
5	UID	-	Dummy variable takes the value of 1 if Aadhar information is available
6	collat	-	Dummy variable takes value 1 for loans accounts with collateral
7	subsidy	-	Dummy variable takes value 1 for subsidised loan accounts
8	Scheme dummies	-	Dummy variable to define various education loan schemes of the bank
9	Year	-	Dummies for year of sanction of the loan
		Continuous variables	
10	ln_dur	in months	Log (Repayment or moratorium period in months)
11	ln_int	Per cent	Log (Interest rate on the loan account)
12	ln_inc	Rupees	Log (borrowers' annual family income in ₹)

In the case of Bank A, which has reported the status of loan accounts in terms of four categories as mentioned above, a generalised ordered logistic model (GOLM) is used. This is specifically because the four categories can be ordered in terms of the severity of loan default and/or chances of recovery, as illustrated in the standard definition of NPA. In an ordered logistic model, the dependent variable Y (observable) is a function of a latent variable Y* and can be classified into M categories based on the M-1 cutoff values of Y*. In the case of an ordered logistic model, the coefficients (βs) as well as the M-1 cutoff points need to be estimated. In an ordered logistic model, the probabilities are given by

$$P(Y_i > j) = g(X\beta_j) = \frac{\exp(X_i\beta - \kappa_j)}{1+[\exp(X_i\beta - \kappa_j)]}, \quad j=1, 2\ldots\ldots M\text{-}1$$

When M>2, the above model produces a series of binary logistic regressions where categories of the dependent variable are combined. For example, when M=4, j=1 contrasts category 1 with 2,3, and 4. For j=2, category 1 and 2 is contrasted with category 3 and 4. For j=3, category 1,2,3 is contrasted with 4. In a special case, where all these M-1 regression lines are parallel, all the βs assume the same value for all the js, hence the model can be rewritten as

$$P(Y_i > j) = g(X\beta) = \frac{\exp(\alpha_j + X_i\beta)}{1 + \exp(\alpha_j + X_i + \beta)}$$

Where j=1,2,…M-1

This is known as the parallel line assumption of the ordered logistic model (McCullagh, 1980), whereby the slope coefficients in the model are the same across response categories. Whether an ordered logistic model satisfies the parallel regression assumption can be tested using the Brant (1990) test. In case the parallel line assumption is violated, a GOLM would be a better fit as the ordered logistic model in such cases would impose additional parameter restrictions which are violated (Quednau, 1988; Clogg and Shihadeh, 1994; Fahrmeir and Tutz, 1994; Williams, 2006; Greene and Hensher, 2010). Hence, in the case of Bank A, first the Brant test is applied to test the parallel line assumption. Since the test results indicate parallel line assumption is strongly violated, a GOLM is used.

Section V
Empirical Results

Before presenting the main results of the logistic model, we did an exploratory study of the variables involved in the model to understand their interrelations. The two panels in Table 5 report the default rate in dichotomous and continuous determinant variables, respectively. In addition, it also reports the results of test of hypothesis of equality between proportion and mean in the defaulted and non-defaulted group, for factor variables and continuous

Table 5: Exploratory Study of Variables

Predictors	Bank A			Bank B			Bank C		
	Proportion of default	Pearson Chi-square/ t stat	P value	Proportion of default	Pearson Chi-square/ t stat	P value	Proportion of default	Pearson Chi-square/ t stat	P value
Dummy variables									
Course specific dummies		10000.00	0.00		182.47	0.00		330.31	0.00
Engineering	20.05			9.65			42.65		
Law	14.69			11.08			50.00		
MBBS	6.53			5.21			10.95		
Dental	8.51			6.73			14.06		
Nursing	16.68			7.12			47.19		
B.Ed				7.18			91.81		
Hotel Management				13.64			50.00		
Law	14.69			11.08			50.00		
BBA/MBA/Commerce	27.54			11.30			25.00		
Arts and diploma				9.74			57.21		
Architecture							15.79		
Veterinary	15.05								
Homeopathy & alternate medicine	16.23								
Pharmacy/paramedical	40.00			9.72			16.13		
M.Tech	24.89						47.06		
MCA/BCA/Polytechnic	39.10			7.70			40.00		
B.Sc/MSc	23.10			12.63			38.46		
Scheme specific dummies									
A1	20.90	192.74	0.00						
A2	27.00								
A3	62.10								
A4	52.30								
A5	69.20								
B1				10.22	959.55	0.00			
B2				0.27					
B3				14.10					
B4				5.57					
B5				0.00					
C1							43.44	2.59	0.11
C2							40.91		
Collateral dummy	12.74	289.50	0.00	23.05	603.54	0.00	23.03	81.99	0.00
Aadhar Dummy	11.02	20000.00	0.00	4.54	2200.00	0.00	23.36	833.30	0.00
Female_dummy	27.50	4.82	0.09	8.89	43.94	0.00	36.33	57.27	0.00
Continuous Variables									
Ln_inc		41.40	0.00	-	9.78	0.00	-	21.85	0.00
Ln_interest		-260.00	0.00	-	-60.44	0.00	-	-26.96	0.90
Ln_duration		149.47	0.00	-	6.76	0.00	-	34.46	0.00

variables, respectively. In the case of continuous variables, the t-test of equality of mean is used. In the case of dichotomous variable, we use the chi-square test for equality of proportion.

In the course category, there were considerable differences in the default rates across the three banks in the sample. Bank A registered the maximum default rate in paramedical/pharmacy courses, followed by polytechnic and management/commerce courses. For Bank B, the occurrence of default is the highest in hotel management, followed by science courses and management/commerce courses. Bank C reported highest rate of default in B.Ed, which had a default rate of nearly 92 per cent, followed by arts and diploma courses, hotel management and law. It is pertinent to note that courses like engineering and nursing too witnessed high default rate in all three banks whereas default rate seems to be relatively moderate in MBBS and dental courses. The Pearson chi-square statistic pertaining to the factor variable course, is found to be highly significant for the three banks, indicating that course specific dummies are important in explaining the default rate. The remaining part of the table shows that other factor variables such as scheme specific dummies, gender, collateral and Aadhar dummies are all significant across the banks indicating their strong candidature for inclusion in the logistic regression. The other three continuous variables, *i.e.,* natural logarithm of loan duration, interest rate and annual family income of the borrower also reported significant t-statistics while testing the significance of the difference between the mean of the defaulter and non-defaulter groups, except in case of ln_interest, for which we get a non-significant t -statistic for Bank C.

The bank-specific estimation results of logistic regressions are reported in Table 6. The model selection is essentially based on trial and error, which involves district and year dummies, apart from all the other predictor variables mentioned in earlier sections. Since simultaneous inclusion of the course, scheme, district and year dummies result in multicollinearity problem in many cases due to increase in the number of independent variables, such dummies are dropped when required and the result of the final models are only presented in Table 6.

Further, since the logistic regression is highly sensitive to extreme values, the influential and/or outliers data points are dropped in the estimation procedure. For identification of outliers, we have used the Pregibon leverage (Pregibon, 1981), plotted against the predicted values. The chi-square statistic for goodness of fit was highly significant in all the models, indicating

Table 6: Bank-specific Logistic Regression Results Dependent variable: NPA_dummy

	Bank A	Bank B	Bank C
ln_dur	-5.776*** (0.065)	-0.203*** (0.024)	-5.233*** (0.576)
ln_inc	-0.049*** (0.010)	-0.105*** (0.011)	-1.480*** (0.451)
ln_int	6.485*** (0.170)	0.041 (0.119)	75.928*** (13.363)
rural	-0.865*** (0.109)	-1.171*** (0.045)	1.477*** (0.262)
semi-urban	-0.817*** (0.107)	-1.172*** (0.045)	1.066*** (0.241)
urban	-0.598*** (0.117)	-1.287*** (0.050)	0.756*** (0.247)
male	-0.263*** (0.028)	-0.017 (0.021)	-0.056 (0.128)
UID	-0.483*** (0.029)	-0.246*** (0.027)	-0.748*** (0.120)
subsidy	-0.077* (0.042)	-0.071** (0.028)	-0.859*** (0.129)
collat	-1.001*** (0.250)	1.373*** (0.054)	-0.814*** (0.257)
_cons	6.043*** (1.267)	-4.448*** (0.678)	-74.562*** (17.090)
Obs.	108354	139216	4731
Pseudo R^2	0.645	0.131	0.679
LR chi^2	71061.53	11590.12	4447.10
Prob > chi2	0.00	0.00	0.00
H-L statistics	1110.5	38.09	7.79
p-value	0.00	0.00	0.45
Scheme dummy	Yes	Yes	Yes
Course dummy	Yes	Yes	No
Year dummy	Yes	Yes	Yes
District dummy	Yes	No	No

Notes: 1. Standard errors are in parentheses
2. *** p<0.01, ** p<0.05, * p<0.1

their overall fit.[14] For Bank C, the Ramsay specification test indicates the presence of non-linearity in the model. To identify the variable associated

[14] The Hosmer Lemeshow (HL) test statistic (Hosmer and Lemeshow 1980; Hosmer *et al*., 2013), which is widely used in risk modelling to test the predictive power of the model by comparing the observed and expected probabilities, is significant for the model used for Bank A and Bank B, while insignificant for the model used for Bank C. This indicates somewhat poor fit for the model used for Bank A and Bank B. However, since in the present case, the logistic models are not used for prediction purpose, results are reported following a significant value of LR chi2. Further, it is often found that HL statistic is not neutral to the choice of bins which is somewhat arbitrary and has low power (Verdes and Rudas 2003, Paul *et al*., 2013).

with non-linearity, the Box and Tidwell (1962) power transformation model is estimated. The test results indicate the presence of non-linearity in the case of variables ln_inc and ln_int. Hence, the model for Bank C involves appropriate transformation of these two variables. From the Box-Tidwell results, the p1 values corresponding to ln_inc and ln_int is 4.66 and 4.23 respectively, suggesting a power transformation of 0.22 and 0.24 for these two variables (Appendix Table 5). The likelihood ratio (LR) Chi^2 as well as the Hosmer-Lemeshow (HL) test statistic in the model estimated using the power transformation indicate overall goodness of fit.

In the case of multivariate regression, the estimated coefficients indicate the marginal effects. Since interpretation of the coefficient of the logistic regression is not straightforward, a better way to understand the implications of the results is to read Table 6 along with the odds ratios of the logistic regressions reported in Table 7.

Table 7: Odds Ratios of the Logistic Regression

	Bank A	Bank B	Bank C
ln_dur	0.003*** (0.000)	0.816*** (0.020)	0.005*** (0.002)
ln_inc	0.952*** (0.010)	0.900*** (0.010)	0.228** (0.142)
ln_int	655.198*** (103.195)	1.042 (0.125)	2859.9*** (3689.9)
rural	0.421*** (0.039)	0.310*** (0.013)	4.381*** (1.091)
semi-urban	0.442*** (0.041)	0.310*** (0.013)	2.904*** (0.643)
urban	0.550*** (0.056)	0.276*** (0.013)	2.129*** (0.486)
male	0.768*** (0.022)	0.983 (0.021)	0.945 (0.119)
UID	0.617*** (0.018)	0.782*** (0.020)	0.473*** (0.056)
subsidy	0.926* (0.039)	0.932*** (0.026)	0.423*** (0.056)
collat	0.367*** (0.095)	3.949*** (0.214)	0.443*** (0.114)

Notes: 1. Standard errors are in parentheses.
2. *** *p<0.01*, ** *p<0.05*, * *p<0.1*

In respect of continuous variables, ln_dur and ln_inc are highly significant in all three regressions. However, ln_int is significant only for Bank A and Bank C but not significant for Bank B. For all the three banks, the ln_dur variable is significant, and the estimated coefficients have negative sign, indicating lower default probability associated with longer duration in the present case. The odds ratios of ln_dur for all three banks is less than one, underlining this negative relationship. It also shows that with every unit increase in ln_dur, the odds of default increases by 0.003, 0.816 and 0.005 for Bank A, Bank B and Bank C, respectively. Intuitively, this result indicates that probably, education loans with a longer duration and more flexible repayment schedule experience lower default rate. Next, for all the three banks, we find a negative and significant coefficient of ln_inc. This result too is on expected lines, as student borrowers with higher family income at the time of sanctioning of loan are expected to have a better repayment capacity and lower default rate. In the case of Bank C, the significant coefficient is with respect to the transformed variable and indicates non-linearity. Estimated coefficient values suggest that for Bank C, the impact of income on reduction in default probability is lesser for richer borrowers.

Third, the positive and significant coefficient of ln_int for Bank A and Bank C indicates loan accounts with higher interest rate have a higher probability of default. This result is also on expected lines as a higher interest burden increases the probability of default due to adverse selection risk in the credit market (Akerlof 1970, Wilson 1989). Given the parameter estimates, it can be inferred that for Bank C, although a higher interest rate is associated with a higher default probability, the impact of interest rate in default probability reduces with rise in interest rate.

Regarding the spatial variables, we did not find any conclusive evidence of higher default probability being associated with any specific population group, though one can conclude that geographical location of the loan account *per se* is a statistically significant predictor of default. Out of the three banks, two PSBs reported negative and significant coefficient for rural, indicating a lower default probability for rural education loan accounts, while it is just the opposite for the PVB. For both the PSBs, we get negative and significant coefficients mostly for rural, semi-urban and urban dummies while for the PVB, all the three are positive and significant, indicating higher default probability associated with loan accounts in these regions as compared with loan accounts in metropolitan regions. It is worthwhile to recall here that both the PSBs have more education loans sanctioned in the rural areas, whereas the PVB's education loan portfolio is more urban in nature. With a larger rural network, PSBs may be in a better position to recover loans extended to rural areas than the PVB in our study.

The signs and statistical significance of the third set of borrower and account specific variables bear important insights. The male dummy is found to be significant only for Bank A while it is insignificant for the other two banks. However, we get a negative coefficient for this variable for all the three banks, indicating lower probability of default for male borrowers as compared to female borrowers. Though a significant coefficient of male dummy in the case of Bank A, which has the largest education loan portfolio in our data-set, suggests that there is some evidence of gender influencing default probability, no conclusive evidence can be drawn given the insignificant value of this statistic for the other two banks.

The most consistent and strong result is obtained in the case of UID dummy, which is highly significant and negative in all the three regression estimations presented in Table 5. The result implies that probability of default is lower for accounts where Aadhar information is available with the bank than for accounts without Aadhar details. It is possible that with Aadhar details, tracking the borrowers becomes easier for the bank, aiding in recovery in case of default. The odds ratios for this variable given in Table 6 implies that for accounts with Aadhar information, the odds of default for Bank A, Bank B and Bank C, are lower by 38.3, 21.8, 52.7, respectively as compared to accounts with no Aadhar information. The negative and significant estimates for subsidy variable of the three banks indicate that default rate is lower for accounts which receive subsidy as compared with non-subsidised accounts.

Lastly, the dummy variable collat, indicating the presence of collateral in borrowal accounts is negative and significant for Bank A and Bank C. This indicates that the presence of collateral reduces the default probability for these two banks. However, for Bank B, the coefficient value is positive. A further investigation of the raw data reveals that for this bank, the accounts with collaterals are also the accounts with higher interest rate. The point biserial correlation coefficient between ln_int and collat is highly significant in the data for Bank B. However, the diagnostic check for collinearity reveals no significant problem in the overall regression, with a mean variance inflation factor (VIF) of around 1 (Appendix Table 6). Hence, the positive coefficient of collat in the case of Bank B could be the impact of higher interest.

The individual coefficient estimates of scheme, course, year and district dummies are not reported in Tables 5 and 6 due to space constraint. For Bank A, significantly higher default probability is observed in case of BBA/MBA, BCA/MCA, homeopathy and alternate medicine, and ME/MS/MTech courses as well as for schemes A4 and A5 listed in Appendix 2. In case of Bank B it is found that engineering, hotel management, law, MBA, nursing and general degree courses in science are significant predictors associated with higher default probability, whereas for MBBS courses, the coefficient sign is negative and significant. Also, loan sanctioned for admissions under management quota has lower default probability, along with scheme B2 listed in Appendix 2. None of the scheme dummies was significant in the case of Bank C and hence, we did not include course dummies to get rid of multicollinearity issues in the case of this bank.

Alternative Model Specification for Bank A: A Generalised Ordered Logistic Framework

As illustrated in Section IV, the detailed classification of the loan accounts provided by Bank A allows us to further investigate the pattern of coefficients in a generalized logistic model framework. Table 8 provides key summary statistics of these four categories for Bank A. Our model selection is based on empirical validation. We started with an ordered logistic model and applied the Brant test developed by Long and Freese (2006) to test the parallel line assumption. The assumption was strictly rejected for all the variables in the model suggesting that an ordered logit model would be too restrictive and a misfit for the present data set. Hence, the GOLM is estimated

Table 8: Key Statistics related to Dependent Variable

Categories specified in GOLM	Duration			Interest rate		
	Mean	Median	SD	Mean	Median	SD
Standard	151.8	152.0	35.6	10.7	10.7	0.7
Sub-standard	124.9	125.0	34.5	12.2	12.5	1.5
Doubtful	134.0	121.0	52.4	12.5	13.0	1.4
Loss	120.5	117.0	40.6	12.1	12.0	1.5

for Bank A (Table 9). Since the coefficients or factor variables are easier to interpret and bear more insights in a GOLM framework, we have not included the continuous variables in this regression. The results presented in Table 9 clearly shows that the parallel line assumption is not met, and we get different coefficient values in the 3 sub-panels of the table.

Table 9: Generalised Ordered Logit Estimates for Bank A

Number of observations=136440
LR chi2(21)=18964.92
Probability > chi2=0.0000
Log likelihood = -87249.098 Pseudo R^2 = 0.0980

Dependent Variable: Default	Coefficient	Dependent Variable: Default	Coefficient	Dependent Variable: Default	Coefficient
Panel I: Category 1 contrasted with 2,3,4		**Panel II: Category 1 and 2 contrasted with 3 and 4**		**Panel III: Category 1,2,3 contrasted with 4**	
rural	-0.086*** (.032)	rural	0.100*** (0.039)	rural	0.085*** (0.039)
semi-urban	-0.218*** (0.032)	semi-urban	-0.057 (0.038)	semi-urban	-0.067** (0.038)
urban	-0.168*** (0.036)	urban	-0.210*** (0.043)	urban	-0.223*** (0.043)
female	-0.002 (0.014)	female	-0.024 (0.017)	female	-0.018 (0.017)
collat	-1.683*** (0.093)	collat	-1.486*** (0.113)	collat	-3.466*** (0.290)
UID	-1.759*** (0.015)	UID	-1.722*** (0.019)	UID	-1.731*** (0.019)
subsidy	-0.447*** (0.014)	subsidy	-0.405*** (0.017)	subsidy	-0.396*** (0.017)
_cons	0.004 (0.032)	_cons	-0.804*** (0.038)	_cons	-0.822*** (0.039)

Note: The dependent variable Default is a categorical variable. Default=1,2,3,4 indicates standard, substandard, doubtful and loss assets respectively. Standard errors are in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

The dependent variable is Default, which takes values 1 (standard), 2 (substandard), 3 (doubtful) and 4 (loss). Panel I in Table 9 contrasts category 1 with 2, 3 and 4. Panel II contrasts categories 1 and 2 with 3 and 4. Panel III contrasts categories 1, 2 and 3 with 4. In the case of rural, the coefficient in Panel I is negative and significant implying rural accounts are more likely to be standard assets. However, the positive coefficients for rural in other two sub-panels also indicate that rural accounts are more likely to become doubtful and loss assets. This suggests a significant presence of rural accounts in both extremes, a pattern which would have been obscured in an ordered logistic model with parallel assumption. For semi-urban, all three coefficients are negative, implying lower default probability. However, the highest value of the coefficient corresponds to Panel I, indicating that the impact of semi-urban is negative on default, but it is particularly more likely to fall in the "standard" category. For urban, all values are significant and negative, and the magnitude is the highest in Panel III, which indicates urban education loan accounts are less prone to default as compared to the base category (metropolitan in this case), but it is particularly unlikely to fall in the "loss" category. The same interpretation applies for the variable collat, which also has the highest negative coefficient in Panel III.

No conclusive evidence emerges regarding the impact of gender on default as all three estimates of female dummy[15] are insignificant. For the variable UID, coefficients are consistently significant and negative with the highest magnitude occurring in Panel I, indicating that availability of Aadhar information reduces default probability, but it particularly influences the accounts which fall in "standard" category. Same interpretation can also be applied for the variable subsidy, *i.e.,* subsidised accounts are less prone to default than non-subsidised accounts and the presence of subsidy drives the outcome to "standard" category.

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[15] Use of male dummy does not alter the results, as all coefficients of male dummy are found to be statistically insignificant, with p values of 0.296, 0.545 and 0.882, respectively for the three Panels.

Section VI
Lenders' Perspective of Education Loan NPA: Results from a Survey of Banks in Tamil Nadu

While the preceding section estimates the default probability based on borrower characteristics using account level data from three banks, this section attempts to present the broader picture of the issue of NPA in education loan from the perspective of the lending banks in Tamil Nadu. In this context, a questionnaire-based survey of PSBs and PVBs operating in the state was undertaken during July 2020 to identify the major reasons for education loan default and the stakeholders that the banks involve in the recovery process. Based on the responses received from 10 PSBs (including one RRB) and 8 PVBs,[16] we outline some important observations in this section.

The proportion of education loan in total loan portfolio in the respondent banks varies from less than one per cent to 18 per cent and the NPA ratio in education loan segment varies from less than one per cent to 33 per cent at all-India level. Both PSBs and PVBs reported sharp fall in education loan applications since the onset of the COVID pandemic, with PSBs reporting a sharper decline than their counterparts in the private sector. Responding to the question on factors investigated before sanction of education loan, the banks stated that know your customer (KYC) document of the borrower/guarantor, CIBIL reports, institution quality or ranking, past academic record of the student, repayment ability of the co-borrower and job prospect of the education course are some of the factors primarily considered. According to one PVB, CIBIL score is checked for all the education loan accounts below ₹4 lakh, for which there is no security requirement. According to a number of banks, assessing the future employment opportunity of the student remains a challenging task for the bank and several market related information available in newspaper or internet is used for the same. Few banks classify institutions into different categories based on courses offered, infrastructure, accreditation,

[16] The questionnaire was sent to all member banks of the State Level Bankers' Committee, of which responses were obtained from 18 public sector and private sector banks which accounted for nearly 78 per cent of the outstanding education loans in Tamil Nadu as on March 2020.

affiliation, rankings, faculty, placement track records, average salary offered, prospective employer list and re-employment capacity.

There were considerable differences between PSBs and PVBs in their responses to the queries regarding reasons for default, measures taken for recovery of loans and stakeholders involved in the loan recovery process. While 70 per cent of PSBs cited unemployment as the most important reason for defaults in education loan, 50 per cent of PVBs felt willful default was the primary reason. Unemployment, however, figured as the second most important reason for default among 50 per cent of the respondent PVBs. Non-completion of course by the student borrower was cited as the third important factor for loan default among 37.5 per cent of the PVBs as against 10 per cent among PSBs. Not responding to the bank's reminders was another concern for both PSBs and PVBs. Other reasons given by PSBs for loan default include partial recovery under the one-time settlement offered by them and migration to another country by the student borrower without prior notice to the bank (Chart 5).

With regard to loan recovery, meeting the customer personally and sending reminders were two main steps taken by the banks, although the relative importance of these measures differed between PSBs and PVBs. While the majority of PSBs (60 per cent) stated that they relied more on personal meetings with the borrowers as the primary mode of loan recovery,

Chart 5: Primary Reasons for Defaults in Education Loan

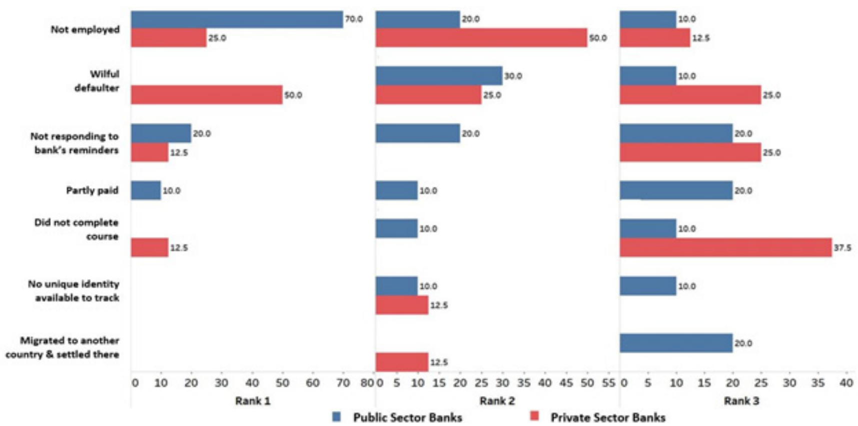
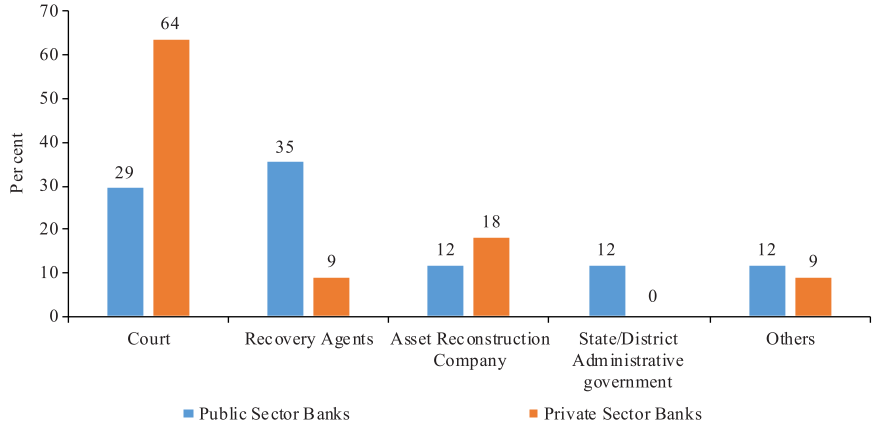


Chart 6: Measures Taken by Banks for Recovery of Educational Loan

half the PVBs stated that they primarily relied on sending frequent reminders. An equal percentage of these banks also stated that personal meetings with the borrower was the second most important mode of loan recovery. Contacting the employer of the student borrower was the primary mode of loan recovery for one fourth of the PVBs and the third most important mode for loan recovery for 60 per cent of PSBs. A higher percentage of PVBs resort to selling off the loan to asset reconstruction companies (ARCs) than PSBs. Contacting educational institution and imposing the SARFAESI Act are other modes employed by PVBs to recover their loans (Chart 6).

Responses to a query about the stakeholders that banks have involved in their educational loan recovery process indicate that court's intervention was sought by 64 per cent of PVBs as against only 29 per cent of PSBs. PSBs appear to rely more on recovery agents (35 per cent) than PVBs (9 per cent). Involvement of asset reconstruction company (ARC) was more in the case of PVBs (18 per cent) than for PSBs (12 per cent) (Chart 7).

Chart 7: Stakeholders in the Loan Recovery Process



Section VII
Concluding Observations

The study throws light on some aspects of education loan in India, with special reference to Tamil Nadu. Over the years, financing of higher education in India has moved from a primarily government aided model to a privately funded one in which the importance of education loan has increased. However, monitoring such loan accounts remains challenging for bankers due to difficulty in assessing the job market for entrants and rapid migration of student loanees in search of job. Despite the rising NPAs in education loan segment, limited available data hampers a detailed analysis of borrower cohort which is more prone to default. The present study tries to fill this gap by using detailed account level information of education loans of select banks in Tamil Nadu.

The major findings of the empirical research presented in the paper have some important policy perspectives. We find that several spatial, borrower and scheme-specific factors are significant predictors of default in the education loan segment. For the two PSBs in our sample, both of which have a significant presence of rural accounts in their education loan portfolio, empirical results suggest rural accounts have a lower probability of default as compared to metropolitan accounts. However, we find it to be the opposite for the PVB in our sample. Further, accounts with higher income of co-borrowers, those backed by collaterals and subsidised accounts are less prone to default. Longer duration reduces default probability while higher interest rate increases the same. Lender's perspective as elicited from the questionnaire-based survey indicates that default primarily stems from the borrower's inability to pay (unemployment) as well as unwillingness to do so (willful default). Public sector banks prefer persuasive measures through personal meetings, failing which they adopt more coercive means to recover their loans, particularly in cases of willful defaults. Survey responses indicate private sector banks take legal recourse more often than their public sector counterparts.

The results highlight the strategic importance of obtaining borrowers' Aadhar information for tracking the loan performance and reducing the default risk. The results also show that a more flexible payment schedule with longer moratorium could potentially reduce default. Though the concept of income contingent loans in financing higher education has gained popularity in other countries, the same is yet to take off in India. In the light of our empirical findings, the policy suggestion is to explore the option of introducing such income contingent schemes in India. However, success of such a scheme largely depends on its structure, as country experiences show that ICL generates adverse selection issues in education loan market.

The study has some limitations stemming from non-availability of appropriate employment and/or income data. Though the study attempts to identify determinants of default from account level information, the aspect of repayment capacity based on availability of employment opportunities as well as salaries offered remain outside the scope of the present paper. In addition, it is important to gain insights from students who obtain loan for higher studies and are about to enter the job market few years down the line to understand what causes default as well as to design a proper income contingent loan scheme. Future work on these topics could provide more macro and micro evidences on the issues and challenges associated with education loan default in India.

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Appendix Table 1: Top 10 Banks in Tamil Nadu in terms of Share on Education Loan Extended during 2019-20

(₹ crore)

Sl. No.	Bank	Education Loan Sanctioned (Numbers)	Education Loan Sanctioned (Amount)	Market Share in terms of Amount (per cent)
1	State Bank of India	9,832	271.08	18.4
2	Canara Bank	17,274	250.20	17.0
3	Indian Bank	2,430	167.45	11.4
4	Indian Overseas Bank	3250	125.45	8.5
5	Bank of Baroda	3,135	98.08	6.7
6	Punjab National Bank	3006	81.41	5.5
7	AXIS Bank	877	62.04	4.2
8	Bank of India	1288	49.04	3.3
9	Tamil Nadu Mercantile Bank Ltd	450	47.69	3.2
10	Syndicate Bank	765	46.28	3.1

Source: Agenda papers of SLBC, Tamil Nadu.

Appendix Table 2: Education Loan Schemes in Sample

Scheme Code	Description of Scheme
Bank A	
A1	IBA model education loan scheme
A2	Education loan for premier institutions
A3	Education loan under differential interest rate (DRI)/for reserved categories
A4	Education loan for physically challenged
A5	Education loan for down payment to counselling authorities
Bank B	
B1	Education loan under IBA model scheme without credit guarantee cover
B2	Uncollaterallised education loan up to ₹7.50 lakh covered under credit guarantee fund scheme.
B3	Education loan for admission into an approved college under management quota.
B4	Education loan for vocational education courses
B5	Education loan for paying coaching fees to prepare for entrance examination of professional courses
Bank C	
C1	Education loan for merit-based admission
C2	Education loan for admission under management quota

Appendix Table 3: Review of Methodologies

Sl. No.	Author(s)	Year	Methodology	Main Findings
1	Thomas A Flint	1994	Logistic regression analysis of survey data	Students' pre-college characteristics are statistically significant in determining probability of default. Though students' grade point average is statistically significant, enrolment choices, amount borrowed, number of loans and reasons for leaving the college are not statistically significant.
2	Seifert and Wordern	2004	Logistic regression	Early intervention to check loan default had significant positive impact, though the impact of such intervention on future behaviour of the borrower was found to be relatively small.
3	Emily A. Andruska, Jeanne M. Hogarth, Cynthia Needles Fletcher, Gregory R. Forbes, Darin R. Wohlgemuth	2014	Logistic regression and ordered logit regression on survey data	Examining awareness amongst students regarding their student loans, the results of the study suggest that although the majority of students are aware that they owe on student loans, many underestimate the amount they owe. The study examines the roles that counsellors, educators, and policy makers can play in improving students' understanding of their student loan debt.
4	Nicholas W. Hillman	2015	Logistic regression on survey data	Using Integrated Postsecondary Education Data System (IPEDS) data from 2008 (N = 4,488) in the context of US, and applying logistic regression, this study finds for-profit colleges, those accredited by vocational education programmes, and those serving diverse student bodies experience more student loan default.
5	Mezza and Somer	2016	Multivariate Tobit model	Credit scores of young borrowers are an important determinant of future student loan delinquency.

Appendix Table 3: Review of Methodologies *(Concld.)*

Sl. No.	Author(s)	Year	Methodology	Main Findings
6	Arindam Bandyopadhay	2016	Multivariate logit and tobit regression on bank lending data	Education loan defaults are mainly influenced by security, borrower margin, and repayment periods. The presence of guarantor or co-borrower and collateral significantly reduce default loss rates. The socioeconomic characteristics of borrowers and their regional locations also act as important factors associated with education loan defaults. The results suggest that by segmenting borrowers by probability of default and loss given default in a multi-dimensional scale, banks can adopt better risk mitigation and pricing strategies to resolve borrower problems.
7	Looney and Yannelis	2015	Logistic regression analysis	Types of institution, debt level and labour market conditions explain a large share of the rise in student loan default in U.SA.

Appendix Table 4: Default Rate in Selected Banks

(Per cent)

Sl. No.	Proportion of NPA	Bank A	Bank B	Bank C
1	Overall	20.94	9.6	43.62
2	Subsidy eligible loans	18.62	9.22	52.63
3	Non-subsidised loans	27.05	10.78	37.65
4	Rural	21.37	9.27	60.68
5	Semi-urban	20.38	9.4	39.33
6	Urban	21.97	8.57	43.23
7	Metropolitan	20.93	19.61	25.62
8	Male	20.65	9.98	46.91
9	Female	20.66	8.88	37.13
10	Above median income	14.42	9.07	20.10
11	Below median income	25.2	10.07	55.67

Appendix Table 5: Box-Tidwell Regression Results for Bank C

Continuous Variables	Nonlinear Deviation	P value	P_1
ln_inc	75.099	0.000	4.660
ln_int	5.784	0.016	4.239
in_dur	0.125	0.724	1.286

Appendix Table 6: Collinearity Diagnostics

	Bank A		Bank B		Bank C	
	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
Ln_dur	1.010	0.992	1.000	0.998	1.070	0.933
Ln_inc	1.020	0.990	1.000	0.999	1.100	0.910
Ln_int	1.020	0.983	1.000	0.999	1.030	0.971
Mean VIF	1.010		1.000		1.070	

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An Alternative Measure of Economic Slack to Forecast Core Inflation

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Assessing macroeconomic demand conditions is critical for monetary policy to gauge imminent inflationary pressures. Generally, measures of output gap, calculated by applying statistical filters on GDP data, are used for this purpose. GDP data, however, are released only at quarterly frequency with a lag of approximately two months. This paper proposes an alternative indicator of economic slack that captures demand conditions efficiently and is also available at higher frequency. A macroeconomic demand index constructed for this purpose using a rich set of high frequency (monthly) indicators emerges as a better predictor of core inflation than other measures.

JEL Classification: C32, C53, E31, E32, E37

Keywords: Demand index, Phillips curve, factor model, inflation forecast

Introduction

Traditionally, output gap and capacity utilisation are widely used to assess economic slack. Output gap is generally calculated by applying statistical filters (Hodrick-Prescott, Band-Pass, Multivariate Kalman Filter, *etc.*) on GDP data, while capacity utilization is derived mainly from surveys on corporate performance. One of the biggest limitations of these measures, however, is that they are available with a time lag. The national accounts data for any quarter is released with a lag of approximately two months after the end of the reference quarter. Similarly, data on capacity utilization from the Order Books,

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Inventories and Capacity Utilisation Survey (OBICUS) of RBI is released with a lag of more than one quarter. In view of the importance of inflation forecasts to the conduct of monetary policy under a flexible inflation targeting (FIT) framework, and the well-established role of economic slack in influencing the near-term evolution of the inflation trajectory, it is useful to explore alternative measures which not only capture economic slack efficiently, but also can be available at higher frequency. This paper attempts to create a macroeconomic demand index using a set of high frequency indicators (HFIs), which are available at monthly frequency.

We use an unobserved components model that combines a Bayesian dynamic factor model (DFM) with a Phillips curve equation to estimate the measure of economic slack. While the Bayesian dynamic factor model extracts a common factor from various high frequency indicators, the Phillips curve equation ensures that this common factor contains information about inflation dynamics. The idea is to estimate not just any measure of economic slack but one that closely resembles inflationary pressures.

In the second part of the paper, we test the predictive ability of the estimated demand index by assessing the inflation-forecasting performance of the constructed demand index *vis-à-vis* other measures of excess demand like HP filtered output gap and capacity utilization. The forecasting performance assessment exercise clearly establishes the superior predictive power of the constructed measure of economic slack relative to conventional measures of demand.

The organisation of the remaining part of the paper is as follows. Section II surveys the relevant literature. Section III describes the econometric model used in the paper. Section IV explains the methodology. Section V presents the empirical results and section VI concludes.

Section II
Literature Survey

The multivariate unobserved components model used in this paper is a synthesis of two different strands of literature – DFMs and Phillips curve. DFMs have been used widely to construct indices of economic activity and more recently to nowcast GDP (Stock and Watson, 1989; Giannone, Reichlin and Small, 2008 in the international context and Biswas, Banerjee and Das, 2012; Bhadury, Ghosh and Kumar, 2020 in the Indian context). Our paper is related to this strand of literature but with one important distinction. We are concerned not only with obtaining the estimate of real activity, but also whether that estimate contains important information about inflationary pressures. In order to incorporate this into the model, we introduce the Phillips curve equation (relating inflation and output gap) into the Bayesian DFM state-space framework. Several studies have used a bivariate framework to extract output gap by using a Phillips curve equation along with the equation relating actual and potential output. Kuttner (1994) initiated this literature by using a bivariate unobserved components model to estimate potential output. Planas (2008) estimated a Bayesian version of Kuttner's model. Building upon this framework, Jarocinski and Lenza (2015) used a DFM equation in the bivariate model to extract the output gap from multiple indicators of economic activity and forecasted core inflation using it. We follow a similar approach.

In doing so, we borrow from the extensive literature on Phillips curve, both in India and abroad. In the Indian context, several studies have found support for the Phillips curve hypothesis (Patra and Kapur, 2012 using WPI data and Behera, Wahi and Kapur, 2017 using CPI data). The specification of the Phillips curve equation in our model draws from these studies, but is estimated using a state-space framework.

Section III
The Econometric Model

We construct a macroeconomic demand index that contains useful information about inflationary pressures. We use the following multivariate unobserved components model to extract the measure of economic slack.

$$y_{i,t} = \lambda_i . DI_t + shock_{i,t}^{idiosyncratic}$$

$$\pi_t = \pi_t^{trend} + a(L). DI_t + z_t + \epsilon_t$$

The first equation represents a Bayesian dynamic factor model wherein $y_{i,t}$ represents high frequency indicators of economic activity (passenger vehicles sales, IIP consumer durables *etc*.), and the common factor is represented by the demand index, DI. Since our objective is to obtain a real-time measure of economic slack, we use only high frequency indicators that are available at monthly frequency, rather than GDP which is available only at quarterly frequency and with a substantial time lag. One way of getting around this issue could be to use GDP forecasts. However, several papers including Bhadury, Ghosh and Kumar (2020) have used HFIs instead of GDP and we follow a similar approach. The dynamic factor model (DFM) represents the evolution of a vector of N observed series in terms of a reduced number of unobserved common factors which evolve over time, plus uncorrelated disturbances which represent measurement error and/or idiosyncratic dynamics of the individual series (Stock and Watson, 2010). This equation suggests that short-run dynamics in all high frequency indicators of economic activity have a common component, besides their own idiosyncratic shocks ($shock_{i,t}^{idiosyncratic}$).

The second equation represents the Phillips curve relationship which relates inflation (π_t) to its trend (π_t^{trend}), demand side dynamics captured by the demand index (DI), and a vector of supply controls (z_t). The lag operator, L allows for contemporaneous as well as lagged relations. ϵ_t represents the Gaussian error term. We use this set-up to estimate the unobserved demand index.

In order to capture the common cyclical dynamics parsimoniously, the demand index is assumed to follow unobserved AR(2) process,

$$DI_t = \phi_1 DI_{t-1} + \phi_2 DI_{t-2} + e_{t,DI}$$

where ϕ_1, ϕ_2 are the autoregressive coefficients and $e_{t,DI}$ is a white-noise with zero mean and constant variance (σ_{DI}^2). Idiosyncratic movements in HFIs which is captured by $shock_{i,t}^{idiosyncratic}$ is assumed to be AR(1) process,

$$shock_{i,t}^{idiosyncratic} = \rho_i . shock_{i,t-1}^{idiosyncratic} + e_{i,t}$$

The supply shocks are also assumed to follow AR(1) process,

$$z_t = \rho_z . z_{t-1} + e_{z,t}$$

where ρ_i, ρ_z denote the autoregressive coefficients and e_i, e_z denote the corresponding white noise terms.

Section IV
Estimation Strategy

After specifying the broad modelling framework in the previous section, we turn to the detailed methodology in this section. The first sub-section explains the identification strategy; sub-section 2 describes the exact specification of the Phillips curve equation; sub-section 3 relates to the selection of HFIs; sub-section 4 presents the final specification and estimation technique of the model, and the last sub-section describes the data.

IV.1 The identification strategy

The broad identification strategy for our empirical estimation rests on the following premise. First, various types of high frequency indicators possess some common information about the macroeconomic demand conditions. Second, core inflation in India reacts well to changing demand conditions, which means there exists a robust Phillips curve type relationship between them.

The first assertion is validated by the way in which we select our high frequency indicators. The second presumption gains credibility from the vast Indian literature which suggests that there exists a robust Phillips curve relationship in India both for core and headline inflation (Kapur and Patra, 2010; Behera, Wahi and Kapur, 2017; Pattanaik, Muduli and Ray, 2019). Taking a cue from these studies, we also estimate the Phillips curve for core inflation using a state-space framework. This not only reinforces the literature but also guides us about the exact specification to be used later for estimation of demand index.

IV.2 The Phillips Curve

We begin with the classic "triangle" model of inflation (Gordon, 1997), which relates inflation to three basic determinants: inertia, excess demand and supply shocks.

$$\pi_t = Inertia + b(L).Index_t^{demand} + shocks_t^{supply} + \epsilon_t$$

Where π refers to inflation, L is the lag operator and ϵ is the random error.

In using this framework for our purpose, we face four major modelling choices: (i) Which measure of inflation should be used, headline or core?; (ii) What is the measure of excess demand to be used?; (iii) What are the supply shocks, if any, to be included?; and (iv) How to capture the inertia component? To resolve these queries, we take guidance from the literature. Where the literature does not provide a clear-cut answer, we decide based on the forecasting performance (for inflation) of alternate measures/specifications. Given that we are primarily concerned about the ability of the demand index in assessing inflationary impulses, inflation forecasting ability seems to be an appropriate test to determine the reliability of the model. Thus, forecasting performance is used as the metric of evaluation to decide upon the correct specification.

We use inflation excluding food and fuel (also referred to as core inflation) as our measure of inflation. Core inflation is expected to be more responsive to demand conditions as it is relatively immune to supply side shocks emanating from food and fuel sectors. This has been corroborated by various studies which find that the impact of excess demand is higher on core inflation compared to headline inflation (Kapur, 2012; Behera *et al*., 2017). We, therefore, use core inflation to extract information about excess demand/economic slack in the economy.

For the measure of excess demand, both output gap and unemployment gap have been used in the literature. Okun's Law holds that the output gap and unemployment gap are closely related. Accordingly, we use HP filtered output gap (applied on real GDP) as a proxy for demand. According to Gordon (1997), inflation depends not only on the level but also on the change in excess demand, and models that do not include the change variable are misspecified. In order to account for the rate-of-change effect, we include both contemporaneous and lagged value of output gap in our specification.

We now turn to the inclusion of supply shocks. We use core inflation as our measure of inflation which largely excludes supply-side inflationary pressures like food and fuel. However, CPI excluding food and fuel includes petrol and gold whose movements are largely determined by supply factors. Some other supply controls that are widely used in the literature include exchange rate and crude-oil inflation. Food inflation has also been included as a control variable in a few studies to assess potential spillovers to core inflation (Behera *et al*., 2017). In order to choose the exact specification of our Phillips curve equation, we use the state-space framework with alternative combinations of all these control variables (change in exchange rate, gold, petrol, food and crude oil prices). We compare the forecasting performance of these specifications and conclude that a specification with only exchange rate is the best specification as it has superior forecasting performance (Table 1).

Turning next to the inertia component, we observe that it has been modelled in various ways in the literature. While Gordon (1997) simply used the lagged values of inflation to capture the inertia, hybrid versions of the New Keynesian Phillips Curve (NKPC) have used a combination of forward and backward looking variables (Gali and Gertler, 1999). In the Indian context, Patra *et al*. (2014) used lagged inflation along with one-period lead inflation in the estimation of the NKPC equation, Behera *et al.* (2017) used only the lagged inflation term to estimate the Phillips curve equation, and Pattanaik *et al.* (2019) used survey-based household inflation expectations in the Phillips curve specification.

In our model, we define inertia in three alternate ways and then check for their forecasting performance in order to select the best specification. In the first case, we use lagged inflation as the measure of inertia in the tradition of Gordon (1997). In the second case, we follow the approach of Jarocinski

Table 1: Relative RMSE of alternate specifications

Model Specification	**Relative RMSE**
No supply shocks + **inertia** (trend inflation)	1
No supply shocks + inertia (inflation expectations)	1.29
No supply shocks + inertia (lagged inflation)	2.13
Supply shocks (petroleum inflation, gold inflation, food inflation, change in rupee-dollar exchange rate) + **inertia** (trend inflation)	0.92
Supply shocks (petroleum inflation, gold inflation, lagged food inflation, lagged change in rupee-dollar exchange rate) + **inertia** (trend inflation)	1.07
Supply shocks (petroleum inflation, change in rupee-dollar exchange rate) + **inertia** (trend inflation)	0.91
Supply shocks (petroleum inflation) + **inertia** (trend inflation)	1.03
Supply shocks (change in rupee-dollar exchange rate) + **inertia** (trend inflation)	**0.87**
Supply shocks (Indian basket crude oil inflation, change in rupee-dollar exchange rate) + **inertia** (trend inflation)	0.88
Supply shocks (Indian basket crude oil inflation) + **inertia** (trend inflation)	1.04

Source: Authors' Estimates.

and Lenza (2015) to model inertia using trend inflation. The trend inflation is assumed to be a random walk process without drift, specified as follows:

$$\pi_t^{trend} = \pi_{t-1}^{trend} + e_{t,\pi^{trend}}$$

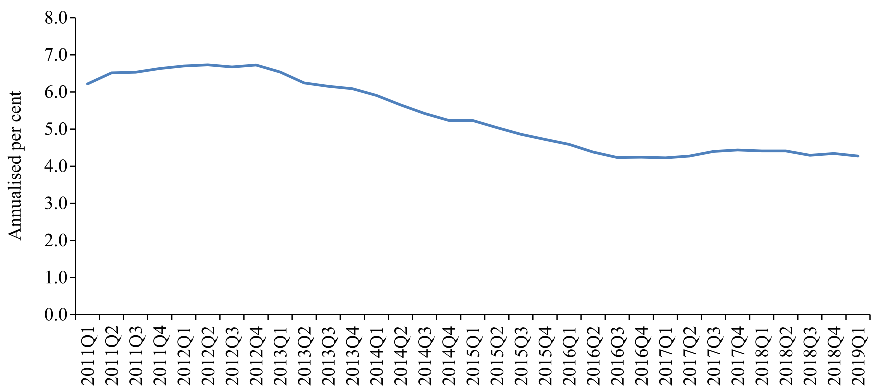
A number of studies have modelled trend inflation as a random walk process (Cogley *et al*., 2010; Stock and Watson, 2007). Defining it in this way removes restriction imposed by mean-reversion associated with stationary specification. Since trend inflation is a medium-term concept that is relatively unaffected by short-term dynamics, a random walk process results in a smoother estimate (Chart 1).

Another way of modelling trend inflation is to relate it to long-run inflation expectations (Faust and Wright, 2013; Clark and Doh 2014; Jarocinski and Lenza, 2015). We follow this approach in the third case, wherein trend inflation is again used as the measure of inertia, but this time it is modelled using household inflation expectations. Accordingly, we use the following equation to derive trend inflation:

$$\pi_t^e = c + \pi_t^{trend} + u_t^e$$

Where, π^e refers to inflation expectations of households, π^{trend} is the trend inflation, and u^e is the Gaussian error term. The constant term, c is included to reconcile two important distinctions between inflation expectations

Chart 1: Trend Inflation (Estimate)



Source: Authors' Estimates using CPI-Core.

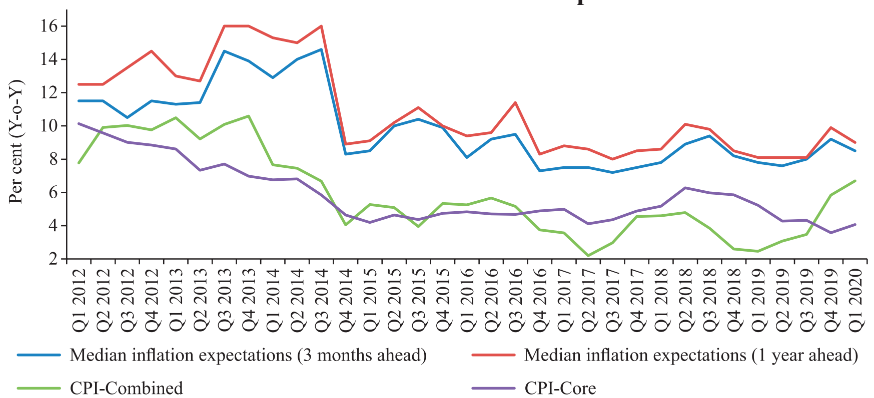
and trend inflation. First, household inflation expectations refer to headline inflation, while the trend inflation in our model is defined in terms of core inflation. Second, household inflation expectations in India have remained above actual inflation, even though the change in inflation expectations may hold important information about the change in actual inflation (Chart 2). The constant term accounts for these factors by allowing a level difference between trend inflation and inflation expectations.

In addition to these alternate measures of intrinsic persistence, lags of demand index/output gap are also used to account for extrinsic persistence. We then estimate the Phillips curve equation and forecast core inflation using these alternate specifications. The specification with trend inflation modelled as a random walk process has the best root mean squared error (RMSE) score among the competing specifications (Table 1). Trend inflation that incorporates inflation expectations does not improve upon the forecasting performance. This is in line with Pattanaik *et al.* (2019) who find that 'the overall explanatory powers of NKPC models with household inflation expectations do not improve relative to similar models with backward looking inflation expectations'. We therefore, specify inertia in our model as trend inflation which is a random walk process without drift.

This gives us the final specification of the Phillips curve as follows,

$$\pi_t^{core} = \pi_t^{trend} + \beta_1 . Index_t^{demand} + \beta_2 . Index_{t-1}^{demand} + \beta_3 . \Delta USD_t + \epsilon_{t,\pi^{core}}$$

Chart 2: Inflation and Inflation Expectations



Sources: NSO, RBI.

IV.3 Selection of High-frequency Indicators

Having finalised the specification of the Phillips curve, we turn to the selection of high frequency indicators. There exist a variety of high-frequency indicators covering different aspects of the economy. The choice of HFIs, therefore, becomes important in order to have a parsimonious specification without losing out on information content. In order to select the HFIs, we broadly follow two steps. First, we peruse the literature to short-list the indicators that could potentially hold relevant information about demand conditions. Second, since we are primarily concerned with obtaining a demand index that can predict core inflation reasonably well, we check the correlation of these indicators with core inflation and HP filtered output gap (henceforth, HP-gap). We select those HFIs which are found to be significantly correlated with core inflation or the output gap.

The literature on coincident economic indicators makes use of a variety of high-frequency indicators (see Bhadury *et al*., 2020 for a detailed survey). We categorise the high-frequency indicators generally used in the literature into the major components of demand: consumption, investment, government spending, and trade.[1] HFIs that cannot be binned into these categories but may be potentially useful to capture demand conditions are listed in the miscellaneous category (Table 2).

Table 2: Classification of HFIs under major heads of aggregate demand

Consumption	Investment-based	Government Spending	Trade	Miscellaneous
• IIP consumer goods o Durables o Non-durables • Petroleum consumption • Passenger vehicle sales • Two-wheeler sales • Government tax revenue • Air passenger traffic (domestic)	• IIP general • IIP intermediate goods • IIP capital goods • IIP basic goods • Commercial vehicle sales • Crude steel production • Cement production • Farm tractor sales	• Government total expenditure • Government revenue expenditure	• Non-oil imports • Non-oil exports	• Non-food bank credit • M3 (broad money) • 91 T-bill yield • Railway freight

[1] Another way to choose HFIs could be based on the sectors (agriculture, industry, services) to which they belong.

Since the emphasis is to estimate a measure of economic slack, we work with the cyclical dynamics present in each HFI, extracted using HP-filter. As a first round of screening, we check the contemporaneous correlation of respective HFIs with HP-gap (Table 3).

Out of these 23 HFIs, six HFIs (freight traffic, SCB non-food credit, M3, 91 T-bill yield, IIP intermediate, and non-oil exports) are contemporaneously negatively correlated with the HP-gap. In order to check the possibility that these HFIs may be associated positively with lead/lag of HP-gap, we calculate the respective cross-correlations. We find that these HFIs are either uncorrelated or negatively correlated with HP-gap at all appropriate lead-lag (Table A.1). From this, we conclude that these HFIs do not possess relevant information about the excess demand in the economy and rather show idiosyncratic dynamics for our period of study. For the remaining 17 HFIs, we also compute correlation with core inflation to assess if they possess information about inflation pressures (Table A.2). We finally obtain a list of 12 HFIs comprising of two-wheeler sales, domestic passenger vehicle sales, domestic commercial vehicles sales, tractor sales, petrol consumption, crude-steel production, air-passenger traffic, IIP-basic, IIP-capital, IIP-consumer durables, IIP- consumer

Table 3: Correlation of HFIs with HP-filter output gap

HFI	Correlation with HP-gap	HFI	Correlation with HP-gap
Domestic Two Wheelers Sales	0.45***	SCB Non Food Credit	-0.56***
Domestic Passenger Vehicle Sales	0.63***	M3	-0.34**
Domestic Commercial Vehicle Sales	0.46***	91 T-bill avg. yield	-0.31**
Farm Tractor Sales	0.11	IIP Basic	0.60***
Freight Traffic	-0.30**	IIP Capital	0.52***
Petroleum Consumption	0.63***	IIP Intermediate	-0.25
Crude Steel Production	0.38*	IIP Consumer durables	0.51***
Cement Production	0.02	IIP Consumer non-durables	0.23
Passenger Traffic Domestic	0.74***	IIP General	0.55***
Government Tax Revenue	0.09	Government Total Expenditure	0.06
Government Revenue Expenditure	0.04	Non-oil Exports	-0.05
Non-oil imports	0.15		

Note: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.
Source: Authors' Estimates.

non-durables, IIP-general, that are found to be significantly correlated with either output gap or core inflation. These 12 HFIs are used to compute our first measure of economic demand, which we name DI-12.

Of these 12 HFIs, 4 HFIs (sales associated with two wheelers, passenger vehicles, commercial vehicles and farm tractors) pertain to the automobile industry. On the one hand, this may be beneficial for our case, as these kinds of sales form a good indicator of the private macroeconomic demand. On the other hand, this also opens up the risk of making one-third of the total HFIs prone to fluctuations in one industry. This may prevent our estimate from being representative of the entire economy. We believe that the degree of this trade-off will depend on whether these four HFIs are well correlated among themselves or not. In case they are highly correlated among themselves, the estimation of latent factor may become more biased towards dynamics common to the automobile sector.

We find that HFIs pertaining to the automobile sector are well correlated among themselves (Table 4). Two-wheeler sales share the highest correlation on an average with other sectoral HFIs. Moreover, commercial vehicle sales and passenger vehicle sales not only share a high correlation among each other, but also show nearly same level of average correlation with their sectoral counterparts. This suggests that the two HFIs possess almost similar kind of dynamics and removing one of them will not lead to a substantial loss of information.

In order to reduce the possible bias of the latent factor, we consider a case in which we drop passenger vehicle sales and two-wheeler sales from the list

Table 4: Correlation among HFIs in the automobile sector

	Two-wheelers	**Passenger vehicles**	**Commercial vehicles**	**Farm tractors**
Two-wheelers	1			
Passenger vehicles	0.67	1		
Commercial vehicles	0.61	0.72	1	
Farm tractors	0.63	0.37	0.38	1
Average Correlation with other Automobile Industry HFIs	0.64	0.59	0.57	0.46

Source: Authors' Estimates.

of HFIs used for the estimation. Thus, we estimate our model using two sets of HFIs. One set includes all the 12 HFIs (DI-12) while the other set uses 10 HFIs (DI-10) after excluding passenger vehicle sales and two-wheeler sales[2].

IV.4 Final Specification and Estimation

Based on the above analysis, we obtain the final specification of the state space model as follows:

$$HFI_{i,t} = \lambda_i . DI_t + shock_{i,t}^{idiosyncratic} \quad .... (1)$$

$$\pi_t^{core} = \pi_t^{trend} + \beta_1 . DI_t + \beta_2 . DI_{t-1} + \beta_3 . \Delta USD_t + e_{t,\pi^{core}} \quad .... (2)$$

$$DI_t = \phi_1 DI_{t-1} + \phi_2 DI_{t-2} + e_{t,DI} \quad .... (3)$$

$$\pi_t^{trend} = \pi_{t-1}^{trend} + e_{t,\pi^{trend}} \quad .... (4)$$

$$USD_t = \rho_{USD} . USD_{t-1} + e_{USD,t} \quad .... (5)$$

Where, ϕ_1, ϕ_2, ρ_{USD} are the autoregressive coefficients. We use Bayesian techniques to estimate parameters and factors of the dynamic factor model. As delineated by Otrok and Whiteman (1998), the essential idea is to determine posterior distributions for all unknown parameters conditional on the latent factor and then determine the conditional distribution of the latent factor given the observables and the other parameters. That is, the observable data are augmented by samples from the conditional distribution for the factor given the data and the parameters of the model. Specifically, the joint posterior distribution for the unknown parameters and the unobserved factor can be sampled using a Markov Chain Monte Carlo procedure on the full set of conditional distributions. So the conditional distribution for the factors f_t and parameters $\theta = (\lambda, \psi, \Gamma_e, \Gamma_\eta)$ are $f \mid \theta, X$ and $\theta \mid f, X$, where $X = (x_{p+1}, \ldots, x_n)$.

The Markov chain samples sequentially from the conditional distributions for (parameters/factors) and (factors/parameters) and, at each stage, uses the previous iterations drawing as the conditioning variable, ultimately yields

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[2] We also consider an alternative case wherein we drop IIP-general as it is found to be highly correlated with the other IIP indices and may result in bias of the latent factor. The estimate demand index in this case (DI-9), however, does not perform better than DI-12 and DI-10 in predicting core inflation.

drawings from the joint distribution for (parameters, factors). Thus, the joint distribution conditioned on the *p* first observations can be approximated by,

$$L\big(X, F \mid \lambda, \psi, \Gamma_e, \Gamma_\eta, x_1, \ldots\ldots, x_p, f_1, \ldots\ldots, f_p \big)$$

$$\propto \quad \Pi_{t=p+1}^{n} \mid \Gamma \mid^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2}(X_t - \lambda(L) f_t)' \Gamma_{\mathrm{e}}^{-1} (X_t - \lambda(L) f_t) \right\}$$

$$\times \quad \mid \Gamma_\eta \mid^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2}(f_t - \psi(L) f_{t-1})' \, \Gamma_\eta^{-1} (f_t - \psi(L) f_{t-1}) \right\}$$

For the estimation, we choose loose priors so that the estimated parameters are determined more by the data, rather than by the choice of the priors (Table 5).

IV.5 Data

The data used in the paper pertains to 23 HFIs listed in Table 3, and also output gap, core inflation, food inflation, change in exchange rate, crude oil inflation, gold inflation and petroleum inflation for the period 2011:Q1 to 2019:Q4. The data description and sources are presented in appendix Table A.3.

While the HFIs and price indices used in the paper are available at monthly frequency, most of the empirical analysis is carried out using data aggregated

Table 5: Parameter Estimates

	Parameter	Prior Distribution	Prior Mean	Prior SD	Posterior Mean (with 12 indicators)	Posterior Mean (with 10 indicators)
Philips curve:	β_1	Beta	0.150	0.09	0.1287	0.1308
Core Inflation	β_2	Beta	0.150	0.09	0.1101	0.1051
	$\sigma_{\pi^{core}}$	Gamma	0.005	0.004	0.0036	0.0035
Demand	ϕ_1	Normal	0	0.9	1.1255	0.9541
Index	ϕ_2	Normal	0	0.9	-0.3495	-0.2463
	σ_{DI}	Gamma	0.005	0.004	0.0040	0.0044
Trend Inflation	$\sigma_{\pi^{trend}}$	Gamma	0.005	0.004	0.0014	0.0014
Supply Controls	ρ_{USD}	Beta	0.5	0.15	0.3382	0.3395
	σ_{USD}	Gamma	0.02	0.01	0.0321	0.0322

Source: Authors' Estimates.

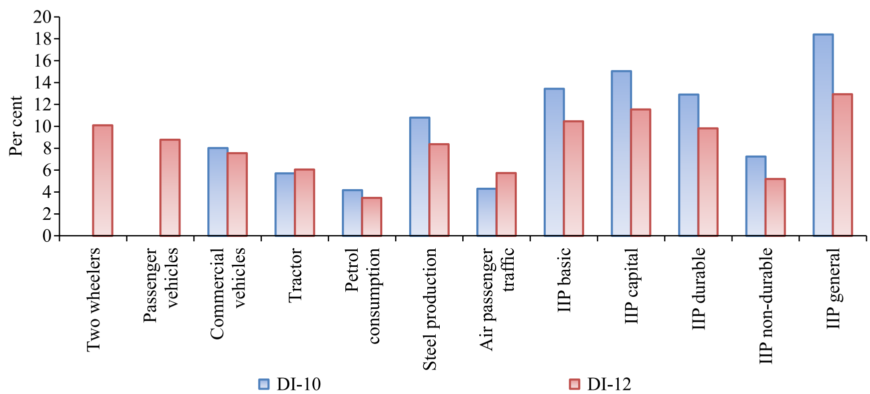
to quarterly frequency. This is done to ensure comparability of the estimated results with other conventional measures of slack, which are available only at quarterly frequency. The data transformation associated with HFIs includes aggregating them to quarterly frequency, taking log, de-seasonalizing using X-13 ARIMA and finally applying HP-filter to extract cyclical dynamics. The inflation figures are calculated by aggregating monthly price indices to quarterly frequency, taking log, de-seasonalising them using X-13 ARIMA, and then taking the first difference. This yields the quarter-on-quarter inflation figures.

Section V
Results

The posterior estimates of some important parameters[3] are presented in Table 5. Results pertaining to different variants of the model (DI-10 and DI-12) suggest that the estimated parameters are robust (in general) to the choice of HFIs used in the model. This adds credibility to our estimation.

The normalized factor loadings across the two sets of demand indicators are shown in Chart 3. Factor loadings show the contribution of different economic indicators in the estimated demand index. Broadly, the economic indicators related to IIP constitute the highest share in the demand index

Chart 3: Normalized Factor Loadings



Source: Authors' Estimates.

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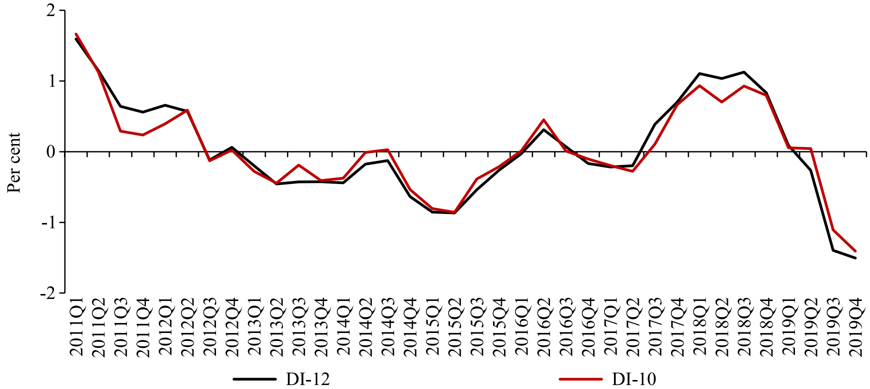
3 The prior-posterior plots are presented as Chart A.1 in the appendix.

Chart 4: Demand Indices

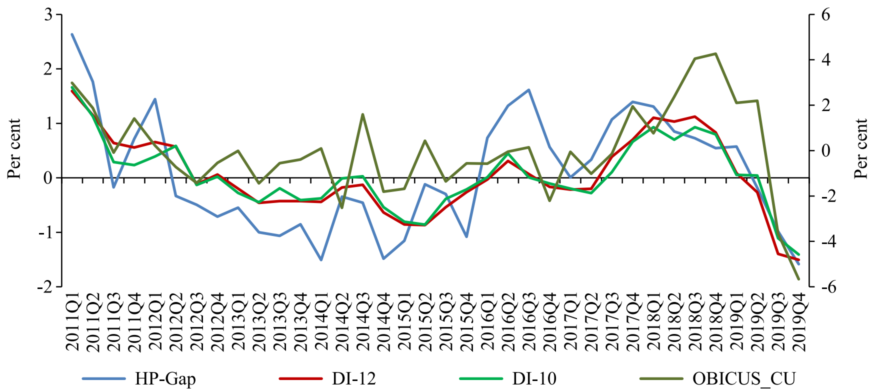


Source: Authors' Estimates.

followed by crude steel production and automobile sales indicators. The time-varying estimates of the estimated demand indices are plotted in Chart 4.

The estimated demand indices are found to move closely with the conventional measures of economic slack such as HP-gap and capacity utilization from the OBICUS[4] (Chart 5).

Chart 5: Different measures of economic slack



Sources: NSO, RBI and Authors' Estimates.

[4] HP-filtered OBICUS CU cycle is used for the analysis in the paper.

Table 6: Correlation between Core Inflation and Different Measures of Economic Slack

	Demand Index (12-indicator)	Demand Index (10-indicator)	HP Output Gap	OBICUS Capacity Utilization	Core Inflation
Demand Index (12-indicator)	1				
Demand Index (10-indicator)	0.98	1			
HP Output Gap	0.79	0.81	1		
OBICUS Capacity Utilisation	0.76	0.77	0.59	1	
Core Inflation	0.49	0.45	0.26	0.28	1

Source: Authors' Estimates.

The estimated demand indices are also found to be well correlated with HP-gap and OBICUS CU (Table 6). In terms of correlation with core inflation, both demand indices are found to be better than both HP-gap and OBICUS CU.

Further, regression analysis suggests that the estimated demand indices have greater explanatory power than other conventional measures of demand (Table 7).

Table 7: Regression Estimates

	(1)	(2)	(3)	(4)
	pi_core	**pi_core**	**pi_core**	**pi_core**
AR(1)	0.973^{***}	0.973^{***}	0.973^{***}	0.969^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
MA(1)	-0.963^{***}	-0.962^{***}	-0.999^{***}	-0.957^{***}
	(0.017)	(0.016)	(0.000)	(0.019)
DI-12	0.314^{***}			
	(0.089)			
DI-10		0.362^{***}		
		(0.102)		
HP-gap			0.116^{*}	
			(0.0635)	
OBICUS_CU				0.089^{***}
				(0.030)
Adj. R^2	0.651	0.650	0.557	0.613
N	35	35	35	35

Note: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;
ARIMA specification has been chosen based on SIC criterion.
Source: Authors' Estimates.

V.1 Forecasting Exercise

In this section, we evaluate various measures of economic slack in terms of their performance in forecasting core inflation, following Coenen, Smets, and Vetlov (2009). As a first step, we determine the ARIMA specification that best describes the data generating process of core inflation. We use this ARIMA specification for generating 1 to 4 quarters-ahead rolling forecasts. Subsequently, we nest this ARIMA specification with different measures of economic slack to form different bivariate models (of core inflation and economic slack measures). The forecasting performance of these different bivariate models are then evaluated and compared to know whether inclusion of economic slack helps predict core inflation better or not. If it does, then which measure of economic slack does it the best? These are some of the questions which have direct practical utility for the central bank.

The general specification of the bivariate model is as follows,

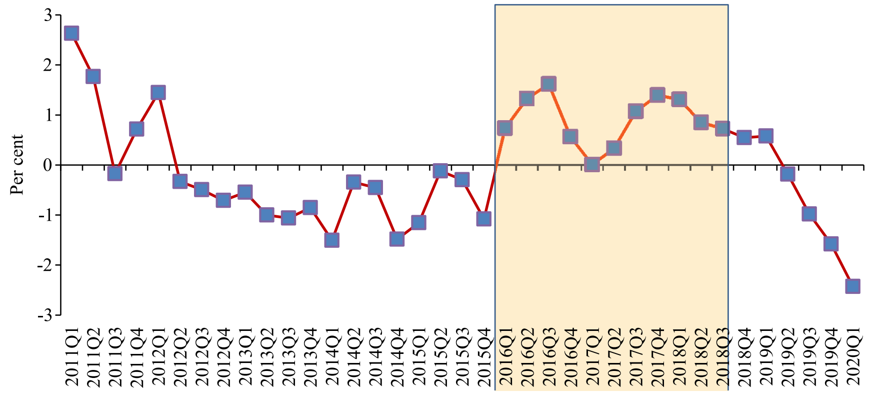
$$\pi_{t+h}^{core} = a + b(L).\pi_t^{core} + Index_t^{economic\ slack} + e_{t+h}$$

where π_{t+h}^{core} is the h-period ahead quarter-on-quarter CPI core inflation, a is the constant term, $b(L)$ is the lag polynomial. Parameters are estimated using ordinary least squares on recursive samples from 2011:Q1 to 2015:Q4 through 2011:Q1 to 2018:Q4. We then calculate the root mean square forecast errors (RMSE) of the bivariate models and a univariate ARIMA model of inflation at forecast horizons (h) of one, two, three and four quarters ahead.

Total number of rolling samples are 13 while total length of our data is 36 quarters (2011Q1-2019Q4). This means we practically use 36 per cent of our data in conducting and evaluating out-of-sample forecasts. Moreover, the period 2015:Q4 to 2018:Q4 includes both upturns and downturns in economic slack (Chart 6).

This ensures that forecasting evaluation/performance is independent of the state of the economic slack, and lends robustness and credibility to our forecasting results. The indicative charts for rolling forecast evaluation are presented below (Chart 7).

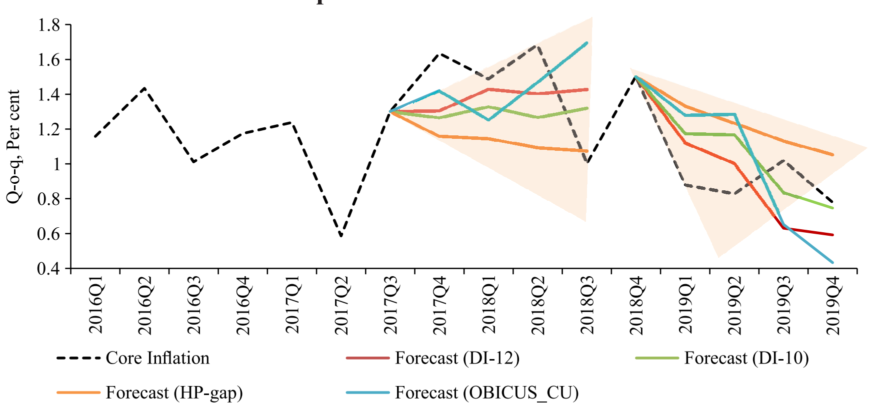
Chart 6: HP-Output Gap



Source: Authors' Estimates.

RMSE results are presented in Table 8. The results suggest that inclusion of economic slack generates mixed results as far as forecasting core inflation is concerned. While model with OBISCUS CU performs badly than univariate ARIMA, model with HP-gap performs better than ARIMA at two, three and four quarter-ahead horizons. However, the estimated demand indices (DI-10, DI-12) perform better than ARIMA and model with HP-gap at all forecasting horizons. Moreover, among the two, DI-10 performs better, making it the best forecaster of core inflation given the framework and time-period considered in our study.

Chart 7: Comparison of Core Inflation Forecasts



Source: Authors' Estimates.

Table 8: RMSE of Forecasts

Specification	Forecast Horizon			
	Q1	Q2	Q3	Q4
ARIMA	0.352	0.387	0.416	0.463
HP Output gap	0.359	0.372	0.412	0.410
OBICUS capacity utilisation	0.413	0.461	0.504	0.499
Demand Index (12-indicators)	0.348	0.355	0.396	0.391
Demand Index (10-indicators)	0.320	0.333	0.362	0.370

Source: Authors' Estimates.

Section VI
Conclusion

Assessing macroeconomic demand conditions is critical for monetary policy to gauge imminent inflationary pressures. Generally, measures of output gap, calculated by applying statistical filters on GDP data, are used for this purpose. However, one of the limitations of these conventional measures of output gap is that the national accounts data used in their calculation are released only at quarterly frequency with a lag of approximately two months. In this paper, we create a macroeconomic demand index using a rich set of high frequency (monthly) indicators by employing a multivariate unobserved components model. In doing so, we face a number of modelling choices regarding different specifications of the structural model, variables used, and assumptions about the underlying structural processes. We resolve these questions based on the forecasting ability of the alternate specifications. We find that the demand index constructed in this paper is a better predictor of core inflation than conventional measures of economic slack like HP-gap and capacity utilization.

The constructed measures of demand conditions, not only provide lead information about the state of economic slack in the economy, but also seem to be an important indicator of inflationary pressures.

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Appendix

Table A.1: Correlation with lead/lag of output gap

HFI	HP-gap(-2)	HP-gap(-1)	HP-gap	HP-gap(+1)	HP-gap(+2)
Freight Traffic	-0.28 (0.12)	-0.31 (0.09)	-0.30 (0.09)	-0.43 (0.01)	-0.56 (0.00)
SCB Non Food Credit	-0.39 (0.03)	-0.47 (0.01)	-0.56 (0.00)	-0.62 (0.00)	-0.66 (0.00)
M3	-0.22 (0.23)	-0.24 (0.18)	-0.34 (0.06)	-0.31 (0.09)	-0.25 (0.17)
91 T-bill avg. yield	-0.02 (0.91)	-0.20 (0.27)	-0.31 (0.09)	-0.35 (0.05)	-0.56 (0.00)
IIP Intermediate	-0.57 (0.00)	-0.35 (0.05)	-0.25 (0.16)	-0.36 (0.04)	-0.29 (0.11)
Non-oil Exports	0.07 (0.69)	0.10 (0.60)	-0.05 (0.79)	-0.24 (0.20)	-0.25 (0.18)

Note: Figures in parenthesis are p-values.

Table A.2: Correlation with core inflation

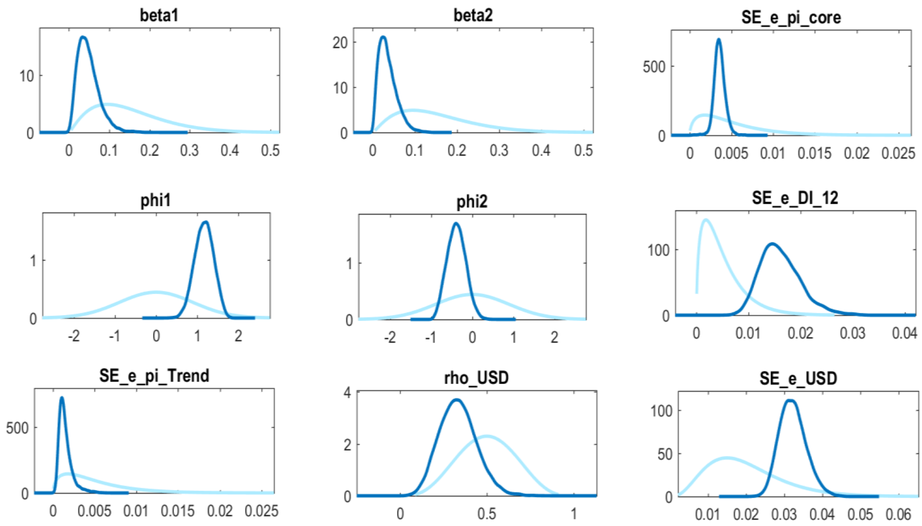
HFI	Correlation with core inflation	HFI	Correlation with core inflation
IIP Basic	0.41 (0.0185)	Farm Tractor Sales	0.32 (0.0717)
IIP Capital	0.41 (0.0212)	IIP General	0.46 (0.0088)
Cement Production	0.14 (0.4593)	Government Total Expenditure	-0.10 (0.5758)
Crude Steel Production	0.31 (0.0852)	Government Revenue Expenditure	-0.13 (0.4906)
Domestic Commercial Vehicle Sales	0.48 (0.0058)	Non-oil imports	0.09 (0.6101)
Domestic Passenger Vehicle Sales	0.49 (0.0043)	IIP Consumer non-durables	0.30 (0.0927)
Domestic Two Wheelers Sales	0.39 (0.0290)	Passenger Traffic Domestic	0.42 (0.0172)
IIP Consumer durables	0.27 (0.1289)	Petroleum Consumption	0.28 (0.1205)
Government Tax Revenue	0.24 (0.1930)		

Note: Figures in parenthesis are p-values.

Table A.3: Data description and sources

Variable	Measure	Source
Output gap	HP-filtered Real GDP	Ministry of Statistics and Programme Implementation
23 high-frequency indicators	Listed in Table 2	CEIC
Core inflation	CPI combined excluding food and fuel	National Statistics Organization, Ministry of Statistics and Programme Implementation
Food inflation	CPI combined food inflation	National Statistics Organization, Ministry of Statistics and Programme Implementation
Change in exchange rate	Change in ₹/$ exchange rate	FBIL reference rate
Crude oil inflation	Change in Indian basket crude oil price in USD.	Petroleum Planning and Analysis Cell, Ministry of Petroleum and Natural Gas
Gold inflation	WPI-gold subgroup inflation	Office of the Economic Adviser, Ministry of Commerce and Industry
Petroleum inflation	WPI-petroleum subgroup inflation	Office of the Economic Adviser, Ministry of Commerce and Industry

Chart A.1: Prior and Posterior Plots of Select Parameters



Note: Light blue lines depict the priors and dark blue lines represent the posterior distributions; beta1 and beta2 are the coefficients of contemporaneous and lagged demand index in equation 2 (in the main text); phi1 and phi2 are the autoregressive coefficients in equation 3; rho_USD is the autoregressive coefficient in equation 5; SE_e_pi_core, SE_e_DI_12, SE_e_pi_Trend, SE_e_USD are the standard errors of the white noise terms in equations 2, 3, 4, and 5 respectively.

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Long Run Saving - Investment Relationship in India

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This paper revisits the Feldstein-Horioka puzzle for the Indian economy. Unlike the observed weakening of the association between saving-investment rates before the global financial crisis of 2008-09, the post-crisis period has witnessed a relatively stronger correlation between them. This outcome has implications in terms of the role of domestic saving in financing the investment requirement of the economy. The study finds that frictions in global financial markets, which manifest in the form of periodic financial crises, trigger shifts in saving-investment relationship. Besides raising the saving rate in the economy, it is also important to enhance the efficiency of the domestic financial system to improve allocation of resources and channelise savings for capital formation.

JEL Classification: E21, E22

Keywords: Saving, Investment, ARDL model, Capital flows

Introduction

For an emerging economy like India, the trajectory of economic growth remains significantly dependent on the pace of capital formation. Capital formation is the outcome of several factors including: (i) saving capacity of households; (ii) a deep and developed domestic financial market for effective and efficient financial intermediation; and (iii) high degree of capital mobility with the rest of the world. In India, domestic investment has generally

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remained higher than domestic savings, and the gap is met by foreign capital inflows within a comfortable level of current account deficit. While private non-financial and government sectors are net borrowers in the economy, the household sector is a net lender. At an aggregate level, households are typically net savers and net lenders. From the investment side, however, households act as entrepreneurs by investing in buildings, machinery, and equipment relating to their business as self-employed workers or sole proprietors (Prakash *et al.*, 2019). On the other hand, despite generating higher gross saving, private non-financial corporation is generally a deficit sector, contributing around 35 per cent of the total gross fixed capital formation.

The gap between domestic savings and investment is the current account balance, which has remained in the range of (-) 4.8 per cent to (+) 0.6 per cent of gross domestic product (GDP) in India. Excluding 2001-04, current account balance has always been in deficit, which is bridged by a surplus in the capital account or a depletion of foreign exchange reserves. While the current account is fully convertible, the capital account is partially convertible[1], which nevertheless has been gradually liberalised over the years.

The degree of capital mobility is a key indicator of a country's extent of financial integration with the rest of the world. As per Feldstein and Horioka (1980) (F-H), if a country's domestic investment is strongly correlated with domestic savings, the country cannot be considered as fully integrated, since savings do not move out of the domestic market seeking higher returns from the global market or flows in to bridge in the shortfall in domestic saving to finance investment options by obtaining better relative returns. Following F-H, many researchers found that India's saving and investment are highly correlated, suggesting this as a low level of capital mobility (Vuyyuri and Sakalya, 2005; Verma, 2007; Singh, 2008; Khundrakpam and Ranjan, 2010; Jangili, 2011; Yadav *et al.*, 2018). As the Indian economy gradually opened up after liberalisation, Khundrakpam and Ranjan (2010) found a relatively lower association between domestic savings and investment in the post-

[1] Capital account convertibility would mean that there is no restriction on the conversion of the domestic currency into a foreign currency to enable a resident to acquire any foreign asset or on the conversion of foreign currency to the domestic currency to enable a non-resident to acquire a domestic asset (RBI, 2015).

reform period than the pre-reform period. Their analysis, however, is limited to the period before the global financial crisis of 2007-09.

Since the global financial crisis, however, some fundamental changes have taken place. First, the role of the rest of the world as a net lender to India has diminished from 2012-13 to 2017-18 (Prakash *et al.*, 2019). Second, both investment and saving rates have declined – with the investment rate dropping more sharply than the saving rate, thereby narrowing the saving-investment gap. Third, the decline in the investment rate is mostly attributed to the private corporate and the household sector. As a result, net borrowings by the private non-financial corporations have declined. The saving-investment gap of the private corporate sector has narrowed, reflective of the waning confidence in undertaking new investment despite an increase in their savings. The combined outcome of all these developments has narrowed the saving-investment gap for India, despite liberalising its regime to attract foreign capital inflows. Therefore, it is worthwhile to revisit the savings-investment nexus, particularly for the post-financial crisis period.

The remaining part of the paper is structured as follows: Section II briefly reviews literature on the subject. An overview of savings, investment and capital flows into India is provided in Section III. Data and methodology are explained in Section IV. Section V discusses empirical results. Section VI provides robustness check with quarterly data. Section VII covers cross-country experience. Concluding observations are set out in Section VIII.

Section II
The Literature

Martin Feldstein and Charles Horioka, in their seminal paper published in 1980, raised three crucial questions relating to how the world's supply of capital is internationally mobile:

Does capital flow among industrial countries to equalise the yield to investors? Alternatively, does the saving that originates in a country remain to be invested there? Or does the truth lie somewhere between these two extremes?

Their empirical work gives a puzzling result that domestic savings and investment within a country are highly correlated. Their finding was contrary to the conventional wisdom. In the open economy models, capital was assumed to be perfectly mobile, and the industrialised countries appeared to be highly financially integrated, particularly since the introduction of floating exchange rates in the early 1970s. Feldstein and Horioka argued that under perfect capital mobility, the association between domestic savings and investment should be negligible or non-existent since savings can move out of the domestic market seeking higher returns from the global market. This implies that a part of the investment in a country can be financed by global funds. By contrast, the saving-investment relationship is expected to be strong for zero capital mobility since savings must be invested domestically. In cross-section regressions for 16 Organisation for Economic Cooperation and Development (OECD) countries for the period of 1960-1974, Feldstein and Horioka failed to reject the null hypothesis of a one-to-one association between savings and investment. They interpreted this as implying zero capital mobility.

Subsequently, several theoretical and empirical studies have examined the saving-investment association following the F-H approach. Sinha and Sinha (1998) tested the F-H hypothesis using the cointegration method for ten Latin American countries[2] and found that savings and investment ratios have a long-run relationship for only four countries. Iorio and Fachin (2011) used data on 18 OECD economies for the period of 1970 to 2007, both for individual countries and in a panel set-up. They found a long-run saving-investment relationship for about half of the OECD countries. Ekong and Kenneth (2015) used Nigerian data from 1980 to 2013 to test the F-H hypothesis and concluded that there is no cointegration between savings and investment. Using the same method, Kaur and Sarin (2019) found that the F-H hypothesis is valid for the East Asian countries, namely, China, Hong Kong, Japan, Korea, Macao and Mongolia for the period of 1982 to 2015.

In the Indian context, Vuyyuri and Sakalya (2005) found that savings influence investment but investment does not influence savings. Verma (2007) studied the relationship among savings, investment and economic growth in India using the autoregressive distributed lag (ARDL) approach to

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[2] Colombia, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Panama and Venezuela.

cointegration using data from 1950-51 to 2003-04. The F-statistic indicated that the null hypothesis of no cointegration could not be rejected only when GDP is treated as the dependent variable. Singh (2008) found a cointegrating relationship between savings and investment; with the long-run slope parameter on savings being significantly different from zero but not from one. This result supports the F-H hypothesis and suggests imperfect mobility of capital and home-bias in the asset portfolio of domestic investors.

Khundrakpam and Ranjan (2010) also found a long-run cointegrating relationship between savings and investment. However, the inclusion of the post-reform period weakens the relationship characterised by a more liberalised era. Their study, however, covers the period before the financial crisis of 2007-09. As highlighted in the introduction section, a sharper decline in the investment rate led to a narrowing of the saving-investment gap in the post-global financial crisis (GFC) period. Yadav *et al.* (2018) covered more recent data, *i.e.* till 2015, but they did not focus on the impact of post-GFC changes discussed above. This paper attempts to fill this gap.

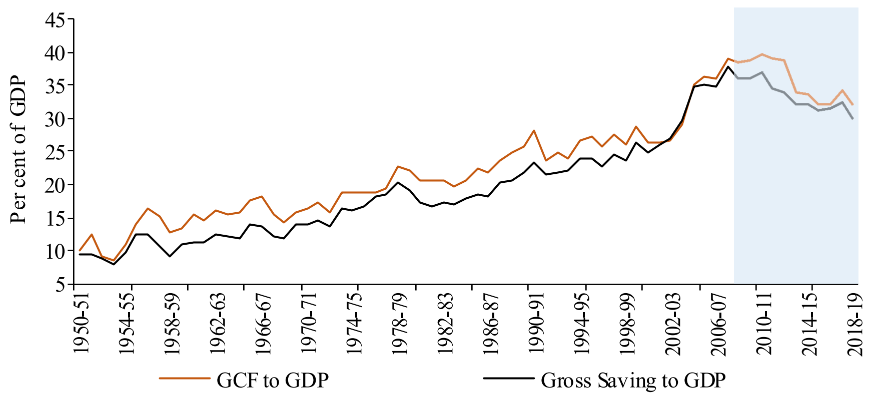
Section III
Savings, Investment and Capital Flows in India

III.1. Savings and Investment

Savings are the backbone of investment, *viz.,* higher savings lead to higher investment and higher growth in an economy, given a conducive macroeconomic environment and the existence of a developed financial system. In India, household sector has the largest share in aggregate domestic savings. Household savings are further disaggregated into physical and financial assets. The other kinds of savings are the private corporate saving, the public sector saving and foreign saving. Similarly, gross investment is also divided into household, private corporate and public sector investment.

Gross domestic investment rate, measured as a ratio of gross capital formation (GCF) to GDP at current prices, increased from a low of 10.1 per cent in 1950-51 to 29.0 per cent in 2003-04 and further to 39.1 per cent in 2007-08 (Chart 1). The improvement in GDP growth from an average of 4.2 per cent during 2000 to 2003 to an average of 7.9 per cent during 2003 to 2008 was due to a sharp rise in investment (RBI, 2019). Supported by fiscal

Chart 1: Saving and Investment Rates

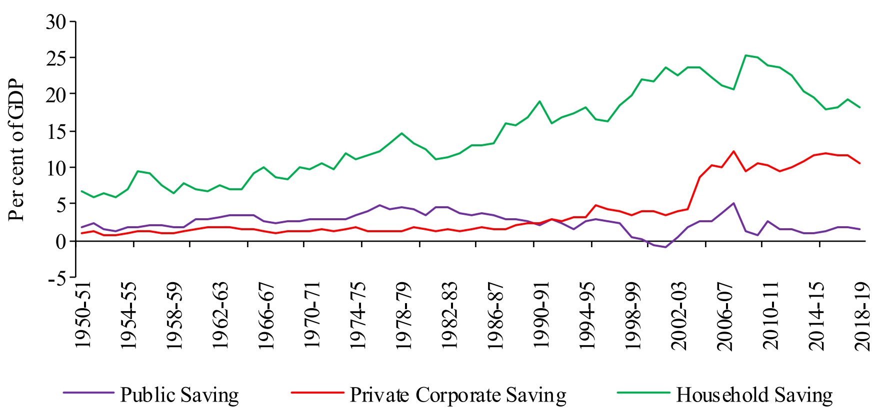


Source: National Statistical Office (NSO).

and monetary stimulus, investment rate touched a peak of 39.8 per cent in 2010-11. Thereafter, it declined gradually due to the twin balance sheet problem which affected both banks and corporates (GOI, 2016). The investment rate dropped to 32.2 per cent in 2018-19.

The gross domestic savings rate increased from 9.4 per cent in 1951-52 to 29.6 per cent in 2003-04 and further to a peak of 37.8 per cent in 2007-08 (Chart 1). Thereafter, the savings rate dropped to 30.1 per cent in 2018-19. At the disaggregated level, household savings and private corporate savings have shown a steady upward trend (Chart 2). Recent years have, however,

Chart 2: Institutional Sector-wise Saving Rate



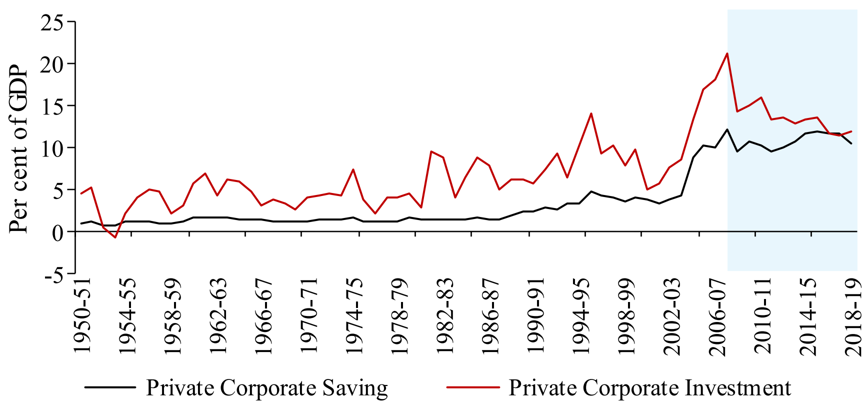
Source: National Statistical Office (NSO).

seen a decline, largely reflected in household savings. Public sector savings declined after 1995-96, turning negative in 2000-01 and 2001-02 on account of an increase in the fiscal deficit. Public sector savings started improving after the introduction of the Fiscal Responsibility and Budget Management Act (FRBM) Act, 2003 (Reddy, 2008).

The private corporate savings rate improved from 4.3 per cent of GDP in 2003-04 to 12.2 per cent in 2007-08, a sharp uptick of around 8 percentage points. Thereafter, it stabilised at around 11 per cent. Similarly, private corporate investment rate increased from 8.6 per cent of GDP in 2003-04 to 21.0 per cent in 2007-08 (Chart 3). In the wake of the global financial crisis, private corporate investment fell sharply by about 7 percentage points and has lingered since then. The savings rate of the household sector, on the other hand, declined to 18.2 per cent in 2018-19 from 25.2 per cent in 2008-09, a drop of around 7 percentage points.

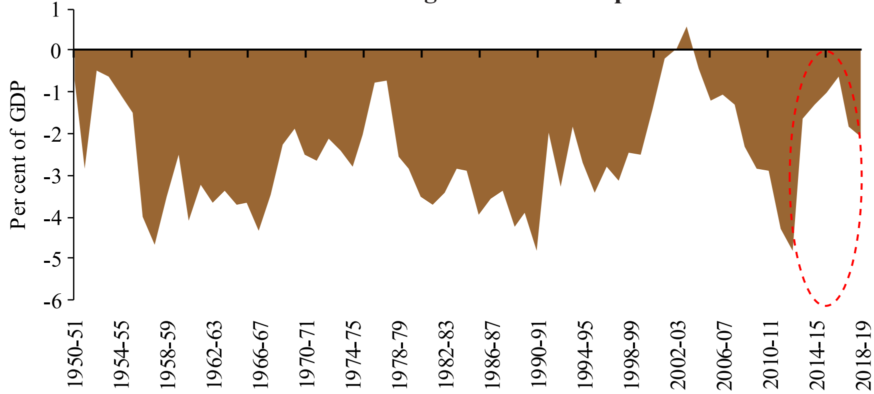
The rate of gross capital formation had remained above the rate of gross domestic savings throughout the study period barring 2002-03 and 2003-04 when the current account was in surplus (Chart 4). In the post-global financial crisis period, the gap narrowed on the back of a sharper decline in the investment rate than the savings rate till 2010-11; since then, investment continued to weaken whereas savings showed a steady increase, resulting in lessening of the saving-investment gap.

Chart 3: Private Corporate Saving-Investment Gap



Source: National Statistical Office (NSO).

Chart 4: Saving-Investment Gap



Source: National Statistical Office (NSO).

III.2. Foreign Capital Flows into India[3]

The balance of payments accounting framework suggests that a country's current and financial accounts have to be balanced *ex-post,* meaning that current account deficits (surpluses) will have to be matched by net capital inflows (outflows). It is the size of the current account deficit (CAD) that determines the absorptive capacity of foreign capital flows from a macroeconomic perspective. In other words, foreign savings only to the tune of CAD will ultimately add to investment. Large CADs, temporarily financed by net capital inflows, however, they are the source of imbalances over medium-term and lead to overheating and unsustainability.

It is a useful yardstick to measure the contribution of capital flows to the domestic capital formation as it comprises flows such as external commercial borrowings (ECBs), foreign direct investments and forms of external assistance that may generally be earmarked for specific capital expenditure purposes. On the other hand, while Non-Resident Indian (NRI) deposits and portfolio flows may not directly contribute to capital formation; however, they may have an indirect effect on domestic capital formation rate through improvement in market liquidity and sentiments, and by serving to equilibrate the receipt–payment imbalance in the current account (Joshi, 2007).

[3] Analysis on capital flows prior to the global-financial crisis is largely drawn from Mohan (2008).

Starting from the time of independence till the 1980s, the external flows took place in the form of multilateral and bilateral concessional finance. The reform process was initiated after the balance of payment crisis in 1991. It included a swift transition to a market-determined exchange rate regime, dismantling of trade restrictions, a move towards current account convertibility and a gradual opening-up of the capital account (Mohan, 2008). In terms of the composition of capital flows, the policy reforms of 1991 intended to shift from debt creating flows to non-debt creating flows (Mohan, 2008). Consequent to the reforms, the Indian economy witnessed a high degree of capital inflows during the first half of the 2000s.

The global financial crisis, 2008-09 led to an adverse situation characterised by global liquidity squeeze and increased risk aversion on the part of international portfolio investors. There were large capital portfolio outflows. While foreign direct investment (FDI) flows exhibited resilience, access to ECBs and trade credits was rendered somewhat difficult.

In the post financial crisis period, different components of capital flows have behaved differently because of distinct factors. FDI, a stable component of foreign capital, declined during the crisis. Thereafter, it either remained stable or increased (Chart 5). In response to macroeconomic reforms undertaken following the exchange market pressure of 2013 and expectations of new structural reforms, foreign investments - both direct and portfolio

Chart 5: Share of Flow of Gross External Investment, NRI Deposits and External Assistance in GDP

Source: RBI.

flows - recorded substantial inflows. Net FDI inflows picked up sharply in response to initiatives that were geared towards a better business environment with policy certainty, *viz*., the 'Make in India' initiative, the Insolvency and Bankruptcy Code 2016, and impressive improvement in the Ease of Doing Business rankings.

An important development in the post-financial crisis period is the lower ECB flows to India relative to the pre-crisis period. This can partly be attributed to the decline in corporate investment and more lately, easier domestic financial conditions which even led corporates to prepay ECBs. Therefore, it is worthwhile to revisit the association between aggregate savings and investment and examine the changes during the post-financial crisis period.

Section IV
Data and Methodology

IV.1. Data

The empirical analysis in the paper is based on annual data for the period 1955-56 to 2018-19 extracted from 'Handbook of Statistics on the Indian Economy' published by the RBI. The nominal savings and investment figures are divided by nominal GDP at market prices at 2011-12 base. To ascertain the incremental impact of the changes that took place during the post-global financial crisis period, we undertake a separate analysis for the (sub-sample) period 1955-56 to 2007-08, and then for the full sample. ARDL model has been applied for the empirical estimation.

IV.2. ARDL Model

The total sample size in our estimation is 63, which is small and may give spurious results if estimated using a method which requires large sample size. Therefore, we apply the bounds test method of cointegration developed by Pesaran *et al.* (1999) and Pesaran *et al.* (2001), which is more efficient in the case of small and finite sample size. Additionally, the technique has the following advantages over other time series methods: (i) the model can be applied on data with a mix of stationary and non-stationary series; (ii) it provides unbiased long-run estimates; and (iii) it can provide both short and long-run relationship between variables along with the error correction process. Stationarity test is required only to ensure that variables are not integrated of order two or higher, as critical bound test values are not valid under these conditions. In the ARDL approach, we have established a long-run relationship among variables using a bound test.

In the bounds test, the null hypothesis of no cointegration is tested against the alternative hypothesis that there is cointegration. Based on the comparison of computed F-statistic with the lower-bound (corresponding to I(0) series) and upper-bound critical value (corresponding to I(1) series), inferences can be drawn about the long-run relationship. If the computed F-statistic is higher than the upper bound critical value, the null hypothesis of no cointegration is rejected, signifying there is a long-run relationship between savings and investment.

In this regard, the original equation estimated by F-H is

$$(\frac{I}{Y}) = \alpha + \beta(\frac{S}{Y}) \qquad \text{...........(1)}$$

where, $(\frac{I}{Y})$ is the ratio of gross domestic investment to GDP and $(\frac{S}{Y})$ is the corresponding gross domestic savings to GDP. Here, the bounds test involves investigating the existence of a long-run relationship between investment-GDP ratio and saving-GDP ratio. The above equation is converted into the following ARDL form:

$$\text{ARDL(p,q)}: (\frac{I}{Y}) = \alpha + \sum_{i=1}^{p} \gamma(\frac{I}{Y})_{(t-i)} + \sum_{i=1}^{q} \beta(\frac{S}{Y})_{(t-i)} + \varepsilon_t \qquad \text{...........(2)}$$

where, ε_t is a random disturbance term and assumed to be serially uncorrelated. p is the lag order of dependent variables, while q is the lag order of independent variables. This method is autoregressive because investment-GDP ratio is, partly, explained by its own lag. Since it is also partly explained by lags of saving-GDP ratio (independent variable), it is a distributed lag model.

Once the long-run relationship is established, the next step is to estimate the long and the short-run coefficients of the cointegrated equation using the following error correction model (ECM):

$$\Delta(\frac{I}{Y}) = \alpha + \sum_{i=1}^{p} \gamma\Delta(\frac{I}{Y})_{(t-i)} + \sum_{i=1}^{q} \beta\Delta(\frac{S}{Y})_{(t-i)} + \varphi EC_{t-i} + \varepsilon_t \qquad \text{...........(3)}$$

where γ and β represent the short run coefficients of lagged investment and saving variables, respectively. φ is the adjustment coefficient and $EC_{t-\mathrm{i}}$ is the error correction term which captures the long-run relationship in the model and can be defined as:

$$EC_{t-1} = (\frac{I}{Y})_{(\mathrm{t-1})} - (\alpha + \beta(\frac{S}{Y})_{(\mathrm{t-1})}) \qquad \ldots\ldots\ldots\ldots(4)$$

where β is the long-run coefficient of saving-GDP ratio. The next section discusses the empirical findings.

Section V
Empirical Findings

We apply three methods to test the stationarity of the variables, *i.e.,* Augmented Dickey-Fuller test (ADF, 1981), Phillips-Perron test (PP, 1988) and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS, 1992). They all suggest that the variables are non-stationary in levels, but stationary in their first difference (Table 1).

Based on stationarity tests, we apply the ARDL model to data for the sub-sample (1955-56 to 2007-08) and then to the full sample (1955-56 to 2018-19). Before discussing the ARDL results, it will be useful to look at the descriptive statistics (Table 2). The additional 11 observations (2008-09 to 2018-19) that distinguish the full sample from the sub-sample contain new information and provide some useful insights. The mean values of investment and saving rates are higher in the full sample. The corresponding average of saving-investment gap was lower for the full sample period. The volatility in the sub-sample period was also lower compared with that in the full sample period, mainly due to higher volatility in investment during the post-2007 period.

Table 1: Unit Root Test

Test	Augmented Dickey-Fuller Test Statistic		Phillips-Perron Test Statistic		Kwiatkowski-Phillips-Schmidt-Shin Test Statistic	
	Level	First Difference	Level	First Difference	Level	First Difference
Investment Rate	-1.296	-8.863***	-1.238	-8.943***	1.017	0.074***
Saving Rate	-0.888	-8.022***	-0.880	-8.021***	1.012	0.088***

Note: ***: indicates significance at 1 per cent level.

Table 2: Descriptive Statistics

Model	No. of Observations	Mean	Standard Deviation	Coefficient of Variation	Max	Min
Sample:1955-56 to 2007-08						
Investment to GDP Ratio	53	21.8	6.3	28.9	39.1	12.7
Saving to GDP Ratio	53	19.2	6.9	35.9	37.8	9.2
Saving-Investment Gap	53	-2.7	1.2	-44.4	0.55	-4.8
Sample:1955-56 to 2018-19						
Investment to GDP Ratio	64	24.2	7.9	32.6	39.8	12.7
Saving to GDP Ratio	64	21.6	8.3	38.4	37.8	9.2
Saving-Investment Gap	64	-2.6	1.2	-46.2	0.55	-4.8

The correlation between savings and investment rate was very high and statistically significant in both the samples, implying a steady co-movement over the years (Table 3). Furthermore, the correlation coefficient of the full sample is marginally higher than the sub-sample.

Table 4 presents the findings from the ARDL bounds test for cointegration between domestic investment and domestic savings. For both the samples, F-statistic is higher than the upper bound critical value, confirming cointegration between variables and hence, a long-run relationship.

The results of the estimated error-correction model are given in Table 5. The usual diagnostic and stability tests suggest the robustness of the estimates. Higher adjusted R-square indicates a good fit of the model. The

Table 3: Correlation between Savings and Investment

Model	Coefficient	P-Value
Sample:1955-56 to 2007-08	0.986	0.00
Sample:1955-56 to 2018-19	0.990	0.00

Table 4: Bounds Test for Cointegration

Model	F-Statistic	99% lower bound	99% upper bound	Inference
Sample:1955-56 to 2007-08	8.60	6.84	7.84	Cointegrated
Sample:1955-56 to 2018-19	8.39	6.84	7.84	Cointegrated

null hypothesis of no serial correlation was accepted by the Breusch–Godfrey Serial Correlation Lagrange Multiplier (LM) test. Similarly, Breusch-Pagan-Godfrey heteroskedasticity test indicates acceptance of the null hypothesis of homoscedastic errors. The cumulative recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMQ) confirm the stability of the long-run coefficients in the ARDL model.

Table 5 shows long and short-run estimates of domestic investment and savings relationship along with the error correction term, which specifies the speed of adjustment if a deviation occurs from the long-run steady path. The long-run coefficient of saving is 0.90 which is statistically significant for the sub-sample period. The statistically significant coefficient increases to 0.94 for the full sample period when the post-financial crisis period is included. The higher magnitude of the coefficient points to a relatively higher association between saving and investment and less use of foreign savings. The outlier dummy used for the years 1976-77 and 1990-91 are statistically significant. The error correction term indicates that the short-run deviation from its

Table 5: Gross Domestic Savings and Investment: Error-Correction Results

Variable	Sample: 1955-56 to 2007-08	Sample: 1955-56 to 2018-19
Long-run		
Savings to GDP ratio	0.90***	0.94***
Short-run		
Constant	2.46***	1.87***
D (Savings to GDP ratio)	0.94***	0.92***
Dum76	-1.37**	-1.29**
Dum90	1.80**	1.63*
Error-Correction Term		
ECR	-0.53***	-0.47***
Diagnostic Tests		
Adjusted R-squared	0.82	0.80
Breusch-Godfrey Serial Correlation LM Test	0.31	0.11
Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.55	0.13
CUSUM	Stable	Stable
CUSUM of Squares Test	Stable	Stable

Note: ** and ***: indicates significance at 5 per cent and 1 per cent level, respectively.

steady-state path is corrected in two years. The adjustment was relatively quicker before the global-financial crisis. In the short-run also, savings play an important role in financing investment.

The results suggest a comparatively lower association between saving and investment in the post-global financial crisis period. This implies a relatively lower use of foreign savings and a higher dependence on domestic savings. The growth in real fixed investment in the post-global financial crisis period turned to a single digit except 2010-11 and 2011-12 and much lower in 2008-09 and 2012-13 to 2015-16. This slowdown was largely due to private corporate investment. Out of 6.3 percentage points decline in the overall investment rate (investment as per cent to GDP) during 2007-08 to 2015-16, private investment accounts for 5 percentage points (GOI, 2017). India's investment slowdown is a balance sheet related slowdown (GOI, 2017). Many companies have had to curtail their investments because their finances are stressed, as the investments made during the boom period have not generated enough revenues to allow them to service the debts that they have incurred.

The decline in domestic saving was led equally by household and public sector saving. The fall in the former was on account of physical saving. The private corporate saving, on the other hand, has increased steadily.

Section VI
Robustness Check

A robustness check of results presented in the previous section is performed by applying the same ARDL model to quarterly saving and investment data. These data are, however, not readily available. The investment includes fixed investment, change in stocks, valuables and errors and omissions.[4] The data for errors and omissions are available at an annual frequency; the quarterly gross capital formation data do not include this

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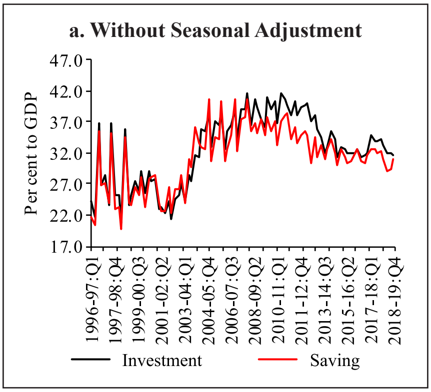
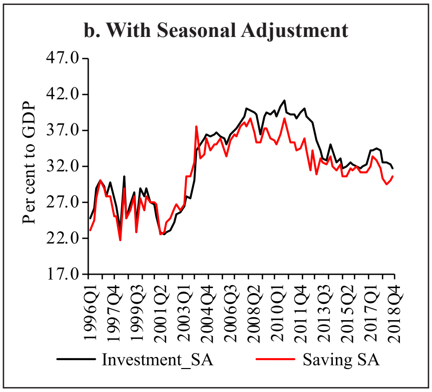
[4] The capital finance account provides information on the gross capital formation (GCF) and gross savings. GCF is estimated using two approaches: (i) through the flow of funds approach, derived as gross savings plus net capital inflow from abroad; and (ii) through the commodity flow approach, derived by the type of assets. By convention, GCF estimated through the flow of funds approach is treated as former, and the difference between the two approaches is taken as 'errors and omissions' (Srivastava *et al.*, 2018).

Chart 6: Quarterly Saving and Investment Rate





Source: NSO and Authors' estimates.

component. Similarly, savings data are available only at an annual frequency. The above limitations suggest that one must construct quarterly saving and investment data in order to run the ARDL model. From the investment side, we have used Denton method[5] of frequency conversion to extract quarterly errors and omissions data from annual figures. After that, quarterly investment is added to quarterly current account balance to arrive at domestic savings. The data are shown in Chart 6a and 6b.

For the empirical exercise, we follow the approach of Bayoumi (1990) and Abbott and Vita (2003), that the use of total investment (which includes inventories as well as business fixed investment) may lead to spurious correlations with savings that reflect endogenous behaviour by private agents. Therefore, we have used gross fixed capital formation. After the construction of data, the long-run relationship between saving and investment is tested. Both variables are seasonally adjusted and used as a per cent to GDP. They are non-stationary in levels but stationary in first difference.

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[5] The proportional Denton procedure converts low-frequency time series into high frequency by using associated indicators. It imposes the condition that the sum of the interpolated series within each year equals the annual sum of the underlying series for that particular year (Rashid and Zanaib, 2013). In particular, the Denton process may be useful in cases where the higher frequency indicators do not considerably associate with the low-frequency time series of the interest. Specifically, this method minimises the distance between the two-time series as much as possible using a quadratic minimisation framework. For details, please see Denton (1970).

Table 6: Bound Tests for Cointegration

Model	Time Period	F-Statistic	99% lower bound	99% upper bound	Inference
1	1996-97: Q1 to 2008-09: Q4	9.32	6.84	7.84	Cointegrated
2	1996-97: Q1 to 2018-19: Q4	15.47	6.84	7.84	Cointegrated

Unlike annual data, quarterly frequency allows more number of observations. We have applied ARDL model to the sub-sample from 1996-97: Q1 to global financial crisis year *i.e.* 2008-09 and full sample (including post-global financial crisis period). Table 6 indicates the cointegrating relationship between saving and investment in both samples, as F-statistics are higher than their respective lower and upper critical bound values.

Table 7 presents the error-correction results of the two samples. The model satisfied all the diagnostic criteria. The error-correction term is negative

Table 7: Gross Domestic Savings and Investment: Error-Correction Results

Variable	Sample: 1996-97:Q1 to 2008-09:Q4	Sample: 1996-97:Q1 to 2018-19Q4
1	2	3
Long-run		
Savings to GDP ratio	0.91***	0.94***
Short-run		
Constant	0.33***	0.09
D(Investment to GDP ratio(-1))	-	-0.05
D(Investment to GDP ratio(-2))	-	0.09
D(Investment to GDP ratio(-3))	-	0.21**
Dum2006Q3	1.24**	-2.92***
Dum2010Q1	-	1.37**
Error-Correction Term		
ECR	-0.17***	-0.17***
Diagnostic Tests		
Adjusted R-squared	0.34	0.49
Breusch-Godfrey Serial Correlation LM Test	0.89	0.10
Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.78	0.77
CUSUM	Stable	Stable
CUSUM of Squares Test	Stable	Stable

Note: ** and ***: indicates significance at 5 per cent and 1 per cent level, respectively.

and statistically significant. The saving coefficients in both the samples are very close to the coefficients in the annual estimated results. Though both coefficients are closer to one, in full sample they are relatively higher than the sub-sample, indicating a relatively higher association between the variables and comparatively lower dependence on foreign saving.

Section VII
Is India an outlier?

Previous sections demonstrate that saving and investment rates in India have displayed a high degree of co-movement except for a brief period. This co-movement has existed despite progressive liberalisation of the capital account. As discussed in Section II, this puzzle is not unique to India. In fact, in most advanced economies the saving-investment correlations are high. In a recent study analysing cross-country experience, David, Gonçalves and Werner (2020) concluded that frictions in global financial markets are the main explanation for the high positive correlation between saving and investment. This is more pronounced in the case of emerging market economies *vis-à-vis* advanced economies. Other explanations provided in the literature are global productivity shocks and international trading cost (Glick and Rogoff, 1995; Obstfeld and Rogoff, 2000). However, during the post-GFC period, India didn't witness a decline in productivity (RBI, 2019) and rise in trading cost. Trading cost, measured by transportation cost, has continued its downward trend[6]. Therefore, frictions emanating from global financial crises could be a possible explanation for high saving investment correlation, reflecting risk aversion among economic agents. This section analyses the changes in cross-country investment and saving after various crises and draws inferences to examine whether India is an outlier.

Accordingly, we analysed movements in saving rate, investment rate and saving-investment gap of crisis-affected economies, starting from the Mexican peso crisis (Table 8). The timing of crises and crisis-affected economies are decided based on a literature survey. For ascertaining a change in saving and investment behaviour of crisis-affected economies, we compare their average saving and investment rates before and after the crises year. We use a five-year average of pre-crises and post-crises saving and investment rates for each affected economy. Accordingly, we have 21 economies with different crisis episodes.

[6] As indicated by Baltic Exchange Dry Index which declined from around 11,600 in June 2008 to 411 in February 2020.

Table 8: National Saving-Investment of Crisis-affected Economies – Pre- and Post-crises

(Per cent)

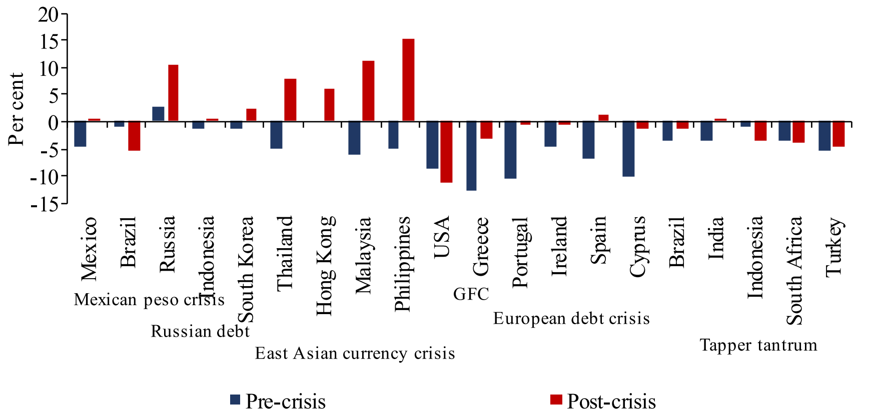
Crisis	Economy	Investment		Saving	
		Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
Mexican peso crisis (Jan 1995)	Mexico	23.6	22.6	18.9	22.9
	Brazil	20.5	17.6	19.5	12.3
Russian flu (August 1998)	Russia	22.3	20.4	25.2	30.8
East Asian currency crisis (July 1997)	Indonesia	30.0	22.1	28.8	22.4
	South Korea	38.3	31.7	37.1	34.1
	Thailand	40.0	22.1	34.9	29.9
	Hong Kong	31.8	25.3	NA	31.4
	Malaysia	41.7	24.6	35.6	35.8
	Philippines	23.9	18.5	19.1	33.7
Global financial crisis (2008)	USA	26.6	27.4	18.1	16.1
European debt crisis (2009-2011)	Greece	22.6	11.6	9.9	8.6
	Portugal	22.3	15.4	11.9	14.7
	Ireland	24.6	21.7	20.1	21.3
	Spain	27.0	18.1	20.0	19.2
	Cyprus	25.0	13.9	14.8	12.4
Taper tantrum (May 2013)	Brazil	21.1	15.5	17.7	14.0
	India	39.2	31.8	35.7	32.5
	Indonesia	31.9	34.1	31.1	30.5
	South Africa	20.6	19.8	17.1	16.0
	Turkey	27.7	29.2	22.4	24.5

NA: Not available,
Note: List of economies is prepared on the basis of literature and contemporary media reports.
Source: Authors' calculation based on World Bank data.

It can be observed that after the crisis, investment rate of all countries, except those of the USA (GFC), Indonesia and Turkey (after 2013), declined significantly (Table 8). Saving rate also declined after the crisis, though at a comparatively moderate pace than the decline in investment rate. In fact, many economies were able to increase their saving rate after the crisis.

The result of this asymmetric behaviour of economies gets reflected ultimately in their saving-investment gap, which records a sharp decline in the post-crises period *vis-à-vis* pre-crises period (Chart 7). Out of 21 crisis-affected country episodes, only the USA (2007-08), Brazil (1994) and Indonesia (2013) recorded a higher saving-investment gap post-crisis, while all others

Chart 7: Saving-Investment Gap Before and After Financial Crises



recorded narrower gaps. This experience reinforces the role of frictions in global financial markets, which manifest from time to time in crises, leading to a higher correlation between domestic saving and investment rate. Thus, the observed saving-investment relationship in India is not an exception.

Section VIII
Conclusion

The capital account in India has been facilitating greater cross-border movement of capital. This paper examines whether the dependence of domestic investment on domestic savings has declined following greater access to availability of foreign capital.

The empirical results confirm a long-run relationship between domestic savings and investment. A comparison of the long-run coefficients for the full sample period (1955-56 to 2018-19) with that for the sub-sample period (1955-56 to 2007-08) indicates a relatively higher degree of association between domestic savings and investment. This, in turn, suggests a reduced role of foreign saving in financing investment activity after the global financial crisis of 2007-09. This largely reflects moderation in private corporate investment rate in the post-global financial crisis period. The error correction term indicates that in the event of short-run deviations from the steady state relationship between savings and investment, the restoration of equilibrium takes about two years. Furthermore, the adjustment was relatively quicker before the global financial crisis.

An analysis of episodes of financial crises behaviour of several economies reveals that in the aftermath of one crisis, there is a decline in saving-investment gap, thereby, emphasising the role of frictions in global financial markets, leading to a higher correlation between domestic saving and investment rate. Thus, the case of India is not an exception. Going forward, as physical capital formation revives, it should also be backed by a commensurate rise in domestic savings for sustained long-run growth. At the same time, it is important to enhance the efficiency of domestic financial system to improve the allocation of resources to the most productive sectors.

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Firefighting: The Financial Crisis and its Lessons by Ben S. Bernanke, Timothy F. Geithner and Henry M. Paulson, Jr., 230 pp., Profile Books Ltd, United Kingdom (2019), ₹499

The global financial crisis of 2008 inflicted tremendous pain on the global economy by disrupting economic activity and causing intense pessimism in the financial system. The worst recession, also known as the 'Great Recession', was triggered by the bursting of the housing bubble in the United States (US) and its spillover effects contaminated the global economy. Much has been written on the 'crisis' covering its genesis, aftermath and policy responses. But this book titled *Firefighting: The Financial Crisis and its Lessons*, written by the three architects of the American policy response to the crisis—Ben S. Bernanke, Chairman of the Federal Reserve (Fed); Henry M. Paulson, Jr., Treasury Secretary under George W. Bush, and Timothy F. Geithner, President of the Federal Reserve Bank of New York—provides a more authentic account of the way the crisis unfolded, its consequences, and the collaborative efforts made by the authors to deal with it. The authors also offer key lessons from their experience that might help to prevent and deal with future crises.

The authors argue that the turmoil in financial markets is usually self-adjusting, except for a few unusual cases, which require limited intervention by policymakers. However, the crisis of 2008 was the worst financial crisis since the Great Depression, which warranted extraordinary interventions from policymakers in the form of conventional and unconventional measures to stabilise the financial system. The crisis of 2008 was essentially a case of 'classic financial panic', a repeat occurrence since the dawn of modern banking. This time the crisis of confidence was triggered in mortgages. The authors profess that overleverage caused by excessive optimism during the period of boom coupled with risk transfer to non-banks, rapid financial innovations and absence of inter-regulatory coordination along with failure of regulatory authorities to keep up with changing market realities contributed to the financial shocks of 2008. As the invisible hand of free markets failed to stop the financial collapse, the visible hand of the government had to intervene to stop the panic, restore confidence and fix the broken financial system. Eventually, normalcy was restored in the system due to the deployment of all feasible range of financial and economic weapons at the disposal of the policymakers. While the implementation of sweeping financial reforms has reduced the probability of another financial crisis in the near future, the occurrence of another crisis cannot be ruled out given the inevitability of panic and overconfidence in human beings.

The book consists of five chapters, starting with the genesis of the crisis in Chapter 1. Chapters 2 through Chapter 5 cover the crisis and the various policy responses undertaken from August 2007 to May 2009, and offer lessons and warnings for the future. The financial system is inherently fragile and vulnerable to panic because of its dependence on investor confidence which is evanescent. The authors discuss how in the years prior to the crisis, the US economy was characterised by excessive optimism resulting in a credit boom in the mortgage market, unsustainable growth in household mortgage debt, reckless expansion in credit facilities to less creditworthy borrowers, securitisation of mortgages with low ratings, and spreading of risk through mortgage-backed securities through financial innovation to the financial system. Overexposure of the financial system to unanticipated risks in the mortgage market and overleverage of systemically important financial firms, especially short-term liabilities, became the triggers for panic market reaction. Furthermore, lack of tougher and more pro-active regulators, failure of the supervisors to recognise the actual level of leverage, a fragmented financial regulatory system with no agency responsible for monitoring systemic risk combined with the migration of the leverage to unregulated shadow banks or non-banks made the fragile financial system susceptible to a disaster. The authors acknowledge that it is exceptionally hard to predict a financial meltdown and they were not sufficiently creative or forceful in taking actions to prevent those risks. There was also a failure of institutional organisation structure within the government and the politics of boom time was not conducive to reforming the system before the crisis. The crisis started to make an appearance with the end of the housing bubble. Creditors and investors shunned not just subprime mortgages, they distanced themselves from anything associated with mortgages.

The authors emphasise that even though recognising a crisis is challenging, it is very important to assess the severity of the crisis, as an overreaction may create a real moral hazard problem, while under-reacting can be costlier and more damaging. In the initial period of the crisis, or during 'the first flames' as the book calls it, the Fed adhered to conventional tools like the discount window for providing emergency liquidity to commercial banks and reduction of federal funds rate. Subsequently, the Fed decided to launch unconventional monetary policy tools such as the Term Auction Facility (TAF) to provide long-term lending to eligible banks at a market determined rate and forex swap lines to increase dollar liquidity with foreign central banks to limit the panic. The US Department of the Treasury also devised fiscal stimulus in the form of temporary tax cuts to support the market. However, as the unusual market conditions persisted, the Fed, with the support of the US Congress, decided to extend liquidity support to non-banks through the Term Securities Lending Facility (TSLF) using emergency lending power. Subsequently, the Fed also created a new lending facility for investment banks called the Primary Dealer Credit Facility (PDCF) for accepting a wider range of collaterals. The intervention through innovative lending facilities helped to rescue firms like Bear Stearns with the support of JP Morgan Chase. During the panic, some much criticised and unpopular interventions had to be resorted to by the authorities, including the nationalisation of systemic institutions Fannie Mae and Freddie Mac, which were constantly pushing the US Congress for more reforms to give more authority to the Fed and the Treasury.

The authors acknowledge that their aggressive interventions to stabilize the financial system also sent unintended messages to the market of higher fragility in the system and the market didn't breathe a sigh of relief. The demise of Lehman Brothers in September 2008 was the most consequential moment, which dramatically accelerated the crisis of confidence in every financial firm. Explaining the crises at Lehman and American International Group (AIG), the authors admit that failing to save AIG a day after Lehman's failure would have been calamitous. Despite concerted efforts from the Fed, the Lehman filed for bankruptcy because of its financial unviability and lack of acceptable collaterals at its disposal. At the peak of the crisis, with a worsening state of the broader economy, the passage of the Troubled Asset Relief Programme (TARP) gave remarkably expanded powers to the Treasury to purchase toxic mortgage-backed securities and quell the panic. Subsequently, it was decided to inject capital directly into financial institutions from TARP cash to adequately capitalise the system.

As the global financial system was still unstable and the economy was deteriorating, additional measures were taken including in the form of liquidity support to the commercial paper market through purchases of commercial papers from eligible issuers under the Commercial Paper Funding Facility (CPFF), a coordinated interest rate cut by the major central banks (led by Fed), and reducing the policy rate to zero by the Fed. The new US government pursued a variety of aggressive measures to bring the economy back to life, including the largest fiscal stimulus bill in American history and the Treasury's effort at forcing partnership with the private sector to buy troubled assets under the Public-Private Investment Programme (PPIP). The authors emphasise that the Supervisory Capital Assessment Programme, or 'the stress test', was the culmination of a long series of emergency interventions. The better than expected results of the stress test along with the previous series of intervention measures restored confidence in the health of the banking system and reassured the market that there would be no more Lehman.

The concluding chapter of the book is cautionary, and discusses the devastating effects of a financial crisis, irrespective of the aggressive nature of interventions and financial strength and credibility of the financial system. To not have another financial crisis is the best outcome for any financial system; however, the occurrence of another crisis is unpreventable. What can and must be ensured is preventing the deepening of a crisis by empowering crisis managers with necessary enabling provisions by the government. The authors acknowledge that their forceful and effective response was made possible by the expanded powers provided to them by the US Congress during the crisis, which eventually controlled the panic. While better regulations and supervisory standards such as the Basel III regulatory framework would be helpful to avoid panic in the future, the authors remain concerned about discontinuation of the new powers that were used to stabilize the system such as expiration of TARP, inoperative of 13(3) emergency authority of Fed, elimination of broad guarantee authority of Federal Deposit Insurance Corporation (FDIC), removal of Treasury's power to use the Exchange Stabilization Fund (ESF) to issue guarantees *etc.* Therefore, the authors insist on restoring the emergency tools of the authorities that helped to manage and contain the crisis of 2008.

The book provides an excellent narration of the 2008 financial crisis and the way it was managed. Beyond the narrative, the lessons drawn by the authors in battling the crisis can serve as an important guide to policymakers in general and central banks in particular. The advice related to the unconventional measures used in a crisis can supplement the Bagehot dictum for central banks. The authors are, however, at times appear prone to self-aggrandisement while responding to criticisms concerning their unpopular interventions. Nevertheless, their admission of not being sufficiently creative or forceful in their actions adds credibility to the analysis. The authors do offer a warning on the certainty of financial crises occurring in the future, and their advice to prepare better by providing stronger emergency time policy tools to the regulators should serve as a useful guide to contain vulnerability of the financial system.

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Agricultural Growth and Rural Poverty Reduction in India by Seema Bathla, Pramod Kumar Joshi and Anjani Kumar, 132 pp., Springer Nature Singapore Pte Ltd. (2020), €114.39

Green revolution transformed the Indian agriculture during 1960s in terms of significant yield improvement and record grain production, achieved with agrarian reforms and public investment towards adoption of high yielding varieties and irrigation development. The benefits, however, have started to fade and new challenges have emerged over time *viz.* uneven performance of agriculture across states, largescale variations in the size of landholdings, non-viability of increasingly smallholdings, moderate private investment, fewer off-farm employment opportunities, price risk and climate risk *etc.* The eastern and few western states could not benefit much from the green revolution on account of moderate public policy support. Public investment has been proven to have positive impact on agricultural productivity and thereby it contributes to reduction in poverty. Prof. Seema Bathla, P. K. Joshi and Anjani Kumar have elucidated these welfare effects of public intervention in Indian agriculture in their book *Agricultural Growth and Rural Poverty Reduction in India.* The authors have well achieved the purpose by clearly emphasising the contributions of social and economic public investments and of private investments to agricultural income and inclusive growth.

The authors have highlighted that the imbalance in sectoral income and employment generation, as evident from the lower share of agriculture in total economic output (14 per cent) relative to the share in total employment (49 per cent), has been the major cause of growing rural-urban and regional divide in the country. Thus, improvement in agriculture sector performance alongside creation of employment opportunities in non-agricultural sectors is necessary for bridging this gap. The performance of Indian agriculture in terms of annual growth has been modest (2-3 per cent) in the past, which moderated from 1996-97 onwards but then rebounded between 2004-05 and 2013-14 (4 per cent) owing to substantial budgetary allocations for agriculture, irrigation and input subsidies, besides increases in minimum support prices. The income inequality (Gini index) for both per capita agricultural and non-agricultural income increased during 1980s and after some moderation in 1990s, it has increased continuously thereafter, particularly for non-agricultural income. This inequality can be attributed to large inter-state discrepancies in public spending, as shown by higher expenditure towards the rural sector by high income states as compared to low income states. Rural areas have more than 50 per cent contribution to aggregate decline in poverty and therefore, technology adoption and increased investment in agricultural research, extension and development have been observed as crucial factors in poverty reduction. Hence, this book explores the relation between public and private investment in agriculture and assesses the impact on farm productivity, income and poverty alleviation at sub-national level by categorising the states into high, middle and low-income category based on average per capita income during the period 1981-82 to 2013-14.

Chapter 2 explains the context and rationale behind public intervention in agriculture and its welfare effects. Public expenditure impacts the production level and employment in an economy by increasing a person's ability to work, save and invest more. Increased public spending also influences private investment, which then increases the size of the market for manufactured goods and hence production and employment. The justification for public intervention in agriculture arises from economic inefficiencies due to market failure resulting from market imperfections, information asymmetries and externalities. Such inefficiencies often do not allow Pareto-optimal outcomes. Public intervention in rural areas aims to achieve social welfare goals *i.e.* income growth and its equitable distribution as well as poverty reduction. Literature often cites the likely trade-off between efficiency and equity in public expenditure, but it happens only when it is linked with economic growth. The book has underlined the strong synergies between the two while pursuing the goal of poverty reduction.

Chapter 3 analyses the temporal and spatial trends in public expenditure, input subsidies and their outcome. There has been a high correlation between level of economic development and a state government's ability to spend, but investment spending has shown much higher growth during 2000s in low income states than high and medium income states. In spite of higher investment expenditure by poorer states, they have not been able to reach the level of richer states in terms of productivity, income and poverty reduction. The composition of government expenditure reflects the spending priorities of respective state governments which has been education, irrigation, agriculture and health across three state groups. The composition of expenditure on agriculture across all three state groups shows crop husbandry being the largest receiver of funds followed by forestry, animal husbandry and food storage. Agricultural research and development received much lower funds in all three state groups, contrary to the other developed countries, which is worrisome because of observed decline in productivity growth and also due to the fact that it is not undertaken by private sector in India. Among the major input subsidies, *i.e.* irrigation, power, fertiliser and credit, highest increase was witnessed in fertiliser subsidies per hectare. Here too, inter-state disparities have been observed as average public spending per hectare on total input subsidies was lower in low income states than in middle income states and high-income states. Considering the outcome of public spending, in spite of sizable public expenditure on irrigation, the percentage of irrigated area under canals has been less than 20 per cent across major states, indicating inefficiency in the use of public resources. However, road density has shown significant improvement across the states. But there has been again a dismal situation for per hectare electricity consumption in agriculture in low income states and the number of years of schooling of rural population. Hence, wide inter-state disparities in investments and their outcome undermine many public policy decisions.

Chapter 4 estimates the responsiveness of private capital formation to public capital formation and input subsidies in agriculture to identify the ‘crowding in’ effect. A perceptible increase in private capital formation has been observed over the study period with largest share of residential plots and buildings which may be an indicative of increasing urbanisation, land fragmentation and shifting of households towards nuclear families. But this increase in the expenditure towards residential plots and buildings has come at the expense of investment in agriculture. The composition of private investment in agriculture and allied activities has been towards agricultural implements, machinery, irrigation sources, transport and livestock. Private investment in agriculture was found to be significantly determined by public investment in agriculture as well as input subsidy across all states barring the middle-income states. The terms of trade or price incentive has been observed as a major determinant of farmers' investment decision. The price incentives for farmers need to be strengthened to encourage higher investments and thus the adoption of new technology and farming practices. State level analysis showed mixed results, suggesting the need for geographical targeting of public investment with an emphasis on the type of investment and input subsidy that will best compound its influence on private investment.

Chapter 5 presents the empirical results and an assessment of marginal returns from various types of incremental investments and subsidies in low, middle and high-income states. The major factors contributing to poverty reduction in rural areas have been agricultural productivity, remunerative farm prices and non-farm employment with better wages. Relative prices were identified to matter most in high income states followed by non-farm employment. The factors influencing land productivity have been spending on agricultural research and development, fertiliser, irrigation, electricity and labour. Irrigation use has been induced more by private than by public investment in agriculture. Rural non-farm employment and non-farm wages were observed to be enhanced by increase in non-farm income, education and health of workers. The study did not find evidence to support the 'crowding-in' or complementarity relation between private irrigation investment and public expenditure in canal irrigation at the national level, except in middle income states. Coming to marginal returns on various categories of investment in agriculture, higher pay-offs were identified for every ₹ 1 new private investment in well irrigation (₹ 9.51) and public investment in agricultural research and development (₹ 2.47), followed by education (₹ 2.39) and health (₹ 1.83). The marginal impact of various public spending on rural poverty was the highest for rural development, followed by investment in well irrigation, public health, energy and education. Finally, a trade-off though a mild one, observed between efficiency and equity objectives across state groups. Overall, to achieve growth with equity, a differential or location-specific public expenditure policy across states is advocated.

The final chapter draws policy inferences at state level for strategising public investment with the overall goal of accelerating private investment and meeting future challenges in agriculture, employment generation and rural development. Owing to the significant effect of public spending ‘in’ (agriculture and irrigation) and ‘for’ (health, education, roads, rural industry, telecommunication) agriculture on agricultural income, more resources should be allocated towards economic services. An increase in public investment *i.e.* well targeted beyond canal irrigation commensurate with farmers’ changing investment portfolio would strengthen the complementarity between public and private investment. This would be again supplemented by making available minor and micro irrigation systems and favourable credit policy in rural areas. The observed spatially heterogeneous effect of input subsidies suggest that these should be redirected towards less favourable areas to enable farmers to increase input uses and facilitate asset creation. The book has also delved into the question of bringing efficiency in the distribution of input subsidies to farmers while maintaining sustainable use of natural resources.

The book’s strength lies in addressing some crucial concerns like whether there is a crowding in or crowding out of private investment by farm households in response to public investment, the impact of investments and input subsidies on agricultural income and poverty alleviation and identifying the nexus between efficiency and welfare objective of public investment. Overall, the book benefits the readers to understand several key issues in the farm sector, the complex interaction between various forms of public policy interventions and outcomes, and different ways to enhance the contribution of public policy to poverty reduction in rural areas.

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