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Green Swans and their Economic Impact on Indian Coastal States

Saurabh Ghosh, Sujata Kundu and Archana Dilip*

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The paper attempts to analyse the causal impact of natural disasters on output growth, agricultural productivity, inflation, tourism, fiscal parameters, and the cost of borrowing of Indian coastal states. It considers five states along the western coastline, *i.e.*, Gujarat, Maharashtra, Goa, Karnataka and Kerala, and four states along the eastern coastline *i.e.*, West Bengal, Odisha, Andhra Pradesh and Tamil Nadu and their eight neighbouring inland states in order to assess the impact. Difference-in-difference regression results covering the sample period 2011-12 to 2019-20 indicate that natural disasters lower output growth, raise inflation and dampen tourist arrivals, while borrowing costs largely remain unaffected. Some of these adverse effects also persist in the subsequent years. Eastern coastal states appear to have learnt and adapted better, given their long history of dealing with fierce natural disasters. For enhancing resilience of those directly affected, it is necessary to strengthen disaster management capabilities, incentivise green projects, undertake scenario analyses for effective policy preparedness and promote green finance.

JEL Classification: C33, E31, O13, Q54

Keywords: Green swan, panel data, difference-in-difference, green finance

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* Saurabh Ghosh (saurabhghosh@rbi.org.in) is Director at the Department of Economic and Policy Research, Reserve Bank of India. Sujata Kundu (skundu@rbi.org.in) and Archana Dilip (adilip@rbi.org.in) are Assistant Advisers at the Department of Economic and Policy Research and the Department of Statistics and Information Management, Reserve Bank of India, respectively. The authors are thankful to Rakhe Paluvai Balachandran and an anonymous referee for their valuable comments and suggestions on the paper. The views expressed in this paper are those of the authors and do not represent the views of the institutions they are affiliated with.

Introduction

Green swans[1] or climate black swans have many features of typical black swans, such as their unexpected and rare nature of occurrences, wide-ranging impact and also that they can be explained only after the event has occurred. The Bank for International Settlements (BIS) defines two sets of risks associated with climate change that are of particular concern, *viz.*, *physical risks and transition risks* (BIS, 2021a). Physical risks arise from climate and weather related catastrophe events, such as droughts, floods, storms and rise in sea levels which cause damages to property, land and infrastructure. Apart from these direct impacts, physical risks could emerge indirectly through ensuing events such as disruption of global supply chains and lower productivity of agriculture and consequently, inflation. The transition risks, on the other hand, refer to the financial risks which emanate from the process of adjustment towards a lower carbon economy. While this transition creates opportunities for innovation, investment and potential green growth, changes in climate policy, technology or market sentiment could lead to re-pricing of a range of assets and may turn out to be crucial for the soundness of financial firms.

Climate-related risks are generally fat-tailed distributions, with both physical and transition risks being characterised by deep uncertainty and non-linearity. According to Weitzman (2009), their chances of occurrence are not reflected in past data, but there is a possibility of extreme values. Green swans are different from black swans in three aspects, *viz.,* certainty, intensity and complexity (Bolton *et al.*, 2020). Although the impact of climate change is uncertain, there is a high degree of certainty that some combination of physical and transition risks will materialise in future (NGFS, 2019).

Central banks are increasingly focusing on the risks from climate change for the economy and financial system. Since the issue is multifaceted, it requires calibrated policy responses, even within a central bank, as climate change and related policies could have a potential impact on key economic indicators relevant to monetary policy. These include output growth, inflation, investment, and the cost of funds.

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[1] Green swans or green swan events, extreme weather events and natural calamities have been used synonymously in this paper.

Given the degree of interconnectedness in the economy and the financial system, it is important to assess both the direct impact of physical and transition risks and the indirect and second-round effects. This implies accounting for exposures along the whole production chain, the transmission of shocks through financial linkages and feedback loops between the macroeconomy and the financial sector. This poses challenges for assessing the channels that could affect the economy and financial system. There is also considerable uncertainty about future developments in policy, technology, natural environment and other factors related to climate change.

India was placed at the seventh position in the list of most affected countries in terms of exposure and vulnerability to extreme weather events in 2019 after Mozambique, Zimbabwe, the Bahamas, Japan, Malawi and Afghanistan (Global Climate Risk Index, developed by Germanwatch), though in terms of long-term average score for the period from 2000 to 2019, India did not feature in the ten worst affected economies. An analysis of major weather-related events in the Indian context since 1901 reveals significant changes in climatic patterns in the past two decades with increased volatility in precipitation patterns relative to the long period average (LPA) and rising annual average temperature levels (Dilip and Kundu, 2020). The dynamics of the South-west Monsoon (SWM) have also changed over the years with the withdrawal dates of monsoon showing a delay which has a significant impact on the cropping seasons/patterns. Importantly, in India, growth and inflation outlook continue to be heavily influenced by the amount of rainfall and its distribution during the SWM season (June-September). Moreover, along with the gradual changes in temperature and rainfall patterns, the incidence of extreme weather events, such as excessive rainfall often leading to floods, severe temperature fluctuations (*e.g.*, heat waves and cold waves) and cyclones are being witnessed with rising frequency and intensity. Unseasonal rainfall, which heavily impacts the outlook on food inflation has also been a rising concern in recent years. The regional spread of these extreme weather events shows that some of the major agricultural states (either food grain or cash crop producers) are the most affected ones (particularly, Andhra Pradesh, Odisha, West Bengal, Gujarat, Maharashtra and Madhya Pradesh). With this background, it would be interesting to study the impact of extreme weather events, in particular cyclones, floods and droughts, that have become a regular feature in India on some of the crucial macro, fiscal and financial indicators.

In the Indian context, we found limited literature that analyses the causal impact of these green swan events with an appropriate identification strategy. We, therefore, attempt to bridge this gap by considering the Indian coastal states that are directly affected by these extreme events and compare the economic parameters of these states with a control set of neighbouring inland states. This research design, using the difference-in-difference (D-i-D) panel data based econometric approach, evaluates the causal impact of green swan events on income, agricultural yields, tourism, inflation, fiscal parameters and cost of borrowings. The findings suggest that natural calamities cause a decline in economic growth and have a lingering impact on income growth; a decline in the yields of vegetables and fruits and tourist arrivals; a rise in inflation; and that the spillover impact of such extreme events persists in the subsequent years.

The paper is structured as follows. Section II provides a brief review of literature related to the impact of climate-related risks on the economy and the available mitigation options. The stylised facts with respect to the changing climate pattern witnessed in India over the years, with a particular focus on coastal states are presented in Section III. Section IV describes the data used in the empirical analysis. Section V presents the D-i-D research design used to study the causal effects of natural calamities on an array of macro variables in India comprising Gross State Domestic Product (GSDP), agricultural yields, inflation, fiscal and financial variables. The empirical findings are also presented in Section V. Section VI provides an overview of the green finance policy and the mitigation policy recommendations. Concluding remarks are provided in Section VII.

Section II
Review of Literature

Studying the impact of climate change on the economy is an age-old area of interest for economists. Some of the earliest works in this sphere date back to as far as Fisher (1925), which examined the effects of rainfall on the yields of wheat. Climate change can be considered as an exogenous factor that drives or influences economic activity and macroeconomic outcomes. In the recent times, with climate change and its associated extreme weather events becoming a major challenge globally, questions concerning weather conditions and their impact on the macroeconomy are increasingly gaining the spotlight.

Across the literature reviewed, many broad themes emerge and most studies have focussed on the range of channels through which extreme weather events affect an economy. The most recent studies including Batten *et al.* (2020) and BIS (2021a; 2021b) have thrown light on the major climate-related risks and their transmission channels. BIS (2021b) provided an overview of the conceptual issues related to climate-related financial risk measurement, methodologies and practical implementation by banks and supervisors. The report addressed the need for sufficiently granular and forward-looking measurement methodologies to capture the unique features of climate-related financial risks. BIS (2021a) explored how climate-related risk drivers, both physical and transition risks, impact the banking system through microeconomic and macroeconomic transmission channels. While the microeconomic transmission channels include the causal chains by which climate risk drivers affect banks' individual counterparties, the macroeconomic transmission channels refer to the mechanisms by which climate risk drivers affect macroeconomic factors like labour productivity and economic growth. These channels also capture the effects of market variables like risk-free interest rates, inflation, and foreign exchange rates. The report also highlighted the variation in economic and financial market impacts of physical and transition risks based on geography, sector and economic and financial system development. The geographical heterogeneity is driven by factors including differences in the likelihood and severity of climate risk drivers, structural differences in economies and markets that affect the importance of various transmission channels and differences in financial systems that impact banks' exposures to climate-related risks. Furthermore, Batten *et al.* (2020) reviewed the channels through which climate risks could affect central banks' monetary policy objectives and the possible policy responses. The paper also discussed various approaches that aim to incorporate climate change in central bank macro-modelling frameworks.

Secondly, there are various studies that have analysed the impact of different dimensions of climate change on different aspects of an economy (Dell *et al.,* 2014). Under this category, studies may be further divided into: (i) studies that consider many countries simultaneously and; (ii) studies that concentrate upon a particular economy. The popular studies in the former category include Kahn *et al.* (2019) that considers 174 countries, and Feyen *et al.* (2020) that considers many countries from East Asia and the Pacific (EAP), Europe and Central Asia (EAC), Latin America and Caribbean (LAC), Middle East and North Africa (MENA), South Asia (SA) and Sub-Saharan Africa (SSA). In order to study the long-term impact of climate change on economic output across countries, Kahn *et al.* (2019) used a panel dataset of 174 countries for the period from 1960 to 2014 and found that per capita real output growth is adversely affected by persistent deviations in temperature from its historical norm. Feyen *et al.* (2020) studied the inter-relation between macro-financial and climate-related risks and highlighted that many countries face the double-jeopardy of simultaneous elevation of both risks. The authors highlighted that the climate changes and consequent macroeconomic changes will have significant impact on the balance sheets of key economic entities. Transition risks are likely to be high for countries that generate a significant share of public revenue from carbon-intensive industries. On the central banking and monetary front, their research indicated that the interactions between climate change, climate policies, and monetary conditions and management are in a relatively nascent stage. However, climate-related financial risks may weaken financial sector balance sheets and induce or amplify macro-financial risks as physical impacts of climate change can lead to heightened operational, credit, market, and liquidity risks for banks. The paper suggested that banks need to build capacity and integrate climate factors into all aspects of their operations. It also suggested a slew of policy measures and concluded that the implementation of climate mitigation and adaptation measures could be a significant driver of economic growth.

Several studies have looked at the influence of changing weather realisations on agricultural and industrial output, labour productivity, demand for utilities like energy and health services and overall economic growth by concentrating on an individual economy. Most of the studies under this category pertain to developed economies. For instance, Bloesch and Gourio (2015), using a panel of states of the United States (US), found evidence supporting the view that weather conditions impact economic activity, particularly in sectors such as utilities, construction, hospitality and retail, even though the impact could be short-lived. Another study using a panel regression framework with GSDP and average seasonal temperature data for US states found that a rise in summer temperature has an adverse effect on GSDP growth, while a rise in the average temperature during the autumn season positively affects GSDP growth, although the impact is weaker and less robust (Colacito *et al.,* 2018). A study by Tokunaga *et al.* (2015) identified the impact of global-warming-induced climate change on Japan's agricultural production using both static (using a function for agricultural products incorporating labour, temperature, solar radiation and precipitation) and dynamic (using a production function for agricultural products incorporating labour, one-period lagged output and the three weather variables indicated above) panel data models on a cross-section of eight regions in Japan for the period 1995-2006. The paper concluded that an increase of 1^{o}C in mean annual temperature results in a fall of rice production by 5.8 per cent and 3.9 per cent in the short-term and long-term, respectively, while in the case of vegetables, production falls by 5.0 per cent and 8.6 per cent in the short-term and long-term, respectively.

Lastly, the emerging research has considered other important channels or dimensions like cross-border effects. While studying the cross-border spillovers of physical climate risks through trade and supply chain linkages, Feng and Li (2021) observed that globalisation increased the similarity of countries' global climate risk exposures. On the basis of historical data from 1970-2018, the paper argued that exposures to foreign climate-related disasters among important trade partner countries could have negative effects on the stock-market valuation of the aggregate market and for the tradable sectors in the home-country. The paper further observed that the extent of financial stability implications depends on country-specific factors like the size of tradable sectors to the overall economy and exposure of domestic banks to tradable sectors.

In the Indian context, the studies are generally based on quantifying physical risks and analysing the impact on different aspects of macro economy. Using a pooled mean group regression technique on state-level panel data, Parida and Dash (2019) found that floods negatively impact per capita GSDP in the long run. Studies focusing specifically on the impact of climate-related risks on the agriculture sector pointed out the adverse impact of weather-related events on crop yields. For example, Barve *et al*. (2019) showed that both rainfall and temperature-related unfavourable shocks adversely affect rice yields. Another paper by Madhumitha *et al.* (2021), studying the impact of adverse rainfall events in the agriculture sector, suggested that crop diversification could be useful towards mitigating climate-related challenges and risks in the agriculture sector particularly in areas that lack specialisation in a particular crop or are lesser advanced in terms of irrigation facilities. However, the paper also indicated that the method may not provide positive results during extreme drought situations.

Empirical findings based on pair-wise Granger-causality tests using annual data (1960-2014) in the Indian context, provided in Dilip and Kundu (2020), showed that economic activity measured by Gross Domestic Product (GDP) per capita causes carbon dioxide (CO_2) emissions, which in turn causes an increase in average temperature. Moreover, the results also indicated the existence of a bi-directional causality between temperature and GDP per capita. With respect to rainfall, the findings showed that rainfall affects the availability of gross irrigated area, which in turn affects agricultural yield (output and/or sown area). Further, it was noted that rainfall deviation is associated with food inflation (particularly inflation in vegetables and fruits), and the impact generally lasts for 5-6 months (Dilip and Kundu, 2020). An increase in the inflation of vegetables and fruits may significantly distort the overall food inflation path as these comprise a significant share of the food basket. The paper also highlighted through empirical analysis that weather conditions have a significant impact on some of the key indicators of economic activity like Purchasing Managers Index (PMI), Index of Industrial Production (IIP), demand for electricity, trade, tourist arrivals, and tractor and automobile sales.

Although there is limited literature on transition risks in the Indian setup, Agarwal (2021) highlighted India's path towards climate change objectives as ratified in the Paris Agreement (PA)[2]. The paper cited the estimates of Climate Action Tracker to argue that India will comfortably surpass the targets set in the PA. The paper also pointed out that India is currently at a developmental stage (although emitting lesser than other countries when they were at a similar stage) and emissions would increase with increasing per capita GDP. However, since emissions and GDP per capita have an inverted U-shaped relationship, emissions are expected to decline after a peak. Further, the author mentioned that the vulnerable groups of the population may be protected while transitioning to carbon neutrality. The author cited research done in this area and inferred that carbon taxes may be used to finance cash transfers to poorer households. Thus, this kind of policy may have a distributional impact on the population of a country.

Finally, in line with the existing global literature, the studies in the Indian context have also reviewed and recommended mitigation policies including green finance policies. Green finance has become a public policy priority all over the world. As noted by Ghosh *et al*. (2021), India has pushed forward green finance in relevant sectors in line with the global practices. Green bonds have constituted around 0.7 per cent of all the bonds issued in India since 2018, and the combined outstanding bank lending (excluding personal loans) by the public sector and private sector banks to the non-conventional energy is around 7 per cent of the outstanding bank credit into the utility sector (electricity, gas and water supply), as on March 2019. Ghosh *et al*. (2021) highlighted that most of the green bonds in India are issued by the public-sector units[3] or corporates with better financial health. Although the

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[2] Under the PA, India is expected to (i) reduce the emissions intensity of GDP by 33-35 per cent below the 2005 level by 2030; and (ii) increase the share of non-fossil energy in total power generation capacity to 40 per cent.

[3] For instance, Indian Railway Finance Corporation Limited, Rural Electrification Corporation Limited and Power Finance Corporation Limited.

value of green bonds issued in India since 2018 has constituted a very small portion of the total bond issuance, India has maintained a favourable position as compared to several advanced and emerging market economies (EMEs). Two sectors that account for a large portion of the fossil fuel consumption in India are power generation and automobile industry. However, the share of automobile production in the aggregate bank credit is much smaller, at only 1.2 per cent (Ghosh *et al*., 2021).

Both Ghosh *et al*. (2021) and Dilip and Kundu (2020) emphasised on the importance of awareness creation as the first step, which would be the prime responsibility of the governing bodies. There is a paucity of data for assessing the awareness regarding green finance and sustainable development from conventional sources (including statutory organisations, central banks). In this regard, Google Trends can be a powerful tool for understanding the dynamics of Google searches made in different locations at different points in time. Evidence based on Google Trends suggests an increase in awareness about green finance and its role in sustainable economic development (Ghosh *et al*., 2021).

Section III
Stylised Facts

The global phenomenon of climate change and the associated extreme weather events have emerged as key risks to the macroeconomic outlook of both developed economies and EMEs. Extreme weather events may be classified into four different types: geophysical (avalanche, landslides, earthquakes, volcanic eruptions); hydrological (floods, tsunami); meteorological (cyclones, droughts, heat waves, cold waves, thunderstorms, tornadoes); and climatological (arising from change in temperature and precipitation patterns).[4]

III.1 Losses due to Natural Disasters

In terms of damage to infrastructure, crops and livelihood, floods are the costliest, causing 63 per cent of damage, followed by cyclones (19 per

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4 Categorisation as used in Munich Re NatCatSERVICE database.

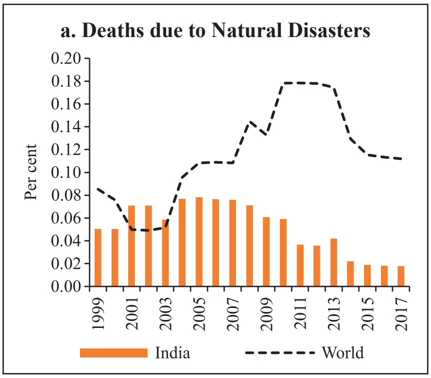
cent), earthquakes (10 per cent) and droughts (5 per cent). In terms of human casualties in India, earthquake is the most lethal with 33 per cent of casualties, followed by floods (32 per cent), cyclones (32 per cent) and landslides (2 per cent) (World Bank, 2012). In 2020, India was ranked third after China and the US in recording the highest number of natural disasters over the last 20 years (UN, 2020).

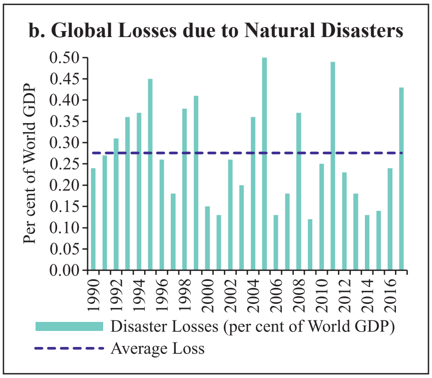
In the demographic front, globally, deaths caused by natural disasters stood at around 0.1 per cent on an average in the previous three decades (1990-2017), while in the case of India it was 0.04 per cent. Importantly, over the years, the percentage of deaths owing to natural calamities has fallen considerably on account of technological advances and improved early warning systems, large-scale government initiatives with regard to relief measures and pro-active disaster management policies (Chart 1a). However, natural calamities take a huge toll on the overall macroeconomic outcomes. Globally, economic loss due to natural calamities during the past three decades has ranged from 0.12 per cent to 0.50 per cent of world GDP (Chart 1b).

III.2 Change in Climatological Pattern in India

Change in overall climatic conditions has become increasingly visible in India. While annual average temperature has recorded a steady rise over the years, annual average rainfall shows a sharp decline (Chart 2a). Further,

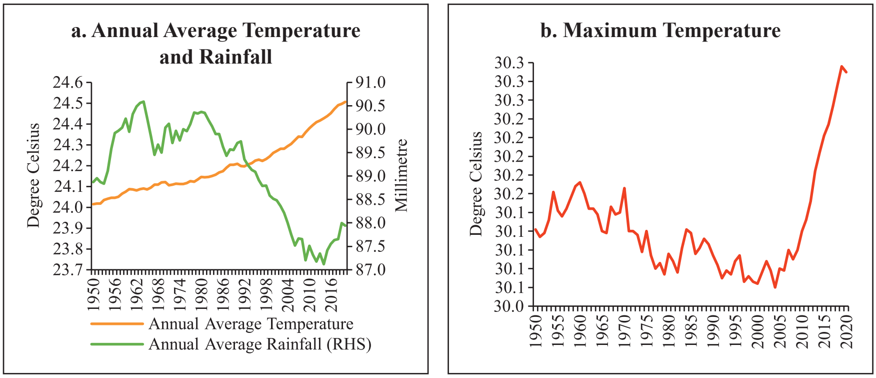
Chart 1: Losses due to Natural Disasters





Note: Chart 1a plots 10-year moving averages of deaths due to natural disasters during 1990-2017.
Source: https://ourworldindata.org/ ; and Authors' calculations.

Chart 2: All India Temperature and Rainfall Pattern



Note: Charts 2a and b plot 50-year moving averages during 1901-2020.

Source: https://climateknowledgeportal.worldbank.org/ ; and Authors' calculations.

annual maximum temperature has witnessed a steep increase during the past two decades (Chart 2b).

III.3 Extreme Weather Events in the Indian Coastal States: Frequency and Intensity

Based on the frequency of occurrence of extreme weather events in the recent times, it can be seen that the coastal states in India are affected mainly by cyclones, floods, droughts and rising sea levels.

III.3.1 Cyclones

Twelve decades of data (1901-2020) on cyclonic storms reveal that over the years, the frequency of severe cyclonic storms (intensity: ≥ 48 knots) has increased in India (Table 1). Further, the distribution of cyclones across the Bay of Bengal and the Arabian Sea show that there is a sharp jump in the occurrence of cyclonic storms over the Arabian Sea, which is in sharp contrast to the historical pattern. The pattern in the recent two decades (2001-2020) reveals that the average number of cyclones in the Arabian Sea equalled that of the Bay of Bengal, which is two cyclones per year. Historically, this number has been lower in the Arabian Sea as compared to that in Bay of Bengal.

Further, a state-wise distribution of severe cyclones reveals that the number of cyclones that occurred in the states of Odisha, Andhra Pradesh and Tamil Nadu in the eastern coast of India during 1961-2020 was much higher

Table 1: Frequency and Intensity of Cyclones

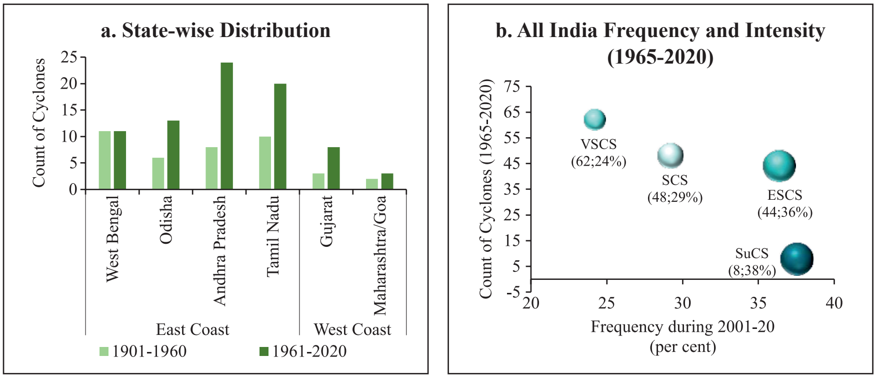
Period	Number of Cyclones			Per cent		Average per Year	
	Cyclones (>=34 knots)[5]						
	Bay of Bengal (1)	Arabian Sea (2)	Total (3)	Bay of Bengal (4)	Arabian Sea (5)	Bay of Bengal (6)	Arabian Sea (7)
Full Period: 1901-2020	474	126	600	79	21	4	1
Sub-period: 1901-1960	267	53	320	83	17	4	1
Sub-period: 1961-2020	207	73	280	74	26	3	1
Sub-period: 2001-2020	49	32	81	60	40	2	2
	Severe Cyclones (>= 48 knots)						
Full Period: 1901-2020	219	78	297	74	26	2	1
Sub-period: 1901-1960	90	30	120	75	25	2	1
Sub-period: 1961-2020	129	48	177	73	27	2	1
Sub-period: 2001-2020	26	22	48	54	46	1	1

Source: India Meteorological Department (IMD); and Authors' calculations.

than that during 1901-1960 (Chart 3a). Additionally, in the west coast, the incidence of severe cyclonic storms in Gujarat increased significantly during 1961-2020 as compared to Maharashtra and Goa. With regard to the intensity of severe cyclonic storms (SCS), the India Meteorological Department (IMD) classifies severe cyclones into the following four categories: severe cyclonic storms (SCS: 48-63 knots), very severe cyclonic storms (VSCS: 64-89 knots), extremely severe cyclonic storms (ESCS: 90-119 knots) and super cyclonic storms (SuCS $\geq$ 120 knots). Data available for the period from 1965 to 2020 show that out of the eight super cyclonic storms that occurred during this period over the north Indian Ocean, three of them (*i.e.,* 38 per cent) occurred during 2001-2020 (Chart 3b).

[5] Columns 4 and 5 in Table 1 report percentages of cyclone occurrences and not actual numbers of cyclones.

Chart 3: Severe Cyclones – State-wise Distribution, Frequency and Intensity



Note: Chart 3a does not include Karnataka and Kerala because Karnataka did not have any severe cyclone during the specified period, while Kerala had 1 severe cyclone during 1901-1960. In Chart 3b bubble size represents frequency of the cyclone during 2001-2020 (in per cent), while bubble colour represents the intensity of the cyclone. The progress from a lighter to a darker shade indicates an ascending order of intensity. SCS: Severe Intensity Storm; VSCS: Very Severe Intensity Storm; ESCS: Extremely Severe Intensity Storm; SuCS: Super Cyclonic Storm.

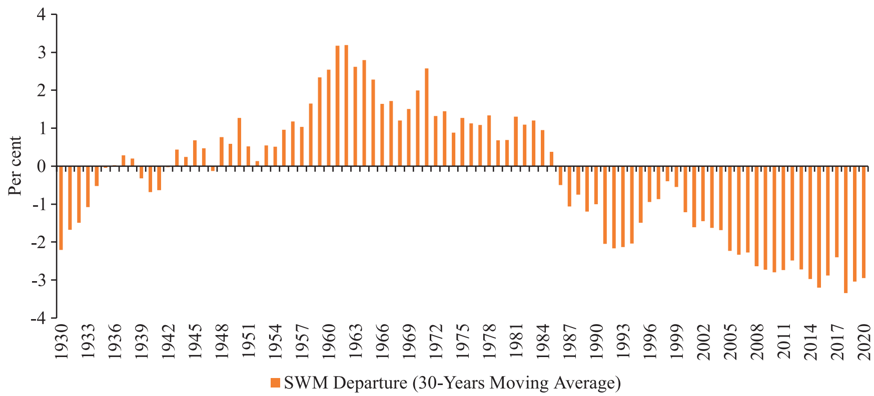
Source: India Meteorological Department (IMD).

III.3.2 Droughts and Floods

Hydroclimatic extremes such as droughts and floods are characteristic features of any monsoonal landscape. Droughts over India are typically associated with prolonged periods of abnormally low monsoon rainfall that can last over a season or longer and may also affect several states at a time (Sikka, 1999). The overall decrease in annual rainfall in India as shown previously in Chart 2a is primarily a result of a decline in the rainfall received during the SWM season. India receives around 75 per cent of its annual rainfall during these four months of the year. However, data reveal that over the years, average monsoon departures from the LPA rainfall have largely tended to be below normal (Chart 4).

This trend is also reflected in the incidence and intensity of droughts in the country. The number of droughts that occurred in India during 1961-2020 stood at 14 as compared to eight during 1901-1960 (Table 2). Further, in terms of drought intensity, years with severe droughts were also higher during 1961-2020.

Chart 4: All India South-west Monsoon Departure from LPA (1901-2020)



Source: IMD; and Authors' calculations.

The frequency and intensity of floods and droughts are significantly associated with the spatial and temporal distribution of SWM in India. In addition, the occurrence of major floods and torrential rains has been reported largely since 2004, while unseasonal rainfall has been an increasing cause of worry since 2011 (Dilip and Kundu, 2020). In this paper, we study in detail the frequency of floods and droughts in the coastal states. We also make a

Table 2: Frequency and Intensity of Droughts in India (1901-2020)

Period	Drought Years (South-west Monsoon Departure)									Drought Frequency (Severe Droughts)
1901-1930	1901 (-13)	1904 (-12)	**1905 (-17)**	1911 (-15)	**1918 (-25)**	**1920 (-17)**				6 (3)
1931-1960	1941 (-13)	**1951 (-19)**								2 (1)
1901-1960	8 drought years (3 severe drought years)									8 (3)
1961-1990	**1965 (-18)**	1966 (-13)	1968 (-10)	**1972 (-24)**	1974 (-12)	**1979 (-19)**	1982 (-15)	1986 (-13)	**1987 (-19)**	9 (4)
1990-2020	**2002 (-19)**	2004 (-14)	**2009 (-22)**	2014 (-12)	2015 (-14)					5 (2)
1961-2020	13 drought years (5 severe drought years)									14 (6)

Note: Here we have considered SWM departure below (-)10 per cent as drought years and below (-)15 per cent as severe drought years. While droughts are generally classified based on standardised precipitation index (SPI), different methods to obtain the SPI may significantly alter the classification of drought years (moderate to severe). Years in bold indicate severe drought years.

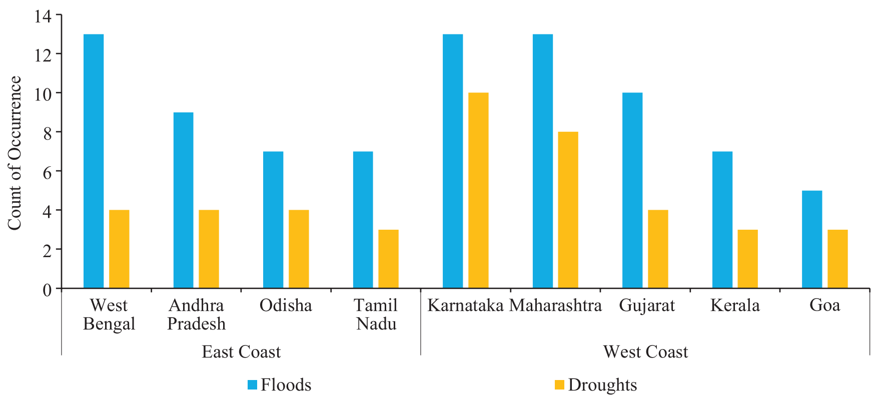
Source: IMD; Nandargi and Aman (2017); and Krishnan *et al.* (2020).

spatial comparison of the regions within these states that are heavily affected by floods and droughts (Annex Table I). Data reveal that the eastern coastal states of West Bengal and Andhra Pradesh are more prone to the occurrence of floods and droughts. On the other hand, in the western coast, Karnataka and Maharashtra are the two states that have seen the highest frequency of floods and droughts during 1951-2020 (Chart 5). In the case of Karnataka, the interior regions of the state are more prone to droughts, while the northern interior region is more prone to floods as compared to the southern interior region. The Central and Vidarbha regions of Maharashtra are more prone to the occurrence of droughts, while both Marathwada and Vidarbha regions are prone to floods.

III.3.3 Rise in Sea Level

The rise in sea level has a significant impact on the densely populated coastal areas and the low-lying islands around the globe. As noted by Krishnan *et al.* (2020), the Indian Ocean region is home to roughly 2.6 billion people (around 40 per cent of the global population) and is rich in marine ecosystem. Therefore, the rise in sea level poses a challenge to population, economy, coastal infrastructure and marine life. Further, some of the largest cities in India are located along India's long coastline, which makes them extremely vulnerable to the impact of rising sea level with the risks including loss of land due to erosion, damage to coastal projects, infrastructure and power plants,

Chart 5: State-wise Frequency of Floods and Droughts



Source: IMD; and Nandargi and Aman (2017).

Table 3: Trends in Sea Level Rise at Selected Tide-gauge Locations

Station	Period	Trends in relative sea level rise (mm/year)	Net sea level rise trend (mm/year)
Mumbai	1878-1993	0.77 ± 0.08	1.08
Kochi	1939-2007	1.45 ± 0.22	1.81
Visakhapatnam	1937-2000	0.69 ± 0.28	0.93
Diamond Harbour (Kolkata)	1948-2010	4.61 ± 0.37	4.96

Note: Table shows sea level trends (relative to land surface) with glacial isostatic adjustment (GIA)-corrected net sea level trends.
Source: Unnikrishnan *et al.* (2015).

salinisation of freshwater and increased vulnerability to flooding (Krishnan *et al.*, 2020). Although data are not available for a comparable period in the Indian context, rising sea level can be witnessed in four major coastal locations *viz.,* Mumbai, Kochi, Vishakhapatnam and Kolkata (Table 3).

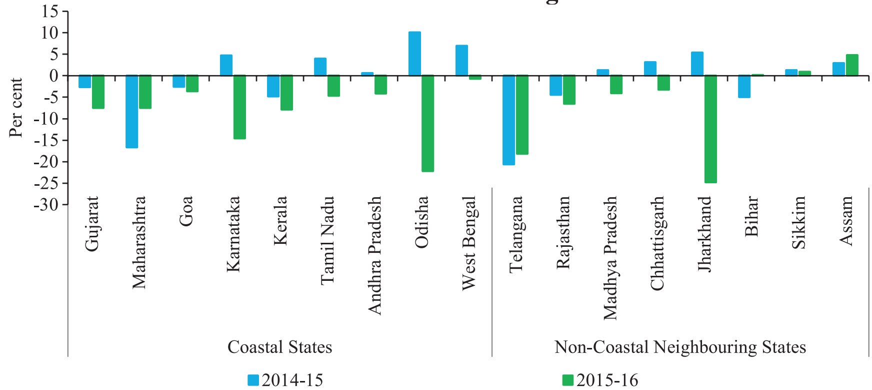
It can be seen that the maximum rise in sea level was witnessed in Diamond Harbour, Kolkata which is along the eastern coastline of India. This may be attributed to the higher frequency of cyclone occurrences along the eastern coastline.

III.4 Impact of Climate Change on Agriculture

Agriculture is one of the most important sectors of the Indian economy. The deviations in the pattern of SWM can adversely affect the agricultural sector and the macroeconomy. In the recent times, highest deficit in rainfall in terms of SWM departure from LPA was witnessed in 2014 and 2015. This period also witnessed late arrivals of SWM (Dilip and Kundu, 2020). Chart 6 shows the comparison of the growth rates in GSVA-Agriculture for coastal states with their neighbouring non-coastal states.

It can be seen that lower than average rainfall is generally accompanied by lower growth in GSVA-Agriculture of coastal states. The negative growth rates are more prominent in the western coastal states than their eastern counterparts. Incidentally, during the considered time periods, the third strongest cyclone of the Arabian Sea, *Nilofar*, peaked in October 2014 causing damage along the western coastline. Like the coastal states, the non-coastal neighbouring states were also seen to be more affected in 2015-16.

Chart 6: Growth of GSVA-Agriculture



Note: GSVA: Gross State Value Added.
Source: NSO, MoSPI; and Authors' calculations.

Section IV
Data and Description

This section presents the data-related details for the empirical section of our paper. Our paper considers the nine coastal states of India and their eight non-coastal neighbours (Chart 7). The coastal states include the five states along the western coastline (Gujarat, Maharashtra, Goa, Karnataka and Kerala) and the four states along the eastern coastline (West Bengal, Odisha, Andhra Pradesh and Tamil Nadu). It may be reiterated that our paper purely focuses on the causal impact of the frequently occurring natural calamities (floods, droughts and cyclones) in the coastal states *vis-à-vis* their non-coastal neighbouring counterparts as these are some of the most densely populated states in India with large-scale economic activity and are adversely affected by these calamities almost every year. As seen in the earlier sections, floods and cyclones have amplified adverse impacts on infrastructure and livelihood and are responsible for a significant number of human casualties in India. Although flood and drought affect both coastal and non-coastal parts of the country, anecdotal evidences suggest that their intensities are more in the coastal states. Moreover, cyclones generally originate in either the Bay of Bengal or the Arabian Sea and, therefore, are more frequent in coastal states. The frequency of inland cyclones in India is minimal. The cyclone proneness of the different districts of India for the period from 1891 to 2008 reveals that districts along the eastern coastline are more prone to cyclones as the highest

Chart 7: Coastal and Non-coastal Neighbouring States

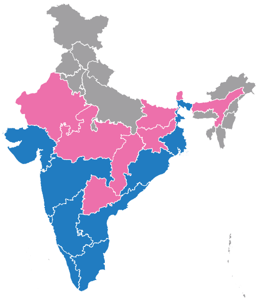
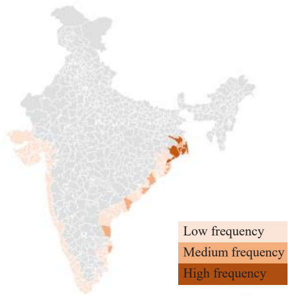


Chart 8: District-wise Cyclone Proneness of Coastal Areas



Note: In chart 7 the coastal states are shown in blue, while the non-coastal neighbouring states (Rajasthan, Madhya Pradesh, Telangana, Chhattisgarh, Jharkhand, Bihar, Sikkim and Assam) are shown in pink. The rest are not a part of our empirical analysis and are shaded in grey.
Source: National Disaster Management Authority.

frequency of cyclone occurrences is witnessed in the districts of West Bengal and Odisha (Chart 8).

The sample period covered for the analysis is 2011-12 to 2019-20 and the natural calamities (extreme weather events based on frequency of occurrence) considered are floods, droughts and cyclones that occurred in the coastal states during this period (Annex Chart I).[6] Although the sample period is short, the consideration of the data period is justified considering the continuously changing climatic patterns across the country. In comparison to the years prior to 2011-12, it is the past decade which has witnessed a considerable reduction in deaths due to extreme weather events (Chart 1a), a significant change in average rainfall pattern (Chart 2a), a drastic increase in maximum temperature (Chart 2b) and changes in SWM departure from LPA (Chart 4). Further, the consideration of this sample period eliminates the possible impact of structural changes in macroeconomic variables and introduction of new base years for some of them. The details of the intensity of the calamities during the period under consideration are provided in Annex Table II.

In order to study the causal effects of the green swan events on macroeconomic and financial variables (including income, agricultural yields, tourism, inflation, fiscal parameter and cost of borrowings) of coastal states

6 The monthly data for inflation spans from January 2011 to March 2021.

by controlling for the neighbouring landlocked states, state-wise data are obtained for all the considered 17 states. Annual growth rates are used in the case of most variables and the detailed description of variables along with their data sources is given in Annex Table III. The variables are categorised into five groups: (i) Output and per capita output; (ii) Agricultural yield; (iii) Inflation (headline and food inflation); (iv) Fiscal parameters (gross fiscal deficit, capital and revenue expenditures); and (v) Financial services [yields of State Development Loans (SDLs)], tourist visits, foreign direct investment (FDI) inflows, area insured under weather-based crop insurance). The data are sourced mainly from the National Statistical Office (NSO) under the Ministry of Statistics and Programme Implementation (MoSPI); Department of Agriculture, Cooperation and Farmers Welfare (DAC&FW) under the Ministry of Agriculture and Farmers Welfare (MoAFW); and the Reserve Bank of India (RBI)'s State Finance: A Study of Budgets.

The select dependent variables aim to represent different aspects of the Indian macroeconomy. The causal impact of green swan events on macroeconomic variables like income, growth, inflation, tourism and agricultural yields is intuitional and straight-forward. In order to meet the targets of pollution curtailment as per the PA, the Government may introduce new environmental policies, including fiscal measures impacting both taxation and expenditure. Therefore, it would be interesting to analyse the impact of green swans on fiscal parameters. Further, the occurrence of green swan events may trigger negative sentiments among the investors and this could adversely affect the cost of borrowing and investment inflows. By considering SDL yields and FDI inflows, we explore the impact of green swans on market sentiments. In order to review the extent of implementation, utilisation and efficiency of measures taken by the Government to ameliorate the adverse effects of climate-related risks, the causal impact of green swan events on weather-based crop insurance, in terms of area insured is analysed.

Section V
Empirical Findings

V.1 Methodology

Our objective in this paper is to study the causal effects of natural calamities on an array of macro variables that include GSDP, agricultural yield, fiscal variables, and a set of financial variables. In the absence of random draws, we use the D-i-D strategy to evaluate the causal effects of these calamities (random experiments), by splitting our sample into treatment and control groups. From geographical locations, we first identify the coastal states as these have been repetitively impacted by natural calamities in the recent years; this constitutes the treatment group for our study. Next, we select a set of neighbouring landlocked states that are: (i) less affected by the natural calamities; and (ii) similar in terms of production and household behaviour. These are the control set of states for our experiment. Though the treatment and control sets are not perfectly comparable, we try to achieve the best matching, in view of the common trend assumption in the D-i-D models. Then we compare the deviation in the common trend between the treatment (coastal) states and the control (neighbouring but landlocked) states before and after an experiment (the occurrence of a natural calamity in our case). The central assumption is that the unobserved differences between the treatment and control groups that are unrelated to natural calamity must be common over time, and therefore, will be cancelled out while differencing, and thereby address the omitted variables problem.[7]

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[7] An attractive feature of the D-i-D estimation technique is that it can remove any surprises from unobserved covariates due to time-invariant differences between the comparison groups by assuming that the effects of these surprises do not change over time. D-i-D also assumes that any time effects (for instance, macroeconomic shocks) are common to the treatment groups under evaluation. The combination of these two assumptions, often referred to as the 'parallel trends assumption', implies that without the intervention, outcomes for the treated and the control groups would have followed parallel trajectories over time. The synthetic control method is another popular approach to analyse causal impact of an exogenous event and/or policy interventions (Abadie and Gardeazabal, 2003; Abadie *et al*., 2010). It relaxes the parallel trends assumption and allows the effects of observed and unobserved predictors of the outcome to be time-variant, while assuming that pre-intervention covariates have a linear relationship with outcomes post-treatment. Therefore, the synthetic control method is popularly employed in cases when the validity of the parallel trends assumption is questionable (particularly, in areas of health policy evaluations). However, the credibility of the synthetic control method depends to a large extent on its ability to steadily track the trajectory of the outcome variable for the affected unit before the intervention. Furthermore, it also requires extensive post-intervention information/data that allows for a complete picture of the intervention effect in time and across the various outcomes of interest. In our study, the adjusted sample period in the estimation exercise spans over a period of 8 years, which may not cover more than one business cycle. Moreover, our analysis attempts to study the impact of exogenous weather-related shocks that are by nature different from artificial policy interventions, in which case the impact of the intervention could be long-drawn. Therefore, D-i-D is an appropriate method in the context of our study.

V.1.1. Model Specification

Our basic D-i-D-equation includes four variables: the dependent variables (y_{it}), a dummy for the treatment states ($coastal_D$), another dummy for the natural experiments, which takes the value one for the calamity years, and zero otherwise ($calyear_D$), and finally an interaction term, which is generated by multiplying these two dummies ($D\text{-}i\text{-}D{=}coastal_D{*}calyear_D$).[8] This is a typical research design in a D-i-D model, where the coefficient of the interaction term captures the causal effect of the natural calamity. Thus, our basic regression model is as under:

$$y_{it} = \beta_0 + \beta_1 \times (coastal_D) + \beta_2 \times (calyear_D) + \delta \times (D - i - D) + \epsilon_{it} \quad \ldots (1)$$

We use each of the state specific macro variables (an exhaustive list is reported in Annex Table III) as dependent variables in our model. Then in each of the regressions, the coefficients could be interpreted as follows:

Mean of non-coastal states, normal times: β_0;

Mean of coastal states, normal times: $\beta_0 + \beta_1$;

Mean of non-coastal states, calamity times: $\beta_0 + \beta_2$;

Mean of coastal states, calamity times: $\beta_0 + \beta_1 + \beta_2 + \delta$;

In equation 1, coefficient β_1 captures systematic differences between our treatment group and control group, while β_2 captures the changes in the treatment group *vis-a-vis* the control group during the calamity times, which is our natural experiment.[9] Finally, and perhaps the most important one is the coefficient δ, which captures the difference between the changes in the coastal states compared to the non-coastal states during the natural calamity years.

In our second model, we modify the interaction term (D-i-D) to include its lead and lag. This helps us to analyse the changes in the dependent variables y_{it} in the coastal states relative to their neighbouring states one year

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8 As the purpose is to compare the mean impact of green swan events for all coastal states *vis-à-vis* their non-coastal neighbouring states, a calamity year dummy is used, which deviates from the usual technique of the number of treatments being restricted to one per cross-sectional unit setup.

9 β_2, unlike a typical textbook D-i-D setup, is not a pure time dummy. Instead, it is a calamity year dummy, which takes the value 1 in a calamity year and the value 0, otherwise.

preceeding the natural calamity and one year succeeding the calamity. Our modified set of equation is as under:

$$y_{it} = \beta_0 + \beta_1 \times (coastal_D) + \beta_2 \times (calyear_D) + \sum_{t-1}^{t+1} \delta_t \times (D - i - D) + \epsilon_{it} \quad \text{... (2)}$$

Where, there are three coefficients of δ that help us to compare calamity year with its immediate past and future.[10]

In our next research design, we replace the uniform coastal dummy ($coastal_D$) by a set of dummies for each state, excluding one. Similarly, we create time dummies for each year, excluding one, for the sample group. This is in the spirit of a fixed effect panel data model, which helps us to control for each of the state specific and time specific effects. Finally, we introduce the D-i-D dummy for estimating the causal interferences. This is in spirit of the research design followed by Angrist and Pischke (2014) in their analysis of Minimum Legal Drinking Age (MLDA) regressions for US. The regression equation is as under:

$$y_{it} = \beta_0 + \sum_{1}^{16} \beta_i \times (State)_i + \sum_{2012}^{2018} \beta_t \times (Year)_t + \delta \times (D - i - D) + \epsilon_{it} \quad \text{... (3)}$$

While such a regression setup helps us to control for any state or time specific effects and relax the common trend assumption, there is a caveat. Such a regression would generally require a large number of observations to estimate all state and time dummies. In the MLDA case, there were 14 years of data for 51 states leading to 714 observations. However, in our case there are a total of 136 observations, and therefore, the estimated coefficients might have some small sample biases.

Using weighted regression rather than ordinary least squares (OLS) generally increases the precision of the regression estimates. Considering the possibility of differences in error variance across states, we consider a cross-section weighted feasible generalised least squares (GLS) specification assuming the presence of cross-sectional heteroscedasticity. In such a specification, inverse of standard errors across groups are used as weights.

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10 In equations (1) and (2), the mean impact of the select natural calamities for all coastal states is compared *vis-a-vis* the non-coastal neighbouring states. This research design is borrowed from the synthetic control literature in D-i-D which involves the construction of a weighted combination of groups used as controls to which the *treatment group* is compared. Here, for simplicity, we use equal weight for the coastal states (treatment group) *vis-à-vis* non-coastal neighbouring states (placebo states).

Further, as state-year panel stacks observations on states over time, they often report serial autocorrelation over time within states or within the same period between states. In such a situation our hypothesis testing result may lead to misleading conclusions. To address this problem, we use clustered standard errors, which takes into account any sort of period dependence observed in the sample dataset. Based on these three equations, our empirical findings are discussed in the following sub-sections.

V.1.2 Matching of Treatment and Counterfactual States

Section IV presented the analysis for the coastal states and their non-coastal neighbouring counterparts. A district-wise matching would have been a better approach as against the state-wise matching based on the criterion if a state is coastal or not. However, the non-availability of data for most of the considered macroeconomic variables at the district level restricted us from performing the matching based on districts. While the states may be similar regarding some of the key macroeconomic parameters, the difference lies in the fact that the coastal states are directly and frequently impacted by the natural calamities such as cyclones as compared to their neighbouring non-coastal counterparts which are impacted only indirectly. The causal inference used in the empirical analysis is based on these characteristics of coastal states and their neighbouring inland states, thus conferring to the requirements of D-i-D framework.[11]

In terms of key macroeconomic indicators like GSDP and per capita net state domestic product (NSDP), the coastal states share similarities with their non-coastal neighbouring counterparts.[12] To achieve a state level matching, state-level correlations were computed spanning the entire sample period for these economic variables, which also reveal similarities with the neighbouring states (Annex Tables IV a and b). The pattern of crop production based on favourable farming conditions across the geographically neighbouring states

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[11] A popular approach that is widely used in the literature for the matching of the cross-sectional units is the propensity score matching technique. However, the method is applicable in frameworks having a fairly large number of cross-sectional observations, among which certain units are selected on the basis of propensity scores. This may not be applicable in this paper, as our sample is restricted to 17 states only.

[12] Correlation between the growth rates of GSDP (per capita NSDP) of coastal states *vis-à-vis* the non-coastal states considered in our sample during 2012-13 to 2019-20 is 0.87 (0.84).

also indicate certain similarities. For instance, Maharashtra, Madhya Pradesh, Rajasthan, Andhra Pradesh and Karnataka are some of the largest producers of pulses and maize in India, while West Bengal, Assam and Bihar are some of the key producers of jute and paddy. Gujarat, Maharashtra and Rajasthan are the key producers of oilseeds. Furthermore, the average headline inflation ranged between 5.3 per cent and 6.5 per cent for the coastal and non-coastal states during the period under consideration.

The correlation matrices, based on the entire sample period, presented in Annex Tables V to VIII reveal that the matching of states (treatment group *versus* placebo group) may not be entirely full-proof as some of the neighbouring states do not share a significantly high correlation across all the select macroeconomic parameters considered in our study.[13] Therefore, all the select macroeconomic parameters and the coefficients may not be perfect as some of the neighbouring states do not share a significantly high correlation. To address this particular concern, we estimate Model-3 [equation (3)] wherein we replace the uniform coastal dummy ($coastal_D$) by a set of dummies for each state (excluding one), and for each year (excluding one) for the sample group. This method, following Angrist and Pischke (2014), is a useful one because it allows for every state to have a different intercept term, which captures that all states are differently placed. As noted by Angrist and Pischke (2014) "... Samples that include many states and years allow us to relax the common trends assumption, that is, to introduce a degree of non-parallel evolution in outcomes between states in the absence of a treatment effect".

Further, there could be a possibility that the selected set of states might have a different time trend altogether and are not comparable under the D-i-D framework. To check for this possibility, following Rambachan and Roth (2019) and Bilinski and Hatfield (2018), we then assume that the pre-existing difference in trends persists, and to simply extrapolate this out we introduce a time trend t [index time from (1, ..., T)] and coastal state dummy interaction by augmenting Model-3. This coefficient, if found significant, assumes that the difference in trends would continue to hold. However, the coefficient

[13] The correlation tables for yields of foodgrains across states could not be presented due to lack of variance in the data related to the same.

associated with the time dummy for our sample turned out to be statistically insignificant.

Though a typical regression coefficient test or propensity matching test of parallel trends may not be appropriate in the present set-up, we attempted to ensure that untreated units provide the appropriate counterfactual based on a reasonable set of logical assumptions, which include neighbouring state matching, incorporating state-specific dummies for different intercepts, and by incorporating a time trend assumption.

V.2 Output and Per Capita Output

A core concern in policymaking is identifying the signs of expansions and contractions in economic activity. In this section, we attempt to evaluate the impact of natural calamities on GSDP, which is our dependent variable for the regression equations. We take GSDP growth rates rather than levels because, in an emerging market like India, we generally witness growth cycles rather than business cycles (Bhadury *et al.*, 2021). Considering the heterogeneity of Indian states in terms of their size and population density, we also consider per capita NSDP growth for the states as a dependent variable. The basic D-i-D regression results [equation (1)] and the interaction coefficient (D-i-D) that reports the causal impact of natural calamities on GSDP growth of the coastal states are reported in Table 4 (columns 1 and 2). The interaction

Table 4: Full Sample Results *(Contd.)*

	Output and Per Capita Output		**Agricultural Productivity**			
	GSDP	**Per Cap. NSDP**	**GSVA Agri**	**Foodgrains Yield**	**Vegetables Yield**	**Fruits Yield**
	(1)	(2)	(3)	(4)	(5)	(6)
Coastal Dummy	1.42***	6.39***	-7.01***	0.20*	6.21***	2.28***
	(0.09)	(0.79)	(1.86)	(0.11)	(0.51)	(0.25)
Calyear Dummy	0.99	5.52***	-9.91***	0.02	0.31***	0.64**
	(1.09)	(0.25)	(0.82)	(0.05)	(0.08)	(0.20)
D-i-D	-1.24***	-5.62***	6.96***	0.11	-0.52***	-0.65**
	(0.29)	(0.84)	(2.00)	(0.07)	(0.09)	(0.26)
Constant	6.01***	-	10.28***	1.86***	13.29***	12.72***
	(1.08)		(0.38)	(0.04)	(0.18)	(0.28)
N	122	122	122	119	111	110
R^2	0.04	-0.19	0.21	0.20	0.83	0.13
F Statistic	1.63	-	10.51	9.57	170.88	5.13

Table 4: Full Sample Results *(Concld.)*

	Fiscal Parameters			Tourism and Other Financial Services			
	GFD	**CAPEX**	**Revenue Exp.**	**Tourist Visits**	**Weather-Based Insurance**	**FDI Inflows**	**SDL Yields**
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Coastal Dummy	-	1.06	-2.73*	8.36***	-4.02	-6.58	-0.07***
		(0.84)	(1.52)	(0.23)	(4.33)	(34.54)	(0.00)
Calyear Dummy	-	0.58	-2.12	0.51	42.24	-44.10	-0.02
		(1.03)	(1.64)	(1.51)	(29.05)	(41.20)	(0.48)
D-i-D	-0.02	3.18**	1.16	-2.61**	-14.14	29.20	0.11
	(0.36)	(1.29)	(1.82)	(0.85)	(8.78)	(51.86)	(0.06)
Constant	3.15***	3.41***	15.50***	5.97***	5.39	57.70	8.12***
	(0.33)	(0.95)	(1.40)	(0.60)	(25.57)	(34.54)	(0.46)
N	50	120	119	120	77	108	117
R^2	0.00	0.09	0.06	0.20	0.11	0.03	0.003
F Statistic	0.01	3.98	2.55	9.89	2.88	0.92	0.12

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

term reports a negative and significant coefficient when GSDP growth is taken as the dependent variable (Column 1). We also observe a similar negative and significant coefficient of the D-i-D term when per capita NSDP is used as the dependent variable.

We also estimate equation (2), which includes the lead and lag of the interaction dummy in addition to the contemporaneous term. These results indicate that the coefficients associated with D-i-D(-1) (*i.e.*, the lagged term) of GSDP growth and per capita NSDP growth are not statistically significant (Table 5). This is in line with our expectation as natural calamities are exogenous events. Further, as in the previous section, the contemporaneous coefficients were found to be statistically significant, supporting substantial damage in GSDP due to these calamities. Furthermore, the negative and significant coefficients after the natural calamity year indicate that the impact of natural calamities could be prolonged and may spill over to the subsequent years. It was indeed intriguing to find that some of these coefficients reported higher numbers as compared to the calamity years indicating long-lasting impact.

Table 5: Difference-in-Differences with lead-lag *(Contd.)*

	Output and Per Capita Output		Agricultural Productivity			
	GSDP	Per Cap. NSDP	GSVA Agri	Foodgrains Yield	Vegetables Yield	Fruits Yield
	(1)	(2)	(3)	(4)	(5)	(6)
Coastal Dummy	4.24***	4.13***	-4.68**	0.10	4.59***	2.32
	(0.66)	(1.10)	(1.67)	(0.15)	(0.56)	(1.80)
Calyear Dummy	-0.77*	-1.22**	-16.58***	-0.01	0.12	0.77
	(0.33)	(0.37)	(0.75)	(0.07)	(0.10)	(0.84)
D-i-D(-1)	-0.82	-0.41	-8.12***	0.02	0.13	0.59*
	(0.51)	(0.84)	(0.96)	(0.02)	(0.39)	(0.28)
D-i-D	-1.79***	-1.15**	8.51***	0.17*	-0.14	-0.88
	(0.31)	(0.44)	(1.18)	(0.10)	(0.25)	(0.88)
D-i-D(+1)	-1.96***	-2.07***	3.73***	0.05	1.21***	0.23
	(0.24)	(0.41)	(0.79)	(0.04)	(0.23)	(0.22)
Constant	7.72***	6.44***	15.58***	1.89***	13.50***	12.47***
	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(1.20)
N	102	102	102	102	96	95
R^2	0.13	0.19	0.38	0.21	0.78	0.17
F Statistic	2.87	4.51	11.53	4.95	62.31	3.71

Table 5: Difference-in-Differences with lead-lag *(Concld.)*

	Fiscal Parameters			Tourism and Other Financial Services			
	GFD	CAPEX	Revenue Exp.	Tourist Visits	Weather-Based Insurance	FDI Inflows	SDL Yields
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Coastal Dummy	-	2.18	-9.10***	5.73**	18.32	8.69	-0.35***
		(9.99)	(2.75)	(2.15)	(39.50)	(42.92)	(0.10)
Calyear Dummy	-	-1.12*	-0.56	-3.05*	130.71***	37.97	0.85***
		(0.46)	(2.47)	(1.40)	(29.71)	(30.80)	(0.08)
D-i-D(-1)	0.37	4.13	1.87*	-0.27	-49.66***	39.60	0.18***
	(0.37)	(5.40)	(0.95)	(1.21)	(13.43)	(21.46)	(0.04)
D-i-D	-0.24	-2.11	2.71	0.98	-19.23	-55.12	0.12
	(0.33)	(4.52)	(2.80)	(1.76)	(34.28)	(34.40)	(0.10)
D-i-D(+1)	0.53	3.85	3.42***	-3.29**	16.74	17.70	0.22***
	(0.33)	(4.85)	(1.22)	(1.03)	(15.92)	(21.46)	(0.06)
Constant	2.74***	5.07***	15.19***	11.53***	-73.68***	7.28***	7.43***
	(0.69)	(0.00)	(2.06)	(0.00)	(27.28)	(0.00)	(0.07)
N	42	101	100	101	72	102	99
R^2	0.06	0.17	0.14	0.08	0.63	0.03	0.40
F Statistic	0.81	3.82	3.11	1.67	22.29	0.67	12.34

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

Further, we estimate equation (3), which includes dummies for each state and year, and thereby controls for state specific heterogeneities and other evolving macroeconomic changes over the years. When GSDP growth is used as the dependent variable, the D-i-D coefficient reports a negative and significant coefficient, which supports our earlier findings (Table 6).

Table 6: Difference-in-Differences with Cross-section (State) and Time Dummies *(Contd.)*

	Output and Per Capita Output		Agricultural Productivity			
	GSDP	Per Cap. NSDP	GSVA Agri	Foodgrains Yield	Vegetables Yield	Fruits Yield
	(1)	(2)	(3)	(4)	(5)	(6)
D-i-D	-0.73*	-0.82	4.57***	0.22***	-0.71	-0.21
	(0.38)	(0.90)	(1.41)	(0.03)	(0.45)	(0.68)
Cross Section Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.60***	6.34***	0.29	1.96***	16.73***	14.08***
	(0.15)	(0.36)	(0.58)	(0.01)	(0.16)	(0.25)
N	122	122	122	119	111	110
R^2	0.44	0.45	0.35	0.91	0.87	0.91
F Statistic	3.14	3.26	2.16	41.50	26.64	42.16

Table 6: Difference-in-Differences with Cross-section (State) and Time Dummies *(Concld.)*

	Fiscal Parameters			Tourism and Other Financial Services			
	GFD	CAPEX	Revenue Exp.	Tourist Visits	Weather-Based Insurance	FDI Inflows	SDL Yields
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
D-i-D	0.01	4.14**	0.64	-2.02	0.93	-0.39	0.02
	(0.40)	(1.71)	(2.62)	(1.91)	(12.39)	(91.54)	(0.06)
Cross Section Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.38***	5.24***	12.34***	11.40***	34.39***	57.90	8.11***
	(0.38)	(0.64)	(1.14)	(0.83)	(5.31)	(37.29)	(0.03)
N	50	120	119	120	77	108	117
R^2	0.72	0.45	0.25	0.30	0.54	0.19	0.95
F Statistic	15.43	3.18	1.32	1.72	3.09	0.84	66.08

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

Our empirical results indicate that natural calamities cause a decline in GSDP growth and per capita NSDP growth. Further, the results also suggest that such calamities could have a lingering impact on income growth and revival could take time, as indicated by the signs and higher magnitudes of the D-i-D(+1) coefficients in Table 5 (columns 1 and 2). This implies that the impact of calamity impacts on output growth could last at least more than a year and might signal lingering macroeconomic risks. Our findings are in line with Cavallo and Noy (2011). The study presented cross-country evidence and argued that natural disasters generally have a negative effect on economic growth. Turning to the EMEs and neighbouring countries of India, Karim (2018) for Bangladesh and Kurosaki (2015) for Pakistan documented adverse impact of natural disasters on income and growth. In the case of India, a recent study found both short-run and medium-run negative impact on economic growth (Sandhani *et al*., 2020). The study shows that for poorer districts, a rise in temperature by 1^{o}C leads to around 4.7 per cent decline in the growth rate of district per capita income.

V.3 Agricultural Productivity

Although the share of agriculture in the national income has been declining over the years, it still accounts for large-scale rural employment generation. Disruptions in foodgrains and vegetables production can result in volatility in inflation. Considering its overall importance and its dependence on weather conditions, particularly rainfall, we analyse the impact of natural calamities on agricultural productivity in this section. Following the seminal paper by Fisher (1925), we use yields of foodgrains, vegetables and fruits for our selected set of states as the dependent variables, as yields help us to standardise production per hectare of land and then compare the impact between coastal and inland states.

We estimate equation (1). The D-i-D coefficients for vegetables yield and fruits yield are reported in columns 5 and 6 of Table 4. These coefficients are negative and significant indicating that natural calamities cause a decline in vegetables yield and fruits yield, which is on expected lines. However, we did not find strong empirical evidence from equations (2) and (3), as most of these coefficients were found to be statistically insignificant.

Turning to foodgrains yield, most of its coefficients are found to be positive, though mostly statistically insignificant. The D-i-D coefficient for foodgrains yield in equation (3) reported a small positive value (Table 6, column 4) and was statistically significant.

Though contradictory, these results are in line with Albala-Bertrand (1993) that documented positive impact of natural disasters on agricultural output, and Loayza *et al.* (2012) which concluded that small disasters might, on an average, positively impact the macroeconomy. For India, natural disasters in the coastal states may not have a major impact on foodgrains production in their inland districts, and therefore, yield of foodgrains may not indicate a significant deterioration. Since foodgrains constitute a major portion of the gross value added (GVA) in the agricultural sector, we estimated all the three regressions using growth in agricultural GVA as the dependent variable and found empirical support of increase in agricultural GVA from the coastal states. While our results did not show any adverse impact of natural calamities on the yield of foodgrains, their impact on the quality of foodgrains is difficult to estimate using this framework.

The results could also indicate the significant role of policy interventions by the Government towards developing climate-resilient production techniques, particularly with respect to foodgrains, such as introducing drought/flood/temperature tolerant varieties in paddy and pulses in these states; water-saving paddy cultivation methods, advancement of *rabi* planting dates in areas with heat stress; and community nurseries as solutions for delayed monsoon arrival (NICRA[14], 2016).

V.4 Tourism

Tourism is an important segment of the Indian economy because of its horizontal and vertical linkages to several employment intensive ancillary segments. It accounts for around 7 per cent of the national GDP[15] and a significant percentage of GSDP of some of the coastal states (*e.g.*, Goa and

[14] National Innovations in Climate Resilient Agriculture (NICRA) was launched by the Indian Council of Agricultural Research with the funding from Ministry of Agriculture, GoI, in 2011.

[15] As per the data available from the World Travel and Tourism Council.

Kerala). Travel and tourism (T and T) is the largest segment of commercialised leisure, and as per the World Travel and Tourism Council, its contribution to the GDP and employment of the Asia-Pacific (APAC) region in 2019 stood at 9.9 per cent and 10.0 per cent, respectively. Expenditure in T and T (and leisure in general) is one of the important channels of transfer from upper-income households to lower-income workers. Considering its importance in overall services sector, some of the GDP nowcasting and forecasting models include activities in tourism sector as a coincident or lead indicator (Bhadury *et al.*, 2021). In this section, we attempt to analyse the causal impact of natural calamities on this crucial industry by considering state-wise total tourist arrivals as the dependent variable in our D-i-D framework.

In equation (1), which is our base model (Table 4, column 10), the interaction coefficient D-i-D is negative and significant, indicating that natural disasters cause a decline in tourist arrivals. In the same table, the coefficient of coastal dummy reports a positive and significant coefficient, indicating that tourist arrivals in the coastal states (the β_1 coefficient) are more than that of non-coastal states. Empirical results from equation (2), on the other hand, indicate that such natural calamities may have a lasting impact on tourist arrivals, as the coefficient of lead D-i-D is also found to be negative and significant (Table 5). These results are in line with the findings reported in Bloesch and Gourio (2015) for US states and Dilip and Kundu (2020) for India, supporting the view that weather conditions impact economic activity particularly in sectors such as utilities, hospitality and retail segments.

Tourism industry is perceived to have huge potential and is particularly an important source of income in some of the states. It has deep-rooted connections with the labour-intensive ancillary segments. Foreign tourist arrivals and air passengers had been secularly improving in India prior to the emergence of COVID-19 and the declaration of global lockdown particularly in 2020. The arrival of foreign tourists recorded an increasing trend during January 2003-March 2020 (Annex Chart IIa). The industry has also documented a seasonal pattern (Annex Chart IIb), which is a source of predictable income for many of the states. Our results indicate an adverse impact of natural disaster on this industry, which could also spill over in the immediate future years.

V.5 Inflation

To examine the impact of the natural calamities on inflation, we consider both headline inflation and food inflation for the select states. Favourable weather conditions are a prime requirement for maintaining robust agricultural output in any economy. In the case of India, the production and domestic availability of agricultural commodities are heavily dependent on conducive weather conditions. Weather-driven adverse supply shocks are a major cause of concern to the policymakers as they severely distort food prices. Since the food group constitutes a significant share (46 per cent) of the overall consumption basket in the all India consumer price index-combined (CPI-C), any upsurge in food prices not only pose significant upside risks for the headline inflation trajectory but may also feed into inflation expectations. Given this backdrop, we expect natural calamities in the coastal states to have an adverse effect on their food inflation *vis-à-vis* their non-coastal neighbours, implying that an occurrence of a natural calamity (cyclone; flood; drought) is expected to increase food inflation in the coastal states as compared to that in their non-coastal neighbouring counterparts. It is also expected that headline inflation, largely *via* the channel of food prices, would also increase in the coastal states owing to the occurrence of the natural calamity.

V.5.1 Annual Inflation

The impact of natural calamities on both headline and food inflation is presented in Table 7a. The basic D-i-D regressions with headline inflation and food inflation as the dependent variables in two separate models are presented in equation (1). The interaction coefficient (D-i-D) indicates the causal impact of the natural calamities on inflation, which is positive and statistically significant. The results suggest that the impact of natural hazards considered in the study is higher on food inflation as compared to headline inflation. The results in the generalised model, *i.e.*, equation (3), has positive and significant (D-i-D) coefficients and thus, support results from equation (1), indicating that a sudden spike in inflation is caused by the natural calamities.

The results corresponding to equation (2), which incorporates the lead and lag terms along with the contemporaneous term of the interaction dummy, seem to suggest that the natural calamities do not have a lasting and

Table 7a: Inflation – Full Sample Results (Annual Data)

Explanatory Variables	Equation (1)		Equation (2)		Equation (3)	
	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation
	(1)	(2)	(3)	(4)	(5)	(6)
Coastal Dummy	-0.84*** (0.17)	-0.44** (0.18)	2.01 (2.92)	6.18 (6.08)	-	-
Calyear Dummy	-2.63 (1.85)	-4.35 (3.10)	0.55 (1.03)	0.52 (1.62)	-	-
D-i-D (-1)	-	-	-2.10 (2.35)	-4.08 (4.34)	-	-
D-i-D	0.96*** (0.24)	1.11*** (0.31)	-0.37 (1.18)	-1.28 (2.26)	0.65*** (0.19)	1.25*** (0.34)
D-i-D (+1)	-	-	-0.34 (0.10)	-2.27 (2.46)	-	-
Constant	7.98*** (1.65)	7.97*** (2.38)	5.01*** (0.00)	4.66*** (0.00)	5.67*** (0.08)	4.43*** (0.14)
Cross-section Dummy	-	-	-	-	Yes	Yes
Time Dummy	-	-	-	-	Yes	Yes
N	136	136	102	102	136	136
R^2	0.13	0.11	0.11	0.11	0.84	0.91
F Statistic	6.63	5.49	2.44	2.39	24.15	47.20

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

persistent impact on inflation, and interestingly available literature supports this result. Studies have found evidence that the impact of natural hazards on food inflation is generally positive and short-lived (Parker, 2018; Freeman *et al.*, 2003; NGFS, 2020). However, Parker (2018) showed that the impact is heterogenous with respect to the type of the hazard and varies between advanced and developing economies. While storms may cause an immediate increase in food inflation, the impact could be reversed subsequently, resulting in no significant impact during the calamity year. Floods also have an immediate impact on food prices, especially in developing economies, and the impact lasts only in the period of flooding. Droughts, on the other hand, may cause headline inflation to rise significantly and the impact may persist for long. In the Indian context, it has been generally observed that the impact of a weather-induced supply shock (especially, floods/droughts) on food prices is largely restricted to perishable items (especially, vegetables and fruits) and the duration of the impact usually lasts for around 5-6 months (Dilip and Kundu, 2020). Pro-active supply management measures taken by the Government have a significant role in containing food price pressures. Our sample period is heavily skewed towards the incidence of floods and cyclones, which generally do not have a lasting impact on inflation. Therefore, in this section, unlike in the case of other macro-economic indicators (especially, GDP), equation (2) may not be an ideal/appropriate way of modelling the impact of the select natural calamities on inflation using annual data.

V.5.2 Monthly Inflation

Due to the availability of state-level monthly inflation data (January 2012-March 2021), we repeat the above analysis using month-wise headline inflation and food inflation. Here, we replace the calamity year dummy in equations (1), (2) and (3) with the calamity month dummy, where the dummy variable takes the value 1 for the calamity month and the value 0 otherwise. Table 7b presents the regression results.

Table 7b: Inflation – Full Sample Results (Monthly Data)

Explanatory Variables	Equation (1)		Equation (2)		Equation (3)	
	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation
	(1)	(2)	(3)	(4)	(5)	(6)
Coastal Dummy	-0.09 (0.07)	0.38*** (0.13)	-0.06 (0.11)	0.28 (0.22)	-	-
Calmonth Dummy	-0.45 (0.86)	0.34 (1.46)	-0.46 (0.86)	0.32 (1.37)	-	-
D-i-D (-1)	-	-	-0.13 (0.61)	0.61 (1.19)	-	-
D-i-D	0.37** (0.16)	0.45* (0.28)	0.49* (0.28)	0.41 (0.45)	0.37** (0.35)	0.46* (0.28)
D-i-D (+1)	-	-	-0.38 (0.80)	-0.34 (1.41)	-	-
Constant	6.06*** (0.27)	5.84*** (0.43)	6.07*** (0.27)	5.93*** (0.42)	5.97*** (0.01)	6.08*** (0.02)
Cross-section Dummy	-	-	-	-	Yes	Yes
Time Dummy	-	-	-	-	Yes	Yes
N	1853	1788	1819	1768	1853	1788
R^2	0.001	0.004	0.003	0.004	0.76	0.77
F Statistic	0.74	2.24	0.92	1.57	42.59	46.82

Note: **Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

We find that the results are broadly similar to that of the annual data, however, the coefficients are relatively lower in magnitude (in annual data there could be multiple calamities spread across months *vis-à-vis* monthly data where the impact largely captures the average impact per calamity in a month).[16] Interestingly, the coefficients associated with food inflation are higher in magnitude as compared to those of headline inflation. The adverse impact of natural calamities on food inflation is also substantiated by Annex Chart III. It shows that the calamity frequency is especially higher during the monsoon season (June-September), which also coincides with the major crop sowing season (*kharif*) in India.

To summarise, our empirical results with respect to inflation indicate that natural calamities have a positive impact on both food inflation and headline inflation with the impact being short-lived and generally restricted to the period of the calamity. Although transitory, the adverse impact on prices generally pose challenges for short-term inflation forecasting that involves nowcasting and near-term forecasting. Moreover, since short-term forecasting models are the satellite models feeding into the medium-term forecasting framework, forecast accuracy in the former becomes crucial from policy perspective. So far, climate-related risks have not been a major challenge for medium-term price stability in India under the flexible inflation targeting (FIT) framework. However, with the rising frequency and intensity of natural calamities, it is important that advanced climate-resilient horticulture techniques are adopted faster and effective supply management measures with a focus on processing, warehousing and storage facilities for the perishables (vegetables and fruits) are developed in order to reduce crop damages (so far, climate-resilient production methods and supply management measures have been mainly targeted towards maintaining the supply of foodgrains in India). Moreover, as India develops further, the demand for vegetables and fruits is expected to pick up. The growing penetration of organised retail chains would also support the demand for

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16 As a robustness check, we repeated a similar exercise done earlier in the case of output and per capita output, after dropping the flood and drought year dummies and only considering the cyclone years. In this case too, the results obtained were consistent with those presented in the paper.

these perishable food items. Thus, climate-related risks, which adversely affect their supply and in turn impact inflation, cannot be ignored.

V.6 Fiscal Parameters

State plays an important role when natural disasters affect life and livelihood as it is involved in safety and reconstruction work. In order to analyse the same, we primarily concentrate on changes in state's expenditure pattern owing to natural disasters.

Our base model [equation (1)] indicates a statistically insignificant revenue expenditure growth coefficient for the interaction dummy (Table 4, column 9)[17]. However, the D-i-D coefficient for capital expenditure (CAPEX) reported a positive and significant coefficient (Table 4, column 8). When we controlled for state and time-specific effects in equation (3), the D-i-D coefficient indicated a CAPEX growth during the natural calamity years (while revenue expenditure growth was found to be statistically insignificant), thus confirming the empirical findings of equation (1). This apparently conflicting empirical findings could be due to the fact that most of the rebuilding expenditures are generally classified as capital expenditure. Turning to the gross fiscal deficit (GFD) of the states, our results were not statistically significant across regression specifications.

In India, generally, state governments play a predominant role in rescue, relief and rehabilitation measures following a natural disaster, while centre has been playing a supporting role in terms of relief aids (Annex Chart IV). As the recurrence of such disasters is increasing over recent years, it is perhaps time to make adequate room in state budgets, at least in the disaster-prone states. This has also been advocated by Balasubramanian (2019) for India and Nakatani (2021) for disaster-prone small countries (*e.g.*, Papua New Guinea). Calamity risk budgeting and stress tests in the budgets of coastal states, especially in the states that experience natural calamities from medium to high intensity, may help mitigate the risks of these green swan events.

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[17] It is generally expected that the immediate relief aids post-natural disasters would show up in increased revenue expenditure. However, this may depend on the nature of disaster, and may be addressed in future research.

V.7 Other Financial Services

V.7.1 Cost of Borrowing - SDL Yields

SDLs in India refer to sovereign securities issued by various Indian states to raise funds. These are generally issued for meeting the state budget shortfalls and yields of these securities are market-determined set by way of consent granted by the Centre under Article 293(4) of the Constitution of India. Each state can borrow through SDL up to a set (yearly) limit, and SDLs are eligible for the RBI's repo and for meeting Statutory Liquidity Ratio (SLR) requirements. They are also eligible for assets as level 1 high-quality liquid assets (HQLA) for liquidity coverage ratio (LCR) maintenance in India, given that states are fiscal sovereigns driving power through the Constitution to raise resources. The cut-off yields of these securities are determined through the RBI's dedicated electronic auction platform (e-Kuber), and secondary market transactions are on Negotiated Dealing and Order Matching System (NDS-OM) that is in line with other dated government securities. In theory, given the marketable nature of such securities, yield is likely to represent the financial health of the issuing state. Using SDL yields as a proxy, we therefore, attempt to evaluate whether a natural disaster could significantly affect borrowing costs or cost of funds.

To analyse the same, we follow the D-i-D research design, as highlighted in section V.1, and evaluate the sign and significance of the interaction term or the D-i-D coefficients. Our regression results indicate that the D-i-D coefficients, though positive, are not statistically significant. These results are uniform across all the three equations (Tables 4, 5 and 6, column 13) indicating that natural disasters do not cause an increase in cost of funds (or SDL yields). The coastal dummy coefficient in equation (1) has a marginally (7 basis points) negative coefficient, which could be due to the fact that some of the financially strong states are in the coastal areas.

This result of insignificant D-i-D coefficient is consistent with literature in the Indian context. Bose *et al.*, (2011) and Saggar *et al.*, (2017) found empirical evidence that suggest no observable relationship between borrowing spreads of SDLs and states' fiscal health, and states could mobilise funds at similar or near similar yields for the similar securities (RBI, 2019). In India, as a market development measure, an Automatic Debit Mechanism (ADM) was introduced for state governments to increase the confidence of investors (RBI, 2020); wherein RBI has the power to repay SDLs. Therefore, SDLs are generally considered risk-free by market participants irrespective of the issuing states and are assigned a zero-risk weight in capital to risk-weighted assets (CRAR) calculations of banks. This may explain our findings regarding the insignificant coefficients of the cost of borrowing caused by these natural calamities. It could also be the case that so far market participants have assigned a limited impact of climate change risks on key macro outcomes of states and therefore, do not expect a higher risk premium on SDLs following a major climate event.

V.7.2 Weather Based Insurance and FDI Inflows

In India, restructured weather-based crop insurance scheme has been published by the DAC&FW, which cover major food crops (cereals, millets and pulses) and oilseeds, commercial / horticultural crops. All farmers, including sharecroppers and tenant farmers, growing the notified crops in the notified areas are eligible for coverage and the state-wise data for the same are available for some of our sample states. Based on the available data, we estimated the D-i-D coefficients for weather-based crop insurance. However, these coefficients were mostly statistically insignificant (Tables 4 to 6, column 11). This could be because of expanding coverage of such insurance schemes and the relatively lower coverage of farmers witnessed in recent years (Annex Chart V).

We also have state-wise data on FDIs, which help to test the causal impact of natural calamities on FDI destinations. However, our regression coefficients were largely found to be statistically insignificant (Tables 4, 5 and 6; column 12). FDIs are generally long-term investments that are undertaken after a large number of field-studies and feasibility analyses. Therefore, it is possible that these projects closely consider the possibility of occurrence of such green swan events before investing and are often located in the inland districts. Therefore, natural calamities may not have significantly impacted the capital inflows.

V.8 Natural Calamities in East Coast vis-à-vis West Coast

India is a large country and the states on the eastern coast differ considerably from those in the western coast in terms of income, production, consumption and other behavioural patterns. Data presented in section III of our paper show that the eastern coastal states have seen a higher incidence of cyclones and floods than their western counterparts historically. However, the section also revealed some facts indicating that these green swan events have increased in the recent years on the western coast. Therefore, considering that the Arabian Sea has emerged as a major source of severe cyclones with their intensity aggravating over time, we analyse the devastation caused by these green swan events in the eastern coastal states *vis-à-vis* their western counterparts in this section.

At the sub-sample level (eastern coastal states *versus* western coastal states), our empirical analysis indicates that natural calamities have a statistically significant negative impact on the GSDP growth of western coastal states, while for the eastern coastal states the impact is rather muted (Tables 8 a and b, Column 1). Turning to fiscal side, CAPEX shows a large positive coefficient for the western coastal states, which may indicate extensive

Table 8a: Sub-Sample Results – Eastern Coastal States

	Output and Per Capita Output		Fiscal Parameters			Tourism and Other Financial Services			
	GSDP	Per Cap. NSDP	GFD	CAPEX	Revenue Exp.	Tourist Visits	Weather-Based Insurance	FDI Inflows	SDL Yields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coastal Dummy	-0.85*	-0.36	0.49***	-0.83	-0.34	3.36	-0.09	25.78	-0.04
	(0.47)	(0.54)	(0.00)	(0.68)	(1.04)	(3.38)	(13.02)	(29.45)	(0.12)
Calyear Dummy	-0.09	0.03	0.15	-0.37	-0.80	1.23	13.74	-25.82	-0.09
	(0.35)	(0.42)	(0.12)	(0.36)	(0.81)	(1.49)	(13.83)	(26.18)	(0.08)
D-i-D	1.17**	0.63	0.49*	0.69	-0.80	-1.80	-29.06*	-6.51	0.04
	(0.55)	(0.63)	(0.22)	(0.57)	(1.17)	(3.31)	(16.34)	(43.71)	(0.12)
Constant	7.14***	5.93***	2.65***	4.56***	13.21***	8.34***	23.57*	44.91***	8.17***
	(0.33)	(0.41)	(0.00)	(0.36)	(0.84)	(1.39)	(11.77)	(15.40)	(0.05)
N	122	122	38	120	119	120	77	108	117
R^2	0.23	0.01	0.19	0.01	0.03	0.02	0.06	0.03	0.01
F Statistic	1.02	0.22	2.59	0.21	1.07	0.68	1.64	1.10	0.24

Table 8b: Sub-Sample Results – Western Coastal States

	Output and Per Capita Output		Fiscal Parameters			Tourism and Other Financial Services			
	GSDP	Per Cap. NSDP	GFD	CAPEX	Revenue Exp.	Tourist Visits	Weather-Based Insurance	FDI Inflows	SDL Yields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coastal Dummy	1.47** (0.70)	1.58*** (0.57)	-1.55*** (0.37)	4.72 (3.19)	-2.01* (1.04)	3.64 (2.45)	-10.40 (10.50)	5.93 (8.80)	0.05 (0.09)
Calyear Dummy	0.19 (0.34)	0.43 (0.40)	0.25 (0.46)	1.21*** (0.37)	-2.06* (1.07)	-2.83** (1.31)	22.53* (11.12)	14.71 (17.17)	-0.23*** (0.05)
D-i-D	-1.01* (0.54)	-0.94 (0.56)	0.05 (0.40)	5.89** (2.80)	2.75* (1.41)	1.71 (2.54)	5.80 (13.97)	-27.70 (24.96)	-0.04 (0.10)
Constant	6.74 (0.27)	5.30*** (0.37)	4.19*** (0.41)	3.17*** (0.36)	13.78*** (0.71)	9.58*** (1.05)	19.74** (7.77)	33.28*** (6.97)	8.23*** (0.06)
N	122	122	50	120	119	120	77	108	117
R^2	0.06	0.07	0.37	0.24	0.04	0.14	0.08	0.01	0.05
F Statistic	2.49	3.01	8.91	12.54	1.80	6.50	1.99	0.22	2.15

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

rebuilding expenditure incurred by these state governments during/after these green swan events (Tables 8 a and b, Column 4).

Next, we evaluate the impact of calamities on inflation of the western and eastern coastal states separately as the overall impact would be a result of how food inflation is impacted in the two treatment groups. The results are presented in Tables 9 a, b and c. The results corresponding to equations (1) and (3) are broadly similar and indicate that western coastal states experience a larger impact of the natural calamities on their inflation as compared to their eastern counterparts. In the case of eastern coastal states, the impact is restricted only to food inflation. One of the possible reasons could be differences in the production baskets of eastern coastal states *vis-à-vis* western coastal states. Literature has showed that natural calamities cause larger damage to the production and supply of perishable food items, particularly vegetables and fruits, and thus, pose a higher upside risk on their prices. The coastal states of India are some of the major producers of the primary vegetables (potato, tomato and onion) in the country. While the western coastal states of Maharashtra and Karnataka largely cater to onions and tomatoes, the eastern

Table 9a: Inflation – Sub-Sample Results [Equation (1)]

Explanatory Variables	Eastern Coastal States (Annual)		Eastern Coastal States (Monthly)		Western Coastal States (Annual)		Western Coastal States (Monthly)	
	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coastal Dummy	0.24	0.08	0.28*	0.29**	-0.77***	-0.08	-0.32***	0.10
	(0.36)	(0.49)	(0.15)	(0.12)	(0.28)	(0.40)	(0.09)	(0.16)
Calyear/Calmonth Dummy	-0.18	-0.79*	0.35**	1.59	-3.60***	-7.14***	-2.37***	-2.74***
	(0.54)	(0.40)	(0.15)	(1.52)	(0.27)	(0.44)	(0.45)	(0.81)
D-i-D	-0.18	0.27	0.22	0.66*	0.99*	0.52	1.01***	1.10**
	(0.51)	(0.88)	(0.20)	(0.39)	(0.52)	(0.71)	(0.22)	(0.48)
Constant	6.03***	5.35***	5.90***	5.93***	7.84***	8.42***	6.23***	6.23***
	(0.21)	(0.24)	(0.11)	(0.40)	(0.19)	(0.27)	(0.27)	(0.45)
N	136	136	1853	1788	136	136	1853	1788
R^2	0.002	0.01	0.002	0.01	0.41	0.48	0.03	0.02
F Statistic	0.10	0.24	1.76	5.39	30.25	41.02	20.81	10.11

Table 9b: Inflation – Sub-Sample Results [Equation (3)]

Explanatory Variables	Eastern Coastal States (Annual)		Eastern Coastal States (Monthly)		Western Coastal States (Annual)		Western Coastal States (Monthly)	
	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D-i-D	-0.04	0.29	0.26	0.62*	0.86**	0.84	1.09***	1.18***
	(0.33)	(0.24)	(0.24)	(0.37)	(0.36)	(0.60)	(0.28)	(0.47)
Cross-section Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.94***	4.88***	5.99***	6.10***	5.81***	4.80***	5.98***	6.09***
	(0.05)	(0.04)	(0.00)	(0.01)	(0.05)	(0.09)	(0.01)	(0.01)
N	136	136	1853	1788	136	136	1853	1788
R^2	0.84	0.91	0.75	0.77	0.84	0.91	0.76	0.77
F Statistic	23.66	45.69	42.52	46.80	24.62	46.39	42.90	46.95

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

Table 9c: Inflation – Sub-Sample Results [Equation (2)]

Explanatory Variables	Eastern Coastal States (Annual)		Eastern Coastal States (Monthly)	
	Headline Inflation	Food Inflation	Headline Inflation	Food Inflation
	(1)	(2)	(3)	(4)
Coastal Dummy	0.20	0.03	-0.26***	0.19
	(0.15)	(0.24)	(0.10)	(0.18)
Calmonth Dummy	0.35	1.54	-2.38***	-2.81***
	(0.93)	(1.57)	(0.45)	(0.81)
D-i-D (-1)	0.87	2.82	-0.64	-0.42
	(0.96)	(1.84)	(0.46)	(1.32)
D-i-D	0.29	0.92**	1.77***	2.13*
	(0.36)	(0.45)	(0.56)	(1.12)
D-i-D (+1)	0.02	1.02	-1.32***	-2.18*
	(1.21)	(1.94)	(0.44)	(1.29)
Constant	5.91***	5.99***	6.24***	6.30***
	(0.24)	(0.42)	(0.28)	(0.45)
N	1819	1768	1819	1768
R^2	0.004	0.01	0.04	0.02
F Statistic	1.46	4.88	14.73	7.87

Note: ***Significant at the 1 per cent level; **Significant at the 5 per cent level; *Significant at the 10 per cent level. Heteroscedasticity consistent clustered standard errors in parentheses.

coastal states of West Bengal and Odisha are the major producers of potatoes and Andhra Pradesh is a key tomato supplier. India's experience with floods/extreme rainfall events suggests a greater impact on the prices of onions and tomatoes as compared to that of potatoes since potatoes are relatively less perishable in nature as well as have a better supply management infrastructure with respect to availability of go-downs and cold storages. Further, the western coastal states are also some of the key producers of fruits like oranges and grapes, the production of which is also impacted by the natural calamities. The blossoming season of Nagpur orange generally overlaps the months when the frequency of natural calamities is high. Another reason could be that with repeated incidence of cyclones and floods, the eastern coastal states may have initiated and developed better crop management practices and climate-resilient horticulture techniques as compared to the west coast of India.

We also consider looking at equation (2) comprising lead and lag interaction dummies along with the contemporaneous one, but we restrict our analysis only to monthly data. Table 9c presents the results. The results are largely in line with what we have obtained for equations (1) and (3), although the contemporaneous interaction dummy shows a higher coefficient for the west coast equations. Further, the coefficient associated with D-i-D(+1) turns out to be negative and significant, indicating that the impact of the calamity could be restricted only to the calamity month for the western coastal states. Our findings are broadly in line with the existing literature (Parker, 2018; Freeman *et al.*, 2003; NGFS, 2020; Dilip and Kundu, 2020; Andersson *et al.*, 2020).

To sum up, our empirical results indicate that the impact of the natural calamities is higher on the western coastal states of India as compared to their eastern counterparts. Historically, since the eastern coastal states have seen a higher incidence of natural calamities (especially cyclones and floods), it seems that they have developed better adaptation mechanisms as compared with the western coastal states. Limited data available on projects related to natural disaster management measures show that the construction of multi-purpose cyclone shelters (MPCS) and underground cabling in the western coastal states are lagging behind their eastern counterparts in terms of project execution (Annex Charts VI a and b).

Section VI
Green Swans and Public Policies in India

Minimising the frequency, intensity and macroeconomic impact of green swan events demand well-designed and internationally coordinated policies. In this section, we try to present a brief note on the policy actions in this regard that have already been initiated in India so far. Through the creation of the National Disaster Management Authority (NDMA) in 2005, the Government of India (GoI) initiated a change in the approach to disaster management in the country, from a relief-centric approach to a more holistic and an integrated approach, that includes processes involving prevention, mitigation, preparedness, response, relief, reconstruction and rehabilitation. Further, the National Action Plan on Climate Change (NAPCC) was formulated in 2008 as a consolidated policy instrument with a focus on a broader set of measures towards adaptation and mitigation of climate change impact, natural resource conservation and promoting energy efficiency. Importantly, the Climate Change Finance Unit (CCFU) was formed in 2011 under the Ministry of Finance to serve as the nodal agency on matters related to 'climate change financing' in India. One of the major functions of this unit is to provide inputs towards the designing, operationalisation and working of the green climate fund in India. Access to green finance, which includes investments seeking to support the accomplishment of environmental objectives, would be a key driver that would tackle India's fight against climate change. The CCFU is expected to function as a coordinating agency for the various institutions responsible for green finance in India.

VI.1 Central Bank Initiatives

RBI has been playing an instrumental role in steering green finance initiatives in India. As part of its green finance drive, the small renewable energy sector has been included under the Priority Sector Lending (PSL) scheme in 2015. Firms in the renewable energy sector are eligible for loans upto INR 30 crore and households are eligible for loans upto INR 10 lakh under this scheme for investing in renewable sources of energy. Moreover, through its various reports, publications and other communication platforms, RBI is actively sensitising the public, investors and banks towards the need, opportunities, and challenges of green finance in India.

RBI has joined the Network for Greening the Financial System (NGFS) and interactions in the group are expected to bring significant learning effects for India and other participating countries. It can benefit from the membership by learning and contributing to the global efforts in green finance. The NGFS, launched in December 2017, is a group of 95 central banks and supervisors and 15 observers as of June 30, 2019. It is a voluntary platform where the members are committed to sharing best practices, contributing to the development of climate-related risk management in the financial sector and mobilising mainstream finance to support the transition to a sustainable economy. In its first comprehensive report published in April 2019, NGFS laid out six recommendations for central banks, supervisors, policymakers and financial institutions to enhance their role in the greening of the financial system and managing environment and climate-related risks, particularly the impact of physical and transition risks on business and society at large (NGFS, 2019). In the second report of NGFS, emphasis is given to a new set of climate scenarios by including countries' commitments to reach net-zero emissions, and the setup of an online NGFS scenarios website providing access to all NGFS publications and data (NGFS, 2021). Some of the important initiatives taken by the central banks globally include: the European Central Bank's (ECB's) inclusion of global warming as a key part of its strategy review; Bank of England's mandate to make its monetary policy greener; and People's Bank of China's inclusion of climate-related risks into the annual stress test of the banks in the country. The Dutch National Bank conducted an energy transition risk stress test to examine the vulnerabilities of financial institutions to a net-zero carbon future.

Banque de France announced a comprehensive climate stress test for banks and insurance companies to assess their exposure to both physical and transition risks. With an increase in frequency and severity of green swan events, there is a likelihood for increase in default rates of loan portfolios. RBI may also consider recommending internal stress tests to the regulated entities to measure their financial exposures.

Some of the other important measures that the central banks globally may examine to mitigate climate-related risks include strengthening their analytical models by incorporating climate-related indicators and factors, bridging data gaps related to various environmental aspects of finance and providing additional/subsidised liquidity support to banks investing in environmentally friendly products/green projects (Krogstrup and Oman, 2019).

VI.2 Fiscal Initiatives

There have been several fiscal measures and financial incentives at work in India with an aim to minimise climate-related risks and use of renewable sources of energy. For instance, the GoI offers 30 per cent of the installation cost of the rooftop solar panels as subsidy to the institutional, residential and social sectors in the non-special category states[18]. In some of the special category states[19], the subsidy is up to 70 per cent of the installation cost. Further, the excess power can be sold at a tariff set by the government. Moreover, the GoI has launched two phases of Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) scheme in 2015 and 2019 to enhance the flow of credit, reduce the upfront purchase price of all vehicles and develop the necessary infrastructure (such as charging stations) to encourage green vehicle production and sales in India (NITI Aayog, 2019). In order to counter the high upfront cost of such vehicles, the State Bank of India has introduced 'green car loans' for electric vehicles (EVs) with concessional processing fee and interest rates as compared to the existing car loans (Jain, 2020). The Union Budget 2022-23 took major initiatives to support green economy and green finance in India, which over time can help mitigate climate risks, including transition risks. An allocation has been made for INR 195 billion to boost manufacturing of solar modules under the Production Linked Incentive (PLI) scheme. Other initiatives include introduction of battery swapping policy for EVs, setting up of more EV charging stations and launch of sovereign green bonds to step up funding of green infrastructure.

In times to come, India can explore the feasibility of introduction of carbon taxation as it can help firms and households to reduce emissions. The implementation of a carbon tax may result in producers investing in less carbon-intensive technologies. In the Indian context, as recommended by Patra *et al.* (2021), the focus should shift towards climate change through carbon pricing, once the ongoing health crisis ends. This may necessitate the incorporation of transition risks in the macroeconomic forecasting models.

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[18] https://economictimes.indiatimes.com/small-biz/productline/power-generation/solar-subsidies-government-subsidies-and-other-incentives-for-installing-rooftop-solar-system-in-india/articleshow/69338706.cms?from=mdr

[19] Uttarakhand, Sikkim, Himachal Pradesh, Jammu and Kashmir, Lakshadweep, as of May 2019.

VI.3 Market Regulators[20]

One of the major strategic moves since 2015 involves the implementation of the sustainability disclosure requirements. The Securities and Exchange Board of India (SEBI) has made it mandatory for the top 100 listed companies in the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) to publish their annual business responsibility reports. Subsequently, with effect from 2022-23, filing of Business Responsibility and Sustainability Report (BRSR) shall be mandatory for the top 1000 listed companies. In addition, the Ministry of Corporate Affairs imposed compulsory reporting of the progress on Corporate Social Responsibilities (CSR) under the Companies Act, 2013.[21]

In addition, with regard to the green financial institutions, Indian Renewable Energy Development Agency (IREDA), a government-backed agency for promoting clean energy investments, announced its plans to become India's first Green Bank in May 2016. Further, the India Infrastructure Finance Corporation Limited (IIFCL) launched 'credit enhancement scheme' in 2012 termed for funding viable infrastructure projects with bond tenors above five years (Jain, 2020). SEBI, in 2015, also initiated a consultation process for disclosure requirements for issuance and listing of Green Bonds in India. The disclosure requirements were based on green bond principles that include the use and management of the proceeds; project evaluation and selection; project monitoring and progress report.

Finally, given the large size of the domestic market and a smaller penetration of green instruments so far in India, there remain vast opportunities to be tapped. In this context, the need of the hour is (i) increased coordination between investment and environmental policies; and (ii) an implementable policy framework for both central and state governments in addressing the existing frictions. In this vein, RBI is actively pursuing some of the policy measures such as deepening of corporate bond market, and removing

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20 Though the study largely focuses on the macroeconomic impact of weather-related adverse shocks (which could be broadly categorised under physical risks), it recognises the important role played by market regulators towards minimising transition risks from the global phenomenon of climate change.

21 https://www.mca.gov.in/Ministry/pdf/FAQ_CSR.pdf

information asymmetry between investors and recipients which can go a long way in developing the green finance market infrastructure. Further, a developed commodity derivatives market can also help mitigate risks by enabling continuous price discovery and providing a strategy for hedging price risk during episodes of uncertainty.

Section VII
Conclusion

Climate change poses a major threat to the optimal functioning of an economy. Climate-related disasters, generally referred to as green swan events due to their unpredictable and cataclysmic character, pose significant physical and transition risks to the overall macroeconomic and financial outcomes. Our paper is unique in its construct and research design as it considers the Indian coastal states that are frequently impacted by some of the extreme weather events, particularly cyclones, unseasonal rains and floods in addition to droughts to study the effects of these natural calamities on their macroeconomic outcomes as compared with their non-coastal neighbouring counterparts. Using a difference-in-difference panel data based econometric approach, the paper analyses the causal impact of the green swan events on macroeconomic indicators such as output growth, agricultural yields, inflation, fiscal parameters, cost of borrowing and key services sectors like tourism.

Our empirical findings suggest that natural calamities cause decline in GSDP growth and per capita NSDP growth and that calamities could have a lingering impact on income growth. We also find that natural calamities cause a decline in the yields of vegetables and fruits. Based on the results obtained for the tourism industry, natural disasters cause a decline in tourist arrivals with the impact being higher for the coastal states. Some of these adverse impacts are also found to persist in the subsequent years. However, the impact of these green swan events on most of the financial variables, including cost of funds, appears to be insignificant. A comparison of the impact between states of the eastern coast *vis-à-vis* the western coast indicates that the former have learnt and adapted better, possibly due to their long history of dealing with such calamities, though their economic performance remains vulnerable.

From the perspective of central banking, we highlight that the green swan events could be an important source of risk to price stability, growth and financial stability, thus, requiring well-designed and coordinated set of mitigation policies. The RBI has been playing an instrumental role in steering green finance initiatives in India, and recently, it has also joined the NGFS as a member in April 2021, which could pave the way towards mitigating risk/ strengthening systems and address climate change challenges. We advocate sustained focus on inclusion of climate risk models and scenario analyses in policy formulations, incentivising green projects, and supporting global initiatives towards green finance.

As a way forward, there is scope for detailed studies on the nature and characteristics of causation between environmental degradation and cyclones (or other green swan events). Analysing the indirect and second-round impact of climate-related risks, with a special emphasis on the transition risks, accompanied by a disaggregated study on the impact across various sectors of the economy would certainly add value to the existing literature. Moreover, future analysis could be extended by increasing the granularity and studying spillovers across districts within a state. Furthermore, to serve the requirement of crisis management preparedness, studies could consider extreme scenarios of double-jeopardy and review the impact of simultaneous incidences of black swan (*e.g.*, a pandemic) and green swan (*e.g.*, *Amphan* or *Tauktae* cyclones) events on likely macroeconomic outcomes.

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Annexure

Annex Table I: Frequency of Droughts/Floods in the Indian Coastal States (1951-2020)

State	Regions	Drought Years	Drought Years: State Total	Flood Years	Flood Years: State Total
West Bengal	Sub-Himalayan	1994; 2009	4	1954; 1955; 1964; 1968; 1980; 1990; 1998	13
	Gangetic	1982; 2010		1971; 1978; 1984; 1999; 2007; 2019	
Odisha	---	1974; 1979; 1986; 2000	4	1956; 1961; 1994; 2001; 2006; 2007; 2008	7
Andhra Pradesh	Coastal	1952; 1968; 1987	4	1983; 1988; 1989; 2007; 2010; 2015	9
	Rayalseema	1952; 1994		1964; 1983; 1988; 1996; 2007; 2020	
Tamil Nadu	---	1952; 1982; 2002	3	1966; 1975; 1981; 1983, 1985; 1996; 2017	7
Kerala	---	1976; 1987; 2002	3	1959; 1961; 1968; 2007; 2013; 2018; 2019	7
Karnataka	Coastal	1966; 1987; 2002	10	1959; 1961; 1975; 1982; 1994; 2019	13
	North-interior	1952; 1972; 1985; 2002; 2003; 2012		1955; 1964; 1979; 1981; 1983; 1988; 2007; 2019	
	South-interior	1952; 1976; 1990; 2002; 2003; 2012		1959; 1961; 1975; 2007; 2019	
Goa	---	1972; 1986; 2015	3	1954; 1958; 1983; 2011; 2019	5
Maharashtra	Central	1972; 1985; 2012; 2015	8	2005; 2006; 2019	13
	Marathwada	1972; 2014		1955; 1983; 1988; 1989; 1998; 2019	
	Vidarbha	1974; 1987; 2009		1959; 1961; 1990; 1994; 2013; 2019	
Gujarat	---	1951; 1974; 1987; 1999	4	1959; 1970; 1976; 1979; 1994; 2005; 2006; 2007; 2010; 2019	10

Source: IMD; and Nandargi and Aman (2017).

Annex Table II: Major Natural Calamities that Affected the Coastal States of India (2012-13 to 2020-21) *(Contd.)*

Year	Flood	Drought	Cyclone
2012-13	–	–	–
2013-14	**West Bengal:** SWM - 1326 mm (-5%); Post-SWM - 320 mm (104%) **Odisha:** SWM - 1116 mm (- 3%); Post-SWM - 392 mm (172%) **Andhra Pradesh:** SWM - 676 mm (11%); Post-SWM - 299 mm (40%)	–	**Odisha:** Cyclone *Phailin* (Extremely severe cyclonic storm in IMD scale) - max wind speed 260 km/hr; **Andhra Pradesh:** Cyclone *Helen* (Severe cyclonic storm in IMD scale) - max wind speed 130 km/hr
2014-15	**Odisha:** SWM - 1256 mm (9%)	**Maharashtra:** SWM - Rainfall departure from LPA: -14%; Post-SWM - Rainfall departure from LPA: - 43%	–
2015-16	**Tamil Nadu:** NEM - 662 mm (52%)	–	–
2017-18	**Tamil Nadu:** SWM - 390 mm (31%); Chennai received 554 mm (74%) of NEM rainfall in just 8 days	–	**Tamil Nadu, Kerala, Maharashtra and Gujarat:** Cyclone *Ockhi* (Very severe cyclonic storm in IMD scale) - max wind speed 185 km/hr; first cyclone in three decades to travel more than 2000 km – forming over Bay of Bengal, emerging into the Arabian Sea and travelling up to Gujarat
2018-19	**Kerala:** SWM - 2516 mm (23%); worst flood in 100 years; **Maharashtra (Mumbai):** Mumbai City (Mumbai Sub-urban) SWM rainfall - June: 788 mm; 42% (793mm; 51%) and July: 743mm; 1% (1139mm; 37%)	–	–

Annex Table II: Major Natural Calamities that Affected the Coastal States of India (2012-13 to 2020-21) *(Concld.)*

Year	Flood	Drought	Cyclone
2019-20	**West Bengal:** Post-SWM - 223 mm (40%) **Maharashtra:** SWM - 1330 mm (32%); Post-SWM - 186 mm (89%) **Gujarat:** SWM - 993 mm (43%); Post-SWM - 73 mm (156%) **Kerala:** SWM - 2310 mm (13%); Post-SWM - 627 mm (27%) **Karnataka:** SWM - 1032 mm (23%); 308 mm (69%) **Goa:** SWM - 3918 mm (32%); Post-SWM - 569 mm (180%)	–	**Odisha:** Cyclone *Fani* (Extremely severe cyclonic storm in IMD scale) - max wind speed: 230 km/hr
2020-21	**Andhra Pradesh:** SWM - 1481 mm (54%)	–	**West Bengal and Odisha:** Cyclone *Amphan* (Super Cyclonic Storm in IMD scale) - max wind speed: 260 km/hr

Note: South-west monsoon (SWM) season: June-September; North-east monsoon (NEM) / Post-SWM season: October-December; Figures followed by mm denote actual rainfall in millimetre (mm), while figures in parentheses denote percentage departure of actual rainfall from LPA.

Source: IMD; and Down to Earth (assisted by the Centre for Science and Environment).

Annex Table III: Variable Descriptions *(Contd.)*

Variable	Description	Source
Output and Per Capita Output		
Gross State Domestic Product (GSDP)	Growth rates of GSDP	National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI)
Per Capita Net State Domestic Product (NSDP)	Growth rates of NSDP	NSO, MoSPI
Agricultural Productivity		
Gross State Value Added (GSVA)-Agriculture	State-wise growth rates of GSVA by economic activity-agriculture (constant prices)	NSO, MoSPI
Yield of Total Foodgrains	State-wise ratio of production of total foodgrains to area of total foodgrains	Department of Agriculture and Cooperation & Farmer’s Welfare (DAC&FW), Ministry of Agriculture and Farmers' Welfare (MoAFW)
Yield of Total Fruits	State-wise ratio of production of total fruits to area of total fruits	DAC&FW, MoAFW; Authors’ calculations
Yield of Total Vegetables	State-wise ratio of production of total vegetables to area of total vegetables	DAC&FW, MoAFW; Authors’ calculations
Inflation		
Headline Inflation	State-wise rates of headline inflation	NSO, MoSPI
Food Inflation	State-wise rates of food inflation	NSO, MoSPI
Fiscal Parameters		
Gross Fiscal Deficit	State-wise gross fiscal deficit as percentage of GSDP	Reserve Bank of India (RBI); Authors’ calculations
Capital Expenditure (CAPEX)	State-wise growth rates in CAPEX	RBI
Revenue Expenditure	State-wise growth rates in revenue expenditure	RBI

Annex Table III: Variable Descriptions *(Concld.)*

Variable	Description	Source
	Financial Services	
State Development Loans (SDLs)	State-wise weighted average yields of SDL	RBI; Authors' calculations
Tourist Visits	State-wise growth rates in tourist visits (both resident and non-resident visits)	Ministry of Tourism
Foreign Direct Investment (FDI) inflows	State-wise growth rates in FDI inflows	Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry in India
Weather Based Crop Insurance Scheme (WBCIS)	State-wise growth rates in area insured under the WBCIS	DAC&FW, MoAFW

Annex Table IVa: State-level Correlation Matrix of GSDP between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.34
Bihar						0.87
Chhattisgarh	-0.33			0.30	0.62	
Jharkhand					-0.15	-0.06
Madhya Pradesh		0.31		0.53		
Rajasthan		0.05				
Sikkim						0.31
Telangana	0.75		0.60	0.33		

Source: NSO, MoSPI; and Authors' calculations.

Annex Table IVb: State-level Correlation Matrix of Per Capita NSDP between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.49
Bihar						0.78
Chhattisgarh	-0.52			0.05	0.44	
Jharkhand					-0.03	-0.03
Madhya Pradesh		-0.04		0.81		
Rajasthan		-0.18				
Sikkim						0.28
Telangana	0.73		0.61	0.50		

Source: NSO, MoSPI; and Authors' calculations.

Annex Table Va: State-level Correlation Matrix of GSVA in Agriculture between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.91
Bihar						-0.07
Chhattisgarh	0.54			0.28	0.11	
Jharkhand					0.44	-0.22
Madhya Pradesh		0.18		0.35		
Rajasthan		-0.02				
Sikkim						
Telangana	0.04		0.19	0.48		

Source: NSO, MoSPI; and Authors' calculations.

Annex Table Vb: State-level Correlation Matrix of Yields of Vegetables between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.27
Bihar						0.47
Chhattisgarh	0.40			0.18	0.65	
Jharkhand					-0.11	-0.31
Madhya Pradesh		-0.32		-0.30		
Rajasthan		-0.16				
Sikkim						
Telangana	-0.48		-0.15	0.19		

Source: DAC&FW, MoAFW; and Authors' calculations.

Annex Table Vc: State-level Correlation Matrix of Yields of Fruits between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						-0.09
Bihar						0.51
Chhattisgarh	0.70			0.94	-	
Jharkhand					-	0.42
Madhya Pradesh		0.50		-0.65		
Rajasthan		0.68				
Sikkim						
Telangana	-0.44		0.00	-0.10		

Note: Correlation coefficients were not obtained due to lack of variation on Odisha's data.
Source: DAC&FW, MoAFW; and Authors' calculations.

Annex Table VIa: State-level Correlation Matrix of GFD between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						-0.12
Bihar						-0.32
Chhattisgarh	0.01			0.10	0.20	
Jharkhand					0.77	0.03
Madhya Pradesh		-0.60		-0.0.8		
Rajasthan		-0.003				
Sikkim						0.82
Telangana	-0.73		0.41	0.32		

Source: RBI; and Authors' calculations.

Annex Table VIb: State-level Correlation Matrix of CAPEX between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.34
Bihar						0.87
Chhattisgarh	-0.33			0.30	0.62	
Jharkhand					-0.15	-0.06
Madhya Pradesh		0.31		0.53		
Rajasthan		0.05				
Sikkim						0.31
Telangana	0.75		0.60	0.33		

Source: RBI; and Authors' calculations.

Annex Table VIc: State-level Correlation Matrix of Revenue Expenditure between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						-0.34
Bihar						0.58
Chhattisgarh	0.17			0.10	0.57	
Jharkhand					-0.67	0.24
Madhya Pradesh		0.35		-0.25		
Rajasthan		0.52				
Sikkim						-0.48
Telangana	-0.87		0.26	-0.09		

Source: RBI; and Authors' calculations.

Annex Table VIIa: State-level Correlation Matrix of Tourist Visits between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.11
Bihar						0.10
Chhattisgarh	-0.87			-0.16	0.17	
Jharkhand					0.14	-0.01
Madhya Pradesh		0.34		0.26		
Rajasthan		0.44				
Sikkim						-0.18
Telangana	0.86		-0.12	-0.18		

Source: Ministry of Tourism; and Authors' calculations.

Annex Table VIIb: State-level Correlation Matrix of Weather-Based Insurance between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						-0.20
Bihar						0.82
Chhattisgarh	0.58			0.47	-0.55	
Jharkhand					0.12	0.86
Madhya Pradesh		-0.51		0.53		
Rajasthan		-0.09				
Sikkim						-
Telangana	0.85		0.79	0.74		

Source: DAC&FW, MoAFW; and Authors' calculations.

Annex Table VIIc: State-level Correlation Matrix of FDI Inflows between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						-0.15
Bihar						-0.20
Chhattisgarh	-			0.19	-0.17	
Jharkhand					-0.49	-0.20
Madhya Pradesh		0.19		-0.54		
Rajasthan		0.20				
Sikkim						-
Telangana	-		-0.60	0.32		

Source: Ministry of Commerce and Industry in India; and Authors' calculations.

Annex Table VIId: State-level Correlation Matrix of SDL Yields between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.96
Bihar						0.94
Chhattisgarh	0.88			0.90	0.79	
Jharkhand					0.91	0.94
Madhya Pradesh		0.98		0.98		
Rajasthan		0.99				
Sikkim						0.93
Telangana	0.98		0.98	0.92		

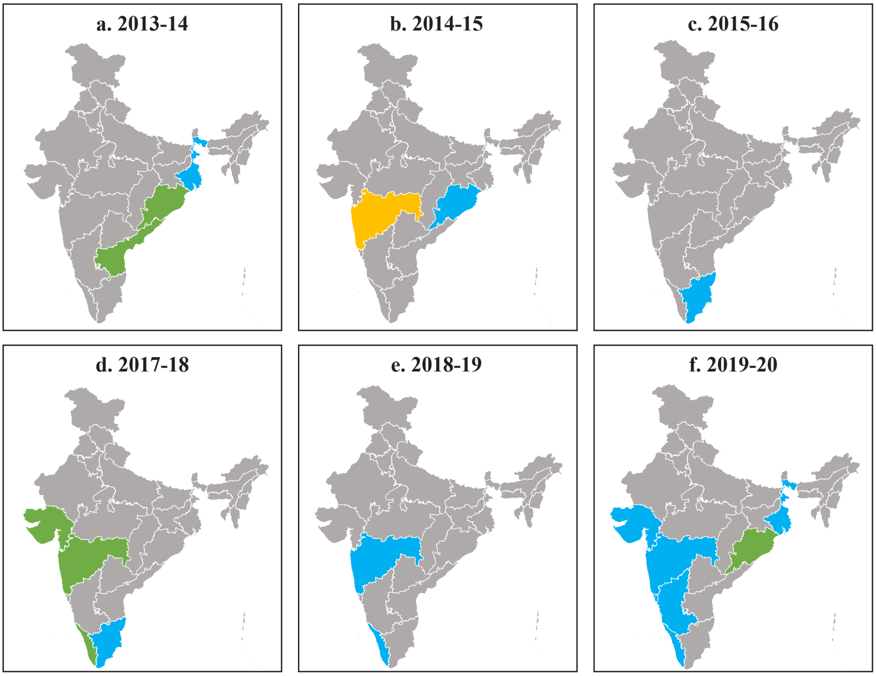
Source: NSO, MoSPI; and Authors' calculations.

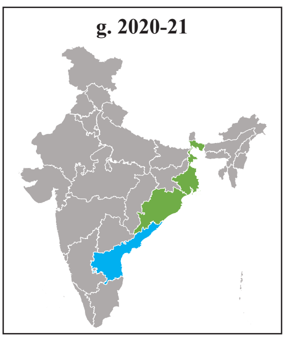
Annex Table VIII: State-level Correlation Matrix of Headline and Food Inflation between Coastal States and their Neighbouring Non-Coastal States

	Andhra Pradesh	Gujarat	Karnataka	Maharashtra	Odisha	West Bengal
Assam						0.87 (0.92)
Bihar						0.93 (0.97)
Chhattisgarh	0.95 (0.97)			0.90 (0.98)	0.95 (0.98)	
Jharkhand					0.89 (0.94)	0.95 (0.96)
Madhya Pradesh		0.93 (0.94)		0.96 (0.96)		
Rajasthan		0.96 (0.96)				
Sikkim						
Telangana	0.92 (0.97)		0.88 (0.96)	0.95 (0.95)		

Note: Figures in parentheses indicate correlation coefficients with respect to food inflation.

Annex Chart I: Natural Calamities and Calamity Years across Coastal States Considered in the Empirical Analysis

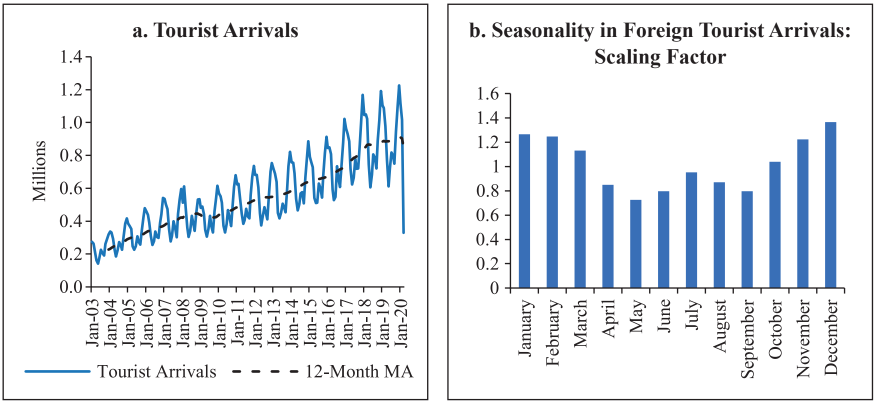




Note: Floods, droughts and cyclones are indicated in blue, yellow and green colours, respectively.

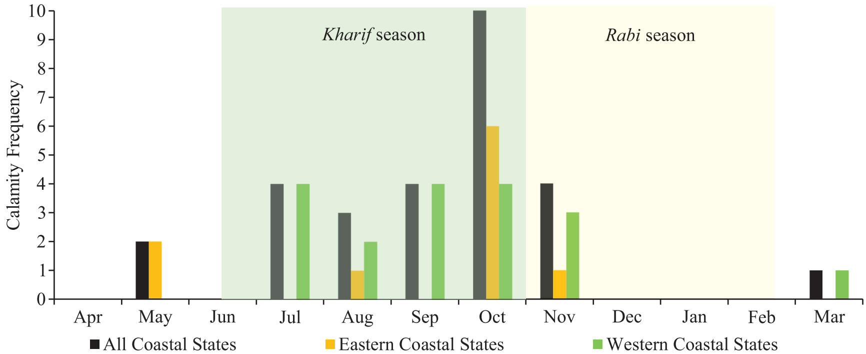
Source: Down to Earth (assisted by the Centre for Science and Environment).

Annex Chart II: Foreign Tourist Arrivals in India and The Seasonality Pattern



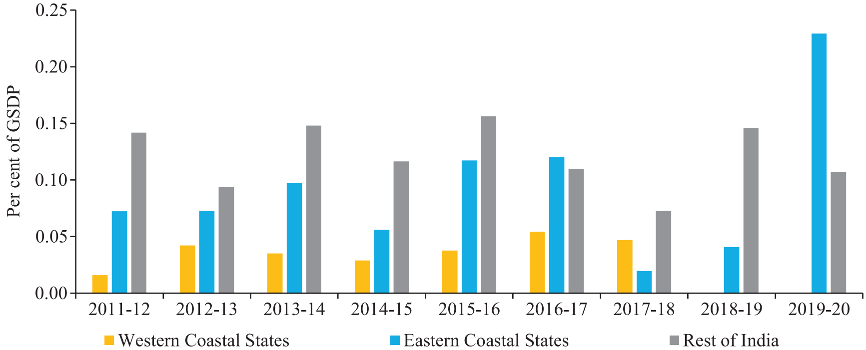
Source: CEIC Database; and Authors' calculations.

Annex Chart III: Calamity Calendar: Month-wise Distribution of Natural Calamities (2012-13 to 2020-21)



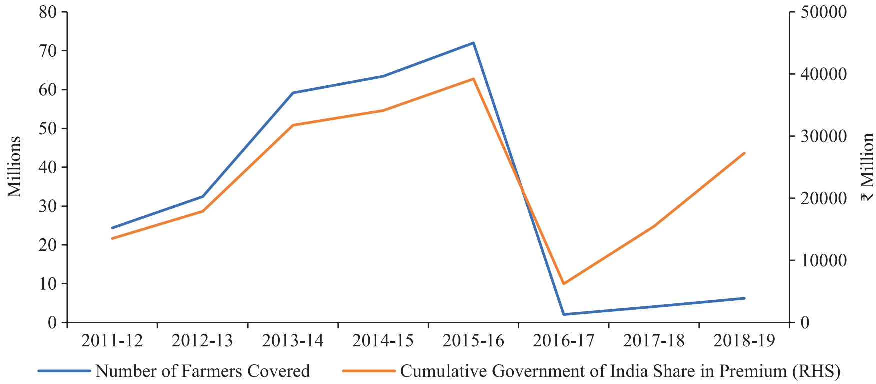
Source: IMD; and Down to Earth (assisted by the Centre for Science and Environment).

Annex Chart IV: Relief on Account of Natural Calamities – Grants from Centre



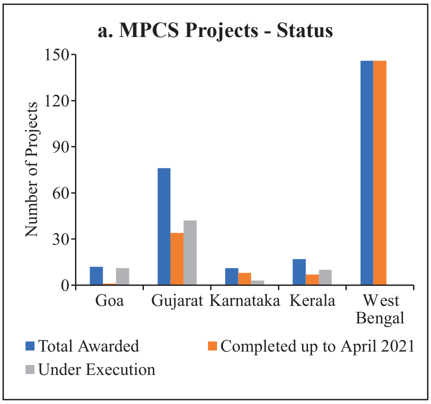
Source: CEIC Database.

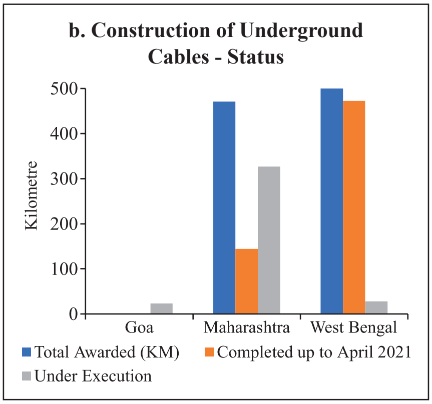
Annex Chart V: Weather Based Crop Insurance Scheme



Source: CEIC Database.

Annex Chart VI: Status of National Cyclone Risk Mitigation Projects





Source: National Cyclone Risk Mitigation Project, GoI.

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Alternative Inflation Forecasting Models for India – What Performs Better in Practice?

Jibin Jose, Himani Shekhar, Sujata Kundu, Vimal Kishore and Binod B. Bhoi*

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This study develops a suite of inflation forecasting models for India and examines their forecasting performance over one-quarter ahead and four-quarters ahead horizons. Besides testing the suitability of a Phillips curve relationship in India for forecasting Consumer Price Index (CPI) inflation, it also uses relevant autoregressive integrated moving average (ARIMA) and structural vector autoregression (SVAR) models. Out of sample forecasts suggest that seasonal ARIMA (SARIMA) models outperform others for one-quarter ahead forecasts, whereas variants of Phillips curve work better for four-quarters ahead forecasts in the case of inflation excluding food and fuel. To account for significant variations in inflation characteristics across CPI components, disaggregated level (food, fuel and excluding food and fuel inflation) forecasts are also generated and then combined to compare with aggregate level forecasts. The results show that disaggregated inflation forecasts based on univariate models generally underperform in comparison to aggregate level forecasts. Disaggregated level forecasts that incorporate Phillips curve dynamics, however, perform better *vis-à-vis* direct forecasts over a longer forecast horizon, validating the utility of disaggregated level analysis of inflation in India. While SVAR models do not score well on forecasting performance, they provide useful insights for evaluating the impact of different shocks on inflation.

JEL Classification: E31, E37, E52, E58

Keywords: Inflation forecasting, ARIMA model, Phillips curve, SVAR model, disaggregated forecast, inflation targeting

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* Jibin Jose, Himani Shekhar and Vimal Kishore are Managers; Sujata Kundu is Assistant Adviser and Binod B. Bhoi is Director in the Department of Economic and Policy Research, Reserve Bank of India. An earlier version of this paper was presented in DEPR colloquium on June 28, 2021. Comments from Prof. Rudrani Bhattacharya, NIPFP and an anonymous reviewer are gratefully acknowledged. The views expressed in the paper are those of the authors and do not represent the views of the Reserve Bank of India. Corresponding author email: jibinjose@rbi.org.in

Introduction

Modelling the dynamics of inflation unerringly for generating reliable inflation forecasts has all along been a daunting challenge for researchers. Given the significant transmission lags in monetary policy, central banks often need to undertake forward-looking policy decisions based on their assessment of the outlook for key macroeconomic variables in order to be able to achieve their policy objectives. Therefore, more accurate, reliable and unbiased the forecasts are, better could be the policy outcomes. Under an inflation targeting monetary policy framework, where inflation forecast acts as the intermediate target, generating reliable inflation forecast assumes even greater importance as systematic forecast errors can hinder the optimal conduct of monetary policy and thereby undermine policy credibility. Accurate inflation forecast is of importance even for economic agents in forming their inflation expectations while negotiating wage-price contracts and also for understanding how policy makers might react in future in their endeavour to achieve the objective of price stability. Achieving and maintaining inflation target on a sustained basis, thus, depends crucially on the accuracy of inflation forecasts.

Given the importance of inflation forecasting for the conduct of monetary policy, central banks use an array of models – time series models such as univariate (ARIMA-based) and multivariate (unconstrained and structural vector autoregressions) models and macro-economic models incorporating measures of economic slack and inflation expectations (especially variants of Phillips curve models) for forecasting and policy analysis purposes. Often a simple random walk model or its variants are found to outperform complex structural econometric models in forecasting (Atkeson and Ohanian, 2001; Garnier, Mertens, and Nelson, 2015). However, some of the cross-country studies, both for advanced and emerging market economies (EMEs), have found variants of vector autoregression (VAR) models also performing relatively well (Banbura, 2010; Duncan and Martínez-García, 2015; Mandalinci, 2017; Duncan and Martínez-García, 2019; Iyer and Sen Gupta, 2019). Furthermore, in the case of advanced economies, studies have shown that models based on Phillips curve are more successful in modelling and forecasting inflation (Coibion and Gorodnichenko 2015; Kabukçuoğlu and Martínez-García, 2018), notwithstanding the overwhelming proliferation of research in the last decade or so arguing that the "Phillips Curve is dead" (Blanchard *et al.*, 2015; Blinder, 2018). Ultimately, inflation forecasting is a country- and time-specific issue, and no single model is sufficient. Moreover, models used for forecasting must be regularly updated to take into account dynamic changes in the inflation process and also new sources of data as and when they become available.

India formally adopted a flexible inflation targeting (FIT) framework in June 2016, following which there has been a shift in the inflation metric from the Wholesale Price Index (WPI) to the Consumer Price Index (CPI). CPI-Combined (CPI-C) inflation is the nominal anchor under this framework, and the Reserve Bank of India (RBI) is mandated with the objective of achieving a 4 per cent inflation target over the medium term[1] with the upper tolerance limit of 6 per cent and the lower tolerance limit of 2 per cent. It has been argued that an established FIT framework with a credible long-run inflation target would serve as an anchor to expectations, and therefore, would provide an effective strategy for dealing with the second-round effects of supply shocks in the Indian scenario (Benes, *et al.*, 2016). As per the mandate of the amended RBI Act, 2016 to publish a half-yearly Monetary Policy Report (MPR) including inflation forecast for 6-18 months, RBI developed a macroeconomic model – Quarterly Projection Model (QPM) – for generating medium term projections and policy analysis (RBI, 2021).[2] In the short-term, nowcasting using high frequency data and forward-looking surveys, and forecasts up to three-quarters following a bottom-up approach employing alternate models are used. In this endeavour to generate accurate and reliable forecasts, there has been a growing interest in exploring different aspects of inflation forecasting in the Indian context in recent times (Dholakia and Kandiyala, 2018; Pratap and Sengupta, 2019; John, Singh and Kapur, 2020). Moreover, as observed by many practitioners, inflation forecasting has become an increasingly

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[1] On August 5, 2016, the Government of India set out the inflation target for the first time for a period of five years up to March 31, 2021. The target was renewed for a further period of five years from April 1, 2021 to March 31, 2026.

[2] QPM is a forward-looking open economy calibrated gap model broadly following a theoretical framework founded on New Keynesian principles embedding key India-specific features like behaviour of different inflation components and their interlinkages as well as monetary-fiscal interactions.

challenging task and the performance of models varies depending upon several factors (Stock and Watson, 2008; Stock and Watson, 2010; Pratap and Sengupta, 2019; John, *et al.*, 2020). Therefore, continous evaluation of forecast performance across models and over time is necessary.

This paper intends to contribute to this strand of literature by developing a suite of inflation models and examining the appropriateness of alternative models based on their forecasting performance over one-quarter ahead and four-quarters ahead horizons using CPI-C inflation data. The time period covered for empirical analysis in this paper begins from 1996-97:Q1 (mainly due to the availability of quarterly GDP data since then) and ends in 2019-20:Q4 (recognising issues in data reporting during Q1:2020-21 following the COVID-19 induced lockdown). Models are estimated for the period 1996-97:Q1 to 2017-18:Q3 and out of sample forecasts are generated for the period 2017-18:Q4 to 2019-20:Q4, which not only allows forecast evaluation over a reasonable period of time but also helps in selecting the appropriate forecasting model at different time horizons. We employ three approaches – univariate models, structural VAR models and Phillips curve (PC) based models – and extend the analysis to three major sub-components of inflation, *viz.*, food, fuel and excluding food and fuel (*i.e.*, 'core inflation' henceforth). The major motivation for such an approach is rooted in the specific structural characteristics of the Indian economy – large share of food in the CPI along with higher food price volatility as well as high sensitivity of core inflation to international crude oil prices. In the face of large relative price movements and idiosyncratic price shocks, aggregate measures of inflation could mask the underlying inflation dynamics. Under such circumstances, a model based on aggregate inflation may run into the risk of producing bias in inflation projections. While the international evidence in this regard is mixed (Hendry and Hubrich, 2006; Huwiler and Kaufmann, 2013), recent findings for India suggest that directly forecasting the aggregate measure is better in case of univariate models (Pratap and Sengupta, 2019). In this endeavour, this paper attempts to model and forecast not only headline inflation (direct approach) but also disaggregated level inflation by factoring in macroeconomic and sector-specific determinants (indirect approach). Furthermore, a comparison is made between models regarding the performance of forecasts generated from direct *versus* indirect methods over one-quarter ahead and four-quarters ahead horizons for choosing the best performing model. Identifying models that perform better in forecasting inflation at different horizons also requires to develop an array of models.

The analysis undertaken in this paper is significant on the following counts: first, our findings corroborate the existence of the PC relationship in the Indian context. Second, it finds that while univariate models perform better in forecasting one-quarter ahead inflation, the PC-based models tend to outperform the former for four-quarters ahead forecast horizon in the case of core inflation. Further, our analysis suggests that the performance of forecasts generated from direct *versus* indirect approaches depends on the underlying model and the forecast horizon – disaggregated level forecasts incorporating Phillips curve dynamics are generally better compared to aggregate level inflation forecasts. The rest of the paper is organised as follows: Section II provides a descriptive analysis of inflation in India; Section III discusses the extant literature; Section IV lays out the empirical strategy and estimation; Section V presents the forecast evaluation; and Section VI concludes the paper.

Section II
Inflation in India – Some Observations

India's inflation developments during the past two decades (1996-97:Q1 to 2019-20:Q4) reveal significant variations in both the level and volatility of inflation at the aggregate and disaggregated level (Table 1).[3] Headline inflation[4] ranged between a high of 17.9 per cent in 1998:Q4 and a low of 0.5 per cent in 1999:Q4. Further, measures of skewness and kurtosis together imply that although the headline inflation distribution showed a positive skew during this period suggesting that most inflation outcomes generally remained below the mean, there were also phases when inflation deviated significantly from its mean. A disaggregated picture of CPI inflation – food, fuel and core – provides further insights into the overall inflation dynamics. Notwithstanding

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[3] Data on CPI-C from January 2011 correspond to the base year 2012. Data prior to that correspond to CPI for Industrial Workers (CPI-IW) with base year 2001 rebased to 2012.

[4] It is measured by the year-on-year per cent change in the all-India CPI-C series with base year 2012 released by the National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI), Government of India. Prior to 2011, CPI-IW rebased series is used.

Table 1: Summary Statistics (1996-97:Q1 to 2019-20:Q4)

(Per cent)

	CPI-C	CPI-Core	CPI-Food	CPI-Fuel
Mean	6.5	6.5	6.5	7.4
Median	5.5	5.7	5.9	6.8
Maximum	17.9	14.6	22.1	24.8
Minimum	0.5	3.1	-3.8	-6.4
Standard Deviation	3.3	2.7	4.8	5.4
Skewness	1.0	1.2	0.6	0.5
Kurtosis	3.9	4.0	3.2	4.2

Note: Skewness and kurtosis are unit-free measures. Data on inflation relate to CPI-C (base: 2012=100) from January 2011 onwards and CPI-IW prior to that.
Source: NSO, Labour Bureau; and Authors' estimates.

similar mean inflation, the food group (with its weight of 45.9 per cent in the CPI-C[5]) is much more volatile than core inflation[6] (weight of 47.3 per cent), which in turn, imparts significant volatility to headline inflation. On the other hand, the fuel group, though has a lower weight (6.8 per cent), recorded the highest average inflation and volatility over the sample period.

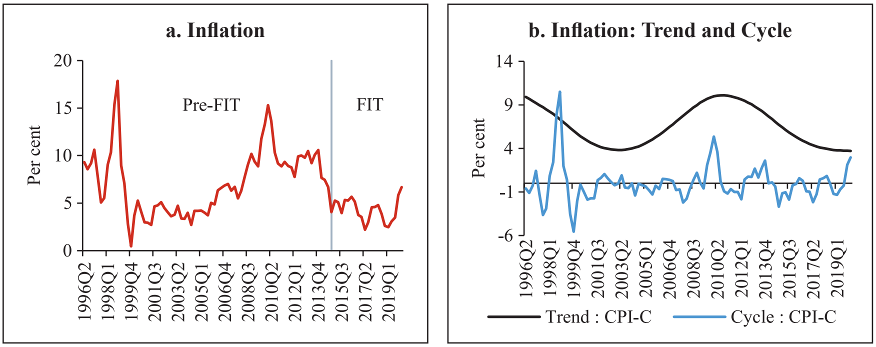
The period since the mid-1990s also witnessed two major shifts in the monetary policy regime: multiple indicators approach (during 1998-99 to 2013-14) and flexible inflation targeting (FIT) preceded by a transitional glide path from 2014-15[7]. The behaviour of inflation has been distinct

5 The weights correspond to the current base year (2012=100) of CPI-C.

6 Core inflation is generally calculated by excluding the volatile components/sub-groups in the CPI. Since, food and fuel groups are largely the broader volatile components in the consumption basket as their prices are more often driven by supply shocks, excluding them from the headline index is considered as one of the several possible measures of core inflation. By its very construct, therefore, core inflation is the least volatile among the three major groups of CPI-C.

7 Multiple indicators approach was adopted in April 1998 (in place of monetary targeting) under which besides monetary aggregates, a host of forward-looking indicators such as credit, output, inflation, trade, capital flows, exchange rate, returns in different markets and fiscal performance constituted the basis of information set used for monetary policy formulation (Das, 2020). In the post-global financial crisis period, however, the credibility of this framework came under question as persistently high inflation and weakening growth began to co-exist. This paved way for transition to FIT with the Expert Committee set up by RBI to revise and strengthen the monetary policy framework recommending headline CPI inflation to be the nominal anchor for monetary policy in January 2014. Consequently, RBI adopted a self-imposed glide path to bring inflation down sequentially, leading up to the Monetary Policy Framework Agreement (MPFA) signed in February 2015 and formal adoption of FIT with the amendment to the RBI Act in May 2016.

Chart 1: CPI-Headline



Note: The quarterly inflation series is decomposed into trend and cycle using the Hodrick-Prescott (HP) filter. Quarters on horizontal axis are based on calendar year.
Source: NSO; Labour Bureau; and Authors' estimates.

during the two regimes – inflation was much more volatile during the multiple indicators regime as compared to the FIT regime, despite the latter period experiencing many structural shocks such as demonetisation and the introduction of goods and services tax (GST) (Chart 1a). The disinflation ahead of FIT was broad-based, driven by easing in domestic food inflation on the back of record food grains and horticulture production as well as sharp reduction in international crude oil prices, even as their benefits were not fully passed on to domestic petroleum product prices. Building on this disinflation, credibility gains accruing to monetary policy on account of its focus on an inflation target together with a stable exchange rate resulted in a relatively low and steady inflation outcome during the FIT period (RBI, 2021).

Measured (actual) inflation, however, does not fully reflect the underlying changes in the inflation process; *i.e.,* whether the observed changes in inflation are driven by the long-term 'trend' component or short-term 'cyclical' fluctuations, which is crucial for understanding future inflation as well as the conduct of monetary policy. Trend inflation is viewed as the level to which actual inflation outcomes are expected to converge after short-run fluctuations die out (Behera and Patra, 2020), whereas the short-run fluctuations emanate from a variety of sources/price shocks mainly on the supply side. The literature suggests that under univariate framework, the overall dynamics of inflation are largely dominated by the trend component (Stock and Watson, 2007). The precise measurement of trend inflation, however, is an empirical issue (refer to Behera and Patra, *op cit.* for an exposition). A simple decomposition of headline inflation using the Hodrick-Prescott (HP) filter reveals that the sharp fall in trend inflation has been the driver of the general easing of headline inflation during the FIT period[8]. However, it can be observed that the HP trend is time-varying, while short-term fluctuations follow a stationary process (Chart 1b). In addition, short-run and long-run components of inflation are crucial in estimating inflation persistence, which has significant implications for the design of monetary policy (Ascari and Sbordone, 2014).

Aggregate level analysis, however, may not fully reflect the observed changes in the volatility and persistence of the sectoral or idiosyncratic (such as food and fuel) price shocks, which are often used for calibrating model-based forecasts for policy purposes. In view of this, an analysis of the trends and cyclical components of the major groups of CPI may be necessary. It can be observed that the trend components of CPI major groups which were widely varying prior to FIT regime have become more aligned since the transition to FIT, suggesting anchoring of inflation expectations (Chart 2a). In contrast, cyclical components of inflation, which are stationary in nature, implying they even out over time, continue to exhibit significant fluctuations, *albeit* with some moderation in amplitudes, thus imparting volatility to actual inflation (Chart 2b). The determinants of sectoral price dynamics, therefore, should be taken into account in inflation modelling and forecasting exercises.

The need for examining sectoral price dynamics may also be necessary from the perspective of understanding the sources of fluctuations in measured headline inflation, *i.e.,* the drivers of inflation given the relative importance of food and non-food items (as represented by their weights in CPI) in the household consumption basket as well as the relative price movements over time. This is because headline inflation is derived from CPI-C, which in turn,

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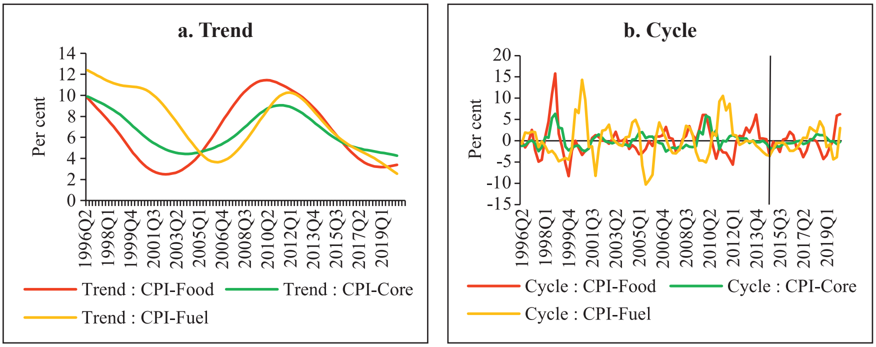
8 Unlike Behera and Patra (2020), the focus of this paper is not on accurate measurement of trend inflation, which is crucial for setting the inflation target, but on forecasting inflation and therefore, we have used two-sided HP filter for deriving a gauge on the trend component for its use in the PC based forecasting models.

Chart 2: CPI Major Groups – Trend and Cycle



Note: Inflation trend and cycle have been measured using HP filter. Quarters on horizontal axis are based on calendar year.

Source: NSO, Labour Bureau; and Authors' estimates.

is compiled following a bottom-up approach.[9] From the monetary policy perspective, if relative price movements are large, persistent and not offsetting, they impinge on monetary policy setting as they can have a lasting influence on inflation expectations through second-round effects (RBI, 2021).

It can be observed that the food group has contributed significantly to headline inflation all through the years (Chart 3a). This is not surprising given the higher weight of food in the CPI (45.9 per cent) and frequent supply side shocks that affect food production leading to higher volatility in food prices. Food price inflation in India has also been observed to be persistent, for instance during the five-year period post-global financial crisis (GFC), reflecting a combination of supply and demand factors (Mohanty, 2014). On the other hand, the contribution of core component to CPI appears to be largely steady throughout. Moreover, relative food prices (the ratio of food to non-food price indices) trended up during 2005-2016, before showing some moderation during the FIT period reflecting record food production and improved supply management by the government (Chart 3b). Fuel (including petrol and diesel) prices, on the other hand, exhibits significant co-movement with international crude oil prices due to India's large dependence on crude

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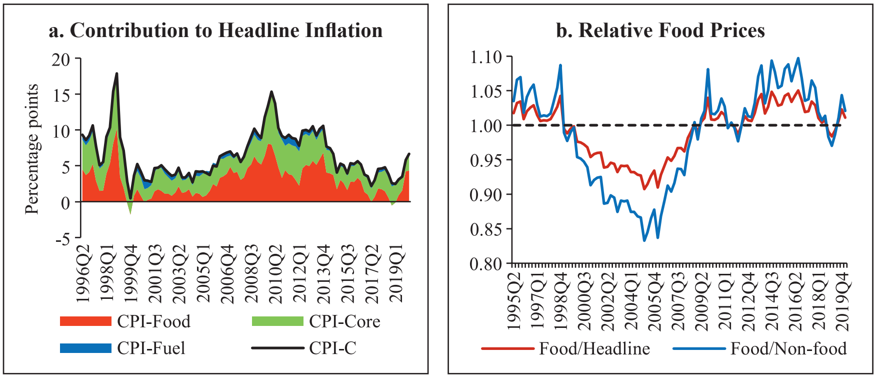
[9] In India, CPI-C (Base: 2012=100) is constructed following a bottom-up approach by first compiling price index at the item level and then at the sub-group/group level for both rural and urban areas across states, which are then combined using respective fixed weights.

Chart 3: Drivers of Inflation in India



Note: Quarters on horizontal axis are based on calendar year.
Source: NSO, Labour Bureau; and Authors' estimates.

imports. Thus, given that both food and fuel prices in India are characterised by distinct inflation process (prone to supply shocks with risks of generating second round effects), aggregate level analysis may need to be strengthened with the modelling of disaggregated level inflation for generating reliable inflation forecasts for policy purposes, which is the focus of this paper.

Section III
Review of Literature

III.1: Time Series Models

Univariate Models

Many time series processes can be expressed as a parsimonious autoregressive integrated moving average (ARIMA) model after appropriate data transformation and differencing. ARIMA models employ a combination of autoregressive (past values of itself) and moving average (lagged values of a 'white noise' error term) models. Given the simplicity and the requirement of just one data series, ARIMA based forecasting has become one of the most common forecasting approaches. Further, by giving more weight to near-term outcomes, ARIMA models are able to beat more complicated structural models in terms of short-term forecast performance (Litterman, 1986; Stockton and Glassman, 1987; Meyler, *et al.* 1998). Also, unlike economic models that are restrictive in their theoretical formulations, which can inflict improper restrictions and specifications on the structural variables, ARIMA models have no such restrictions imparting the necessary flexibility to capture the dynamic properties and, thus, possess significant advantages in short-run forecasting (Saz, 2011). These models are also flexible to include deterministic effects (interventions), outliers, trading day and festival effects (Gómez and Maravall, 1998). ARIMA models can also handle seasonality in time series data and hence, forecasters give similar importance to the simplest univariate forecasting methods as econometric models.

However, these models have certain drawbacks as they do not ingrain any underlying theoretical or structural relationships. ARIMA models are primarily 'backward-looking' which means that they are poor at predicting turning points, unless the turning point represents a return to a long-run equilibrium (Meyler, *et al.* 1998). Furthermore, ARIMA models are considered to be too simplistic, subjective, agnostic and atheoretic in nature (Saz, 2011). To overcome these limitations of univariate forecasting, time series models are often extended to include other variables in the form of single equation models with exogenous explanatory variables or a structural or non-structural system of equations.

Multivariate Models

Within multivariate models, a notable approach is to model multiple time series predictor variables simultaneously along with inflation using high-dimensional VARs (Stock and Watson, 2008; Bańbura, *et al.* 2010; Canova, 2011). One of the principal uses of a VAR model is to generate forecasts. These models involve constructing subsidiary models for the predictor variables, or alternatively, modelling inflation and the predictors jointly and iterating the joint model forward while imposing certain parameter restrictions which could involve complex macroeconomic structure and linkages. The merit of these models over univariate approaches is that of using additional information available from other related time series as well as theory-based structural relationships among them to obtain better forecasts. Out-of-sample forecasts are obtained *via* forward iteration which in practice is done by a "rolling one-period-ahead" forecast where the estimated VAR coefficients are updated each period in order to account for the latest data release of the variables.

III.2: Macro-economic Models

Another important modelling framework within the class of economic models is the Phillips curve[10]. The study of the nature of the PC trade-off has non-trivial implications for the conduct of monetary policy and business cycle fluctuations, and is routinely undertaken with the objective of modelling and forecasting inflation. The literature on PC has undergone significant changes overtime, with the New Keynesian Phillips Curve (NKPC) and its appealing theoretical microfoundations gaining popularity and becoming a standard feature of many analyses (Nason and Smith, 2008; Dees *et al.,* 2009). The PC-based models happen to be the most widely used for inflation forecasting after the univariate approaches.

III.3: The Indian Scenario

Several studies have used the univariate approach to forecast inflation in the case of India. Some of the studies have used ARIMA models as benchmark to evaluate forecasting performance of their economic models (John, *et al.* 2020), while others, like Pratap and Sengupta (2019) have evaluated a set of models using CPI data for forecasting performance and concluded that the best forecasting performance is achieved by the SARIMA model of the form (3,1,1) (2,1,1). On the other hand, Srivastava (2016) uses ARIMA based approaches and compares direct and indirect forecasts of food inflation with the conclusion that a disaggregated approach performs better in the case of food inflation.

A few papers in the Indian context have used VARs not only to estimate or determine inflation but also to study the factors that influence inflation expectations. An analysis of core inflation in a structural VAR (SVAR) framework with a vertical long-run supply curve as the identifying condition points towards the role of both demand and supply side shocks in inflation dynamics (Goyal and Pujari, 2005). The results using quarterly data from 1996-97:Q1 to 2013-14:Q3 identify crude oil price, output gap,

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[10] The idea that there is a trade-off between rates of inflation and unemployment – the formal empirical evidence for which was originally provided by Phillips (1958) using data on wage inflation in the United Kingdom – has occupied the centre stage of policy decisions and debates in this sphere over the last sixty years.

fiscal policy and monetary policy as the determinants of inflation in India along with pointing out significant changes in India's inflation dynamics after the global financial crisis (Mohanty and John, 2015). Further, a 7-variable SVAR framework finds evidence of inflation expectations anchoring with the Reserve Bank communications as well as headline inflation affecting inflation expectations in the short-run and core inflation dominating in the long-run (Goyal and Parab, 2019).

Empirical explorations on PC in the Indian context in the last two decades have been mainly influenced by two strands of the literature: (i) The first one is an augmented PC put forth by Gordon (1998), generally referred to as the triangle model of inflation, in reference to the three basic determinants of inflation in the model – inertia, demand, and supply side factors; (ii) The second one is a modified version of the purely forward-looking NKPC (Gali and Gertler, 1999; Gali, Gertler, and Lopez-Salido, 2005). Such an *ad-hoc* modification was necessitated because of the lack of empirical support for the purely forward-looking NKPC as lagged inflation remained an important determinant of inflation dynamics. Consequently, a hybrid PC was born – with both forward and backward-looking components in the data generating process. While a majority of the empirical work using Indian data has been centred around these two approaches, one cannot fail to observe that there is considerable heterogeneity in the specifics of each of the studies, leading to a range of point estimates of the slope of the PC. This heterogeneity primarily arises due to the following factors: assumptions on the data generating process (inclusion/exclusion of the forward-looking component); the choice and structure of the economic activity variable [Index of Industrial Production (IIP) *versus* GDP]; the time period; and the specific econometric methodology used. However, despite these apparent differences, there is a general consensus on the existence of a PC relationship in the Indian scenario.

Several papers have estimated the backward-looking PC similar to Gordon (1998). Using this approach on annual data from 1970-71 to 2000-01, Kapur and Patra (2000) estimate the sacrifice ratio – output forgone to achieve lower inflation – and find that lagged inflation and the demand variable, proxied by the output gap, are significant in determining inflation. Some studies using the backward-looking version of PC on annual data during 1994-2005 (Srinivasan, Mahambare and Ramachandran, 2006) and hybrid version of PC on annual data from 1996-2007 (Mishra and Mishra, 2012) find no evidence for the PC relationship, while some others find evidence for the same for the sub-sample of 2004-2009 (and not for the period 1997-2003) (Singh, Kanakaraj and Sridevi, 2011) and statistically on the borderline during the period 1996-2005 (Dua and Gaur, 2009). However, once this period of study is extended even slightly or a longer horizon is considered, the relationship comes back alive as can be found in Paul (2009), Mazumder (2011), and Patra and Kapur (2012).

Similarly, Patra and Ray (2010) explore the dynamics of inflation expectations and find output gap to be one of the determinants along with lagged inflation, food and fuel price changes and real interest rate. Revisiting the PC relationship under the triangle model, Kapur (2013) concludes that the demand variable is significant even when supply shocks are not incorporated, and that rainfall shortage and minimum support price (MSP) affect inflation. Further, PC based forecasts outperform random walk model forecasts. Patra, Khundrakpam and George (2014) estimate a hybrid augmented PC and find the coefficient of output gap to be positive and significant as well as a rise in the contribution of expectations to inflation persistence, measured by the coefficient of one-period lead inflation, in the post-crisis period. Ball, Chari, and Mishra (2016) employ a backward-looking PC and explain inflation rate as a function of slow-moving average of past inflation and the deviation of output from its trend.

A notable observation is that in most of the empirical work mentioned so far, inflation was represented by the WPI as the formulation of monetary policy was anchored on movements in WPI inflation[11]. In contrast, a number of recent papers (such as Chinoy, *et al.* 2016; Behera, *et al.* 2017; Pattanaik, *et al.* 2019; Sharma and Padhi, 2020; Patra, *et al.* 2021) have estimated similar models using the CPI based inflation in view of the switch from WPI to CPI as the inflation metric under the FIT framework in India since 2016. While Chinoy, *et al.* (2016) and Pattanaik, *et al.* (2019) explore inflation dynamics

[11] With the exception of Dua and Gaur (2009) and Singh, Kanakaraj and Sridevi (2011).

in a standard time series framework with the latter focusing exclusively on inflation expectations, Behera, *et al.* (2017) estimate the PC using state-level data; Sharma and Padhi (2020) propose an alternative indicator of economic slack that captures demand conditions efficiently to forecast core inflation; Patra, *et al.* (2021) explicitly address the time-varying and convexity properties of PC – all these papers corroborate the existing evidence on PC relationship in India. A survey on the range of point estimates of the slope coefficients and methodologies used in the literature suggests that all the studies have remained close to Gordon (1998) and Gali and Gertler (1999) in terms of the econometric methodology employed – choosing either ordinary least squares (OLS) or Instrumental Variables-Generalised Method of Moments (IV-GMM) techniques (Table 2).

Table 2: Select Studies on Phillips Curve (PC) Estimates in India *(Contd.)*

Paper	Presence of PC/ Coefficient of the Output gap measure (β)	Inflation Measure/ Output gap measure	Time period/ Methodology
Kapur and Patra (2000)	Estimates a backward-looking PC using WPI and GDP deflator; β is significant and varies in the range of 0.47 to 0.87 (for WPI) and 0.30 to 0.54 (for GDP deflator).	WPI and GDP deflator/ Real GDP gap (Using HP filter)	1976-2001 (Annual data); OLS
Srinivasan *et al.* (2006)	No evidence for PC; In some specifications, the coefficient is even negative and significant.	WPI/Index of Industrial Production (IIP) (Using HP filter)	1994-2005 (Monthly data); OLS
Dua and Gaur (2009)	Hybrid and backward-looking PCs; β is significant in some specifications (varies in the range of 0.10 to 0.15).	CPI/ Real GDP gap (Using HP filter)	1996-2005 (Quarterly data); IV-GMM
Paul (2009)	Backward-looking PC; β is significant when IIP manufacturing is used as a measure of output gap; varies in the range of 0.46 to 0.52.	WPI/ Real GDP gap, IIP gap and IIP manufacturing gap (Using HP filter)	1956-2007 (Annual data); OLS
Patra and Ray (2010)	Models inflation expectations in a PC framework; β is 0.14 and significant.	WPI/ Real GDP gap	1997-2008 (Monthly data); OLS

Table 2: Select Studies on Phillips Curve (PC) Estimates in India *(Concld.)*

Paper	Presence of PC/ Coefficient of the Output gap measure (β)	Inflation Measure/ Output gap measure	Time period/ Methodology
Singh *et al.* (2011)	Estimates a backward-looking PC for 1997-2003 and 2004-2009; β is significant in the latter period and varies in the range of 0.7 to 2.0.	CPI/ Real GDP gap (Using Kalman filter)	1997-2009 (Quarterly data); OLS and IV - 2SLS
Mazumder (2011)	Backward-looking PC; β is estimated to be 0.49 and significant.	WPI and CPI/ IIP gap (Using HP filter)	1970-2008 (Quarterly data); OLS
Patra and Kapur (2012)	Hybrid and backward-looking PCs; β is significant and ranges from 0.05 to 0.35.	WPI and GDP deflator/ Real GDP gap (Using HP filter)	1997-2009 (Quarterly data); OLS and IV-GMM
Mishra and Mishra (2012)	Hybrid PC; β is positive but not significant.	WPI/ IIP gap (Using HP filter)	1996-2007 (Monthly data); IV-GMM
Kapur (2013)	Backward-looking PC; β is significant and varies in the range of 0.19 to 0.30.	WPI/ Real GDP gap (Using HP filter)	1996-2011 (Quarterly data); OLS
Patra *et al.* (2014)	Hybrid PC; β is significant and varies in the range of 0.16 to 0.22.	WPI/ Real GDP gap (Using HP filter)	1997-2012 (Quarterly data); IV-GMM
Behera *et al.* (2017)	Backward-looking PC in a state-level panel framework; β is significant and varies in the range of 0.35 to 0.52.	CPI/ Real Gross State Domestic Product (GSDP gap) (Using HP filter)	2007-2016 (Annual data); Dynamic Panel Estimation using difference/ system GMM
Pattanaik *et al.* (2019)	New Keynesian PC using survey-based inflation expectations; β is significant and varies in the range of 0.25 to 0.48.	CPI/ Real GDP gap (Using HP filter)	2008-2018 (Quarterly data); OLS

Note: OLS: Ordinary Least Squares; IV: Instrumental Variable; 2SLS: Two-stage Least Squares; GMM: Generalised Method of Moments.

Section IV
Empirical Strategy and Estimation

IV.1 Univariate Models

An AR (p) process may be represented as a combination of its past values and a "white noise" error term:

$$\varphi(\mathrm{B})Y_t = \varepsilon_t \qquad \text{... (1)}$$

where ε_t is a white noise process with zero mean and variance σ^2, B is the backshift operator and φ(B) is polynomial of degree p representing the AR terms. It models a time series as a function of its past values. Partial autocorrelation function (PACF) plots are used to take a view about the order of polynomial p.

Similarly, an MA (q) process may be represented as a weighted average of a "white noise" series:

$$Y_t = \theta(\mathrm{B})\varepsilon_t \qquad \text{... (2)}$$

where, ε_t is a white noise process with zero mean and variance σ^2, B is the backshift operator and θ(B) is polynomial of degree q representing the MA terms. Autocorrelation function (ACF) plots are used to take a view about the order of polynomial q.

When a time series is related to its past values as well as past residuals, a mixed ARMA model can satisfactorily describe it. In general, fewer parameters are required to be estimated in this case compared to a pure AR or pure MA model. An ARMA (p, q) can be represented as:

$$\varphi(\mathrm{B})Y_t = \theta(\mathrm{B})\varepsilon_t \qquad \text{... (3)}$$

A parsimonious ARMA (p, q) model may perform well in forecasting if inflation is stationary (Ang *et al.*, 2007). In case of non-stationary series (as is the case with CPI data in India, Appendix Table A1b), an extended form of ARMA models, *i.e.,* ARIMA, where differencing is done to make the data stationary, may describe the time series adequately. ARIMA combines autoregressive and moving average models and can be represented as:

$$\varphi(\mathrm{B})(1-B)^d Y_t = c + \theta(\mathrm{B})\varepsilon_t \qquad \text{... (4)}$$

where, ε_t is a white noise process with zero mean and variance σ^2, B is the backshift operator, φ(B) and θ(B) are polynomials of degree p and q representing AR and MA terms, respectively, and d represents the order of integration that make the data stationary (Pankratz, 1983; Meyler, Kenny and Quinn, 1998). The ARIMA model expects the input time series to be non-seasonal or seasonally adjusted. Many time-series data, on the other hand, show seasonal fluctuations which may be used to supplement any forecasting information contained therein. The characterisation of seasonal series occurs by a strong serial correlation at the seasonal lags (of four and eight) in the case of CPI-headline and CPI-food in India (Appendix Table A2). Therefore, in this study we have attempted both ARIMA and Seasonal ARIMA (SARIMA) models to forecast inflation. SARIMA is a generalised form of ARIMA that supports the seasonal component in time series (Box and Jenkins, 1976). Researchers suggest that it may be irrational to assume the seasonal component to repeat itself in the same way cycle after cycle in practice (Özmen and Şanli, 2017). SARIMA models allow for irregularity in the seasonal pattern from one cycle to the next (Brockwell and Davis, 1991). While the process of seasonal adjustment may often be regarded as an integral part of modelling framework, there is always some loss of information from seasonal adjustment even when the seasonal adjustment process is properly conducted (IMF, 2017). Furthermore, de-seasonalising the data may remove certain peaks and troughs that may contain useful insights and may also come in conflict with economic theory (Depalo, 2009). SARIMA models thus assume significance in the forecasting literature.

A SARIMA model is generally represented as SARIMA (p, d, q) (P, D, Q), with p standing for the non-seasonal autoregressive order, d standing for the non-seasonal integration order and q for the non-seasonal moving average order. In the seasonal part, P stands for the seasonal autoregressive order, D stands for the seasonal integration order, Q stands for the seasonal moving average order and m for the period or length of the season (in the monthly case 12, in the quarterly case 4). It can be expressed as follows:

$$\phi_P(B^m)\varphi(\mathrm{B})(1-B^m)^D(1-B)^d Y_t = c + \Theta_Q(B^m)\theta(\mathrm{B})\varepsilon_t \qquad \text{...(5)}$$

where, $\phi_P(B^m)$ and $\Theta_Q(B^m)$ are polynomials of orders P and Q, respectively.

There are two approaches to identify ARIMA models – the Box-Jenkins methodology and the penalty function statistics such as the Akaike

Information Criterion (AIC), Schwarz Criterion (SC) and Hannan Quinn Criterion (HQC). The Box-Jenkins methodology infers the correct form of ARMA model from the sample autocorrelogram, partial autocorrelogram and inverse autocorrelogram plots. However, these plots are often difficult to interpret in the case of higher order mixed ARMA models. Additionally, presence of seasonality (Gómez and Maravall, 1998) and random noise in time series (Meyler, *et al.* 1998; Saz, 2011) further complicates Box-Jenkins model identification. Therefore, penalty function statistics, which is computationally simpler and objective, is often preferred for identifying ARIMA models.

Accordingly, in this paper, our model identification is based on the AIC penalty function criteria (Brockwell and Davis, 1991; Burnham and Anderson, 2004). We estimate ARIMA using the maximum likelihood-based techniques on the log transformed CPI data for the sample period 1996-97:Q1 to 2017-18:Q3[12] and then forecast one-period ahead and four-periods ahead inflation[13]. We also estimate SARIMA models for the same period as an alternative to the ARIMA model to check for any improvement in the forecasting performance in view of the observed seasonality in food prices in India.

The identified model satisfies the standard diagnostic checks such as autocorrelation and heteroscedasticity on residuals (Appendix Table A3). The models chosen for the headline and three major groups of CPI based on AIC are presented in Table 3.

Table 3: ARIMA Models[14] based on AIC

(Sample period: 1996-97:Q1 to 2017-18:Q3)

Models	CPI-C	CPI-Core	CPI-Food	CPI-Fuel
ARIMA	(3,1,2)	(4,1,3)	(3,1,2)	(0,1,2)
SARIMA[15]	(3,1,3)(1,0,1)4	(2,1,0) (1,0,1)4	(4,1,1)(0,0,1)4	(0,1,2)(0,0,0)4

Source: Authors' estimates.

12 Sample period of estimation for various models is restricted to 2017-18Q3 to facilitate a comparison of out of sample forecasts of relatively longer period for model evaluation.

13 ARIMAX models have not been attempted here as we wanted the simplest univariate model as a benchmark. Other exogenous variables are taken into account in the SVAR and PC based models.

14 All specifications are obtained using logarithmic transformed data.

15 Results of seasonal unit root test (HEGY test) indicate seasonal differencing is not needed.

IV.2 Structural Vector Auto Regression (SVAR) Models

In order to introduce structural characteristics into the time series, a four variable SVAR model is estimated on quarterly data from 1996-97:Q1 to 2017-18:Q3, which apart from CPI-C/CPI-Core includes nominal exchange rate (INR-USD), real output or gross domestic product (GDP) and weighted average call money rate (WACR)[16]. Price of the Indian basket crude oil and absolute rainfall deviation from long period average (LPA) are incorporated as the two exogenous variables in the model given their significance in influencing India's inflation dynamics (Chand 2010; Sonna *et al.* 2014; Mohanty and John 2015; Anand *et al.* 2016).[17] All the variables, except WACR and rainfall deviation, are de-seasonalised using Census X-13ARIMA, converted to their natural logarithms, and used in their first-differenced forms [*i.e.,* quarter-on-quarter change (q-o-q)] in the model as they are non-stationary. Stationary property of the variables is tested by employing the augmented Dickey-Fuller test of unit roots (Appendix Table A1b).[18]

The choice of the variables and the structural identification restrictions that the model assumes for the purpose of estimation closely resemble that in the available literature (Christiano, Eichenbaum and Evans, 1999; Kim and Roubini, 2000; Uhlig, 2005; Mohanty and John, 2015). The model adopts the following ordering of the variables $\{INR - USD_t, GDP_t, CPI_t, WACR_t\}$ in their first-differenced form (barring interest rate) and uses the recursive identification method for the identifying restrictions in line with Eichenbaum and Evans (1995), and Christiano, *et al.* (1999).[19] INR-USD exchange rate is considered to be the most pre-determined variable in the model and a shock to exchange rate impacts all the variables contemporaneously. It is assumed that

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16 The month-wise average WACR is used to obtain quarterly averages.

17 Moreover, a set of dummy variables to capture exchange rate fluctuations during the Asian financial crisis of 1997-98, global financial crisis of 2007-08, food price upsurge in 2010-11 and taper tantrum episode of 2013-14 were also incorporated as exogenous variables in the model to enhance model performance.

18 Before going into SVAR, the three non-stationary variables CPI-C/CPI-Core; INR-USD; GDP were checked for the existence of any long-run cointegrating relationship and the results did not pass the Johansen Cointegration Test. It was not explored further given the objective of the paper on forecasting.

19 An alternate specification with output gap instead of real GDP was also attempted. However, it did not produce statistically significant results.

the real GDP in the economy responds to exchange rate variations and crude oil price movements. Domestic price is assumed to be sensitive to exchange rate variations and changes in real GDP. The monetary policy represented by WACR responds contemporaneously to all the variables. In this type of models, it is generally assumed that the central bank of the economy looks at the current prices and output, among other indicators, when setting the monetary policy instrument at time *t*. The recursiveness assumption implies that exchange rate, output and prices respond only with a lag to a monetary policy shock. While such an assumption has attracted a lot of attention and debate in the literature, abandoning the assumption may also lead to a substantial cost, in the sense that the identifition of a broader set of economic relations becomes complicated (Christiano, *et al.* 1999).

Accordingly, let Y_t denote a $k \times 1$ vector of {INR – USD$_t$, GDP$_t$, CPI$_t$, WACR$_t$} at time *t*. Considering the structural identifying restrictions stated above, the model in a VAR framework can be written as:

$$AY_t = F_1 Y_{t-1} + \; F_2 Y_{t-2} + \cdots + F_s Y_{t-s} + u_t \qquad \text{... (6)}$$

where, u_t is a $k \times 1$ vector of structural shocks following $N = (0, \Sigma)$; $\Sigma = diag(\sigma_j)$; F_i is a $(k \times k)$ matrix of parameters for *1, 2 ,...,s*; while matrix *A* is the contemperaneous matrix (F_o)

For identifying the above model, $k(k+1)/2$ restrictions are required to be imposed on A matrix, of which k restrictions could be satisfied by normalising the diagonal elements of A to unity. In our model $k = 4$. Therefore, we need to impose 6 additional restrictions on the contemporaneous correlations for identification of the four structural shocks (exchange rate shock, output shock, price shock and monetary policy shock). This is done by specifying A as a lower triangular matrix.

Therefore, equation (6) can be rewritten as a reduced form VAR model as: $Y_t = B_1 Y_{t-1} + \; B_2 Y_{t-2} + \cdots + B_s Y_{t-s} + \varepsilon_t$ ... (7)

where, $B_i = A^{-1} F_i$ and ε_t follows $N = (0, I)$.

This model is estimated on two measures of inflation: Model 1 with CPI-C as the headline inflation measure and Model 2 with CPI excluding food and fuel as the measure of core inflation. The lag lengths for the models are chosen based on the AIC and SC criteria. The models satisfy the stability test (roots of characteristic polynomial were inside the unit circle) as well as the residual autocorrelation test (Appendix Tables A4.1 and A4.2).

The structural impulse response functions (IRFs) of inflation with respect to the exchange rate shock, output shock and policy rate shock broadly meet our expectations (Chart 4). On transformation [of standard error (SE) shock to equivalent per cent], a one per cent appreciation of the exchange rate leads to a fall in headline inflation (core inflation) by 12 basis points (bps) (9 bps) in the first quarter itself[20]; a one per cent increase in output pushes up headline inflation (core inflation) by 27 bps (28 bps) accumulated over the first two quarters, with the peak impact of 22 bps (18 bps) in the second quarter; while the impact of policy rate changes on inflation lasts longer – a one per cent increase in interest rate results in a fall in headline inflation (core inflation) by 15 bps (16 bps) in the second quarter and a cumulative fall of 50 bps (35 bps) over a span of 3 years (Appendix Table A5). The IRFs also indicate that the impact of an interest rate shock on inflation is highly persistent as compared to the exchange rate shock and output shock.[21] Further, in terms of the channel *via* which policy rate shock impacts inflation, the IRFs

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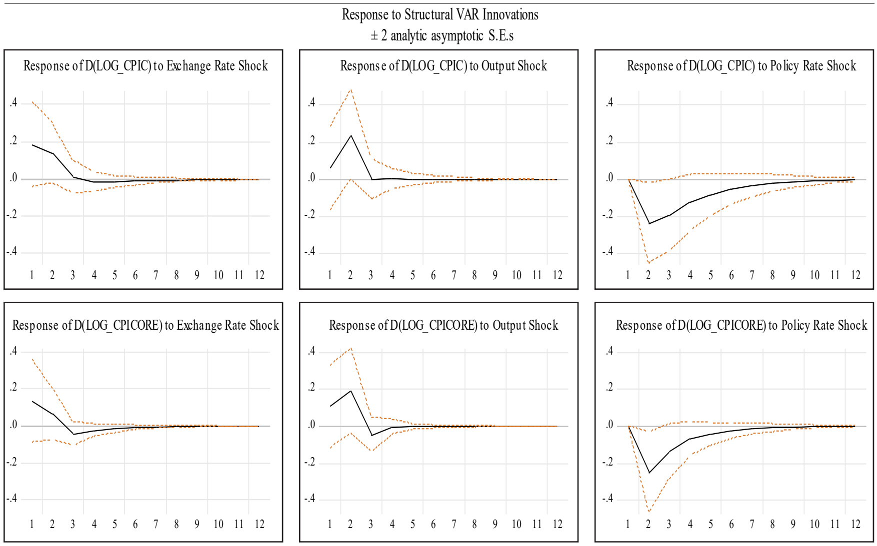
20 These estimates are in line with the findings in the literature in India, that show a cumulative pass through of exchange rate impact on headline inflation in the range of 10-15 per cent over a period of 4-5 months (Bhattacharya *et al.* 2008; Patra *et al.* 2018; RBI, 2021).

21 IRFs based on the applied SVAR framework (standard monetary VAR in line with the interest rate rule in which the monetary authority responds to the current level of output and/or output gap and inflation, augmented with an exchange rate variable) generally display impulse response anomalies – *'price puzzle'* and *'exchange rate puzzle'* (Barnett *et al.* 2015; Ouliaris *et al.*, 2016; Goyal and Parab, 2019). Price puzzle is the one in which monetary policy shocks have a positive effect on inflation instead of a negative effect, while the exchange rate puzzle is where a monetary policy shock that raises interest rates depreciates rather than appreciates a currency. In the Indian context, Goyal and Parab (2019) find evidence of price puzzle. Literature provides methods that may eliminate such puzzles, broadly centring around re-specifying the SVAR model in some manner. Some of the methods are: incorporating additional/latent variables into the SVAR framework (such as, global crude oil prices, global commodity prices or any other variable that influence inflation or price-setting mechanism); re-defining the variables (using output gap instead of output); and different model specifications. Our SVAR model also showed both the puzzles. However, the introduction of rainfall deviation and Indian basket crude oil price as exogenous variables in the model helped to eliminate the price puzzle, while the exchange rate puzzle remains (Appendix Charts A.3 and A.4).

Chart 4: Structural IRFs of CPI-C/CPI-Core with respect to Exchange Rate (INR-USD), GDP and WACR



Note: Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation). Accordingly, the IRFs with respect to the exchange rate shock start on the positive axis (which would be the opposite when nominal effective exchange rate is used).

Source: Authors' estimates.

suggest that the impact is *via* output, where a positive policy rate shock leads to a fall in output (Appendix Charts A.1 and A.2)[22].

In order to quantify the relative importance of various shocks in explaining the fluctuations in inflation, a variance decomposition analysis was conducted. The results show that the fluctuations in inflation is explained mostly by its own shock. Among the other shocks, the policy rate shock is most important explaining about 7-9 per cent of the variance in inflation over the medium term, as compared to about 2-4 per cent in case of exchange rate and output. Thus, the variance decomposition analysis along with impulse response functions clearly point out the significance of policy rate shock over exchange rate and output shocks for both headline inflation and core inflation in India (Appendix Table A6).

22 Among the alternative channels of monetary policy transmission (Mathai, 2009), the SVAR here focuses only on the interest rate channel - a hike in the policy rate raises borrowing costs of consumers and investors and thereby reduces aggregate demand and brings down inflation – in view of the current operating framework of monetary policy in India.

IV.3 Phillips Curve (PC) Based Models

In this section, inflation dynamics is modelled in three ways: the backward-looking triangle model of Gordon (1998); a purely forward-looking NKPC; and a hybrid NKPC which incorporates forward and backward-looking components similar to Gali and Gertler (1999), Patra and Kapur (2012) and Patra, *et al.* (2014). More precisely, we estimate the following specifications:

$$\pi_t = \gamma\pi_{t-1} + \beta_1 X_{t-k} + \beta_2 \triangle (X_{t-1}) + \delta Z_{t-1} + \varepsilon_t \quad \ldots(8)$$

$$\pi_t = \gamma' E_t \pi_{t+1} + \beta_1 X_{t-k} + \beta_2 \triangle (X_{t-1}) + \delta Z_{t-1} + \varepsilon_t \quad \ldots(9)$$

$$\pi_t = \gamma\pi_{t-1} + (1-\gamma) E_t \pi_{t+1} + \beta_1 X_{t-k} + \beta_2 \triangle (X_{t-1}) + \delta Z_{t-1} + \varepsilon_t \quad \ldots(10)$$

where, π_t is a measure of inflation, X_t is a measure of economic activity represented by output gap [(actual output *minus* potential output[23]/potential output)*100], $\triangle$ stands for first difference, and Z_t is a vector of supply side factors; $E_t\pi_{t+1}$ is the expected future inflation and ε_t is the white noise term (refer to Appendix Table A1a for a detailed description of variables). In equation (10), the coefficients of the inflation terms on the right-hand side are restricted to sum up to unity[24], implying the existence of a vertical long-run Phillips curve. All variables, except minimum support prices (MSP) and absolute rainfall deviation from LPA (part of the Z vector), are deseasonalised using Census X-13ARIMA. The presence of unit roots in the variables is tested by employing the augmented Dickey-Fuller test and the test results are presented in the Appendix Table A1b. The difference between the PC specifications in (8), (9) and (10) and the standard ones generally found in extant literature in the Indian context is the presence of the additional term $\triangle X_{t-1}$ – change in output gap – which is included to capture the possibility of *speed limit effects* (Fisher, Mahadeva and Whitley, 1997; Gruen, Pagan and Thompson, 1999; Malikane, 2014). The speed limit gets its name from the suggestion that more rapid changes in economic activity may cause larger changes in the inflation rate for a given level of the economic activity

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23 Potential output is measured by the HP filtered trend output.

24 This restriction also implies that inflation is dynamically homogenous.

(Fuhrer, 1995). The coefficients, β_1 and β_2, therefore provide measures of the flexibility in price adjustment.

Equations (8), (9) and (10) are estimated on quarterly data for the sample period 1996-97:Q1 to 2017-18:Q3 with q-o-q change in headline CPI as well as its major components – core, food and fuel – as dependent variables, using OLS method. Even though PC estimation is typically undertaken using headline or core inflation as the inflation metric, we delve into other major sub-components (food and fuel) for two reasons: first, to understand the drivers of sub-component level inflation dynamics; and second, to generate inflation forecasts from the indirect approach to compare with aggregate level inflation forecast, given the focus of the paper in generating inflation forecasts while capturing the changes in the inflation process. Furthermore, the final form of the equations is derived by starting with a general form with several lags of the output gap and choosing an appropriate model based on the significance of relevant coefficients and overall fit. The results are given in Tables 4, 5, 6 and 7, respectively.

Two variables are used to capture inflation expectations $E_t\pi_{t+1}$ – the lead q-o-q change in headline CPI (in specification 2) and the lagged headline trend[25] (q-o-q) (in specifications 3 and 4) in Table 4. Trend headline inflation can be used as a proxy for expected inflation: (i) as inflation outcome is expected to converge to its trend after the shocks to inflation die out (Behera and Patra, 2020) and (ii) as a substantial portion of observed inflation persistence can be attributed to variation in trend inflation, which in turn is related to changes in monetary regimes (Garnier *et al.,* 2015). Moreover, there was no unique inflation target for the whole sample period (there was a change in the inflation metric for policy from WPI to CPI with the adoption of FIT) which could be used as a proxy for inflation expectations. As can be observed, the leads and lags of price changes are generally significant. The coefficient of lagged headline CPI trend[26] is greater compared to lag of headline CPI q-o-q change

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[25] Trend inflation is slow moving and there may not be any difference between its one period lag and lead, and therefore lagged trend is used which facilitates estimation by OLS.

[26] 'Inflation trend' is constructed by applying the HP filter on the CPI headline q-o-q series and is used to represent trend in case of food, fuel and core inflation.

Table 4: Headline CPI (q-o-q change in per cent)

	(1)	(2)	(3)	(4)
	Headline (Triangle Model)	**Headline (NKPC)**	**Headline (NKPC 2)**	**Headline (Hybrid)**
$\Delta CPIC_{t-1}$	0.214** (0.106)	-	-	0.000890 (0.109)
ΔCPI_{t+1}	-	0.389*** (0.116)	-	-
$Inflation\ trend_{t-1}$	-	-	1.030*** (0.227)	0.999*** (0.109)
$Output\ gap_{t-7}$	0.150* (0.0831)	0.197** (0.0788)	0.218*** (0.0747)	0.217*** (0.0760)
$\Delta Output\ gap_{t-1}$	0.205** (0.0943)	0.241*** (0.0899)	0.191** (0.0849)	0.191** (0.0848)
$MSP\ variation_{t-1}$	0.0480* (0.0243)	0.0214 (0.0252)	-0.00548 (0.0256)	-0.00356 (0.0213)
$\Delta Exchange\ rate_{t-1}$	0.0819* (0.0448)	0.0785* (0.0415)	0.0620 (0.0396)	0.0634 (0.0394)
$\Delta Global\ nonfuel\ price_{t-1}$	0.0482* (0.0263)	0.0585** (0.0237)	0.0458** (0.0227)	0.0463* (0.0234)
$Rainfall\ deviation_{t-2}$	0.00174 (0.00682)	-0.00403 (0.00676)	0.0000645 (0.00616)	0.000125 (0.00614)
[27]R^2	0.521	0.564	0.611	-
N	80	80	80	80
Portmanteau test for white noise (Q statistic *p-value*)	0.8503	0.8885	0.9637	0.9606

Notes: 'Inflation trend' is constructed by applying the HP filter on the CPI headline q-o-q series. Specifications 1-4 include the following quarter dummy variables – 1998q4; 1999q1; 2000q3; 2005q4; and 2012q2. Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation).
Standard errors in parentheses.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$
Source: Authors' estimates.

(Table 4, specification 4), indicating its relative importance in determining inflation dynamics in India. The coefficients of the measure of economic activity – real output gap (7 quarters before) and the change in real output gap (1 quarter before) – are both positive and significant in all the specifications suggesting that demand factors play an important role in determining inflation in India. In other words, inflation depends as much on the change in output gap as on the level implying the presence of speed limit effects. However, the

[27] In constrained regressions, a comparable R^2 cannot be obtained, and hence not reported.

Table 5: Core CPI (q-o-q change in per cent)

	(1)	(2)	(3)	(4)
	CPI Core (Triangle Model)	**CPI Core (NKPC)**	**CPI Core (NKPC 2)**	**CPI Core (Hybrid)**
$\Delta CPI\ Core_{t-1}$	0.187^{*} (0.0941)	-	-	0.00989 (0.108)
$\Delta CPI\ Core_{t+1}$	-	0.242^{**} (0.116)	-	-
$Inflation\ trend_{t-1}$	-	-	0.707^{***} (0.181)	0.990^{***} (0.108)
$Output\ gap_{t-7}$	0.161^{**} (0.0627)	0.183^{***} (0.0679)	0.152^{**} (0.0638)	0.142^{**} (0.0646)
$\Delta Output\ gap_{t-1}$	0.224^{***} (0.0808)	0.277^{***} (0.0887)	0.208^{**} (0.0805)	0.198^{**} (0.0827)
$\Delta Exchange\ rate_{t-1}$	0.0653^{*} (0.0359)	0.0617^{*} (0.0349)	0.0438 (0.0331)	0.0321 (0.0330)
$\Delta Indbasket\ crude_{t-1}$	0.00811 (0.00560)	0.00849 (0.00614)	0.00702 (0.00572)	0.00696 (0.00583)
R^2	0.550	0.431	0.501	-
N	80	80	80	80
Portmanteau test for white noise (Q statistic *p-value*)	0.3757	0.5816	0.1835	0.2395

Notes: 'Inflation trend' is constructed by applying the HP filter on CPI headline (q-o-q change). Specification 1 includes the following quarter dummy variables – 1998q3; 2005q1; 2009q4; 2010q1; and 2012q1. Specifications 2-4 include the following quarter dummy variables – 2009q4; and 2010q1. Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' estimates.

less than proportional impact of output gap on inflation (the lower coefficients) indicates lower degree of flexibility in price adjustment. Other variables that affect headline inflation are MSP, exchange rate and global non-fuel inflation.

Similar to the headline specification, $E_t\pi_{t+1}$ in the case of core is captured by two variables – lead core q-o-q inflation (specification 2 in table 5) and lagged q-o-q inflation trend derived from headline (specifications 3 and 4). The lags and leads of price changes are significant here too. Besides, the coefficient of lagged headline trend is greater compared to lag of core q-o-q inflation (Table 5, specification 4) as was the case in headline. The coefficients of the level as well as change in the output gap are statistically significant and positive, corroborating the speed limit effects.

Table 6: Food CPI (q-o-q change in per cent)

	(1)	(2)	(3)
	CPI Food	**CPI Food**	**CPI Food**
$\Delta CPI\ Food_{t-1}$	0.271***	-	0.180**
	(0.0866)	-	(0.0867)
Inflation trend$_{t-1}$	-	1.532***	0.820***
		(0.361)	(0.0867)
MSP variation$_{t-1}$	0.0824**	0.0114	0.0392
	(0.0313)	(0.0368)	(0.0286)
Rainfall deviation$_{t-2}$	0.0166*	0.0169*	0.0163*
	(0.00944)	(0.00900)	(0.00889)
$\Delta Global\ foodprice_{t-1}$	0.0159	0.0473	0.0304
	(0.0319)	(0.0306)	(0.0302)
R^2	0.543	0.583	-
N	87	87	87
Portmanteau test for white noise (Q statistic *p-value*)	0.1962	0.5367	0.3371

Notes: 'Inflation trend' is constructed by applying the HP filter on CPI headline (q-o-q change). Specifications here include the following quarter dummy variables – 1998q1; 1998q4; 1999q1; 2006q2; 2010q4; 2011q1; and 2011q1.
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' estimates.

Food inflation is modelled in a similar fashion except that it leaves out the output gap variable, as food prices are determined more by supply side factors, given the broadly inelastic nature of food demand[28]. MSP and rainfall deviation influence food inflation significantly and positively, apart from the lags of inflation. Once again, the lagged headline CPI trend is highly significant, and the magnitude of its coefficient is comparatively higher (Table 6).

Analogously, output gap variables are omitted in the case of fuel inflation as well. The results show that fuel inflation (q-o-q change) is significantly and positively influenced by crude oil inflation. Moreover, identical inferences can be made with regard to lagged headline CPI trend (Table 7).

[28] Alternate specifications with output gap (up to four lags) for food inflation were attempted; however, the coefficient turned out to be statistically insignificant and therefore have been dropped from the final set of models.

Table 7: Fuel CPI (q-o-q change in per cent)

	(1)	(2)	(3)
	CPI Fuel	**CPI Fuel**	**CPI Fuel**
$\Delta CPI\ Fuel_{t-1}$	0.156***	-	0.149***
	(0.0571)		(0.0562)
$Inflation\ trend_{t-1}$		0.576**	0.851***
	-	(0.230)	(0.0562)
$\Delta Indbasket\ crude_{t-1}$	0.0214***	0.0219***	0.0209***
	(0.00754)	(0.00769)	(0.00741)
$\Delta Indbasket\ crude_{t-2}$	-	0.00661	-
		(0.00712)	
$\Delta Exchange\ rate_{t-1}$	0.0551	0.0583	0.0199
	(0.0402)	(0.0410)	(0.0391)
R^2	0.756	0.757	-
N	90	89	90
Portmanteau test for white noise (Q statistic *p-value*)	0.8643	0.1340	0.3172

Notes: 'Inflation trend' is constructed by applying the HP filter on the CPI headline q-o-q series. Specifications here include the following quarter dummy variables – 2000q2; 2000q4; 2002q1; 2005q2; 2010q3; and 2011q1. Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' estimates.

The Reserve Bank has been collecting 3-months ahead and 1-year ahead inflation expectations of households through quarterly surveys since 2005. Similar to the analysis undertaken in Pattanaik, *et al.* (2019), we use these survey-based inflation expectations in an NKPC framework for a truncated sample period (and find the results to be qualitatively similar to that of the longer time period discussed in this section (Appendix Table A7) – inflation expectations (both 3-months and 1-year ahead) and output gap are signficant in determining inflation. These results are also in line with Pattanaik, *et al.* (2019). As a robustness check, these specifications were estimated using IV-GMM as well, and the results were found to be broadly similar (Appendix Tables A8 and A9).

Section V
Evaluating Forecasting Performance

Given the objective of this paper, an evaluation of the forecasting performance is done based on the root mean square errors (RMSEs) and mean absolute errors (MAEs) calculated by comparing the derived y-o-y inflation forecasts generated from these alternative models discussed in section IV with the actual y-o-y inflation.[29] Additionally, in line with the literature, we also provide forecasts generated from a random walk model as a benchmark[30]. We do not go into forecasting inflation at a disaggregated level in the case of SVAR because these models are generally backed by economic theories and linkages that largely work at the macro-level. Moreover, literature also tends to use SVAR models more on validating and establishing larger macroeconomic theories.

In the case of PC models, headline and core inflation forecasts are based on specifications (1), (3) and (4) in Tables 4 and 5 – *i.e.,* we do not employ specification 2 in which inflation expectations are captured through lead headline (core) inflation, as it is useful for modelling but not amenable for out-of-sample forecasting. As discussed earlier, a key objective here is to evaluate the merit of a disaggregated approach; we, therefore, compare the forecasts of headline inflation obtained directly and indirectly (a weighted average[31] of the forecasts of the three sub-components – core, food and fuel – based on their fixed weights in the CPI-C). Forecast periods are restricted to 2017-18:Q4 to 2019-20:Q4 (9 quarters) for one-period ahead and 2018-19:Q3 to 2019-20:Q4 (6 quarters) for four-periods ahead inflation forecasts to allow forecast comparison over a reasonably long period.

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29 The models are based on log first-differenced quarterly data on CPI with seasonal adjustment in case of SVAR and PC models and without seasonal adjustment in case of ARIMA and SARIMA models. The forecast output is in the form of the respective indices (barring PC-based models where the forecast output is quarter-on-quarter change in the index), which are then used to derive year-on-year (y-o-y) inflation forecasts, and then compared with the actual inflation outcomes to generate the respective model RMSEs.

30 A random walk model, which is defined as a process where the current value of a variable is composed of its past value plus an error term defined as a white noise $(\pi_t = \pi_{t-1} + \varepsilon_t)$, is often used as a common benchmark for forecast evaluation (Raj *et al*., 2019). Studies have shown that persistent stationary processes may be better predicted by drift less unit-root-based forecasts than by forecasts coming from a model that is correctly specified but that is subject to a higher degree of parameter uncertainty (Pincheira and Medel, 2012). Comparing the forecast performances of various Phillips curve-based inflation models with a random walk model, another study finds that for the US, the random walk forecasts perform better (Atkeson and Ohanian, 2001).

31 Weights correspond to the weights of these groups in the CPI-C basket (Core: 47.30 per cent; Food: 45.86 per cent; and Fuel: 6.84 per cent).

The results indicate that SARIMA outperforms both SVAR and PC models in one period ahead headline forecasts, reflecting gains from flexibility as there are no restrictions (unlike the economic models) to capture the dynamic properties (Litterman, 1986; Stockton and Glassman, 1987). Secondly, in the case of one-period ahead ARIMA forecasting, direct forecasts perform better than indirect ones (sum of component forecasts), indicating that noise associated with volatile food and fuel groups plausibly contaminates the aggregation of forecasts (Table 8). This is in line with the findings of Pratap and Sengupta (2019) for India. Along similar lines, many other studies have concluded that disaggregation does not necessarily imply forecast improvement (Benalal, Diaz del Hoyo, Landau, Roma and Skudelny, 2004; Hubrich, 2005; Cushing, 2014). Finally, while a simple ARIMA on core is better, SARIMA models are better in the case of headline primarily indicating the existence of seasonality in food prices that is captured in headline inflation.

An assessment of four-periods ahead forecasts, however, suggests that the PC-based models (NKPC and hybrid NKPC) perform better than ARIMA/ SARIMA models in the case of CPI core; in the case of headline, NKPC and hybrid NKPC outperform every model apart from SARIMA under direct approach (Table 9). Although SVAR model may be capturing the structural dynamics factoring in the role of policy variable, it falls behind PC models

Table 8: One Period Ahead Forecasts: 2017-18:Q4 to 2019-20:Q4 (9 Quarters)

Models	CPI – Direct		CPI Core		CPI C – Indirect	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Random Walk	1.02	0.75	0.62	0.51	1.03	0.76
ARIMA	0.81	0.70	0.45	0.38	0.86	0.74
SARIMA	0.64	0.49	0.48	0.37	0.85	0.72
SVAR	0.77	0.72	0.69	0.52	_	_
Phillips Curve (PC) Models						
Model 1 – Backward-looking PC	1.22	1.06	0.52	0.39	1.17	1.01
Model 2 – NKPC (with lagged trend inflation)	0.94	0.75	0.45	0.38	0.92	0.75
Model 3 – Hybrid NKPC (with the constraint)	0.96	0.78	0.47	0.43	0.90	0.70

Source: Authors' estimates.

Table 9: Four-Periods Ahead Forecasts: 2018-19:Q3 to 2019-20:Q4 (6 Quarters)

Models	CPI C – Direct		CPI Core		CPI C – Indirect	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Random Walk	2.57	2.27	1.54	1.36	2.55	2.27
ARIMA	2.82	2.35	1.88	1.76	2.92	2.46
SARIMA	1.42	1.29	1.91	1.79	2.93	2.47
SVAR	2.32	2.00	2.40	2.25	_	_
Phillips Curve (PC) Models						
Model 1 – Backward-looking PC	3.80	3.23	2.10	2.07	3.19	2.69
Model 2 – NKPC (with lagged trend inflation)	1.78	1.67	1.00	0.82	1.58	1.49
Model 3 – Hybrid NKPC (with the constraint)	1.78	1.66	0.74	0.68	1.71	1.67

Source: Authors' estimates.

in forecasting inflation, which better captures the role of expectations in determining the inflation dynamics in India.

Furthermore, we employ a formal test for comparing forecast accuracy – the Diebold-Mariano (DM) test (Diebold and Mariano, 1995). The null hypothesis of the DM test is that the forecast accuracy of any given two models is equal. We find that direct forecast outperforms the indirect forecast in the case of univariate models both for one-quarter and four-quarters ahead horizons; while in the case of PC-based models, indirect forecasts are generally better compared to direct forecasts[32].

These findings indicate that apart from aggregate forecast, disaggregated forecasts may also be useful from the perspective of four-quarters ahead inflation forecasting under different PC models, which better capture the varying properties of the data generating processes of the sub-components of CPI-C in India, which is not possible to capture simply by its own past as in

[32] DM test results imply that in the case of ARIMA and SARIMA models, across both forecast horizons, the null hypothesis of equal forecast accuracy is rejected in favour of direct forecasts. In the case of PC-models, indirect forecasts are better in 4-period ahead forecasts, while the null hypothesis is not rejected in the case of 1-period ahead forecasts.

ARIMA models. However, over one-quarter ahead horizon, inflation model based on the behaviour of past inflation alone produces the best forecast. On the other hand, despite poor performance of SVAR models in forecasting, impulse-responses from these models provide useful insights in identifying the direction of linkages and the impact of shocks, which are important in policy analysis and therefore, should be a part of any modelling and forecasting exercise of inflation.

Section VI
Conclusion

Under a flexible inflation targeting monetary policy framework, inflation forecast acts as the intermediate target. Therefore, generating accurate, reliable and unbiased inflation forecasts for the conduct of monetary policy assumes significance. Forecast accuracy helps in the optimal conduct of monetary policy and thereby promotes policy credibility.

This paper models and forecasts CPI inflation using both univariate and multivariate models following two approaches – direct (based on aggregate data) and indirect (based on disaggregate data, *i.e.,* major components of CPI, which are then combined). It corroborates the existence of a PC relationship in India and finds that the dynamics of sub-components of CPI-C are different. While output gap and exchange rate affect core inflation, changes in MSP and rainfall deviation influence food inflation. Fuel inflation is mainly determined by international crude oil prices. Notwithstanding the varying dynamics at the disaggregated level, forecasts generated using the indirect approach do not perform as well as the univariate forecasts at the aggregate level. Furthermore, simple univariate models produce better forecasts compared to structural multivariate models for the one-quarter ahead forecast horizon.

For four-quarters ahead forecasts horizon, however, the PC-based models outperform others in the case of CPI core; in the case of headline, they outperform every model apart from SARIMA under direct approach. Further, PC-based forecasts generated *via* the indirect approach is better than those generated through the direct approach, indicating that disaggregated level dynamics of inflation could also be useful for generating inflation projections in India. The question on suitability of direct *versus* indirect forecasts, thus, crucially depends on the forecast horizon and the underlying model. SVAR models, despite having poor forecast performance, provide valuable insights for evaluating the impact of shocks, which are useful from the perspective of policy analysis. As a way forward, inflation forecasting models based on time-varying parameter VAR combined with stochastic volatility may be considered to take into account the changing inflation dynamics over time driven by both structural changes taking place in the economy and shifts in policy regimes.

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Appendix

Table A1a: Variable Description

Sl. No.	Variable	Description
1	Real Output gap	Log of actual series less its Hodrick-Prescott filtered trend*100 (based on seasonally adjusted real GDP)
2	ΔReal output gap	Difference of log of actual series less its Hodrick-Prescott filtered trend*100
3	ΔCPI C	Difference of log of CPI C*100 (q-o-q, seasonally adjusted)
4	ΔCPI core	Difference of log of CPI Core*100 (q-o-q, seasonally adjusted)
5	ΔCPI food and beverages	Difference of log of CPI Food*100 (q-o-q, seasonally adjusted)
6	ΔCPI fuel	Difference of log of CPI Fuel*100 (q-o-q, seasonally adjusted)
7	ΔIndbasket crude	Difference of log of Crude Oil Prices (Indian Basket) *100 (q-o-q, seasonally adjusted)
8	ΔExchange rate	Difference of log of Exchange rate (INR/USD) *100 (q-o-q, seasonally adjusted)
9	ΔGlobal non-fuel price	Difference of log of Global non-fuel commodity price index*100 (q-o-q, seasonally adjusted)
10	ΔGlobal food price	Difference of log of Global food and beverages price index*100 (q-o-q, seasonally adjusted)
11	MSP (Production weighted) variation	(log MSPt – log MSPt-4)*100 (y-o-y change)
12	Rainfall deviation	Absolute value of rainfall deviation from its LPA

Table A1b: Results of the Unit Root Tests

Variables	Augmented Dickey Fuller (ADF) Test Statistic	
	Log X	Δ Log X
Log(CPIC)	-1.28	-6.73***
Log(CPI-Core)	-1.75	-4.14***
Log(CPI-Food)	-1.46	-7.30***
Log(CPI-Fuel)	-2.43	-4.83***
Log(INR-USD)	-1.93	-6.13***
Log(GDP)	-2.62	-10.04***
Real Output gap	-4.06***	-
Difference of Real output gap	-10.76***	-
Log(Price of Indian basket crude oil)	-1.73	-7.12***
Rainfall Deviation	-9.56***	-
WACR	-5.10***	-
Log(Global non-fuel commodity price)	-1.68	-6.01***
Log(Global food price)	-2.07	-7.44***
Log(MSP-Production weighted) variation (y-o-y)	-4.37***	-

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively. The null hypothesis of ADF is that the data series is nonstationary. High significance of the test statistic implies that the series is stationary. All variables, except WACR, rainfall deviation and MSP were de-seasonalised before checking for the presence of unit roots.

Source: Authors' estimates.

Table A2: Seasonality Check

Correlogram (D(CPI-C))

Date: 01/06/21 Time: 02:37
Sample: 1996Q2 2020Q1
Included observations: 95

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.260	0.260	6.6432	0.010
		2	-0.240	-0.330	12.363	0.002
		3	0.188	0.430	15.911	0.001
		4	0.586	0.395	50.709	0.000
		5	0.205	0.048	55.029	0.000
		6	-0.186	-0.070	58.617	0.000
		7	0.177	0.176	61.905	0.000
		8	0.612	0.330	101.64	0.000
		9	0.178	-0.082	105.02	0.000
		10	-0.224	-0.054	110.48	0.000
		11	0.179	0.111	114.01	0.000
		12	0.482	-0.036	139.76	0.000

Correlogram (D(CPI-Core)

Date: 06/11/21 Time: 11:13
Sample: 1996Q2 2020Q1
Included observations: 95

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.146	0.146	2.0772	0.150
		2	0.565	0.556	33.719	0.000
		3	0.199	0.121	37.705	0.000
		4	0.467	0.210	59.772	0.000
		5	0.227	0.085	65.035	0.000
		6	0.331	-0.008	76.393	0.000
		7	0.273	0.098	84.201	0.000
		8	0.342	0.134	96.582	0.000
		9	0.235	-0.003	102.49	0.000
		10	0.235	-0.074	108.50	0.000
		11	0.210	-0.031	113.32	0.000
		12	0.245	0.043	119.98	0.000

Correlogram (D(CPI-Food))

Date: 06/11/21 Time: 11:13
Sample: 1996Q2 2020Q1
Included observations: 95

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.146	0.146	2.0772	0.150
		2	0.565	0.556	33.719	0.000
		3	0.199	0.121	37.705	0.000
		4	0.467	0.210	59.772	0.000
		5	0.227	0.085	65.035	0.000
		6	0.331	-0.008	76.393	0.000
		7	0.273	0.098	84.201	0.000
		8	0.342	0.134	96.582	0.000
		9	0.235	-0.003	102.49	0.000
		10	0.235	-0.074	108.50	0.000
		11	0.210	-0.031	113.32	0.000
		12	0.245	0.043	119.98	0.000

Correlogram (D(CPI-Fuel))

Date: 01/06/21 Time: 02:43
Sample: 1996Q2 2020Q1
Included observations: 95

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.121	0.121	1.4392	0.230
		2	0.163	0.151	4.0757	0.130
		3	0.036	0.001	4.2053	0.240
		4	-0.024	-0.055	4.2652	0.371
		5	-0.014	-0.012	4.2851	0.509
		6	0.092	0.111	5.1564	0.524
		7	0.059	0.048	5.5268	0.596
		8	0.187	0.151	9.2391	0.323
		9	0.083	0.030	9.9827	0.352
		10	0.062	0.005	10.406	0.406
		11	0.043	0.022	10.605	0.477
		12	0.011	0.003	10.618	0.562

Table A3: ARIMA Models - Diagnostics

Models	CPI-C		CPI-Core		CPI-Food		CPI-Fuel	
	DW Test Statistic	ARCH Test for Heterosce-dasticity (P value)	DW Test Statistic	ARCH Test for Heterosce-dasticity (P value)	DW Test Statistic	ARCH Test for Heterosce-dasticity (P value)	DW Test Statistic	ARCH Test for Heterosce-dasticity (P value)
ARIMA	2.00	0.82	1.96	0.98	2.00	0.65	1.99	0.77
SARIMA	1.98	0.77	2.02	0.96	1.97	0.51	1.99	0.77

Source: Authors' estimates.

Table A4.1: Roots of Characteristic Polynomial

Model 1		Model 2	
Root	Modulus	Root	Modulus
0.64	0.64	0.59	0.59
0.20	0.20	-0.053194 - 0.117008i	0.128532
-0.18	0.18	-0.053194 + 0.117008i	0.128532
0.10	0.10	0.02	0.02

Note: No root lies outside the unit circle. VAR satisfies the stability condition.
Source: Authors' estimates.

Table A4.2: VAR Residual Portmanteau Tests for Autocorrelations

Lag	Model 1		Model 2	
	Adj Q-Stat	Prob.*	Adj Q-Stat	Prob.*
1	6.69	---	5.75	---
2	15.19	0.51	23.88	0.09
3	37.86	0.22	46.46	0.05
4	50.36	0.38	60.76	0.10
5	60.49	0.60	74.88	0.17
6	83.47	0.37	91.11	0.19
7	95.42	0.50	107.19	0.20
8	103.01	0.72	119.11	0.31
9	116.51	0.76	132.21	0.38
10	130.4	0.78	150.02	0.35
11	142.67	0.83	169.03	0.30
12	158.13	0.83	180.73	0.39

Note: Null Hypothesis: No residual autocorrelations up to lag h. *Test is valid only for lags larger than the VAR lag order. df is degrees of freedom for (approximate) chi-square distribution; *df and Prob. may not be valid for models with exogenous variables.

Source: Authors' estimates.

Table A5: Percentage Change in Inflation due to a One Percentage Change in Exchange Rate, Output and Interest Rate

Qtr.	Headline Inflation			Core Inflation		
	Exchange Rate Shock	Output Shock	Interest Rate Shock	Exchange Rate Shock	Output Shock	Interest Rate Shock
1	0.12	0.06	0.00	0.09	0.10	0.00
2	0.09	0.22	-0.15	0.04	0.18	-0.16
3	0.01	0.00	-0.13	-0.03	-0.04	-0.09
4	-0.01	0.00	-0.08	-0.01	-0.01	-0.04
5	-0.01	0.00	-0.05	-0.01	0.00	-0.03
6	-0.01	0.00	-0.03	0.00	0.00	-0.02
7	0.00	0.00	-0.02	0.00	0.00	-0.01
8	0.00	0.00	-0.01	0.00	0.00	-0.01
9	0.00	0.00	-0.01	0.00	0.00	0.00
10	0.00	0.00	-0.01	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00

Note: Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation).
Source: Authors' estimates.

Chart A.1: Structural IRFs of GDP with respect to Nominal Exchange Rate (INR-USD), CPI-C and WACR

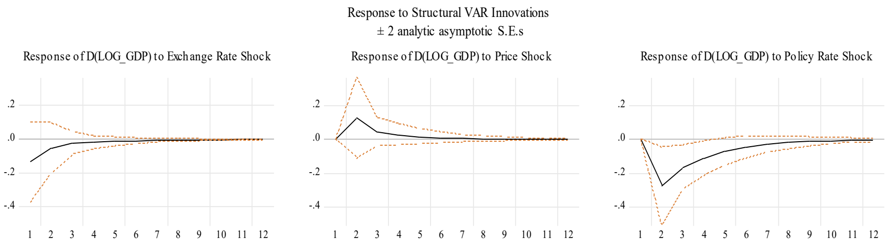


Chart A.2: Structural IRFs of GDP with respect to Nominal Exchange Rate (INR-USD), CPI-Core and WACR

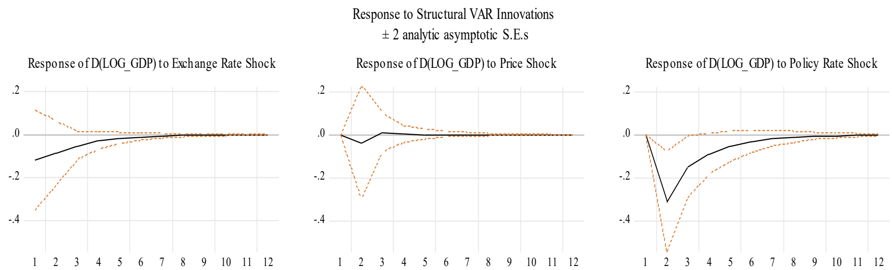


Chart A.3: Structural IRFs of Nominal Exchange Rate (INR-USD) with respect to GDP, CPI-C and WACR

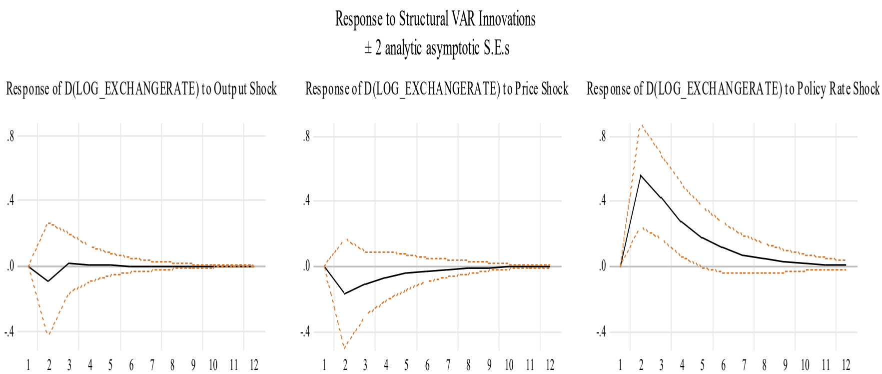
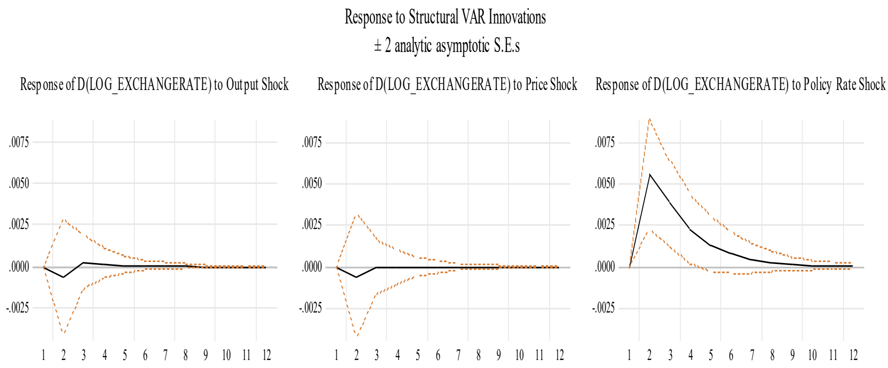


Chart A.4: Structural IRFs of Nominal Exchange Rate (INR-USD) with respect to GDP, CPI-Core and WACR



Source: Authors' estimates.

Table A6: Variance Decomposition of D(Log CPIC) using SVAR Factors

Qtr.	Headline Inflation				Core Inflation			
	Exchange Rate Shock	Output Shock	Own Shock	Interest Rate Shock	Exchange Rate Shock	Output Shock	Own Shock	Interest Rate Shock
1	3.16	0.37	96.47	0.00	1.68	1.08	97.24	0.00
2	4.16	4.65	86.95	4.25	1.90	4.06	88.75	5.29
3	4.02	4.48	84.57	6.93	2.01	4.16	87.06	6.76
4	3.98	4.43	83.61	7.98	2.04	4.15	86.68	7.13
5	3.97	4.41	83.21	8.41	2.05	4.14	86.54	7.26
6	3.97	4.40	83.05	8.59	2.05	4.14	86.50	7.31
7	3.97	4.39	82.98	8.66	2.06	4.14	86.48	7.33
8	3.97	4.39	82.95	8.69	2.06	4.14	86.47	7.33
9	3.97	4.39	82.94	8.70	2.06	4.14	86.47	7.33
10	3.97	4.39	82.93	8.71	2.06	4.14	86.47	7.33
11	3.97	4.39	82.93	8.71	2.06	4.14	86.47	7.33
12	3.97	4.39	82.93	8.71	2.06	4.14	86.47	7.34

Source: Authors' estimates.

Table A7: NKPC with Survey-based Inflation Expectations (Sample period: 2008-09 to 2017-18Q3)

	(1)	(2)
	CPI-C (q-o-q change)	**CPI-C (q-o-q change)**
1-year ahead Inflation expectations (y-o-y)	0.192^{***} (0.0497)	-
3-months ahead Inflation expectations (y-o-y)	-	0.238^{***} (0.0546)
$\Delta Output\ gap_{t-1}$	0.234^{**} (0.0984)	0.225^{**} (0.0941)
$\Delta Output\ gap_{t-6}$	0.267^{**} (0.111)	0.301^{***} (0.108)
$MSP\ variation_{t-1}$	0.0398 (0.0556)	0.0436 (0.0530)
$Rainfall\ deviation_{t-2}$	0.0154^{*} (0.00834)	0.0148^{*} (0.00799)
$\Delta Exchange\ rate_{t-1}$	-0.0148 (0.0487)	-0.00943 (0.0460)
$\Delta Global\ nonfuel\ price_{t-1}$	0.0585^{*} (0.0335)	0.0638^{*} (0.0318)
R^2	0.627	0.659
N	43	43
Portmanteau test for white noise (Q statistic *p-value*)	0.8912	0.9042

Notes: 1. Specifications 1 and 2 include the following quarter dummy variables – 2014q1; 2015q1; 2016q3; and 2018q3. Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation).
2. Inflation expectations are expressed on a y-o-y basis, and therefore, its coefficients need to be multiplied by 4 to make it approximately comparable with the coefficients of trend inflation (which is used as a proxy for inflation expectations) in Table 4.
Standard errors are in the parentheses.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$
Source: Authors' estimates.

Table A8: IV-GMM Estimation – Headline CPIC (q-o-q change in per cent) (Sample period: 1996-97Q1 to 2017-18Q3)

	(1)	(2)
	CPIC	CPIC
$\Delta CPIC_{t+1}$	1.045*** (6.03)	-
Inflation trend$_{t-1}$	-	1.077*** (5.52)
$\Delta CPIC_{t-1}$	-	0.0197 (0.20)
Output gap$_{t-7}$	0.206*** (3.13)	0.191*** (2.91)
Δ*Output gap*$_{t-1}$	0.265*** (2.65)	0.204*** (2.63)
MSP variation$_{t-1}$	-0.0319 (-1.35)	-0.00666 (-0.32)
Δ*Exchange rate*$_{t-1}$	0.0151 (0.32)	0.0307 (0.82)
Δ*Global nonfuel price*$_{t-1}$	0.0407* (1.70)	0.0366* (1.74)
Rainfall deviation$_{t-2}$	-0.0113 (-1.50)	-0.00106 (-0.20)
Uncentred R^2	0.767	0.875
Centred R^2	0.324	0.638
Adjusted R^2	0.214	0.579
Sargan statistic (p-value)	0.266	0.361
LM statistic (p-value)	0.0162	0.000
N	80	80

Note: Autocorrelation-adjusted standard errors are used in these regressions. Dummy variables as in the case of earlier models are employed here as well. Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation).

ΔCPI_{t+1} is instrumented with the following variables: *Output gap*$_{t-6}$; Δ*Output gap*$_{t-2}$; *MSP variation*$_{t-2}$; *Exchange rate variation*$_{t-2}$; ΔCPI_{t-1}; $\Delta CPIC_{t-2}$; and *Inflation trend*$_{t-2}$. *Inflation trend*$_{t-1}$ is instrumented with *Inflation trend*$_{t-2}$; and *Inflation trend*$_{t-3}$.

t statistics are in the parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' estimates.

Table A9: IV-GMM Estimation – Core CPI (q-o-q change in per cent) (Sample period: 1996-97Q1 to 2017-18Q3)

	(1)	(2)
	CPI Core	**CPI Core**
$\Delta CPI\ Core_{t+1}$	0.855*** (5.32)	-
$Inflation\ trend_{t-1}$	-	0.715*** (3.59)
$\Delta CPI\ Core_{t-1}$	-	-0.00979 (-0.09)
$Output\ gap_{t-7}$	0.188*** (3.23)	0.153** (2.17)
$\Delta Output\ gap_{t-1}$	0.375*** (4.03)	0.209*** (2.75)
$\Delta Exchange\ rate_{t-1}$	0.0484 (1.31)	0.0442 (1.35)
$\Delta Indbasket\ crude_{t-1}$	0.0139** (2.30)	0.00689 (1.25)
Uncentred R^2	0.762	0.851
Centred R^2	0.206	0.501
Adjusted R^2	0.129	0.445
Sargan statistic (p-value)	0.245	0.547
LM statistic (p-value)	0.00171	0.00280
N	80	80

Note: Autocorrelation-adjusted standard errors are used in these regressions. Dummy variables as in the case of earlier models are employed here as well. Exchange rate is represented by INR-USD rate and therefore, an increase (decrease) in exchange rate here implies depreciation (appreciation). $\Delta CPI\ Core_{t+1}$ is instrumented with the following variables: $\Delta CPI\ Core_{t-1}$; $\Delta CPI\ Core_{t+1}$; $Crude\ Oil\ price\ variation_{t-1}$; and $Inflation\ trend_{t-2}$.
$Inflation\ trend_{t-1}$ is instrumented with $Inflation\ trend_{t-2}$ and $Inflation\ trend_{t-3}$.
t statistics are in the parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' estimates.

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Monetary Policy Transmission Through the Lens of Monetary Conditions Index for India

Manu Sharma, Arvind Kumar Jha, Anoop K. Suresh and Bikash Maji*

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The appeal of Monetary Conditions Index either as an operating target or a monetary policy rule has waned over time. Its utility for assessing the monetary policy stance through the lens of alternative channels of monetary policy transmission, however, continues. This paper attempts to construct MCIs for India by approximating four major channels of transmission – interest rate, exchange rate, credit, and asset prices – and examine their suitability to assess the stance of monetary policy as well as the inflation outlook. The weights for these MCIs have been derived using ordinary least squares (OLS) as well as by employing impulse responses of shocks within a structural vector autoregression (SVAR) framework. Empirical findings establish the dominant influence of the interest rate channel in India and support MCIs as useful coincident indicators of monetary policy stance and as a relevant lead indicator of inflation.

JEL Classification: C22, C32, E47, E52, E58

Keywords: Monetary conditions index, interest rate channel, monetary policy, coincident and leading indicator, inflation forecasts

Introduction

The concept of the Monetary Conditions Index (MCI) was introduced by the Bank of Canada (BoC) in 1994, as a weighted average of changes in the domestic short-term interest rate and exchange rate, relative to their respective

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* Manu Sharma, Arvind Kumar Jha, Anoop K. Suresh and Bikash Maji are working in the Reserve Bank of India. The authors express sincere thanks to the editorial team, an anonymous referee, Shri Soumya Suvra Bhadury and other particiapnts of the DEPR Study Circle Seminar (in which a previous version of this paper was presented) for their valuable suggestions and feedback. The authors are also thankful to Shri Sitikantha Pattanaik for his valuable guidance. The views expressed in the paper are those of the authors and do not necessary represent the views of the institution to which they belong. Corresponding author's email: manusharma@rbi.org.in

values in a base period. It was subsequently used in other central banks for specific purposes. MCI measures the degree of easing/tightening in monetary conditions, and thus, reflects the overall stance (expansionary/ contractionary) of monetary policy for a given period (Freedman, 1994, 1995). Apart from its role as an indicator of monetary stance, the literature suggests that MCI can be used as a monetary policy operating target (Freedman, 1994) or even as a policy rule (Ball, 1999). For its use as an operating target of monetary policy, a target level of MCI needs to be identified in accordance with the policy objectives, and monetary policy operations conducted to make the actual level of MCI as close as possible to the target level. On the other hand, the use of MCI as a policy rule is close to exchange rate targeting since it requires interest rate to be set in such a way that it ensures alignment with the changes in the exchange rate (Batini and Turnbull, 2002). The use of MCI as an operating target for monetary policy or as policy rule has serious caveats (Freedman, 1994) that range from inability to identify shocks to the economy in general to the volatile nature of exchange rates in particular. As a result, while no central bank uses MCI as a policy rule, the Reserve Bank of New Zealand discontinued using MCI as a monetary policy target in the wake of the MCI led monetary policy uncertainties in New Zealand (Svensson, 2001; Mishkin and Schmidt-Hebbel, 2001). On the other hand, since MCI also indicates the resultant effect of monetary transmission channels on aggregate demand and inflation, its potential to act as a leading indicator for short to the medium-term impact of monetary policy on the economy has come to the forefront (Goodhart and Hofmann, 2001; Guillaumin and Vallet, 2017; Horry *et al.*, 2018).

In India, against the backdrop of ongoing financial deregulation/ innovations, a vibrant banking sector and increasing integration among the financial markets; multiple channels of monetary policy transmission play a role in influencing the overall monetary conditions. Therefore, this paper attempts to construct MCI in a 'broad' way for India covering the four major monetary policy transmission channels *viz.,* interest rate, exchange rate, credit, and asset prices[1] (as a weighted average of four real variables - short-term interest rate, exchange rate, bank credit and BSE Sensex - representing

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1 These channels have been described in Section II.

the four channels). The weights are expected to provide a gauge on the relative importance of different channels in monetary policy transmission. This study not only attempts to address the much-discussed challenges that have been put forward in the literature relating to the econometric techniques employed in deriving weights of MCI[2] but also briefly covers the fact that the very construct of the index is equally important. It further analyses the ability of the MCI to capture the monetary policy stance of the Reserve Bank as well as its potential in predicting Consumer Price Index (CPI) inflation in India.

The structure of the rest of this paper is as follows. Section II describes the four channels of monetary policy from the standpoint of their specific dynamics in relation to the ultimate goal variables. Section III specifies the theoretical construct that underpins MCI. Section IV presents a brief literature survey covering empirical findings of available research on the subject and international experiences. Section V describes the data and methodology employed for deriving the weights of different variables in the construction of MCI for India. Section VI presents the results and empirical analysis, validating the utility of MCI in the Indian context. Section VII provides concluding observations.

Section II
Monetary Policy Transmission Channels – A Foundation for MCI

The choice of an intermediate target of monetary policy depends upon the information content it may have to forecast the goal variable. At times, using the intermediate target is equivalent to targeting the forecast of the goal variable (Bernanke and Mishkin, 1997). During the monetary targeting regime in India, with Cash Reserve Ratio (CRR) as a major instrument and Reserve Money as an operating target, the choice of monetary aggregates (Money Supply) as intermediate target seemed justified due to the ability of the operating target to directly influence the intermediate target which itself had a stable relationship with prices and output (Mohanty, 2011). In the Multiple Indicators/Augmented Multiple Indicators Approach, a host of forward looking macro-economic indicators and a panel of times series

2 These challenges have been described in Section IV.

models were used to shape an outlook of growth and inflation (Mohanty, 2011). Money supply projections still served as an important information variable. However, owing to growing instability in the relationship between the money supply and the ultimate goal variables (inflation and growth) as well as the difficulties faced by the Reserve Bank in controlling the money supply through CRR and Statutory Liquidity Ratio (SLR) in the 1990s, its position as an intermediate target became untenable. Under flexible inflation targeting (FIT) framework with weighted average overnight call money rate (WACR)[3] as an operating target, although the Expert Committee (RBI, 2014) did not explicitly mention the intermediate target, it is argued that 'inflation forecast' acts as the intermediate target in practice[4].

The stance of the monetary policy affects the intermediate target and further the final target through monetary policy transmission channels. The literature and also the Expert Committee (RBI, 2014) identifies four such major channels:

1. Interest rate channel: Expansionary (contractionary) monetary policy stance → decrease (increase) in interest rate → decrease (increase) in the cost of capital → increase (decrease) in investment → increase (decrease) in aggregate demand → prices rise (fall)[5]
2. Exchange rate channel: Expansionary (contractionary) monetary policy stance → depreciation (appreciation) in domestic currency → net exports rise (fall) → increase (decrease) in aggregate demand → prices rise (fall)[6]

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3 WACR represents unsecured overnight money market and its movement showcases systematic liquidity mismatches.

4 In the Thirteenth Meeting of the Monetary Policy Committee (MPC) dated October 3-5, 2018, Dr. Michael Debabrata Patra, the then Executive Director, Reserve Bank of India, and member of MPC categorically mentioned "*The forecast – the intermediate target that provides a proximate view of how the goal variables are forming*".

5 Interest rate channel often interacts with bank lending channel since higher investments and associated augmentation in economic activities act as pull factors for credit demand.

6 Depreciation of domestic currency may directly increase the domestic prices of the imported goods mainly crude oil. However, due to administered prices and other price distortions, this route of exchange rate channel is debatable. Moreover, depreciation increases external debt which impacts aggregate demand and price level accordingly.

3. Credit channel: Expansionary (contractionary) monetary policy stance → fall (rise) in the interest rate and expansion (contraction) in loanable funds → decrease (increase) in the cost of funds and bank lending rates → demand for bank credit rise (fall) → increase (decrease) in aggregate demand → prices rise (fall)[7]

4. Asset price channel: Expansionary (contractionary) monetary policy stance → cheaper (dearer) borrowing costs → higher (lower) asset prices → higher (lower) household/corporate wealth effect and cash flows→ increase (decrease) in aggregate demand → prices rise (fall)[8]

It is indeed difficult to gauge the individual impact of these monetary policy transmission channels since they tend to co-exist with different degrees of effectiveness, often interact with each other, thus, supplementing/offsetting each other (Acharya, 2017) through a host of variables. They simultaneously impact the intermediate target (inflation forecast under FIT) which itself gives a proximate view of the course of policy goal variables (inflation and economic growth), in fulfilment of the overall policy goal of price stability and economic growth. The lags at which monetary policy impacts final demand and inflation differs depending upon the stage of the business cycle, fiscal position, liquidity and financial conditions and the health of the financial system. In the case of India, on average, the monetary policy action takes around 2 to 3 quarters to show its impact on output and 3 to 4 quarters in impacting inflation and the impact persists for 8 to 12 quarters (Acharya, 2017). The interest rate channel has been highlighted in the empirical research in India as the most important channel for monetary policy transmission (RBI, 2014).

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7 For bank lending channel to work, bank balance sheets should be strong with enough loss-absorption capacity so that an unhindered supply of credit is ensured in response to a higher credit demand due to lower lending rates. Relying too much on policy rate cuts without resolving bank balance-sheet problems may not bear the desired results, and, on the contrary, may lead to poor investment of funds, misallocation of resources, productivity losses, false perception of future growth and unaccomplished structural reforms in the banking sector (Acharya *et al*., 2019). From the firm side, a parallel Balance Sheet channel also works by impacting collateral valuation and net worth of firms.

8 Higher asset prices can supplement the bank lending channel by improving the collateral value/borrowers' net worth, thus, enhancing the capacity to borrow more. This can enhance investment and consumption.

Hence, within the overall monetary policy framework, although studying the movement of the operating target (WACR) may be enough to draw a perspective of monetary policy stance[9], to study the implications of this stance on key policy goal variables like inflation and growth, the multiple monetary policy transmission channels, and the related variables (with different lags at which they impact the policy goal variables) should be factored in. This understanding is of utmost importance for constructing MCI, which, in this study, is envisaged as a coincident indicator of monetary policy stance as well as a leading indicator of inflation.

Section III
Literature Review and International Experience

The Canadian monetary policy, over time, has been one that has been subjected to drastic changes. In the pre-1990s, the focus of the Canadian monetary policy was the attainment of intermediate targets. However, since the early 1990s, the BoC has adopted inflation targeting alongside MCI as an operational target. The central banks of New Zealand, Sweden, Norway, and European Monetary Union had also used MCI, customised to their requirements. The compilation of MCIs periodically is also undertaken by several international organisations such as the IMF, OECD, and commercial banks for cross country assessment of monetary policy and their monetary conditions.

Kesriyeli and Kocaker (1999) constructed MCI for Turkey utilising monthly data on prices, interest rates and exchange rate covering the period 1988-1997, wherein exchange rate turned out to be a significant factor determining adjustments in prices in Turkey. Batini and Turnbull (2000) undertook a survey of MCIs constructed for the UK by various multinational institutions. Through a macro-econometric simulator model (covering 15 years from 1984 to 1999), they constructed another MCI for the UK, paying adequate attention to overcoming several drawbacks of the exiting MCIs. Kodra (2011) constructed the MCI of Albania by using the ordinary

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[9] Changes in the key policy rate transmit through WACR to the term structure of the interest rates. An expansionary monetary policy stance is reflected by a reduction in the key policy rates and *vice versa*, with which WACR is closely aligned as an operating target.

least squares (OLS) estimator and data between 1998 and 2008. The author undertook an assessment of exchange rate and interest rate in real terms and found that a rise in the real exchange rate by 3.8 could be equivalent to a rise in real interest rate by one per cent.

Siklar and Dogan (2015) assessed the effect of changes in exchange rate and interest rate on Turkey's monetary policy by using MCI. The estimation of MCI using Kalman Filter is a special feature of this paper (*i.e.,* the time-variant component *vis-à-vis* the constant weighted MCI in several other papers). The study concludes that movements in price level could lead to movement in both exchange rate as well as interest rates. In line with the findings of other major studies on MCI, it concludes that the interest rate channel creates a profound impact on the economy (*vis-à-vis* exchange rate channel). Jovic *et al.,* (2018) undertook the construction of MCI for Bosnia and Herzegovina (BH) utilising a multiple linear regression approach. The study brought out two important findings. First, in the post-2008 crisis period, there has been an improvement in monetary conditions in BH. Second, the interest rate channel when compared with the exchange rate channel does not turn out to be very dominant.

Apart from these studies at the cross-country level, there have been few studies that attempted constructing an MCI for India. In one of the pioneer works in India during the monetary targeting regime, Patra and Pattanaik (1998) attempted to develop indices of exchange market pressure, intervention activity and monetary conditions using a sample period of April 1990 to March 1998. Kannan *et al.,* (2006) constructed an MCI based on both the exchange rate and interest rate channels as well as incorporating an additional component *(i.e.,* credit). According to this study, interest rate turns out to be the most significant variable that determines India's monetary settings. Bhattacharya and Ray (2007) introduced a measure of the stance of India's monetary policy covering the period from 1973 to 1998. Utilising an autoregressive approach, the authors connected the constructed MCI with prices as well as output, and find the monetary policy in India to be more effective in combating price rise rather than catalysing output expansion. Samantaraya (2009) introduced an index for evaluating the effect of monetary policy on key macroeconomic variables.

Section IV
Theory and Construct

The exercise for constructing MCI can be broadly divided in four consecutive stages with one complementing the other – (1) Identification of the monetary policy transmission channels and the respective relevant representative variables; (2) Finalising the Construct of MCI equation; (3) Selection of the target variable (defined subsequently) for deriving weights of MCI; and (4) Estimating the weights using econometric models to generate the index. These aspects are discussed in detail in this section.

(1) Identification of the monetary policy transmission channels and the representative variables

MCI has conventionally been defined as a weighted average of changes in the short-term interest rate and changes in the exchange rate for an open economy. However, off-late many versions of MCI cover multiple monetary policy transmission channels[10]. In this study, we have accounted for the four channels (Acharya, 2017 and RBI, 2014) which are already discussed in Section II. Their representative variables – real WACR, real effective exchange rate (REER) index, real bank credit and real stock price index – are described in Appendix I.

(2) Finalising the construct of MCI

In most of the studies related to MCI, much of the attention is given to the econometric methods employed to estimate the weights of the constituent variables, while the construct of MCI itself often takes a backstage. As a result, the final understanding of the construct and the variables employed is left to the imagination of readers. The original structure of MCI as provided by Freedman (1994) is:

$$MCI_t = \alpha_1(r_t - r_b) + \alpha_2\left[\left(\frac{e_t}{e_b}\right) - 1\right] * 100 \qquad \text{...(1)}$$

[10] While certain studies like Kannan *et al*., 2006; Guillaumin and Vallet, 2017; and Horry *et al*., 2018 use either interest rate and exchange rate or interest rate, exchange rate and credit in constructing MCI, other studies like Goodhart and Hofmann, 2001 use interest rate, exchange rate, house prices and asset prices for constructing a financial conditions index.

where, r_t is the real short-term interest rate and e_t is the real effective exchange rate index (where a rise represents an appreciation) at time *t*, while r_b and e_b represent the values of corresponding variables in a given base period *b*. α_1 and α_2 are the weights assigned to the two variables, respectively.

It is important to note that since interest rates are presented in percentage terms, the exchange rate is also taken as per cent change *i.e.,* the units of measurement of both interest rates as well as exchange rate are kept the same. Somewhat similar is the approach adopted by Batini and Turnbull (2002), who create a 'Dynamic MCI' wherein logarithm values of real effective exchange rate are used, and interest rates are presented as fractions by dividing interest rate data by 100. Toroj (2008) uses a similar construct, but instead of presenting interest rate as a fraction, he divides interest rate and exchange rate variables (logarithm values) by their respective standard deviations across the sample period. In all these approaches, the synthesis imparts uniformity of scale/measurement to the weighed impact of different variables (representing different monetary transmission channels) on MCI.

Another set of studies, *e.g.,* Hataiseree (1998) and Kannan *et al.* (2006)[11] alternatively present MCI as:

$$MCI_t = \alpha_1 (r_t - r_b) + \alpha_2 (e_t - e_b) \quad \text{... (2)}$$

where, the real exchange rate/effective exchange rate is expressed in the logarithm values while no transformation is reported for interest rates. This construct makes MCI closely reflect the short-term interest rate path, which gets partly complemented/offset by the movement in the exchange rate, and thus, quite appealing as a reflection of the monetary stance of the central bank.

Another construct proposes de-trended MCI by doing away with the concept of 'base period'. This non-conventional approach brings MCI closer to the much-discussed Financial Conditions Index[12] (Goodhart and Hofmann, 2001; Khundrakpam, 2017):

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[11] Kannan *et. al.*, 2006 go on further to present a 'Broad MCI' where they include credit growth as a third variable. However, the same has not been discussed here because this section talks about only a generic structure in this context.

[12] Although, as two parallel concepts, MCI and FCI are fundamentally different with former based on instruments of the monetary policy and the latter exclusively on transmission of the monetary policy.

$$MCI_t = \sum_{i=1}^{n} \alpha_i (q_{it} - \bar{q}_{it}) \qquad \ldots(3)$$

where, q denotes the price of asset *'i'* and $\bar{q}$ is the long-run trend or equilibrium value of q. However, while Khundrakpam (2017) transforms the variables by normalising them, the treatment done by Goodhart & Hoffman (2001) is unclear.

In the present study, we have broadened the concept of MCI by including economic/financial variables representing the four major transmission channels thus endorsing its usefulness in gauging the impact of monetary policy instruments on financial variable as a result of monetary policy transmission. However, for maintaining the ability of MCI to act as a coincident indicator of the stance of monetary policy, the basic approach as indicated in equation 2 has been adopted. This has been augmented with the de-trending method as suggested in equation 3. Accordingly, for this study, MCI has been computed using four real variables *i.e.,* real short-term interest rate, real effective exchange rate (REER) index, real bank credit and real stock price index, such that[13]:

$$MCI_t = \sum_{i=1}^{n} w_i (x_{it} - x_{ib}) \qquad \ldots(4)$$

where, $n=4$, w_i is the relative weight assigned to the i^{th} variable in MCI such that, $\sum_{i=1}^{n} w_i = 1$, x_{it} is the value of the i^{th} variable at time *'t'* and x_{ib} is the value of i^{th} variable at a base period. Logarithm values are used for the REER index, real bank credit and real stock price index.

Generally, the variables in MCI are set in relation to their respective levels in a base period. Accordingly, two MCIs are constructed using this base period approach by taking the start of the sample period as 1996-97:Q1. This way, MCI starts at 0 for 1996-97:Q1 and the subsequent tightening or loosening of the monetary stance can be viewed in relation to the base period. While it's important to note that the numerical value of MCI at any time 't' is meaningless, it's the movement in MCI *vis-a-vis* the base period that reflects the monetary stance. An increase in MCI depicts expansionary monetary policies and *vice versa*. However, when the base period is used, the analysis

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[13] Further details about these variables and justification for their selection are available in Section IV.

of MCI movement becomes bi-dimensional *i.e.,* in relation to the base period as well as in relation to the lagged value. In the study, we follow a de-trending approach for the construction of a third MCI, wherein variable values are set in relation to long-run trend or equilibrium such that:

$$MCI_t = \sum_{i=1}^{n} w_i (x_{it} - \bar{x}_{it}) \quad \ldots(5)$$

where, $\bar{x}_{it}$ is the long-term trend or the equilibrium value of i^{th} variable at the time 't' and the rest is the same as in equation (4). This not only helps in de-trending the MCI since, most of the variables used in constructing the MCI are trending variables[14], but also imparts the necessary 'dynamism' to the MCI thereby making it useful for inflation forecasting purpose as explained in section VI.

(3) Selection of the target variable for deriving weights of MCI

The target variable for MCI is the variable which the monetary conditions try to influence. The choice of target variable for constructing MCI coincides with the choice of the final target variable for monetary policy framework since MCI incorporates the impact of different transmission channels (although at different degrees) that finally influence the policy goal variables in fulfilment of the policy goal. Thus, aggregate demand and inflation[15] automatically emerge as the preferred choices. Under monetary targeting, the sensitivity of money demand to changes in the exchange rate and interest rate provides the relevant target for MCI (Patra & Pattanaik, 1998). Under the inflation targeting, the sensitivity of aggregate demand and/or inflation to changes in the interest rate and exchange rate could provide more relevant targets for MCI. In this study, real GDP growth has been used as the target variable for MCI, while Consumer Price Index-Combined (CPI-C) based inflation has also been considered separately as a target. The choice of CPI-C based inflation is commensurate with the present monetary policy framework and usage of real GDP growth instead of the output gap is justified because the dynamics

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[14] Stock price index and bank credit are trending for obvious reasons. In the case of India, even REER index has a long-term trend which can be understood as a consequence of the famous Balassa-Samuelson effect.

[15] However, Stevens (1998) is sceptical towards the use of inflation since it is determined differently for tradeable goods (exchange rate pass-through and global prices play a major role) and non-tradeable ones (output gap and inflation expectations play a major role).

of an evolving/emerging economy make it difficult to estimate the economy's optimal level of operating efficiency and thus, the potential output, which is required to generate the final output gap.

(4) Estimating the weights using econometric models to build an index

Different methods can be used for estimating MCI weights (Batini and Turnbull, 2002; Guillaumin and Vallet, 2017):

1. OLS equation-based weights: The weights of MCI are derived from the coefficients of a regression equation estimating either aggregate demand or inflation. This is the most common method owing to its simplicity. In the case of India, Kannan *et al.*, 2006 estimated MCI using this technique.
2. Trade share-based weights[16]: The weight for the exchange rate is obtained from the long-run exports-to-GDP ratio. The weight for the interest rate is one minus the weight for the exchange rate.
3. VAR impulse response functions-based weights: The weights are obtained using the impulse responses of the target variable to the shocks in endogenous variables in a reduced form Vector Auto Regression (VAR) framework (Eika *et al.*, 1996). Either cumulative (as is the practice at Goldman Sachs for the UK) or average (Goodhart and Hofmann, 2001) of the impulse responses can be used.
4. Large-scale simulations based macro-econometric models: These include certain complex and exhaustive models used by the central banks/institutions which take many variables at a time into account for modelling the overall structure of the economy (Mayes and Viren, 2001; Costa, 2000).[17]

[16] For present study, this methodology is not contextual since MCI is constructed using credit and stock prices index in addition to interest rate and exchange rate. However, since this methodology finds its place in the extant literature related to MCI, hence it has been included for information purpose only.

[17] Apart from the discussed models, there are a few other methods that have been used in the existing literature to estimate the weights of MCI. For example, Batini and Turnbull (2002) estimate the weights using a system of multiple equations estimated simultaneously.

In general, the literature is flourished with critics of the econometric methods employed for deriving the weights of MCI (Eika *et al.,* 1996; Ericsson *et al.*, 1998; Stevens, 1998). Some downsides most commonly cited critics are model dependence, lack of dynamism in the model specification, parameter inconstancy, non-exogeneity of regressors, cointegration among non-stationary variables and the choice of variables. This study attempts to minimise these issues in a variety of ways. The issue of model dependence, like any other econometric exercise, is valid in this case too. Since weights obtained depend upon the model specification, adequate attention has been given to ensure that the model is suitably specified keeping in view the overall dynamics of monetary policy transmission. Further, to analyse the impact of the choice of model, both- single equation models, as well as impulse responses derived from a structural VAR (SVAR) model have been used, to estimate the weights for MCI and compare them. Variables are found to be stationary and so chances of co-integration are ruled out. Structural breaks have been tested for and dummy variables have been included wherever required, along with necessary stability tests to ensure the model stability. The non-exogeneity issue does seem to apply to this study due to forward-looking nature of the variables, potentially leading to problems such as simultaneity bias. However, a central bank responds to macroeconomic changes by taking a monetary stance which in turn impacts various economic variables, and hence, it would be naive to consider monetary conditions as totally exogenous. Moreover, monetary transmission works by impacting its target variable (aggregate demand or inflation) with lags and dynamic interaction of endogenous/ exogenous variables, taking care of simultaneity to some extent. Nonetheless, we attempt to address these problems by additionally specifying a SVAR model, which identifies a system of equations for endogenous variables interacting with each other (as against a single equation with a built-in assumption of *ceteris paribus*) and identifies structural shocks for impulse responses, imposing required restrictions as per the economic theory, to confine the contemporaneous relationships.

The theory suggests that the decrease in real interest rates and REER index, and an increase in real credit and real stock price index reflects an expansionary stance and hence increasing the MCI and *vice versa*. Thus, it is expected that in the MCI, the weights of real short-term interest rate and REER are negative while those for real credit and real stock price index are positive.

Section V
Data and Methodology

The data used for empirical analyses are sourced from the Database on Indian Economy (DBIE) and Reserve Bank of India website (www.rbi.org.in), for the period 1996-97:Q1 to 2019-20:Q3. The choice of this period is guided by the availability of quarterly GDP at Market Prices (Constant Prices) Data Series (Base 2011-12). Further details about data are furnished in Appendix I.

Two methodologies *i.e.,* reduced form estimates of coefficients in an OLS model [both Aggregate Demand (AD) and Phillips Curve (PC) equation] and impulse response functions in a SVAR model, have been adopted for estimating the weights for three alternative MCIs: MCI_AD, MCI_PC and MCI_SVAR. All the variables are Stationary at levels (Appendix II).

Ordinary Least Square Model

MCI_AD: The weights have been derived by estimating the generalised backward looking aggregate demand equation, which is represented as:

$$gdpg_t = \alpha_1 + \sum_{i=1}^{n1} \beta_{1_i}\, gdpg_{t-i} + \sum_{j=0}^{n2} \beta_{2_j}\, wacr_{t-j} + \sum_{k=0}^{n3} \beta_{3_k}\, reertg_{t-k} + \sum_{l=0}^{n4} \beta_{4_l}\, bcrg_{t-l} + \sum_{m=0}^{n5} \beta_{5_m}\, snsxr_{t-m} + \epsilon_t \quad ...(6)$$

where *gdpg* is the y-o-y growth rate of real GDP, *wacr* is the real weighted average call rate, *reertg* is the y-o-y growth rate of trade weight-based real effective exchange rate (36 currency based), *bcrg* is the y-o-y growth rate of real total bank credit, *snsxr* is the real y-o-y sensex returns, ϵ_t is the residual term and α_1 is a constant signifying natural rate of real GDP growth. *t* refers to the contemporaneous time specification while *i, j, k, l,* and *m* are lags for the specific variable.

Inclusion of long-term interest rates in equation (6) in many studies (Hyder and Khan, 2006; Deutsche Bundesbank, 1999; Mayes and Viren, 2001) presents another school of thought where long term interest rates are equally relevant for estimating aggregate demand conditions. Although, there is existing literature in relation to long term real interest rates in India (Behera *et al.,* 2015), in accordance with the limitation of such long term interest rates (Wahi and Kapur, 2018) and also in line with the views of Goodhart and Hofmann (2001), we believe that such real long term interest rates are difficult to get (owing to challenges in obtaining long-term inflation expectations/long term inflation measures matching the maturity of the bond underlying the long-term yield).

No significant structural breaks were found in the data. A dummy variable named "dumgfc" is included to account for the impact of the global financial crisis that dampened aggregate demand in India during 2008:Q2 - 2008:Q4. The dynamics of the model had been specified by incorporating only the most significant lags of the dependent variable as well as independent variables.

MCI_PC: The weights have been derived by estimating a backward-looking Phillips curve equation which can be derived on the lines of Fisher *et al.,* (1997), using the following relationship between the rate of inflation and output gap:

$$\Delta p = \lambda \Delta p_{-t} + (1-\lambda)\Delta p^{e} + \gamma(\hat{y}) \quad \text{... (7)}$$

where, Δp is the rate of inflation, Δp_{-t} is the rate of inflation witnessed in the past, Δp^{e} is the inflation expectation, $\hat{y}$ is the output gap and λ is a measure of persistence. The equation summarises the role of the economy as well as the economic agents in setting up the prices. The economic agents indeed respond to the past value of inflation as well as its expectation which can be given as:

$$\Delta p^{e} = \mu p' + (1-\mu)\Delta p_{-t} \quad \text{... (8)}$$

where, p' is the central bank's inflation target and μ measures the credibility of the central bank's inflation target. Hence, the inflation expectation can be thought of as a weighted average of the past inflation and the central bank's inflation target.

Equation 7, therefore, can be written as:

$$\Delta p = (1-\lambda)\,[\mu p' + (1-\mu)\Delta p_{-t}] + \lambda \Delta p_{-t} + \gamma(\hat{y}) \qquad \text{... (9)}$$

$$\Delta p = \alpha + \beta \Delta p_{-t} + \gamma(\hat{y}) \qquad \text{...(10)}$$

where,

$$\alpha = \mu(1-\lambda)p' \; and \qquad \text{... (11)}$$

$$\beta = \mu\lambda + (1-\mu) \qquad \text{... (12)}$$

Based on equation 10, the following Phillips curve equation has been estimated:

$$cpicinf_t = \alpha_2 + \sum_{i=1}^{n1} \lambda_{1_i}\, cpicinf_{t-i} + \sum_{j=0}^{n2} \lambda_{2_j}\, wacr_{t-j} + \sum_{k=0}^{n3} \lambda_{3_k}\, reertg_{t-k} + \sum_{l=0}^{n4} \lambda_{4_l}\, bcrg_{t-l} + \sum_{m=0}^{n5} \lambda_{5_m}\, snsxr_{t-m} + \in'_t \qquad \text{... (13)}$$

where *cpicinf* is the y-o-y inflation based on CPI combined; and wacr, reertg, bcrg and snsxr have already been discussed earlier. $\in'_t$ is the residual term and α is a constant signifying natural rate of inflation which reflects the central bank's inflation target (equation 11).

The independent variables of this regression, including real WACR, REER growth, real bank credit growth and real stock market returns, are the determinants of aggregate demand (equation 6). Since the output gap more or less represents the cyclical component of this aggregate demand, the independent variables can be considered as a part of the broad economic frame that determines the output gap[18]. No significant structural breaks were found in the data, barring a few instances of volatilities including the peaks in inflation on account of implementation of 5th and 6th Central Government Pay Commissions. However, upon entering a dummy variable to account for these in the equation, the same was found to be insignificant and hence excluded from estimation. The dynamics of the model have been specified by

[18] An attempt was also made to account for impact of movement in global crude oil prices by including Indian crude basket (Dubai Sour and Brent Crude) in the regression equation, however, the same was found to be insignificant. Moreover, long term real interest rates have been excluded from the model due to reasons as discussed earlier in this section.

incorporating only the most significant lags of the dependent variable as well as independent variables.

Structural Vector Autoregression (SVAR) model

MCI_SVAR: The SVAR model is used instead of the standard reduced-form VAR model because the former provides explicit behavioural interpretations of all parameters, and thus, reflects the well-defined dynamics (in terms of the economic structure) among the variables considered in the model.

Within a SVAR framework, a reduced form VAR model has been specified as follows:

$$X_t = AZ_t + \sum_{i=1}^{n} B_i X_{t-i} + e_t$$

where, X is the vector of six endogenous variables – *cpiinf, wacr, reertgap, crgap, snsxgap* and *gdpgap*. *wacr* represents short term interest rates expressed as per cent; *cpcinf* is the four-quarter lag of log difference in seasonally adjusted CPI-C (y-o-y) inflation; and *reertgap, crgap, snsxgap* and *gdpgap* represent the ratio of the cyclical to trend component of the logarithm value of REER, real bank credit, real sensex and real GDP (seasonal adjustment is done wherever needed), respectively.[19] The cyclical and trend component have been derived using HP filter with a lambda value of 1600 owing to the use of quarterly data. This gap approach presents a departure from the commonly used growth approach and appears more appealing in a context where the aim is to measure the impact of deviation of variables from their potential levels. This novel approach finds support in the existing literature too (Goodhart and Hofmann, 2001; Guillaumin and Vallet, 2017).

Z_t contains exogenous variables including intercept and two dummy variables to account for outliers in the residuals; e_t is the vector of error terms/forecast errors of the VAR process and *n* is the number of lags included. Based on AIC, 5 is chosen to be the lag length (Appendix V).

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[19] The authors refrain from taking variables in the form of first log difference or in the form of per cent annual growth since these may lead to data distortions due to base effect. Another treatment is provided by Goodhart and Hofmann (2001) by removing linear trend using OLS regression.

B_1 to B_n are n x n coefficient matrices of lagged endogenous variables and A is the matrix of coefficients of exogenous variables.

Moving further, SVAR has been estimated by decomposing residuals into structural shocks by ascertaining the contemporaneous relationship between standard reduced form and structural innovations. For this matrix B needs to be calculated, such that:

$$e_t = C\epsilon_t$$

where e_t is the vector of estimated residuals/forecast errors of the standard VAR system and ϵ_t is the vector of structural shocks/innovations.

Having assumed that structural shocks are orthogonal[20] to each other, matrix C contains the contemporaneous influence of structural disturbances on endogenous variables, such that:

$$\begin{bmatrix} e_t^{reertgap} \\ e_t^{wacr} \\ e_t^{gdpgap} \\ e_t^{crgap} \\ e_t^{cpiinf} \\ e_t^{snsxgap} \end{bmatrix} = \begin{bmatrix} 1 & c_{12} & c_{13} & 0 & c_{15} & 0 \\ 0 & 1 & c_{23} & 0 & c_{25} & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & c_{42} & c_{43} & 1 & c_{45} & 0 \\ 0 & 0 & c_{53} & 0 & 1 & 0 \\ c_{61} & c_{62} & c_{63} & c_{64} & c_{65} & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^{reertgap} \\ \epsilon_t^{wacr} \\ \epsilon_t^{gdpgap} \\ \epsilon_t^{crgap} \\ \epsilon_t^{cpiinf} \\ \epsilon_t^{snsxgap} \end{bmatrix}$$

The c_{ij} element of the structural matrix is the magnitude by which the j^{th} structural shock affects the i^{th} variable simultaneously. In a broad manner, the C matrix represents that real GDP responds rather slowly to shocks in inflation, real interest rate, real effective exchange rate, real bank credit and real stock returns. Response of inflation is slow to shocks in real interest rate, real effective exchange rate, real bank credit and real stock returns but inflation reacts immediately to shocks in real GDP. Real interest rates react instantaneously to shocks in real GDP and inflation (the construct of Taylor's Rule) while the same is not true for the shocks on real bank credit, real effective exchange rate and real stock returns. Moreover, real bank credit and real effective exchange rate respond immediately to shocks in real GDP, inflation,

20 The orthogonality restrictions differentiate SVAR model from dynamic simultaneous equation approach. For more details for identifying restrictions and the intuitions behind orthogonality, please refer Bernanke (1986) and Gottschalk (2001).

and real interest rates. On the other hand, stock returns that reflect market sentiments respond contemporaneously to shocks in all the given variables.

For identification purposes[21], the point zero restriction approach (Vonnak, 2005; Khundrakpam, 2012) has been used, which restricts some elements of matrix C to zero. This strategy has the advantage that a structure of contemporaneous impacts can be translated to delayed reaction (Khundrakpam, 2012).

Section VI
Results

The result of the OLS regression for aggregate demand equation is summarised in Table 1.

As evident, the signs of the coefficients of independent variables are in sync with the economic theory. An increase in interest rates and a rise in the effective exchange rate (leading to domestic currency appreciation), *ceteris*

Table 1: OLS estimates of aggregate demand equation

Dependent Variable	**Coefficient estimates for independent variables**					
gdpg	**gdpg(-1)**	**wacr(-4)**	**reertg(-6)**	**bcrg(-9)**	**Snsxr(-6)**	**Dumgfc**
	0.51*** [6.24]	-0.13** [-2.33]	-0.09** [-2.18]	0.05* [1.67]	0.01* [1.81]	-3.74*** [-3.75]
	R-squared: 0.61			**Adjusted R-squared: 0.58**		

Note: Figures in small parentheses denote the significant lags and those in square brackets denote the t-statistic. *, ** and *** indicate the significance of a coefficient or a test statistic at the 10 per cent, 5 per cent and 1 per cent levels, respectively.
Source: Authors' calculations.

[21] For identifying/imposing restrictions, an accommodative approach has been undertaken based on three aspects in the following order: 1) Economic theory, 2) Statistical significance of the restriction and 3) Averting over-identification to the extent possible. Nevertheless, an over identified system, if based on sound economic theories, poses no serious threat to the estimation and the parameters can be uniquely identified. However, it is often advised that validity of such additional restrictions should be ascertained by estimating the SVAR model with as well as without additional restrictions to obtain the restricted as well as unrestricted variance covariance matrices, respectively, the difference between the determinants of which follows a $\chi 2$ distribution with degrees of freedom equal to the number of additional restrictions resulting from exceeding the just identified system (Barnett *et al.*, 2016). This study reports the $\chi 2$ test statistic used to test the restricted system using LR test of over identification.

paribus, dampens aggregate demand while the reverse is true for an increase in bank credit and stock returns during the period of the study.

The results for diagnostic tests and stability tests for the model are summarised in Appendix III. They rule out the presence of autocorrelation in the residuals as well as heteroskedasticity. Moreover, they confirm that the residuals are normally distributed. Additionally, parameter stability is established in CUSUM and CUSUM of squares test. The estimated coefficients in aggregate demand equations suggest the weights of MCI_AD for real WACR, REER index, real bank credit and real sensex to be -0.47 and -0.32, 0.16 and 0.05, respectively. Accordingly, MCI_AD has been created following the classical approach as mentioned in equation 4 *i.e.,* on a base period that has been fixed at the beginning of the data sample *i.e.,* 1996Q1.

The result of the OLS regression for the Phillips Curve equation are summarised in Table 2.

The signs of the coefficients of independent variables in Table 2 are as expected. An increase in interest rates and effective exchange rate, *ceteris paribus* reduces inflation while the reverse is true for bank credit and stock returns during the period of the study. Except for REER, all other variables are significant at a 5 per cent level of significance. R squared and adjusted R squared measures have also improved. This marks an improvement over the previous model.

Appendix IV summarises the results for diagnostic checks and model stability tests which confirm the absence of heteroskedasticity and

Table 2: OLS estimates of Phillips Curve equation

Dependent Variable	**Coefficient estimates for independent variables**				
Cpicinf	**cpicinf(-1)**	**wacr(-7)**	**reertg(-6)**	**bcrg(-8)**	**Snsxr(-8)**
	0.74*** [11.67]	-0.16*** [-2.88]	-0.05* [-1.64]	0.06** [2.16]	0.01** [2.25]
R-squared: 0.80 Adjusted R-squared: 0.79					

Note: Figures in small parentheses denote the significant lags and those in square brackets denote the t-statistic. *, ** and *** indicate the significance of a coefficient or a test statistic at the 10 per cent, 5 per cent and 1 per cent levels, respectively.
Source: Authors' calculations.

autocorrelation in the residuals and that the residuals are normally distributed. Additionally, parameter stability is established by CUSUM and CUSUM of squares tests. The estimated coefficients in the aggregate demand equation suggest the weights of MCI_PC for real WACR, REER index, real bank credit and real sensex to be -0.58 and -0.17, 0.20 and 0.05, respectively. Accordingly, MCI_PC has been created following the classical method as given in equation 5 *i.e.*, on a base period which has been fixed at the beginning of the data sample *i.e.,* 1996-97:Q1.

For the SVAR system, the LR test for over-identification cannot be rejected at 5 per cent significance level, thus validating the imposed restrictions. Moreover, the SVAR is found to be stable since the inverse roots of the characteristic polynomial lie within the unit circle (Appendix V), which can also be viewed as a general fallout of all the endogenous variables being stationary. Appendix V further summarises the result of other diagnostic tests which confirm that VAR residuals are normally distributed and do not suffer from serial correlation and heteroskedasticity. For calculating the weights of MCI_SVAR, impulse response functions are obtained for responses of cpiinf to one standard deviation positive structural innovations/ shocks in wacr, reertgap, crgap and snsxgap in a two standard error band over a period of 12 quarters (Appendix V). The direction of responses is mostly as expected. A positive shock in wacr decreases inflation and a positive shock in crgap and snsxgap increases cpiinf. These impulse responses are statistically significant at around the period of peak impact. The response of cpiinf to a positive shock in reertgap is not highly significant and is also mixed in terms of direction. The average[22] of the numerical value of the response of inflation to one standard deviation positive shock to each variable over 12 quarters suggests the weights of MCI_SVAR for real WACR, REER index, real bank credit and real sensex to be -0.35 and -0.14, 0.35 and 0.16, respectively. Accordingly, MCI_SVAR has been created. However,

[22] An alternative method can be taking the average of the numerical responses of only those periods when it is significant, in the spirit of Batini and Turnbull, 2002. However, the authors find that the weights generated following this method are almost similar to the applied methodology mentioned here. Another commonly used method is taking the accumulated/ cumulative responses (Toroj, 2008; Khundrakpam *et al.,* 2017).

this MCI follows the detrending approach as mentioned in equation 5 *i.e.,* without fixing a base period, as discussed earlier.

Table 3 summarises the obtained weights of real WACR, REER, real bank credit and real sensex using the above-mentioned three methods *i.e.,* aggregate demand equation, Phillips Curve equation and SVAR.

The weights for the variables (representing the respective channels) have been derived by normalising the coefficients/impulse responses of the concerned variables such that they add up to one in the case of each MCI. Hence, their magnitude represents the relative ability of the respective channel of transmission in influencing MCI and thus, the overall monetary conditions. Irrespective of the model applied, the direction/sign of the estimated weights (negative/positive) are in sync with the economic theory validating the robustness. A positive sign indicates an increase in MCI reflecting easing of the monetary conditions and *vice versa*. Further, parameter stability is established, as already discussed in this section, thus ensuring the stability of weights. Further, this is in direct consensus with a plethora of available literature which suggests that credit exerts a pro-cyclical impact on aggregate demand (Kannan *et al*., 2006; Bernanke and Gertler, 1995). This is all the more important for a banking dominated economy like India where bank credit movements are often tracked to assess the effectiveness of the monetary policy. Moreover, the impact of the stock market on aggregate demand is well established (Blanchard, 1981; Khundrakpam *et al.*, 2017), operating through wealth effect and expectations. Although there is no denying the fact that the credit channel assumes importance, the interest rate channel dominates with the highest weight, justifying its suitability as the instrument of monetary policy.

Table 3: MCI Weights

	Real WACR	REER	Real Bank Credit	Real Sensex Returns
MCI_AD	-0.47	-0.32	0.16	0.05
MCI_PC	-0.58	-0.17	0.20	0.05
MCI_SVAR	-0.35	-0.14	0.35	0.16

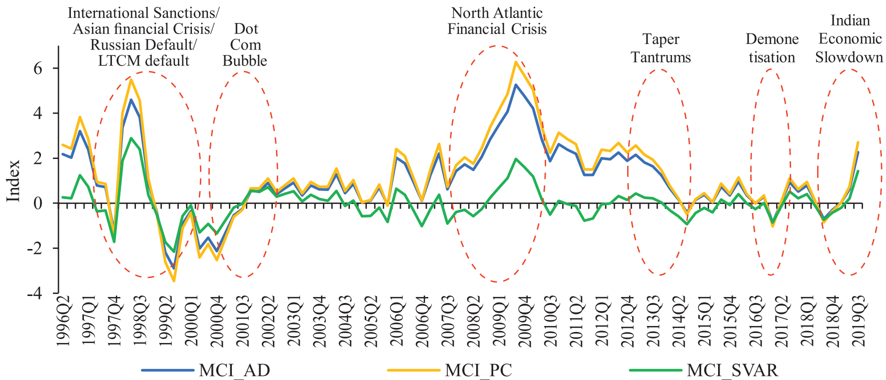
Source: Authors' Calculations.

MCI and the Monetary Stance

The obtained MCIs are presented in Chart 1. As discussed earlier, rather than the exact values of MCIs at any point of time, it is the direction of movement which is relevant. All the three MCIs exhibit broadly similar patterns with the major difference that MCI_SVAR lacks a specific long-term trend as per its construct. The MCIs provide some useful information about various phases of monetary easing/tightening.

The 'monetary targeting approach'[23] was replaced in India by the 'multiple indicator approach'[24] during 1998. The period from 1997-1999 witnessed some massive upheavals including economic sanctions over India due to the Nuclear testing programme, followed by the Asian Financial Crisis, Russian debt crisis and the Long-Term Capital Management (LTCM) debacle. In response, despite inflationary pressures, an expansionary monetary stance was adopted initially to support the growth momentum and maintain comfortable liquidity conditions, anticipating the international liquidity and

Chart 1: MCI versions



Note: An increase in MCI suggests easing and a decline in MCI suggests tightening in monetary conditions.
Source: Authors' calculations.

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23 Under this approach, quantitative monetary aggregates, mainly the money supply (M3) was used as intermediate target for monetary policy.

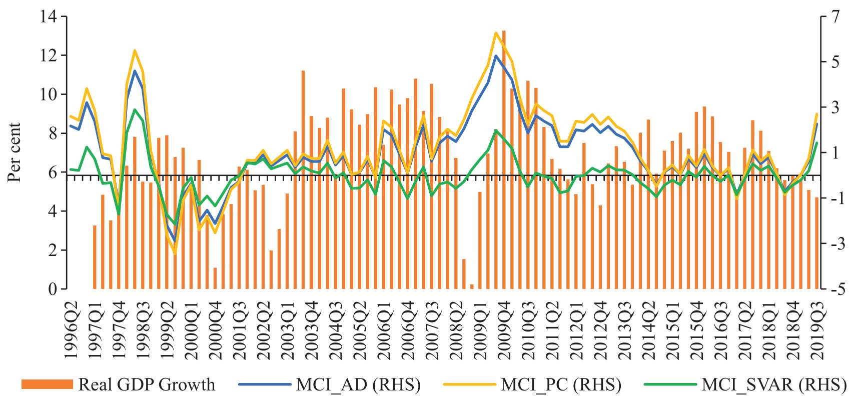
24 Under this approach, interest rates as well as other high frequency variables such as currency, credit, fiscal stance, trade, capital flows, inflation rate, exchange rate, refinancing and forex transactions were utilised for drawing policy perspective. Although there was no explicit nominal anchor, one of the primary objectives was to ensure low and stable inflation utilising interest rate channel as prime source of monetary policy transmission.

export restrictions, which nevertheless shifted to a tightening mode in the wake of a price spiral, depreciating currency and capital outflows requiring the interventions in forex markets. This was shortly followed by an expansionary stance during the early 2000s, amidst benign inflation, in view of the economy experiencing a slowdown in growth due to domestic reasons (weakened demand due to deficient monsoons in 2000) and external disruptions (due to the Dot com bubble which impacted stocks of various international IT firms, there was a need to insulate Indian IT firms from the said shock).

The period from 2003-2008 witnessed the firming of economic growth (Chart 2) and concomitant expansion in credit demand. Moreover, aggregate demand pressures overheated the economy following high capital inflows which led to surplus liquidity conditions fuelling credit supply and asset prices soared.

On the inflation front, although the implementation of fiscal rules in 2004-05 and real appreciation in exchange rates due to steady capital inflows eased inflationary pressures till 2005-06. An upswing in the general commodity prices and the lagged pass-through of an upsurge in global crude prices to administered prices in India pulled up inflation afterwards. In response, the repo rate was raised to 9 per cent by 2008-09, having witnessed a cumulative increase of nearly 300 basis points from 2005-06 to 2008-09. However, in real terms, it witnessed a steep fall. As a result, a range of monetary policy

Chart 2: MCI *vs* Real GDP Growth



Source: Authors' calculations.

actions were simultaneously undertaken, including increment in cash reserve requirement (CRR) to the tune of 400 bps (from 5 per cent to 9 per cent during 2004-08) and introduction of a market stabilisation scheme to absorb surplus domestic liquidity and sterilise the impact of intervention operations carried out in the wake of unparalleled capital inflows. Implementation of stricter risk weights and other provisioning norms to moderate the credit boom, were some of the additional macro-prudential measures undertaken to control asset price inflation. Thus, the whole period was marked by a cautious and prolonged tightening in the monetary policy stance. MCI_SVAR reflects this in a slightly better way.

The following period marked the advent of the much-debated North Atlantic Financial Crisis of 2007-08, which escalated into the so-called 'Global Financial Crisis'. Although owing to its strong economic fundamentals and also limited exposure to global mortgage and derivative markets, India remained insulated from the crisis at large, however, transient disruptions in short-term inter-bank markets and a temporary but sharp slump in the economic activities was witnessed due to contraction in external demand and the squeezed bank lending. This was met with expansionary monetary as well as fiscal measures. Macro-prudential measures (including easing of risk weights and provisioning norms for standard assets, focused primarily on real estate and NBFC sector) were undertaken and the economy witnessed a sharp growth rebound. Inflation as reflected by CPI, on the other hand, remained high through the crisis period till 2013 owing to persistent food and fuel inflation. While monsoon shocks of 2009 fed to supply-side pressures, fiscal interventions through a substantial increase in minimum support prices (MSP) and a considerable increase in the coverage under the MGNREGA aided the demand-side pressures. Thus, apart from normalising the crisis led expansionary monetary policy, tightening monetary policy measures were further undertaken attuned to persisting inflation and fiscal expansion till the beginning of 2012. Subsequently, in the wake of the growth concerns and stabilising inflation, monetary policy easing was pursued during 2012 and the first half of 2013.

The global impact of the crisis culminated in the much-discussed 'taper tantrum' of 2013. The Reserve Bank stepped in with stabilising measures to curb excessive volatility in the foreign exchange market. The persistently high inflation during the post-crisis period, however, exposed the fault lines in macro-financial stability and paved the way for a review of the monetary policy framework, leading to the Reserve Bank endorsing the 'glide path' of CPI inflation in the beginning of 2014 and the subsequent adoption of FIT in 2016.

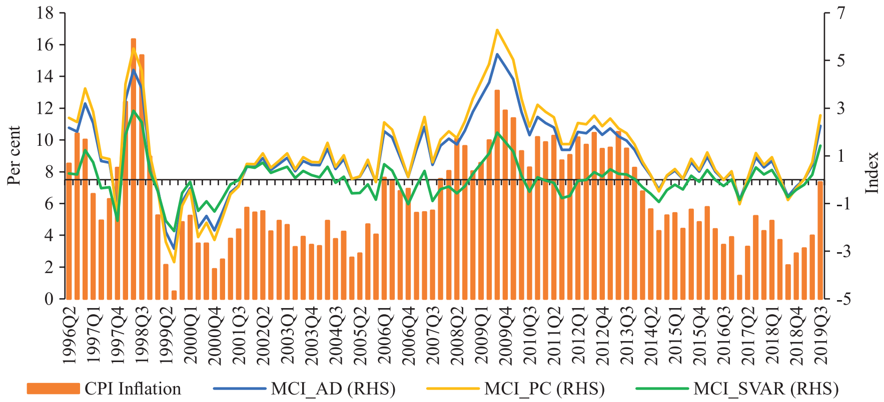
Meanwhile, falling commodity prices including crude oil prices, softening food inflation and more or less steady exchange rates led to a broad-based decline in inflation in accordance with the prescribed 'glide path'. Accordingly, an expansionary monetary policy stance was adopted till April 2016 to support growth. Finally, in May 2016, the Reserve Bank of India Act, 1934 was amended, enabling the adoption of FIT with price stability as the primary objective and CPI as the nominal anchor for monetary policy. In the ensuing period, monetary policy response balanced the need of moderating inflation and inflationary expectations while supporting growth, steering the economy through some major events including demonetisation until 2018, when the economic slowdown hit the Indian economy and the monetary stance became accommodative with a lower interest regime kicking in.

A historical analysis of the past economic events in a phase-wise manner endorses the role of MCI as a coincident indicator of monetary stance. A multivariate VAR has been estimated with MCI's, inflation, and real GDP growth. Lag order has been selected based on recommended lag order selection criteria (Hannah Quinn lag selection criteria). The results suggest that inflation and real GDP growth Granger causes MCIs at 1 per cent to 5 per cent significance level (Appendix VI). This indicates that the developments on the front of the economic growth and inflation are feeding back on the course of monetary policy actions by the Reserve Bank in the form of the monetary stance which further gets reflected in the movement of MCIs. This endorses the ability of MCIs to reflect the monetary stance of the Reserve Bank in response to the two policy goal variables in light of the primary objective of monetary policy under the FIT framework *i.e.,* to maintain price stability while keeping in mind the objective of growth.

MCI and Inflation Prediction

In view of the forward-looking nature of monetary policy; particularly under FIT framework, and the importance of inflation forecasts as the intermediate target; the MCI could be useful as a leading indicator of inflation (Chart 3 plots MCIs along with CPI inflation).

Chart 3: MCI *vs* CPI Inflation



Source: Authors' calculations.

In the multivariate VAR set up mentioned before, the results (Appendix VI) suggest that only MCI_SVAR exhibits a bi-directional causality with inflation *i.e.,* inflation Granger causes MCI_SVAR at 5 per cent significance level and MCI_SVAR Granger causes inflation at 1 per cent significance level. This shows that the lagged values of MCI_SVAR may contain information about future inflation. To further support this finding, as also to address the much-discussed reservation that the Granger causality proposed by Granger (1969) may suffer from specification bias and spurious regression (in addition to a probable nonstandard distribution in the presence of unit roots and structural breaks), we further test the TYDL Granger causality (Toda and Yamamoto, 1995; Dolado and Lutkepohl, 1996) based on augmented VAR. The results (Appendix VII) endorse the bi-directional causality between MCI_SVAR and inflation at 1 per cent significance level.

Moreover, the impulse response functions (including accumulated ones), identified based on Cholesky as well as Generalised factorisation on a bivariate VAR set up including inflation and MCI_SVAR, also indicate that shock in MCI_SVAR generates strong and significant impulse responses of inflation.

To summarise, if the information contained in the lagged values of inflation can be controlled, the lagged values of the MCI_SVAR can predict current CPI inflation and thus MCI_SVAR can be used as a leading indicator/ high-frequency indicator for forecasting CPI inflation.

Results of Forecasting Performance of MCI_SVAR

We attempt an inflation forecasting exercise (out of sample forecast) to evaluate the predictive power of MCI_SVAR for future inflation by estimating the following equations:

1. Autoregressive (AR) Model:

$$cpiinf_{t+h} = \alpha_1 + \beta_1(L)cpiinf_t + \epsilon_t$$

2. Augmented (Aug) Model (AR+ MCI_SVAR):

$$cpiinf_{t+h} = \alpha_2 + \beta_2(L)cpiinf + \gamma(L)MCI\_SVAR_t + \epsilon_{1t}$$

where h is the horizon of forecast; MCI_SVAR is the estimated monetary conditions index based on SVAR and $\beta_1(L), \beta_2(L)$ and $\gamma(L)$ are polynomials in the lag operator L. A rolling window of 10 lags has been taken for different values of h, where h ranges from 1 to 3 quarters *i.e.,* generating three different forecasts, and only the significant lags are considered. First of all, the AR and Aug equations have been estimated independently for a shortened sample period (1996Q2 to 2017Q3), and these estimations are then used to forecast the inflation over the remaining sub-sample period (2017Q4 to 2019Q3). The respective R-squared and adjusted R-squared values are compared for AR and Aug equations and the root mean square errors (RMSEs) are calculated for both models at different forecasting horizons. Higher values for R squared and adjusted R squared denote better explanatory power of the model, while a lower RMSE value denotes better predictive ability. The results (Tables 4, 5 and 6) confirm that the Augmented model has higher explanatory as well

Table 4: R-squared and adjusted R-squared

	Forecast Horizon		
Model	**One quarter**	**Two quarters**	**Three quarters**
AR	0.84 (0.83)	0.57 (0.55)	0.45 (0.42)
Aug	0.85 (0.83)	0.70 (0.67)	0.67 (0.63)

Note: Figures denote the value of R-squared and figures in parentheses denote the value of adjusted R-squared.

Source: Authors' calculations.

Table 5: Root Mean Squared Error (RMSE)

	Forecast Horizon		
Model	**One quarter**	**Two quarters**	**Three quarters**
AR	1.98	1.51	1.89
Aug	1.85	0.87	1.48

Source: Authors' calculations.

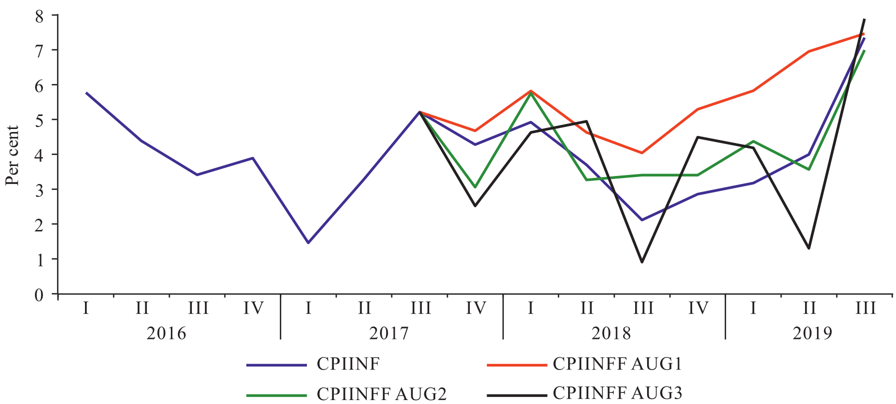
Table 6: Relative Root Mean Squared Errors (RRMSE)^

Forecast Horizon		
One quarter	**Two quarters**	**Three quarters**
0.93	0.58	0.78

Note: ^: Root Mean Squared Error of Augmented model relative to that of Autoregressive model.
Source: Authors' calculations.

as predictive power over the AR model at all the forecasting horizons, thus justifying MCI as a leading indicator for the inflation. Moreover, an Augmented model can be best used to generate a short-term, two quarters ahead forecast for inflation (Chart 4).

Chart 4: Inflation Forecast



Source: Authors' calculations.

Section VII
Summary and Conclusion

MCI has been widely used as an indicator of monetary policy stance or even as a leading indicator of inflation. Monetary policy impacts aggregate demand and inflation through a variety of transmission channels and ideally, an MCI should account for, at least, four such major channels *viz.*, interest rate, exchange rate, bank credit, and asset prices. Accordingly, this study attempts to broaden the conventional concept of MCI by including bank credit and stock prices, apart from short-term interest rate and exchange rate in weighted average terms.

The study estimates three MCIs *viz.,* MCI_AD, MCI_PC and MCI_SVAR such that the weights for MCI_AD and MCI_PC have been derived using reduced form OLS estimates of coefficients in a single Aggregate Demand (AD) equation and Phillips Curve (PC) equation, each estimated separately. On the other hand, weights for MCI_SVAR have been derived on the basis of impulse responses of inflation in SVAR model. Moreover, a de-trending approach has been utilised for creating MCI_SVAR. The weights so derived highlight the dominance of the interest rate channel in monetary policy transmission in India, besides underscoring the importance of the credit channel.

All the three MCIs tend to broadly capture the expansionary/contractionary phases of monetary policy stance of the Reserve Bank during the past two decades, including some major crisis events, with real GDP growth and inflation feeding back to monetary policy actions and Granger causing all three MCIs in a multivariate VAR set up. On the front of forecasting inflation, MCI_SVAR emerges to be the candidate of choice, Granger causing CPI inflation under the same setup, and thus, ascertaining its better predictive ability for future inflation. Hence, the study validates the usage of MCI as a coincident indicator for assessing monetary policy stance as well as a leading indicator for forecasting inflation. One limitation of the study is that the weights for MCIs are static and thus they may not adjust fully in response to dynamic financial markets and business cycles. This leaves a further scope to extend the study using time varying weights.

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Appendix

I. Details of Data

For any analysis as well as for deflating nominal variables, inflation data based on consumer price index combined (CPI-C with the base year 2012) has been used which is available from 2000: Q4 onwards. For data prior to this period, CPI-Industrial Workers (IW) has been used to back-cast CPI combined. This is in line with the usage of CPI combined in the present FIT framework of monetary policy in India. The data used for estimating MCI weights consist of:

1. Real short-term Interest rate: Quarterly average of monthly weighted average call rate (WACR) has been used. WACR is the operating target of monetary policy and the market forms expectation of the policy stance through this short-term rate in India. Although there are many short-term interest rates including, but not limited to, treasury bills rate, commercial paper rate, certificate of deposit rate or secondary market G-sec yield (Hyder and Khan, 2006; Gottschalk, 2001), the fact that most of such markets are not deep enough to provide a continuous term structure, the Reserve Bank uses WACR to decide on the extent and timing of intervention in the money market. This rate is expressed in real terms after been deflated using CPI combined[25.] The authors refrain from using a long-term interest rate or a weighted average of short- and long-term interest rate (an approach followed by Deutsche Bank and Goldman Sachs) since long-term inflation expectations/long term inflation measure matching the maturity of the bond underlying the long-term yield is difficult to obtain.

2. Real Effective Exchange Rate (REER): Quarterly average of the monthly real effective exchange rate of Indian Rupee (representing a

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[25] Ideally, inflation expectations should be used to deflate a short-term nominal interest rate to get a real interest rate in an *ex ante* sense. However, owing to their heterogeneity across economic sectors/agents, they become non observable. Hence, one can broadly follow two approaches namely, deflating the nominal rate by inflation of the previous period (Toroj, 2008), thus, assuming perfect adaptive expectations or using actual inflation for the same period to calculate the real interest rate in an *ex post* sense. For simplicity, the latter approach is undertaken in this study.

basket of 36 – currency with trade-based weights, the base year 2004-05 and deflated by respective CPIs of the countries) has been taken. Owing to its wider coverage and, since it serves as a better tool for economic interpretation, REER has been preferred over a simple real exchange rate that represents the value of the concerned currency in terms of Indian Rupee adjusting for the price differential. REER with trade-based weights is preferred over its counterpart with export-based weights for the purpose of ensuring comprehensive coverage.

3. Real Bank Credit: It represents the consolidated stock of total credit extended by the banking system as a whole (including scheduled commercial banks, cooperative banks, and regional rural banks) as at the end of a quarter, which has been deflated using CPI combined. Owing to its broader coverage, the stock of credit for the entire banking industry is preferred over that for scheduled commercial banks only (as taken in previous such studies in the Indian case) in light of the former's role in shaping overall aggregate demand.

4. Real stock price index: Quarterly averages of BSE-Sensex and financially sound companies are listed on BSE. Although with comparatively lesser coverage, BSE-Sensex has been chosen against another comparable Indian stock index called Nifty-50 since the former was launched in 1986, much earlier than the latter which came into existence only in 1996 and thus, the latter's origin coincides with the period under consideration in this study, raising data validity/stability concerns. The index has also been deflated using CPI combined. The other choices as a proxy to the asset prices could have been house prices and 10-year G-sec yields. However, the lack of availability of data on house prices in India for the period of study constrains its use as a proxy of asset prices on one hand, while usage of g-sec holdings as a legit proxy to asset prices is debatable owing to its lack of representation in an individual's asset portfolios in a developing economy like India.

II. Test of stationarity of variables

Variable	Test Type	t-statistic/test statistic
Gdpg	Augmented Dicky Fuller	-4.2***
Cpicinf	Phillips-Perron/KPSS	-3.1**/0.15*
Wacr	Augmented Dicky Fuller	-3.4**
Reertg	Augmented Dicky Fuller	-4.9***
Bcrg	Phillips-Perron/KPSS	-2.6*/0.42*
Snsxr	Augmented Dicky Fuller	-5.3***
Gdpgap	Augmented Dicky Fuller	-4.3***
Cpiinf	Phillips-Perron/KPSS	-3.0**/0.15*
Reertgap	Augmented Dicky Fuller	-6.0***
Bcrgap	Augmented Dicky Fuller	-4.3***
Snsxgap	Augmented Dicky Fuller	-4.8***

Note: ***: @ 1 per cent level of significance; **: @ 5 per cent level of significance; *: @ 10 per cent level of significance.

Source: Authors' calculation.

III. Aggregate Demand Equation: Results for Diagnostic Tests

R-squared	0.61	Jarque-Bera statistic test for normal distribution of residuals	1.16 (0.55)
Adjusted R-squared	0.58	Breusch-Godfrey Serial Correlation LM Test	0.02# (0.98)
Durbin-Watson statistic	2.01	Breusch-Pagan-Godfrey Test for Heteroskedasticity	0.39# (0.88)

Note: Figures denote the statistic value/test statistic and figures in parentheses denote the p-value. #: F statistic.
Source: Authors' calculation.

IV. Phillips Curve Equation: Results for Diagnostic Tests

R-squared	0.80	Jarque-Bera statistic test for normal distribution of residuals	0.55 (0.76)
Adjusted R-squared	0.79	Breusch-Godfrey Serial Correlation LM Test	0.34# (0.71)
Durbin-Watson statistic	1.73	Breusch-Pagan-Godfrey Test for Heteroskedasticity	0.94# (0.46)

Note: Figures denote the statistic value/test statistic and figures in parentheses denote the p value.
#: F statistic.
Source: Authors' calculation.

V. SVAR Model Results

LR test for over-identification

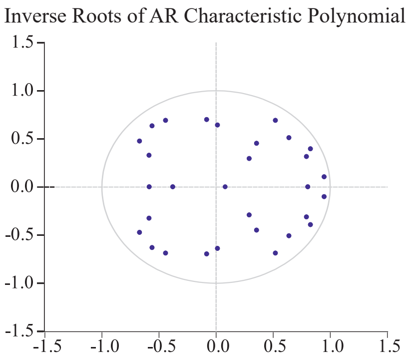
Chi-Square (1): 2.86

Probability: 0.09

Result for VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-69.90593	NA	3.11e-07	2.044324	2.558024	2.251065
1	212.2922	505.3316	1.02e-09	-3.681215	-2.140113*	-3.060993*
2	247.0753	57.43258	1.07e-09	-3.652915	-1.084412	-2.619212
3	288.1779	62.13174	9.85e-10	-3.771579	-0.175675	-2.324394
4	339.3606	70.22750	7.43e-10	-4.124666	0.498639	-2.264000
5	383.0107	53.80127*	6.99e-10*	-4.302575*	1.348132	-2.028427

Note: * indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5 per cent level); FPE: Final prediction error AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion
Source: Authors' calculation.

<table>
<tr><th>VAR Stability Diagnostics</th><th>Diagnostic checks for VAR</th></tr>
<tr><td>
</td>
<td><table>
<tr><td>Jarque-Bera statistic for VAR Residual Normality test</td><td>16.42
(0.17)</td></tr>
<tr><td>VAR Residual Serial Correlation LM Tests (lag 5)
- LRE stat

- Rao F-stat</td><td>35.55
(0.49)
0.99
(0.49)</td></tr>
<tr><td>VAR Residual Heteroskedasticity Tests (Levels and Squares)
- Chi-sq. stat</td><td>1282.53
(0.64)</td></tr>
</table></td></tr>
</table>

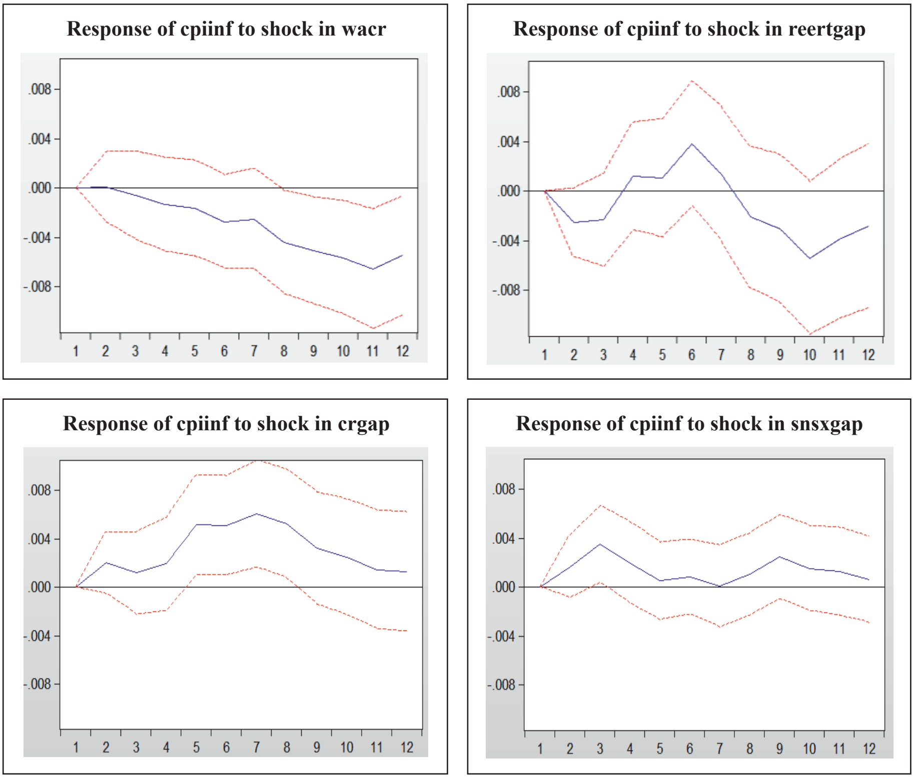
Note: Figures denote the statistic value/test statistic and figures in parentheses denote the p value.
Source: Authors' calculation.

Result for VAR Residual Heteroskedasticity Tests (Levels and Squares)

Joint test:		
Chi-sq.	**Df**	**Prob.**
1282.527	1302	0.6445

Source: Authors' calculation.

Impulse Response to SVAR innovations ± 2 S.E.



Source: Authors' calculations.

VI. Result for VAR Granger Causality/Block Exogeneity Wald Tests between MCIs, Inflation, and real GDP growth

Dependent variable: CPIINF			
Excluded	**Chi-sq**	**df**	**Prob.**
GDPREALGR	4.828935	2	0.0894
MCI_SVAR	11.90380	2	0.0026
All	15.23447	4	0.0042

Dependent variable: MCI_SVAR			
Excluded	**Chi-sq**	**df**	**Prob.**
GDPREALGR	9.001006	2	0.0111
CPIINF	7.270319	2	0.0264
All	15.25066	4	0.0042

Source: Authors' calculation.

VII. Result for VAR Granger Causality/Block Exogeneity Wald Tests between MCI_SVAR Inflation and real GDP growth based on TYDL method

Dependent variable: CPIINF			
Excluded	**Chi-sq**	**df**	**Prob.**
GDPREALGR	3.319855	2	0.1902
MCI_SVAR	10.66474	2	0.0048
All	12.62512	4	0.0133

Dependent variable: MCI_SVAR			
Excluded	**Chi-sq**	**df**	**Prob.**
GDPREALGR	6.128485	2	0.0467
CPIINF	13.09467	2	0.0014
All	17.05457	4	0.0019

Source: Authors' calculation.

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OTC Derivatives in Emerging Market and Developing Economies: The Role of Global Liquidity and Regulatory Reforms

Rajib Das, Narayan Chandra Pradhan and Rajat Malik*

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This paper examines the impact of post-Global Financial Crisis of 2007-08 liquidity conditions and implementation of regulatory reforms on the 'over-the-counter' (OTC) derivatives market activity in select emerging market and developing economies (EMDEs). Results based on a panel regression analysis suggest that the regulatory changes in the OTC derivatives market have resulted in the reduction of systemic risk in EMDEs. Cross-border liquidity flows and specific derivatives market reforms are found to stimulate OTC market volumes. Some evidences of regulatory burden coming in the way of greater volumes in OTC markets is also observed.

JEL Classification: G11, G14, G18, G23

Keywords: Over-the-counter markets, financial instruments, government policy and regulation

Introduction

Many of the world's largest financial markets remain decentralised with bulk of the derivatives trading taking place 'over-the-counter' (OTC). These

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* Authors are Adviser, Assistant Adviser and Manager, respectively, in International Department of the Reserve Bank of India (RBI), Central Office, Mumbai – 400001, India.

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contracts are negotiated bilaterally, and the customised nature of such contracts is a hallmark of OTC derivatives. Modern electronic exchanges, in turn, are easily accessible and often involve lower transaction costs. In comparison, OTC trading is relatively costly for the need to agree on prices and lower order of automation. Despite this, an increasing portion of trades occurs in OTC. OTC markets are mostly self-regulated and industry associations such as the International Swaps and Derivatives Association (ISDA) provide the OTC markets with standard legal contracts and some advantages over organised exchange markets.

Duffie *et al*. (2005) in their seminal work mentioned that the decentralised OTC market structure probably entails better price discrimination. OTC markets are also characterised by the absence of a centralised trading mechanism. In contrast, listed exchanges typically use a central limit order book to aggregate the trading interests of buyers and sellers. This permits participant in listed markets to trade with each other safely as well as anonymously (BIS, 1998).

Advances in electronic trading platforms have changed the trading process in many OTC markets, and this has sometimes blurred the distinction between traditional OTC markets and exchanges (Tuttle, 2014). On the other hand, there is a risk of imposing regulatory burden in the developing markets. Therefore, an attempt has been made in this study to assess the overall impact of these regulatory reforms on the EMDEs.

After the Global Financial Crisis (GFC) of 2007-08, there were regulatory concern regarding the interconnectedness among market participants and systemic risk propagation involving several large institutions. The third meeting of the G20 at Pittsburgh in September 2009 discussed the ways to strengthen the international financial regulatory system, including through fundamental changes to the regulations for OTC derivatives markets. The intent was to increase the disclosure of OTC operations so as to decrease the probability of a crisis. The G20 reform programme stressed that, ‘where appropriate’, trades involving standardised OTC derivatives must be executed on exchanges or electronic trading platforms and cleared through a central clearing counterparty (CCP). It also imposed higher capital requirements for non-centrally cleared trades and the reporting of all OTC derivatives trades to trade repositories (G20, 2009). The G20 had assigned the responsibility to monitor and assess the implementation of these reforms to the Financial Stability Board (FSB).

In addition, after the GFC, the G20 economies agreed on several financial reforms aimed at reducing systemic risk, improving transparency in the derivatives market and protecting against market abuse. These reforms included mandating centralised trading and clearing for standardised OTC derivatives, requirement of margins for derivatives that are not centrally cleared, and regulatory reporting of all derivatives transactions. Accordingly, several changes have been observed in OTC derivatives markets that are consistent with the G20 objectives of promoting central clearing and enhancing systemic stability.

The clearing reforms created a series of new operational and risk management processes involving trade execution and contract settlement to minimise risks. Central counterparties emerged as the entities providing clearing and settlement services for seamless execution of trade, much like an exchange (FSB, 2018).

Central clearing of derivatives can support financial stability in several ways. It may create greater opportunities for netting of derivatives and reducing counterparty credit risk. Technological advances enabled the creation of several electronic platforms for trading standardised OTC products, some of which seem very close to the system of central limit order book framework being operated on exchanges (Smyth and Wetherilt, 2011). In these platforms, the trade execution arrangements are constantly evolving and can still be quite complex. One of the aims of FSB regulations is to reduce the complexity of the OTC contracts. Bilaterally negotiated smaller and customised derivatives contracts are, however, the trademarks of conventional OTC derivatives. The relative attractiveness of OTC markets can be ascribed partly to the fact that OTC markets now yield many of the benefits of exchanges (Hull, 2018).

The operational aspects of OTC derivatives markets had no centralised trading, clearing, or settlement mechanisms earlier. Transparency and even database is generally limited, other than the semi-annual central-bank surveys [by the Bank for International Settlements (BIS)]. Information about market concentration and distribution of risks is generally unavailable (Schinasi *et al*., 2000). FSB reforms have addressed some of the operational hindrances. Apart from the safety of trade, it has partially relieved participants of the costs usually involved in search for trading opportunities in OTC derivatives market (Duffie *et al*., 2007). The introduction of CCP has also changed the features of OTC derivatives market significantly in terms of the management of counterparty (credit) risk, centralised limits on individual positions, restrictions in terms of leverage, or margining, *etc.*, where there were no formal rules for risk and burden sharing earlier and, therefore, of the market stability and integrity for safeguarding the interests of the participants (Duffie *et al*., 2017).

In the Indian context, Gopinath (2010) mentions that unlike the developed financial markets, the OTC derivatives market in India have evolved within a regulated space. The major elements of this regulatory framework include a broad specification of products to be permitted, nature of participants in the markets, distinct responsibilities for market makers and users for all OTC derivatives, effective reporting systems for capturing systemic information and focus on developing market infrastructure for post-trade clearing and settlement. Within this space, interest rate and forex derivatives will continue to operate in a regulated manner with increased transparency. A recent paper (Kumar and Kamate, 2020) provides empirical evidence on the presence of considerable price discrimination in the Indian OTC currency derivatives market through an analysis of transaction level data. In contrast to Gopinath (2010), it finds that a large majority of all clients (83 per cent) transacted with a single dealer. The authors have made a case for improving market access to enhance competition, which may result in better pricing for clients with lower transaction costs.

The G20 Leaders together made five commitments to reform OTC derivatives market (G20, 2009). These are: (i) standardised OTC derivatives should be centrally cleared; (ii) non-centrally cleared derivatives should be subject to higher capital requirements; (iii) non-centrally derivatives should be subject to minimum standards for margin requirements; (iv) OTC derivatives should be reported to trade repositories; and (v) standardised OTC derivatives should be traded on exchanges or electronic trading platforms, where appropriate. There is a broad acceptance that the G20 reform measures have helped strengthen the resilience of large financial institutions, and that meaningful progress has been made towards mitigating systemic risk (FSB, 2017).

The remainder of this paper is organised as follows: Section II presents an analysis of OTC derivatives volumes trends, globally as well as in select EMDEs, and in relation to the global liquidity. Data, methodology and empirical findings are reported in Section III. Section IV concludes the paper by highlighting key policy implications.

Section II
OTC Derivatives Market and Global Liquidity

II.1. Analysis based on BIS semi-annual data

The risk related to an OTC derivatives contract depends on various factors, such as the concentration of positions and the volatility of the underlying asset. Notional amount and gross market values are two of the several metrics used to calculate the risk exposure of OTC derivatives. However, both measures show a decline from respective pre-crisis peaks as also since the G20 Pittsburgh Summit in 2009, when major reform measures on OTC derivatives were introduced. The gross market value[1] of derivatives contracts, which provides a more meaningful measure of amounts at risk, has continued on its declining trend since the GFC of 2007-08.

According to the BIS semiannual data[2], the notional amounts of global OTC derivatives have increased from USD 544 trillion in December 2018 to USD 640 trillion in June 2019, which marks a continuation of the rising trend generally evident since end-2016. The gross market values of all outstanding OTC derivatives fell to USD 9.7 trillion by end-December 2018 from the peak

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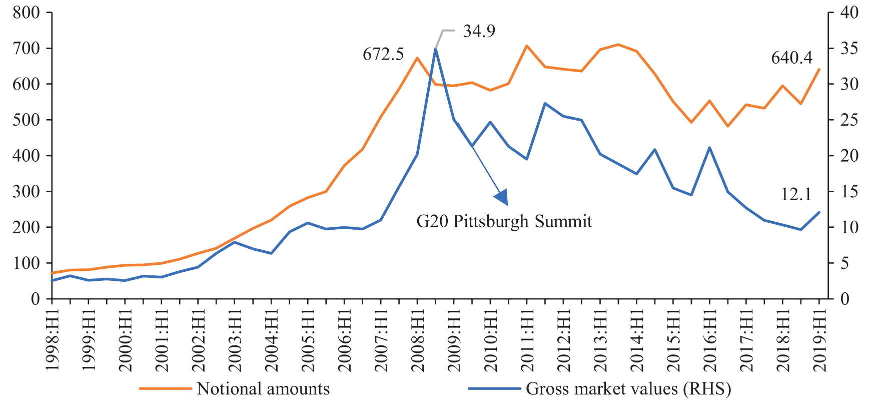
1 As per the BIS, the gross market value refers to the sum of the absolute values of all outstanding derivatives contracts with either positive or negative replacement values evaluated at market prices prevailing on the reporting date. Further, notional amount is the gross nominal or notional value of all derivatives contracts concluded and not yet settled on the reporting date. It provides information about economic significance or potential scale of market risk in derivatives transactions and the associated financial risk transfer that is taking place across markets and products.

2 The semi-annual data captured about 94 per cent of global OTC derivatives positions.

Chart 1: Global OTC Derivatives Outstanding (USD trillion)



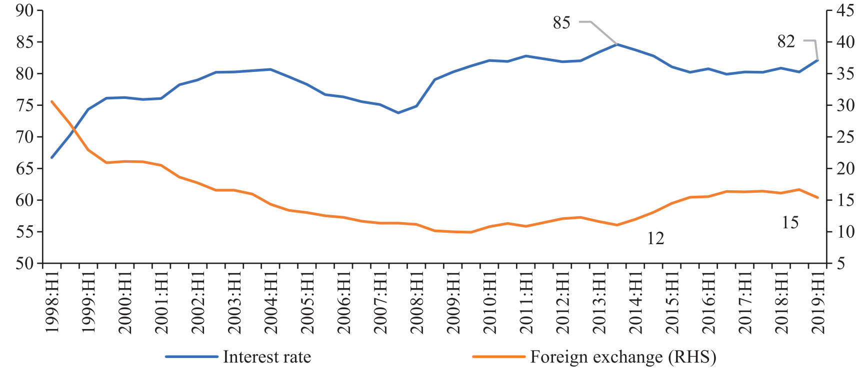
Source: BIS OTC derivatives semi-annual statistics.

of USD 35 trillion at end-December 2008, before witnessing a rebound to USD 12 trillion in June 2019. In both the cases, this was led mainly by interest rate derivatives, both USD and Euro denominated contracts and generally in the short-term contracts. OTC derivatives have witnessed structural changes in the past decade with the rise of central clearing as a major driver (Chart 1). This change has gone hand in hand with an increase in trade compression – the elimination of economically redundant derivatives positions – both of which primarily affected interest rate contracts, driving down their market values.

OTC derivatives are mainly dominated by the foreign exchange (FX) and interest rate (IR) derivatives with their combined share at about 97 per cent of the overall outstanding global OTC notional amounts, up from 90 per cent in June 2009. Similarly, their share in terms of gross market values has also risen from 66 per cent in June 2008 to 91 per cent in June 2020. This was driven entirely by IR contracts, despite its share falling marginally from its recent peak. The gross market value share of IR contracts fell from 80 per cent at end-June 2014 to 66 per cent at December 2018 before rising to 73 per cent in H1 2019, while that of FX contracts rose sharply from 11 per cent to 23 per cent and falling subsequently to 18 per cent in H1 2019 (Charts 2 and 3).

Much of the increase in notional amounts for IR derivatives occurred in short-term contracts (less than 1-year). The total IR derivatives rose from USD

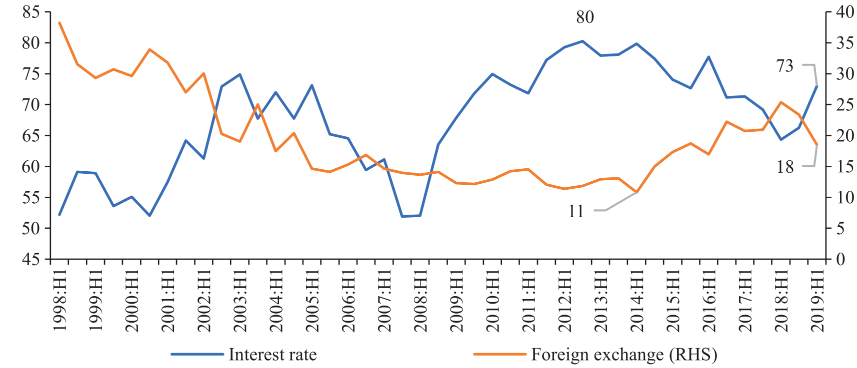
Chart 2: Share of OTC FX and IR Derivatives - Notional Outstanding (per cent)



Source: BIS OTC derivatives semi-annual statistics.

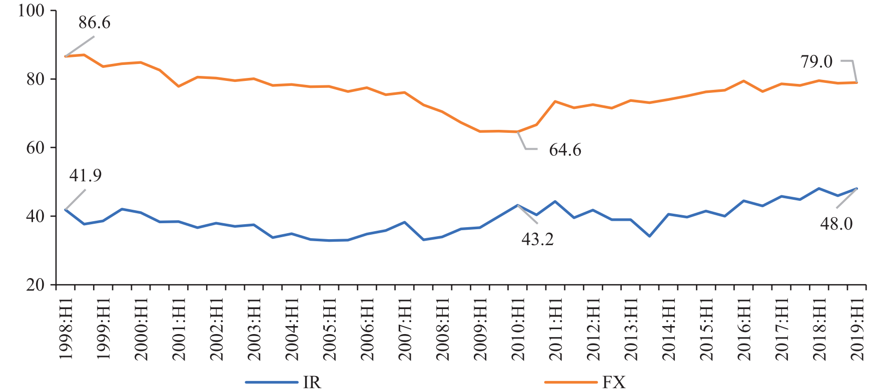
481 trillion in June 2018 to USD 524 trillion in June 2019, while the segment with maturity up to and including one year rose from USD 231 trillion to USD 253 trillion in the same period. The share of short-term IR derivatives fluctuated at around 40 per cent before witnessing a moderate rise to 48 per cent by June 2019 (Chart 4). For the FX derivatives, this number witnessed a constant decline from 87 per cent in 1998 to 65 per cent in June 2009 before recovering to 79 per cent by June 2019. The predominance of short-term FX contracts may be a reflection of the response to quantitative easing (QE)

Chart 3: Share of OTC FX and IR Derivatives - Gross Market Value (per cent)



Source: BIS OTC derivatives semi-annual statistics.

Chart 4: Share of less than 1 year contract (per cent of total)

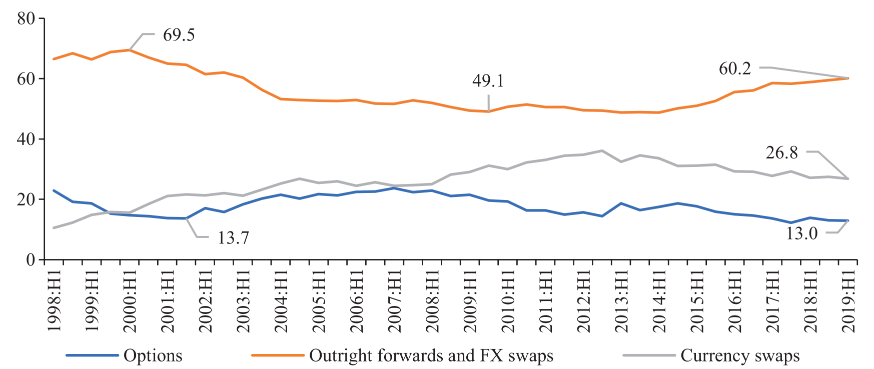


Source: BIS OTC derivatives semi-annual statistics.

adopted by several systematically important central banks. On the other hand, the share of short-term IR derivatives can be reflective of a prolonged period of low interest rates as compared to the pre-GFC phase.

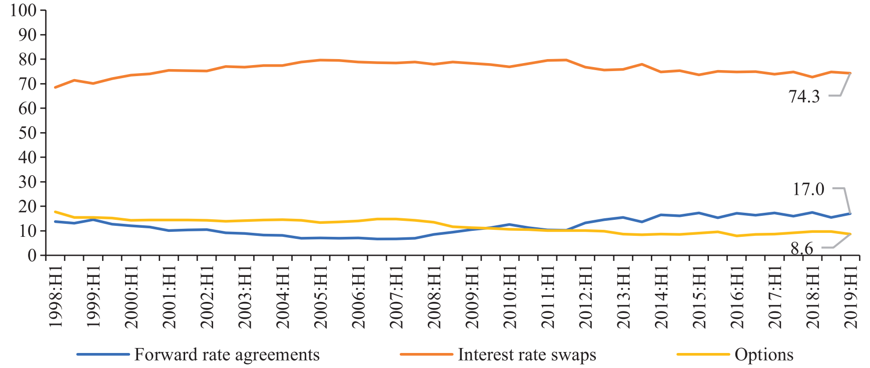
The composition of instruments within FX as well as IR derivatives has undergone changes over the past two decades. In the FX derivatives, the change is considerable (Chart 5). The share (per cent of total notional outstanding) of outright forwards and swaps declined from 69 per cent in June 2000 to 49 per cent in December 2009, before recovering to 60 per cent in

Chart 5: Share of Instruments within FX OTC Derivatives- Notional Outstanding (per cent)



Source: BIS OTC derivatives semi-annual statistics.

Chart 6: Share of Instruments within IR OTC Derivatives - Notional Outstanding (per cent)

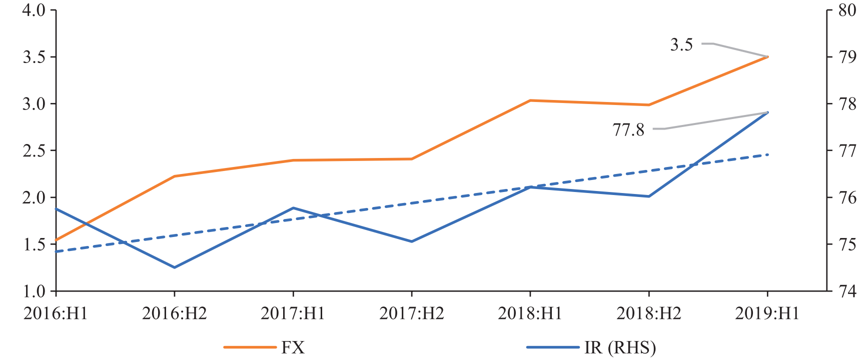


Source: BIS OTC derivatives semi-annual statistics.

June 2019. On the other hand, the share of currency swaps has risen from 10 per cent in June 1998 to 30 per cent in December 2017, and this has been offset by a decline in the share of options from 23 per cent in 1998 to 13 per cent in June 2019. Within the IR OTC derivatives (Chart 6), the composition has changed only marginally. As of June 2019, the share of swaps remains dominant at around 74 per cent, while the share of forward rate agreements (FRAs) and options stood at 17 per cent and 9 per cent, respectively.

Central clearing is steadily expanding in the OTC derivatives market for many years. The share of outstanding OTC derivatives cleared through central counterparties remained over 78 per cent for IR contracts as against only 3 per cent for FX derivatives during 2019:H1 (Chart 7). The relatively low share of FX derivatives can be explained by differences in regulations. Regulators in most of the major derivatives markets require certain standardised OTC derivatives to be centrally cleared, particularly IR swaps, Credit Default Swaps (CDS) and non-deliverable FX forwards; deliverable FX derivatives and equity derivatives are generally not covered. Also, some instruments, such as options, are currently not offered for clearing by CCPs. That said, regulators continue to expand clearing requirements, and many are also starting to require higher capital and margins for non-centrally cleared derivatives (FSB, 2016). Overall, the CCP led changes possibly enabled lower market concentration especially in the case of IR derivatives. During the period, June 2009 to June

Chart 7: Percentage of Notional Amounts of OTC Derivatives Cleared with Central Counterparties



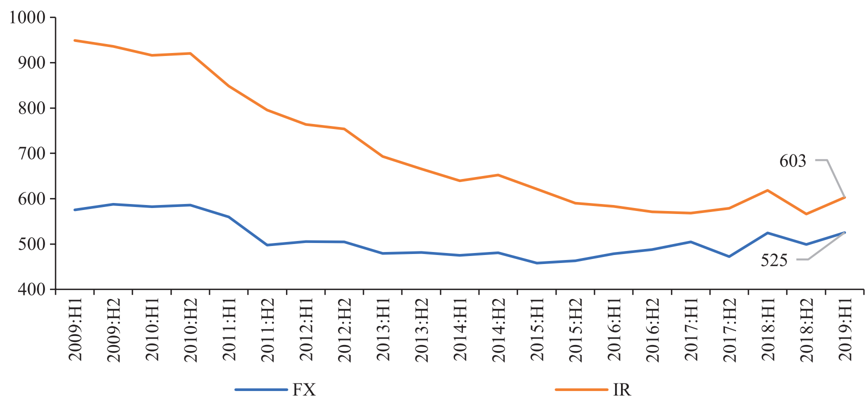
Source: BIS OTC derivatives semi-annual statistics.

2019, the Herfindahl index[3] for IR declined from 892 to 603; for FX it came down from 575 to 525 (Chart 8).

II.2 Analysis based on BIS triennial survey data

As the previous analysis is confined to aggregate data, this sub-section focuses on OTC derivatives of EMDEs. As on June 2019, the 12 jurisdictions covered under semi-annual data reporting by BIS accounts for about 92 per

Chart 8: Herfindahl Index (US and USD contracts)



Source: BIS OTC derivatives semi-annual statistics.

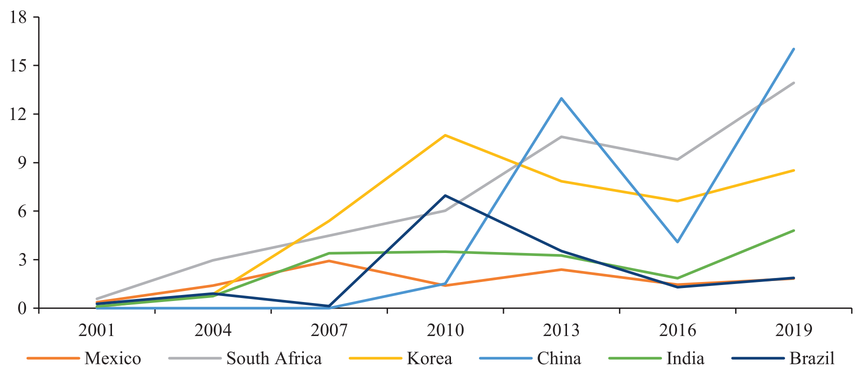
3 Herfindahl index: Measure of market concentration, defined as the sum of the squared market shares of each individual entity. The index ranges from 0 to 10,000. If only one entity dominates the market, the measure will have the (maximum) value of 10,000.

cent of global notional outstanding OTC derivatives positions and 87 per cent in gross market value terms. These 12 jurisdictions, however, are all advanced economies (Australia, Canada, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, UK and US) Thus, to understand the remaining roughly 8 per cent of the global OTC derivatives positions, one needs to depend on the BIS triennial survey on trade volume data of additional 33 jurisdictions which cover many EMDEs. Although, the overall share of remaining countries is about 6 per cent, their share in FX derivatives is relatively higher at around 14 per cent.

A cursory look at the trade volume data from the BIS triennial survey for select EMDEs reveals the impact of global reforms on these markets over a period, the magnitude of which varies from country to country based on the level and timeline of implementation of reforms. In the EMDEs, the turnover of OTC derivatives (IR as well as FX) has been volatile, though the trend has been rising even before the implementation of reforms (Charts 9 and 10).

A further examination of the triennial survey in terms of the relative turnover share of different categories of countries shows that the EMDEs[4] gained turnover shares in FX, which rose from 2.0 per cent in 1998 to 4.5 per cent in 2019 (Table 1).

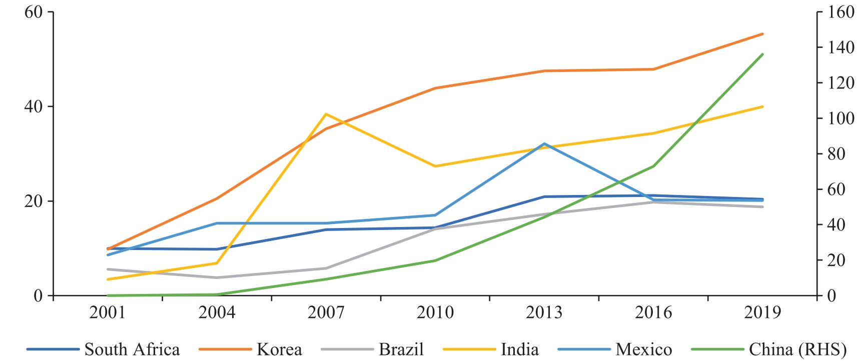
Chart 9: Daily Average Turnover of OTC Interest Rate Derivatives (USD Billion)



Source: BIS OTC derivatives triennial survey data 2019.

4 The 11 EMDEs are China, India, Brazil, Russia, South Korea, South Africa, Indonesia, Mexico, Saudi Arabia, Turkey and Argentina.

Chart 10: Daily Average Turnover of OTC FX Derivatives (USD Billion)



Source: BIS OTC derivatives triennial survey data 2019.

Notably, the increase in EMDEs share in FX derivatives has been at the expense of diminishing share of the G20 nations other than the US and the UK. Again, among 11 EMDEs, the rise in EMDEs share has come mostly due to expansion of share by China. In fact, the FX derivatives share of 10 EMDEs other than China declined from 3.7 per cent in 2013 to 2.9 per cent in 2019, when most of them implemented global reforms in OTC derivatives market. Similar pattern is also seen in case of IR derivatives, although the US and the UK have remained the most dominant in IR derivatives trade. In fact, for both FX and IR contracts, the shares in trade of the US and the UK increased to

Table 1: OTC Derivatives in EMDEs by Market Values

	FX Contract (in per cent)				IR Contract (in per cent)			
	US and UK	11 EMDEs	China	Rest G20 (ex-EU)	US and UK	11 EMDEs	China	Rest G20 (ex-EU)
1998	50.9	2.0	-	20.9	52.8	0.3	-	33.3
2001	47.8	3.2	-	24.0	52.3	0.1	-	32.3
2004	51.1	3.7	0.02	22.4	66.2	0.5	-	21.6
2007	52.1	4.2	0.2	17.7	68.2	0.8	-	19.1
2010	54.7	4.1	0.4	16.9	70.8	1.1	0.1	16.7
2013	59.7	4.4	0.7	14.1	73.1	1.5	0.5	16.2
2016	56.5	4.6	1.1	14.1	79.7	0.8	0.1	10.9
2019	59.6	4.5	1.6	11.0	82.4	0.7	0.2	7.4

Source: BIS.

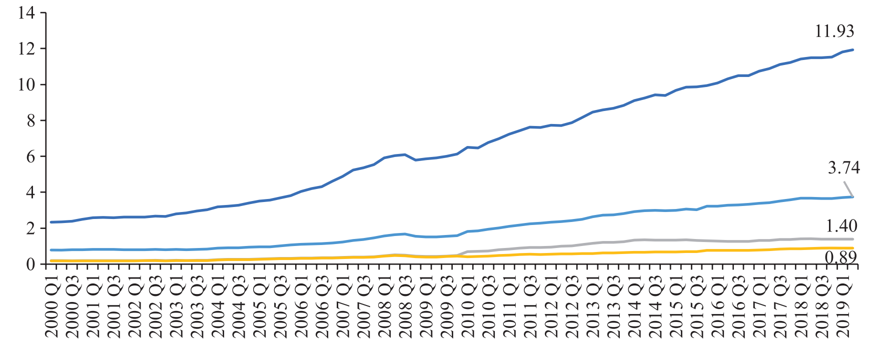
59.6 and 82.4 per cent, respectively, by 2019. Rest of the G20 countries lost their shares in both IR and FX derivatives.

II.3 Analysis based on BIS global liquidity data

The above analysis provides a snapshot on the size and structure of global derivatives markets and motivates us to explore the possible drivers shaping the same, *e.g.*, cross border flow of liquidity and G20 reforms. Global liquidity is one of the factors which may directly be related to the OTC derivatives in EMDEs in terms of creating risky exposures driving volumes in OTC derivatives, particularly for FX derivatives through demand for currency cover and risk to marketable securities. The demand for IR derivatives could also be coming from the faster interest rate movements driven by the international investors including institutional investors. Overall, the global liquidity flow to a country can be driven by a combination of global factors, capitals flows to EMDEs, country specific developments like financial market regulations and the state of derivatives markets.

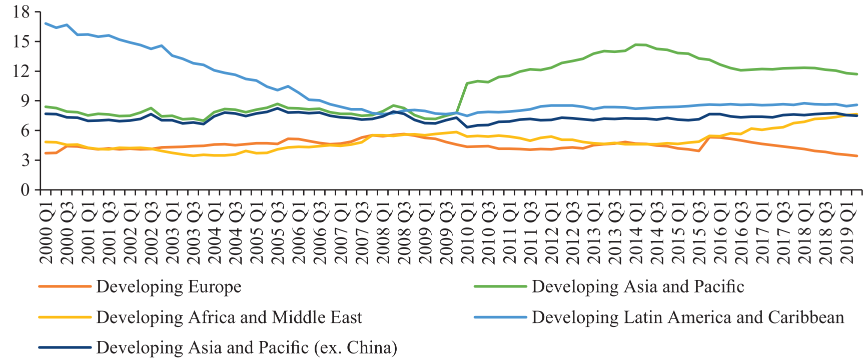
USD credit to non-bank borrowers from non-residents grew continuously since 2001 and reached approximately USD 12 trillion by March 2019. Within this, credit to EMDEs increased to USD 3.7 trillion as of March 2019. Moreover, the USD denominated credit to EMDEs constitutes about 80 per cent of the total credit in EMDEs by March 2019 (Chart 11).

Chart 11: USD Denominated Credit to Non-bank Borrowers (USD Trillion)



Source: BIS.

Chart 12: Share of non-bank USD credit to Developing Countries by Region (per cent of total)

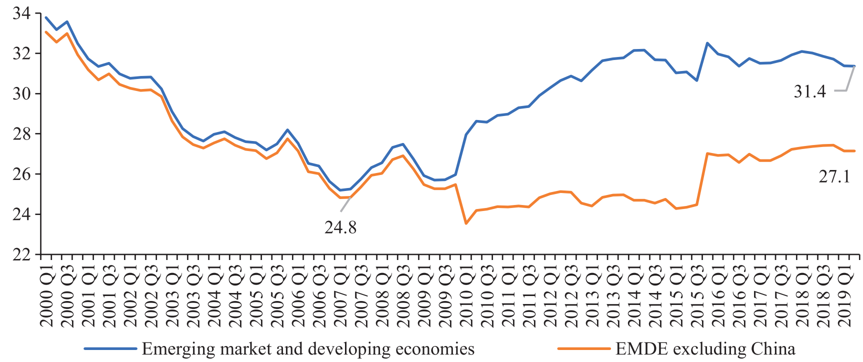


Source: BIS.

Amongst the developing countries, the share of non-financial credit to developing countries by region reflects the rise in share of Developing Asia and Pacific after the GFC. However, almost the entire rise in the share of credit could be explained by China as the credit share of Developing Asia and Pacific excluding China remained by and large steady for the entire period. The rise in credit share to China happened post 2008-09, while a considerable drop was seen for the Latin America and Caribbean region pre-2008 (Chart 12). The share of Africa and Middle East also increased in more recent period to 8 per cent in June 2019, while for the other regions it remained nearly constant. Overall, the share of EDMEs in USD credit has clearly gone up, which holds true even if the EMDEs share is calculated excluding China. EMDEs share of credit grew from 25 per cent in 2010 to 27 per cent in 2019 excluding China (25 per cent to 31 per cent if China is included) (Chart 13).

To understand the impact of global liquidity on average OTC (IR+FX) trade volumes, it may be useful to plot data for eleven EMDEs (Annex 1). It may be observed that while there is a general correspondence between OTC derivatives trade volumes and global liquidity, the strength of the relation varies across countries. While there could be several other factors behind these differences, we believe that the difference in the pace and intensity of adoption of G20 OTC reforms could be one of them. The OTC volumes and global liquidity seem to be somewhat correlated in the case of India, South Korea and China, but not so in the case of Mexico and Brazil.

Chart 13: Share of total non-financial USD credit to Developing Countries-Overall (per cent of total)



Source: BIS.

II.4 Parameters of G20 OTC Derivatives Reforms by FSB

The FSB has been coordinating and periodically assessing the state of implementation of G20 reforms in the OTC markets. FSB assesses member countries in terms of identifiable parameters and publishes their status of reform compliance through annual or more frequent publications titled 'OTC Derivatives Market Reforms', known as the FSB Progress Report on Implementation.

Although definitions of compliance on each of the parameters are evolving over various FSB progress reports based on the course of reforms at the time of assessment, for the sake of analysis and quantification of its assessment, it is possible from its various reports to identify if an EMDE is fully, partially or not complied on any parameter of reforms at a given year. Broadly, the current definition of these assessments can be laid down in broader terms as:

- Full compliance of FSB reform, which implies some final statute, regulation, rule, policy statement, standard, *etc.* are already operative (at least 90 per cent of the transactions) in member countries as assessed by FSB;
- Where final statute, regulation, *etc.* are enacted or published but it is either not fully operative and/or does not have been in its full effect, it is treated as partially complied by the FSB;

- Reform measures are taken as not complied if members have failed to create any new or use existing authorities/framework to implement them, if so assessed by FSB.

Based on the FSB reports over the years, it is possible to create a matrix on the state of reforms by various member countries in respect of all these parameters. Table 2 brings out the state of reforms implementation across the EMDEs, for years of BIS Triennial Survey, which is later mapped to OTC trade volumes.

Some of the observations that can be derived from Table 2 are as follows:

- Among EMDEs, the best track record on reform implementation appears to be in Mexico, Brazil and South Korea, who could fully implement 4 of the 5 major reforms. Brazil and South Korea have only partial compliance with respect to platform trading, while Mexico lags on margin implementation. By implementing more difficult reforms like platform trading, central counterparties and margin requirements on non-centrally cleared derivatives (NCCDs), the EMDEs, could be argued, to be moving towards a level playing field between standardised/centrally cleared product *versus* customised/non-standardised bilaterally traded products without compromising systemic concerns. However, the challenging nature of these reforms in terms of infrastructure developments and compliance cost can have short-term impact on OTC trade volumes, which has been examined more closely later in the paper.
- On the other hand, China, systemically the most important EMDE in terms of liquidity flows and OTC trade volumes, seems to have a relatively inconsistent track record of reform implementation. It is the only FSB member country until 2018 to not even initiate margin related reform on NCCD. The early focus on standardisation effort to fully implement platform trading was in 2013; however, it was given up by 2016 for reasons not fully understood.

Table 2: Status of Reform Implementation in 11 EMDEs

	Implementation*	2010	2013	2016	2019
Trade Reporting	Full Compliance	0	6	8	9 (excluding South Africa)
	Partial Compliance	4 (Brazil, China, India, Indonesia)	10	11	11
Central Clearing	Full Compliance	0	1 (China)	4 (Brazil, China, South Korea, Mexico)	5 (South Africa +4)
	Partial Compliance	2 (Argentina, China)	6	11	11
Platform Trading	Full Compliance	0	1 (China)	1 (Mexico), China no more Full Compliance	1 (Mexico)
	Partial Compliance	3 (Argentina, China, Indonesia)	5	11	11
Higher Capital on NCCD	Full Compliance	0	7	11	11
	Partial Compliance	0	9	11	11
Margin on NCCD	Full Compliance	0	0	1 (Saudi Arabia)	3 (Saudi Arabia, South Korea, Brazil)
	Partial Compliance	0	2 (Argentina, India)	10 (China, non-compliant)	11

*: Reform implementation status of a year corresponds to the status in subsequent year's available report.
Source: BIS.

- Most of the other EMDEs fall in between, generally remaining compliant on higher capital requirement on NCCD and trade reporting, while avoiding/delaying platform trade and margin requirement on NCCD related reforms owing to infrastructure/cost challenges they impose. There is a risk that partial implementation of reforms could be driving *de facto* standardisation through higher capital and lack of margining on NCCD, while greater incentives were created under the reforms for clearing through central counterparties. For instance, FX standardisation of India can be considered very high as market participants are often required to clear products through central counterparties.

From the above discussions, it may be inferred that the pace of reform process across the nations has varied because the challenges faced by EMDEs are different from that by the advanced countries in terms of the nature and evolution of the OTC derivative markets, the nature of participants, the systemic risks and regulatory priorities. For instance, as pointed out by Gopinath (2010), in India, unlike many of the developed financial markets where OTC derivative markets epitomised complex, unregulated financial innovations and grew exponentially during 1990-2010, the markets have generally continued to evolve slowly within a conservatively regulated space, serving more of retail and customised contracts. The approach included many prudential restrictions on participation and requirements such as requirements of an underlying exposure for undertaking OTC derivative transactions.

The above facts necessitate a deeper understanding of the precise relation between global liquidity and OTC trade through the prism of FSB reforms. As expected, it turns out that the identified reform leaders have lost out on OTC trade volumes post implementation *vis-à-vis* the relatively slow implementers (Charts 14, 15, 16 and 17). In the next section, we study the impact of global liquidity and FSB reforms on OTC derivatives trade of selected EMDEs in a panel regression framework.

Chart 14: Reform leaders - Average (South Korea+Brazil+Mexico)

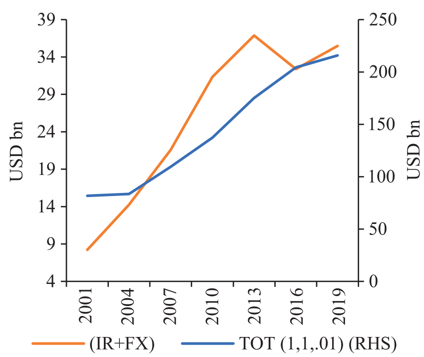
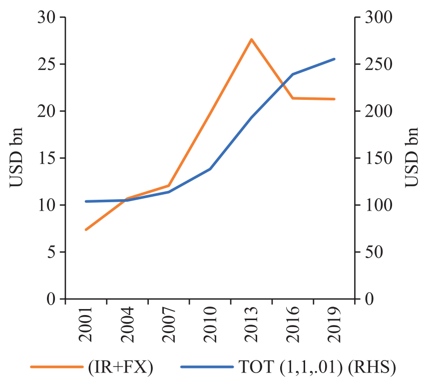


Chart 15: Average (Mexico+Brazil)



Source: BIS

^TOT refers to total credit to non-bank borrowers computed by summing USD + Euro +0.01JPY

Chart 16: China

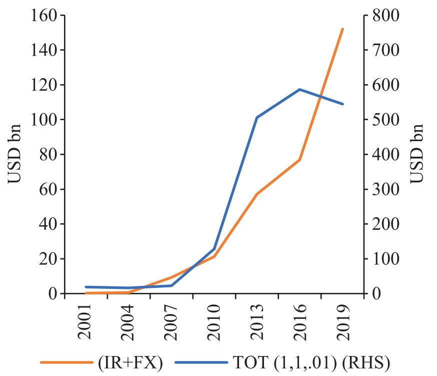
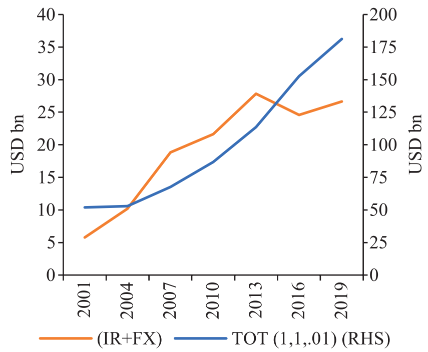


Chart 17: Average 10 EMEs (excluding China)



Source: BIS

^TOT refers to total credit to non-bank borrowers computed by summing USD + Euro +0.01JPY

Section III
Data and Empirical Analysis

A panel regression model is used to ascertain the impact of global liquidity and FSB reforms on FX and overall OTC derivatives for the period 1998 to 2019 (the latest available data from BIS). Aggregate level information on average turnover in FX and IR instruments are obtained by summing up these two series in each BIS triennial surveys. To obtain information on the course of FSB reforms and their implementation, various FSB Progress Reports on OTC derivatives market reforms have been used for each country covering all the five parameters Trade Reporting – (TR), Central Clearing (CC), higher capital (CAP), Platform Trading (PT) and Margin requirements (M) – classifying them either full, partial, or not compliant - as per the assessment. For liquidity mapping to BIS Triennial Survey OTC derivatives trade data, BIS global liquidity indicators — the country-wise information on total credit to non-bank borrowers by currency of denomination (USD, Euro and JPY), cross-border and local financing in foreign currency and loans and debt securities issuance by non-banks — have been aggregated on a 3-year average basis.

Accordingly, the following generic equation has been used to quantify the impact of liquidity and reforms on OTC volumes under alternate data.

$$OTC_{i,t} = \alpha_i + \beta GLiq_{i,t} + \gamma Reg_{2010} + \sum_{j=1}^{5} \emptyset_j \, Reg_{2010} * RegPIj_{i,t} + \sum_{j=1}^{5} \mu_j \, Reg_{2010} * RegFIj_{i,t} + \varepsilon_{i,t}$$

where, OTC $_{i,t}$ stands for OTC daily average overall (FX + IR) or FX volumes (in USD Billion) for the ith country and tth year. *GLiq* measures Global liquidity as a combination of USD, Euro and JPY credit or only USD Total Credit. *Reg2010* is a Dummy taking value '1' for 2010 or after and '0' otherwise. *RegPIj* is the jth OTC regulation: (TR, CC, CAP, PT and M) taking a value '1' when a country implements them partially and '0' otherwise. *RegFIj* is the jth OTC regulation (TR, CC, CAP, PT, M) taking a value '1' when a country implements them fully and '0' otherwise. Panel estimations are made with country specific effects with cross section GLS weights but without taking any time dummy.

The panel of equations covers eleven EMDEs: Argentina, Brazil, China, India, Indonesia, Mexico, Russia, Saudi Arabia, South Africa, South Korea, and Turkey. Besides pooling partial and full implementation, the fixed effects model is also estimated for 1998-2019 with either partial or full status of implementation as assessed by FSB, *i.e.*, $\theta = 0$ and $\mu = 0$. The results of the OTC specifications of regressions are provided in Table 3.

It is possible that the above regression with overall OTC derivatives may turn out to be inefficient due to thin trading of IR derivatives in EMDEs and aggregation of liquidity in various currencies. Therefore, the generic regressions are conducted on only FX derivatives and USD liquidity as also various other specifications which yield broadly unchanged results. The results of the FX OTC trade specifications as a function of USD liquidity regressions are provided in Table 4.

The panel regression results suggest that global liquidity is a prime driver of OTC trade volumes (Tables 3 and 4). The association is stronger for USD liquidity and for FX products (Table 4). This is along the expected lines as cross border liquidity is expected to raise the demand for cover against market risks. As discussed earlier in Section II.3, the USD credit to non-bank borrowers from non-residents to developing countries increased to USD 3.7 trillion by March 2019, while the trade in OTC derivatives in the 11 EMDEs under consideration rose to USD 418.4 billion during the same period. The

Table 3: Dependent Variables - All OTC (FX + IR) Daily Average Volumes and Total Global Liquidity (USD billion)

Indicators	Variable	*Coefficient*		
		(Full + Partial)	(Only Full)	(Only Partial)
Global Liquidity	ALL Liquidity (USD + Euro +0.01JPY) in USD billion	0.120***	0.107***	0.08***
Global regulation	Post 2010	6.03**	6.89***	8.01**
Higher Capital on NCCD	Full Compliance	-5.15	-3.25	-
	Partial Compliance	6.38	-	-4.53
Central Clearing	Full Compliance	13.33***	10.64***	-
	Partial Compliance	9.21	-	10.76*
Margin on NCCD	Full Compliance	1.47	-1.89	-
	Partial Compliance	-7.34	-	-1.10
Platform Trading	Full Compliance	-23.72***	-23.04***	-
	Partial Compliance	-9.74	-	-10.9*
Trade Reporting	Full Compliance	-8.44**	-4.38	-
	Partial Compliance	4.64	-	3.88
Adj. R Square		0.82	0.82	0.81
F-statistic		17.01	20.80	20.50
Prob (F-statistic)		0.00	0.00	0.00
Durbin-Watson stat		1.703	1.71	1.28

***: Significant at 1 per cent. **: Significant at 5 per cent. *: Significant at 10 per cent.

rise has not been similar across countries, especially for the OTC volumes, which could be due to the country specific conditions relating to the timeline and impact of the FSB reforms.

The FSB regulations are found to have a strong impact on the OTC trade volumes, both at the aggregate as also for OTC FX trade, which perhaps indicates the possible impact of reforms either through the associated benefits of a robust regulatory set up or *via* compliance costs. The trade volumes are impacted generally by the timeline of reforms implementation and also specifically by the process of reforms. Overall, the regulation dummy has a favourable impact in terms of pushing up trade for general OTC and OTC FX. In addition, some of the individual parameters of reforms are also seen to help enhance the OTC trade volumes - overall or only FX. However, certain other parameters of reforms like platform trading and trade reporting tend to pull down the volumes of OTC trade – general or FX trade - as evident from their respective coefficient values.

Table 4: Dependent Variables: OTC FX Daily Average volumes and USD global liquidity in billion USD

Indicators	Variable	*Coefficient*		
		(Full + Partial)	**(Only Full)**	**(Only Partial)**
USD Liquidity	USD Liquidity in billion USD	0.134***	0.120***	0.09***
Global regulation	Post 2010	6.89***	6.06***	7.92***
Higher Capital on NCCD	Full Compliance	-4.27	-3.6*	-
	Partial Compliance	5.16	-	-0.67
Central Clearing	Full Compliance	9.76***	7.12**	-
	Partial Compliance	7.6	-	7.71
Margin on NCCD	Full Compliance	0.15	-2.08	-
	Partial Compliance	-3.77	-	-0.34
Platform Trading	Full Compliance	-20.84***	-18.44***	-
	Partial Compliance	-9.35		-8.28
Trade Reporting	Full Compliance	-5.23*	-3.42	-
	Partial Compliance	-9.35	-	-2.08
Adj. R Square		0.81	0.80	0.78
F-statistic		15.76	19.87	17.46
Prob (F-statistic)		0.00	0.00	0.00
Durbin-Watson stat		1.82	1.78	1.54

***: Significant at 1 per cent. **: Significant at 5 per cent. *: Significant at 10 per cent.

As discussed in section II.4, the average daily OTC derivatives volumes in 11 EMDEs have witnessed a rise from USD 5.3 billion in 2001 to USD 38 billion in 2019. Our results suggest that the central clearing is particularly improving trade volumes by reducing credit risk in bilateral trade. However, much of the positive impact is outweighed by the adverse impact of regulation on platform trading and trade reporting, particularly the former. In some cases, this impact is visible even with partial implementation. While trade reporting could be acting as a barrier to more trade by increasing the compliance costs, the negative impact of platform trade could be appearing from reluctance of the market to standardise OTC products beyond a point. This is more impactful as most of the EMDEs are lagging on margin requirement but are generally compliant with higher capital requirement on NCCD. This is possibly prompting participants against any required customisation of OTC trade, while encouraging standardisation for platform trade and central clearance, wherever possible, to economise on capital. This could have enhanced safety of trade but only at the cost of giving up the required customisation and innovation of OTC markets in most EMDEs.

There is no independent impact of margin as well as higher capital requirement of NCCD on the total OTC volumes in the results. One of the possible reasons for this could be that they are shifting the composition of trade from bilateral to platform and central counterparties, appearing in the regression coefficients separately with a net negative impact. While every country could fully introduce higher capital charges on NCCD, only a few of them could introduce margin on NCCD, leading to a lack of level playing field between standardised and customised products. Absence of netting attracts imposition of capital charge on gross positions of market participants in most of the countries. Also, non-standardised products attract higher margin on platform/central clearings.

No consistent patterns could be observed while trying similar regressions on IR OTC derivatives volumes. The market size of IR is quite limited as compared to FX in EMDEs and still evolving in almost all EMDEs. Despite small volumes, they are standardised and collateralised and, therefore, the impact of FSB regulations could not be observed. Thus, the global reforms since 2010 have led to some benefits along with a few pressing unintended consequences. Our results also reflect a few unintended impacts of the reforms on the volumes of the OTC derivatives market for EMEs.

Section IV
Concluding Observations

An empirical assessment of the impact of G20 OTC derivatives market reforms on market volumes in EMDEs is the focus of the study. More specifically using panel regression the impact of global liquidity and OTC derivatives market reforms is studied on the volumes of the OTC derivatives - both foreign exchange and interest rate derivatives separately - for 11 systemically important EMDEs. The analysis also segregates the marginal impacts of each reform parameter on trade volumes.

The results suggest that cross-border liquidity flows provide necessary impetus to the OTC derivatives market in EMDEs. Global liquidity is found to be influencing OTC volumes, which is more prominent for USD liquidity and FX derivatives products.

In addition, global regulatory reforms undertaken by FSB are also observed to be helping in promoting an orderly development of the market. The FSB regulations impact OTC FX volumes when the implementation is assessed as complete. Irrespective of the individual dimension of reforms, there has been an overall increase in trade volumes since the onset of reforms. Particularly, we observe that central clearing helped improve trade volumes significantly.

The effect of trade reporting as well as platform trading, however, is found to reduce OTC trade volumes in EMDEs. It is possibly showing the reluctance and inability of markets to standardise instruments beyond a point. Also, there could be added costs due to enhanced disclosures and regulatory reporting standards. There is no independent impact that could be measured due to higher capital requirement of non-centrally cleared derivatives and implementation of margining requirement as they may be impacting the composition of trade more than total volumes of the trade. Overall, we find some evidence of regulatory burden that is coming in the way of greater OTC trade activity in EMDEs.

In a broader sense, there are many challenges and adjustment costs associated with these reforms especially for EMDEs. A few of these may be short term in nature while others have proved long lasting, which explains why some of the suggested reforms have taken greater time and costs and witnessed hesitancy on the part of countries before full implementation. Overall, one may argue that a more flexible, phased and country specific implementation strategies could have been better, keeping in view the varied state of markets, maturity levels and ability to adjust, even though the observed broad benefits and resilience in terms of rising trading volumes in EMDEs.

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Annex 1: Global Liquidity and Average Daily OTC Volumes (USD billion)

(Three-year averages are given in right hand side)

Chart 1: Argentina

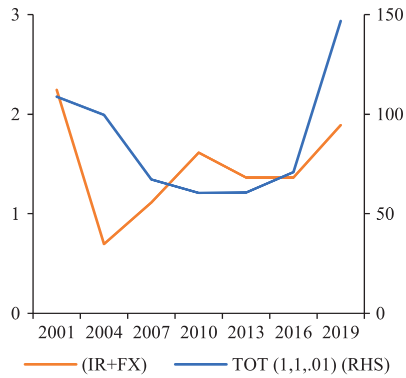


Chart 2: Brazil

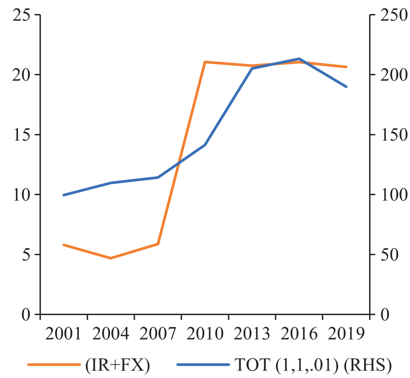


Chart 3: China

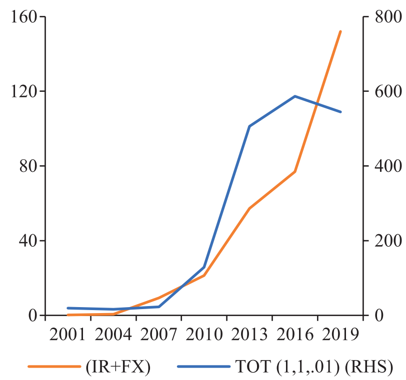


Chart 4: India

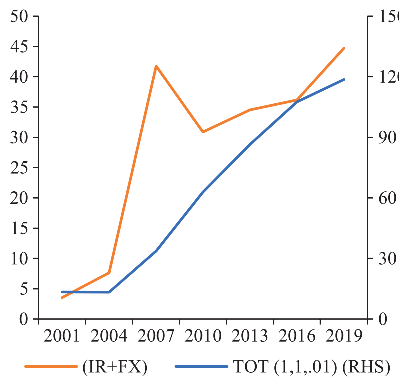


Chart 5. Indonesia

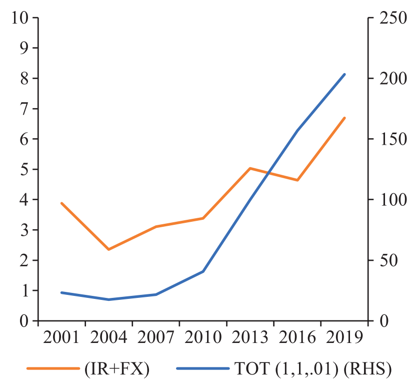
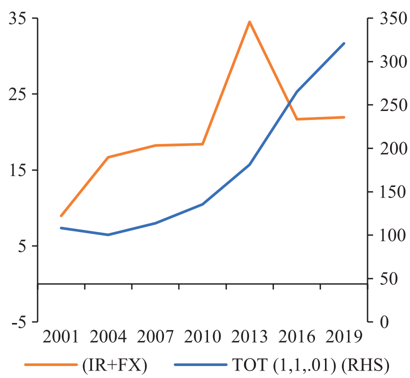


Chart 6: Mexico



Source: BIS.

Chart 7: Russia

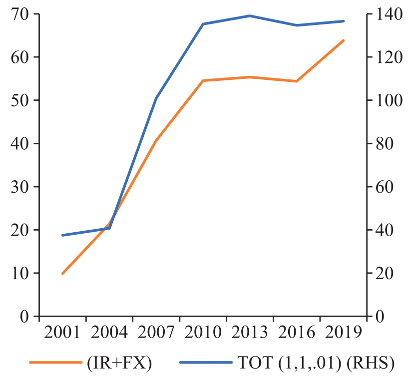


Chart 8: Saudi Arabia

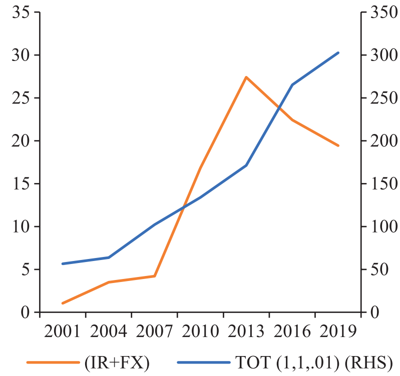


Chart 9: South Africa

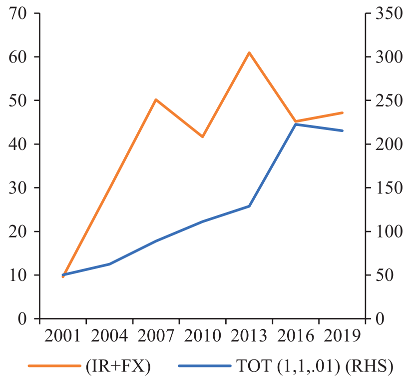


Chart 10: South Korea

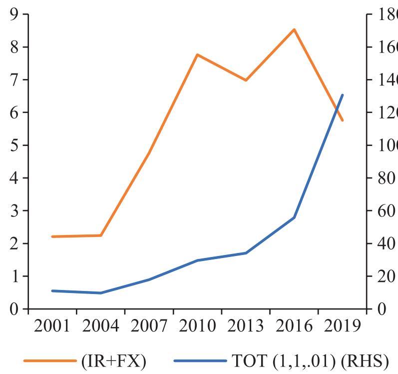
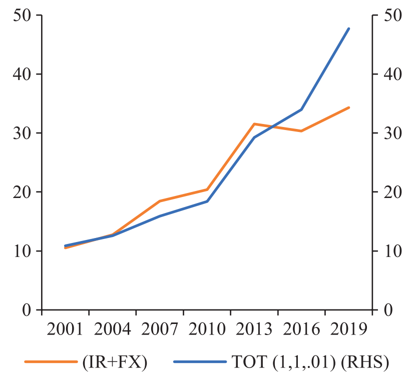


Chart 11: Turkey



Source: BIS.

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The Deficit Myth: Modern Monetary Theory and How to Build a Better Economy by Stephanie Kelton, 325 pp., John Murray (2020), ₹799

There are quite a few thought provoking books in economics which have been revolutionary in proposing new concepts with powerful messages; the book, Deficit Myth: Modern Monetary Theory and How to Build a Better Economy, is one of them of our times. The book raises some of the most fundamental questions and contemporary issues in public finance and monetary economics and tries to examine them using research findings and cogent arguments. Though the topics discussed are debatable and contentious, the narrative of the book is lucid, comprehensible and rich with illustrations from real life examples. Stephanie Kelton, its author, is a professor of economics and public policy in Stony Brook University and has been named as one of the most creative people in business by Fast Company, an American monthly business magazine.

The uniqueness of the book is that it has mass appeal and caught the imagination of readers world-wide across diverse fields. The author has tried to bust six myths that are deeply rooted under the shelter of conventional economic theories. By using the framework of modern monetary theory (MMT) she has challenged the new consensus macroeconomics head-on and repudiated many common economic beliefs by providing diametrically opposite perspectives.

The first popular myth is that federal governments should live within the means like a household. According to the author, central governments, however, should not constrain their spending like households as they are the creator of money. While households are users of money that they receive as payments for work, in exchange of goods and services or as transfers, central governments through their respective central banks can print legal tenders as they only have the exclusive authority to do so. The author nevertheless cautions that this principle should be applied with utmost care. Countries that lack control over issuance of their domestic currencies in normal times, borrow in foreign currencies and have fixed exchange rate regimes, adoption of this principle may prove fatal for them.

The second myth is that fiscal deficit implies over spending. According to the author, real overspending however, occurs, only when inflation rises after an economy attains full level of employment. She further explains that, one would have worried about deficit spending if a country was still under the Bretton Woods System. The system requires issue of currencies backed by gold in contrast to the system of fiat currencies without the backing of gold reserves after the collapse of bretton wood system. The author postulates that higher inflation could be a sign of overspending and not deficit budget. The author advocates that government budget deficit is not a cause of concern, as long as resources remain unemployed or underemployed. Once the economy reaches its full employment level, however, deficit spending can lead to a rise in demand, which in turn may lead to a situation of scarcity of resources, resulting in a rise in prices. She questions the mainstream economics that propagates that there exists a tradeoff between inflation and unemployment, *i.e.*, to reduce inflation the economy has to live with certain amount of involuntary unemployment. Through the lens of MMT, she recommends federal job guarantee schemes as a solution which could help to keep in check both unemployment and inflationary pressures.

According to the book, the third myth is that public debt is a burden. The author views public debt of the US economy from a different perspective, viewing them as mere adjustment in holding of assets and liabilities instead of borrowing. In her illustrations, China holding large US Treasury securities does not pose a threat to the US economy as these are not borrowings by the US, rather these are China's investment arising as a result of its huge trade surpluses. Even when China sells off the assets held in the form of US Treasury securities, it may not influence bond yields since the US has command over management of both short-term and long-term interest rates. Countries like Greece, Italy and Spain *etc.*, who have abandoned their local currencies and adopted the Euro faced the sovereign debt crisis because they had borrowed from markets at market interest rates and they had no control over these interest rates. So, borrowing in domestic currency is not a burden.

Public borrowing crowds out private investment is the fourth myth. Conventional economic theories state that higher budget deficit leads to higher public borrowing, leading to competition for funds between government and the private sector. As savings are limited, the rate of interest rises, private investment gets discouraged and production activities get hampered leading to a reduction in wealth of the society. According to the author, however, it is the government budget surplus that is detrimental to a society. MMT rejects the loanable funds theory which emphasises that borrowing is limited by access to limited financial resources. Any borrowing supplies equal amount of bonds, leaving total saving in the economy unaltered. When government spends more than taxes, it leaves the banking system with larger cash reserves. Moreover, interest rate on government bonds is a matter of policy choice. The Fed has the ability to retain rates lower even if deficits soar. The crowding-out theory, hence, may not work in countries like the US, UK and Japan that borrow in their own sovereign currencies. In fact, well targeted public spending can crowd-in private investment and improve disposable income.

Trade deficit as a bane rather than trade surplus is the fifth myth. She argues that countries need not worry about trade deficit as long as fiscal policy ensures full employment at home. Further, since the USA is the sole issuer of dollar, the principal reserve currency of the world, it may not face great difficulty in financing imports; the same, however, may not hold for developing nations. If developing nations run huge trade deficits, they have to make payments in dollar, which could undermine their monetary sovereignty. Further, they do not have deep capital markets and can experience sharp swings in exchange rate.

The sixth myth is that government funded entitlement programmes are financially unsustainable. The power of funding social security schemes comes from the exclusive right of the government to issue currency. Instead of fiscal deficit, therefore, greater attention should be given to the other deficits of real concern, *i.e.,* deficit in jobs, health infrastructure, education facilities, clean climate, *etc.*

Post-COVID-19 ultra-accommodative monetary policy and expansionary fiscal policy provide the relevant context to examine the utility as well as futility of MMT as a guide to conduct macro-economic policies for the future. The Deficit Myth, though persuasive, can be misleading for emerging market economies (EMEs). Fiscal deficit can cure economic malaise if utilised judiciously. As the entire world is reeling under the impact of COVID-19, governments are facing the dual challenge of falling revenues due to subdued economic activities and rising expenditure to mitigate the impact of the pandemic. Application of MMT can provide breathing space to nations, which may be difficult to justify under conventional economic theories. It is important to recognise, however, that, this book is written keeping the US economy in mind; the analysis and examples that relate to the US economy may not be suitable for EMEs, in particular high fiscal deficit and debt, and unrestricted expansion in money supply which have been the well-established sources of macro-economic instability in these countries. The book nevertheless provides an intellectual challenge to the established norms guiding the conduct of macro policies and may necessitate a revisit of policy frameworks to prioritise real economy issues while safeguarding sustainability.

Madhuchhanda Sahoo*

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* Madhuchhanda Sahoo is a Manager in Department of Economic and Policy Research, Regional Office, Reserve Bank of India, Bengaluru.

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Quantitative Social Sciences: An Introduction by Kosuke Imai, 432 pp., Princeton University Press, USA (2018), US$95.00

Over the last few decades, quantitative social sciences have flourished in various areas at an exponential rate. Quantitative social sciences are an interdisciplinary field encompassing subjects such as economics, education, public policy, political science, psychology, and sociology. Data and computational revolution have contributed to the rapid growth in quantitative social sciences. Due to these technological changes, the sheer volume of data available to quantitative social scientists has increased drastically. With a wide variety of data availability, the boundaries of quantitative social sciences research have expanded. The book *Quantitative Social Sciences: An Introduction* written by Kosuke Imai, an eminent Professor in the Department of Government and the Department of Statistics at Harvard University, follows this modern trend. The author raises the concern that the traditional statistical approaches cannot meet the current demands of a society. The author believes that one can contribute to the society through data-driven discoveries requiring greater emphasis on learning to analyze data, interpret the results and communicate the findings. This book introduces three elements of data analysis for social science research: research context, programing techniques, and statistical methods. The book extensively uses R, which is a powerful programing language for data analysis. As an open-source statistical programing language it is available for free download and runs on any Macintosh, Windows, and Linux computer.

The book consists of eight chapters. Chapter 1 explains how vital quantitative social science research is to a modern society. This chapter also provides a brief introduction to R. Chapter 2 introduces causality, which plays an essential role in quantitative social science research. It helps us to understand whether a particular policy or program (intervention) changes the outcome of interest. In this chapter, the author discusses the fundamental issue of causal inferences. An estimation of causal effect involves a comparison between factual and counterfactual outcomes. The chapter begins with the study of racial discrimination in the labor market, trying to understand whether a black American candidate who did not receive a job offer would have otherwise received it if the candidate was white. In this study, researchers sent fictitious job applicants' resumes to potential employers after randomly choosing the applicant's name as either black American or Caucasian. This kind of study is known as experimental. From this study, one could understand how randomization of treatment assignment (intervention) enables researchers to identify the average causal effect of treatment. The author also discusses causal inference in observational studies where researchers do not control the treatment assignment (no intervention). It is demonstrated by understanding the impact of increasing the minimum wage on employment. Many economists argue that an increase in minimum wage can reduce work because employers must pay higher wages to their workers, and as a result, employers hire a few workers. But the decision to increase the minimum wage is not random, and may depend on many factors, which could influence how firms find themselves in the treatment group—A simple comparison between those who received treatment and those who did not may lead to biased inferences. The author introduces various research design strategies to reduce bias, such as cross-sectional (comparing treatment units with control units after a treatment), before-and-after (comparing the same unit before and after a treatment), and difference-in-difference (evaluating pre-treatment and post treatment measurements obtained for both treatment and control groups). The results reported in the book suggest that an increase in minimum wage had no negative impact on employment.

Chapter 3 investigates measurements. Accurate measurement is essential for any data-driven discovery because the bias in measurement can lead to incorrect conclusions and faulty managerial decisions. The author explains how to measure public opinion through sample surveys and illustrates this by showing how researchers attempted to measure the degree of support among Afghan citizens for international forces and the Taliban during the Afghanistan War. The results show that civilian attitudes are asymmetric. The harm inflicted by international forces is met with reduced support for international forces and increased support for the Taliban. But Taliban inflicted harm does not translate into greater support for international forces. This chapter shows the ability of randomization in survey sampling. Here the author discusses potential biases in survey sampling and how nonresponses can undermine the representativeness of a sample. Also, in survey sampling, misreporting poses a severe threat to statistical inferences. Further, the author discusses the measurement of latent or unobserved concepts essential for social science research. In order to explain this notion, the author discusses political ideology. The author demonstrates by showing how overall ideological orientation in the US Congress has changed over time by using the voting records of each member of congress. The result shows that political polarization has increased in recent years among major political parties. For data analysis, the author introduces a basic clustering algorithm called K means algorithm, an unsupervised learning technique. (In unsupervised learning, there is no outcome variable. Instead, the goal is to discover hidden structures in data).

Chapter 4 dwells on prediction. Prediction is the first step towards understanding the complex causal relationships that underlie human behavior. Prediction is an essential component of the policy and decision-making processes. The author illustrates this by predicting the US presidential election results through prelection polls. The exercise makes an accurate prediction by combining multiple polls. The author also analyses data from a psychological experiment in which subjects are shown the facial pictures of unknown political candidates and asked to rate their competence. The analysis indicates that quick facial impressions can predict election outcomes. The author uses the regression technique to forecast the values. The chapter also introduces regression discontinuity design for making causal inferences. It is demonstrated by investigating how British politicians accumulated wealth when they were holding political office.

Chapter 5 is about the discovery of patterns from various types of data. This chapter analyses textual data to discover topics and predict the authorship of documents based on the frequency of words used. The application illustrated here is the authorship prediction of The Federalist Papers, which forms the basis of the US constitution. Some of the papers have known authors, while others do not. By analysing the frequency of certain words in papers with known authorship, the author can predict the unknown authorship of papers. Further, the author uses network data to record the relationship among various entities. It is illustrated by exploring the marriage network in Renaissance Florence and a modern example of the twitter-following network among politicians. Here, the author discusses various measures of centrality (this is done to identify influential entities in a given network). Finally, the author discusses spatial and spatial-temporal data. The author shows how maps can visualize spatial patterns effectively using John Snow's famous study of the Cholera outbreak in London during the 19th century. John Snow utilized a natural experiment to uncover the primary cause of the outbreak in London. John Snow showed that sewage-contaminated water caused the outbreak. Finally, the author illustrates using maps the expansion of Walmart stores in the US over the last several decades. To understand how the spatial pattern changes over time, the author uses animation that sequentially displays a series of maps.

Chapter 6 shifts the focus from data analysis to probability. It discusses the two dominant perspectives on probability: Frequentist and Bayesians. Further, it discusses Baye's rule and uses it in predicting individual ethnicity using surnames and resident location when no survey data is available. Further, it discusses the essential concepts of random variables and probability distribution. The author uses these concepts to quantify the sampling uncertainty regarding polling prediction of election results. This chapter explains two fundamental theorems in probability: the law of large numbers and the central limit theorem. Chapter 7 introduces a framework for methods of statistical inference. It enables quantifying the degree of uncertainty regarding the estimates. This chapter shows us how to distinguish signals from noise through the computation of standard errors and confidence intervals, and hypothesis testing. This chapter also discusses the pitfalls of multiple testing and publication bias. It concludes by describing ways to make inferences from linear regression models with measures of uncertainty. The last chapter offers a brief discussion of what readers may need to pursue after finishing this book. To become a practicing methodologist, the authors convey the importance of a solid foundation in multivariable calculus, linear algebra and probability theory, after which, individuals need to learn about statistical theories and various modeling strategies in a rigorous fashion.

I wholeheartedly recommend this book to beginners of social science research and those having interest in designing and implementing quantitative research techniques. All data sets used in this book are available online. An added advantage is the online review questions, enabling one to learn the basics first before attempting the exercises. While the datasets and most of the examples in the book relate to the USA, that should not work as a constraint to effective learning. Importantly, the book requires no prior programming experience and exposure to only elementary algebra. Through this book, the researchers can discover the true power of data analysis.

Mayank Gupta*

* Mayank Gupta is Consultant (Applied Econometrics) in Department of Economic and Policy Research at the Reserve Bank of India, Mumbai.

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