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Monetary Policy Transmission in India: Do Global Spillovers Matter?

Michael Debabrata Patra, Sitikantha Pattanaik, Joice John and Harendra Kumar Behera*

This paper employs a dynamic factor model to develop an Indicator of Global Spillovers (IGS) to examine the impact of unconventional monetary policies on transmission of monetary policy in India. Estimates from a Time-Varying Parameter Vector Autoregression (TVP-VAR) model indicate that monetary policy transmission through the money and credit markets is unaffected by global spillovers. In the debt market, however, transmission is impacted, producing occasional overshooting and over-corrections, but market microstructure seems to have a stronger influence and drives mean reversion. Heightened sensitivity of foreign exchange and equity markets to global spillovers notwithstanding, there is no statistically strong evidence of domestic monetary policy losing traction because of global spillovers.

JEL Classification : C54, E52, E58

Keywords : Global spillovers, Monetary policy transmission, Dynamic factor model, M-GARCH, Time-varying parameter VAR

Introduction

In the aftermath of the global financial crisis (GFC), spillovers from the divergent courses for monetary policy set by systemic advanced economies (AEs) have posed a dilemma: will externalities from this transatlantic schism imprison interest rates in emerging market economies (EMEs) like India that are reasonably well-integrated into the global financial cycle? Will it be possible for these countries to conduct independent monetary policy as

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capital and asset prices are stirred up by the core financial centres? These questions form the theme of this paper. We ask them in the context of a rapidly proliferating strand in the empirical literature that is finding increasing evidence of significant spillovers, not just for fixed income markets and longer-term interest rates (Miyajima *et al*., 2014; Obstfeld, 2015; Sobrun and Turner, 2015; Turner, 2014), but for short-term interest rates and policy rates as well (Edwards, 2015; Gray, 2013; Hofman and Takáts, 2015; Takáts and Vela, 2014). Furthermore, as this evidence accumulates, the channel of propagation – global economic and financial integration – are becoming clearer and, as a consequence, more real and present for open EMEs (Hofman and Takáts, 2015), with investor arbitrage playing out through EME allocations in globally mobile funds and foreign participation in local markets (Barroso, Kohlscheen and Lima, 2014); and foreign currency denominated credit (He and McCauley, 2013). While considerable heterogeneity is found across EMEs (Chen *et al*., 2015), the constraining effects of spillovers on domestic monetary policy is observed irrespective of the exchange rate regime (Rey, 2015).

The persuasiveness of this strand notwithstanding, there is a contrarian view too that seems to be standing up to the tests imposed by episodes of volatility, relative to the overwhelming effects of the taper caper.[1] It is argued that the concept of monetary policy independence needs to distinguish between the ability to set monetary policy independently and the willingness to do so, the latter implying the extent to which external developments enter policy reaction functions of central banks in EMEs and the coefficients attached to them. The effects of spillovers or contagion, when appropriately measured, seem to be less severe for EMEs than generally assumed or observed in financial phenomena such as co-movements in interest rates across borders (Disyatat and Rungcharoenkitkul, 2015). First, in the taper caper and its aftermath, several EMEs allowed exchange rate adjustments, with some of them being large and apparently disruptive, but this enabled them to set domestic interest rates to domestic conditions. The exchange rate change was a measure of the importance of external developments in their reaction functions and their willingness to accommodate them rather than a loss of monetary policy independence. By the same logic, several EMEs are regarded as engaged in pursuing exchange rates that reflect domestic goals — competitive depreciations. Both interest rates and exchange rates can

[1] A term coined by the former chairman of the US's Federal Reserve, Ben Bernanke, in his autobiography.

be regarded as instruments that serve domestic objectives. Secondly, some EMEs with large reserves actively intervened to stem turmoil in their foreign exchange markets. By all counts, they succeeded effectively in preventing the trilemma from breaking down to a dilemma *a la* Rey (2015), and set in motion what has been termed as quantitative tightening that supported domestic conditions. Also, many EMEs continue to retain both macro-prudential and administrative policies that can influence capital flows in both directions, and this is acknowledged to being effective in securing monetary policy autonomy. Thirdly, several EMEs, including India, have repaired and strengthened macroeconomic fundamentals and policies. As the events after the taper caper showed, these actions buffered their economies considerably, contrary to the view that in the face of spillovers, fundamentals do not matter (Eichengreen and Gupta, 2014).[2] This view itself has been questioned by the evidence of investors differentiating among EMEs based on fundamentals, and especially in favour of economies having deeper markets and tighter macro-prudential policies (Mishra *et al.*, 2014a). Moreover, differentiation was found to have set in early and persisting (Ahmed *et al.*, 2017). In fact, this has led several central banks to urge the United States Federal Reserve (Fed, hereafter) to stop stoking speculation and to 'just get on with it' in normalising US monetary policy (Harrison, 2015; Parussini, 2015).

This paper is an empirical exploration of these two sets of issues in the Indian context. The rest of the paper is organised into five sections. The next section presents stylised evidences on channels of contagion and their impact on financial markets in India. Section III develops a measure of global spillover. Section IV presents and discusses empirical results. Section V concludes the paper with implications for the conduct of monetary policy in open EMEs.

Section II

Living with Spillovers: The Indian Experience

In a spillover-rich environment, the behaviour of the spectrum of domestic interest rates and asset prices alters in responce to global shocks, sometimes significantly and persistently. Perturbations in India's domestic financial market segments during the period of study-which coincides with unconventional monetary policies (UMPs) of AEs, as well as high intensity

[2] In fact, India exited the 'fragile five' grouping and escaped the recent 'troubled ten' epithet.

global shocks such as the European sovereign debt crisis, the taper caper, the ‘bund tantrum’ and the Chinese devaluation-is the focus of this section. The discussion is arranged in terms of the stages in which each market segment transmits monetary policy impulses.

Money Market

In India, the money market provides the first leg of monetary policy transmission: policy rate changes impact the uncollateralised weighted average call money market rate (WACR) — the operating target — instantaneously and, in turn, all other money market rates evolve around the WACR with varying spreads. Typically, the money market is insulated from external shocks by active liquidity management by the RBI, which tend to offset fluctuations in market liquidity conditions brought on by domestic factors such as changes in government balances, currency demand and the like. The absence of prolonged disruptions in interbank overnight and money markets is largely corroborated in the country experience (Moreno and Villar, 2011).

During the GFC and the taper caper, money market spreads widened significantly, dispelling the sense of insulation. Even though this was short-lived it provoked unconventional policy responses from the RBI, which lowered its policy repo rate by 425 bps cumulatively and injected liquidity/opened up liquidity windows aggregating to 10 per cent of gross domestic product (GDP) to avert a liquidity freeze. In May-September 2013, as the taper caper hit EMEs, the RBI again responded unconventionally. It widened the policy corridor by raising the marginal standing facility rate by 200 bps while draining out liquidity by tightening reserve requirement maintenance and restricting access to liquidity under normal repos. These actions effectively raised the WACR by 300 bps, with a view to preventing a free fall of the rupee (Pattanaik and Kavediya, 2015). Significantly, the policy rate was kept unchanged to reflect the domestic focus of monetary policy through these troubled times. On both occasions, exceptional monetary measures were normalised quickly.

Besides active liquidity management, money markets in India are also shielded from global spillovers by statutory liquidity ratio (SLR) requirements which entail that banks maintain a fixed proportion of liabilities in gilts. SLR maintenance in excess of the statutory requirement allows banks to get access to central bank liquidity as well as to secured markets, thus obviating a collateral constraint. Furthermore, banks largely fund themselves through retail deposits rather than wholesale funding, the latter identified elsewhere as a source of vulnerability to external contagion (Mesquita and Torós, 2010).

Bond Market

Much of the international debate in the empirical literature highlights co-movement of long-term yields as an example of possible loss of independence of domestic monetary policy. India's 10-year government securities (G-sec) yield did, in fact, exhibit a high degree of co-movement with US and German government bond yields, but only during three episodes — the GFC, the taper caper and the bund tantrum. During the first two of these episodes, however, G-sec bond yields largely reflected the domestic monetary policy stance, which adjusted to insulate domestic macroeconomic conditions and quite successfully so. The Indian experience with regard to spillovers and G-sec yields is also borne out in the literature in which a broad consensus suggests that when markets are on edge, they pay greater attention to country-specific fiscal fundamentals rather than global correlations (Jaramillo and Weber, 2013a). In the short run, however, financial vulnerabilities may matter in spread formation (Bellas *et al*., 2010), but here too, it is important to recognise country specifics. Domestic prudential policies have also helped in insulating domestic bond markets. First, large non-resident holdings of locally-issued domestic government bonds, which expose domestic bond markets to cross-border co-movements and spillovers, are relatively small in India: the share of foreign portfolio investors in the stock of government bonds is less than 5 per cent. Secondly, the recent jump in direct issuances of US dollar denominated bonds by corporates in EMEs in international capital markets — which more than doubled since 2008 — has largely bypassed India which has accounted for only 5 per cent of this surge. Much of these issuances were driven by the lure of carry trade, *i.e.*, financial risk-taking rather than real investment (Bruno and Shin, 2015). Thirdly, unlike in some EMEs such as Poland, Mexico, and Hungary (Moreno, 2010), changes in short-term domestic interest rates appear to be the lead driver of changes in nominal G-sec yields in India (Akram and Das, 2015). This is also found in broader surveys of country experiences, although stable inflation expectations tend to dampen the direct impact (Mohanty and Turner, 2008). Corporate bond yields in India essentially track the 10-year G-sec yield, with changing risk spreads over time. But for occasional deviations of risk spreads from normal levels, the evolution of bond yields is consistent with domestic monetary policy cycles. Corporate bond yields tend to follow G-sec yields in overshoots in response to global shocks and their speed of adjustment is also faster.

Credit Market

The recent literature also documents the credit channel of spillovers across EMEs in emerging Europe (Brzoza-Brzezina *et al*., 2010) and Asia (He and McCauley, 2013): low interest rates on major currencies provide an incentive to substitute foreign currency credit-mostly dollar denominated-for local currency credit. In India, the share of non-resident participation in deposits and loans has been very low. Non-resident deposits (excluding rupee denominated deposits of non-residents) priced off a foreign interest rate constitute barely 3 per cent of banks' total liabilities. On the assets side, 3 per cent of outstanding bank assets are externally sourced. Banks' access to external finance is also governed by prudential regulations that limit it to 100 per cent of their Tier 1 capital. Moreover, open positions and gap limits attract capital charges.

Several EMEs faced the compulsion of keeping their interest rates lower than what might have been warranted by Taylor-type rules on account of the accommodation of external developments in their policy reaction functions (BIS, 2014). By contrast, the RBI's main instrument to smooth excessive exchange rate volatility has been active capital account management along with interventions in the foreign exchange market (Mohan and Kapur, 2009). Furthermore, the introduction of the Fed funds rate generates instability in the reaction function — the long-run coefficient on inflation falls below unity, while the coefficient on the output gap turns insignificant (Patra and Kapur, 2010).

Section III
Measuring Global Spillovers

UMPs have produced strong co-movements in a host of economic and financial variables across borders. In order to examine spillovers in relation to a specific country, elements driving these co-movements can be identified and aggregated into an Indicator of Global Spillovers (IGS). It has been empirically shown that one or two common factors extracted from these innumerable variables may effectively capture a reasonably large part of the common information contained in them while maximising degrees of freedom (Breitung and Eickmeier, 2006). Accordingly, dynamic factor models (DFMs) have been favoured for extracting latent dynamic factors in co-movements and synchronisations represented in high dimensional vectors of time series variables. DFMs overcome the limitations of standard Vector Autoregression (VAR)/Global Vector Autoregression approaches — restrictive assumptions on the structure of the economy; which variables to include and, therefore, the number of shocks; difficulties in segregating global and country-specific factors; limitations on inclusion of number of countries and the like (Crucini *et al*. 2011; Giannone *et al.*, 2004; Hirata, *et al*., 2013; Watson, 2004). Originating in seminal work on time series extensions of factor models developed for cross-sectional data (Geweke, 1977; Sargent and Sims, 1977), DFMs are able to simultaneously model data sets in which the number of variables can exceed the number of time series observations (Stock and Watson, 2011). Another advantage is that idiosyncratic movements from measurement errors or localised shocks can be eliminated, yielding more reliable policy signals (Breitung and Eickmeier, 2006). A similar parsimonious philosophy has driven the quest for financial conditions indices (Matheson, 2012; Osorio *et al*., 2011).

A three-step procedure is adopted here. First, the extensive application of DFMs in the context of equity, bond and foreign exchange markets sheds light on the variables that are likely candidates for measuring global spillovers[3]: (i) VIX, as an indicator of risk perception or the confidence channel, exhibits strong co-movement with capital flows to EMEs in the role of a push factor (Nier *et al*., 2014); (ii) LIBOR-OIS spread as an indicator of the liquidity channel reflects US dollar liquidity stress (Ree and Choi, 2014) as well as risk of default associated with lending to other banks (Thornton, 2009); (iii) term spread, *i.e*., 10-year US treasury yield minus three-month US treasury yield, represents the portfolio balance channel (Bernanke, 2013)[4]; (iv) risk spread — US 10-year corporate yields minus US 10-year treasury yields (Bethke *et*

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[3] Two broad weighted sum approaches are commonly used to assimilate information embodied in a range of variables which entail common elements as also idiosyncratic effects and use it to develop weights for aggregation. One involves estimating factor loadings either through simulations of macro-models or reduced form VARs. The second is the principal component approach which extracts common factors that explain a large part of variations in all variables. Unlike in a VAR or macro-model, imposing a structure of the economy *a priori* is not required in the second approach. However, the extracted common factor may suffer from the challenge of direct economic interpretation.

[4] Since government securities are assumed to be free of credit risk, the term premium is essentially the compensation to investors for uncertainty about future evolution of short-term nominal rates, inflation and the natural real interest rate relative to current expectations. In EMEs, the term premium may also reflect a risk premium to compensate for default risk in government bonds and the currency risk premium embedded in exchange rate volatility (Miyajima *et al*., 2014).

al., 2015; Jaramillo and Weber, 2013b); and (v) DXY — the dollar index — represents the exchange rate channel of transmission of spillovers (Bergsten, 2013; Glick and Leduc, 2013). Hereafter, these variables are referred to as the spillover variables.

In the second step, these variables are subjected to the Occam's razor of being relevant to channels of transmission of monetary policy in India — the money market (spread between weighted average call rate and policy repo rate, with net injection/absorption of liquidity by the RBI as the control variable to capture market specific characteristics); the government bond market (10-year yield, with foreign portfolio investments (FPI) in debt securities as the control variable); the stock market (BSE Sensex returns, with foreign portfolio equity investment as the control variable); and the foreign exchange market (returns on or daily change in the INR-USD exchange rate, with net FPI investment, debt and equity together, as the control variable). For each domestic market segment, the relevant spillover variable is considered: LIBOR-OIS spread for the money market; the US term spread/risk spread for the bond market; the US VIX for the stock market; and LIBOR-OIS spread/DDXY (dollar index returns) for the foreign exchange market. These domestic market variables are hereafter referred to as domestic variables.

Each postulated relationship is evaluated in a bivariate Baba, Engle, Kraft and Kroner (BEKK) - GARCH model[5] which involves a system of conditional mean equations with exogenous regressors in VARX(p, q) form:

$$Y_t = \mu + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \sum_{j=1}^{q} \Lambda_j X_{t-j} + \varepsilon_t \tag{1}$$

where $Y_t=(y_{1t},y_{2t})$, y_{1t} is the domestic financial market variable of interest at time t, y_{2t} is the control variable which interacts with y_{1t} and $X_t = (x_{1t},x_{2t},\ldots)$ are exogenous variables, including the relevant spillover variable, $\Lambda_j=(\lambda_1,\lambda_2,\ldots)$ is a vector of λ_j s which captures mean spillover effects. The residuals $\varepsilon_t=(\varepsilon_{1t}, \varepsilon_{2t})$ are normally distributed $\varepsilon_t|\Omega_{t-1}\sim N(0, H_t)$, with the corresponding conditional variance-covariance matrix given by $H_t|\Omega_{t-1}$ – an information set at time t-1.

[5] See Engle and Kroner (1995). Bollerslev *et al.* (1988) provided the basic framework for a MGARCH model by extending the univariate GARCH representation in the framework to a vectorised conditional-variance matrix (VECH). The VECH parameterisation involves estimation of a large number of parameters, making estimation and interpretation of results difficult. Furthermore, it fails to assure the positive definiteness of the conditional variance matrix. However, BEKK parameterisation of MGARCH model incorporates quadratic forms in a way that ensures the positive semi-definiteness of the covariance matrix.

For the conditional variance equation, we also use a BEKK framework augmented with the spillover variables in view of the associated advantages of estimating less number of parameters and ensuring positive semi-definiteness of the conditional variance matrix. The equation takes the following form:

$$H_t = C' C + A' \varepsilon'_{t-1}\varepsilon_{t-1} A + G' H_{t-1} G + D' X_t D \quad (2)$$

in which H_t is a linear function of its own lagged values, lagged squared innovations (ε_{t-1}) and their crossproduct, and exogenous spillover variables. Volatility transmission between domestic financial variables is represented by the off-diagonal parameters in matrices A and G while the diagonal parameters in those matrices capture the effects of their own past shocks and volatility. The parameters in matrix D measure international spillovers. Eq. (2) is estimated by the maximum likelihood method.

Daily data for the period April 1, 2004 through October 15, 2015 are used, with estimations for the full sample period as well as for sub-samples covering the pre-crisis period (up to August 9, 2007) and the post-crisis period (from August 10, 2007 to October 15, 2015), as robustness checks. Impulse responses of the spillover variables on domestic variables in the unconditional VARX(p,q) models are found to be statistically significant though short-lived, with the impact persisting up to a maximum of one week[6]. When examined in a conditional VAR framework that allows for interactions of volatilities in variance equations, the mean spillover effects are found to be only marginally different (Appendix, Tables A.1 to A.4). Thus, even after controlling for interactions with volatility, there is evidence of spillover.

Spillovers on to the call money market are found to be significant only in the post-crisis sample, essentially reflecting transient dollar liquidity shortages impacting the rupee leg. Of the two spillover variables relevant for the foreign exchange market, the impact of the LIBOR-OIS spread on the exchange rate of the rupee is found to be significant — though at 10 per cent level — in the post-crisis period and the full sample period, but it is insignificant in the pre-crisis sub-sample. Importantly, spillover is found to transmit through Foreign Institutional Investors (FII) investment flows, particularly in the post-crisis period. When the LIBOR-OIS spread is substituted with the DDXY, the impact is found to be significant in all sample periods, indicating that the rupee is directly influenced by movements of the US dollar *vis-à-vis* other

[6] Impulse response charts are not provided for the sake of brevity.

major currencies. Mean spillovers on stock prices (daily returns) are found to be significant for the full sample as well as for the pre-crisis period; in the post-crisis period, spillovers are more evident in stock price volatility rather than in mean returns. The mean spillover on government bond yields is found to be insignificant in all sample periods, though FPI debt flows are influenced by both the term spread and the risk spread.

Turning to volatility, shocks to the LIBOR-OIS spread and the DXYSQ (*i.e.*, squared dollar index return) are found to increase volatility in the exchange rate of the rupee in a statistically significant manner. Similar results are also obtained in the case of stock market volatility in response to shocks to the VIX, with a significantly large impact in the post-crisis period. The impact on volatility of bond yields is also statistically significant, but the signs of coefficients reverse when the risk spread is considered, making the interpretation of the impact on mean and volatility difficult. An increase in the LIBOR-OIS spread is found to increase volatility in the call rate, despite the fact that net LAF liquidity — which should control both mean and volatility — is introduced in the model as a control variable. Overall, the five selected global spillover variables are found to influence volatility in domestic financial markets, and their effects on mean levels of variables are also found to be statistically significant but transitory.[7]

In the third stage, we estimate the IGS by applying a DFM to the selected spillover variables identified in the second stage.[8] It is assumed that each variable (standardised) Y_t can be decomposed into an unobserved common component, F_t, and a disturbance term ε_t. F_t is modelled as an autoregressive process and the disturbance term ε_t is assumed to be autocorrelated:

$$Y_{t,i}=\gamma * F_t+\varepsilon_{t,i} \text{ (factor loadings)} \tag{3}$$

$$F_t=\beta * F_{t-1}+\omega_t \text{ (auto correlated factor)} \tag{4}$$

$$\varepsilon_{t,i}=\alpha * \varepsilon_{t-1,i}+\xi_{t,i} \text{ (auto correlated errors)} \tag{5}$$

[7] It needs to be mentioned, however, that impulse response paths of domestic financial market variables are in response to one period (or one day) shocks to spillover variables. In reality, shocks may persist beyond one day for which monthly/quarterly data would be better suited as shown in Section IV, unlike daily data used in this section.

[8] The IGS is constructed to capture the overall dynamics of global uncertainties as a composite indicator that can jointly capture spillover effects on Indian financial markets. Hence, only such global variables that are found to have statistically significant effects on any of the markets in India in the second stage are used to construct the IGS.

Before estimation, all five spillover variables were converted to monthly frequency[9] and standardised. The sample period for the analysis is from January 2002 to September 2015. The parameters are obtained by maximum likelihood estimation using the Kalman filter (Appendix, Table A.5), which produces substantial improvements in the estimates of factors relative to principal components when the common factor is persistent (Stock and Watson, 2011). The estimated factor loadings[10] are provided in Table 1.

The Portmanteau (Q) test suggests that all innovations are white noise, validating the goodness of fit of the DFM. Table 1 shows the IGS is significantly correlated with all five spillover variables, and especially with the VIX. This result is consistent with the central tendency in the empirical literature (Nier *et al*., 2014).

IGS tracks global financial conditions nicely, particularly the GFC, the events relating to UMPs of the Fed, the sovereign debt crisis in Europe, the Chinese devaluation, the Bund Tantrum and the growing certainty around the Fed's lift off (Chart 1). It does not, however, adequately capture the impact of the 2013 Taper Tantrum. Capital flows to EMEs reversed between May 2013 and January 2014, but recovered across all major EMEs by Q1 of 2014. This short-lived episode was also suffused with domestic policy responses in a number of countries, some dramatic and unconventional, which might be blurring the clear indications reflected, for instance, in US yield spreads (Section II).

Table 1: Factor Loadings for IGS and Correlation

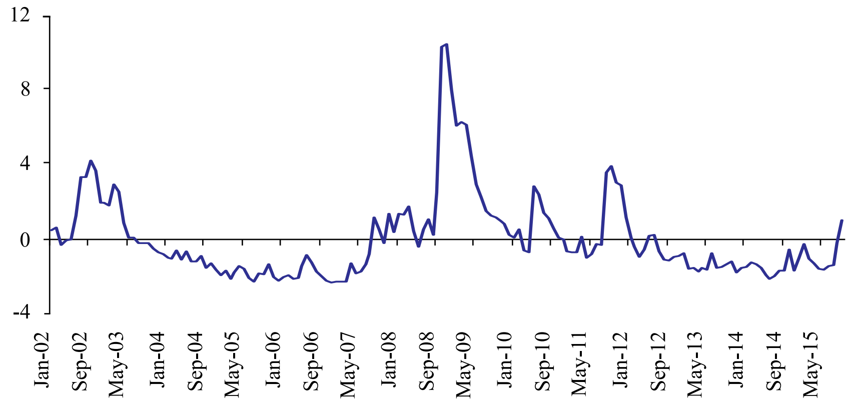
Variables	Factor Loadings	Correlation
VIX	0.44 (0.00)	0.99 (0.00)
LIBOR-OIS	0.30 (0.00)	0.74 (0.00)
DXYSQ	0.15 (0.00)	0.34 (0.00)
TMSPREAD	0.01 (0.97)	0.35 (0.00)
RISKSPREAD	0.16 (0.00)	0.67 (0.00)

Note: Figures in parentheses are p-values.

[9] VIX, LIBOR–OIS spread, dollar index and term spread are available at daily frequency, which are converted to monthly frequency by taking simple averages.

[10] The number of dynamic factors is identified to be one using the methodology suggested by Amengual and Watson (2007). First, the number of static factors is identified using scree plot. Then, the Bai and Ng (2002) estimator is used to find the number of dynamic factors by applying it on the errors obtained by using static factors.

Chart 1: Indicator of Global Spillovers (Standardised)



Section IV

Impact of Spillovers on Monetary Policy Transmission Channels in India

In this section, we set out to empirically evaluate the hypotheses proposed in the introductory section, armed with the lessons drawn from the available literature and the specifics of the Indian experience. With the failure of large macroeconometric models in predicting turning points of business cycles the world over, especially after the stagflation experience following the oil price shocks of the 1970s, economists turned to the use of VAR models, drawing on seminal work to capture the dynamics in multiple time series (Sims, 1980). While the VAR model has the advantage of being free of *a priori* strong commitment to structural restrictions, the imposition of constancy in parameters as well as error variances may produce misleading results, especially when policy reaction functions and transmission are changing either due to structural breaks/regime shifts and/or the changing nature of shocks. This is particularly relevant in the context of the period of study of this paper which covers a catastrophe of global dimensions and aftershocks as well as significant structural transformation in the Indian economy. These developments can and have forced changes in monetary policy transmission due to: (a) unconventional policy responses despite a stated objective function, leading to excessive accommodation/contraction, depending on the compulsion faced by central banks; and (b) exogenous non-policy factors influencing transmission such as asset quality concerns in the banking system and associated risk aversion, competition from non-banks/shadow banks, administered interventions in setting interest rates and macro-prudential and regulatory interventions impacting flow and pricing of credit. Accordingly, the methodology adopted here draws upon a recently growing strand in the literature which employs VAR models involving time-varying parameters (TVPs) with stochastic volatility in the tradition started by Primiceri (2005)[11]. The TVP-VAR also allows for the checking of impulse responses at different points of time. Following Imam (2015), the estimated cumulative impulse responses from the TVP-VAR — representing the impact of monetary policy shocks — are regressed on the IGS developed in Section III, while controlling for relevant domestic factors, in order to assess the impact of spillovers on monetary policy transmission in India. The interpretation of exogeneity in this context relates to non-policy factors, even though financial market variables included in the TVP-VAR reflect both policy and non-policy influences.

The TVP-VAR Framework

The measurement equation is specified as

$$Y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t,\ t = s+1\ldots.n. \tag{6}$$

in which Y_t denotes a (n×1) vector $\{p_t, tb_t, gsec_t, walr_t\}$ of four variables at time t: p_t – effective policy rate; tb_t – 91-day treasury bill (TB) yield; $gsec_t$ – 10-year government securities bond yield; and $walr_t$ – weighted average lending rate (WALR). $X_t = I_s \otimes (Y_{t-1}' \ldots Y_{t-s}')$; A_t is the time varying lower triangular matrix of structural restrictions. Following Pétursson (2000) and Evans and Marshall (1998), these structural identification restrictions, which enable inferences about structural relationships, are ordered as follows: (a) the RBI does not respond contemporaneously to shocks to financial market rates; (b) the 91-day TB rate responds immediately to policy rate changes while longer-term bond yields as well as bank loan rates respond with a lag; (c) longer-term bond yields are affected by both monetary policy innovations as well as innovations in short-term bond market rates; and (d) loan rates in the credit market respond to innovations in the short-term as well as to long-term rates. $\Sigma = dia(\sigma_{jt}^2)$ and ε_t follows N(0,I). β_t is a vector of time-varying coefficients. It is assumed that

[11] Other important contributions are Cogley *et al.*, 2010; Mumtaz and Sunder-Plassmann (2013); Nakajima (2011); Nakajima *et al.* (2011); John (2015).

parameters in (6) follow a random walk process (Primiceri, 2005; Nakajima, 2011).

A_t can be represented as a stacked vector of the lower-triangular elements $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, \ldots, a_{54})$; and $h_{jt} = \log\sigma^2_{jt}$ with $h_t = (h_{1t},\ldots, h_{kt})$ for $j = 1,\ldots, k$; and $t = s+1,\ldots, n$. The state equations can be depicted as:

$$\begin{aligned} \beta_{t+1} &= \beta_t + u_{\beta t} \\ a_{t+1} &= a_t + u_{at} \\ h_{t+1} &= h_t + u_{ht} \end{aligned} \quad \text{with} \begin{bmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{bmatrix} \sim N\left(0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix}\right) \tag{7}$$

for $t = s+1,\ldots n$

in which Σ_β, Σ_a and Σ_h are the variance and covariance structure for the innovations of the time-varying parameters, and are assumed to be diagonal (Nakajima, 2011). Furthermore, a TVP-VAR requires somewhat tighter priors for the βs since the state variables capture both gradual and sudden changes in the underlying economic structure, which can lead to over-identification (Cogley *et al.*, 2010; Nakajima, 2011; Primiceri, 2005). Accordingly, a tighter prior is set for Σ_β and a relatively diffuse prior for Σ_a and Σ_h. While the hyper-parameters of Σ_β are simulated from an inverse Wishart distribution, the elements of Σ_a and Σ_h are drawn from an inverse gamma distribution. The prior density of $\omega = (\Sigma_\beta, \Sigma_a, \Sigma_h)$ is $\pi(\omega)$. Samples of the posterior distribution $\pi(\beta, a, h, \omega|y)$ are drawn by using a Bayesian Markov Chain Monte Carlo (MCMC) method. Due to lack of sufficient data points in the sample, we choose a reasonably flat prior for the initial state from the standpoint that we have no information about the initial state *a priori*. To compute[12] the posterior estimates, 5,000 samples are drawn. The convergence diagnostics of the estimation results of the TVP-VAR model shows that the sample paths are stable. After the initial draws, the sample autocorrelations are low. Quarterly data from Q1:1996–97 to Q2:2015–16 are used.[13]

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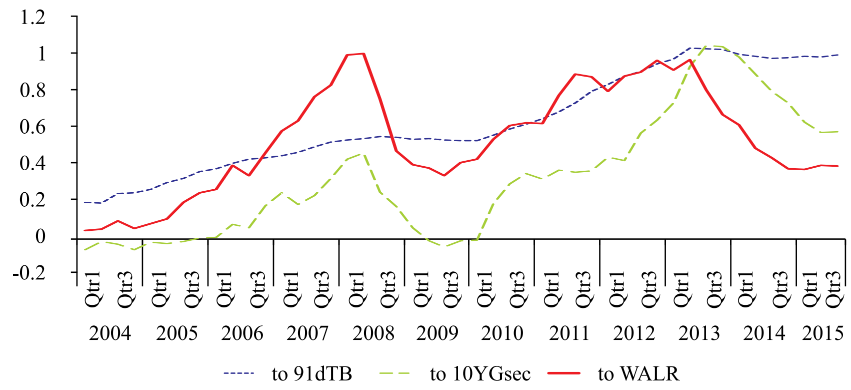
[12] We used Matlab codes developed by Nakajima (2011); available at (http://sites.google.com/site/jnakajimaweb/TVP-VAR).

[13] https://www.rbi.org.in/. For data on lending rates prior to 2011–12, annual data are linearly interpolated and converted to quarterly frequency.

***Results*[14]**

The accumulated time-varying impulse response functions (IRFs[15]) of monetary policy innovations for tb_t, $g\text{-}sec_t$, $walr_{t,}$ exhibit sustained improvement in transmission over time, interrupted by spillover-induced disruptions which produce short-lived overreactions to global event shocks. Nevertheless, monetary policy transmission has always been positive around a rising trend (Chart 2). Transmission to 91-day TB yeild is almost complete and instantaneous in more recent years. Long-term rates, *i.e.* the 10-year G-sec yield and the WALR showed significant loss of traction to domestic monetary policy shocks during the financial crisis (2008–09), but transmission improved to pre-crisis levels and even strengthened till the taper caper of May 2013. Long-term rates overreacted to the exceptional monetary tightening in the second half of 2013, and corrected only gradually, showing up in a decline in the accumulated IRFs which still remained above pre-crisis levels. The estimated time-varying IRFs are presented in the appendix (Chart A.2).

Chart 2: Time-Varying Monetary Policy Transmission: Accumulated IRFs of 1 Percentage Point Shock to Policy Repo Rate



[14] Before applying TVP-VAR, a time invariant VAR has been used with the same set of variables along with IGS as an exogenous variable, while retaining the structural restrictions. These impulse response functions (IRFs) are compared with the IRFs of a VAR with the same structural restrictions, but without using IGS as an exogenous variable. These results suggest that global spillovers do not have much impact on the transmission of monetary policy to WALR; however, transmission to the 91-day TB and 10 year G-sec yeilds gets diluted modestly (Appendix Charts A.1a and A.1b).

[15] For three month TB yield, the contemporaneous quarter is considered, as most of the transmission takes place within three months. For 10-year G-sec yield, IRFs are accumulated for 0-1 quarters and for WALR, IRFs are accumulated for 0-2 quarters. The lag structure for identifying monetary policy transmission to different interest rates are based on the statistical significance of the respective IRFs (Appendix, Chart A.Ia and A.Ib).

There are several market-specific idiosyncratic factors in operation which explain the time variation in the IRFs. Accordingly, the cumulative IRFs are regressed individually on the IGS while controlling for domestic market-specific factors — the size of the G-sec market in terms of volumes (G-sec volume/GDP) and inflation expectations — in the case of the 91-day TB rates and the 10-year G-sec yield IRFs. The Newey–West regression estimator is used to overcome autocorrelation and heteroscedasticity in the error term that are commonly associated with time series data relating to financial markets. Given the need to identify the relative importance of each of the factors considered in the regression, standardised coefficients[16] are reported in Tables 2 and 3. IGS has a statistically significant damping impact on monetary policy transmission to both g-sec and 91-day TB yields, but domestic factors such as volumes in the g-sec market and inflation expectations have a stronger influence.[17]

With regard to the bank lending rate, the IRF is regressed on IGS while controlling for financial development in the credit market measured

Table 2: Monetary Policy Transmission to G-sec Market

Dependent / Independent	Monetary Policy Transmission to 91 day TB yield	Monetary Policy Transmission to g-sec 10 year yeild*
Index of global spillover (IGS)	-0.274 (0.002)	-0.494 (0.013)
Market size (G-sec volume/GDP)	0.722 (0.000)	0.680 (0.023)
Long-term inflation expectations	---	0.522 (0.011)
R-square	0.548	0.422
F statistic	28.40 (0.000)	7.06 (0.001)

Notes: Figures in parentheses are p-values. Newey–West regression with autocorrelation and heteroscedasticity adjusted SEs.

*: As the data on long-term inflation expectations are available from 2008, the sample period for this regression is from Q4:2007–08.

[16] Beta coefficients obtained from regressions using standardised variables.

[17] Monetary policy transmission to long-term yields often declines when long-term inflation expectations fall (Moreno, 2008; Roley and Sellon, 1995). We have used 10-year ahead inflation forecasts from the RBI's *Survey of Professional Forecasters*.

Table 3: Monetary Policy Transmission to Credit Market

Dependent variable: Monetary Policy Transmission to WALR	**Regression 1**	**Regression 2**	**Regression 3**	**Regression 4**
Index of global spillover (IGS)	-0.010 (0.912)	-0.011 (0.921)	-0.083 (0.473)	-0.010 (0.911)
Financial development (credit/GDP)	0.849 (0.000)			0.775 (0.000)
Asset quality (GNPA/credit)		-0.732 (0.000)		-0.087 (0.674)
Financial development x Asset quality			-0.512 (0.000)	
R-square	0.694	0.527	0.247	0.697
F statistic	52.94 (0.000)	27.74 (0.000)	8.30 (0.000)	34.81 (0.000)

Notes: Figures in parentheses are p-values. Newey–West regression with autocorrelation and heteroscedasticity adjusted SEs.

by credit to GDP ratio (credit/GDP) and asset quality measured by gross non-performing assets to credit ratio (GNPA/credit).[18] The standardised regression coefficients on IGS are not statistically significant. By contrast, credit/GDP and GNPA/credit ratios are statistically significant and together explain more than 50 per cent of variations in transmission over time. Thus, there is no statistically strong evidence of domestic monetary policy losing traction in respect of bank lending rates because of spillovers.

To summarise, the empirical results indicate that monetary policy transmission through the money market — the first leg of transmission — has improved substantially over time and is found to be almost complete even in the face of global spillovers. In the debt market, however, global spillovers affect transmission of monetary policy to yields and can even produce overshooting and over-corrections, but domestic factors such as market microstructure have a stronger influence. The latter may be influential in rendering the reactions to global perturbations short-lived and in ensuring mean reversions to normalcy. In the credit market, lending rates reflect low and incomplete transmission of monetary policy, even absent global spillovers. Spillovers have no significant influence, and asset quality and financial deepening play the more important

[18] Financial development and asset quality are significant determinants of monetary policy transmission to lending rates (Saborowski and Weber, 2013).

role in determining policy transmission. These findings do not, however, negate the overwhelming effects that global spillovers can produce on global output and inflation gaps and, in turn, on domestic gaps. To that extent, spillovers do pose challenges to the successful conduct of monetary policy in pursuit of domestic goals.

Section V
Conclusion

The mainstream view that global spillovers overwhelm monetary policy independence is being questioned by specific country experiences. The effects of UMPs on monetary policy transmission and goal variables is however, still an unsettled issue. Here, global real business cycles may be at work rather than financial forces. The arena shifts to the spectrum of financial markets which provide the transmission lines.

In India, money market is largely sheltered from spillovers and so too is credit market, highlighting the shielding influence of the RBI's active liquidity management, besides country-specific factors that impart a distinct home bias. In bond, forex and equity markets, in which foreign presence provides a conduit for contagion, capital flows management buffered by foreign exchange reserves has provided a buffer, but it will be tested for endurance in the period ahead by the exhaust fumes of Fed normalisation and the idling engines of monetary super accommodation.

VAR and MGARCH estimates provide statistically significant evidence of spillovers transitorily affecting domestic financial markets. Extracting common elements in these spillovers through a dynamic factor model shows that global spillovers do dampen time-varying monetary policy transmission in the domestic bond market. The credit market is impervious.

Thus, there is no statistically strong evidence of domestic monetary policy losing traction to global spillovers in India. Monetary policy does respond directly to volatility-driven stress in domestic financial market conditions, but this needs to be regarded as a policy choice with the ultimate objective of meeting domestic goals, rather than a loss of monetary policy independence. Global shocks in a globalised economy are unavoidable, but stabilising the domestic economy, irrespective of the nature and sources of shocks to domestic transmission channels, remains a key task for domestic monetary policy.

References

Ahmed, S., B. Coulibaly, and A. Zlate (2017), "International Financial Spillovers to Emerging Market Economies: How Important are Economic Fundamentals?", *Journal of International Money and Finance*, 76, 133-152.

Akram, T. and A. Das (2015), "Does Keynesian Theory Explain Indian Government Bond Yields?", Working Paper No. 834, March, Levy Economics Institute, Working Papers Series. Available at: http://www.levyinstitute.org/publications/does-keynesian-theory-explain-indian-government-bond-yields (last accessed 15 March 2018).

Amengual, D. and M.W. Watson (2007), "Consistent Estimation of the Number of Dynamic Factors in a Large N and T Panel", *Journal of Business and Economic Statistics*, 25(1), pp. 91–96.

Bai, J. and S. Ng (2002), "Determining the Number of Factors in Approximate Factor Models", *Econometrica*, 70(1), pp. 191–221.

Bank for International Settlements (BIS) (2014), *Annual Report 2013/14*, 29 June.

Barroso, J.B., E. Kohlscheen and E.J. Lima (2014), "What have Central Banks in EMEs Learned About the International Transmission of Monetary Policy in Recent Years? ", BIS Papers No. 78, pp. 95–109.

Bellas, D., M.G. Papaioannou and I. Petrova (2010), "Determinants of Emerging Market Sovereign Bond Spreads", in A.P. Braga and C. Vincolette, *Sovereign Debt and the Financial Crisis*, Washington D.C., The World Bank, pp. 77–101.

Bergsten, C.F. (2013), "Currency Wars, the Economy of the United States and Reform of the International Monetary System", 12th Stavros Niarchos Foundation Lecture, Peterson Institute for International Economics, Washington D.C.

Bernanke, Ben S. (2013), "Long-Term Interest Rates", A Speech at the Annual Monetary/Macroeconomics Conference: The Past and Future of Monetary Policy, sponsored by Federal Reserve Bank of San Francisco, San Francisco, California.

Bethke, S., M. Gehde-Trapp A. and Kempf (2015), "Investor Sentiment, Flight-to-Quality, and Corporate Bond Comovement", CFR Working Papers 13-06, University of Cologne, Köln.

Bollerslev, T. and R.F. Engle and J.M. Wooldridge (1988), "A Capital Asset Pricing Model with Time-Varying Covariance", *Journal of Political Economy*, 96, pp. 116–31.

Breitung, J. and S. Eickmeier (2006), "Dynamic Factor Models", *Allgemeines Statistisches Archiv*, 90(1), pp. 27–42.

Bruno, V. and H.S. Shin (2015), "Capital Flows and the Risk-taking Channel of Monetary Policy", *Journal of Monetary Economics*, 71, pp. 119–32.

Brzoza-Brzezina, M., T. Chmielewski and J. Niedźwiedzińska (2010), "Substitution Between Domestic and Foreign Currency Loans in Central Europe, Do Central Banks Matter? ", ECB Working Paper Series, No 1187, May.

Chen, Q., A. Filardo, D. He and F. Zhu (2015), "Financial Crisis, US Unconventional Monetary Policy and International Spillovers", BIS Working Papers No. 494, Bank for International Settlements.

Cogley, T., G.E. Primiceri and T.J. Sargent (2010), "Inflation-gap Persistence in the US", *American Economic Journal: Macroeconomics*, 2(1), pp. 43–69.

Crucini, M.J., M.A. Kose and C. Otrok (2011), "What are the Driving Forces of International Business Cycles?", *Review of Economic Dynamics*, 14(1), pp. 156–75.

Disyatat, P. and P. Rungcharoenkitkul (2015), "Monetary Policy and Financial Spillovers: Losing Traction?", BIS Working Papers No. 518, Bank for International Settlements.

Edwards, S. (2015), "Monetary Policy Independence under Flexible Exchange Rates: An Illusion?", *The World Economy*, 38(5), pp. 773–87.

Eichengreen, B. and P. Gupta (2014), "Tapering Talk: The Impact of Expectations of Reduced Federal Reserve Security Purchases on Emerging Markets", World Bank Policy Research Working Paper No. 6754, World Bank, Washington D.C.

Engle, R. and F.K. Kroner (1995), "Multivariate Simultaneous Generalized ARCH", *Econometric Theory*, 11, pp. 122–50.

Evans, C.L. and D.A. Marshall (1998), "Monetary Policy and the Term Structure of Nominal Interest Rates: Evidence and Theory", in Carnegie-Rochester Conference Series on Public Policy, 49, North-Holland, pp. 53–111.

Geweke, J. (1977), "The Dynamic Factor Analysis of Economic Time Series Models", in D.J. Aigner and A.S. Goldberger (eds.), *Latent Variables in Socio-Economic Models*, Amsterdam, North-Holland.

Giannone, D., L. Reichlin and L. Sala (2004), "Monetary Policy in Real Time", in *NBER Macroeconomics Annual 2004*, Vol. 19, MIT Press, pp. 161–224.

Glick, R. and S. Leduc (2013), "The Effects of Unconventional and Conventional US Monetary Policy on Dollar", Working Paper 2013-11, Federal Reserve Bank of San Francisco.

Gray, C (2013), "Responding to a Monetary Superpower: Investigating the Behavioural Spillovers of US Monetary Policy", *Atlantic Economic Journal*, 41(2), pp. 173–84.

Harrison, D. (2015), "Central Bankers Urge Fed to Get On With Interest-Rate Increase", *Wall Street Journal*, 11 October.

He, D. and R.N. McCauley (2013), "Transmitting Global Liquidity to East Asia: Policy Rates, Bond Yields, Currencies and Dollar Credit", HKIMR Working Paper No. 15.

Hirata, H., M.A. Kose and C. Otrok (2013), "Globalization vs. Regionalization", IMF Working Paper 13:19.

Hofmann, B. and E. Takáts (2015), "International Monetary Spillovers", *BIS Quarterly Review*, September, pp. 105–118.

Imam, P.A. (2015), "Shock from Graying: Is the Demographic Shift Weakening Monetary Policy Effectiveness", *International Journal of Finance and Economics*, 20(2), 138–54.

Jaramillo, L. and A. Weber (2013a), "Bond Yields in Emerging Economies: It Matters What State You Are In", *Emerging Markets Review*, 17, pp. 169–85.

— (2013b), "Global Spillovers into Domestic Bond Markets in Emerging Market Economies", IMF Working Paper No. 13/264.

John, J. (2015), "Has Inflation Persistence in India Changed over Time?", *The Singapore Economic Review*, 60(4), 1550095.

Matheson, T.D. (2012). "Financial Conditions Indexes for the United States and Euro Area", *Economics Letters*, 115(3), pp. 441–46.

Mesquita, M. and M. Torós (2010), "Brazil and the 2008 Panic", BIS Papers No. 54, 113–20, Bank for International Settlements.

Mishra, P., Moriyama, K., N'Diaye, P. and Nguyen, L. (2014). "Impact of Fed Tapering Announcements on Emerging Markets", IMF Working Paper No. 14/109.

Miyajima, K., M.S. Mohanty and J. Yetman (2014), "Spillovers of US Unconventional Monetary Policy to Asia: The Role of Long-term Interest Rates", BIS Working Paper No. 478, Bank for International Settlements.

Mohan, R. and M. Kapur (2009), "Managing the Impossible Trinity: Volatile Capital Flows and Indian Monetary Policy", Working Paper No. 401, November, Stanford University.

Mohanty, M.S. and P. Turner (2008), "Monetary Policy Transmission in Emerging Market Economies: What is New?", BIS Papers No 35, pp. 1–59.

Moreno, R. (2008), "Monetary Policy Transmission and the Long-term Interest Rate in Emerging Markets", BIS Papers No. 35, pp. 61–80.

— (2010). "Central Bank Instruments to Deal with the Effects of the Crisis on Emerging Market Economies", BIS Papers No. 54, pp. 73–96.

Moreno, R. and A. Villar (2011), "Impact of the Crisis on Local Money and Debt Markets in Emerging Market Economies", BIS Papers No. 54, pp. 49–72.

Mumtaz, H. and L. Sunder-Plassmann (2013), "Time-Varying Dynamics of the Real Exchange Rate: An Empirical Analysis", *Journal of Applied Econometrics*, 28(3), pp. 498–525.

Nakajima, J. (2011), "Time-varying Parameter VAR Model with Stochastic Volatility: An Overview of Methodology and Empirical Applications", *Monetary and Economic Studies*, November, pp. 107–42.

Nakajima, J., M. Kasuya and T. Watanabe (2011), "Bayesian Analysis of Time-varying Parameter Vector Autoregressive Model for the Japanese Economy and Monetary Policy", *Journal of the Japanese and International Economies*, 25(3), pp. 225–45.

Nier, E.W., T. Saadi-Sedik and T. Mondino (2014), "Gross Private Capital Flows to Emerging Markets: Can the Global Financial Cycle Be Tamed? " IMF Working Paper No. 14/196.

Obstfeld, M. (2015), "Trilemmas and Trade-offs: Living with Financial Globalisation", BIS Working Papers No. 480.

Osario, C., Unsal, D. F. and Pongsaparn, R. (2011). "A Quantitative Assessment of Financial Conditions in Asia", IMF Working Papers, No. 11/170, pp. 1-21.

Patra, M.D. and M. Kapur (2010), "A Monetary Policy Model Without Money for India", IMF Working Paper No. 10/183.

Pattanaik, S. and R. Kavediya (2015), "Taper Talk and the Rupee–Preconditions for the Success of an Interest Rate Defence of the Exchange Rate", *Prajnan*, 44(3), pp. 251–77.

Pétursson, T.G. (2000), "The Representative Household's Demand for Money in a Cointegrated VAR Model", *The Econometrics Journal*, 3(2), pp. 162–76.

Primiceri, G.E. (2005), "Time Varying Structural Vector Autoregressions and Monetary Policy", *The Review of Economic Studies*, 72(3), pp. 821–52.

Parussini, G. (2015), "India's Central Bank Cuts Key Interest Rate More Than Expected", *Wall Street Journal*, 29 September.

Ree, J.J.K. and S. Choi (2014), "Safe-Haven Korea?: Spillover Effects from UMPs", IMF Working Paper No. 14/53, Asia and Pacific Department, International Monetary Fund.

Rey, H. (2015). "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence", NBER Working Paper No. 21162, May.

Roley, V. V. and G.H. Sellon (1995), "Monetary Policy Actions and Long-term Interest Rates", *Federal Reserve Bank of Kansas City Economic Quarterly*, 80(4), pp. 77–89.

Saborowski, C. and S. Weber (2013). "Assessing the Determinants of Interest Rate Transmission Through Conditional Impulse Response Functions", IMF Working Paper No. 13/23.

Sargent, T.J. and C.A. Sims (1977), "Business Cycle Modeling Without Pretending to Have Too Much A Priori Economic Theory", in C.A. Sims (ed.), *New Methods in Business Cycle Research*, 1, Federal Reserve Bank of Minneapolis, pp. 145–68.

Sims, C.A. (1980), "Macroeconomics and Reality", *Econometrica*, 48(1), pp. 1–48.

Sobrun, J. and P. Turner (2015), "Bond Markets and Monetary Policy Dilemmas for the Emerging Markets", BIS Working Papers No. 508.

Stock, J.H. and M.W. Watson (2011), "Dynamic Factor Models", *Oxford Handbook of Economic Forecasting*, vol. 1, pp. 35–59.

Takáts, E. and A. Vela (2014), "International Monetary Policy Transmission", BIS Papers No. 78, pp. 25–44.

Thornton, D.L. (2009), “What the LIBOR-OIS Spread Says”, *Economic Synopses*, No. 24, Federal Reserve Bank of St. Louis.

Turner, P. (2014), “The Global Long-term Interest Rate, Financial Risks and Policy Choices in EMEs”, BIS Working Papers No. 441.

Watson, M.W. (2004). “Comment on Giannone, Reichlin, and Sala”, *NBER Macroeconomics Annual 2004*, Vol. 19, MIT Press, pp. 216–21.

Appendix

Table A.1: Spillover Impact in Money Market

a. Mean Equation

Dependent Variable: CALLSPREAD	Full Sample	Pre-Crisis	Post-Crisis
Constant	-0.27 -(23.11)***	-0.04 -(2.74)**	-0.13 -(6.78)***
$CALLSPREAD_{t-1}$	0.39 (18.96)***	0.55 (12.62)***	0.36 (13.06)***
$CALLSPREAD_{t-2}$	0.01 (0.28)	0.12 (2.73)**	0.06 (1.98)**
$CALLSPREAD_{t-3}$	0.07 (3.10)***	0.03 (0.79)	0.14 (5.16)***
$CALLSPREAD_{t-4}$	0.00 (0.00)	0.06 (1.56)	0.07 (2.43)**
$CALLSPREAD_{t-5}$	0.08 (3.88)***	0.08 (2.66)**	0.14 (5.83)***
LAF_{t-1}	0.00 (9.41)***	0.00 (4.36)***	0.00 (5.99)***
LAF_{t-2}	0.00 (1.93)**	0.00 -(0.93)	0.00 (1.36)
LAF_{t-3}	0.00 -(2.58)**	0.00 (0.00)	0.00 -(2.28)**
LAF_{t-4}	0.00 -(0.34)	0.00 -(1.57)	0.00 -(0.72)
LAF_{t-5}	0.00 -(0.69)	0.00 -(0.34)	0.00 (0.31)
$LIBOR\_OIS_{t-1}$	0.00 -(2.52)**	0.00 -(2.17)**	0.00 -(2.05)**
Dependent Variable: LAF			
Constant	0.52 (0.21)	-5.18 -(1.78)*	21.25 (3.40)***
$CALLSPREAD_{t-1}$	2.49 (2.63)**	1.63 (1.65)*	-0.81 -(0.16)
$CALLSPREAD_{t-2}$	-0.36 -(0.36)	0.02 (0.02)	3.29 (0.59)
$CALLSPREAD_{t-3}$	-1.08 -(1.00)	-1.46 -(1.52)	-3.23 -(0.54)
$CALLSPREAD_{t-4}$	0.57 (0.53)	0.85 (0.88)	9.62 (1.79)*
$CALLSPREAD_{t-5}$	-0.31 -(0.33)	-0.74 -(0.88)	3.26 (0.67)
LAF_{t-1}	0.94 (48.90)***	0.97 (32.69)***	0.99 (41.70)***
LAF_{t-2}	-0.02 -(0.74)	-0.07 -(1.81)*	-0.04 -(1.22)
LAF_{t-3}	-0.07 -(2.63)**	0.00 (0.05)	-0.12 -(3.67)***
LAF_{t-4}	0.02 (0.71)	-0.03 -(0.90)	0.00 (0.11)
LAF_{t-5}	0.11 (5.94)***	0.09 (3.42)***	0.15 (6.57)***
$LIBOR\_OIS_{t-1}$	-0.06 -(0.80)	0.09 (0.65)	-0.25 -(2.64)**

b. Variance Equation

	Full Sample		Pre-Crisis		Post-Crisis	
A{1}(1,1)	0.56	(17.23)***	0.76	(11.06)***	0.70	(20.83)***
A{1}(1,2)	0.49	(0.39)	2.83	(2.12)**	-5.91	-(0.78)
A{1}(2,1)	-0.00002	-(0.14)	-0.002	-(7.31)***	0.0004	(6.52)***
A{1}(2,2)	0.27	(11.15)***	0.05	(1.00)	0.20	(6.48)***
A{2}(1,1)	0.69	(17.80)***	0.45	(5.60)***	0.50	(8.43)***
A{2}(1,2)	3.18	(1.84)*	1.22	(1.06)	47.99	(4.45)***
A{2}(2,1)	-0.001	-(10.24)***	-0.001	-(2.73)**	-0.001	-(7.59)***
A{2}(2,2)	0.19	(5.14)***	0.13	(3.31)***	0.28	(6.27)***
B{1}(1,1)	0.43	(6.59)***	-0.06	-(0.33)	-0.31	-(3.86)***
B{1}(1,2)	13.47	(5.86)***	0.81	(0.66)	16.87	(1.90)*
B{1}(2,1)	0.00	-(5.36)***	0.00	-(0.30)	0.00	-(2.01)**
B{1}(2,2)	-0.91	-(17.07)***	-0.23	-(1.40)	-0.60	-(7.27)***
B{2}(1,1)	0.59	(16.16)***	0.59	(16.73)***	0.57	(11.54)***
B{2}(1,2)	3.32	(1.79)*	-0.61	-(0.76)	32.42	(2.79)**
B{2}(2,1)	0.00	-(1.34)	0.00	(0.20)	0.00	-(2.19)**
B{2}(2,2)	0.25	(1.49)	0.85	(15.37)***	-0.11	-(0.83)
$LIBOR\_OIS_{i,\,t-1}$	0.002	(4.29)***	-0.01	-(8.59)***	0.002	(5.95)***
$LIBOR\_OIS_{j,\,t-1}$	0.16	(4.67)***	0.59	(6.07)***	-0.34	-(2.73)**
Maximum eigenvalue	0.78		0.77		0.74	
MV-ARCH-Q(12)	48.62	(0.45)	59.32	(0.13)	70.63	(0.18)

Notes: $LIBOR\_OIS_{i,t-1}$ $LIBOR\_OIS_{j,\,t-1}$ are the exogenous variables in variance equations of CALLSPREAD and LAF, respectively.Figures in parentheses are t-statistics when they are placed after coefficients and p-value, in case of ARCH tests. Constants in variance equation are not presented here to save space.

,,***: indicates significant at 10%, 5% and 1% levels, respectively.

Table A.2a: Spillover Impact in G-sec Market

a. Mean Equation

Dependent Variable: IN10YGS	Full Sample	Pre-Crisis	Post-Crisis
Constant	0.05 (4.42)***	0.04 (2.32)**	0.06 (3.31)***
$IN10YGS_{t-1}$	1.04 (55.40)***	1.08 (31.52)***	0.99 (38.17)***
$IN10YGS_{t-2}$	-0.05 -(2.46)**	-0.09 -(2.49)**	-0.001 -(0.04)
$NFIIDR_{t-1}$	-0.00001 -(0.11)	0.00003 (0.06)	0.00002 (0.23)
$NFIIDR_{t-2}$	0.00004 (0.40)	0.00036 (0.73)	-0.00008 -(0.71)
$TMSPREAD_{t-1}$	0.00124 (1.59)	-0.00031 -(0.17)	0.00224 (1.34)
Dependent Variable: NFIIDR			
Constant	1.26 (3.73)***	0.45 (1.43)	-2.16 -(1.00)
$IN10YGS_{t-1}$	1.02 (1.38)	-1.36 -(2.10)**	-1.04 -(0.45)
$IN10YGS_{t-2}$	-1.17 -(1.58)	1.31 (2.03)**	1.45 (0.62)
$NFIIDR_{t-1}$	0.27 (11.41)***	0.18 (4.07)***	0.30 (9.91)***
$NFIIDR_{t-2}$	0.02 (0.71)	-0.01 -(0.48)	0.23 (7.89)***
$TMSPREAD_{t-1}$	-0.19 -(5.70)***	-0.12 -(3.62)***	-0.14 -(0.50)
b. Variance Equation			
A{1}(1,1)	0.17 (5.59)***	0.31 (12.52)***	0.28 (14.77)***
A{1}(1,2)	-8.12 -(9.10)***	-0.54 -(0.29)	-3.04 -(0.87)
A{1}(2,1)	-0.0001 -(0.73)	0.00 (3.70)***	-0.0002 -(1.46)
A{1}(2,2)	0.81 (29.97)***	0.93 (18.92)***	0.63 (16.48)***
A{2}(1,1)	-0.40 -(17.90)***		
A{2}(1,2)	2.02 (1.63)*		
A{2}(2,1)	0.00002 (0.13)		
A{2}(2,2)	0.10 (1.31)		
B{1}(1,1)	-0.13 -(1.72)*	-0.91 -(89.38)***	0.95 (172.86)***
B{1}(1,2)	0.29 (0.40)	1.88 (1.65)*	-3.46 -(1.88)*
B{1}(2,1)	-0.0001 -(1.39)	0.004 (5.82)***	0.00004 (0.38)
B{1}(2,2)	0.53 (9.73)***	0.20 (1.64)*	0.64 (12.12)***
B{2}(1,1)	-0.88 -(62.09)***		
B{2}(1,2)	0.46 (0.39)		
B{2}(2,1)	-0.0003 -(1.90)*		
B{2}(2,2)	0.59 (14.27)***		
$TMSPREAD_{i, t-1}$	-0.002 -(6.52)***	0.01 (11.29)***	0.003 (5.36)***
$TMSPREAD_{j, t-1}$	0.000 (0.00)	-0.18 -(5.50)***	0.08 (0.32)
Maximum eigenvalue	0.66	0.93 0.99	
MV-ARCH-Q(12)	32.17 (0.96)	21.21 (0.99)	19.74 (0.99)

Notes: $TMSPREAD_{i,t-1}$ $TMSPREAD_{j,t-1}$ are the exogenous variables in variance equations of IN10YGS and NFIIDR, respectively.

Figures in parentheses are t-statistics when they are placed after coefficients and p-value, in case of ARCH tests.

Constants in variance equation are not presented here to save space.

,,***: indicates significant at 10%, 5% and 1% levels, respectively.

Table A.2b: Spillover Impact in G-sec Market

a. Mean Equation

Dependent Variable: IN10YGS	Full Sample	Pre-Crisis	Post-Crisis
Constant	0.05 (4.16)***	0.04 (2.72)***	0.08 (3.23)***
$IN10YGS_{t-1}$	1.06 (54.89)***	1.10 (35.48)***	1.01 (46.06)***
$IN10YGS_{t-2}$	-0.07 -(3.39)***	-0.10 -(3.35)***	-0.018 -(0.81)
$NFIIDR_{t-1}$	-0.00007 -(0.62)	0.0004 (0.72)	-0.00005 -(0.46)
$NFIIDR_{t-2}$	0.00007 (0.69)	0.0007 (1.08)	-0.00006 -(0.56)
$RISKSPREAD_{t-1}$	0.00376 (1.91)*	-0.0006 -(0.12)	0.00062 (0.11)
Dependent Variable: NFIIDR			
Constant	-0.70 -(1.58)	0.09 (0.34)	5.37 (1.79)*
$IN10YGS_{t-1}$	0.58 (0.63)	-1.36 -(2.25)**	-2.96 -(1.40)
$IN10YGS_{t-2}$	-0.48 -(0.52)	1.40 (2.31)**	2.86 (1.37)
$NFIIDR_{t-1}$	0.21 (8.82)***	0.23 (5.24)***	0.30 (10.30)***
$NFIIDR_{t-2}$	0.06 (2.40)**	-0.05 -(1.56)	0.22 (8.54)***
$RISKSPREAD_{t-1}$	-0.103 -(0.82)	-0.386 -(3.95)***	-2.03 -(3.12)***
b. Variance Equation			
A{1}(1,1)	-0.19 -(9.33)***	0.24 (7.96)***	0.16 (5.71)***
A{1}(1,2)	-1.62 -(1.25)	1.64 (0.89)	-1.30 -(0.47)
A{1}(2,1)	-0.0001 -(0.93)	0.001 (0.94)	-0.001 -(4.14)***
A{1}(2,2)	0.68 (19.25)***	0.91 (16.21)***	0.67 (16.36)***
A{2}(1,1)	0.37 (16.73)***	0.49 (13.63)***	0.29 (13.62)***
A{2}(1,2)	2.96 (3.03)***	-0.89 -(0.77)	1.33 (0.38)
A{2}(2,1)	-0.0001 -(0.46)	-0.001 -(0.90)	0.0001 (0.42)
A{2}(2,2)	0.20 (1.85)*	-0.10 -(0.70)	-0.15 -(1.05)
B{1}(1,1)	0.05 (0.61)	-0.01 -(0.11)	0.05 (0.56)
B{1}(1,2)	2.59 (2.66)***	0.88 (1.05)	-18.19 -(5.61)***
B{1}(2,1)	-0.0003 -(2.14)**	0.0002 (0.20)	-0.0001 -(0.53)
B{1}(2,2)	0.77 (44.84)***	0.40 (4.33)***	0.45 (4.05)***
B{2}(1,1)	0.90 (93.50)***	0.84 (53.46)***	-0.94 -(131.65)***
B{2}(1,2)	-3.02 -(3.22)***	-2.39 -(1.44)	3.61 (1.32)
B{2}(2,1)	0.0003 (1.80)*	-0.002 -(1.08)	-0.001 -(4.47)***
B{2}(2,2)	0.03 (0.28)	-0.23 -(2.81)***	-0.36 -(5.01)***
$TMSPREAD_{i, t-1}$	-0.004 -(4.38)***	0.01 (3.60)***	-0.03 -(7.48)***
$TMSPREAD_{j, t-1}$	-2.89 -(14.51)***	-0.39 -(0.96)	-4.43 -(5.80)***
Maximum eigenvalue	0.49	0.99	0.99
MV-ARCH-Q(12)	15.23 (1.00)	61.57 (0.10)	24.66 (0.99)

Notes: $RISKSPREAD_{i, t-1}$ $RISKSPREAD_{j,t-1}$ are the exogenous variables in variance equations of IN10YGS and NFIIDR, respectively.

Figures in parentheses are t-statistics when they are placed after coefficients and p-value, in case of ARCH tests.

Constants in variance equation are not presented here to save space.

,,***: indicates significant at 10%, 5% and 1% levels, respectively.

Table A.3a: Spillover Impact in Foreign Exchange Market

a. Mean Equation

Dependent Variable: DINR	Full Sample	Pre-Crisis	Post-Crisis
Constant	0.00 -(0.39)	0.00 (0.21)	0.00 (0.34)
DINR$_{t-1}$	0.01 (0.29)	-0.01 -(0.18)	0.01 (0.48)
DINR$_{t-2}$	-0.01 -(0.72)	0.02 (0.73)	-0.04 -(1.83)*
DINR$_{t-3}$	-0.02 -(1.32)	-0.06 -(2.14)**	-0.01 -(0.55)
DINR$_{t-4}$	0.00 (0.20)	-0.06 -(1.88)*	0.02 (0.89)
NFII$_{t-1}$	-0.01 -(0.42)	-0.02 -(0.45)	-0.01 -(0.35)
NFII$_{t-2}$	-0.07 -(2.36)**	-0.10 -(1.90)*	-0.01 -(0.30)
NFII$_{t-3}$	-0.04 -(1.40)	-0.08 -(1.46)	-0.03 -(0.89)
NFII$_{t-4}$	0.03 (0.98)	0.09 (1.84)*	-0.03 -(0.70)
LIBOR_OIS$_{t-1}$	0.00 (1.65)*	0.00 -(0.16)	0.00 (1.71)*
Dependent Variable: NFII			
Constant	0.03 (6.39)***	0.02 (4.38)***	0.07 (9.50)***
DINR$_{t-1}$	-0.06 -(8.39)***	-0.04 -(2.96)***	-0.07 -(7.14)***
DINR$_{t-2}$	-0.02 -(2.52)**	-0.02 -(1.33)	-0.03 -(3.49)***
DINR$_{t-3}$	0.00 (0.08)	-0.01 -(0.61)	-0.02 -(2.01)**
DINR$_{t-4}$	-0.01 -(0.97)	0.00 (0.29)	-0.02 -(2.39)**
NFII$_{t-1}$	0.25 (10.53)***	0.33 (10.21)***	0.29 (10.31)***
NFII$_{t-2}$	0.14 (6.32)***	0.02 (0.53)	0.14 (5.45)***
NFII$_{t-3}$	0.09 (4.25)***	0.12 (3.52)***	0.09 (3.93)***
NFII$_{t-4}$	0.09 (4.87)***	0.08 (2.48)**	0.06 (2.96)***
LIBOR_OIS$_{t-1}$	0.00 -(2.09)**	0.00 -(1.72)*	0.00 -(3.56)***

b. Variance Equation

	Full Sample	Pre-Crisis	Post-Crisis
A(1,1)	0.29 (16.93)***	0.47 (11.84)***	0.22 (12.17)***
A(1,2)	0.00 -(0.30)	-0.01 -(0.76)	0.01 (0.46)
A(2,1)	-0.04 -(2.22)**	0.00 (0.01)	-0.08 -(1.60)
A(2,2)	0.25 (18.51)***	0.31 (13.75)***	0.50 (10.80)***
B(1,1)	0.96 (192.97)***	-0.87 -(34.35)***	0.97 (165.32)***
B(1,2)	0.00 (0.61)	0.09 (3.82)***	-0.02 -(1.76)*
B(2,1)	0.01 (1.30)	-0.50 -(4.98)***	0.08 (1.24)
B(2,2)	0.97 (398.46)***	0.98 (131.86)***	0.55 (9.37)***
LIBOR_OIS$_{i, t-1}$	0.00 (2.41)**	0.00 (3.38)***	0.00 (2.68)***
LIBOR_OIS$_{j, t-1}$	0.00 (1.75)*	0.00 (0.00)	0.00 -(1.85)*
Maximum eigenvalue	0.99	0.93	0.98
MV-ARCH-Q(12)	41.44 (0.74)	39.49 (0.80)	33.61 (0.94)

Notes: LIBOR_OIS$_{i, t-1}$ LIBOR_OIS$_{j, t-1}$ are the exogenous variables in variance equations of DINR and NFII, respectively.

Figures in parentheses are t-statistics when they are placed after coefficients and p-value, in case of ARCH tests.

Constants in variance equation are not presented here to save space.

,,***: indicates significant at 10%, 5% and 1% levels, respectively.

Table A.3b: Spillover Impact in Foreign Exchange Market

a. Mean Equation

Dependent Variable: DINR	Full Sample	Pre-Crisis	Post-Crisis
Constant	0.01 (0.97)	0.00 (0.09)	0.02 (1.81)*
$DINR_{t-1}$	-0.02 -(1.15)	-0.03 -(0.90)	-0.01 -(0.29)
$DINR_{t-2}$	-0.01 -(0.59)	0.03 (1.13)	-0.04 -(1.56)
$DINR_{t-3}$	-0.02 -(0.98)	-0.05 -(1.85)*	-0.01 -(0.45)
$DINR_{t-4}$	0.01 (0.70)	-0.05 -(1.70)*	0.02 (0.85)
$NFII_{t-1}$	0.00 -(0.49)	0.00 -(0.59)	0.00 -(0.96)
$NFII_{t-2}$	0.00 -(2.75)***	0.00 -(1.99)	0.00 -(0.28)
$NFII_{t-3}$	0.00 -(0.75)	0.00 -(2.17)**	0.00 -(1.06)
$NFII_{t-4}$	0.00 (1.51)	0.00 (1.91)*	0.00 -(0.86)
$DDXY_{t-1}$	0.09 (7.94)***	0.08 (5.15)***	0.07 (3.11)***
Dependent Variable: NFII			
Constant	23.50 (7.45)***	13.40 (4.04)***	51.79 (8.75)***
$DINR_{t-1}$	-50.86 -(7.21)***	-29.88 -(2.89)***	-64.88 -(6.54)***
$DINR_{t-2}$	-17.72 -(2.50)**	-7.93 -(0.71)	-29.42 -(2.81)***
$DINR_{t-3}$	-6.05 -(1.00)	-1.82 -(0.19)	-21.84 -(2.09)**
$DINR_{t-4}$	-5.13 -(0.82)	-0.17 -(0.02)	-19.46 -(1.90)*
$NFII_{t-1}$	0.26 (11.55)***	0.33 (9.97)***	0.30 (10.27)***
$NFII_{t-2}$	0.18 (8.89)***	0.03 (0.73)	0.14 (5.63)***
$NFII_{t-3}$	0.06 (3.02)***	0.13 (3.94)***	0.10 (5.37)***
$NFII_{t-4}$	0.07 (3.48)***	0.07 (2.48)**	0.06 (3.34)***
$DDXY_{t-1}$	-19.55 -(3.40)***	-4.29 -(0.75)	-12.19 -(1.16)
b. Variance Equation			
A(1,1)	0.24 (20.74)***	0.50 (11.88)***	0.22 (11.71)***
A(1,2)	-42.79 -(5.19)***	7.47 (0.69)	17.11 (0.70)
A(2,1)	0.00 (0.70)	0.00 (0.46)	0.00 -(2.09)**
A(2,2)	0.44 (18.66)***	0.30 (13.46)***	0.54 (11.85)***
B(1,1)	0.97 (343.97)***	0.84 (36.74)***	0.97 (166.98)***
B(1,2)	11.12 (4.71)***	-1.25 -(0.29)	-19.63 -(1.79)*
B(2,1)	0.00 -(2.16)**	0.00 -(2.73)***	0.00 (2.21)**
B(2,2)	0.91 (98.95)***	0.96 (169.98)***	0.52 (9.03)***
$DXYSQ_{i, t-1}$	0.04 (3.98)***	-0.13 -(4.67)***	0.04 (3.03)***
$DXYSQ_{j, t-1}$	-19.84 -(2.87)***	-17.14 -(2.98)***	-11.60 -(1.07)
Maximum eigenvalue	0.99	0.95	0.98
MV-ARCH-Q(12)	46.96 (0.52)	28.16 (0.99)	(0.93)

Notes: $DXYSQ_{i, t-1}$ $DXYSQ_{j, t-1}$ are the exogenous variables in variance equations of DINR and NFII, respectively.

Figures in parentheses are t-statistics when they are placed after coefficients and p-value, in case of ARCH tests.

Constants in variance equation are not presented here to save space.

,,***: indicates significant at 10%, 5% and 1% levels, respectively.

Table A.4: Spillover Impact in Stock Market

a. Mean Equation

Dependent Variable: DLSENX	Full Sample	Pre-Crisis	Post-Crisis
Constant	0.23 (3.55)***	0.79 (5.17)***	0.13 (1.90)*
$DLSENX_{t-1}$	0.05 (2.45)**	0.04 (1.18)	0.03 (1.53)
$DLSENX_{t-2}$	-0.01 -(0.65)	-0.08 -(2.23)**	-0.03 -(1.11)
$DLSENX_{t-3}$	0.00 -(0.11)	0.01 (0.21)	-0.03 -(1.17)
$DLSENX_{t-4}$	0.02 (0.91)	0.01 (0.26)	0.006 (0.26)
$NFIIEQ_{t-1}$	0.00 -(0.58)	0.00 (0.58)	-0.0005 -(0.20)
$NFIIEQ_{t-2}$	0.00 (0.44)	0.00 (0.65)	-0.0023 -(1.04)
$NFIIEQ_{t-3}$	0.00 -(1.04)	-0.01 -(1.22)	-0.0015 -(0.65)
$NFIIEQ_{t-4}$	0.00 -(1.12)	-0.01 -(1.88)*	-0.0036 -(1.51)
VIX_{t-1}	-0.01 -(2.44)**	-0.04 -(4.15)***	-0.0033 -(0.89)
Dependent Variable: NFIIEQ			
Constant	2.40 (8.80)***	3.45 (4.97)***	3.53 (10.20)***
$DLSENX_{t-1}$	0.59 (6.59)***	0.27 (3.10)***	0.60 (6.24)***
$DLSENX_{t-2}$	0.03 (0.34)	-0.09 -(1.08)	0.15 (1.69)*
$DLSENX_{t-3}$	0.02 (0.28)	0.06 (0.74)	-0.14 -(1.58)
$DLSENX_{t-4}$	-0.09 -(1.05)	-0.08 -(0.99)	0.07 (0.75)
$NFIIEQ_{t-1}$	0.30 (12.57)***	0.29 (7.31)***	0.36 (12.03)***
$NFIIEQ_{t-2}$	0.13 (4.90)***	0.03 (0.78)	0.04 (1.25)
$NFIIEQ_{t-3}$	0.07 (2.89)***	0.12 (3.28)***	0.09 (4.43)***
$NFIIEQ_{t-4}$	0.11 (5.22)***	0.07 (2.13)**	0.07 (3.86)***
VIX_{t-1}	-0.06 -(5.81)***	-0.19 -(4.25)***	-0.08 -(8.12)***
b. Variance Equation			
A(1,1)	0.25 (18.12)***	0.38 (11.24)***	-0.02 -(0.99)
A(1,2)	-0.19 -(1.60)	-0.22 -(2.58)**	-0.06 -(0.54)
A(2,1)	-0.01 -(4.20)***	0.00 (0.17)	-0.01 -(1.75)*
A(2,2)	0.70 (18.31)***	0.48 (14.69)***	0.75 (17.35)***
B(1,1)	0.94 (138.82)***	0.86 (31.51)***	-0.16 -(0.52)
B(1,2)	0.41 (4.54)***	0.07 (1.70)*	0.10 (0.28)
B(2,1)	0.01 (4.81)***	0.01 (1.74)*	0.00 -(0.07)
B(2,2)	0.60 (11.20)***	0.88 (75.45)***	0.39 (8.86)***
$VIX_{i, t-1}$	0.02 (8.19)***	0.03 (3.68)***	0.05 (15.07)***
$VIX_{j, t-1}$	-0.04 -(3.93)***	-0.39 -(13.24)***	-0.18 -(16.26)***
Maximum eigenvalue	0.98	0.99	0.72
MV-ARCH-Q(12)	56.02 (0.20)	39.51 (0.80)	63.22 (0.21)

Notes: $VIX_{i, t-1}$ $VIX_{j, t-1}$ are the exogenous variables in variance equations of DLSENX and NFIIEQ, respectively.

Figures in parentheses are t-statistics when they are placed after coefficients and p-value, in case of ARCH tests.

Constants in variance equation are not presented here to save space.

,,***: indicates significant at 10%, 5% and 1% levels, respectively.

Table A.5: Estimated Coefficients – Dynamic Factor Model

	Coef.	SE	z	p-value	95%CI	
Autocorrelated Factor						
Factor Lag 1	0.890	0.036	24.700	0.000	0.819	0.960
Factor Loadings						
VIX Factor	0.444	0.042	10.450	0.000	0.361	0.527
LIBOR-OIS Factor	0.301	0.040	7.520	0.000	0.223	0.379
DXYSQ Factor	0.151	0.034	4.470	0.000	0.085	0.217
TMSPREAD Factor	0.001	0.017	0.040	0.972	-0.032	0.034
RISKSPREAD Factor	0.160	0.029	5.550	0.000	0.103	0.217
Autocorrelated Residuals						
VIX Residual Lag1	0.720	0.403	1.790	0.074	-0.070	1.511
LIBOR-OIS Residual Lag1	0.786	0.049	16.140	0.000	0.690	0.881
DXYSQ Residual Lag1	-0.020	0.079	-0.260	0.796	-0.174	0.134
TMSPREAD Residual Lag 1	0.975	0.015	63.850	0.000	0.945	1.004
RISKSPREAD Residual Lag 1	0.913	0.031	29.830	0.000	0.853	0.974

Chart A.1a: Structural IRFs – Without controlling for IGS

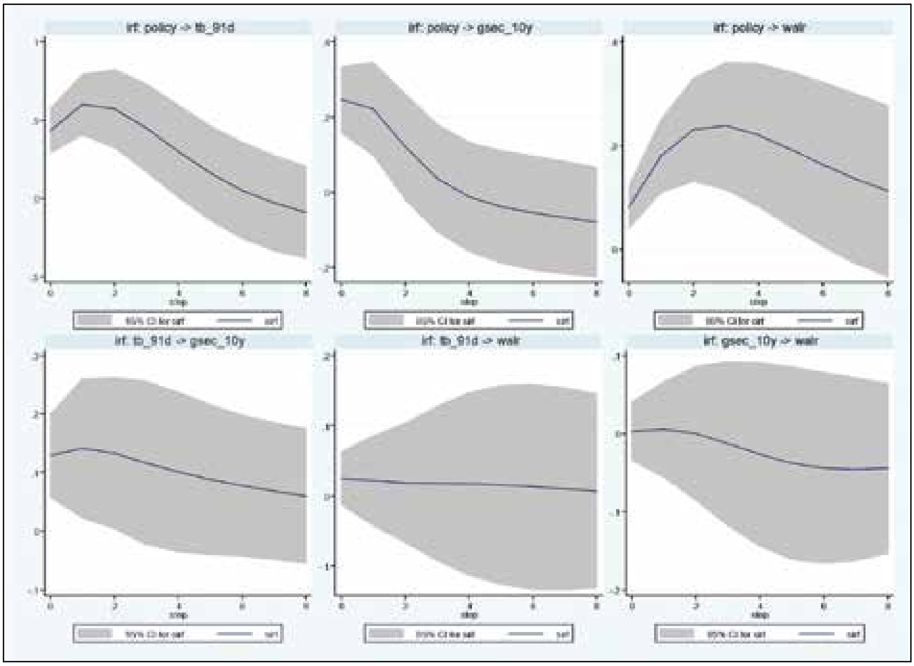


Chart A.1b. Structural IRFs – Controlling for IGS

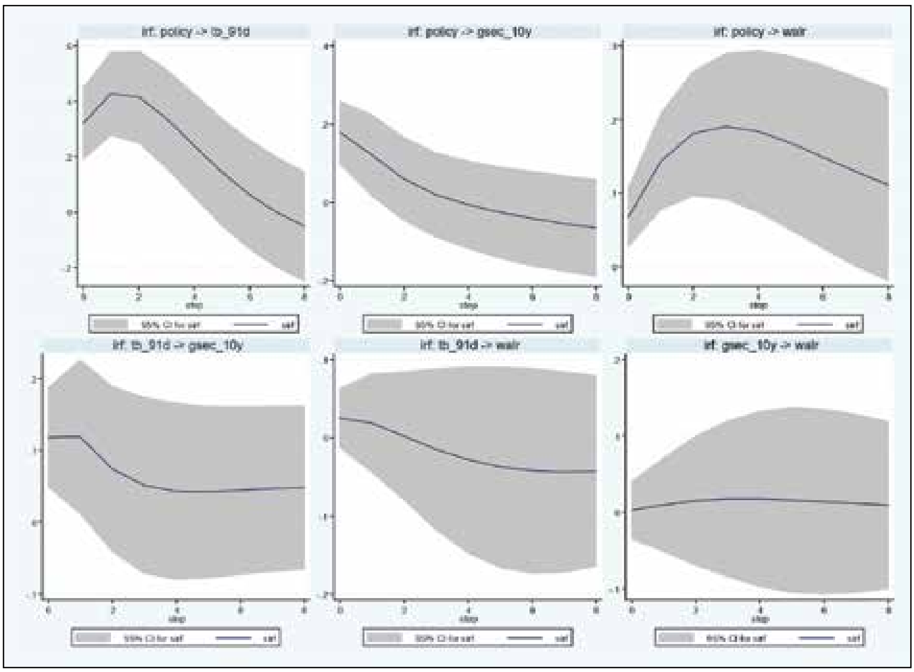
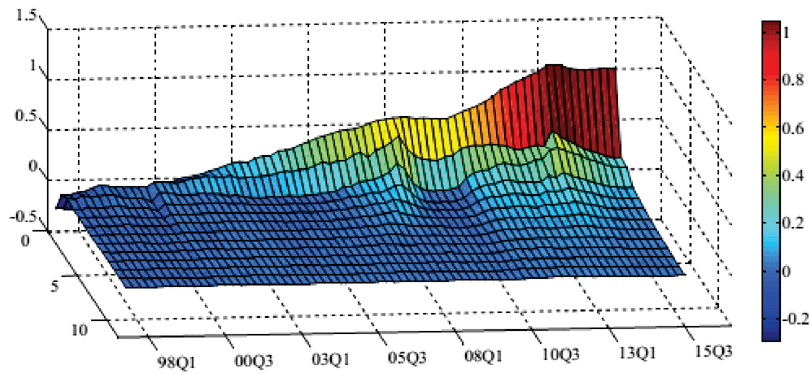
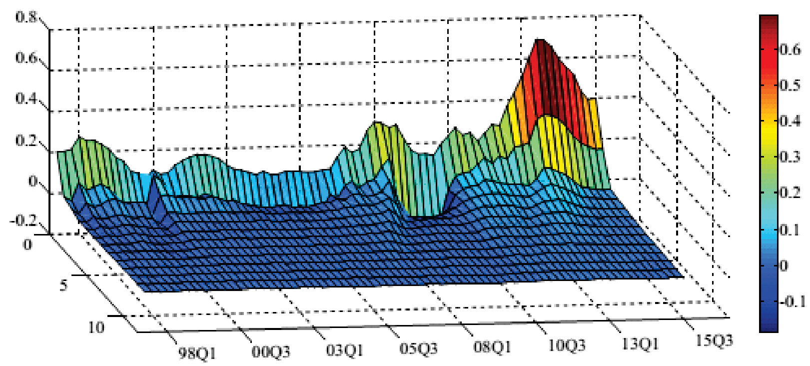


Chart A.2: Time Varying IRFs – TVP-VAR

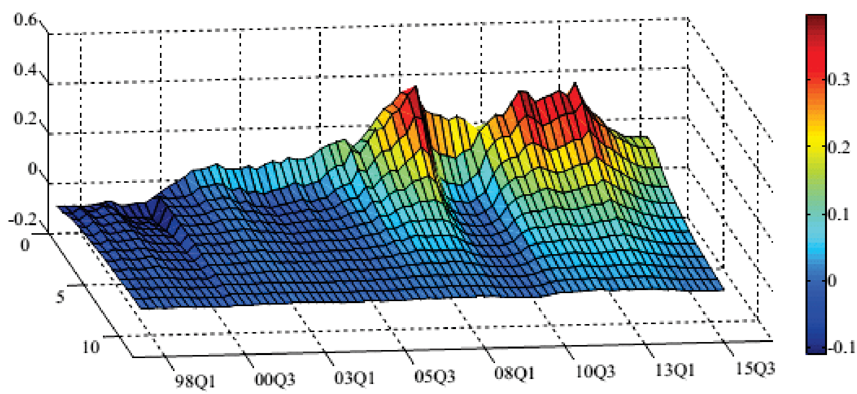
a. Policy to 91 day T-bill



c. Policy to WALR



b. Policy to 10 year G-sec



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Asset Quality and Monetary Transmission in India

Joice John, Arghya Kusum Mitra, Janak Raj and Deba Prasad Rath*

This paper assesses the impact of asset quality of banks in India on monetary transmission. This is attempted through a detailed analysis of determinants of net interest margin (NIM). Using quarterly data for the period (Q1:2010-11 to Q1:2017-18) and dynamic panel data regression, the study finds that credit risk, proxied separately by the gross non-performing assets (NPA) ratio and the stressed assets ratio (NPA plus restructured assets), had a statistically significant and positive impact on the NIM of scheduled commercial banks, suggesting that deterioration in asset quality impeded monetary transmission. The analysis of two sub-periods suggests that monetary transmission was impaired through the interest rate channel when the gross NPA ratio was at a relatively low level but rising. At a high level of gross NPA ratio, NIMs came under pressure as banks were not able to sufficiently increase their spreads in a competitive market to compensate for credit risk. However, banks became risk averse and reduced their loan exposures, which impacted monetary transmission through the lending channel. This was further corroborated by the results of bank group-wise analysis. Overall, it emerges that the deterioration in asset quality has impaired monetary transmission in India.

JEL Classification : E43, E44, E5

Keywords : Net interest margin, Asset quality, Non-performing assets, Monetary transmission

Introduction

Robust monetary policy transmission is a *sine qua non* for achieving the ultimate objectives of monetary policy, *i.e.,* growth and inflation. In a bank-

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dominated financial system, monetary policy impulses are transmitted largely through the banking system. Banks' financial health could impact monetary transmission, both by amplifying the effect of changes in short-term policy/ money market interest rates on lending interest rates, or by changing banks' lending standards and their use of non-price measures while sanctioning loans. As such, sound health of the banking system becomes extremely important for effective monetary transmission. A healthy bank with low default risk in its loan portfolio will be able to pass on interest rate changes of the central bank symmetrically on its deposits and loans. On the other hand, a bank faced with a high level of non-performing assets (NPA) – prospective or realised – will seek to build up provisions by loading credit risk premia on its performing loans, thereby pushing up the lending rates and hence its net interest margin (NIM)[1]. In the process, notwithstanding lower funding costs in response to the policy rate cut by the central bank and comfortable liquidity conditions, banks may not reduce their lending rates or may reduce them only partly, thereby impeding monetary transmission. Thus, movements in NIM of banks, among others, could provide an important indication of the effectiveness of monetary transmission.

In India, asset quality of scheduled commercial banks (excluding that of regional rural banks) has deteriorated steadily since 2011.[2] The pace accelerated following the withdrawal of regulatory forbearance on restructured advances effective April 1, 2015[3] and asset quality review (AQR) in July 2015. This resulted in a marked increase in the NPA ratios of domestic commercial banks – both public and private sectors – increasing from 3.4 per cent of gross advances in March 2013 to 4.7 per cent in March 2015, and further to 9.9 per

[1] The difference between the rate of interest at which a borrower obtains loans from a bank and the rate of interest at which a depositor is compensated for parting with his liquidity with the bank is a measure of efficiency in financial intermediation. A common indicator of efficiency of financial intermediation is the NIM of a bank, which is the difference between interest income and interest expenditure (as per cent of total assets). The NIM is an important measure of how efficiently banks transmit monetary impulses in fulfilling the ultimate monetary policy objectives of price stability with growth. Low NIM typically signifies a low transaction cost, thereby promoting growth by giving a fillip to saving and investment. It is assumed here that banks have priced risk prudently. A relatively high NIM may reflect high-risk premia, taking into account the macroeconomic environment or information asymmetry (Claeys and Vennet, 2008; Schwaiger and Liebeg, 2008; and Dumicic and Ridzak, 2013).

[2] The gross NPA as per cent of gross advances increased from 2.3 per cent in March 2011 to 3.6 per cent in March 2013 and further to 9.3 per cent in March 2017 (RBI, 2011; 2013; 2017).

[3] In 2008-09, after the global financial crisis, the Reserve Bank agreed to "forbear on certain kinds of stressed loan restructuring, hoping that this was a temporary need pending stronger growth" (Rajan, 2016).

cent by March 2017.[4,5] NIM of scheduled commercial banks (SCBs), which had declined from 3.0 per cent in 1999-2000 to 2.2 per cent in 2009-10 – the lowest in 2000s – increased to 2.9 per cent in 2010-11 before secularly declining to 2.5 per cent in 2016-17.[6] Returns on assets/equity of public sector banks remained negative during 2015-16 and 2016-17.[7]

The Reserve Bank's Sixth Bi-Monthly Monetary Policy Statement of 2016-17 (February 2017), *inter alia*, noted that "*the environment for timely transmission of policy rates to banks' lending rates will be considerably improved if the banking sector's non-performing assets (NPA) are resolved more quickly and efficiently*…". In the recent period, deterioration in asset quality and losses incurred by public sector banks, and the prolonged absence of their adequate recapitalisation appeared to have hampered effective monetary transmission through bank lending rates and credit supply.[8]

There are several studies related to the relationship between NIM and asset quality but do not present a clear picture. While in some countries, deterioration in asset quality is associated with a higher NIM, in some other countries, it is negatively related. However, in advanced economies and emerging market economies, there has hardly been any study focusing on asset quality and monetary transmission. For India also, many studies have estimated the determinants of NIM. However, almost all of such studies have focused on the ownership and regulatory aspects and not much on asset quality.[9] Besides, the existing studies on India are based on annual balance sheet data and are somewhat dated as they are prior to the measures taken since 2015 to improve the bank balance sheets. In the above backdrop, this

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[4] RBI (2017a).

[5] Based on balance sheet data, the gross NPA (as per cent of gross advances) of SCBs (including foreign banks) increased to 9.3 per cent in 2016-17 from 7.5 per cent in 2015-16; the same for public sector banks increased to 11.7 per cent from 9.3 per cent over the same period (RBI, 2017).

[6] RBI (2011).

[7] RBI (2017).

[8] The Reserve Bank's *Monetary Policy Report*, *April 2016* and *Annual Report,* 2016-17 have studied the implications of the deterioration of a bank's asset quality on NIM in India. The *Monetary Policy Report*, April 2016 noted that banks, when "faced with large stressed assets, may either (i) strive to maintain/ increase their NIM and/or (ii) reduce supply of credit." It further observed that "banks could protect their NIM up to Q3:2014-15. Thereafter, however, their NIM declined, which also coincided with the sustained deceleration in credit growth. After the Asset Quality Review initiated in April 2015, decline in income associated with the explicit recognition of NPA lowered the NIM. This amplified risk aversion and led to further deceleration of credit growth." The *RBI Annual Report, 2016-17* noted that "Regression analysis based on the data for the period Q1:2010-11 to Q3:2016-17 suggests that an increase in stressed assets is associated with higher NIM."

[9] One of the exceptions is Das (2013).

study is an attempt to fill the existing gap in the literature in the Indian context. The study analyses whether and to what extent the recent deterioration in asset quality of banks has impaired monetary transmission. This, in turn, is analysed through the behavior of NIMs of banks.

The study focuses on the determinants of NIM for the period Q1:2010-11 to Q1:2017-18 and also for the two sub-periods - Q1:2010-11 to Q1:2015-16 (sub-period I) and Q2:2015-16 to Q1:2017-18 (sub-period II). The sub-period II shows the true picture of the health of banks following AQR. The period under study was marked by two easing and two tightening cycles of monetary policy and lowering of statutory liquidity ratio (SLR), while allowing the increased carve out for the liquidity coverage ratio.[10] The period also saw a transition from the Benchmark Prime Lending Rate (BPLR) system to the base rate system in July 2010 and from the base rate system to the marginal cost of funds based lending rate (MCLR) system, effective April 1, 2016.

The study is organised in six sections. A brief survey of the literature on asset quality and monetary transmission is presented in Section II. Some stylised facts on the health of the Indian banking system are set out in Section III. Section IV details the methodology of the study. Section V sets out the results, while Section VI sums up the main findings of the study.

Section II

Survey of Literature

In the literature, asset quality of a bank's balance sheet is interpreted in terms of credit risk inherent in the loan portfolio. Credit risk in a bank's asset portfolio, *i.e.*, the probability of a bank asset turning into NPA is proxied by variables such as (i) NPA to total assets/interest income earning assets; and (ii) loan loss provisions to total assets/total loans (Almarzoqi and Naceur, 2015). Most empirical studies – particularly, those relating to advanced economies and a few pertaining to EMEs – show that NPAs are associated with higher spreads (Angbazo, 1997; Maudos and De Guevara, 2004; and Maudos and Solis, 2009). This means that banks are able to cope with the credit risk inherent in their loan portfolio by appropriately pricing it, *i.e.,* by setting the spread on lending rates over deposit interest rates such that banks are able to

[10] The tightening cycle from July 2010 to March 2012 was followed by the easing cycle up to June 2013; the tightening cycle up to December 2014 was again followed by the easing cycle.

successfully absorb the loan losses arising out of risky exposures (Marinkovic and Radovic, 2014). Banks, thus charge additional credit risk premia from their borrowers to compensate themselves for higher credit risk in order to protect their margins, meet their targeted return on assets as well as build up loan loss provisions.

In contrast, however, there are quite a few studies that show an inverse relationship between NIM and NPA such as those by Brock and Rojas-Suarez (2000) for Latin American countries, Dumicic and Ridzak (2013) for banks in Central and Eastern Europe, Marinkovic and Radovic (2014) for Serbia and Almarzoqi and Naceur (2015) in respect of banks in Caucasus and Central Asia. In their analyses of banks' interest spreads in Latin American countries, Brock and Rojas-Suarez (2000) observed that in all the countries in the region barring Colombia, "non-performing loans are associated with smaller spreads. This result could be due to inadequate provisioning for loan losses: higher non-performing loans would reduce banks' income, thereby lowering the spread in the absence of adequate loan loss reserves." While analysing the determinants of NIM for banks in Caucasus and Central Asian countries, Almarzoqi and Naceur (2015) observed that "a negative correlation between credit risk and interest margins reflects inadequate interest spreads to compensate for provisions for NPAs".

In the case of Serbia also, Marinkovic and Radovic (2014) noted that while banks attempt to charge a higher spread on the performing loans, their ability to do so may get constrained by the degree of competition in the banking industry. They found that contrary to what is suggested by theory, there was a statistically significant and inverse relation between default risk and the NIM. The ratio of loan loss reserves to gross loans was used to capture the default risk. Because of rules imposed on the banks by the regulator, banks are unable to window-dress the NPA figures. From the inverse relationship between default risk and the NIM, they inferred that there were inadequate build-up of loan loss reserves by banks. Secondly, following Fisher (1933), they argued that changes in banks' exposure to default risk coincide with credit cycles. During normal times, banks re-price existing loans when they become due, to protect their margins, as default risk rises. However, in recessionary times, banks may turn risk averse resulting in credit crunch, which cause both lending rates and lending volumes to fall, resulting in decline in NIM, all factors considered.

Dumicic and Ridzak (2013) measured the influence of NPA on NIM through the coverage of impaired loans with reserves for banks in Central and Eastern Europe. They found that reserves for impaired loans are significantly negatively correlated with NIM. They inferred that the negative correlation between impaired loans and NIM was due to the fact that banks were not allowed to charge interest accrued on bad loans. Mispricing of risk and inadequate build-up of loan loss provisions result in an inverse relationship as also found by a few other studies such as Williams (2007), Hesse (2007) and Chortareas *et al.* (2010).

A third possibility is countercyclical provisioning by banks so that provisions for bad loans are used as a tool for income smoothing (Fonseca and Gonzalez, 2008). Thus, during good times, provisions made are higher than the expected losses but are lower during bad times. In that case, the link between NPA and NIM may become ambiguous (Dumicic and Ridzak, 2013).

There have been some studies on the impact of asset quality of Indian banks on the NIM of banks, though the focus of most of these studies has been on the influence of ownership on NIM. Kannan *et al.* (2001) found that NPA impacted NIM negatively and significantly. Using balance sheet data of scheduled commercial banks (excluding regional rural banks) for the period 1997-98 to 2000-01, Sensharma and Ghosh (2004) found that high NPA caused NIM to decline and attributed it to banks' shifting their loan portfolio in favour of less risky assets that yield lower return. They concluded that not only low NIM characterises a bank with high NPA, but also that low current NIM is the result of high NPA in the past. In his study on the impact of global financial crisis on NIM, Das (2013) found that it was foreign banks whose margins came under pressure due to NPA; the average NPA of foreign banks was found to be around 18 per cent during 2001-05 as against less than 10 per cent for other bank groups. Thus, all the studies in the Indian context have found an inverse relationship between asset quality and NIM.

Given the complex nature of the relationship between asset quality and NIM, various alternative and apparently contrasting hypothetical scenarios can be worked out, insofar as their impact on monetary transmission is concerned. This exploits the mathematical identity of profits as the difference between income and expenditure net of provisions (a proxy for NPA), and decomposing income/expenditure into interest and non-interest income/expenditure, respectively, and dividing each of the variables by total assets.

This then allows one to work out several scenarios of the relationship between NIM, return on assets, net non-interest income and provisions (Annex I).[11]

We start with the baseline scenario where the banks maintain provisions at a prudent level, *i.e.,* aligned with the level of NPA (Scenario A). Also, the banks are able to maintain their return on assets (RoA) at the targeted level. In the baseline scenario, NIM is assumed at 2.5 per cent of total assets. Now, if there is a deterioration in asset quality entailing higher provisioning requirement (from 2.0 per cent of total assets to 2.3 per cent), banks would be prompted to load credit risk premia on lending interest rates on fresh loans or when the existing loans are due and renegotiated, so as to maintain their profitability at the targeted level. This would increase the NIM to 2.8 per cent (Scenario B). The wedge between lending and deposit rates can increase further under the easing monetary policy stance of the central bank that lowers the funding costs. As a result, the interest rate channel of monetary transmission gets impeded. This, of course, presumes that the banks facing asset quality issues are able to price risk appropriately, as also possess pricing power, which enable them to demand higher lending rates and maintain higher NIM.

Some of the studies mentioned earlier, especially those pertaining to emerging market economies, show that the banks often lack pricing power and are unable to raise their NIM by loading higher credit risk premia. In that case, banks can raise their provisions to the prudent level only at the cost of a decline in bank profitability by an equal amount (Scenario C). In this scenario, monetary transmission is not impeded initially as credit risk premia and hence, NIM remains unchanged. However, over the medium term, the decline in profitability can have implications for bank capital and that could constrain bank's capacity to lend, particularly if the bank's capital is at the regulatory minimum. Thus, monetary transmission in this case could get impacted through the bank lending channel.

Faced with higher NPA, the only option through which banks can maintain NIM at the baseline level as also the targeted RoA is by under-provisioning, *i.e.,* keeping provisions at a lower than the prudent level (Scenario D). By under-provisioning, banks can report artificially higher profitability (Brock and Rojas-Suarez, 2000). Banks can also camouflage NPA through loan

[11] The identity is: RoA = NIM + net non-interest income – provisions; or, NIM = RoA + provisions – net non-interest income. Based on this identity and assuming that banks desire to maintain their RoA at the targeted level (ΔRoA = 0), changes in NIM can be worked out as ΔNIM = Δprovision - Δnet non-interest income (Das, 2013). Hence, if provisions increase, NIM should also increase, other components remaining unchanged.

restructuring as was done in India prior to AQR (Vishwanathan, 2016). The reported figures of NPA and NIM then do not reveal the true health or efficiency of the banking system. Banks can continue to report healthy credit growth, but only through 'ever greening' or 'zombie lending'. However, there is no 'real' monetary transmission in this case.

At times, banks may be compelled to make higher provisions and cover expected losses, and in the process, have to lower their profit expectations (RoA) as also their NIM (Almarzoqi and Naceur, 2015) (Scenario E). In this scenario, lower NIM is not a proof of an efficient interest rate channel of monetary transmission, as lower return on assets may weaken the bank's lending channel of transmission as banks may get capital constrained.

Finally, there may be an extreme case, *i.e.*, the NPA situation is so grim that even after under-provisioning, banks may face lower return on assets and also a lower NIM (Scenario F). This situation is not at all inconsistent with an increase in the risk premia charged by banks. It only means that in a competitive market, banks cannot increase NIM by hiking the risk premia too high due to fear of losing customers and they are in such a financially precarious position that they are neither able to maintain their return on assets at the targeted level, nor make full provisions. Thus, an increase in risk premia that impede transmission is consistent with a fall in NIM and RoA as also under- provisioning.

Section III

Key Indicators on Health of Banks – Some Stylised Facts

The bank level quarterly data (72 select scheduled commercial banks – 26 public sector banks, 19 private sector banks and 27 foreign banks) on NIM and various indicators of health of individual bank balance sheets collated from RBI's supervisory returns (RBI OSMOS database) for the period from Q1:2010-11 to Q1:2017-18 suggest the following: first, despite the gross NPA to total assets ratio rising three times and the stressed assets to total assets ratio twice for the median bank, SCBs were by and large able to protect their NIM, which declined only marginally by 7 bps during the period – 4 bps during sub-period I (Q1:2010-11 to Q1:2015-16) and 3 bps during sub-period II (Q1:2015-16 to Q1:2017-18)[12] (Table 1). Across bank groups, the median NIM of private sector banks remained unchanged during sub-period I and

[12] The annualised numbers would be four times the figures reported here.

Table 1: Key Indicators of Bank Balance Sheet: Median

(Per cent of Assets)

Quarter	NIM*	Gross NPA	Stressed Assets	CRAR	Return on Assets
Public Sector Banks					
Q1:2010-11	0.66	1.36	3.03	12.44	1.02
Q1:2015-16	0.56	3.83	9.18	11.06	0.41
Q1:2017-18	0.50	8.91	11.26	11.65	-0.28
Private Sector Banks					
Q1:2010-11	0.74	1.03	1.95	14.52	1.36
Q1:2015-16	0.74	1.38	4.56	13.23	1.01
Q1:2017-18	0.76	2.31	2.76	14.42	0.99
Foreign Banks					
Q1:2010-11	0.86	0.91	1.08	25.84	1.68
Q1:2015-16	0.79	0.53	0.54	19.25	1.62
Q1:2017-18	0.75	0.90	1.38	21.67	1.38
Scheduled Commercial Banks					
Q1:2010-11	0.69	1.09	1.85	14.06	1.21
Q1:2015-16	0.65	2.02	4.59	13.06	0.81
Q1:2017-18	0.62	2.88	4.05	13.65	0.61

Note: CRAR: Capital to Risk-Weighted Assets Ratio. RoA: Return on Assets (Annualised). All variables (barring CRAR) are ratios to total assets. *: Quarterly (Not annualised).
Source: RBI OSMOS Database.

increased marginally by 2 bps during sub-period II. NIM of public sector banks declined by 16 bps during the full period (10 bps in sub-period I and 6 bps in sub-period II) as against a decline of 11 bps in the case of foreign banks. Thus, over the entire period, while NIM of SCBs remained broadly unaffected despite a sharp spurt in gross NPA/stressed asset ratios, NIM of public sector banks was impacted to an extent.

The decline in NIM of public sector banks (*vis-à-vis* a marginal rise for private sector banks) does not suggest that public sector banks were more efficient in transmitting monetary policy signal. Rather, the decline in NIM coupled with a sharp fall in the RoA (the latter turning negative during the second phase) was a tell-tale sign of vulnerabilities in the health of public sector banks that turned them risk averse. Public sector banks slowed down the expansion of credit as they did not receive fiscal support for recapitalisation, nor could they raise capital from the market during the period of study, thereby chocking the bank lending (credit) channel of monetary policy transmission.

Table 2: Distribution of Indicators (Q1:2010-11 to Q1:2017-18)

Variable	Mean	Median	SD	5th Percentile	95th Percentile
NIM*	0.72	0.67	0.36	0.37	1.24
Gross NPA	2.20	1.55	2.30	0.00	7.24
Stressed Assets	3.97	3.02	3.76	0.00	11.36
CRAR	22.40	13.71	34.13	10.30	56.59
RoA	1.03	0.93	2.11	-1.39	3.78
Non-interest Income	0.49	0.26	0.95	0.07	1.67
Operating Expense	0.64	0.44	0.82	0.23	1.82

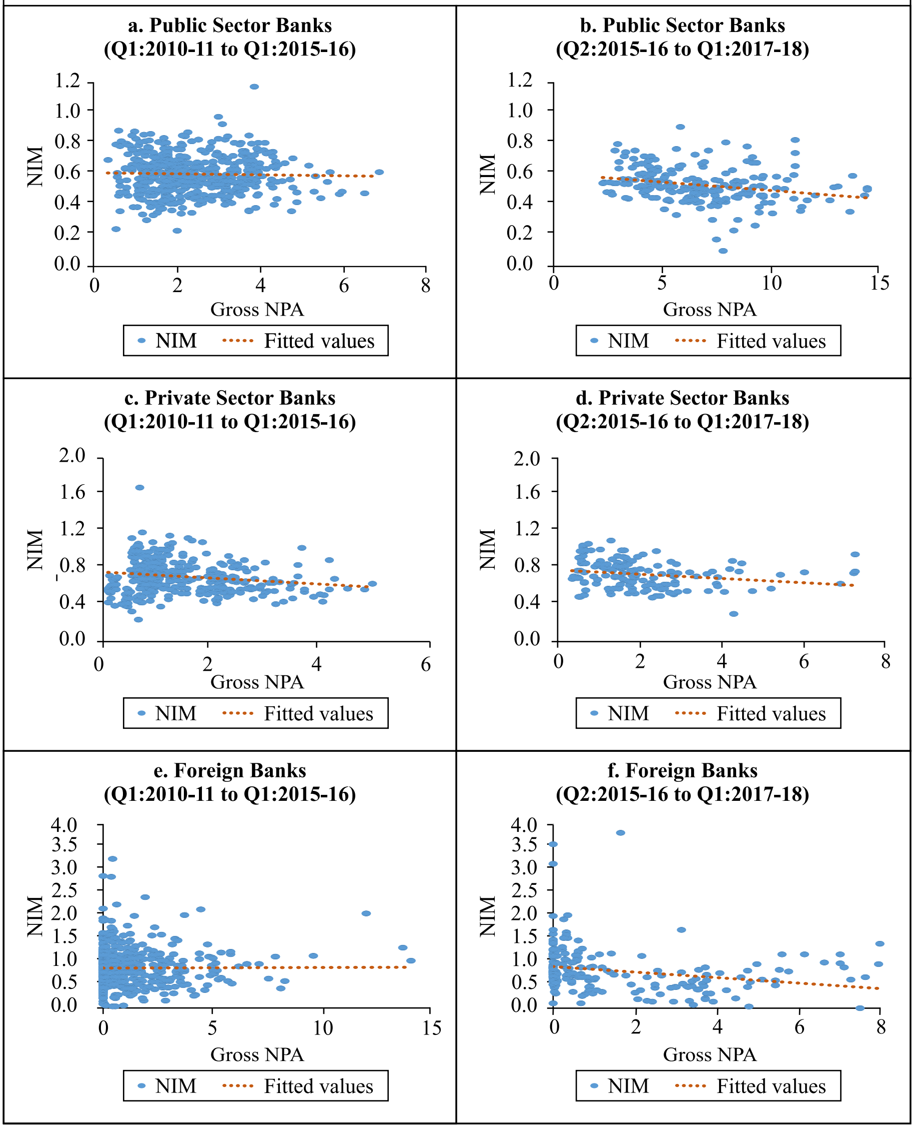
Note: CRAR: Capital to Risk-Weighted Assets Ratio. RoA: Return on Assets (annualised). All variables (barring CRAR) are ratios to total assets. *: Quarterly (not annualised).
Source: RBI OSMOS Database.

The distribution of indicators shows that there was a wide variation in credit risk among banks. The gross NPA ratio of banks ranged from nil (5^{th} percentile) to 7.24 per cent (95^{th} percentile) (Table 2).

The relationship between NIM and gross NPA ratio for two sub-periods for various bank groups was analysed using scatter plots (Chart 1). The scatter plots show a negative relationship between NIM and the gross NPA ratio for each of the bank groups and during both the phases. The slope is steeper for public sector banks during the latter sub-period marked by the deterioration in the gross NPA ratio, implying that at a higher level of gross NPA ratio, public sector banks were unable to protect their NIMs. The flatter slope in the initial phase, when the gross NPA ratio on an average was much lower, indicates that as gross NPA ratio rises from a low level, NIM remained unaffected. Thus, the relationship between the gross NPA ratio and NIM is non-linear – a flatter slope at lower level of gross NPA ratio and a steeper slope otherwise.

The median individual bank-wise data suggest that the deterioration in asset quality of public sector banks was much more pronounced *vis-à-vis* private sector banks or foreign banks. The story is similar if the data for bank groups are aggregated. The gross NPA ratio of public sector banks increased from 3.8 per cent at end-March 2013 to 5.4 per cent at end-March 2015 and further to 12.5 per cent at end-March 2017, while that of private sector banks increased from 1.9 per cent to 2.2 per cent to 3.5 per cent over the same period.

Chart 1: Relationship between NIM and Gross NPA Ratio of SCBs



Contemporaneously, banks increased their provision coverage ratio (PCR) - from 40.3 per cent at end-March 2014 to 41.9 per cent in March 2016 and further to 43.5 per cent at end-March 2017; this, however, fell short of the objective to have "clean and fully provisioned bank balance sheets by March 2017" (Rajan, 2016). With provisions and contingencies increasing by 45.2

per cent at end of 2015-16 (₹2,094 billion), net profits shrank by 61.7 per cent.[13] Provisions and contingencies increased further by ₹2,437 billion at end of 2016-17, reflecting the continued stress in asset quality. Net NPA increased to ₹4,331 billion (5.3 per cent of net advances) at end of 2016-17 from ₹3,498 billion (4.4 per cent of net advances) a year earlier, reflecting the requirement for further provisioning in the years to come.[14]

Section IV

Methodology – Determinants of NIM

This section spells out the methodology for estimating the determinants of NIM covering the period Q1:2010-11 to Q1:2017-18 with the thrust being on the impact of asset quality. The relationship between asset quality and NIM can be used to understand the implications for monetary transmission with the different scenarios explained in Annex I and described in Section II. The period of study has been divided into two parts, *viz.* sub-period I (Q1:2010-11 to Q1: 2015-16) when the gross NPA and stressed assets ratios were low but rising, and sub-period II (Q2:2015-16 to Q1:2017-18) when the gross NPA and stressed assets ratios were relatively high and rising.

The determinants of NIM typically used in the literature are grouped under three heads: (i) individual bank-specific factors, (ii) banking sector specific factors, and (iii) macroeconomic factors. Apart from the bank-specific variables, we introduce time and bank-fixed effects in the regression equations. This being a study on banks operating in one country, the macroeconomic variables like growth, inflation and policy rates are uniform across different banks for a given time period and can be appropriately controlled by introducing the time-specific effects in the regression equations. These effects also capture the role of regulatory policies such as the cash reserve ratio and the liquidity coverage ratio, which are common across all banks. Further, introducing time-specific effect is expected to capture even other time-fixed factors that could have otherwise got omitted. Similarly, industry /banking sector specific characteristics such as ownership of banks, labour productivity and competitiveness are more or less subsumed in the bank-fixed effects. Hence, we have used only the individual bank-specific factors as the explanatory variables in the regression equations.

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[13] RBI (2017).

[14] RBI (2017).

The impact of asset quality on NIM being the focus of our study, all other variables need to be controlled so as to understand the relationship between asset quality and NIM. In this backdrop, the determinants of NIM have been estimated with the following model specification:

$$NIM_{b,t} = c + \alpha_b + \gamma_t + \delta_1 * NIM_{b,(t-1)} + \delta_2 * NIM_{b,(t-2)} + \Psi * X + \varepsilon_{b,t} \quad (1)$$

where α_b represents the bank fixed effects, and γ_t represents the time fixed effects and X represents a vector of explanatory variables at different time periods and for various banks.

We have used the following variables as regressors for NIM (interest income *minus* interest expense divided by total assets): lagged NIM (one quarter and two quarter), operating expenditure (measured by operating expenditure to total assets ratio), credit risk (proxied alternatively by the gross NPA to total assets ratio and the stressed assets - restructured assets *plus* gross NPA - to total assets ratio), capital adequacy measured by the capital to risk-weighted assets ratio (CRAR), profitability measured by return on assets (RoA), bank size (measured by natural logarithm of total assets) and non-interest income (measured by the non-interest income to total assets ratio). All the data were seasonally adjusted with X-12 ARIMA at the bank level.

Empirical literature on the determinants of NIM suggests that there is no consensus on the direction (positive/negative association) and the significance of the relationship between bank-specific variables (other than operating cost) and NIM. The relationship also differs across countries, among bank groups (domestic, foreign *etc*.) and over time. The literature on relationship between asset quality and NIM has already been discussed in Section II. The nature of the relationship of other individual bank-specific variables and NIM as observed in empirical literature is discussed below.

i. *Operating Cost*: Operating cost is a proxy for servicing and monitoring transactions (Almarzoqi and Naceur, 2015). Operating costs include salaries and pensions and other expenses such as depreciation, administrative expenses, occupancy costs, software costs, and lease rental (Dumicic and Ridzak, 2013). There is a consensus in the literature that banks pass on the operating costs to customers. Therefore, an increase in the operating cost increases the net interest margin. Operating costs were found to be the most important driver of interest spreads in the Caucasus and Central Asia (Almarzoqi and Naceur, 2015).

ii. *Capital Adequacy*: The relationship between capital adequacy and NIM is not straightforward. Capital adequacy is a proxy for the creditworthiness of a bank: a bank having higher capital adequacy is likely to be more solvent, which would reduce its funding costs, thereby increasing the NIM. With capital well above regulatory requirement, well-capitalised banks can also afford to invest in riskier assets without facing possible erosion of capital below the stipulated regulatory norms, which can lead to a high spread. Likewise, under-capitalised banks or banks facing capital erosion may be subject to regulatory restrictions, forcing them to adopt risk averse strategy. When the above-mentioned conditions hold, the capital adequacy ratio is found to have a positive and significant impact on banks' spreads (Saunders and Schumacher, 2000; Brock and Suarez, 2000). Under other circumstances, capital adequacy has a negative and significant impact on NIM (Dumicic and Ridzak, 2013; Tan, 2012; and Almarzoqi and Naceur, 2015). A risk averse but well-capitalised bank may find bankruptcy to be a costly proposition. For a poorly capitalised bank, depositors and not equity holders are at a risk when the bank faces bankruptcy, and the bank may gamble by investing in risky assets to improve its NIM. When such a gamble pays off, such poorly-capitalised banks may have high spreads. Again, there are cases where a statistically significant relationship is not found between capital adequacy and NIM, possibly reflecting the fictitious nature of capital in some countries in Caucasus and Central Asia (Almarzoqi and Naceur, 2015).

iii. *Return on Assets*: A higher return on assets is expected to be associated with a higher NIM.

iv. *Size*: Empirical literature presents contrasting results on the relationship between banks' net interest margins and size (proxied by the natural logarithm of loans or total assets). Ho and Saunders (1981) and Maudos and Solisc (2009) find a positive relationship because the larger the transaction, the larger the potential loss will be. Maudos and De Guevara (2004) and Angbazo (1997), among others, report a negative association between bank size and interest margins, pointing to the cost reduction attributed to economies of scale. While focusing on the ownership of banks, Sensarma and Ghosh (2004) found that size of Indian banks affected NIM positively and significantly of Indian banks.

v. *Non-interest Income*: More recent studies find that banks with well-developed non-interest income sources have lower net interest margins. This suggests that banks may tend to offer loans with small or even negative margins to attract clients and compensate with higher fees (Dumicic and Ridzak, 2013; Maudos and Solis 2009; and Carbo and Rodriguez 2007, among others). The difference between non-interest income and non-interest expenditure is referred to as 'burden' in the literature, measuring the extent of burden it can share with the NIM from the standpoint of profitability (Das, 2013). Kannan *et al*. (2001) found that the fee income significantly impacted NIMs of Indian banks.

Estimation

For estimation, we have used dynamic panel data regression technique, using approaches specified by Arellano-Bover (1995) and Blundell-Bond (1998), that is, linear generalised method of moments (GMM). These estimators are suitable in situations where the dependent variable – in the present case NIM – is dynamic and depends on its own past realisations, while the right-hand side variables are not strictly independent, *i.e.,* Hug are correlated with error, and have heterogeneity arising from fixed individual effects – both bank specific and time specific. Arellano-Bover estimator extends Arellano-Bond (1991) estimator, commonly known as "difference GMM", by incorporating the assumption that first differences of instrument variables are uncorrelated with the fixed effects. This can increase the efficiency of the estimator (Roodman, 2009), as it incorporates two sets of equations and is known as "system GMM". Further, we have estimated the regressions in an instrumental variable framework, which uses the lagged values of dependent and explanatory variables as instrumental variables (to overcome the problem of endogeneity in the explanatory variables). This is particularly important as many explanatory variables may be endogenous. All the models are estimated with appropriately choosen lags – systematically dropping the insignificant ones – that could produce satisfactory model properties. The robustness of the reported models was tested using model diagnostics tests: (i) difference in Sargan test for over identification – checks for the validity of instruments; and (ii) Arellano-Bond test for first order and second order residual auto correlation – the first order auto correlations should be negative and significant and the second order ones should be insignificant. As alluded to earlier, the regressions were estimated including bank- and time-fixed effects.[15]

The regressions were first estimated for the full sample period (Q1:2010-11 to Q1:2017-18) for scheduled commercial banks. However, given the non-linearity in the impact of asset quality on the net interest margins (as evident from scatter plots in Chart 1), separate regressions were estimated for two sub-periods, *viz*., (a) sub-period I: Q1:2010-11 to Q1:2015-16; and (b) sub-period II: Q2:2015-16 to Q1:2017-18. Furthermore, regressions were also estimated for different bank groups – public sector banks, private sector banks and foreign banks – for the full sample period.

Section V
Results

V.1 Results for the Full Sample Period

Results in Table 3 suggest that credit risk – proxied separately by the gross NPA and stressed assets (gross NPA *plus* restructured assets) ratios – impact NIM of SCBs positively, implying that banks in India, generally, charged additional premia to compensate for credit risk, which was reflected in their lending rates. This suggests that deterioration in asset quality did impact monetary transmission through higher NIM (Scenario B in Annex I). Banks either utilised the higher spread to fund loan loss reserves (provisions) or to maintain their return on assets at the targeted level.

Though the main purpose of the analysis is to assess the impact of health of banks on monetary transmission, the regression results also provided some other interesting findings. First, operating expense, as expected, was positively related to NIM indicating that less efficient banks, experiencing higher operating costs, require higher NIM. On the other hand, more efficient banks could reduce lending rates, and charge a lower NIM. Second, as expected, non-interest income and NIM were negatively related indicating that banks with higher non-interest income were able to offer lending interest rates on better terms. Third, the capital adequacy ratio, which represents solvency,

[15] For robustness, different model specifications were also used in this study - with and without time- and bank-fixed effects. The results were found to be broadly similar.

Table 3: Determinants of NIM of SCBs

Dependent: NIM	Full Sample		Q1:2010-11 to Q1: 2015-16		Q2:2015-16 to Q1: 2017-18	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
NIM(-1)	-0.0052	0.0045	-0.0204	-0.0254	-0.1052***	-0.1115***
	(0.7667)	(0.7984)	(0.3771)	(0.2721)	(0.0000)	(0.0000)
NIM(-2)	0.0332	0.0423**	0.0005	-0.003	0.0082	-0.0018
	(0.1069)	(0.0384)	(0.9819)	(0.8970)	(0.8389)	(0.9653)
Stressed assets	0.0067**		0.0071*		-0.0144*	
	(0.0494)		(0.0728)		(0.0649)	
Gross NPA		0.0057*		0.0211***		-0.0202***
		(0.0915)		(0.0013)		(0.0037)
Operating expense	0.4986***	0.5066***	0.4358***	0.4313***	0.5483***	0.5444***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Non-interest income	-0.0838***	-0.0855***	-0.0468**	-0.0437**	-0.0512***	-0.0503***
	(0.0000)	(0.0000)	(0.0152)	(0.0232)	(0.0000)	(0.0000)
CRAR	0.0008**	0.0006*	0.0013***	0.0013***	-0.0082***	-0.0085***
	(0.0244)	(0.0725)	(0.0008)	(0.0004)	(0.0000)	(0.0000)
Size	0.0522	0.0368	-0.1587***	-0.1480***	-0.0477	-0.0582
	(0.1007)	(0.1951)	(0.0002)	(0.0005)	(0.6080)	(0.5266)
RoA	0.0525***	0.0532***	0.0380***	0.0415***	0.0316***	0.0291***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0011)
RoA(-1)	0.0148***	0.0137***	0.0123**	0.0128**	0.0112	0.0092
	(0.0040)	(0.0074)	(0.0346)	(0.0277)	(0.2693)	(0.3580)
Time-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Difference-in-Sargan test (p-value)	1.0000	0.96660	0.2350	0.2570	1.0000	1.0000
A-B test for AR(1) (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A-B test for AR(2) (p-value)	0.6174	0.6841	0.7499	0.7495	0.1298	0.1610
Observations	1944	1944	1368	1368	576	576

p-values in parentheses. *: p<0.10, **: p<0.05, ***: p<0.010.

Note: Even though in some alternative specifications we got statistically insignificant estimates for lags of NIM, we retained the specification of two lags for NIM, for making the comparison for the estimates of gross NPA/stressed assets ratios fair and comparable.

was found to have a positive relationship with NIM indicating that banks in India seek higher margins to compensate for higher cost of equity. Although the Modigliani-Miller model suggests that it does not matter how a firm is financed in terms of its debt-equity composition, as far as the value of the firm is concerned, it is now widely recognised that equity is more expensive than debt. In the Indian context, banks with excess CRAR (*i.e.,* above their regulatory requirement) were not capital constrained; they may prefer to extend credit rather than invest in lower yielding sovereign bonds or top rated corporate bonds, thus boosting their NIMs. On the other hand, banks that are capital constrained became risk averse, cutting back on lending activity and face a lower NIM. Fourth, the coefficient of bank size – measured by natural logarithm of total assets – was found to be statistically insignificant, suggesting that NIM was not sensitive to the size of a bank.

V.2 Results for the Sub-Periods:

The regression analysis for the two sub-periods threw up some interesting results insofar as the impact of asset quality on NIM is concerned (Table 3).

First, credit risk (measured by the gross NPA and stressed asset ratios) positively impacted NIM during sub-period I. However, in sub-period II credit risk was negatively associated with NIM, *i.e.,* NIM declined with the rise in stressed assets/gross NPA ratios. In sub-period I, the level of stressed assets/ gross NPA ratio was relatively at a much lower level *vis-à-vis* sub-period II. Credit growth was also relatively strong. Hence, banks were able to charge additional risk premia to compensate for credit risk (Scenario B in Annex I). It is, however, difficult to establish whether banks were genuinely able to protect their NIM or had fudged the account classification norms to recognise incomes through 'zombie lending' or 'ever greening of loans' on assets that merited classification as NPA.[16] However, during sub-period II, when gross NPA ratio rose sharply following asset quality review led reclassification of assets, banks

[16] As noted by Vishwanathan (2016), "During the five years to March 2015, banks have resorted to restructuring of loans in many cases to postpone recognition of non-performance, or what we now call 'extend and pretend', rather than using it as a tool to preserve the economic value of the units as intended. As a result, until 2016 the restructured assets constituted more than 50 per cent of the stressed assets of all scheduled commercial banks masking the actual extent of deterioration of the loan portfolios". It, therefore, appears that banks would have falsely recognised interest income on what ought to have been classified as NPA in the first place during sub-period I. Banks could thus protect their NIM artificially during sub-period I, which they could not sustain during sub-period II, following AQR. It is also anyone's guess whether banks would have mispriced credit risk and whether they would have made adequate provisions since they were, during sub-period I 'postponing recognition of non-performance'.

could no longer recognise income on an accrual basis under IAS (International Accounting Standard) 39, nor could they pass on the entire burden of NPAs to their borrowers (Scenario E or F in Annex I). In a competitive market, there are limits up to which banks can compensate themselves through an additional risk premium. The NPA ratios were at an elevated level and would have necessitated a much higher credit risk premium to provide for expected losses and meet the targeted return on assets, which was not possible in a competitive environment. The decline in NIM might also reflect the inability of banks to have made adequate provisioning during this period.[17] The inverse relation between gross NPA ratio and NIM could have reflected lower provision coverage as also stress in earnings.[18] As noted by Acharya (2017), many banks "*are precariously placed in case the provisioning cover for loan losses against their gross non-performing assets is raised to international standards and made commensurate with the low loan recoveries in India*".

The above analysis suggests that asset quality had a significant bearing on monetary transmission in India. At a low level of gross NPA ratio, banks were able to pass on the burden of deterioration in asset quality to their borrowers in the form of higher lending rates, which were reflected in increase in NIM. However, as the gross NPA ratio rose, banks were unable to increase interest rates further due to competitive pressures. In contrast, banks might have made provisions for bad assets and also might not have been allowed to recognise interest income on such assets. All this resulted in the decline in NIM.

The results of two sub-periods were broadly on the same lines as of the full sample period, excepting the following two cases. First, the higher capital adequacy was found to affect NIMs positively in the first sub-period in line with the full sample period. However, in sub-period II, characterised by monetary policy easing and AQR, higher capital adequacy was negatively associated with NIMs. This was possibly due to the risk aversion by banks following revelation of large NPAs brought out by AQR, which forced banks to refrain from taking further large credit exposure so as to maintain the CRAR above the regulatory level. Left to themselves, banks barely meeting the capital

[17] A similar conclusion was drawn by Brock and Suarez (2000) for Latin American countries.

[18] "High levels of NPA have been progressively causing increasing stress on banks' earnings. As a result, banks' provisioning capacity has also come under pressure leading to a spike in the net NPA levels as well. Higher net NPAs indicate lower provision coverage" (Vishwanathan, 2016).

requirements would want to generate capital quickly, focusing on high interest margins at the cost of high loan volumes (Acharya, 2017). However, their ability to generate high NIM – which had both price and quantity components – appeared to have been circumscribed by a surge in NPAs for three reasons: (i) interest income could no longer be recognised: (ii) competitive pressures refrained banks from loading extra credit risk premium; and (iii) credit growth slowed down sharply from 18.3 per cent in Q1:2010-11 to 9.2 per cent in Q1: 2015-16 and further to 5.9 per cent in Q1:2017-18. Second, unlike the sub-period I when credit growth was robust because of which larger banks were able to offer loans at lower rates and operate with lower NIM, in sub-period II, co-efficient of size turned statistically insignificant as credit growth collapsed during this phase. Large NPA on the one hand and a sharp decline in credit volumes on the other, possibly resulted in the coefficient of size turning statistically insignificant. This also impacted NIMs of banks.

V.3 Results - Bank Group-wise

Table 4 presents estimates of the relationship of NIM with gross NPA and stressed asset ratios for the three bank groups – public, private and foreign. The results show divergence across bank groups. While the gross NPA ratio had a negative and statistically significant impact on NIM of public sector banks, they had a positive but statistically insignificant impact in the case of private sector and foreign banks. The gross NPA ratio of public sector banks was much higher than that of private banks and foreign banks. Thus, the results of bank group-wise analysis corroborated the finding of two sub-periods analysis, *i.e.*, at a high level of the gross NPA ratio, banks were unable to load the cost by jacking up their lending rates and hence their NIM. Thus, the sub-period wise and bank-group wise analyses suggest that at high gross NPA ratio, banks could not charge credit risk premia and increase their NIM, indicating that the impact of the gross NPA ratio on NIM is non-linear.[19]

[19] The presence of non-linearities was also formally tested by introducing slope dummies for the gross NPA ratio in (1) for the full sample period.

$$NIM_{b,t} = c + \propto_b + \gamma_t + \delta_1 * NIM_{b,(t-1)} + \delta_2 * NIM_{b,(t-2)} + \beta_1 * d * GNPA + \beta_2 * (1 - \mathrm{d}) * \mathrm{GNPA} + \Psi * X1 + \varepsilon_{b,t} \quad (2)$$

Where $\propto_b$ represents the bank-fixed effects, and γ_t represents the time-fixed effects, GNPA is the gross NPA to assets ratio and X1 represents a vector of other explanatory variables and d =1 when the gross NPA to asset ratio is below the sample median of 1.6 per cent of total assets and 0 otherwise. β_1 and β_2 represent the slope of GNPA on NIM when GNPA is low and high, respectively. It was found that β_1 is positive and statistically significant, showing a positive relationship between GNPA and NIM when GNPA is low, while β_2 is negative and statistically significant, showing a negative relationship between GNPA and NIM when GNPA is high.

Table 4: Determinants of NIM – Bank Group-wise

	All SCBs		Public Sector Banks		Private Sector Banks		Foreign Banks	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NIM(-1)	-0.0052 (0.7667)	0.0045 (0.7984)	0.1333*** (0.0001)	0.1305*** (0.0001)	0.1127*** (0.0007)	0.1131*** (0.0006)	-0.0118 (0.6788)	-0.0101 (0.7219)
NIM(-2)	0.0332 (0.1069)	0.0423** (0.0384)	0.1819*** (0.0000)	0.1794*** (0.0000)	0.1830*** (0.0000)	0.1828*** (0.0000)	0.0138 (0.6861)	0.0163 (0.6325)
Stressed asset	0.0067** (0.0494)		-0.0016 (0.3736)		0.0042 (0.2491)		0.0168* (0.0675)	
Gross NPA		0.0057* (0.0915)		-0.0128*** (0.0001)		0.0097 (0.1183)		0.0123 (0.2212)
Operating expense	0.4986*** (0.0000)	0.5066*** (0.0000)	0.5628*** (0.0000)	0.5614*** (0.0000)	0.6568*** (0.0000)	0.6585*** (0.0000)	0.4872*** 0.0000	0.4870*** 0.0000
Non-interest income	-0.0838*** (0.0000)	-0.0855*** (0.0000)	-0.0362 (0.3781)	-0.034 (0.4034)	-0.0608** (0.0129)	-0.0585** (0.0170)	-0.0869*** 0.0000	-0.0867*** 0.0000
CRAR	0.0008** (0.0244)	0.0006* (0.0725)	0.0001 (0.9638)	0.0007 (0.8053)	0.0021 (0.1547)	0.0024 (0.1140)	0.0007 (0.1907)	0.0007 (0.2152)
Size	0.0522 (0.1007)	0.0368 (0.1951)	-0.2034*** (0.0000)	-0.2568*** (0.0000)	0.0113 (0.5765)	0.0206 (0.3456)	-0.0502 (0.1799)	-0.0524 (0.1611)
RoA	0.0525*** (0.0000)	0.0532*** (0.0000)	0.0464*** (0.0000)	0.0368*** (0.0000)	0.0999*** (0.0000)	0.1039*** (0.0000)	0.0567*** 0.0000	0.0556*** 0.0000
RoA(-1)	0.0148*** (0.0040)	0.0137*** (0.0074)	-0.0222** (0.0163)	-0.0311*** (0.0010)	-0.0213* (0.0978)	-0.0211* (0.0931)	0.0143* (0.0823)	0.0141* (0.0857)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference-in-Sargan test (p-value)	1.0000	0.96660	1.0000	1.0000	0.9980	0.9990	0.9740	0.9610
A-B test for AR(1) (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A-B test for AR(2) (p-value)	0.6174	0.6841	0.1285	0.2523	0.1694	0.3200	0.9872	0.9766
Observations	1944	1944	702	702	513	513	729	729

p-values in parentheses. *: p<0.10, **: p<0.05, ***: p<0.010

Note: Even though in some alternate specifications we got statistically insignificant estimates for lags of NIM, we retained the specification of two lags for NIM, in order to make the comparison for the estimates of gross NPA/stressed asset ratios fair and comparable.

Since banks cannot recognise interest income accruing on their NPA, they could increase or protect their NIM only by raising the credit risk premia on their fresh loans and outstanding standard assets so as to meet their targeted RoA as also to build up provisions. Public sector banks did not make enough provisions as seen from their high net NPA ratio of 6.9 per cent (as against 2.2 per cent and 0.6 per cent for private sector and foreign banks, respectively) as at end-March 2017. It was also possible that public sector banks pursued a risk averse strategy, particularly when they were not able to raise capital. Public sector banks instead responded by significantly reducing supply of credit as compared with other bank groups, as reflected in the sharp fall in the credit growth during this period. The case of foreign banks, however, was different. They were most successful in keeping provisions high and reducing the level of the net NPA ratio[20] – the PCR of foreign banks stood at 82.3 per cent as at end-March 2017, as against 42.2 per cent and 47.9 per cent for public sector banks and private sector banks, respectively.[21] With higher provisions requiring a higher NIM so as to maintain profitability, the relationship between the gross NPA ratio and NIM for foreign banks turned out to be positive.

Other results of bank group-wise analysis were similar to the aggregate analysis, barring in the following two cases. First, non-interest income coefficient turned out to be negative, as expected, but statistically insignificant in the case of public sector banks, while it was statistically significant in the case of foreign and private sector banks. This implies that non-interest income was not a significant factor influencing the lending rates and margins of public sector banks, while it was significant in the case of private sector and foreign banks. Second, the bank size had a negative association with interest margins in the case of public sector banks, suggesting that large public sector banks were able to keep NIM lower as they enjoyed economies of scale. The size coefficients of private and foreign banks were, however, statistically insignificant, suggesting that the size had no impact on NIMs of private and foreign banks.

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[20] The level of net NPA ratio of foreign banks stood at only 0.6 per cent at end-March 2017 as against gross NPA of 4.0 per cent. In the case of private (as well as public) sector banks, the figures were 2.2 per cent (6.9 per cent) and 4.1 per cent (11.7 per cent), respectively, indicative of the ability of foreign banks to make suitable provisions aided by their ability to raise their NIM *(vis-à-vis* private and public sector banks) (RBI, 2017).

[21] RBI (2017).

Section VI
Conclusion

In a bank-dominated financial system such as India, monetary transmission works mainly through the banking system. Hence, health of the banking system plays a key role in effective monetary transmission. This paper was an attempt to assess whether the recent deterioration in the health of the banks in India had any adverse impact on monetary transmission. The analysis suggests that credit risk, proxied separately by the gross NPA and stressed asset ratios, had a positive impact on the NIMs of scheduled commercial banks for the period Q1:2010-11 to Q1:2017-18, implying that deterioration in asset quality impaired monetary transmission. While deterioration in asset quality was positively associated with NIM in sub-period I (Q1:2010-11 to Q1:2015-16), it was negatively associated in sub-period II (Q2:2015-16 to Q1:2017-18). In sub-period I, when the gross NPA/stressed assets ratio was relatively low, but rising, banks were able to pass on the burden of deterioration in asset quality on to their lending rates and protect NIMs. In sub-period II, however, when the gross NPA ratio was high and rising, banks were not able to protect their NIMs as in a competitive environment there are limits up to which banks can charge extra credit risk premia. This finding was corroborated by bank group-wise analysis. NIMs of public sector banks, which had large NPA/stressed assets, were negatively impacted, while NIM of private sector and foreign banks were not. The key findings of the study are that deterioration in the health of the banking sector at the initial stages impairs monetary transmission through interest rate channel as banks are able to charge extra credit risk premium for possible loan losses. However, when NPAs keep rising, banks are unable to protect their NIMs due to competitive pressures, but they become risk averse and cut sharply their lending, which impacts monetary transmission through bank lending channel.

The key focus of study was to assess how the health of the banking system impacted the strength of the interest rate channel of monetary transmission. The asset quality is also expected to play a key role in the bank-lending channel of monetary transmission. This channel, however, has not been explicitly examined in this paper. This is an area which needs further research.

References

Acharya, V. V. (2017), "The Unfinished Agenda: Restoring Public Sector Bank Health in India", Speech delivered at the 8th R K Talwar Memorial Lecture organised by the Indian Institute of Banking and Finance at Hotel Trident, Mumbai, September 7, https://www.rbi.org.in/Scripts/BS_SpeechesView.aspx?Id=1046.

Almarzoqi, R. and. Naceur S. B. (2015), "Determinants of Bank Interest Margins in the Caucasus and Central Asia" *IMF Working Paper* 15/87, April.

Angbazo, L. (1997), "Commercial Bank Net Interest Margins, Default Risk, Interest-Rate Risk, and off-Balance Sheet Banking", *Journal of Banking and Finance*, 21, 55-87.

Arellano, M., and Bond, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *The Review of Economic Studies*, *58*(2), 277-297.

Arellano, M., and Bover, O. (1995), "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics*, *68*(1), 29-51.

Blundell, R., and Bond, S. (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics*, *87*(1), 115-143.

Brock, P. L., and Rojas-Suarez L. (2000), "Understanding the Behavior of Bank Spreads in Latin America", *Journal of Development Economics*, 63, 113-134.

Carbo V.S., and Rodriguez, F. F. (2007), "The Determinants of Bank Margins in European Banking", *Journal of Banking and Finance*, 31(7), p. 2043-2063.

Chortareas, G. E., Girardone C., and Gustavo Garza-Garcia J. (2010), "Banking Sector Performance in Some Latin American Countries: Market Power versus Efficiency," *Banco de México Working Papers* 20, Mexico City.

Claeys, S., and Vennet, V.R. (2008), "Determinants of Bank Interest Margins in Central and Eastern Europe: A Comparison with the West", *Economic Systems* 32 (2), 197–216.

Das, T. B. (2013), "Net Interest Margin, Financial Crisis and Bank Behaviour: Experience of Indian Banks", *RBI Working Paper Series*: 10, October.

Dumicic, M. and Ridzak, T. (2013), "Determinants of Banks' Net Interest Margins in CEE", March *https://www.researchgate.net/publication/305387302.*

Fisher, I. (1933), "The Debt-deflation Theory of Great Depressions", *Econometrica*, 1, 337–357.

Fonseca, A.R. and Gonzalez F. (2008), "Cross-country Determinants of Bank Income Smoothing by Managing Loan-Loss Provisions", *Journal of Banking and Finance*, 32(2), 217-228.

Hesse, H. (2007), "Financial Intermediation in the pre-consolidated banking sector in Nigeria", *World Bank Policy Research Working Paper Series* 4267, Washington DC.

Ho, T. S. Y., and Saunders A. (1981), "The Determinants of Bank Interest Margins: theory and Empirical Evidence", *Journal of Financial and Quantitative analysis*, 16, 581-600.

Kannan, R., Narain, A. and Ghosh, S. (2001), "Determinants of Net Interest Margin under Regulatory Requirements: An Econometric Study", *Economic and Political Weekly*, January 27, 337-44.

Marinkovic, S. and Radovic O. (2014), "Bank Net Interest Margin Related to Risk, Ownership and Size: An Exploratory Study of the Serbian Banking Industry", *Economic Research- Ekononska Istrazlvanja*, 27(1), 134-154.

Maudos, J., and De Guevara, F. J. (2004), "Factors Explaining the Interest Margin in the Banking Sectors of the European Union", *Journal of Banking and Finance,* 28 (9), 2259–2281.

Maudos, J., and Solísc, L. (2009), "The Determinants of Net Interest income in the Mexican Banking System: an Integrated Model", *Journal of Banking and Finance*, 33 (10), 1920–1931.

Rajan, R. (2016), "Issues in Banking Today", 2016 - a*t CII's first Banking Summit*, Mumbai, February 11, https://www.rbi.org.in/Scripts/BS_SpeechesView.aspx?Id=992

Reserve Bank of India (2011), *Report on Trend and Progress of Banking in India*.

— (2013), *Report on Trend and Progress of Banking in India*.

— (2017), *Report on Trend and Progress of Banking in India*.

— (2017a), *Statistical Tables Relating to Banks in India*.

Roodman, D. (2009), "How to do xtabond2: An introduction to difference and system GMM in Stata", *Stata Journal*, *9*(1), 86-136.

Saunders, A., and Schumacher L. (2000), "The Determinants of Bank Interest Rate Margins: An International Study", *Journal of international Money and Finance*, 19, 813-832.

Schwaiger, M.S. and Liebig, D. (2008), "Determinants of the Interest Rate Margins in Central and Eastern Europe", *Financial Stability Report (Osterreichische National Bank)*, 14, 68-87.

Sensharma, R., and Ghosh, S. (2004), "Net Interest Margin: Does Ownership Matter", *Vikalpa*, 29 (1), 41-47.

Subbarao, D. (2010), "Five Frontier Issues in Indian Banking", Inaugural Address at 'BANCON 2010' in Mumbai on December 3, https://www.rbi.org.in/Scripts/BS_SpeechesView.aspx?Id=539.

Tan, T. B. P. (2012), "Determinants of Credit Growth and Interest Margins in the Philippines and Asia", *IMF Working Paper*, WP/12/123, May.

Vishwanathan, N. S. (2016) "Asset Quality of Indian Banks: Way Forward" - at National Conference of ASSOCHAM on "Risk Management: Key to Asset Quality", New Delhi, August 30, https://www.rbi.org.in/Scripts/BS_SpeechesView.aspx?Id=1023.

Williams, B. (2007), "Factors Determining Net Interest Margins in Australia: Domestic and Foreign Banks", *Financial Markets, Institutions and Instruments,* 16(3), 145-165.

Annex. I: Relationship between NIM, Return on Assets and Asset Quality (Provisions /NPA) – Hypothetical Scenarios *(contd.)*

(Per cent of total assets)

	Scenario	NIM	Return on Assets	Net non-interest income	Provision	Impact on transmission during easing phase of monetary policy
A	**Baseline -** Provisions are at a prudent level and RoA at the targeted level.	2.5	1	0.5	2.0	
B	**Banks have pricing power** – In order to provide for higher provisioning requirements on account of a rise in NPA, banks raise NIMs and at the same time, are able to maintain RoA at the targeted level.	2.8	1	0.5	2.3	Transmission is impeded.
C	**Banks do not have pricing power -** Faced with the higher provisioning requirement, banks cannot increase NIM while simultaneously keeping RoA at its targeted level. Banks are only able to prudently provide for higher NPAs but at the cost of non-adherence to RoA target as NIM remains unchanged at the baseline level.	2.5	0.7	0.5	2.3	The impact of higher provisioning is absorbed by the return on assets and NIM remains unchanged. There is no adverse impact on transmission. However, due to lower profitability, banks may become capital constrained in future.
D	Increase in provisioning requirements - Prudence demands that banks increase provisioning requirement to 2.3 per cent from 2.0 per cent. However, banks do not have pricing power – cannot increase NIM. They still maintain targeted RoA by inadequate provisioning (non-recognition of NPA). Zombie lending (ever greening of NPA) may help banks maintain profitability artificially.	2.5	1	0.5	2.0	Through inadequate provisioning, banks maintain NIM at base line level. Transmission appears not to be impacted although there is no real monetary transmission. Also, transmission may get impacted in future as and when banks are required by the regulator to make provisioning.

Annex. I: Relationship between NIM, Return on Assets and Asset Quality (Provisions /NPA) – Hypothetical Scenarios (*concld.*)

(Per cent of total assets)

	Scenario	NIM	Return on Assets	Net non-interest income	Provision	Impact on transmission during easing phase of monetary policy
E	**Banks do not have pricing power:** Nevertheless, banks recognise NPA and make adequate provisioning. A sharp fall in interest income leads to a fall in NIM. RoA declines by much more as compared with C, reflecting both a fall in NIM and a rise in provisions.	2.3	0.5	0.5	2.3	Since banks are unable to increase lending rates in the absence of pricing power, transmission is not visibly impacted. However, due to lower profitability, banks may become capital constrained in future.
F	Banks do not have pricing power - Higher NPA reduce banks' interest income, thereby lowering NIMs. Banks make inadequate provisioning (non-recognition of NPA). RoA falls, but only marginally due to under-provisioning even as higher NPAs reduce interest income and hence, NIM.	2.2	0.9	0.5	1.8	As above.
G	Banks make over - (under) provisioning during economic upswing (downswing) even as NPAs decline (rise). Counter cyclical provisioning causing income smoothing results in a negative relationship between NPAs and NIM (*i.e.*, when NPAs are relatively high during the easing phase, provisioning is relatively low and therefore, NIM is relatively low.)	2.4	1.0	0.5	1.9	When credit growth is low (monetary easing phase), lower provisioning keeps lending rates low (even though NPA may be high). When credit growth is high (during monetary tightening phase), banks are required by the regulator to raise provisioning (even as NPAs are low) so that banks raise their NIMs by raising lending rates. Thus, transmission is facilitated during both the easing and tightening phases through counter - cyclical provisioning.

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Operating Target Volatility: Its Implications for Monetary Policy Transmission

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Volatility in the operating target of monetary policy could increase uncertainty about the cost of access to liquidity for any given policy interest rate, thereby pushing up the term premium and long-term interest rates. Empirical estimates of this paper indicate that conditional volatility in daily change in the Weighted Average Call Rate (WACR) - the operating target of monetary policy in India - exerts modest but statistically significant influence on volatility in daily change in other interest rates, namely nominal yields on government papers of three-month, six-month, nine-month, twelve-month, two-year and ten-year maturities. In the credit market, a one percentage point increase in WACR volatility (measured in terms of quarterly standard deviation) is estimated to cause about 26 basis points increase in bank lending rates.

JEL Classification : E43, E52, E58

Keywords : Operating target volatility, Monetary policy transmission, Liquidity management

Introduction

The implementation of monetary policy has to often contend with episodic liquidity shocks and the associated risk of significant and sustained deviation of the operating target from the policy rate, notwithstanding proactive deployment of a variety of liquidity management tools by the Reserve Bank of India (RBI) to anchor the operating target close to the policy rate. The objective of minimising volatility in the operating target is largely conditioned by its potential ramifications on monetary policy transmission, and, therefore, the ultimate objectives of monetary policy. Long-term interest rates, which influence economic activity, reflect the expected future

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path of short-term interest rates, plus a term premium as compensation for uncertainty. One could argue that volatility in the overnight money market rates should not matter because economic decision-making in the real world would invariably be based on medium- to long-term interest rates (Cohen, 1999). The counter argument, which has shaped the designs of mainstream operating frameworks of monetary policies of major central banks, would suggest that lower volatility in the short-term overnight rates in the bank funding market could depress the term premium by limiting uncertainty about funding costs (Carpenter *et al.*, 2016). The resultant lower medium- to long-term rates can influence economic activity.

In empirical research, the causal influence of financial market volatility on macroeconomic outcomes is well-documented (Chiu *et al.*, 2016). Unlike the short-run mean reverting component of volatility, the slow-moving long-run component often causes deterioration in macroeconomic fundamentals. An expansionary monetary policy has a much greater stimulating impact on output and employment in times of low-market volatility relative to periods characterised by high market volatility (Eickmeier *et al.*, 2017). In the Advanced Economies (AEs), there is ample evidence of limited but statistically significant spillover of volatility from money market rates to long-term rates. Refinements in the operating frameworks over time, however, have reduced the scope for such spillover effects to very close to zero (Colarossi and Zaghini, 2009). Transparent operating frameworks and regular central bank communication on liquidity conditions have reduced uncertainty about the overnight money market rates, which has contributed to lower volatility of term rates (Osborne, 2016). Term rates, as opposed to overnight rates, are important to transmission. Therefore, central banks try to clearly communicate their views on the macro-financial outlook, so that the risk of uncertainty-induced volatility in the term premium is minimised. Aversion to volatility in long-term rates has even motivated researchers to put volatility in long-term bond yields explicitly in the objective functions of central banks (Stein and Sunderam, 2017). Unlike the AEs, in Emerging Market and Developing Economies (EMDEs) stronger and persistent volatility transmission from the overnight rates to long-term rates is observed, particularly during the transition to a more forward-looking inflation targeting regime, which highlights the importance of a stronger commitment to the operating target in these countries while implementing monetary policy on a day-to-day basis (Alper *et al.*, 2016). Interest rate volatility has also been found to be a source of an upward pressure on spreads charged by banks over deposit rates while lending (Brock and Suarez, 2000).

An operating framework of monetary policy that can dampen volatility on a sustained basis, during both normal and exceptional times, is therefore congenial to monetary policy transmission. If long-term rates are higher due to increased volatility in the operating target, then monetary policy can be viewed as tighter than actually intended while setting the policy rate (Carpenter *et al.*, 2016). In other words, volatility in the operating target is not internalised, but transmitted to rates that matter for consumption and investment decisions (Ayuso *et al.*, 1997). Monetary policy, though assessed often in terms of the current policy rate, is more about managing expectations about future short term rates. Therefore, transparent communication on the central bank's macroeconomic outlook and its objective function is an important component of the modern-day monetary policy frameworks. The operating framework, which sub-serves the monetary policy framework and the monetary policy stance can enhance the effectiveness of monetary policy by minimising uncertainty about liquidity conditions that are critical to the overnight and short-term money market rates on a day-to-day basis.

In India, after the announcement of demonetisation on November 8, 2016, there was a surfeit of surplus liquidity in the banking system, which exerted a sustained downward bias to the overnight money market rates. In an easing cycle of the monetary policy that started in January 2015 (with a cumulative cut in policy repo rate by 200 bps), any increase in volatility in the operating target could have dampened the transmission of monetary policy to the lending rates. Against this setting, an important research question is to empirically examine the role of volatility in the operating target in influencing long-term interest rates, and, therefore, the effectiveness of transmission. Section II sets out how the operating framework of monetary policy has evolved in India over time to, *inter alia*, minimise volatility in the operating target, while also responding to the exceptional liquidity shocks like demonetisation by using a mix of conventional and unconventional instruments of liquidity management. Section III discusses the research methodology and empirical results. Key findings and policy inferences are presented in Section IV.

Section II

The Operating Framework of Monetary Policy in India

Unlike monetary policy, which is about setting the appropriate policy interest rate based on a comprehensive assessment of macro-financial conditions and the outlook to achieve the mandated objectives, the operating framework is about day-to-day implementation of monetary policy and involves conducting appropriate liquidity management operations to ensure the first leg of transmission. Liquidity forecasting – or how the reserve demand of the banking system will behave ahead over successive days – is a critical component of the operating framework to guide the choice of relevant instruments for liquidity management as well as the timing of liquidity operations. While much of the normal overnight and term operations of the central banks draw on their liquidity forecasts, intra-day reassessment of liquidity conditions often guide fine-tuning operations. All such liquidity management operations aim at anchoring the operating target close to the policy interest rate, but that does not rule out its possible deviations from the policy rate, and the scope for time-varying volatility. In India, the post-global financial crisis liquidity scare, post-taper tantrum liquidity shock, and post-demonetisation liquidity glut, are the major instances when the RBI had to use exceptional liquidity management measures to align the operating target with the monetary policy stance. The following have been discussed in this section to provide a background to the key research hypothesis of this paper: a brief overview of the specific aspects of the RBI's liquidity management during periods of exceptional liquidity conditions; and reforms in the operating framework of monetary policy in recent years that have enhanced marksmanship in keeping the operating target close to the policy rate during both normal and exceptional conditions.

Even as a formal inflation targeting framework was adopted by the RBI after the amendment of the RBI Act, effective June 2016 (preceded by the Agreement of Monetary Policy Framework of February 2015), the operating framework-related reforms had started much earlier. While experimenting with a multiple-indicator framework after abandoning the monetary targeting framework in 1998, to allow monetary policy decisions to be communicated through an interest rate and facilitate its transmission through the financial system, gradual deregulation of (deposit and lending) interest rates of banks was emphasised leading to a system of fully market-determined interest rates by 2011. Banks were allowed full discretion to determine interest rates even on savings deposits. That created conditions for monetary policy impulses to be communicated through the single policy rate – the repo rate – to transmit through the term structure of interest rates in the financial markets. It is important to note that while reforming the operating framework is essential to effectively implement the monetary policy decisions of the Monetary Policy Committee (MPC), this alone is not sufficient to address all the impediments to monetary policy transmission in Indian conditions. These are discussed in detail in the *Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework in India* (RBI, 2014) and the *Report of the Internal Study Group to Review the Working of the Marginal Cost of Funds based Lending Rate (MCLR) System* (RBI, 2017a). The focus of this paper is on the operating framework-related challenges to monetary policy transmission, rather than all aspects of transmission.

Since the adoption of a new operating framework in May 2011, the repo rate has emerged as the single policy rate, and a series of reforms comprised narrowing of the width of the policy rate corridor; altering the nature of liquidity operations – term versus overnight, repo/reverse-repo *versus* outright purchase/sale, normal *versus* fine-tuning, variable rate *versus* fixed rate, and standing access *versus* auctions; and introducing policy measures to enhance depth and liquidity of the money market (Table 1).

Table 1: Key Features of the Operating Framework Reforms in India

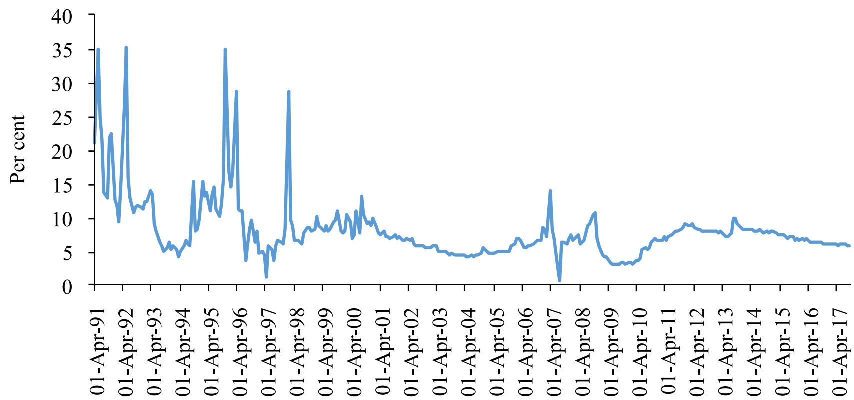
The New Operating Framework of Monetary Policy (May 2011)	Revised Liquidity Management Framework (September 2014)	Modified Liquidity Framework (April 2016)
● Repo rate - Single policy rate. ● WACR is the operating target. ● Corridor of +/- 100 bps around the repo rate ○ 100 bps above the repo rate for the MSF and 100 bps below the repo rate for the reverse repo rate. ● Full accommodation of liquidity demand at the fixed repo rate, *albeit* with an indicative comfort zone of +/-1 per cent of NDTL of the banking system. ● Transmission of the changes in repo rate through the WACR to the term-structure of interest rates.	● Access to assured liquidity of about 1 per cent of Net Demand and Time Liability (NDTL) on an average ○ Bank-wise overnight fixed rate repos of 0.25 per cent of NDTL, and the balance through 14-day variable rate term repos. ● More frequent auctions of 14-day term repos during a fortnight (every Tuesday and Friday of a week). ● Introduction of variable rate fine-tuning repo/ reverse repo auctions.	● The corridor around the repo rate narrowed from +/- 100 bps to +/- 50 bps. ● Commitment to progressively lower the *ex ante* system level liquidity deficit to a position closer to neutrality in the medium-term. ● Reducing the minimum daily maintenance of the Cash Reserve Ratio (CRR) from 95 per cent of the requirement to 90 per cent.

The operating framework, also termed as liquidity management framework, sub-serves the monetary policy framework in the sense that once the MPC announces the policy repo rate, based on its assessment of the macro-financial outlook for the economy, liquidity operations are conducted to keep the WACR (the operating target) close to the repo rate every day. The WACR emerges from the inter-bank unsecured segment of the overnight money market, and therefore best reflects the system-wide liquidity mismatch every day. Anticipating this liquidity mismatch through forecasting, and conducting liquidity injection/absorption operations to square the mismatch on a daily basis, hold the key to keeping the WACR close to the policy rate. The Liquidity Adjustment Facility (LAF) has a corridor around the policy repo rate with a Marginal Standing Facility (MSF) as its ceiling. This allows market participants to access central bank liquidity, at the end of the day, at a rate set currently at 25 basis points above the policy rate. Also, it allows a fixed rate overnight reverse repo window as the floor that allows market participants to place surplus liquidity at the end of the day with the RBI at a rate set at 25 basis points below the policy rate. Thus, the corridor restricts the extent of deviation of the WACR from the repo rate to (+/-) 25 bps. But proactive liquidity operations of the RBI aim at minimising recourse to either the ceiling or the floor of the corridor by the banks, which in turn contributes to finer alignment of the WACR to the repo rate. The LAF corridor was narrowed from +/-100 bps to +/-50 bps in April 2016, driven by the marksmanship of RBI's liquidity operations in keeping the WACR close to the repo rate. The corridor was narrowed further to +/-25 bps in April 2017, in response to one-sided liquidity conditions post-demonetisation which imparted a sustained soft bias to the WACR relative to the repo rate (as discussed in greater detail later). The framework for dealing with frictional liquidity mismatch (Pillar I) and durable liquidity requirements of the economy (Pillar II) is set out in the *Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework in India* (RBI, 2014).

The LAF deficit/surplus is the key indicator of net 'liquidity' demand of the banking system and of the economy as a whole on any single day, even though the magnitude of LAF deficit/surplus at any point of time need not be a reflection of the 'liquidity conditions (*i.e.,* tight/comfortable/easy)' in the system. This is because of full accommodation of liquidity mismatch by the RBI that prevents both tightening of WACR during LAF deficits and its softening during LAF surpluses. The demand for funding liquidity of all non-banking sectors (households, corporates, and non-banking financial entities) in the economy, on every single day, needs to be met by the banking system. It can deal with this mismatch because of its exclusive access to the RBI's LAF. Market liquidity (*i.e.*, the ease with which any financial asset could be liquidated – sold or repoed – by an economic agent without altering its price), funding liquidity (*i.e.,* ability of a bank to meet calls on liquidity from any of its customers), and central bank liquidity, are intertwined in a loop. Any market/funding liquidity pressure eventually gets manifested as LAF deficit/surplus, because of full accommodation by the RBI. The banking system's net demand for liquidity is effectively a reflection of the demand of the entire economy (*i.e.,* non-banks and banks taken together). Liquidity transformation undertaken by banks – creating long-term assets based on liquid liabilities, or borrowing short to lend long – is necessary to harness the contribution of bank financing to growth and economic development. For banks, even while meeting the funding needs of the rest of the economy, their own access to funding liquidity (particularly from the money market, both collateralised and uncollateralised), market liquidity (that allows the use of liquid assets in their portfolio to raise funds when needed), and central bank liquidity, becomes critical. On a net basis, in India, the LAF position reflects the impact of all autonomous drivers of liquidity conditions (such as currency demand of households, liquidity impact of forex market interventions of the RBI, and changes in government's cash balances maintained with the RBI) as well as non-LAF discretionary liquidity management operations [such as the Open Market Operations (OMOs), use of Market Stabilisation Scheme (MSS) securities/cash management bills (CMBs), and changes in the CRR]. Non-LAF operations minimise the pressure on LAF and also help meet the durable liquidity needs of a growing economy.

The objective of a stable WACR could be achieved in India only after several years of reforms of the operating framework. As a brief background, the Committee on Banking Sector Reforms (Narasimham Committee II) first recommended the introduction of a liquidity adjustment facility (LAF) in 1998. Work towards transition to a full-fledged LAF started in June 2000 but, till 2003-04, the RBI's market operations were dominated by outright purchase/sale of government securities. After the transition to LAF, the volatility in monthly average call rates, which used to move between a wide range of 5 to 35 per cent during 1990-98, declined significantly to a range of 5 to 10 per cent during the subsequent period (Mohan, 2006) (Chart 1). Repo and reverse repo rates operated as the ceiling and floor of the corridor, whose width changed several times in a year between 150 and 300 bps, up to the global financial crisis (GFC).

Chart 1: Weighted Average Call Money Rate

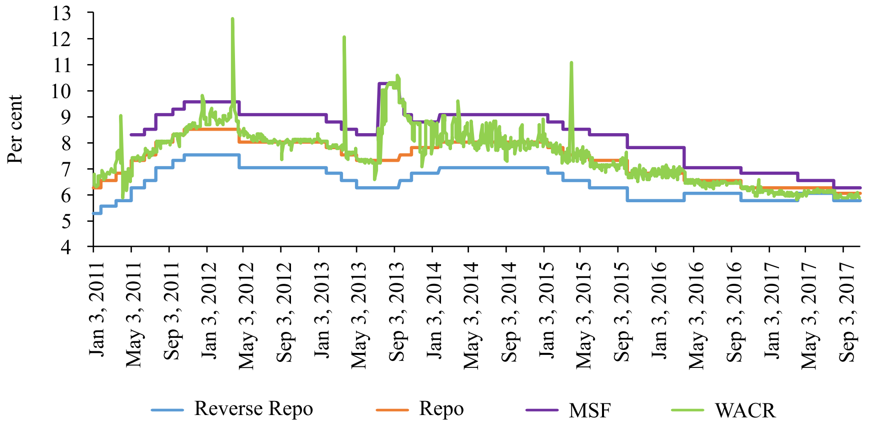


Three major exceptional periods since the GFC have tested liquidity management operations of the RBI. First, the post-GFC liquidity scare, when the RBI made available actual/potential liquidity of as high as 10 per cent of Gross Domestic Product (GDP). It did this through different instruments, such as cut in CRR, redemption/buyback of MSS securities, opening liquidity windows for Non-Banking Financial Companies (NBFCs), mutual funds and housing finance companies (through banks), besides the normal LAF and OMOs (Mohanty, 2009). Sudden spikes followed by significant easing of the WACR during this period reflected the initial scare-related scramble for liquidity, and the subsequent return of calm in the money market after the 425 bps cumulative cut[1] in the policy rate and ample liquidity conditions created by the RBI. Two distinct aspects of liquidity operations of the RBI standout during this period: liquidity to non-banks, such as mutual funds, NBFCs and housing finance companies was provided only through banks; and, there was no dilution of collateral standards for allowing access to liquidity.

Second, after the taper tantrum in mid-2013, the RBI used a monetary defence of the exchange rate by tightening liquidity conditions significantly and raising the effective money market rates by 300 bps (Pattanaik and Kavediya, 2015). Tighter daily average CRR maintenance norm (at 99 per cent) and caps on access to liquidity from the RBI (*i.e.,* no full accommodation of liquidity demand) tightened the WACR, which started to ease when exceptional monetary measures were phased out (Chart 2).

[1] The repo rate was cut by 425 basis points from 9.00 per cent to 4.75 per cent while the reverse repo rate was cut by 275 basis points from 6.00 per cent to 3.25 per cent. With the LAF mode switching from repo to reverse repo, the effective policy rate got reduced by 575 basis points (from 9.00 per cent to 3.25 per cent).

Chart 2: Policy Corridor and WACR



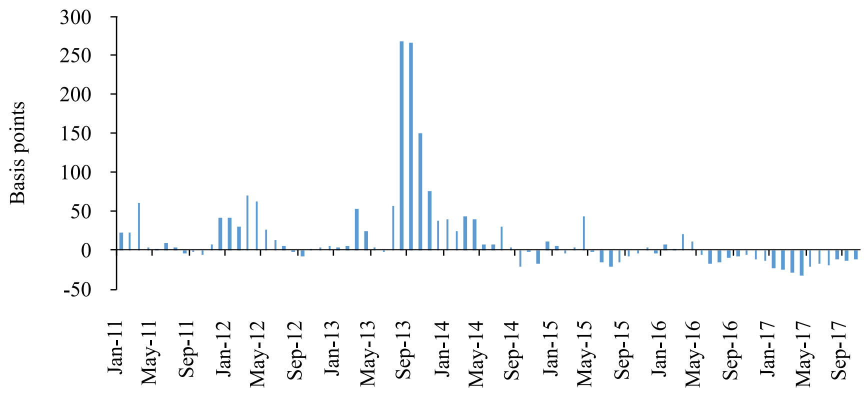
Third, the glut of surplus liquidity created after demonetisation in November 2016 prompted the RBI to use exceptional unremunerated incremental CRR of 100 per cent, temporarily, for one fortnight (RBI, 2017b). The liquidity overhang continued for more than a year after demonetisation, and persistent surplus conditions imparted a softening bias to the WACR through the year.

The post-demonetisation behaviour of the WACR is particularly striking from the standpoint of empirical implications for monetary policy transmission. Because of the sustained soft bias, the spread between WACR and the policy repo rate remained persistently negative, averaging about 30 bps in March 2017 (after rising over successive months). And as a result of this the LAF corridor was narrowed from +/- 50 bps to +/-25 bps in April 2017. Since then, the average spread has declined to about (-) 13 bps[2] (Chart 3). Unlike the volatile daily spread, however, conditional volatility of WACR generally remained very low, but for the usual year-end effects associated with balance sheet adjustment by banks (Chart 4).

The available empirical research on different aspects of the operating framework of monetary policy in India provide useful insights for the empirical approach adopted in the next section. Spread (defined as the bid-ask difference in the inter-bank call money market, rather than the difference between the WACR and the repo rate) was found to be influenced by liquidity conditions (*i.e.,* size of LAF deficit/surplus) and uncertainty (*i.e.,* conditional

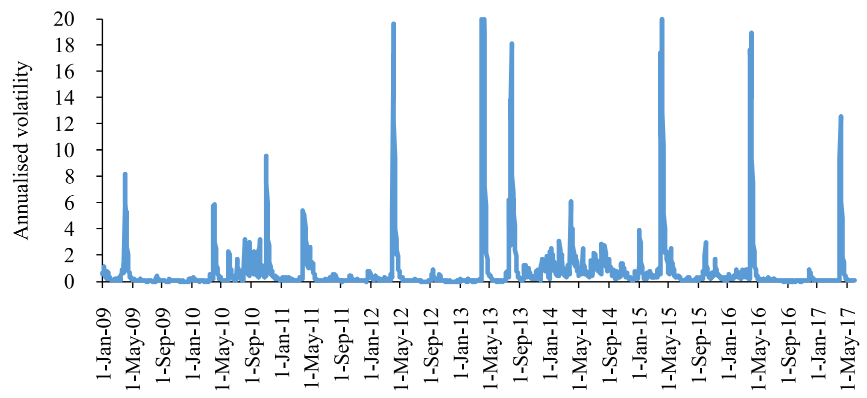
[2] September, October and November, 2017.

Chart 3: Average Spread of WACR over Repo Rate



variance of the cumulative average of reserve maintenance ratio during the fortnightly CRR maintenance period). The impact of uncertainty on the spread, however, has diminished significantly in recent years, reflecting the role of operating framework reforms in reducing uncertainty about liquidity conditions (Kumar *et al.*, 2017). A different measure of uncertainty used in another study, *i.e.,* conditional volatility of the WACR, was also found to be imparting an upside to the spread (defined also as the bid-ask difference, but between Mumbai Inter-Bank Bid Rate and Mumbai Inter-Bank Offer Rate) (Ghosh and Bhattacharyya, 2009). From the standpoint of assessment of the effective functioning of the operating framework, what may be more

Chart 4: Estimated Conditional Volatility using GARCH(1,1) Model



important is to study spread in terms of deviation of the WACR from the policy repo rate. Both these rates, as one would expect, are co-integrated, and the error-correction term suggests that deviations of the WACR from the repo rate are short-lived (Patra *et al*., 2016). Volatility in WACR was found to have a statistically significant and positive impact on the 90-day Treasury Bills rate. But after excluding the GFC period from the sample, the statistical significance of the impact disappeared. Unlike these studies, the emphasis of this paper is on the entire term structure (across the yield curve) and also bank-lending rates which are critical to influence consumption and investment decisions and, therefore, to an assessment of monetary policy transmission.

Section III

Data, Methodology and Empirical Findings

This paper uses daily data for the period January 2009 to May 2017, which covers all the three major liquidity shocks mentioned in the previous section. It also starts before the crucial May 2011 reform of the operating framework. The interest rates across the term-structure considered comprise yields on three-month, six-month, nine-month and twelve-month treasury bills and two-year and ten-year government securities. Stationarity of these interest rates is examined using the Augmented Dickey-Fuller (ADF), the Phillips-Perron and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, which suggest that all of them are stationary in their first difference (Table 2). Accordingly, variables are used in their first difference form in subsequent analysis.

The summary statistics of WACR and daily change in WACR are presented in Table 3. On an average, daily change in WACR is minimal over the sample period. The variance of daily WACR is 3.20 while the variance of daily ΔWACR is 0.08. The negative skewness coefficient indicates that the distribution of daily changes in WACR is negatively skewed. The large value of kurtosis reflects the thick tails of the distribution. The Jarque-Bera statistics, besides skewness and kurtosis, indicate non-normal distribution of daily changes in WACR.

The residuals obtained by modelling the first difference of WACR, using the Ordinary Least Squares (OLS) method[3], suggested that large residuals tend

[3] First difference of the WACR is modelled as a function of its own lag, past and current changes in the policy repo rate, dummies to control for specific events such as the year-end balance sheet adjustments in the banking system, taper tantrum, demonetisation and also to capture the impact of a bank's behaviour in meeting the fortnightly reserve requirements.

Table 2: Unit Root Test Results

	ADF test						Phillips-Perron Test						KPSS Test*	
	None	p-val	Inter-cept	p-val	Intercept and trend	p-val	None	p-val	Inter-cept	p-val	Inter-cept and trend	p-val	Inter-cept	Inter-cept and trend
Level														
WACR	-0.42	0.53	-1.94	0.31	-1.92	0.64	-0.32	0.57	-3.09	0.03	-3.45	0.05	2.22	1.33
tb3m	-0.09	0.65	-1.57	0.50	-1.21	0.91	-0.10	0.65	-1.56	0.50	-1.20	0.91	2.24	1.32
tb6m	0.01	0.69	-1.57	0.50	-1.12	0.92	-0.01	0.68	-1.58	0.49	-1.13	0.92	2.21	1.32
tb9m	0.05	0.70	-1.59	0.49	-1.10	0.93	0.04	0.70	-1.58	0.49	-1.10	0.93	2.19	1.33
tb12m	0.17	0.73	-1.49	0.54	-0.87	0.96	0.11	0.72	-1.59	0.49	-1.07	0.93	2.16	1.33
gsec2yr	0.20	0.74	-2.20	0.21	-1.62	0.78	0.20	0.74	-2.21	0.20	-1.67	0.76	1.93	1.32
gsec10yr	0.34	0.78	-3.23	0.02	-3.07	0.12	0.24	0.76	-3.40	0.01	-3.28	0.07	1.10	1.09
First Difference														
dWACR	-25.22	0.00					-75.31	0.00					0.19	0.08
dtb3m	-14.48	0.00					-51.38	0.00					0.22	0.06
dtb6m	-15.29	0.00					-51.31	0.00					0.27	0.06
dtb9m	-15.01	0.00					-49.86	0.00					0.29	0.06
dtb12m	-33.70	0.00					-63.11	0.00					0.35	0.06
dgsec2yr	-13.22	0.00					-65.51	0.00					0.39	0.02
dgsec10yr	-35.54	0.00					-44.61	0.00					0.59	0.05

*: Cut-off value of KPSS test with 'intercept' and 'intercept and trend' at 1 per cent level of significance are 0.74 and 0.22, respectively.

Table 3: Summary Statistics of WACR and Daily Change in WACR

	WACR	ΔWACR
Mean	6.78	0.00034
Variance	3.20	0.0846
Skewness	-0.64	-0.5540
Kurtosis	2.89	99.45
Jarque-Bera Statistic	149.8*	850880*

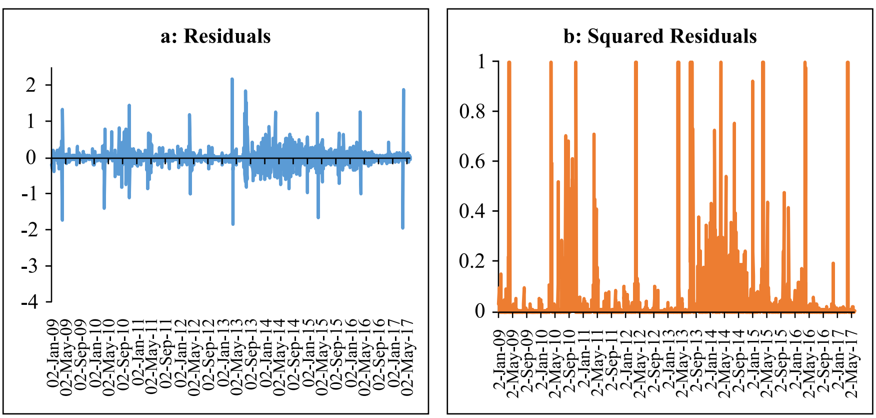
*: Significant at 1 per cent level.

to be followed by large residuals and small residuals tend to be followed by small residuals, pointing to the presence of volatility clustering (Chart 5). While the Breusch-Pagan-Godfrey test suggested the presence of heteroskedasticity, the Ljung-Box test indicated the presence of serial autocorrelation in residuals. All these pre-tests suggested the GARCH model as appropriate for modelling volatility in the operating target.

Estimation of Volatility of WACR

The WACR, as in the case of many other financial market variables, displays periods of volatility and periods of calm. Further, while modelling the volatility of financial variables, it is often found in the literature that the sum of the estimated parameters of standard GARCH (1, 1) are close to unity, which is an indication of strong volatility persistence. Taking into account the persistence of volatility in WACR, the integrated GARCH (IGRACH)

Chart 5: WACR Residuals Based on OLS Estimation



model proposed by Engle and Bollerslev (1986) is used to model volatility. Specifically, the following IGARCH (1, 1) model is used:

Mean equation:

$$\Delta r_t = c + \rho\,(r - o)_{t-1} + \sum_i \beta_i\, \Delta r_{t-i} + \sum_j \gamma_{t-j} \Delta o_{t-j} + \theta liq_t + \omega DX_t + \varepsilon_t \quad (1)$$

Variance equation:

$$\sigma_t^2 = \mu + \alpha\, \varepsilon_{t-1}^2 + \delta \sigma_{t-1}^2 + \tau DX_t,\ \ \alpha > 0\ ,\ \delta > 0 \text{ and } \alpha + \delta = 1 \quad (2)$$

where r_t denotes daily WACR, o_t is the policy repo rate, liq_t is the daily net LAF position or the daily mismatch in system level liquidity and Δ represents daily change in respective variables. The error correction term, *i.e.,* the lagged spread between WACR and the policy repo rate, is also incorporated in the mean equation. The impact of specific developments affecting the WACR – taper tantrum, demonetisation, year-end liquidity effects, and banks' fortnightly reserve maintenance pattern – are controlled through the use of dummy variables represented by DX_t. The conditional variance equation (2) can help estimate the time-varying volatility of the residuals generated from the mean equation (1). The conditional variance σ_t^2 is expressed as a function of the weighted average of its long-term average (the constant term), past squared error term (the ARCH term) and the past conditional variance (the GARCH term), which is augmented to capture the impact of dummies mentioned above. The coefficients in the variance equation can be interpreted as the autocorrelation (α) factor and the volatility persistence (α + δ) factor. The sum of the ARCH and GARCH coefficients measures the persistence of volatility and should be less than unity. Values closer to 1 indicate that shocks will persist for a longer time. Errors were found to be significantly non-normal and are assumed to follow the Student's t-distribution. The mean and variance equations are jointly estimated using the maximum likelihood method. Results are presented in Table 4.

Diagnostic tests of residuals suggest that the model is specified correctly to capture the volatility in WACR. The Ljung-Box Q-statistic and ARCH-LM statistics indicate that the model is free from autocorrelation. Also, the Ljung-Box Q-statistic at 20th lag of the squared standardised residuals was at 0.1844 (with p-value close to 1), indicating that the standardised squared residuals are serially uncorrelated.

The WACR is found to be negatively autocorrelated. A one percentage point increase in the policy repo rate leads to 0.8 percentage point rise in

Table 4: Conditional Volatility of WACR using IGARCH(1,1)*
Dependent Variable: ΔWACR

	Coefficient	p-value		Coefficient	p-value
Mean Equation			**Volatility Equation***		
Constant	-0.001	0.19	RESID(-1)^2	0.244	0.00
∑ΔWACR	-0.24	0.00	GARCH(-1)^2	0.756	0.00
∑ΔRepo Rate	0.80	0.03	DUM_MARCH	0.342	0.00
Net Liquidity	0.002	0.00			
ECT	-0.050	0.00			
Dum_March	1.186	0.00			
Dum_April	-1.413	0.00			
Dum_Taper	0.136	0.00			
D3	0.039	0.00			
D10	0.004	0.09			
D11	-0.010	0.00			
D13	-0.004	0.04			
T-DIST. DOF	3.244	0.000			
Q(10)	12.446	0.256			
Q(20)	23.144	0.282			
ARCH LM (5)	0.430	0.828			

*: The dummy representing the impact of demonetisation is insignificant in both mean and variance equations, while the dummy relating to the taper tantrum event is insignificant in the variance equation.

WACR in the same time period. Thereafter, remaining gap between WACR and repo rate is adjusted through the Error Correction Term (ECT) at the rate of 0.05 percentage point per day. The impact of liquidity conditions on changes in WACR is estimated to be positive and significant. This may be interpreted as any pressure on WACR is essentially an indication of higher demand for liquidity, which is fully accommodated through the central bank's liquidity windows, leading to higher net LAF injection. Calendar effects are statistically significant. The positive and significant effect of taper tantrum is in line with the intuition, since during this phase the RBI restricted access to central bank liquidity and made the ceiling of the LAF corridor as the effective policy rate. In the variance equation, both ARCH and GARCH terms are significant.

Transmission of Volatility

The estimated conditional volatility of daily changes in WACR is used as a determinant of the term structure of interest rates in respective mean and variance equations, while retaining the same structural specifications as in equations 1 and 2.

Mean equation

$$\Delta r_t^m = c^m + \sum_i \beta_i^m \, \Delta r_{t-i}^m + \sum_j \gamma_{t-j}^m \Delta o_{t-j} + \theta^m \sigma_t^{2,ON} + \omega^m DX_t + \varepsilon_t^m \quad (3)$$

Variance equation

$$\sigma_t^{2,m} = \mu^m + \alpha^m \varepsilon_{t-1}^{2,m} + \delta^m \sigma_{t-1}^{2,m} + \lambda^m \sigma_t^{2,ON} + \tau^m DX_t$$

$$\alpha^m > 0, \delta^m > 0 \; and \; \alpha^m + \delta^m = 1 \quad (4)$$

where, r_t^m denotes nominal yield on government papers with maturity (m) equal to three-month, six-month, nine-month, twelve-month, two-year and ten-year; o_t is the policy repo rate and DX_t stands for dummies capturing the impact of year-end balance sheet adjustment effects, taper tantrum and demonetisation. The superscript ON represents overnight market. Results are presented in Table 5, which suggest that conditional volatility in WACR is not a significant determinant in the mean equation across the term structure. Mean values of daily changes in interest rates across the yield curve are not influenced in a statistically significant manner by the volatility in daily change in WACR. Unlike the mean values, however, volatility in interest rates across the term structure shows some modest sensitivity to volatility in WACR. These findings would suggest that the RBI's operating framework reforms over the years (as discussed in Section II) has helped in minimising the WACR volatility, which in turn has contained risks to monetary policy transmission. Further, the policy repo rate is estimated to have a positive and significant impact on all interest rates across the term structure, though the impact at the longer end of the yield curve is relatively smaller. The GARCH coefficients closer to unity indicate that volatility across the term structure is persistent, which itself could be a source of higher-risk premium.

Impact of Volatility in WACR on Banks' Lending Rates

Transmission of a monetary policy-easing action to retail interest rates could be impeded if an inter-bank rate volatility shock occurs at the same time when the policy rate is lowered (Bouvatier and Chahad, 2014). On the contrary, the impact of a restrictive monetary policy can be amplified in times

Table 5: Volatility Transmission from the Overnight Segment to Interest Rate Term-structure

Dependent	**DTB3M**		**DTB6M**		**DTB9M**		**DTB12M**		**DG-sec 2_yr**		**DG-sec 10_yr**	
Variable	Coeff	P-val	Coeff	P-val	Coeff	P-val	Coeff	P-val	Coeff	P-val	Coeff	P-val
Mean Equation												
Constant	0.0011	0.02	-0.0005	0.30	0.0003	0.48	0.0002	0.69	-0.0002	0.00	-0.0003	0.65
dep(-1)	**-0.0468**	**0.00**	**-0.0295**	**0.01**	**-0.0532**	**0.00**	**-0.0949**	**0.00**	**-0.0873**	**0.00**	0.0258	0.13
D_Repo	**0.1350**	**0.00**	**0.2077**	**0.00**	**0.2317**	**0.00**	**0.1586**	**0.00**	**0.0028**	**0.00**	**0.0401**	**0.00**
Net Liquidity	-0.0001	0.69	0.0003	0.24	0.0002	0.49	0.0004	0.13	0.0002	0.00	-0.0002	0.62
Dum_March	**-0.0585**	**0.00**	**-0.0512**	**0.00**	**-0.0240**	**0.00**	**-0.0215**	**0.00**	0.0004	0.42	**-0.0206**	**0.00**
Dum_Taper	0.0146	0.37	0.0018	0.87	0.0191	0.17	0.0058	0.80	-0.0198	0.69	0.0007	0.96
Dum_demonetisation	-0.0031	0.53	-0.0055	0.10	-0.0029	0.65	0.0005	0.93	**-0.0123**	**0.00**	-0.0050	0.48
Garch ON vol	-0.0052	0.37	-0.0016	0.69	-0.0039	0.39	-0.0047	0.54	0.0000	0.98	-0.0005	0.88
Variance Equation												
RESID(-1)^2	**0.0339**	**0.00**	**0.0234**	**0.00**	**0.0591**	**0.00**	**0.1596**	**0.00**	**0.0265**	**0.00**	**0.0579**	**0.00**
GARCH(-1)	**0.9661**	**0.00**	**0.9766**	**0.00**	**0.9409**	**0.00**	**0.8404**	**0.00**	**0.9735**	**0.00**	**0.9421**	**0.00**
Garch ON vol	**0.0004**	**0.00**	**0.0002**	**0.00**	**0.0003**	**0.00**	**0.0014**	**0.00**	0.0000	0.58	**0.0002**	**0.00**
DUM_MARCH	**0.0024**	**0.02**	0.0005	0.41	0.0000	0.99	**-0.0008**	**0.00**	**-0.0004**	**0.00**	**-0.0007**	**0.00**
Q(10)	14.7	0.14	11.2	0.34	8.1	0.62	5.5	0.86	0.1	1.00	8.7	0.56
Q(20)	21.0	0.39	13.6	0.85	10.4	0.96	7.7	0.99	1.1	1.00	13.1	0.87
ARCH LM (5)	0.001	0.99	0.02	0.98	0.001	0.99	0.0	0.99	0.0	0.99	0.1	0.92

Note: Coefficients in bold font are statistically significant at 5 per cent or lower levels.

of high inter-bank rate volatility. Ritz (2012) argued that a rise in funding uncertainty dampens interest rate pass-through. In a cross-country study, however, Raunig and Scharler (2009) found limited impact of transmission of volatility in money market rates to volatility in retail interest rates.

With a view to examining the impact of volatility in WACR on banks' lending rates (rather than identifying all determinants of lending rates), quarterly data for a panel of fifty-eight banks (covering public, private and foreign banks) are used over the period June 2012 to June 2017, for which data on bank-wise weighted average lending and deposit interest rates are available. The following dynamic panel model is estimated:

$$LR_{i\,t} = c + \alpha\, LR_{i\,t\text{-}1} + \beta_1\, GNPA_{i,\,t\text{-}1} + \beta_2\, WADTDR_{i\,t} + \beta_3\, ON\_vol_{t\text{-}1} + \gamma_i + \varepsilon_{i\,t},\ |\,\alpha\,| < 1 \quad (5)$$

for i = 1,2,…N and t = 1,2,…T , where i and t refer to cross-section and time dimensions of panel data, respectively; γ_i represents the individual fixed effects and $\epsilon_{i\,t} \sim N(0, \sigma_\epsilon^2)$. $LR_{i\,t}$ is lending rate of bank i on outstanding loan portfolio at time t, GNPA represents ratio of gross non-performing assets to total advances, WADTDR stands for weighted average domestic term deposit rates and ON_vol is the quarterly standard deviation of WACR. Both weighted average lending rate on outstanding rupee loans and WADTDR are taken as spread over the repo rate.

By construction, $LR_{i\ t\text{-}1}$ depends on individual fixed effects, leading to the endogeneity problem. The OLS, or fixed effect models, generally provide biased estimates for small T and large number of cross-section N. Further, inclusion of lagged dependent variables gives rise to the problem of autocorrelation. To estimate the dynamic panel regression (5), with the panel having a larger number of banks relative to the time period, we use the difference GMM approach proposed by Arellano and Bond (1991). This approach controls for the unobserved individual bank-specific effects and also addresses the issue of endogeneity of explanatory variables. The first-difference of the panel data helps to remove the time-invariant fixed effects. The values (levels) of the lagged dependent variables work as valid instruments for the first-differenced variables, provided that the residuals are free from second-order serial correlation. For testing autocorrelation, Arellano-Bond test is used, while the validity of the instrument is tested using the Sargan test of over-identifying restrictions.

Empirical findings suggest that lending rates of banks are positively autocorrelated with their past values. Also, volatility in overnight WACR

Table 6: Impact of Volatility in WACR on Lending Rates of Banks

Dependent Variable: Lending Rate (LR)

	Coeff.	P-value
Constant	1.74	0.00
LR(-1)	0.42	0.00
WADTDR	0.80	0.00
GNPA	0.09	0.06
ON_vol(-1)	0.26	0.01
	Wald Chi-square	184.3 (0.00)
	AR(1)	-3.12 (0.00)
	AR(2)	-0.09 (0.92)
	Sargan stat. (2-step)	55.35 (0.28)

has a positive and statistically significant impact on banks' lending rate. A one percentage point increase in overnight volatility may lead to about 26 basis points increase in bank lending rates. The GNPA ratio, as expected, has a positive and statistically significant relationship with bank lending rates (Table 6).

Section IV
Conclusion

The operating framework of monetary policy, which is about implementation of monetary policy on a day-to-day basis, strives to ensure the first leg of monetary policy transmission by aligning the overnight money market rates close to the policy rate. The combination of a LAF corridor that restricts intra-day volatility in overnight rates and proactive liquidity management by a central bank that limits the need for recourse to its liquidity at the upper/lower bounds of the corridor helps in keeping the overnight money market rates close to the policy rate. In the assessment of the role of an effective operating framework, however, besides the first leg of transmission, the scope for influencing the entire term structure of interest rates by minimising volatility in the overnight rates, and in the operating target in particular, has also gained prominence. Long-term rates, which matter to the real economy, essentially reflect the expected future path of short-term rates and a time-varying term premium as a compensation for uncertainty. Recognising the importance of expectations about the future path of short-term rates to effective monetary policy transmission, monetary policy frameworks have strived to become increasingly more predictable and transparent, with an emphasis on communication relating to the central bank's assessment of the macroeconomic outlook as well as the likely policy reaction function. An operating framework of monetary policy that emphasises stability of the operating target can sub-serve the monetary policy framework better by limiting transmission of volatility from the operating target to the term premium, and, therefore, to the term structure of interest rates.

In India, successive reforms in the operating framework have enabled finer alignment of the WACR – the operating target of monetary policy – to the policy repo rate. Nevertheless, WACR being a market-determined rate, its volatility has been non-zero, though modest. This paper examined whether volatility in WACR has had any statistically significant influence on the term structure of interest rates.

Conditional volatility in daily change in WACR – extracted from an IGARCH (1,1) model – does not exert any statistically significant influence on daily change in other interest rates, namely nominal yields on government papers of three-month, six-month, nine-month, twelve-month, two-year and ten-year maturities. Volatility in other interest rates, however, is found to have been influenced by volatility in daily change in WACR, particularly up to a one-year tenor. The magnitude of the impact is estimated to be low – a one percentage point increase in conditional volatility of daily change in WACR leading to higher volatility in other interest rates by 0.02 to 0.14 basis points. To examine the impact of volatility in WACR on bank lending rates, which is more important to the credit market and therefore aggregate demand, a panel regression approach was adopted covering quarterly data from June 2012 to June 2017 for fifty-eight banks and the model was estimated using difference GMM. In the panel regressions, volatility is captured as actual observed volatility in WACR in terms of quarterly standard deviations, as against the conditional volatility of daily change in WACR used in other equations to study the impact on market interest rates. A one percentage point increase in WACR volatility is estimated to cause about 26 basis points increase in bank lending rates. The impact assessment on the lending rates suggests the need for reducing the volatility in WACR even further through proactive liquidity management.

References

Alper, E., C. Morales, and F. Yang (2016), "Monetary Policy Implementation and Volatility Transmission along the Yield Curve: The Case of Kenya", IMF Working Paper No. 16/120, 20 June. Available at: https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Monetary-Policy-Implementation-and-Volatility-Transmission-along-the-Yield-Curve-The-Case-of-43995.

Arellano, M. and S. Bond. (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *The Review of Economic Studies*, 58, pp. 277–97.

Ayuso, J., A. Haldane and F. Restoy (1997), "Volatility Transmission along the Money Market Yield Curve", *Review of World Economics*, 133(1), pp. 56–75.

Bouvatier, V. and Chahad, M. (2014), "Interest Rate Pass-through and Interbank Rate Volatility Shocks: A DSGE Perspective", February. Available at: http://www.touteconomie.org/afse2014/index.php/meeting2014/lyon/paper/viewFile/439/233.

Brock, Philip L. and Liliana Rojas Suarez (2000), "Understanding the Behavior of Bank Spreads in Latin America", *Journal of Development Economics*, 63, pp. 113–34.

Carpenter, Seth B., Selva Demiralp and Zeynep Senyuz (2016), "Volatility in the Federal Funds Market and Money Market Spreads during the Financial Crisis", *Journal of Financial Stability*, 25, pp. 225–33.

Chiu, Ching-Wai, Richard D.F. Harris, Evarist Stoja, and Michael Chin (2016), "Financial Market Volatility, Macroeconomic Fundamentals and Investor Sentiment", *Bank of England Working Paper No. 608*, August 23.

Cohen, Benjamin (1999), "Monetary Policy Procedures and Volatility Transmission along the Yield Curve," CGFS Papers, Bank for International Settlements (ed.), *Market Liquidity: Research Findings and Selected Policy Implications*, 11, pp. 1–22.

Colarossi, Silvio and Andrea Zaghini (2009), "Gradualism, Transparency and Improved Operational Framework: A Look at Overnight Volatility Transmission', *International Finance*, 12(2), pp. 151–70.

Eickmeier, Sandra, Norbert Metiu and Esteban Prieto (2017), "Monetary Policy Effectiveness in Times of Financial Market Volatility", Deutsche Bundebank, Research Brief 11th edn., March. Available at: http://www.bundesbank.de/Redaktion/EN/Kurzmeldungen/Research_brief/2017_11_monetary_policy_financial_market.html.

Engle, Robert and Andrew Patton (2001), "What Good is a Volatility Model?", *Quantitative Finance*, 1, pp. 237–45.

Engle, Robert and Bollerslev, T. (1986), "Modeling the Persistence of Conditional Variances", *Econometric Reviews,* 5, pp. 1–50.

Gaston Gelos, R. (2006), "Banking Spreads in Latin America", *IMF Working Paper 06/44*, February.

Ghosh, Saurabh and Indranil Bhattacharyya (2009), "Spread, Volatility and Monetary Policy: Empirical Evidences from the Indian Overnight Money Market", *Macroeconomics and Finance in Emerging Market Economies*, 2(2), pp. 257–77.

Kumar, Sunil, Anand Prakash and Krishna Kushwaha (2017), "What Explains Call Money Rate Spread in India?", *RBI Working Paper 7/2017*, April.

Mohan, Rakesh (2006), "Coping With Liquidity Management in India: A Practitioner's View", Address at the 8th Annual Conference on Money and Finance in the Indian Economy at Indira Gandhi Institute of Development Research (IGIDR), March 27, 2006.

Mohanty, Deepak (2009), "Global Financial Crisis and Monetary Policy Response in India", *RBI Bulletin*, December.

Osborne, Matthew (2016), "Monetary Policy and Volatility in the Sterling Money Market", *Bank of England Working Paper No. 588*, April.

Patra, Michael Debabrata, Muneesh Kapur, Rajesh Kavediya and S.M. Lokare (2016), "Liquidity Management and Monetary Policy: From Corridor Play to Marksmanship", in Kenneth M. Kletzer and Chetan Ghate (eds.), Monetary Policy in India.

Pattanaik, Sitikantha and Rajesh Kavediya (2015), "Preconditions to the Success of an Interest Rate Defence of the Exchange Rate", *Prajnan*, December.

Raunig, B. and J. Scharler (2009), "Money Market Uncertainty and Retail Interest Rate Fluctuations: A Cross-country Comparison", *German Economic Review*, 10(2), pp. 176–92.

Reserve Bank of India (RBI) (2014), *Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework* (Chairman: Dr. Urjit R Patel). Available at: https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/ECOMRF210114_F.pdf.

— (2017a), *Report of the Internal Study Group to Review the Working of the Marginal Cost of Funds Based Lending Rate System* (Chairman: Dr. Janak Raj). Available at: https://rbi.org.in/scripts/PublicationReportDetails.aspx?ID=878.

— (2017b), "Macroeconomic Impact of Demonetisation - A Preliminary Assessment", RBI, March 10, 2017. Available at: https://rbidocs.rbi.org.in/rdocs/Publications/PDFs/MID10031760E85/BDAFEFD497193995BB1B6DBE602.PDF.

Ritz, R. A. (2012), "How do banks respond to increased funding uncertainty?" *Cambridge Working Papers in Economics CWPE 1213*, Faculty of Economics, University of Cambridge.

Stein, Jeremy C. and Adi Sunderam (2017), "The Fed, the Bond Market, and Gradualism in Monetary Policy", April. Available at: http://scholar.harvard.edu/files/stein/files/gradualism_20170428_002.pdf.

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Nowcasting Indian GVA Growth in a Mixed Frequency Setup

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This paper attempts to nowcast quarterly real non-agricultural Gross Value Added (GVA) growth for India using a dynamic factor model (DFM), following two different approaches. Multi-level variable selection using turning-point analysis and elastic-net framework has been adopted to overcome the over-fitting problem while selecting of variables. The paper finds significant improvement in forecast accuracy of one-quarter ahead forecast using nowcasting framework as compared with the naïve models. The two-factor model is found to be the most precise when compared with other higher-order factor models and naïve models. The forecast performance improves marginally when stochastic volatility is introduced in the model.

JEL Classification : C51, C52, C53, C32, C38, E50, E17

Keywords : Nowcasting, Cross-correlation, Business cycle, LARS-EN, Dynamic factor model, Kalman filter, Principal component, Cross-section

Introduction

Central banks track various macroeconomic indicators for forward-looking assessment of the state of an economy. Gross Domestic Product (GDP) is an important component for policy analysis. However, data relating to GDP are released with a lag and the release calendar is often asynchronous with the monetary policy calendar. In the absence of any real-time information on GDP, 'central banks' adopt different strategies to deal with the data gaps. Forecasting is one option which can provide forward-looking guidance on economic growth. Model-based forecasting is often criticised for limited

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information content, while incorporating a larger information set brings in the problem of dimensionality. The other approach, namely 'multiple indicator' approach, is governed by tracking high-frequency data of economic indicators. The challenge arises when different indicators depict diverging scenarios about the state of the economy. In such a situation, summarising the information content from a larger information set and incorporating only the relevant information in the forecasting model provides a viable solution. Such an approach, also called nowcasting, gained popularity among forecasters in the aftermath of the global financial crisis of 2007.

The background of nowcasting goes back to the introduction of bridge models, which were formulated to bridge the gap between target series using available indicators (Bessec, 2013). However, the 'curse of dimensionality' restricted the use of a large information set. Stock and Watson (1999, 2002) introduced the first static and dynamic factor model for incorporating a larger information set using factors. The nowcasting framework builds upon the dynamic factor model (DFM) in a mixed-frequency setup in such a manner that the factors are updated based on the latest available information. In this context, the nowcasting framework suggested by Giannone *et al*. (2008) used around 200 high-frequency economic indicators with a varying data release calendar for nowcasting the US GDP using DFM. Later on, other central banks started incorporating similar nowcasting frameworks for short-term forecasting (Angelini *et al.*, 2011; Altissimo *et al.*, 2001, 2007; Schumacher, 2007, 2010; D'Agostino *et al.*, 2008; Marcellino *et al.*, 2013). The emergence of nowcasting and its wide adaptability point towards its growing popularity among economic forecasters and policymakers. Over fifty-four different research papers on short-term forecasting have been published in different top-ranked international journals between 2014 and 2016, which highlights the sustained interest in the methodologies for improving short-term forecasting.

While nowcasting has been adopted across advanced economies in the aftermath of the financial crisis of 2007, the emerging market economies (EMEs), which face comparatively more severe data release lags and revisions, started exploring the potential of nowcasting only in recent times. In India, the Central Statistics Office (CSO) releases quarterly GDP/ GVA data after a lag of about 60 days. For instance, GDP/GVA estimates for Q3: 2016-17 were released on February 29, 2017 *i.e.*, after a lag of about two months. Hence, any assessment of growth in the current quarter has to rely on the information available on high-frequency indicators. Nowcasting can help estimating GVA using the latest available information on such economic indicators, before the release of first advance estimate by the CSO. It can also incorporate the periodic data revisions for updating the short-term forecast of GVA.

In this paper, an attempt has been made to apply two main available nowcasting approaches to Indian data. The short-term forecasts generated from these nowcasting approaches have been validated against the available short-term forecasting models (also called naïve models) using an expanding-window approach. The variable selection for factor model has been carried out by applying a multi-level approach to turning point analysis mimicking business cycle approach. The paper finds significant improvement in short-term forecast precision using nowcasting models as compared to naïve models. The rest of the paper is organised as follows. Section II presents a brief literature review on the different approaches to use DFM in nowcasting. Section III illustrates the methodology along with a separate discussion on selection of variables. Details of data used are presented in Section IV, followed by the empirical findings in Section V. Section VI concludes with a few remarks on the proposed approach for nowcasting Indian GDP/GVA.

Section II
Literature Review

Dynamic factor models emerged as an effective mechanism for reducing dimensionality in the forecasting domain. Unlike the first and second generation DFM, the third generation deals with the time invariant correlation structure, using a larger data set in state space framework (Stock, 2010). In this approach, a principal component analysis (PCA) is used to derive the initial estimates of the factors and subsequently the factors are updated based on the latest available observations of the constituent economic indicators in a state-space framework. The use of factor models for nowcasting in a mixed frequency setup was formally introduced by Giannone *et al.* (2008), where the nowcasting model was developed using monthly data on a large set of macroeconomic and other indicators. The use of DFM for nowcasting GDP was first used in 2005 by the Board of Governors of the US Federal Reserve. Angelini *et al.* (2011) introduced a similar framework for the European Central Bank (ECB). The research work of Altissimo *et al.* (2011), Schumacher (2007 and 2010), and D'Agostino *et al.* (2008) in the related area helped to introduce this framework in Banca d'Italia, Bundesbank and Central Bank of Ireland, respectively. Barhoumi *et al.* (2010) compared the forecast performance of dynamic factor models with other quarterly models (AR, VAR and bridge equations) for select European countries and they observed significant improvement in forecasting performance in case of dynamic factor models that used monthly data. As regards variable selection, soft data which are primarily obtained through different surveys and available in a timely manner are used in DFM. However, the forecasting precision using such soft indicators is often found to be weaker than that using hard data (Banbura and Runstler, 2011). With this background, Giannone *et al.* (2008) used both hard and soft indicators for nowcasting GDP. Camacho *et al.* (2010) used a similar approach for developing the Euro-STIN. Euro-STIN represents a model that combines short-run economic indicators along with GDP revisions for increasing the precision of short-term forecasts of GDP in the Euro area. Their approach incorporated the Kalman filter model of Mariano and Murasawa (2003) to deal with mixed frequency on top of the 'strict DFM' framework of Stock and Watson (1991). The information content of GDP data revisions was previously used by Evans (2005) and Coenen *et al.* (2005). However, the incorporation of revision history along with soft and hard data was first introduced in Euro-STIN. The framework used in Euro-STIN was later extended by Marcellino *et al.* (2013) for nowcasting the Euro area GDP. The novelty of this framework was that stochastic volatility was introduced using the time-varying variance parameter. The model was estimated using multi-move Gibbs sampling approach as suggested by Carter and Kohn (1995). While nowcasting GDP of Germany, Girardi *et al*. (2016) observed improvement in short-term forecast performance using the partial least square approach for deriving the factor estimate. Lamprou (2016) and Feldkircher (2016), however, observed that DFM using bridge model had better forecast precision compared to time series models. The forecast performance of these models, nevertheless, was found to be changing over time and that suggested for a continuous review of the modelling framework to improve forecast performance (Feldkircher, 2016).

Section III
Framework

India's GVA data are released by the CSO at a quarterly frequency with a lag of about 60 days. The quarterly growth rate of GVA (Y_t^q) for any current quarter, therefore, has to be forecast based on monthly available data. In this process, two different situations generally arise – firstly the data vintages change after the release of data and accordingly, the information base of nowcasting changes; secondly, as the new data become available, the old data get revised and the dynamics change. Also, the data release calendars of different indicators in any month vary across months and thus at any point of time, the chance of getting 'Jagged Heads' or 'unbalanced panel' is significantly high. This paper considers a dynamic factor model for nowcasting GDP using approaches suggested by Giannone *et al.* (2008) and Marcellino *et al.* (2013).

Considering Θ_t^n be the information set comprising of n indicators up to time t, the nowcasting problem boils down to predicting $(Y_t^q|\Theta_t^n)$. The information set Θ_t^n comprises two parts, namely soft information ($\Theta_t^{n_1}$) and hard information ($\Theta_t^{n_2}$). Soft information primarily incorporates survey-based sentiment. Further, hard information is segregated into two subsets – core data which have been used for estimating GVA growth in India and other hard data. Here, the data release calendar of $\Theta_t^{n_1}$ and $\Theta_t^{n_2}$ are not synchronous in nature and hence jagged edges develop in the information set infusing complexity in the modelling.

Let $\Theta_n^{r_j} = \{X_{it}|r_j, i = 1, 2, \dots n\}$ for t=1,2,3,4,……,T be the information available on n economic indicators at time t as per vintage r_j. Then the information set of each data vintage $\Theta_{r_j}^n$ and $\Theta_{r_{j-1}}^n$ differ from each other as new data get released and older data get revised.

Now, in order to forecast GVA, a mixed-frequency setup arises as GVA data are released at quarterly frequency and $\{X_{it}\}$is available at higher frequency (*i.e.*, monthly). For that, let us assume that quarterly GVA growth is tagged at the last month of the quarter which means that q=3m where (3m-2) and (3m-1) are two other months within the same quarter. Having assumed that, the next step is to consider the different data vintages $\Theta_n^{v_j}$ as the monthly data releases create multiple data vintages depending upon the date of release

Given these notations, the nowcasting exercise boils down to:

$Proj\left(\widetilde{Y_{r_j}^{3k}}\middle|\Theta_{r_j}^n\right) = E\left(Y_{r_j}^{3k}\middle|\Theta_{r_j}^n, Model\right) for\ r_j \in [(3m-2), 3m]$ where $(\widetilde{Y_{r_j}^{3k}}|\Theta_{r_j}^n)$ is the projected value of target variable and expectation is taken as the latest available vintage using suitable model.

The forecast precision is calculated as an inverse of uncertainty which is defined as

$$Uncertainty_{r_j}^{3k} = E\left[\left(\widetilde{Y_{r_j}^{3k}} - Y^{3k}\right)^2\middle| Model\right]$$

As more and more monthly data are released, $\Theta_n^{r_j}$ expands and throws more information for the forecast. Hence, we can expect the precision of the forecast to improve with more data releases, *i.e.*;

$$Uncertainty_{v_j}^{3k} \leq Uncertainty_{v_{j-1}}^{3k}$$

Framework used by Giannone

Giannone *et al.* (2008) used a dynamic factor model encompassing a large set of indicators. As the number of indicators increases, the number of unknown parameters also increases, and the curse of dimensionality crops up which limits degrees of freedom for residual estimates. The factor models are used for overcoming the dimensionality problem while capturing the information to a major extent.

The factor models are typically expressed as follows:

$$X_{it|r_j} = \mu_i + \lambda_i F_t + \epsilon_{it|r_j} \quad for\ i = 1(1)n \tag{1}$$

where μ_i is the intercept part indicating common level and F_t (Order: k x 1) relating to the factors spanning the information set. Also λ_i F_t and $\epsilon_{it|v_j}$ are assumed to be independent.

Eq(1) can be written as:

$$X_{t|r} = \mu + \Lambda F_t + \mathrm{E}_{t|r_j} \tag{2}$$

The significance of F_t lies in the fact that the components of F_t span the information set $\mathrm{E}_{t|r_j}$ but reduce dimensionality problem. The idiosyncratic component $\mathrm{X}_{t|r_j}$ is the unexplained part and consists of variable specific shocks primarily attributed to the exogenous impact and possible revisions in macroeconomic variables.

Due to changing dynamics among different macroeconomic variables, the dynamics of common factors play an important role. For the sake of simplicity, the dynamics of the common factors F_t can be expressed as an AR(1) process as below:

$$F_t = AF_{t-1} + B\eta_t \tag{3}$$

where A is AR(1) coefficient matrix of order $k \times k$ and B (*Order:* $r \times q$) represents structural relationship between common factors. The shock to common factors is a white noise process. Forni *et al.* (2005) preferred using a larger set of common factors over idiosyncratic shocks in order to capture the lead-lag relationship among the variables $\{X_t\}$ along the business cycle movements.

Since the data release calendar of different variables within the information set $\{X_t\}$ differs, the chance of getting an unbalanced panel cannot be ruled out. For that, we assume that:

$$E\left(\epsilon^2_{it|v_j}\right) = \tilde{\phi}_i = \begin{cases} \phi_i & where \quad Y_{it|r_j} \text{ is available} \\ \infty & where \quad Y_{it|r_j} \text{ is not available } (NA) \end{cases} \tag{4}$$

Here $E\left(\epsilon^2_{it|v_j}\right) = \infty$ ensures that no weightage would be given to variables having missing data at information vintage Θ_{r_j}.

Thus from (4), we get

$$\text{L } E\left(\epsilon_{t|v_j}\, \epsilon'_{s|v_j}\right) = \begin{cases} diag\left(\tilde{\phi}_i, i = 1(1)N\right) & if \;\; t = s \\ \infty \;\; if \;\; t \neq s \end{cases} \tag{5}$$

Also $E(\epsilon_{t|v_j}\, \eta_{s|v_j}) = 0$ for all s indicates independence between idiosyncratic shocks and shocks to common factor. Once the coefficients of equation (2) and (3) are estimated, the factors are estimated based on the latest available vintage Θ_{r_j} and estimated coefficients.

Equations (2) and (3) correspond to state-space representation. Assuming the errors follow a Gaussian process, the factors can be estimated by Kalman filter and the precision of the estimate is assessed as follows:

$$Precision_{s|v_j} = E[(F_t - \widehat{F}_t)(F_{t-s} - \widehat{F_{t-s}})'|\Theta_{v_j}]$$

The news content of vintage v_j is represented by

$$News_{v_j} = Proj\left[Y_{t|v_j}\right] - Proj[Y_{t|v_{j-1}}]$$

which indicates the incremental information content in the latest available vintage over the previous data release.

Framework used by Marcellino

Marcellino *et al.* (2013) assumed that the quarterly estimate of GVA is assumed to be a geometric average of monthly unobserved GVA figures. Such assumption is viable in case the month on month changes in GVA are expected to be minimal. Under this assumption,

$$\ln(Y^L_{3M}) = \frac{1}{3} \times (\ln(Y^*_{3M-2}) + \ln(Y^*_{3M-1}) + \ln(Y^*_{3M}))$$

$$\Rightarrow Y^{3M} = \frac{1}{3} \times (y_{3M} + 2y_{3M-1} + 3y_{3M} + 2y_{3M-4} + y_{3M-5})$$

Here $y^{3M} = \Delta\ln(Y^L_{3M})$ and $y_i = \Delta\ln(Y^*_i)$, $i = 1,2,3, \ldots$

The dynamic factor model framework can be written as:

$$\begin{pmatrix} y_t \\ X_t \end{pmatrix} = \begin{pmatrix} \theta_0 \\ \theta_1 \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} F_t + \begin{pmatrix} \epsilon_t^q \\ \epsilon_t^m \end{pmatrix} \tag{6}$$

Factor estimates are assumed to follow random walk process with lag=1 whereas the components of stochastic volatility follow AR process. Accordingly, the transition equations can be represented as:

$$\begin{aligned} \Phi^1(L)F_t &= \eta_t e^{\lambda_{f,t}/2} \\ \Phi^2(L)\epsilon_t^q &= \eta_t^1 \sigma_q e^{\lambda_{q,t}/2} \\ \Phi^3(L)\epsilon_t^{m_j} &= \eta_t^2 \sigma_m e^{\lambda_{m_j,t}/2} \end{aligned} \tag{7}$$

where are independent N(0,1) random variables and $\Phi^{i}(L)$ are polynomials of order a_i:

$$\Phi_i(L) = 1 - \sum_{j=1}^{P_i} \phi_i L^i$$

The stochastic volatility is induced in the system through transition equation of λ_{it} which is assumed to follow a drift-less random walk, *i.e.*,

$$\lambda_{it} = \lambda_{it-1} + \eta_t^4, where\ \eta_t^4 \sim N(0, \sigma_\lambda^2)$$

Following Kim and Nelson (1999), the model was estimated using the multi move Gibbs Sampling approach with Metropolis Hastings algorithm for selecting the draws.

Naïve Models

The forecast performance of the nowcasting models has been analysed using the rolling forecast approach with expansionary window size. The benchmark models considered in this paper fall under time series and structural models. A list of naïve models used in this paper is given below:

Time Series Models	Structural Models
ARIMA Holt-Winters SETAR 2 regime SETAR 3-regime LSTAR AAR Artificial Neural Network	VAR Models (Interest Rate, CPI Inflation and GVA) TVP-VAR Model

The lag selection of VAR models has been decided using SIC criteria. Further, the time varying models of VAR have been framed in line with Primeceri (2005) and estimated using multi move Gibbs Sampling following Cater and Cohn (1994). In-sample residual diagnostics and test of convergence[1] have been validated for goodness of fit and stability.

Section IV
Selection of Variables

The success of a dynamic factor models lies in extracting factors from a pool of economic variables which contain information on the target variable. Thus, the information content of each variable should be cross checked before selecting a final pool. Stock and Watson (1999 and 2002) advocated the use of very large information sets, which have also been considered in a majority of the papers that use DFM. Giannone *et al.* (2008) incorporated 200 odd economic indicators for nowcasting US GDP growth. However, a different stance was adopted by Bai and Ng (2008) and Boivin and Ng (2006), who suggested the use of a relatively smaller set of variables to start with. Following that methodology, Angelini *et al.* (2011) and Camacho *et al.* (2010) used a smaller set of variables (also called core variables) and then incrementally included more variables one by one, based on improvement in forecast performance.

One most commonly accepted way to check the nature of dependence among the variables is the cross-correlation test which not only provides the significance of cross-correlation at various lags but also suggests the nature of dependence using the sign of correlation. In this context, the variables showing significant cross correlation at lag = 0 and having appropriate signs comprise the first pool of variables. However, while high cross-correlation affirms a co-movement among the series, it does not address one of the major aspects of a business cycle, that is switching of processes between which is identified as the most critical property of any business cycle indicator by Burns and Mitchell (1946). In view of this, Lahiri and Yao (2006) used turning point analysis by applying Bry-Boschan (1971) algorithm. The turning point analysis of the target variable and other economic indicators provide sufficient

[1] The authors are grateful to Primiceri for sharing his views on the assessment of convergence criteria in a time varying setup.

insight about the different phases of business cycle movement observable in each series. Though Lahiri and Yao (2006) proposed statistical coherence tests for identifying regime changes, the scrutiny of turning point analysis of any business cycle indicator requires sufficiently large number of observations, which is not suitable for our study due to the limitation of adequate data points. So, we rely on visual inspection of regime switches in the target variable and the explanatory variables. Comparing the regimes of target series, any variable (or regressor) having recession and boom regimes during different periods would be suspected for the fact that the concerned regressor would not be able to predict the turnaround points of the target variable efficiently. Hence, the cross-correlation test along with regime switching behaviour would provide sufficient screening of regressors for nowcasting. Adding up variables based on the above criteria could be one solution to define a larger pool of variables.

On the contrary, as identified by Boivin and Ng (2006), adding more and more variables into dataset may not result in improvement of forecasting performance, as some of the variables may have influences from other variables which do not impact the target variable. Also, if the idiosyncratic components are large and correlated with each other, adding further variables may not result in better accuracy in forecasting. Thus, pre-selection of variables poses a crucial challenge to forecasting. Marie (2013) used elastic net framework using Least Angle Regression - ElasticNet (LARS-EN) algorithm for selecting the regressor. LARS-EN algorithm typically uses sequential backward selection of variables using ARDL model for checking the explanatory power of regressors and penalising L1 and L2 norm of regression coefficients.

The ARDL framework can be written as:

$$S_t = \alpha + \beta_1 S_{t-1} + \beta_2 S_{t-2} + \cdots + \beta_k S_{t-k} + \gamma X_t + \zeta_t \qquad (A.1)$$

EN criteria (suggested by Zou and Hastie, 2005) is represented as:

$$\min_{\beta} \sum_{t=1}^{T} \left(S_t - \widehat{S_t}\right)^2 + \lambda_1 \sum_{i=1}^{N} |\gamma_i| + \lambda_2 \sum_{i=1}^{N} \gamma_i^2$$

where λ_1 and λ_2 are the penalty parameters of L^1 and L^2 norms of regression coefficients. Basically, EN criteria is a combination of LASSO and Ridge regression which Zoe and Hastie (2005) suggested as more efficient than LASSO and Ridge. So we resort to LARS-EN algorithm for the final selection of pooled regressor.

Section V
Data Used

In this paper, GVA at basic price has been considered for nowcasting. As a supply-side measure, GVA at basic prices (real) comprises three major sectors namely agriculture (around 14-15 per cent), industry (around 22-23 per cent) and services (around 57-62 per cent). Among these three sectors, agriculture growth remains highly seasonal in nature and depends upon exogenous variables like rainfall, reservoir status and sowing pattern, the information on some of which are not available at higher frequency. Hence, GVA excluding the agriculture sector (also called non-agriculture GVA) has been considered as the target variable for the nowcasting exercise in this paper. GVA data are available from Q1: 2011-12, only after the latest rebasing exercise carried out by the CSO. The back series of GVA at basic prices has been constructed using a bottom-up approach. Using this approach, the linking factor has been estimated separately for agriculture, industry and services based on the common overlapping period of 2004-05 base and 2011-12 base. The back series of this sectoral GVA were first estimated by applying the linking factor and then aggregated to derive GVA at basic prices.

As indicated in the previous section, the indicators pool used in this paper can be segregated into three major parts:

$$\Theta_t = (\Theta_t^C, \Theta_t^H, \Theta_t^S)$$

where $\Theta_t^C, \Theta_t^H, \Theta_t^S$ indicate core indicators, hard indicators and soft indicators, respectively.

The quarterly estimate of GVA is obtained using the benchmark indicator approach, where selected high-frequency variables are tracked to extrapolate the YoY growth rate of different sectors of GVA. Finally, the overall GVA estimate is obtained by aggregating the sectoral GVA estimates. The list of indicators used by CSO for estimating GVA is provided in Table 1.

Table 1: List of Core Indicators Used

Sectors	Indicators Used	Frequency
Industry	IIP Mining	Monthly
	IIP Electricity	Monthly
	GVA of Manufacturing Companies	Quarterly
	GVA of Petroleum Companies	Quarterly
Services	Cement Production	Monthly
	Steel Consumption	Monthly
	Production of Commercial Motor Vehicles	Monthly
	Sales of Commercial Motor Vehicles	Monthly
	Cargo Handled at Major Ports	Monthly
	Air Traffic (Passenger & Freight)	Monthly
	Foreign Tourist Arrival	Monthly
	Hotel Occupancy Rate	Monthly
	Sales Tax	Monthly
	Service Tax	Monthly
	GVA of Wholesale Trade Companies	Quarterly
	GVA of Hotel & Restaurants	Quarterly
	Aggregate Deposits	Monthly
	Bank Credit	Monthly
	Insurance Premium	Monthly
	GVA of Real Estate Companies	Quarterly
	Profitability of IT Companies	Quarterly
	Central Government Non-plan Expenditure	Monthly

Hard indicators considered in the paper are provided in Table 2.

As far as soft variables are concerned, both the PMI-manufacturing and services-along with their components have been considered in this paper. Since PMI data are available from April 2005 for manufacturing and from December 2005 for services, the data for the target variable and other economic indicators have been considered for the period January 2006 to September 2016.

Table 2: List of Hard Indicators Used

IIP and its Components	IIP Basic Goods IIP Capital Goods IIP Consumer Goods IIP Consumer Durables IIP Consumer Non-durables IIP Intermediate Goods IIP Manufacturing (NIC 2 digit)
Eight Core	Overall Eight Core (EC) Index
Interest Rate	Weighted Average Call Money Rate 10-years G-sec Yield 91-days T-Bills Rate
Demand Condition	Passenger Car Sales Three-wheeler Production Three-wheeler Sales Two-wheeler Production Two-wheeler Sales
Inflation	WPI Headline WPI Core Inflation WPI Manufacturing
External Sector	Exports (USD) Non-oil Imports (USD) Non-oil, Non-gold Imports (USD)
Money & Banking	Currency in Circulation Currency with the Public Reserve Money Narrow Money Broad Money
Global Variables	IMF Commodity Prices IMF Metal Prices Crude Oil Prices (Indian Basket) Baltic Dry Index

Section VI
Empirical Findings

The business cycle dating algorithm proposed by Bry and Boschan (1971) has been adopted to track the turnaround points of the target variable (*i.e.*, non-agriculture GVA or NAGVA). Similar analysis was carried out on quarterly transformed data for the select economic indicators (hard and soft). The final set of hard and soft indicators used for the nowcasting exercise is provided in Table 3.

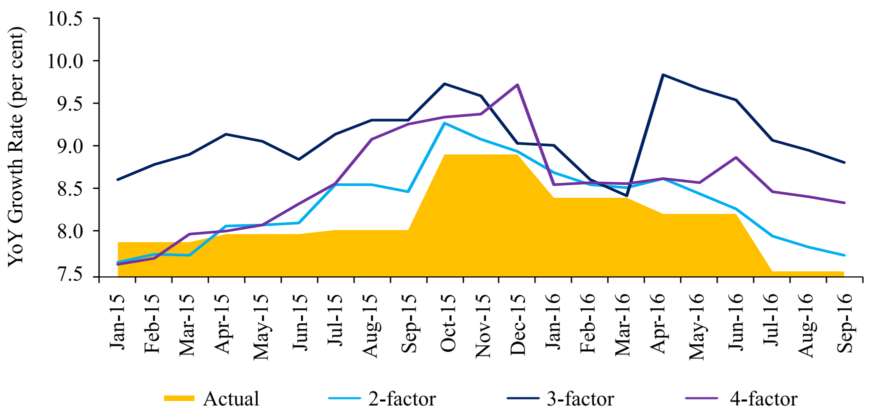
Table 3: Final List of Indicators Used

Broad Category	Indicators
IIP and its Components	IIP Basic Goods IIP Consumer Goods IIP Consumer Durables IIP Consumer Non-durables IIP Intermediate Goods IIP Manufacturing (NIC 2 digit)
Eight Core	Overall EC Index
Interest Rate	Weighted Average Call Money Rate 10-years G-sec Yield 91-days T-bills Rate
Demand Condition	Passenger Car Sales Three-wheeler Sales Two-wheeler Sales
Inflation	WPI Headline WPI Core Inflation WPI Manufacturing
External Sector	Exports (USD) Non-oil Imports (USD)
Money & Banking	Currency in Circulation Currency with the Public Reserve Money Narrow Money Broad Money

Broad Category	Indicators
Global Variables	IMF Commodity Price IMF Metal Price Baltic Dry Index
PMI Manufacturing	Overall Index Output New Orders Output Price Input Cost
PMI Services	Overall Index New Business Price Charged Input Price

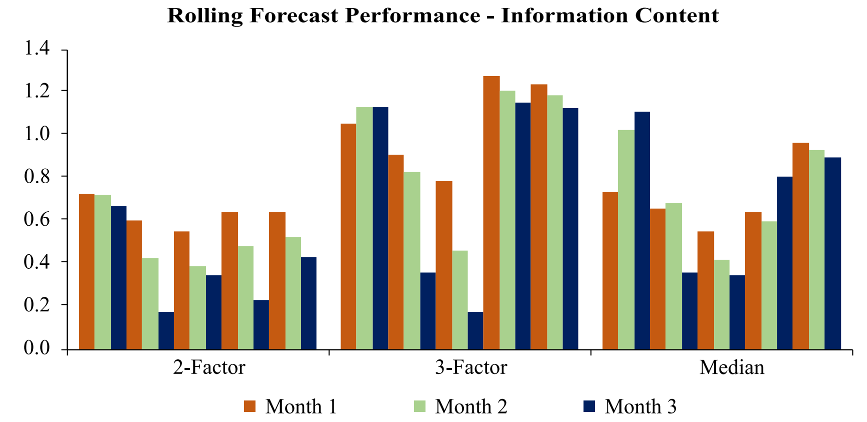
Using these indicators, the dynamic factor model was developed following Giannone *et al.* (2008) and Marcellino *et al.* (2013). Initially, the forecast precision of two-factor, three-factor and four factor models[2] was analysed using the rolling forecast mechanism in an incremental (or expansionary) window approach. The forecast performance of the two-factor model was found to be most precise among these models for immediate one-quarter ahead forecast (Chart 1).

Chart 1: Rolling Forecast Performance



[2] 2-factor model explains 76 per cent of total variability, 3-factor model explains 85 per cent variability whereas 4-factor model explains 90 per cent variability.

Chart 2: Improvement in Forecast Performance over Data Releases



The forecast performance was found to gradually improve over time during a quarter as more and more data became available and old data got revised (Chart 2). Beyond one-quarter also the forecast performance of two-factor model was found to be comparatively more precise (Chart 3).

Finally, the rolling forecast errors summarised in terms of root mean square error (RMSE) indicate significant improvement in the performance of forecast provided by the nowcasting models *vis-à-vis* that provided by Naïve Models. Among the two different approaches, the approach followed by Marcellino *et al.* (2013) was found to be marginally more precise than Giannone *et al.* (2008) approach (Table 4).

Chart 3: Forecast Performance of Two-factor Model

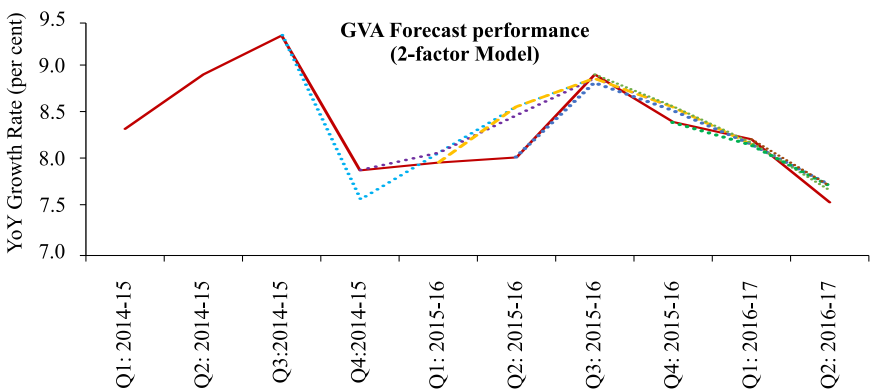


Table 4: Rolling RMSE – Nowcasting Model *vs* Naïve Model

Model	1-Q	2-Q	3-Q	4-Q
Naïve Models				
ARIMA	1.6	3.0	1.8	2.0
Holt Winters	1.7	2.2	2.3	2.4
SETAR - 3 Regime	1.1	1.2	1.5	2.2
SETAR - 2 Regime	1.3	2.9	2.6	2.0
LSTAR	1.2	1.9	1.9	1.4
AAR	1.6	3.2	3.0	3.2
Neural Network	1.5	2.5	2.4	2.8
Time Varying VAR	0.8	1.1	1.2	1.7
Nowcasting Model				
DFM-1	0.3	0.9	1.2	1.3
DFM-2	0.2	0.7	1.1	1.2

Note: 1-Q = 1 quater ahed forecast; similarly 2-Q, 3-Q, 4-Q.

Section VI
Conclusion

Nowcasting of GDP has become popular in the aftermath of the global financial crisis in 2007. The limited information problem cropped up prominently in the post-crisis scenario as most of the economic forecasting models failed to predict the crisis with significant probability. The nowcasting framework of Giannone *et al.* (2008) provided a convenient way to include a larger information set without facing the curse of dimensionality. Another novelty of the approach was to use the mixed frequency setup, given the asynchronous data release calendar. The emergence of nowcasting in an information overloaded environment helped in devising an alternative to the limited information approach of forecasting. This paper provide an assessment of the nowcasting experience in India using two different approaches.

The paper contributes to the growing literature of nowcasting and tries to implement the available frameworks to Indian high-frequency data. Following the estimation methodology of the CSO, an attempt has been made to use the available information sets for forecasting non-agricultural GVA. The paper finds significant improvement in forecast precision using nowcasting framework over naïve models. Also, it was observed that the nowcasting models are capable of forecasting NAGVA growth beyond one-quarter with a reasonable degree of precision. Further, the stochastic volatility approach suggested by Marcellino *et al.* (2013) is found to improve nowcast precision only marginally for NAGVA, compared to the approach suggested by Giannone *et al.* (2008).

References:

Altissimo, F., Bassanetti, A., Cristadoro, R., Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2001), "EuroCOIN: A Real Time Coincident Indicator of the Euro Area Business Cycle", CEPR Discussion Papers, 3108.

Baffigi, A., Golinelli, R., and Parigi, G. (2004), "Bridge Models to Forecast the Euro Area GDP", *International Journal of Forecasting,* 20 (3), 447–460.

Bai, J. (2003), "Inferential Theory for Factor Models of Large Dimensions", *Econometrica,* 71 (1), 135–171.

Bai, J. and Ng, S., (2002), "Determining the Number of Factors in Approximate Factor Models", *Econometrica,* 70 (1), 191–221.

Banbura, Marta, Giannone, Domenico, Modugno, Michele and Reichlin, Lucrezia (2013), "Now-casting and the Real-time Data Flow", Working Paper Series, European Central Bank, 1564.

Barhoumi, Karim et al. (2008), "Short-Term Forecasting of GDP using Large Monthly Datasets – A Pseudo Real-time Forecast Evaluation Exercise", Occasional Paper Series, European Central Bank, 84.

Bates , Brandon J., Plagborg-Møller, Mikkel, Stock, J. H. Stock and Watsonc, M. W. (2013), "Consistent Factor Estimation in Dynamic Factor Models with Structural Instability", *Journal of Econometrics*.

Bessec, Marie, (2013), "Short-Term Forecasts of French GDP: A Dynamic Factor Model with Targeted Predictors", *Journal of Forecasting,* 32, 500–511.

Bhattacharya, Rudrani, Pandey, Radhika and Veronese, Giovanni (2011), "Tracking India Growth in Real Time", Working Paper, *National Institute of Public Finance and Policy,* 2011-90.

Boivin, J. and Ng, S. (2005), "Understanding and Comparing Factor-based Forecasts", *International Journal of Central Banking,* 3, 117–151.

Camacho, Maximo and Perez-Quiros, Gabriel (2010), “Introducing the Euro-sting: Short-term Indicator of Euro Area Growth”, *Journal of Applied Econometrics,* 25, 663–694.

Carter, C., & Kohn, R. (1994). On Gibbs Sampling for State Space Models. Biometrika, 81(3), 541-553. doi:10.2307/2337125.

Chow, G.C. and Lin, A. (1971), “Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series”, The Review of Economics and Statistics 53 (4), 372–375.

D’Agostino, A. and Giannone, D. (2006), “Comparing Alternative Predictors based on Large-panel Dynamic Factor Models”, Working Paper Series, European Central Bank, 680.

D’Agostino, A., Giannone, D. and Surico, P. (2006), “(Un) Predictability and Macroeconomic Stability”, Working Paper Series, *European Central Bank,* 605,

Doz, Catherine Giannone, Domenico and Reichlin, Lucrezia (2011) “A step-step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering”, *Journal of Econometrics,* 164, 188-205.

Eichler, Michael Motta, Giovanni and Sachs, Rainer von (2011), “Fitting Dynamic Factor Models to Non-stationary Time Series”, *Journal of Econometrics,* 163, 51-70.

Evans, M.D.D., (2005), “Where Are We now? Real-time Estimates of the Macroeconomy”, NBER Working Paper, 11064, *International Journal of Central Banking,* 1 (2), 127–175.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2005), “The Generalised Dynamic Factor Model: One-sided Estimation and Forecasting”, *Journal of the American Statistical Association,* 100 (471), 830–840.

Giannone, D., Reichlin, L. and Sala, L. (2004), “Monetary Policy in Real Time”, *NBER Macroeconomics Annual,* MIT Press, Cambridge, 161–200.

Giannone, Domenico Reichlin, Lucrezia and Small, David (2008), “Nowcasting: The Real Time Informational Content of Macroeconomic Data”, *Journal of Monetary Economics,* 55, 665-676.

Giannone, Domenico, Reichlin, Lucrezia and Small, David (2005), "Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases", Finance and Economics Discussion Series, Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington, D.C.

Huang, Jih-Jeng Tzeng, Gwo-Hshiung and Ong, Chorng-Shyong (2006), "A Novel Algorithm for Dynamic Factor Analysis", *Applied Mathematics and Computation,* 175, 1288–1297.

Kitchen, J. and Monaco, R. M. (2003), "Real-time Forecasting in Practice: The U.S. Treasury Staff's Real-time GDP Forecast System", *Business Economics,* 10–19.

Koenig, E.F. Dolmas, S. and Piger, J. (2003), "The Use and Abuse of Real-time Data in Economic Forecasting", *The Review of Economics and Statistics,* 85 (3), 618–628.

Lahiri , Kajal and Monokroussos, George (2011), "Nowcasting US GDP: The Role of ISM Business Surveys", *International Journal of Forecasting*.

Lahiri , Kajal and Yao, Vincent Wenxiong (2006), "Economic Indicators for the US Transportation Sector", *Transportation Research Part A,* 40, 872–887.

Marcellino, M., Stock, J. H. and Watson, M. W. (2003), "Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-wide Information", *European Economic Review,* 47 (1), 1–18.

Marcellino, Massimiliano Porqueddu, Mario and Venditti, Fabrizio (2013), "Short-term GDP Forecasting with a Mixed Frequency Dynamic Factor Model with Stochastic Volatility", Working Papers Number, Banca D'Italia, 896.

Mario Forni et al., (2007), "Opening the Black Box – Structural Factor Models with Large Cross Sections", Working Paper Series, *European Central Bank,* 712.

Negro, Marco Del, and Otrok, Christopher (2008), "Dynamic Factor Models with Time-Varying Parameters: Measuring Changes in International Business Cycles", Staff Report, *Federal Reserve Bank of New York.*

Orphanides, A., (2002), "Monetary-policy Rules and the Great Inflation", *American Economic Review,* 92 (2), 115–120.

Primiceri, Giorgio (2005), 'Time Varying Structural Vector Autoregressions and Monetary Policy', *Review of Economic Studies,* 72, 821–852.

Runstler, G. and Se´dillot, F. (2003), "Short-term Estimates of Euro Area Real GDP by Means of Monthly Data", Working Paper Series, 276, *European Central Bank*.

Silvia, John E, and Lahiri, Kajal (2011), "Transportation Indicators and Business Cycles", *Business Economics,* Vol. 46, Issue 4, 260-261.

Stock, J.H. and Watson, M. W. (2002), "Forecasting Using Principal Components from a Large Number of Predictors", *Journal of the American Statistical Association,* 97 (460), 147–162.

Stock, J.H. and Watson, M. W. (2002), "Macroeconomic Forecasting Using Diffusion Indexes", *Journal of Business and Economics Statistics,* 20 (2), 147–162.

Zou, Hui and Hastie, Trevor. (2005), "Regularization and Variable Selection via the Elastic Net", J.R. Stat Soc. B 67, Part 2, 301 – 320.

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Contemporary Issues in the Post-Crisis Regulatory Landscape by Imad A. Moosa, 398 pp. World Scientific (2017), US$148.

The global regulatory landscape for banking sector, which changed dramatically after the Global Financial Crisis (GFC), created hope that banking systems complying with such regulations should become more resilient and sound in future. In Contemporary Issues in the Post-Crisis Regulatory Landscape, Imad A. Moosa, Professor of Finance at Royal Melbourne Institute of Technology, Melbourne, Australia, dwells on the debate on 'more *versus* less' regulation, what exactly constitutes an optimal mix of regulation and controls, the ultimate objectives that should drive the approach to regulation of financial systems, and the effectiveness of any best regulatory standards to prevent a financial crisis (which nevertheless remains largely unsettled). The author explores the possible causes of the GFC from a regulatory perspective and discusses contemporary issues in financial regulation in the post-GFC period. The main theme running through the book is the role of rampant corruption, fraud and deregulation in causing the GFC. It offers justification for tighter financial regulation in order to avoid a repeat of a crisis like the GFC.

The book explains three broad viewpoints on the foremost factor causing the GFC. At one extreme, the excessive regulation is highlighted as a factor responsible for the crisis, while at the other extreme deregulation, which is contested by some on the ground that no major deregulation has occurred in the last thirty years. According to the author, deregulation and self-regulation, as propounded by the ex-Chairman of the US Federal Reserve, Alan Greenspan, was the major cause of the crisis. He argues that corruption and fraud provide the best justification for regulation. The reasons for the GFC included regulatory failure and regulatory capture of the US Fed and other regulators in the financial sector by the regulated institutions. It got further amplified as other countries blindly emulated the regulatory practices introduced in the US. The book discusses how negligence, incompetence, complacency and fraud, on the part of various players, resulted in the crisis. According to Moosa not enough has been done after the GFC to avert another similar crisis.

He gives various examples of the nexus among the finance industry, the regulatory systems and the government that have thwarted any attempt for tightening regulation of financial institutions before the GFC. According to the author, a contributory role in the genesis of the GFC was also played by credit rating agencies (CRAs), academia (who provided justification for deregulation), investment analysts, boards of directors of financial companies, fund managers, mortgage brokers, home buyers and the governments of the US and other western countries.

In his book, Moosa also analyses at length the pros and cons of deregulation with some examples.

The author finds that proposals on ring-fencing between commercial banking and investment banking and Total Loss Absorbing Capacity (TLAC) are half-hearted measures without substantive processes to rein in financial oligarchy. He argues that the TLAC is meant to ensure the adequacy of loss-absorbing and recapitalisation capacity of the Global Systemically Important Banks (GSIBs) in case of resolution, so that critical functions could continue without requiring tax payers' support or threatening financial stability. However, in this case, bailouts will be replaced by bail-ins. Thus, bankers will still get their bonuses from the confiscated depositors' money. Also, Moosa feels that the place of depositors in the liquidation waterfall is a very contentious issue. Regarding the 'too big to fail' (TBTF) problem of GSIBs, he suggests that the TBTF problem can be put to an end by reducing the bank size, separating investment banking from commercial banking, and allowing TBTF banks to fail.

Moosa gives the example of Iceland where some bold measures have been taken to put bankers under check. He elaborately discusses the proposal by the Government of Iceland, contained in a report released in 2015, regarding the abolition of fractional reserve banking which caused 'out of control' money supply. The report suggests replacing it with a sovereign money system in which the amount of money in the economy is directly controlled by the central bank. In this system, the risk of sudden bank runs is greatly reduced and deposit guarantee schemes become unnecessary. Further, Icelanders showed exceptional courage by putting bankers behind bars in place of giving them bonuses and golden parachutes as was done in New York and London. They did not follow the slippery slopes of TBTF bailouts, bail-ins and quantitative easing which hurt the small savers hard. According to Moosa, Iceland's example shows that the myth of TBTF propaganda has been spread by banks themselves and is supported by regulators, some politicians, and academicians. He suggests that regulators should learn from the Icelandic experience.

Moosa highlights that, despite immense damage done by securitisation (through exotic products such as Mortgage-Backed Securities and Collateralised Debt Obligations or CDOs) during the GFC, securitisation is being brought back and supported by the Basel Committee on Banking Supervision (BCBS) and the European Central Bank. He argues that the return of securitisation with a vengeance reflects a missed opportunity for regulators to reform the financial system. Regarding sub-prime loans and inferior mortgage underwriting standards in various mortgage products, the author argues that if we had learnt anything from the savings and loan crisis of the 1980s and 1990s and had taken proper regulatory actions, the GFC could have been avoided. He also discusses the role of the 'great moderation' and consequent build-up of leverage in the GFC and the failure to learn from the Long-Term Capital Management (LTCM) crisis in 1998. He discusses whether the GFC was a liquidity crisis, and if it could have been avoided, had liquidity-risk mitigation been part of Basel II standards, which was only adopted in Basel III by the BCBS.

Moosa questions the contribution of financial innovations and financial engineering to human welfare and argues that financial innovations such as synthetic CDOs and CDO-squared served no purpose other than generation of revenue for their inventors and bosses. The book highlights that current mathematical models used by financial institutions often under-price risk as they underestimate the tail risk. The author questions the models used in stress tests by the regulators for the purpose of determining regulatory capital and suggests use of simple and conservative capital standards based on reliable capital ratios instead of unreliable models.

The author also discusses other issues such as vulnerabilities of the shadow banking system, increasing financialisation of the economy and its implications for the real economy, failure of corporate governance and consequent excessive risk-taking by the managers/executives at the cost of shareholders. Moosa also discusses the issue of regulation of remuneration in the financial sector and issues related to the regulation of CRAs and why CRAs are still in business. The failure of the neo-classical financial economics in foreseeing the GFC and the shortcoming of the rational expectation hypothesis, Efficient Market Hypothesis (EMH), Washington Consensus policy prescriptions and theories of trickle-down effect have also been discussed in detail in the book. Moosa asserts that EMH provided the intellectual underpinning for embracing financial deregulation, which in turn led to the GFC. However, EMH was also a casualty of the GFC as the crisis exposed its implausibility and put it under scrutiny. The book has also devoted a full chapter to regulatory implications of quantitative easing and the ultra-low interest rates.

The author enumerates various frauds that big banks indulge in, such as money laundering, frauds against local governments, shaving money off pension transactions, frauds while initiating mortgage loans and while foreclosing them. According to the author, big banks also indulge in pledging the same mortgage multiple times to different buyers, cheating homeowners by gaming laws, indulging in insider trading, pushing investments that they know are terrible, participating in various Ponzi schemes, cooking the books, and bribing and bullying rating agencies to inflate ratings of risky investments.

To restrain the fraudulent behaviour of financial oligarchs, Moosa suggests some radical measures: GSIBs should not be told that they are systemically important, rather they should be reduced in size and allowed to fail; fraudulent accounting rules must be prohibited so that financial institutions recognise their losses rather than announcing profits on whose basis the management can claim bonuses; the culture of bonuses and golden parachutes needs to be abolished; perpetrators of frauds must be prosecuted; financial innovations must be curbed and financial engineers should be sent to factories and labs. He even suggests that regulators who dislike regulation and defend deregulation should be fired.

The book has explained the issues in the operating environment of the banking industry, largely from the perspective of financial stability. Though the book has been written in the context of advanced economies, many issues such as deregulation of the financial sector, implementation of the Basel III regime, regulation of CRAs, regulation of remuneration in the financial sector, questions related to deregulation driven by faith in EMH, issues related to domestic systemically important banks (DSIBs), corporate governance in financial institutions and trickle-down effects, are very much pertinent for emerging market economies such as India. Though many books have been written about the GFC, this book gives a fresh perspective of the GFC and sees it from the angle of regulatory failure, corruption and fraud committed in the financial sector. The book is a good reading for anyone who is interested in understanding the genesis of the GFC and regulatory developments of which certain aspects still remain debatable, despite the efforts to develop global regulatory standards based on a consensus.

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The Curse of Cash by Kenneth Rogoff, 248 pp. Princeton University Press, Princeton, New Jersey (2016), US$29.95.

Money has been an integral part of our society for nearly 3,000 years, and has acquired varied forms under different monetary systems, including its most recent digital version, made possible by advances in technology, *i.e.*, crypto currencies. Over time, however, the difference between money held in its most conventional form — currency — and money in its modern form,which reflects the influence of financial innovations and advances in technology, has widened considerably. This has triggered a debate on cash versus non-cash modes of money, and the importance of downsizing or completely eliminating high-denomination currency notes. In this context, Kenneth Rogoff, the former chief economist of the International Monetary Fund (IMF), has also been propagating the idea of getting rid of the US$100 bill for the last two decades. His book, *The Curse of Cash*, highlights the still very important role of currency in the modern era, and how it can constrain monetary policy to deal with recession — particularly in recent times when interest rates are quite low. The book covers the history as well as future prospects of paper currency by exploring various related theoretical paradigms and different viewpoints, spread over fourteen chapters in three parts.

The initial chapters of the book provide an outline of the intriguing history of money and showcase its deep interlinkages with the development of technology and society. The book highlights that 'as societies become more developed, however, with diverse goods and large populations, achieving allocation without some form of money has long proven nearly impossible'. Rogoff recounts the history of money through metal coinage, Lydian coins and innovative ideas on the usage of coins by Alexander the Great during the fourth century BC. The book provides an insightful narrative of how various commodities and items were seen as alternatives to money. Rogoff suggests that the biggest benefit of cash is that it is a solution to the problem of "double coincidence of wants" as it eliminates the need to enter into a barter transaction. Also, cash generates revenue for the government if the value of money exceeds its production costs. Lastly, cash provides anonymity of transactions and allows individuals to enter into transactions without any oversight by the government authorities.

The book highlights the important role that cash plays across developed countries, despite proliferation of alternative payment mechanisms. In the United States, for example, per capita use of cash is roughly about US$4,200, 80 per cent of which is in high denomination bills of US$100 (84 per cent if US$50 denomination is also included). Even in Japan and the Euro area, high denomination notes still exist, *i.e.*, 10,000-yen note (equivalent to about US$93 at present) and the Eurozone's €500 note (equivalent to about US$570). The author argues for gradually moving towards a less cash economy in the advanced economies, by phasing out large denomination notes. For instance, in the United States, the author suggests the phasing out of US$100 notes first, then US$50 notes, and, eventually, the smaller currency notes like US$20 and perhaps even US$10. The speed of the proposed transition, however, needs to be slow, over at least ten to fifteen years.'Gradualism helps avoid excessive disruption and gives institutions and individuals' time to adapt'.

The idea of phasing out high-denomination currency is based on two arguments. The first is that a majority of high-denomination notes are the preferred mode of transaction for unlawful activities and, therefore, promote a broad range of criminal activities, including drug trafficking, racketeering, extortion, corruption of public officials, human trafficking and money laundering. The author supports this argument by extrapolating the estimates gathered by the Internal Revenue Service (IRS) of the United States (US) of the legally-earned but unreported taxes from 2006 to 2015. He estimates that there is a net tax gap of US$500 billion, and more than half of it originates from cash transactions. He suggests that eliminating cash can help close this tax gap by at least 10 per cent, leading to an annual potential gain of US$50 billion for the US government, and an additional US$20 billion gain for the state and local tax authorities. The author provides estimates of unreported legal activity in other economies at 28.9 per cent of Gross Domestic Product (GDP) for Turkey, 22.3 per cent for Italy, and 15.3 per cent for Sweden, compared to 7.1 per cent for the US. The author further states that, despite having a similar overall GDP as the US, Europe's shadow economy at about US$3 trillion, is more than double the size of the shadow economy of the former. And this may be attributed to higher tax rates and more burdensome regulations in Europe.

The book provides several interesting facts highlighting the link between money and criminal activities such as illegal drugs, corruption, and human trafficking. To weigh the importance of cash in the drugs market, Rogoff points out that about 90 per cent of all the US currency has traces of cocaine. The RAND Corporation's estimates placed the market of four major illegal drugs in the US, namely cocaine (including crack), marijuana, meth and heroin, at more than US$100 billion in 2010. Phasing out high-denomination cash would be a significant blow to drug cartels in the US, as other means for doing such transactions are quite hard to adopt and are not as safe for routine use on a large scale. Furthermore, the use of other forms of money such as commodities (as in the barter era), foreign currency, or even over-reporting of invoices do not provide the convenience or anonymity that cash offers.

Rogoff's second reason for proposing elimination of high currency notes relates to monetary policy and macroeconomic stability. He argues that monetary policy may turn ineffective in dealing with deep and prolonged recessions in a high-cash economy. Negative interest rate policies may make cash more attractive than bank deposits and bank reserves, leading to weaker transmission of such policies.

The second part of the book explores the area of negative interest rates in terms of the relationship between paper currency and a central bank's policy. Ever since the financial crisis of 2008, the global economy, particularly the advanced economies, are experiencing a phase of low interest rates and inflation along with slow output growth rate. Macroeconomic theory suggests that the central bank of a country can lift an economy out of recession by pushing down the interest rates. However, a zero lower bound for nominal interest rates could constrain conventional monetary policy. Quantitative easing and negative interest rate become unconventional policy options in such cases. The author explains that paper currency can be thought of as a zero-interest-rate bond. As long as people have the choice of paper money, they will not prefer any instrument with a negative rate of interest. Central banks of Denmark, Switzerland, Sweden, the Eurozone, and Japan are the early adopters of negative interest rate policy on bank reserves. This policy puts pressure on private banks to charge negative rates on deposits with them. The private banks in some of the countries that used the negative interest rate policy (e.g., Denmark, Switzerland, and Sweden) have been able to pass on negative rates to their large clients, but they have not yet dared charge negative rates to their ordinary retail customers, at least not in a transparent fashion. However, banks that are charging negative interest rates will recoup their costs either by charging customers higher on other services or by charging higher for loans that the banks provide. One of the criticisms related to negative interest rates is that it might be regarded as a violation of the trust that citizens place in their government by giving it a monopoly over the currency supply. Rogoff thinks that these people are victims of the illusion of money, as one should actually see the real rate of interest on currency.

The negative interest rate policy might lead to instability in prices, financial markets, and a departure from rule-based monetary policy. Rogoff mentions that Friedman's alternative of limited monetary expansion, according to a fixed rule,would not work. Friedman thought that there was a fixed relationship between the quantity of money and prices, but this has not always proved to be the case. Rogoff argues that the ideal monetary system is the one that balances flexibility and commitment. If central banks had an option of setting interest rates to negative levels without limit, they would have had far more scope than they do today for pushing an economy quickly out of a deflationary spiral and also for counteracting the effects of credit contraction after a systemic financial crisis. To achieve monetary policy goals, therefore, it is necessary to enhance the likely effectiveness of a negative rate policy by discouraging cash holdings through the implementation of various legal, tax, and institutional changes.

Rogoff's proposal for less cash or elimination of currency leads to a few concerns though. The radical change will imply erosion in the income of central bank or seigniorage, which is the difference between the face value of currency minted by the government or the central bank and the cost of inputs, including both materials and production costs. The author places the estimated loss of revenue for various advanced economies' central banks at 0.3 per cent of GDP, which is way below the estimated tax evasion of 2.7 per cent of GDP for federal taxes alone, and perhaps another percentage point higher if state and local taxes are included. Nonetheless, the central bank would still earn money from electronic bank reserves even in a situation where there is a complete elimination of paper currency. The second crucial concern relates to the disruptive effect it will have on the poor who use currency intensively. Rogoff suggests that this concern can be addressed by providing subsidised access to financial services for the poor, giving them equal access to electronic currency, and, at the same time, helping reduce some of the costs associated with financial exclusion. These measures aimed at improving financial inclusion will have numerous collateral benefits in fighting domestic inequality as well.

The Curse of Cash is a well-written and engaging book with many intriguing claims and insights. The book has more to offer than just the narrative of the claims and debates over the benefits and costs of cash. Rather it covers a broad range of related issues which provide clarifications to many popular misconceptions. Topics such as international policy dimensions and the future of cash, in terms of exploring the digital currencies, provide food for thought to the readers.

Rogoff acknowledges that digital currencies indeed have important implications for financial technology going forward, and they raise important questions and challenges for the regulators. However, they are simply not central to the case for drastically scaling back paper currency. Regardless of whether the first generation of crypto currencies survives the next decade, the public ledger encryption technology they pioneer might provide a roadmap to better security over a broad range of financial transactions. Further, the author is of the view that international factors are important and can potentially affect the design and implementation of any plan to phase out paper currency, but, overall, these issues should not alter the scenario where the costs outweigh the benefits. A coordinated phase-out of currencies in advanced countries could be the most desirable policy.

This book, which is backed by compelling arguments and evidence, has the potential to serve as an important guide for moving towards a less cash economy and ultimately towards a cashless economy. The book is persuasive enough to motivate policymakers to recalibrate their own currency reforms.

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