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Night-time Luminosity: Does it Brighten Understanding of Economic Activity in India?

Anupam Prakash, Avdhesh Kumar Shukla, Chaitali Bhowmick and Robert Carl Michael Beyer*

In view of the growing popularity of night-time luminosity as a measure of economic activity, this study explores the scope for using such data as a supplement for gross domestic product (GDP) in the Indian context. We found that night-light data exhibit reasonably robust correlataion with GDP and other important macroeconomic indicators like industrial production and credit growth at the national level. Quarter-on-quarter growth of night lights tracks growth of GDP reasonably well. Even after controlling for seasonal factors, the relationship of night lights with value-added in agriculture and private consumption expenditure turns out to be statistically significant. In addition, night lights are strongly correlated with gross state domestic product (GSDP). The elasticity of night lights with respect to GSDP (*i.e.,* the so-called inverse Henderson elasticity) is found to be statistically significant, though relatively smaller in magnitude than similar estimates available at the global level.

JEL Classification : E58, O33, O47, R11

Keywords : Night lights, luminosity, satellites, economic growth, Henderson elasticity, GDP

Introduction

Night-light data, which provide a numerical measure of brightness of the earth during the night, is a direct result of human activities and hold enormous potential in economic analysis (Basihos, 2016; Doll *et al*., 2006;

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Donaldson and Storeygard, 2016; Forbes, 2013; Henderson *et al*., 2012). Night-light data are found to be particularly useful in countries where the quality of official statistics on gross domestic product (GDP) are released with some time-lag, which also get revised several times subsequently. As is the practice in most other countries, initial releases or advance estimates of GDP in India are often revised, and the estimates are improved gradually through successive revisions with the progressive increase in data coverage. The average absolute revisions in India's GDP growth numbers since the financial year (FY) 2004-05 has been around 0.7 percentage points (Prakash *et al*., 2018; World Bank, 2017). The state level data on gross state domestic product (GSDP) are often published with a substantial lag. Further, district-level GDP data are not compiled for all the districts, and even if they are compiled, it is not done on a regular basis. This has encouraged analysts and policymakers to supplement the National Accounts Statistics (NAS) with new and innovative data sources including the use of big data to produce better estimates. In recent years, economists are increasingly turning to data from satellite images as a supplementary measure of economic activity that could help assess the state of the economy before revised estimates of GDP become available (Chakravarty and Dehejia, 2017; World Bank, 2017; Henderson *et al*., 2012).

From a policymaking perspective, night-light data can be useful in several ways. First, policies regarding the allocation of resources through various schemes require detailed information at a disaggregated level, which in most cases may not be available in the form of hard data. In India, for example, the Reserve Bank of India (RBI) performs several developmental roles *viz.,* promoting banking habits through financial outreach programmes, encouraging small savings, or making provision of credit facilities to agriculture, industry and other priority sectors, besides its principal function as a central bank (Subbarao, 2013). A proper assessment of the impact of such initiatives is often hindered due to lack of adequate information at disaggregated level. Given the high degree of spatial granularity, night lights could serve as a useful proxy indicator for measuring economic activity across regions in India. Second, with the availability of high frequency night-light data since April 2012, it could be used as an additional lead indicator to improve short-term projections of economic activity.

In a large and geographically diverse country like India, a careful exercise is also required to understand the relationship between night lights and other economic variables. This study primarily complements findings of previous studies by Beyer *et al*. (2018), Bundervoet *et al.* (2015) and Henderson *et al*. (2012) in investigating the relationship between night lights and economic activity in the case of India. In addition to an analysis based on annual data, we analyse quarterly night-light data and their relationship with GDP and other crucial macroeconomic variables, such as industrial production and credit growth. Furthermore, we apply, for the first time, the methodology developed by Henderson *et al*. (2012) at the subnational level in India to study the long-run relationship between night lights and state-level economic activity for the period from 1992 to 2017. The paper is structured as follows. Section II presents a brief review of the relevant literature. Section III provides a description of the night-light data. Section IV examines the salient features of the night-light data in the Indian context and its behaviour *vis-à-vis* GDP and other macro-economic variables. Econometric analysis using state-level data is presented in section V. Section VI concludes the paper.

Section II

A Brief Survey of Related Literature

The application of satellite data in understanding issues of social sciences traces back at least to the early 2000s, and therefore is not of a recent origin. One can document numerous studies using such data on topics as diverse as population dynamics, urbanisation, use of natural resources, regional disparities, poverty, inequality, distribution of wealth, relationship between wealth and health indicators, pollution research, and so on (Asher *et al.*, 2017; Economic Survey, Government of India, 2016-17; Donaldson and Storeygard, 2016; Hodler *et al.*, 2014). Night-light data have also been used to examine the impact of various events, for example, major natural catastrophes, policy actions or outbursts of conflict (Beyer *et al.*, 2018; Chodorow-Reich *et al.*, 2018; Bundervoet *et al.*, 2015). In this section, we present a brief survey of the literature which links luminosity with economic output and growth, particularly in the Indian case.

Night lights and Economic Growth

In a seminal paper, Henderson *et al.* (2012) use night lights as a tool to augment the GDP series of 188 countries, and motivate research employing night-light data in the field of economics. The elasticity of night lights with respect to GDP, popularly known as the Henderson elasticity, is estimated empirically in a panel regression framework with GDP as a dependent variable and night lights as an explanatory variable along with other relevant variables. The coefficient of night lights is the inverse of Henderson elasticity and it is statistically significant. Henderson *et al.,* (2012) also show how the spatial granularity of the night-light data can provide new insights. For example they find that growth in coastal areas of sub-Saharan Africa was against expectation and lower than growth in hinterland.

Luminosity as a proxy of output has also been used to compare the quality of statistical data across countries, both at the country level and at the '1° latitude × 1° longitude grid-cell level' for the period from 1992 to 2008 (Chen and Nordhaus, 2011). Luminosity adds little value for countries with high-quality statistical systems, but is useful in countries with low statistical capacity. Another study comes to a similar conclusion and argues that the measurement of GDP per capita in middle- and low-income countries is less precise and, therefore, night lights can play an important role in improving GDP aggregates of these economies (Hu and Yao, 2018). Interestingly, in the case of China, night lights adjusted GDP growth was found to be lower than the official estimates (Zhou and Zeng, 2018). Similarly, night-light data have been used to compare the accuracy of GDP per capita reported in national accounts *vis-à-vis* income measures based on surveys in India and Angola, where national accounts data were found to be superior compared with income estimates derived from household surveys (Pinkovskiy and Sala-i-Martin, 2015).

The spatial granularity of night-light data is found to be very useful for regional studies. For example, night lights have been used to map regional economic activity in 11 European Union (EU) countries and the United States (US), for which a strong positive relationship has been found between night lights and GDP across a range of spatial scales (Doll *et al.*, 2006). For Turkey, night lights were used to estimate the gross provincial product (GPP) from 2001 onwards, a period for which no official estimates are available (Basihos, 2016). Similarly, the subnational GDP of Kenya and Rwanda were estimated using night-light data (Bundervoet *et al.,* 2015). The correlation between GDP and night lights has also been examined for the Metropolitan Statistical Areas (MSA) of Florida (Forbes, 2013). For these areas, strong correlations with different measures of economic activity within each MSA allow to detect even specific industries contributing most to the variance of night lights.

However, a few studies indicate that night lights may not be a good proxy for sub-regional GDP. Bickenbach *et al.* (2016), for example, tested a hypothesis like the one in Henderson *et al*. (2012) for long-term growth rates of GDP at the subnational level for Brazil, India, Europe and the US. They conclude that growth elasticities are not stable across the geographies of each country or region. Addison and Stewart (2015) also argue that growth elasticities of night lights with respect to economic activity are too small and unstable over time limiting their utility for any practical use.

With the night-light data becoming available at a monthly frequency, some new applications focusing on short-term growth became possible. Bhadury *et al*. (2018) use night-light data and other high frequency information in a nowcasting model and illustrate that the inclusion of night lights reduces the early nowcast errors in the 'trade, hotels, transport, communication and services related to broadcasting' sub-sector of India's gross value added (GVA) estimates.

Literature Related to India

In India, the relationship between night lights and GDP has been explored at the district level, for which reliable estimates of economic activity are not available. Bhandari and Roychowdhury (2011) use a multinomial regression technique to establish that differences in GDP at the district level are largely captured by night lights. In their case, non-linear models provide better results than linear models, which tend to underestimate GDP in the urban areas and overestimate GDP in areas dominated by agriculture and forestry activities.

Another interesting application of night-light data in India is to test for inter and intra-regional convergence/divergence. Chakravarty and Dehejia

(2017) show that intra-state divergence across districts is as significant as inter-state divergence. Their analysis reveals that ten out of the twelve largest states exhibit divergence at district-level within the states. Chanda and Kabiraj (2018) employ night-light data to study the divergence of Indian districts both at the aggregate district level as well as along the rural and urban dimension for the period from 2000 to 2010. Contrary to the results reported by other studies such as Chakravarty and Dehejia (2017), Kalra and Sodsriwiboon (2010) and Bandyopadhyay (2012), Chanda and Kabiraj (2016) find evidence of both absolute and conditional convergence in rural areas, but not in the urban areas.

In most of the studies related to India, night lights have been used as a proxy for economic activity at the state level or district level. However, to the best of our knowledge, there are hardly any studies which examine the relationship for a longer time horizon after controlling for various state-specific and time-varying effects. Secondly, given the range of economic, social and cultural diversity among Indian states, this study is also a first attempt to understand whether state-specific factors such as sectoral composition, population and income levels have any significant impact on the relationship between night lights and GDP. The objective is to develop a coherent understanding of the nature of the relationship between night lights and GSDP in the Indian context which might provide further direction for future studies in this area in terms of choice of variables and model specification.

Section III
A Brief Description of the Data

Night-light Data

Night-light data are basically the visible lights emanating from the earth captured by satellites from outer space. For the period 1992 to 2013, night-light data are publicly available on an annual basis as a by-product of the Defence Meteorological Satellite Program (DMSP) of the United States Department of Defense, which includes a main weather sensor Operational Line Scan System (OLS). It captures night lights daily between 8.30 p.m. to 9.30 p.m. In addition to lights emanating from economic activity, it may also detect lights originating from gas flaring, shipping fleets, auroral activity, forest fires, *etc*. Therefore, the National Oceanic and Atmospheric Administration (NOAA) has developed an algorithm which allows it to identify stable lights by removing sunlit, glare, and moonlit (Addison and Stewart, 2015). Luminosity is measured by a digital number on a linear scale between 0 and 63. The numbers are then aggregated to arrive at the sum of lights for a geographical location. Night-light intensity for an area is then obtained by dividing the sum of light by total size of the area. One limitation of this data is that there is an upper limit of 63, which implies that in case a number 63 gets assigned, any further growth in the light would not be captured. For South Asia, however, this is not a problem as only very few metropolitan areas are that bright.

From April 2012 onwards, a new data product became available at monthly frequency from a different satellite programme called the Suomi National Polar Partnership Satellite with a Visible Infrared Imaging Radiometer Suit (SNPP-VIIRS). Apart from being available at a higher frequency, this data-set has some improved features compared to the DMSP-OLS data. For example, as the unit of measurement is nanowatt, there is no upper limit in the case of DMSP-OLS data. The data available in the public domain still include some temporary lights and background noise. Hence, we use cleaned VIIRS night-light data based on Beyer *et al*. (2018) in this study.

Advantages and Limitations of the Night-light Data

There are some major advantages of night-light data as a measure of economic activity. First, as the data are available at monthly frequency, it provides a useful alternative for data that come with a lag. Second, it gives more freedom to researchers due to their availability beyond state borders. Third, it is available at a more granular level. Besides, one major advantage of night-light data is that one can altogether escape the difficulty of measuring informal activities as it captures economic activities regardless of whether it is formal or informal. Moreover, there is no scope for subjective interference and the cost of acquisition is also less. Finally, measurement errors of official GDP estimates are uncorrelated with the errors resulting from physical conditions affecting luminosity record quality.

Despite several advantages, night-light data are, however, no silver bullet for solving all issues related to the measurement of economic activity. The data are noisy and the relationship between night lights and economic activity is also not homogenous. Night-light intensity depends on various exogenous and endogenous factors such as the level of electricity generation, the sectoral composition of output, and the existing level of development. All these factors tend to vary across time and space. For example, at the global level, the responsiveness of night lights intensity to changes in the manufacturing sector are found to be larger than that of changes in the services sector. For South Asian countries, however, the opposite result is observed (World Bank, 2017). In addition, for South Asian countries, night lights seem to be a poor indicator of activity of the agricultural sector, as agricultural activities mostly take place during the day and hence may emit less light. Therefore, one may expect that night lights may not be a good indicator of economic activity in rural areas with higher share of agricultural output. Moreover, electricity generation capacity emerges as a major determinant of night-light intensity of any region. At early stages of development, when power sector infrastructure develops at a fast pace, night lights growth tend to be high. In more developed regions, where power infrastructure is already in place, the rate of growth of night lights may be lower. In view of the above considerations, one needs to carefully assess various other time-specific and region-specific factors.

Other Data used in the Study

Along with night-light data, official statistics such as real GDP, real GSDP, sectoral GVA, and the Index of Industrial Production (IIP) published by the National Statistical Office (NSO), as well as real money and credit data published by the RBI are used in our study. For the panel regression analysis, we use real net state domestic product (NSDP) at factor cost up to 2010-11 and real net state value added (NSVA) at basic prices from 2011-12 onwards, as historical time series data on GSDP are not available.

One caveat is that while GDP and GSDP data are available on a financial year basis (April to March), the annual night-light data prior to 2013 are available on a calendar year basis (January to December)[1]. This problem

1 The Indian financial year runs from April to March. In this study, the year containing the first nine months of the financial year is denoted as financial year. Hence, if data pertain to the period April to March 2011–12, then it is denoted as 2011.

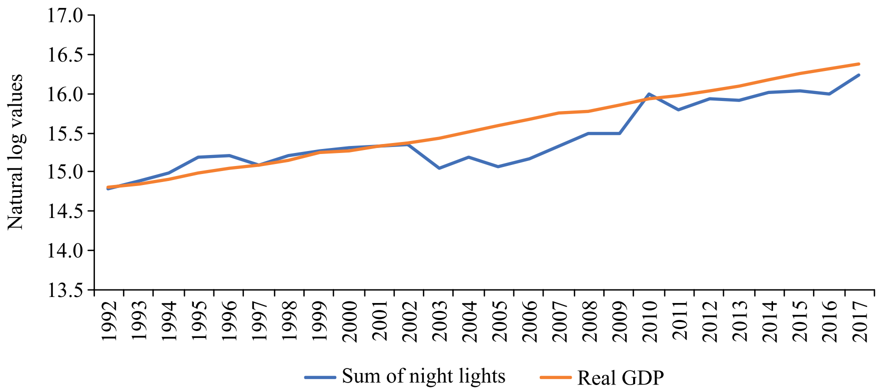
is overcome for the later years (*i.e.,* 2013 onwards), for which monthly night-light data are available.

Section IV
Night lights and GDP: An Assessment at the National Level

This study examines some basic features of night-light data and its relationship with GDP and other macroeconomic variables. We first examine a few standard time series properties of the annual night-light data for India from 1992 to 2017, followed by an examination of the quarterly data from 2012 onwards. Both the natural logarithm of GDP[2] and the sum of night lights portray a linear upward trend (Chart 1). A closer look at the growth trajectory separately for each decade of the period covered in this study suggests that the long-run average growth in real GDP and night lights moved in close proximity to each other (Table 1). For the overall period (1992 to 2017), average annual growth in GDP and night lights were 6.5 per cent and 7.1 per cent, respectively.

Quarterly figures of night lights from the first quarter of 2012 to the second quarter of 2017 have been generated from the monthly VIIRS night-light data. The quarter-on-quarter (q-o-q) movement in GDP clearly depicts a seasonal pattern with a peak in October to December quarter and

Chart 1: Movement of sum of night lights and GDP



Source: NSO, DMSP-OLS and VIIRS.

2 The back-series data at 2011-12 base for the period 2004-05 to 2011-12 released by the NSO have been used in this study. All amounts are in rupees crore (1 crore = 10 million).

Table 1: Average Annual Growth Rates in GDP and Night Lights

(in per cent)

Variable	1993–2002	2003–2012	2013–17	1992–2017
GDP	5.8	7.0	7.1	6.5
Night lights	6.1	8.5	6.6	7.1

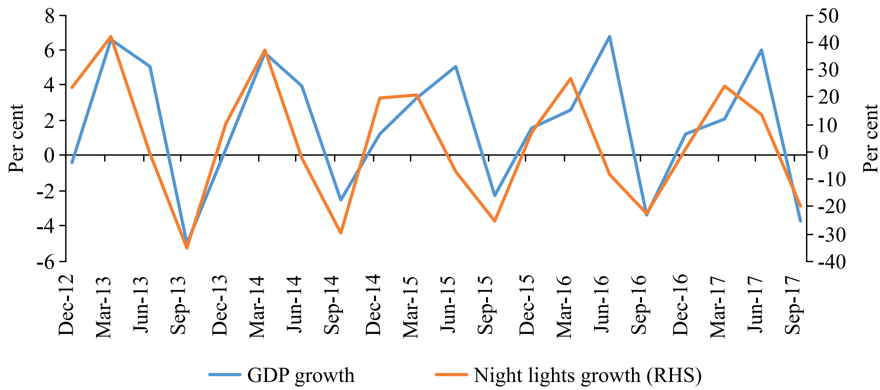
Source: NSO, DMSP-OLS and VIIRS.

a trough in April to June (Chart 2). The seasonal movement in night lights captures the seasonal variations in GDP quite closely. *Prima facie*, it turns out that night lights track both trend and seasonal variations in GDP.

Next, we examine how night lights relate to other macroeconomic variables in India. Night lights exhibit strong correlation with some other major macroeconomic variables as well. Table 2 presents the correlation coefficient matrix of night lights, GDP, non-agricultural GDP, industrial production (general, electricity, and manufacturing), money and credit growth.

The correlation coefficient between night lights and overall GDP is 0.75 and with non-agricultural GDP it is 0.55, both the coefficients being statistically significant at the 5 per cent level. Night lights also relate reasonably well to industrial production. The correlation of night lights with

Chart 2: Q-o-Q growth rate of night lights and GDP



Source: NSO, DMSP-OLS and VIIRS.

Table 2: Correlation Matrix (June 2012 – December 2017)

Variables	Night lights	GDP	Non-agri GDP	IIP-Gen	IIP-E	IIP-M	Real M4	Real credit
Night lights	1							
GDP	0.75*	1						
Non-agri GDP	0.55*	0.94*	1					
IIP-Gen	0.75*	0.99*	0.91*	1				
IIP-E	0.56*	0.89*	0.96*	0.84*	1			
IIP-M	0.72*	0.98*	0.91*	0.99*	0.84*	1		
Real M4	0.66*	0.98*	0.96*	0.95*	0.94*	0.94*	1	
Real credit	0.68*	0.98*	0.95*	0.96*	0.93*	0.95*	0.99*	1

*: Indicates statistically significant at 5 per cent level.
Note: Correlation coefficients between the variables are calculated at levels.
Source: NSO, the RBI and VIIRS.

money supply and credit flows is also strong and statistically significant. Strong and statistically significant correlation coefficient of night lights with some important macroeconomic indicators further strengthens the case for night lights to qualify as an indicator of economic activity. Though correlation between night lights and other macroeconomic variables is strong in levels, it is significantly weaker with regards to growth rates.

As established above, q-o-q growth of night lights track q-o-q growth of GDP reasonably well. However, one may suspect that night lights and GDP may both be driven by seasonality and time-trend factors. To control for seasonality, following Wooldridge (2012), we regress q-o-q GDP growth and q-o-q night-light growth on quarterly dummies, and then regress the residuals of the GDP growth regression equation on the residuals of the night-light regression equation. The coefficient of this regression equation reveals the impact of night lights on q-o-q GDP growth rate. Next, we include a time trend in the regression. We regress quarterly GDP, GVA and GVA of agriculture and allied activities, as well as private final consumption expenditure on q-o-q growth rate of night lights (Tables 3a and 3b).

Table 3a: Regression Results of Residuals of Q-o-Q GDP Growth and its Components on Residuals of Night lights after Controlling Seasonality

Variables	GDP	GVA	Agriculture and Allied Activities	PFCE
Residuals of night lights	0.088***	0.074***	0.196***	0.067*
	(0.016)	(0.014)	(0.038)	(0.035)
Constant	0.000	0.000	-0.000	0.000
	(0.206)	(0.217)	(0.458)	(0.428)
Observations	22	22	22	22
R-squared	0.463	0.358	0.464	0.103

***: p<0.01; **: p<0.05; *: p<0.1.

Note: The figures in parentheses are robust standard errors.

In all the cases, the coefficient of night lights is statistically significant with a positive sign. The results for GVA as well as agriculture and allied activities are particularly interesting as they suggest a stronger relationship with night lights. The coefficient of night lights for agriculture is positive and higher in magnitude than that of GDP. This finding is against the hypothesis that night lights may not adequately capture the changes in agricultural growth.

Table 3b: Regressions Results of Residuals of Log of GDP and its Components over Residuals of Log of Night lights after Controlling Seasonality and Time-trend

Variables	GDP	GVA	Agriculture and Allied Activities	PFCE
Residuals of night lights	0.039**	0.043**	0.152***	0.004
	(0.018)	(0.020)	(0.047)	(0.023)
Constant	0.000	-0.000	0.000	0.000
	(0.002)	(0.002)	(0.004)	(0.003)
Observations	23	23	23	23
R-squared	0.101	0.132	0.254	0.001

***: p<0.01; **: p<0.05; *: p<0.1.

Note: The figures in parentheses are robust standard errors.

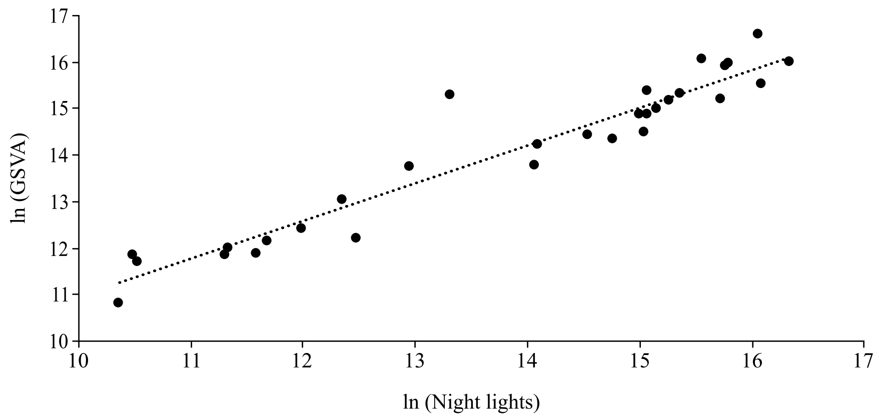
In the case of private final consumption expenditure (PFCE), we also observe a positive and statistically significant coefficient. A possible explanation of these results is that agricultural production is the major determinant of India's consumption demand. Additionally, harvesting seasons also coincide with major Indian festivals when use of night lights increases. Overall, the results show that night lights do have statistically significant predictive power for economic activity in India even after controlling for seasonal factors.

Section V
Econometric Analysis at the Level of States

In this section, we examine whether night lights provide any insights on the behavior of macroeconomic variables at the sub-national level. A scatter plot of the logarithm of gross state value added (GSVA) and the logarithm of night lights for 32 states and union territories for the financial year 2015-16 indicates a strong positive relationship between the two variables (Chart 3). These observations yield a high correlation coefficient of above 0.7 between GSVA and night lights. For other years too, we find very similar results.

The above discussions suggest that based on night-light data for a given state, one can predict GSVA for that state. The efficiency of the prediction may, however, depend on state-specific characteristics. We, therefore, examine if there exists a relationship between the prediction errors, defined as the national account estimate minus the prediction based on night lights,

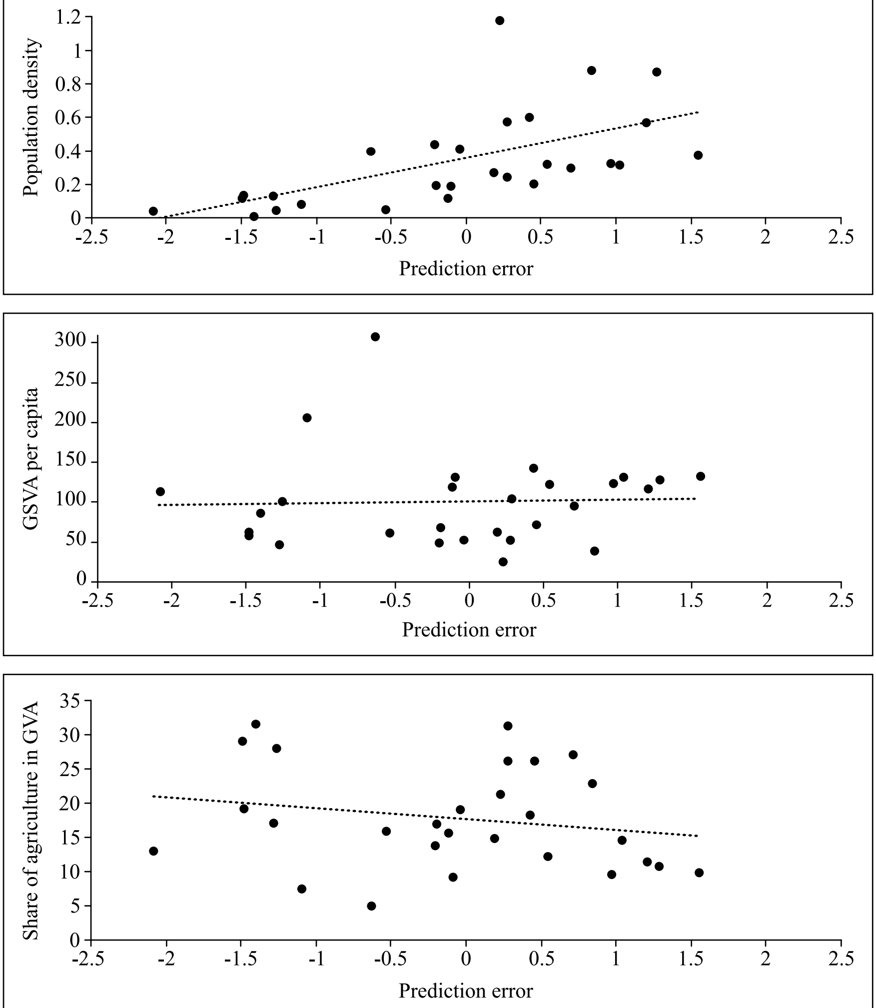
Chart 3: Relationship between GSVA and Night lights in 2015-16



and state-specific characteristics, *viz.,* the population density, the income level, and the share of agriculture in GSVA. Scatter plot of errors from the predicted GSVA and state characteristics are given in Chart 4.

Interestingly, the prediction error rises with population density which means that in more densely populated states, predictions based on night lights alone will result in an under-estimation of GSVA. With increase in population density, the amount of GSVA per unit of light increases.

Chart 4: Prediction Errors and State Characteristics



In other words, in more densely populated states, each unit of GSVA is associated with lesser night lights compared to sparsely populated states. The relationship between the prediction error and the population density is found to be significant at 1 per cent level.

Regarding the per capita income levels and shares of agriculture in GSVA, none of them systematically affects the prediction errors. The scatter plots indicate that the amount of GSVA per unit of light does not increase with income per capita and hence gives some confidence that night lights can approximate GSVA across all states in India, independent of the income level. For the share of agriculture in GVA, there is a weak relationship wherein with a higher share of agriculture, the prediction based on night lights tends to over-predict GSVA. However, this relationship is not statistically significant, which indicates that night lights are able to predict economic activity independent of the sector generating the value added. This is in line with the regression results presented in Table 3.

It reassures that the amount of night lights and economic activity at the state level are strongly correlated. However, to use night lights as a credible measure of economic activity, one needs to establish that the changes in economic activity translate into changes in night lights. The question, therefore, is whether more economic activity in a state is associated with more night lights and, if so, then how strong this relationship is. In other words, we are interested in the elasticity of night lights with respect to changes in state economic activity.

Following the methodology developed by Henderson *et al.* (2012), we estimate a panel regression for Indian states which will provide the elasticity of night lights with respect to state level economic activity. We estimate different variants of the following baseline model:

$$ln(Y_{c,t}) = a + b_c + c_t + \delta\, ln(lintensity_{c,t}) + \varepsilon_{c,t} \qquad (1)$$

where $ln(Y_{c,t})$ is the natural logarithm of economic activity of state c in year t, measured at constant prices, $ln(lintensity_{c,t})$ is the natural logarithm of light brightness per km^2, b_c represents state fixed effect, c_t represents a year fixed effect, and $\varepsilon_{c,t}$ is the random error component. The state fixed effect controls for differences among states in terms of cultural specificities, sectoral composition, *etc*. The time trend captures sensor ageing and changing technologies.[3]

We estimate the above model, first for the sub-period from 1992 to 2013 using only the clean annual data from the DMSP-OLS series. Next, we use a spliced series of night lights that extend the DMSP-OLS series with VIIRS data following Beyer *et al.* (2018). This allows us to estimate the model for the full sample period from 1992 to 2017.

The results are presented in Table 4. The first variant of the model, given in Column 1, does not include a time trend. Since both series have increasing trends (as described above), the coefficient is very high. In the second variant of the model given in Column 2, we include a time trend, which makes this regression identical to the one specified above and the one estimated for the world by Henderson *et al.* (2012). The coefficient of night lights is 0.15 and it is statistically significant at the 10 per cent level. The magnitude of the coefficient is only half of what Henderson *et al.* (2012) find for the world and the one that Beyer *et al.* (2018) find for South Asia. Next, we include the squared night lights as a variable to account for the possibility of a non-linear relationship. While the squared term itself is not statistically significant, it strengthens the significance of the linear coefficient of night lights to the 5 per cent level. Even though we do not find a significant relationship between the income level and the errors from predicting NSDP based on night lights, the elasticity may still depend on the income level. Indeed, it has been argued that the elasticity increases with higher income levels, at least for low and medium income regions (World Bank, 2017). To account for this possibility, we next include an interaction term of night lights and per capita NSDP. Results, reported in Column 4, are found to be in line with the hypothesis that the relationship strengthens with higher income per capita.

The model is estimated for the full sample period (1992-2017) and the results are reported in Columns 5 to 8 in Table 4. They suggest that the relationship between economic activity and night lights measured by DMSP-

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3 For more explanations regarding the usefulness of this regression specification, please refer to Henderson *et al.* (2012).

Table 4. Henderson Elasticity for Indian States

Item	**1992–2013 DMSP-OLS**				**1992–2017 DMSP-OLS & VIIRS**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Night lights	0.835***	0.149*	0.180**	0.175**	0.874***	0.108	0.120	0.154*
	(0.0369)	(0.0831)	(0.0826)	(0.0724)	(0.0421)	(0.0900)	(0.0825)	(0.0788)
Night lights squared			0.0131				0.00598	
			(0.0117)				(0.0133)	
Night lights #NSDP per capita				0.870***				0.656***
				(0.220)				(0.192)
Constant	5.971***	5.583***	5.552***	5.587***	5.999***	5.582***	5.567***	5.602***
	(0.00772)	(0.0418)	(0.0558)	(0.0404)	(0.0136)	(0.0432)	(0.0623)	(0.0431)
Time trend	NO	YES	YES	YES	NO	YES	YES	YES
State fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	673	673	673	670	785	785	785	782
R-squared	0.649	0.945	0.946	0.954	0.713	0.950	0.951	0.957
Number of states	32	32	32	32	32	32	32	32

***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Note: The figures in parentheses are robust standard errors.

OLS and night lights measured by VIIRS may be different. The coefficient for night lights in Columns (6) and (7) are not statistically significant even at the 10 per cent level. This may very well be due to a change in the relationship caused by the switch from DMSP-OLS to VIIRS. However, when the interaction term between lights and income per capita is included in the model, the coefficient turns out to be statistically significant again. So far, VIIRS data exists only for five years and hence no separate relationship can be estimated using just VIIRS data. In the future, as more data from VIIRS become available, it will be interesting to test for a structural break in this relationship.

Furthermore, the long-run relationship between NSDP and night lights are analysed using panel cointegration tests to check robustness of earlier results. The Im-Pesaran-Shin unit root test for both NSVA and night lights confirms the presence of unit roots and thereby non-stationarity in both the series (Table 5). We, therefore, perform panel cointegration test covering data for 28 states[4] and union territories for the period 1992-93 to 2016-17 in order to examine whether the covariance between NSVA and night lights remained constant over time. Both the Kao test and the Pedroni test (which are based on the Engle-Granger two-step cointegration test) for cointegration reject the null hypothesis of no cointegration and therefore confirm existence of a long-run relationship between NSVA and night lights (Table 6).

After finding a long-run relationship (at levels) between state economic activity and the sum of night lights, we briefly analyse the

Table 5: Panel Unit Root Test Results

Method: Im-Pesaran-Shin unit-root test - Number of periods: 25		
H0: All panels contain unit root Ha: Some panels are stationary		
Variable	t-statistic*	p-value
Night lights	-0.7482	1.0000
NSVA	3.8574	1.0000

*Critical values at 1 per cent, 5 per cent and 10 per cent are -1.820, -1.73 and -1.690, respectively.

4 States and union territories for which data are not available for the entire period are excluded from the analysis.

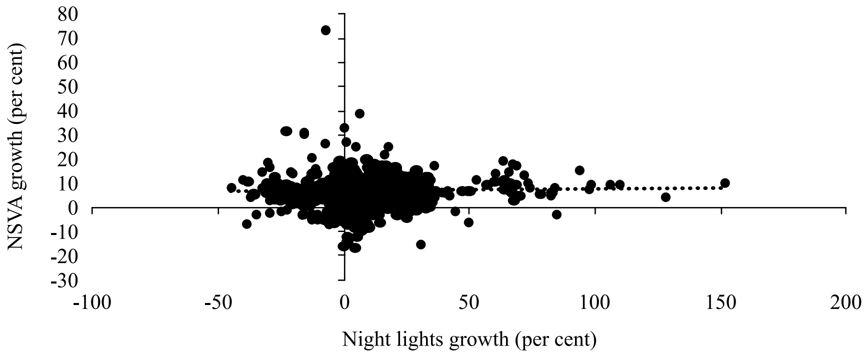
Table 6: Panel Cointegration Test Results

Kao's Residual Cointegration Test results		
Statistic	**Value**	**p-value**
Modified Dickey–Fuller t	-1.3592	0.0870
Dickey–Fuller t	0.0683	0.4728
Augmented Dickey–Fuller t	3.6279***	0.0001
Unadjusted modified Dickey–Fuller t	-1.5553*	0.0599
Unadjusted Dickey–Fuller t	-0.0507	0.4798
Pedroni's Residual Cointegration Test results		
Modified Phillips–Perron t	-3.2064***	0.0007
Phillips–Perron t	-3.9759***	0.0000
Augmented Dickey–Fuller t	-4.4904***	0.0000
Westerlund Cointegration Test Results		
Variance ratio	-0.7924	0.2141

***: p<0.01; **: p<0.05; *: p<0.1.

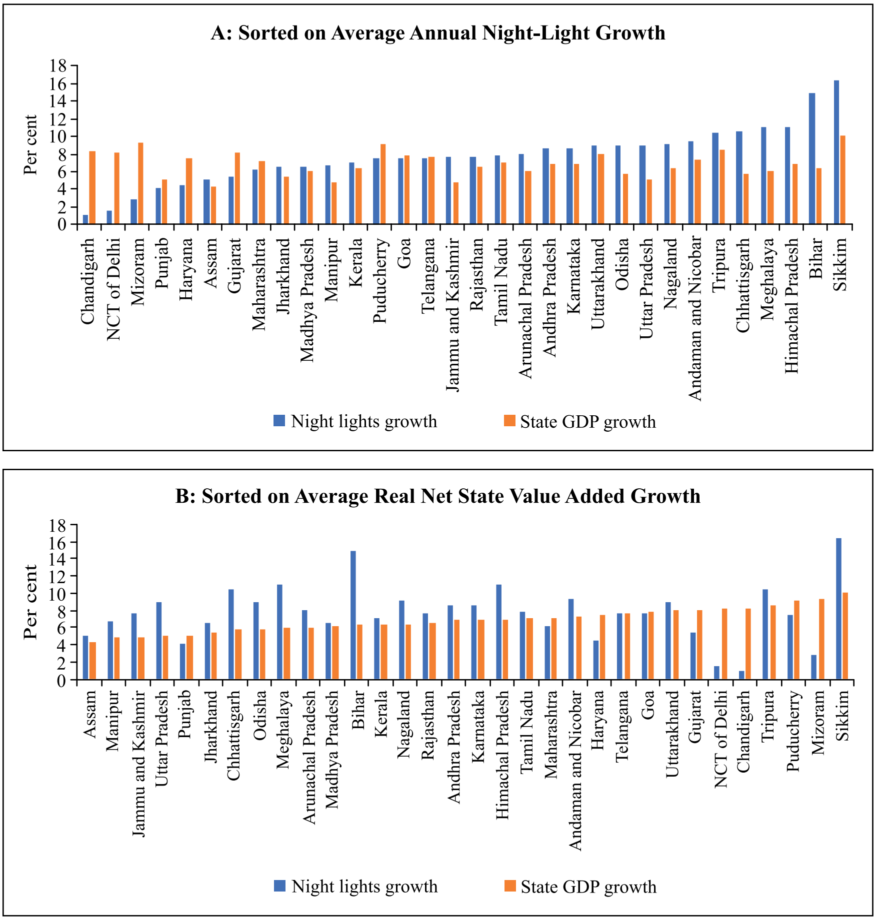
relationship between annual GSDP growth and night-light growth. Scatter plot of annual growth rates of the sum of night lights and of state GDP depicts that correlation is close to zero and statistically not significant (Chart 5).

Chart 5: Scatter Plot of Annual Growth Rates of Sum of Night Lights and Net State Value Added (1993-2017)



Source: NSO, DMSP-OLS and VIIRS.

Chart 6: State-wise Average Annual Night lights and Real Net State Value Added Growth (1993–2016)



Source: NSO, DMSP-OLS and VIIRS.

We further plot the average annual growth rates of the sum of night lights and NSVA (Chart 6). Among major states, night lights grew the most during this period in Bihar, Chhattisgarh, Uttar Pradesh and Odisha. However, economic activity in these states grew at a much slower pace. The national capital region Delhi, Gujarat and Haryana recorded the fastest GDP growth during this period, but the night lights growth in these states was found to be relatively low. The high growth in night lights observed in relatively poorer states perhaps reflects the catching up process *i.e.,* the progress being made in terms of electrification of unelectrified households.

Section VI

Conclusion

The analyses presented in this study confirm that night lights are a reasonably robust indicator of economic activity in India as it tracks both trend growth and seasonal variations in GDP reasonably well. In addition, the relationship of night lights with quarterly GDP and its components (*viz*., GVA-agriculture and allied activities and PFCE) is found to be statistically significant even after controlling for seasonality and time trend.

The state-level analysis showed the presence of a long-run cointegrating relationship between night lights and GDP. The prediction precision of state income using night lights may, however, depend on state specific characteristics. For densely populated states, the prediction of economic activity based on night lights alone tends to underpredict the level of activity. For India, we find a statistically significant inverse Henderson elasticity, the magnitude of which is about half of what Henderson estimated at the global level. However, annual growth rates of income of the states and night lights, are found to be uncorrelated.

Notwithstanding the presence of a statistically significant relationship between night lights and GDP, there are certain limitations of using night-light data for economic measurement. First, given that it is just a rough approximation of economic activity, it should be considered at best as an additional indicator and not a substitute. Second, although night lights correlate strongly with GDP, the correlation weakens substantially when growth rates are considered, which suggests that one needs to be careful while using night-light data for analysing short-term events. The existing literature finds similar result for other countries as well (World Bank, 2017). Third, night lights as a proxy for economic activity do not distinguish between value added in different sectors.

Despite its limitations, the findings of this study suggest that night-light data can be a useful source of information for valuable macroeconomic analysis and research in India, as it is in other countries.

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Spatial Inflation Dynamics in India: An Empirical Perspective

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This study provides a generalised perspective and empirical evidence for various demand, supply, policy and structural factors impinging on consumer price inflation for agricultural labourers and industrial workers across major Indian states. The empirical results show statistically significant effect of inflation persistence, per capita income growth, supply side factors, oil price, interest rate, state government expenditure and taxes, and structural factors such as power and water inputs on regional consumer price inflation. The multivariate dynamic panel data analysis and the empirical approach of the paper would facilitate further research on transmission mechanism at a disaggregated level.

JEL Classification : C31, C23, R11

Keywords : Inflation, regional economy, panel data

Introduction

Monetary policy across countries is known for its national character, as central banks enjoy the status of sole monetary authority with the policy objective defined in terms of price stability and economic growth postulated at the aggregate national level. The policy instrument *i.e.,* short-term interest rate, like the repo rate in India, also applies at the aggregate level. Fiscal policy, on the other hand, is of decentralised nature, as the instruments of government expenditure and taxes can be set differently by central, state and local governments owing to constitutional provisions (Dhal, 2010). A mute question arises here. Is there a need for research on transmission mechanism at the disaggregated regional level with regard to inflation and growth conditions? And, can monetary policy have a common stabilising

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effect on regional inflation? It is pertinent to note that after years of intense deliberations and taking sides between classical and Keynesian perspectives, economists in modern times recognise the usefulness of both fallacies; *what is true for the parts may not entirely hold for the aggregate and what is true for the aggregate may not entirely hold for the parts.* Though, there exists a large body of literature on regional inflation differential, studies in the Indian context are scarce. Thus, this paper is motivated by the need for an analysis of spatial inflation dynamics across major Indian states. We consider a generalised perspective, unlike the New Keynesian Phillips curve (inflation depends on unemployment or output gap or wage cost) and monetarist perspective (inflation is purely a monetary phenomenon), and recognise a variety of proximate factors. We use the dynamic panel data model to provide evidence on the role of some important demand, supply, structural, monetary and fiscal factors in regional inflation dynamics. Apart from the introduction, the paper is organised in four sections: review of literature, methodology and data, empirical findings and conclusion.

Section II
The Literature

Studies on regional inflation offer alternative perspectives relating to theoretical propositions, policy implications, underlying sources and empirical methodology. The literature generally owes to asymmetric effects of monetary policy (Bernanke and Gertler, 1995; Kashyap and Stein, 1995; Garrison and Kort, 1983), which emphasises the usefulness of a disaggregated monetary transmission mechanism across different sectors, industries and regions for policy analysis.

From a theoretical perspective, the literature provides contrasting viewpoints. One viewpoint is that regional inflation differential should not be a policy concern within a nation or group of nations characterised by a common monetary policy because the inflation differential might serve as an equilibrating mechanism, ensuring regional economic convergence between relatively poor and rich regions (De Grauwe, 2007). This viewpoint derives from the Balassa–Samuelson effect (Balassa, 1964; Samuelson, 1964) which states that regional inflation differentials in a monetary union can be attributed to differences in productivity growth between tradable and non-tradable sectors. Illustratively, Arnold and Kool (2003) suggested that regional inflation differentials within a monetary union have an important role to play in the natural adjustment towards a new equilibrium following asymmetric shocks. Instead of investigating the sources of regional price or inflation differences or their speed of convergence, it is important to know how regional inflation differentials are transmitted through national or regional economies and contribute to the adjustment mechanism within a monetary union.

A contrasting perspective in this context is that inflation differentials can either be benign or unkind depending upon whether such differentials arise from productivity differentials or structural rigidities (Alberola, 2000). According to Beck *et al.,* (2009), a regional inflation differential can be harmful when it manifests itself in economic distortions through nominal price rigidities or other structural inefficiencies, which in turn will have adverse implications for policy effectiveness at the aggregate level. Regions having excess aggregate demand will experience (due to capacity constraints and the price-setting power of the producers) higher inflation and *vice-versa.* Thus, non-synchronisation of regional business cycles may lead to inflation differentials (*ibid.*). In the real world, however, every nation can be characterised by diverse regions with some degree of integration but differential response to aggregate economic policy. Thus, Carlino and DeFina (1998, a and b) argue that regional inflation studies can provide a richer perspective on the sources of differential responses. Cavallo and Ribba (2014) emphasise the need for stability of regional inflation as an important condition for price stability at the aggregate level and effective functioning of a common monetary union. They argue that the regional inflation differential from the aggregate inflation should be transitory in nature so that the former can be predicted by the latter. In this context, Honohan and Lane (2003) offer two arguments: (i) the fear of sustained inflation, and (ii) a weaker adjustment mechanism in relative prices leading to boom-bust cycles for which the regional inflation differential should be studied for policy purposes.

The persistence in regional inflation and its implications for monetary policy is another aspect covered in the literature (Cecchetti *et al.,* 2002; Gali *et al.,* 2001). A central bank will be effective in achieving the inflation target when inflation is less persistent. Moreover, the sacrifice ratio (output cost) will be low with low inflation persistence (Ascari and Vaona, 2010).

In this context, some studies have focused on the welfare implications of regional inflation divergences (Andrés *et al.,* 2008; Benigno and López-Salido, 2002). Drawing from the important works of Romer and Romer (1999), Easterly and Fisher (2000) and Fielding (2004), studies on regional inflation differential and persistence emphasise the welfare implications of asymmetric monetary policy transmission in regions with relatively higher poverty levels. Thus, policy formulation which undermines regional heterogeneity in inflation can be welfare depreciating (Coleman, 2012; De Grauwe, 2000; Fielding, 2004).

From an applied perspective, the literature recognises a variety of factors or sources underlying the regional inflation dynamics (ECB, 2003, 2005). Most studies recognise inflation persistence or inertia as an integral part of regional inflation dynamics. In this context, it has been argued that empirical measures of persistence can be biased in the absence of critical regional factors. Accordingly, non-synchronous business cycles and regional supply and demand conditions as reflected in per capita income, output gap and agriculture output growth are considered for analysing the regional inflation dynamics (Angeloni and Ehrmann, 2007; Beck *et al.,* 2009; Carlino and DeFina, 1995; Cavallero, 2011; De Grauwe, 2000; Honohan and Lane, 2003; Mehrotra *et al.,* 2007; Ridhwan, 2016; Rogers, 2007). Prices are also affected by nominal variables for which interest rate, credit, monetary aggregate and financial system structure are considered as possible factors to explain inflation behaviour (Honohan and Lane, 2003; Mehrotra *et al.*, 2007; Nagayasu, 2010, 2011; Woodford and Walsh, 2005). The role of decentralised fiscal policy, through regional taxes, revenue, expenditure and budget deficits, is exemplified by Canova and Pappa (2003), Duarte and Wolman (2008), Honohan and Lane (2003) and Tirtosuharto and Adiwilaga (2013).

Structural economic characteristics of regions in terms of share of tradable goods and non-tradable goods, labour market conditions such as productivity and cost push induced wages are emphasised in studies on different countries (Andrés *et al.,* 2008; Arize *et al.,* 2005; Beck et al., 2009; Beck and Weber, 2005; Bowdler and Nunziata, 2007; Campolmi and Faia, 2006; Carlino and DeFina, 1998a, 1998b; Christopoulos and Tsionas, 2005; De Grauwe and Skudenly, 2000; Duarte and Wolman, 2008; Honohan and Lane, 2003; Jaumotte and Morsy, 2012; Mehrotra *et al.,* 2007; Nagayasu, 2010; Ridhwan, 2016; Rienzo, 2017; Rudd and Whelan, 2005; Sbordone, 2002; Willis, 2003). Furthermore, while recognising the role of asset prices and wealth channel of policy transmission mechanism, some studies have considered housing prices as a source of regional inflation differential (Arnold and Kool, 2003; Honohan and Lane, 2003; Ridhwan, 2016). Oil prices, reflecting supply shocks, are considered by Wilkinson (2011), Atems and Lam (2013), Tirtosuharto and Adiwilaga (2013) and Honohan and Lane (2003). External sector conditions reflecting changes in exchange rate are considered by Nagayasu (2010), Ridhwan (2016), Angeloni and Ehrmann (2007), Honohan and Lane (2003) and Rogers (2007).

In the Indian context, regional inflation dynamics have been examined with a focus on the cross-sectional dependence and convergence argument (Das and Bhattacharya, 2008; Kundu *et al.,* 2018; Pillai *et al.,* 2012) and the existence of the Phillips curve at the state level (Behera *et al.,* 2017). The objective of this paper is to provide a generalised perspective on regional inflation dynamics.

Section III
Methodology and Data

For the empirical methodology, we follow the studies focused on sources of regional inflation and use a dynamic panel data model (Holmes, 2002; Honohan and Lane 2003; Licheron, 2007; Rogers 2007). Since the dynamic panel data model is widely popular, we skip its technical details and confine to a synoptic presentation of non-technical aspects of the empirical strategy. The dynamic panel data (DPD) model is suitable when an economic model involves a lagged dependent variable. Illustratively, a model of inflation can involve inflation persistence, usually captured through lagged inflation as the explanatory variable. In this case, ordinary least square (OLS) estimation will produce biased and inconsistent parameter estimates. Thus, Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) suggested DPD model based on Generalized Method of Moments (GMM). They suggested one-step and two-step GMM estimation procedures for implementing DPD model. Although the two-step estimator is asymptotically more efficient than the one-step estimator and relaxes the assumption of homoscedasticity, the efficiency gains are not that important even in the case of heteroscedastic errors (Arellano and Bond, 1991; Blundell and Bond

1998; Blundell *et al.,* 2000). This result is supported by Judson and Owen (1999). Moreover, the two-step estimator imposes a downward (upward) bias in standard errors (t-statistics) due to its dependence on estimated values as it uses the estimated residuals from the one-step estimator, which may lead to unreliable asymptotic statistical inference (Bond, 2002; Bond and Windmeijer, 2005). This issue should be taken into account, especially in the case of data samples with a relatively small cross-section dimension (Arellano and Bond, 1991; Blundell and Bond, 1998).

From an empirical perspective, a dynamic panel model parameter estimates are valid when the estimated model is free from (i) residual serial autocorrelation; and (ii) model misspecification problems. The first aspect can be solved with the inclusion of additional instruments or higher lags of the dependent variables, which may further lead to an over-parameterized model. The validity of the instruments used in the moment conditions as well as the assumption of serial independence of the residuals is crucial for the consistency of the GMM estimates. Here, a practical issue is that the system GMM can generate moment conditions prolifically (Roodman, 2009). Too many instruments in the system GMM may overfit an endogenous variable even as it weakens the Hansen test for joint validity of the instruments. In order to deal with the instruments' proliferation, studies rely on alternative techniques for limiting the number of instruments such as using only certain length of lags instead of all available lags for instruments (Roodman, 2009b). We overcome this aspect by including some select period specific dummy variables to account for notable adverse economic and structural developments. Illustratively, the year 2008-09 was marked by the global financial crisis. At the same time, there was a poor monsoon in India in 2009. Again, in recent years, 2013-14 witnessed a global economic slowdown alongside domestic development such as monsoon failure, which may not be fully captured in agriculture production (since the sector growth accounts for kharif as well as rabi crops). With regard to the model specification condition, studies rely on the Sargan specification test proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). Under the null hypothesis of valid moment conditions, the Sargan test statistic is asymptotically distributed as chi-square distribution. Arellano and Bond (1991) find a tendency for the Sargan test to under-reject and over-reject the null hypothesis in the presence of heteroscedasticity in the case of the two-step estimator and one-step estimator, respectively. As an alternative, they suggested estimating the dynamic panel model using the robust estimator approach in the case of one-step estimation. Because asymptotic distribution is not known under the assumptions of robust estimator, the Sargan test is not computed. Thus, we have estimated the dynamic panel model with one-step estimation and robust standard error approach.

The data set comprises of annual indicators for major states for which CPI data are available for the period 1999-2000 to 2015-16. We experiment with two inflation indicators: CPI inflation for agricultural labourers (CPI-AL) and industrial workers (CPI-IW). These two indicators, in some ways, represent rural and urban inflation conditions. For the CPI-IW inflation, we work out the CPI-IW for various states, for which data are available for select centres, as the weighted index and then the annual variation in the combined index for each state. For the sake of consistency, we define the variables in annual growth form and ratio form as applicable. For explanatory variables, apart from inflation persistence, we consider four sets of factors comprising demand, supply, structural, and policy variables. First, the demand effect is captured through states' real per capita income growth and fiscal policy induced government expenditure growth. For government expenditure, the impact is shown alternatively through the growth of states' overall spending and social sector spending. Credit conditions are measured in terms of growth of bank credit and credit-to-deposit ratio based on credit utilisation data for the states. Generally, increases in demand variables are expected to increase the inflation. Second, among the supply side factors, we have taken growth rate of output under agriculture and allied activities. High real growth of the agriculture output is expected to induce lower inflation. On the other hand, common oil price shock measured in terms of one period lag of fuel price inflation is considered as a supply shock – higher oil price leading to increase in overall inflation. Third, structural characteristics of a region are captured through growth of utilities (electricity, gas and water supply) – crucial inputs for producing sectors including agriculture, industry and services. Also, we consider real growth of transport and communications services. Fourth, from a policy perspective, the monetary policy effect is measured through a common variable, the call money interest rate. From the fiscal policy perspective, apart from the government spending, we consider the tax rate measured by states' own tax revenue.

Section IV
Empirical Findings

Some stylised facts on the heterogeneity of regional inflation and economic conditions are provided in Tables A1, A2, A3 in the Appendix. Table A1 presents year-wise cross-section mean, median and standard deviation of CPI-AL inflation and the number of states above and below cross-sectional mean inflation for the sample of 19 states. It is evident that the states did not witness similar inflation conditions during any particular year; for all the years we find as many states below and above cross-sectional mean inflation. Similar findings emerge for CPI-IW inflation for 26 states and union territories (UTs) for which data were available (Table A2). Regional differences were also discernible for the explanatory variables. As an illustration, Table A3 provides summary statistics for the growth rate of real per capita state domestic product.

We begin with the empirical analysis of regional inflation dynamics based on CPI-AL inflation (Table 1). We estimated 11 models with alternative combination of variables, beginning with a basic model (M1) of inflation and growth relationship along with inflation persistence (lagged dependent variable) and then extending the model to include other variables pertaining to the supply side (states' agricultural output growth and fuel price inflation), monetary policy (call money rate), fiscal policy (alternatively characterised by government's overall spending and social sector spending, and states' own indirect tax revenue), structural conditions in terms of real growth of power, gas and water supply sectors (crucial inputs for production), and, finally, the transaction cost (inflation in the prices of transport and communications sectors).

In the basic model (M1), the income growth showed a positive influence on inflation, though the coefficient was significant at 10 per cent level of significance. The persistence effect was highly significant. We derive insights relating to the role of supply side factors – agriculture sector growth and fuel price inflation in models M2 and M3. When supply side variables are included in the regression equation, the income effect strengthens considerably,

Table 1: Regional Inflation Dynamics (Based on CPI-AL) *(Contd...)*

Variables	Alternate Dynamic Panel Data Models: Dependent Variable – Inflation: CPI-AL										
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M09**	**M10**	**M11**
Persistence (1-Lag) CPINF.L1	0.5606 (0.00)	0.5546 (0.00)	0.3108 (0.00)	0.3803 (0.00)	0.3674 (0.00)	0.3403 (0.00)	0.3424 (0.00)	0.3641 (0.00)	0.3579 (0.00)	0.3803 (0.00)	0.4209 (0.00)
Per capita Income Growth: PYG	0.1541 (0.09)	0.3493 (0.00)	0.4324 (0.00)	0.2728 (0.00)	0.2448 (0.00)	0.2018 (0.00)	0.2110 (0.00)	0.1836 (0.01)	0.1642 (0.01)	0.1758 (0.00)	0.1495 (0.00)
Supply Shock (Agriculture Growth): GAG		-0.1105 (0.01)	-0.1259 (0.00)	-0.1078 (0.00)	-0.1014 (0.00)	-0.0856 (0.01)	-0.0856 (0.01)	-0.0801 (0.01)	-0.0844 (0.01)	-0.0877 (0.00)	-0.0846 (0.00)
Oil Price Inflation (INFCPALPOL)			0.3742 (0.00)	0.3795 (0.00)	0.3773 (0.00)	0.3909 (0.00)	0.3916 (0.00)	0.3926 (0.00)	0.3869 (0.00)	0.3363 (0.00)	0.2747 (0.00)
Monetary Policy (CMR)				-0.7748 (0.00)	-0.7904 (0.00)	-0.8096 (0.00)	-0.7976 (0.00)	-0.7923 (0.00)	-0.8268 (0.00)	-0.8570 (0.00)	-0.8252 (0.00)
State Fiscal Policy: Growth of Total Expenditure (GBE)					0.0393 (0.01)						
State Fiscal Policy: State Social Expenditure Growth (GSE)						0.0489 (0.00)	0.0498 (0.00)	0.0517 (0.03)	0.0531 (0.00)	0.0562 (0.00)	0.0476 (0.00)

Table 1: Regional Inflation Dynamics (Based on CPI-AL) *(Concld...)*

Variables	Alternate Dynamic Panel Data Models: Dependent Variable – Inflation: CPI-AL										
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M09**	**M10**	**M11**
Structural Development (GEW1)							-0.0228 (0.05)	-0.0241 (0.05)	-0.0210 (0.05)	-0.0238 (0.03)	-0.0372 (0.00)
Financial Access (GBC)								0.0405 (0.01)	0.0368 (0.01)	0.0299 (0.07)	0.0414 (0.00)
State Fiscal Policy: Growth of Own Tax Revenue (GOTX)									0.0635 (0.03)	0.0668 (0.00)	0.0532 (0.01)
Transaction Cost											0.0721 (0.00)
Intercept	1.3340 (0.02)	0.7260 (0.00)	-0.9780 (0.04)	4.4549 (0.00)	4.2609 (0.00)	4.4257 (0.00)	4.4256 (0.00)	3.5577 (0.00)	0.1532 (0.93)	3.4841 (0.00)	3.8899 (0.00)
Wald Chi-sq (P value)	543 (0.00)	415 (0.00)	540 (0.00)	678 (0.00)	711 (0.00)	1133 (0.00)	1125 (0.00)	1216 (0.00)	2498 (0.00)	1789 (0.00)	2531 (0.00)
AB Test: AR(2) test: Z (probability)	-1.27 (0.21)	-0.46 (0.64)	-0.85 (0.40)	-0.70 (0.48)	-0.66 (0.51)	-0.81 (0.42)	-0.82 (0.42)	-0.74 (0.46)	-0.93 (0.35)	-1.04 (0.30)	-1.69 (0.09)

Note: Figures in parantheses indicate the significance/probability ‘z’ statistic associated with the coefficient of explanatory variables.

while the persistence effect reduces, especially in the presence of fuel price inflation (M3).

In the fourth specification given in M4, the monetary policy variable (call money rate) is included as an explanatory variable. It has a highly statistically significant impact on inflation with the expected negative sign. It suggests that the monetary policy could have a strong potential to stabilise regional inflationary pressures. An interesting finding is that the coefficient of income growth moderated significantly when monetary policy variable was included in the regression. In terms of the direction and magnitude of the monetary policy impact, the results are comparable to the literature in the Indian context. Illustratively, Mohanty and John (2015), using the SVAR model and impulse response analysis, showed that a one percentage point increase in call money rate is associated with a 120 basis points reduction in inflation over a six-month period. Mohanty (2012), Khundrakpam (2012), and Kapur and Behera (2012) show the effectiveness of the interest rate channel but do not provide accumulated impulse response analysis for which a comparison could be possible.

Next, we include the fiscal policy measured in terms of growth rate of states' overall government spending in model 5 and developmental social expenditure in model 6. Though government expenditure growth has statistically significant positive effect on inflation, the impact (coefficient size) is quite low when compared to the impact of other variables like income, supply side factors and monetary policy. An interesting point is that the social sector spending could be more conducive to effective demand than overall spending. Given the low inflationary impact, social spending induced effective demand could be desirable from the growth perspective. This is evident when we compare M5 and M6 with M4; the inflationary impact of per capita income is reduced to the extent of fiscal impact.

The growth of utilities (power, water and gas), reflecting upon the structural development, is introduced in model 7 (M7). The coefficient of this variable, though smaller in size, is statistically significant with negative sign. It implies that substantial real improvement in structural conditions can have a negative impact on inflation.

In model 8 (M8), we included bank credit growth. As expected, credit growth has statistically significant positive impact on inflation. Higher credit growth and better access to credit can contribute to demand and thus spur inflation. However, the coefficient of credit growth was much smaller than the coefficient of interest rate. This finding is in line with RBI (1998) and Dhal (2000), exemplifying the role of the interest rate channel compared with the credit channel of monetary transmission mechanism in the Indian context during the reform period.

In the models M9 and M10, we explore the impact of states' tax policy in the model using the ratio of own tax revenue to GSDP and growth rate of own tax revenue, respectively. Here we find M10 (with growth of own tax revenue) a plausible model rather than M9, as the intercept term is more or less similar to other models (M4-M8). In the model M10, the coefficient of growth rate of own tax revenue is positive and statistically significant. Similar to government expenditure, the coefficient size is low. Finally, we consider the role of transaction cost, which turned out to be statistically significant with a positive sign. As compared with Model 10, the presence of transaction cost leads to some moderation in the impact of oil price inflation, income growth and tax revenue growth but a strengthening of persistence, and financial access (credit growth).

Overall, we derive a couple of generalized perspectives. First, across the models, M4 to M11, the coefficient of interest rate does not change much. Thus, monetary policy through interest rate channel has the potential to stabilize inflation condition across the states. Second, similar to the interest rate effect, oil shock effect does not change much across the models. Thus, it is a significant source of supply shock to inflationary pressure. Third, the income effect can be exaggerated unless we consider other important demand, supply and policy variables. This is crucial finding as quantum of growth and inflation relationship is critically important for policy purposes.

Table 2 provides estimates for the inflation based on CPI-IW. Here, we have introduced additional variables like industrial wage inflation and house price inflation. Results show some similarities as well as striking differences with the estimates for CPI-AL given in Table 1. Models M1 to

M3 with fewer variables, like income growth and supply shocks, cannot be robust in terms of intercept terms when compared with the models with more explanatory variables. Moreover, models M1 to M3 are likely to suffer from serial autocorrelation problem. On the other hand, as we estimate the models with several variables, M4 to M11, we get plausible and robust results.

A couple of important insights must be mentioned here. Similar to CPI-AL, inflation persistence emerges as a significant source of CPI-IW inflation; a finding similar to other studies on inflation in India including Kapur and Behera (2012). Monetary policy induced interest rate variable has a significant inverse relationship with CPI-IW inflation also. Again, government social expenditure has a statistically significant effect compared with insignificant effect of overall spending. Agricultural production and structural conditions (real growth of power and utility sectors) – supply side factors – share inverse relationship with both types of inflation. Wage inflation and house price inflation have statistically significant positive effect on CPI-IW inflation. In the presence of these two additional variables, transaction cost showed lower effect on CPI-IW than CPI-AL. A major difference pertains to insignificant effect of credit growth on CPI-IW inflation. This result needs further analysis. Furthermore, the role of taxes can be subdued when we consider transaction cost, house prices and wage inflation.

Finally, a comparison of results in Tables 1 and 2 suggests that the impact of interest rate on CPI-AL inflation is more than that on CPI-IW inflation. As a general perspective, this finding is in line with asymmetric monetary transmission mechanism discussed in the literature; greater the financial constraints, greater the monetary policy effect. De (2017) provided a consumption channel explanation. Using household survey data for rural and urban areas, De (2017) showed that the expenditure of a poor household with higher share of food expenditure will have more sensitivity to fluctuations in relative food prices and monetary policy shocks. The sutdy also reported that in response to expansionary monetary policy, real consumption expenditure declined to a lower bound of 1.4 per cent in rural areas and 1.2 per cent in urban areas in India. Furthermore, in response to expansionary monetary policy, food consumption inequality rose by 3.2 per cent in rural areas and 2.9 per cent in urban areas.

Table 2: Regional Inflation Dynamics (Based on CPI-IW) *(Contd...)*

Variables	Alternate Dynamic Panel Data Models: Dependent Variable – Inflation: CPI-IW										
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M09**	**M10**	**M11**
Persistence (1-Lag) CPINF.L1	0.4981 (0.00)	0.4776 (0.00)	0.4448 (0.00)	0.5469 (0.00)	0.5356 (0.00)	0.5249 (0.00)	0.5448 (0.00)	0.5476 (0.00)	0.5186 (0.00)	0.5303 (0.00)	0.4879 (0.00)
Per Capita Income Growth: PYG1	0.2096 (0.00)	0.3458 (0.00)	0.4445 (0.00)	0.3973 (0.00)	0.4048 (0.00)	0.3716 (0.00)	0.3713 (0.00)	0.3675 (0.00)	0.2506 (0.00)	0.3605 (0.00)	0.2256 (0.00)
Agriculture Output Growth: GAG1		-0.0741 (0.00)	-0.1031 (0.00)	-0.0884 (0.00)	-0.0897 (0.00)	-0.0845 (0.00)	-0.0836 (0.00)	-0.0829 (0.00)	-0.0515 (0.00)	-0.0848 (0.00)	-0.0612 (0.00)
Oil Price Inflation			0.0680 (0.01)	0.1015 (0.00)	0.1040 (0.00)	0.1153 (0.00)	0.0975 (0.00)	0.0976 (0.00)	0.0647 (0.00)	0.1086 (0.00)	0.0747 (0.00)
Monetary Policy (Call Money Rate)				-0.6523 (0.00)	-0.6528 (0.00)	-0.6708 (0.00)	-0.6180 (0.00)	-0.6173 (0.00)	-0.7016 (0.00)	-6099 (0.00)	-0.5650 (0.00)
Fiscal Policy (GBE)					0.0254 (0.04)						
Fiscal Policy (GSE)						0.0421 (0.00)	0.0398 (0.00)	0.0399 (0.00)	0.0491 (0.00)	0.0388 (0.00)	0.0434 (0.00)
Structural Development (GEW1)							-0.0360 (0.00)	-0.0357 (0.00)	-0.0327 (0.00)	-0.0370 (0.00)	-0.0298 (0.00)
Financial Access (GBC)								0.0047 (0.79)	0.0057 (0.77)	-0.0032 (0.87)	0.0131 (0.53)
Fiscal Policy (ZTXR1 / GOTX1)									0.1014 (0.00)	0.0509 (0.10)	0.0443 (0.16)

Table 2: Regional Inflation Dynamics (Based on CPI-IW) *(Concld.)*

Variables	Alternate Dynamic Panel Data Models: Dependent Variable – Inflation: CPI-IW										
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M09**	**M10**	**M11**
Transaction Cost (TCOST)											0.0379 (0.01)
HPINF											0.0722 (0.06)
WGINF											0.0967 (0.00)
Intercept	1.6486 (0.00)	1.3595 (0.00)	0.5637 (0.18)	4.0937 (0.00)	3.7780 (0.00)	3.7291 (0.00)	3.7364 (0.00)	3.6342 (0.00)	3.6355 (0.00)	3.0229 (0.00)	2.4556 (0.00)
Wald Chi-sq (P value)	391.7 (0.00)	557.2 (0.00)	494.1 (0.00)	712.5 (0.00)	629.6 (0.00)	668.1 (0.00)	779.8 (0.00)	1033.7 (0.00)	1485.1 (0.00)	892.3 (0.00)	1846.2 (0.00)
AB Test AR(2) test: Z (probability)	-2.3 (0.02)	-2.0 (0.05)	-1.8 (0.08)	-0.92 (0.36)	-0.93 (0.35)	-0.66 (0.51)	-0.79 (0.42)	-0.85 (0.40)	-0.42 (.67)	-0.80 (0.42)	-1.41 (0.16)

Note: Figures in parentheses indicate the significance/probability 'z' statistic associated with the coefficient of explanatory variables.

GBE: Growth in Government Expenditure; GSE: Growth in Government Social Expenditure; GEW: Growth of Electricity and Water Supply Output; GBC: Growth of Bank Credit; ZTXR: States Own Tax revenue to GSDP ratio; GOTX: Growth of States own Tax revenue; WGINF: Growth rate of wages; HPINF: Housing Price Inflation.

Section V
Conclusion

This study has attempted an empirical analysis of regional inflation dynamics in the Indian context, using demand, supply, structural and policy variables in a dynamic panel data framework. The study has analysed two consumer price inflation series pertaining to agriculture labourers and industrial workers, which, to some extent, relate to rural and urban inflation conditions. The results of the study confirmed some standard economic premises. Monetary policy through interest rate can have a significant common influence in stabilising inflation conditions across states. Inflation could be positively affected by variables such as real per capita income growth, government expenditure growth and bank credit growth, but negatively by supply side factors such as real agriculture sector growth. Among the structural factors, inflation could decline with growth of utilities such as power, water supply and gas. On the other hand, States' own tax revenue rate can have positive but low impact on inflation. Thus, the study provides an applied perspective that the information available from national accounts on states' GSDP and states' budget documents could be exploited to evaluate the policy transmission mechanism at a disaggregated level. Going forward, the empirical approach can be extended as longer time series data become available for CPI rural and urban areas, which is used for policy purposes.

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Appendix

Table A1: Cross-sectional Summary Statistics of Inflation (CPI-AL)

Year	Mean	Median	Standard deviation	Maximum	Minimum	Count 1	Count 2	Average of deviation from mean (Count 1)	Average of deviation from mean (Count 2)
1999	11.1	10.8	3.3	19.0	5.2	7	12	3.1	-1.6
2000	5.1	4.7	2.4	10.8	1.2	8	11	2.5	-1.5
2001	0.7	1.0	2.6	4.4	-5.8	12	7	1.7	-2.2
2002	0.6	0.7	2.0	4.2	-3.5	11	8	1.5	-1.6
2003	2.4	2.6	2.6	8.7	-3.0	12	7	1.6	-2.1
2004	3.2	3.3	1.9	5.8	-2.0	11	8	1.4	-1.5
2005	2.7	2.6	1.7	5.4	-1.7	9	10	1.5	-1.1
2006	3.9	4.0	2.2	9.2	-1.2	11	8	1.5	-1.7
2007	7.6	7.8	2.0	10.6	3.6	11	8	1.5	-1.7
2008	7.3	7.2	1.5	10.8	3.4	10	9	1.0	-0.9
2009	9.7	10.0	2.2	13.2	5.7	13	6	1.4	-2.2
2010	13.7	13.9	2.5	17.2	8.0	11	8	1.9	-2.1
2011	10.0	10.0	2.3	14.7	6.3	10	9	1.9	-1.7
2012	8.2	8.0	2.7	13.8	4.1	8	11	2.7	-1.7
2013	10.0	10.0	1.3	11.8	7.1	12	7	0.8	-1.1
2014	11.1	11.0	2.6	17.2	6.6	10	9	2.1	-1.9
2015	7.3	6.9	2.1	12.1	2.2	8	11	2.0	-1.2
2016	4.0	4.4	2.4	8.5	-2.1	11	8	1.6	-1.8

Note: Count 1: No. of states above or equal to the cross sectional mean.
Count 2: No of states below the cross-sectional mean.

Table A2: Cross-sectional Summary Statistics of Inflation (CPI-IW)

Year	Mean	Median	Standard Deviation	Maximum	Minimum	Count 1	Count 2	Average of deviation from mean (Count 1)	Average of deviation from mean (Count 2)
1999	13.22	13.21	4.86	24.40	2.62	12	14	3.99	-3.42
2000	2.85	3.40	5.25	12.17	-18.74	16	10	2.32	-3.71
2001	3.91	3.45	2.39	9.90	0.10	9	17	2.62	-1.39
2002	3.62	3.90	2.42	9.60	-0.02	14	12	1.77	-2.07
2003	3.19	3.70	3.14	7.90	-7.10	16	10	1.62	-2.60
2004	4.40	4.00	1.32	7.57	1.70	11	15	1.26	-0.92
2005	4.97	4.10	3.19	15.83	0.50	10	16	2.65	-1.66
2006	5.15	5.00	2.34	12.39	1.64	10	16	2.16	-1.35
2007	6.99	6.20	3.26	19.42	2.80	8	18	3.49	-1.55
2008	6.28	6.20	1.42	9.70	3.76	12	14	1.20	-1.03
2009	9.51	8.65	5.26	31.89	1.43	9	17	4.06	-2.15
2010	9.62	12.15	7.12	16.20	-16.92	19	7	3.20	-8.69
2011	11.09	10.90	3.15	23.27	4.20	12	14	2.00	-1.71
2012	9.11	8.55	2.99	18.14	4.40	8	18	3.12	-1.38
2013	9.68	10.05	2.73	14.50	3.00	14	12	1.85	-2.16
2014	8.92	8.85	3.05	13.61	-1.08	13	13	2.16	-2.16
2015	5.03	5.75	4.27	10.10	-13.98	16	10	1.80	-2.88
2016	4.47	5.15	3.42	8.00	-7.97	19	7	1.41	-3.82

Note: Count 1: No. of states above or equal to the cross sectional mean.

Count 2: No of states below the cross-sectional mean.

Table A3: Cross-sectional Summary Statistics of Per capita Income Growth

Year	Mean	Median	Standard Deviation	Maximum	Minimum	Count 1	Count 2	Average of deviation from mean (Count 1)	Average of deviation from mean (Count 2)
1999	4.2	4.0	3.5	11.2	-1.6	10	10	2.7	-2.7
2000	4.2	4.4	2.9	9.7	-2.6	10	10	2.2	-2.2
2001	0.9	1.7	5.5	12.9	-8.8	12	8	3.6	-5.3
2002	3.2	3.9	4.3	13.9	-7.6	12	8	2.6	-3.9
2003	2.1	3.2	4.8	10.3	-11.4	12	8	2.8	-4.2
2004	6.8	5.4	6.2	26.2	-6.9	7	13	5.6	-3.0
2005	6.0	6.6	3.6	12.0	-3.7	11	9	2.4	-3.0
2006	5.9	4.6	3.9	13.2	-3.3	7	13	4.2	-2.3
2007	8.0	7.6	3.5	14.3	-0.2	9	11	2.9	-2.4
2008	6.5	6.5	2.9	12.1	2.0	10	10	2.3	-2.3
2009	5.9	5.2	2.9	12.8	1.1	9	11	2.3	-1.9
2010	6.2	6.6	2.7	10.1	0.2	11	9	2.1	-2.5
2011	6.8	6.2	3.6	13.4	-2.7	8	12	3.2	-2.2
2012	5.5	5.4	2.0	9.8	2.6	10	10	1.5	-1.5
2013	4.1	4.2	3.0	9.8	-1.6	10	10	2.4	-2.4
2014	5.2	6.0	2.1	8.4	-0.3	12	8	1.4	-2.2
2015	4.2	4.5	3.2	9.1	-4.8	12	8	1.8	-2.6
2016	7.0	6.4	2.4	13.0	2.8	8	12	2.2	-1.5

Note: Count 1: No. of states above or equal to the cross sectional mean.
Count 2: No of states below the cross-sectional mean.

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Rural Wage Dynamics in India: What Role does Inflation Play?

Sujata Kundu*

This paper analyses the trends in rural wages in India during January 2001 to February 2019, with a view to identifying the key factors that could explain the recent slowdown in agricultural wage growth. The paper examines the role of rural prices in explaining wage movements in India and assesses the risk of a wage-price spiral to the inflation trajectory. The results show that agricultural and non-agricultural wages both share a long run positive relationship with rural prices. For the period from November 2013 to February 2019, the paper finds that the changes in rural prices had a positive and significant impact on changes in nominal agricultural wages, even after controlling for other determinants such as non-agricultural wages, Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) wages, and rainfall departure from normal. The nominal agricultural wages showed stickiness and a significant positive influence of non-farm wages. This paper does not find any robust empirical evidence of a wage-price spiral in India during the period under the study.

JEL Classification : J21, J31, E24, E31, E52

Keywords : Rural wage, inflation, MGNREGS, construction wage

Introduction

Rural wages in India have witnessed sharp movements in the past few years. During the last 10-year period, a high growth phase in rural wages from 2007-08 to 2012-13 was followed by a phase of significant deceleration. Because of a spell of high inflation during October 2015 to September 2016, growth in real agricultural wages slipped into the negative territory and

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subsequently turned positive but remained low.[1] Since rural wages play a major role in determining the living standard of a large section of population in the country, it is worthwhile to examine the factors behind the changing rural wage dynamics and the subdued growth in wages in the recent years. It is crucial to note that two major factors, *viz.,* the implementation of the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) and a healthy growth of the construction sector (as measured by the sector's gross domestic product), that contributed to the high growth phase in rural wages up to 2012-13, have weakened in terms of their significance in the recent period. The high wage growth period also coincided with elevated inflation in the economy. In the post 2012-13 period, inflation has eased significantly, which was also accompanied by a sharp fall in nominal wage growth. For agricultural wages, it has been observed that growth in the agricultural sector influences wages positively (Bhalla, 1979; Himanshu, 2006; Jose, 1974; Lal, 1976; Venkatesh, 2013). The agricultural output growth was subdued during 2014-16 due to sub-normal monsoon. The growth improved during 2016-18 with the normal monsoon. The rural wage growth during these years, however, remained low indicating that the role of agricultural output in influencing rural wages has become limited.

While an appropriate understanding of the factors responsible for movements in rural wages is important from the perspective of welfare consequences for the rural economy, it is also crucial to recognise the fact that rural wage dynamics have implications for inflation and overall economic growth in an emerging market economy like India. Most of the early empirical literature on rural labour market in India has looked into various factors determining movements in rural wages at different periods in time. Some of the recent studies have specifically focussed on the upsurge in rural wages between 2007-08 and 2012-13. Some of them have reported the implementation of MGNREGS as an important factor behind the surge in rural wage growth (Chand *et al.*, 2009; Pandey, 2012), while another study found that besides MGNREGS, a healthy performance of the construction sector and general urbanisation trend also led to the upswing (Himanshu

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[1] Rural inflation is measured in terms of year-on-year (y-o-y) growth in consumer price index of rural labourers (CPI-RL) for major part of the study in view of the availability of a longer time series. These data are published by the Labour Bureau, Shimla, Ministry of Labour and Employment, Government of India.

and Kundu, 2016). This period was characterised by wages growing at a considerably higher rate than the overall inflation in the economy and many researchers went on to argue that such rise in wages, if unaccompanied by increase in productivity, could induce a wage-price spiral by raising aggregate demand on the one hand and pushing up cost of production on the other (Guha and Tripathi, 2014; Nadhanael, 2012). Rural wage growth moderated noticeably after 2012-13. Although a lot of mainstream media reports have highlighted this fact, a careful and broader analysis of the long-term trends in rural wages is needed.

In this backdrop, this paper analyses the trends in rural wages – both farm (agricultural) and non-farm (non-agricultural) wages – in India over the past decade, while trying to identify the possible major factors that could explain the recent slowdown in agricultural wage growth. In particular, the paper tries to examine the role of rural prices in explaining wage movements in India. In comparison to the earlier studies in this area (Goyal and Baikar, 2014; Guha and Tripathi, 2014; Nadhanael, 2012), this study uses longer time series data on rural wages and prices. Also, given the structural transformation of the rural labour market following the growth in non-farm employment in the rural economy and a decline in agricultural employment since 2004–05 (Chand *et al.*, 2017; Himanshu *et al.*, 2013; Himanshu and Kundu, 2016), the study also looks at the interplay between rural non-agricultural wages and prices, using construction sector wage as a proxy for non-agricultural wage.[2]

Furthermore, this paper also examines as to why the fall in agricultural wage growth has been higher than that in the non-agricultural wages after 2012-13. While doing so, it seeks to provide an answer to the question as to whether the moderation in inflation was a key factor in bringing down growth in agricultural wages?

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2 According to the National Sample Survey (NSS) Employment and Unemployment Survey (EUS) Rounds, construction was the largest employer of male labour force and the second largest employer of females after manufacturing in the rural non-farm sector in 2011-12. Also, workers who moved out of agriculture and those who entered the rural labour force largely got absorbed in various construction activities, as employment growth in rural services and manufacturing was inadequate. Thus, the construction sector has played a major role in drawing the rural labour out of the farm sector, thereby leading to some tightening of the agricultural labour market. Further, a study by Himanshu *et al.*, (2013) has showed that with the growing integration of villages with the urban and semi-urban labour markets, the non-farm sector not only influences rural wages in isolation but also in conjunction with changes in the agricultural sector.

The paper has been structured as follows. Section II presents a brief review of the literature on interlinkages between rural wages and inflation, and factors contributing to rural wage growth. Section III covers major data sources on rural wages in India, the data used in this study, data limitations, and issues encountered in the empirical analysis. Section IV presents the trends in rural wages, both in nominal and real terms from 2001 to 2018. Section V discusses methodology and empirical results on the long-term relationship between changes in rural farm/non-farm wages and prices, and the factors that contributed to the deceleration in agricultural wage growth in the recent years. Section VI concludes the paper.

Section II
Wage-Price Dynamics: A Review of the Literature

Standard macroeconomic models generally discuss wage inflation in conjunction with price inflation and unemployment. In a simplified framework, the price and wage equations that capture the interaction among them are as given below:

$$\Delta logP_t = \alpha_p + \Delta logW_t + \epsilon_{pt} \text{ ... (1)}$$

$$\Delta logW_t = \alpha_w + \Delta logP_{t\text{-}1} - \beta\, u_t + \epsilon_{wt} \text{ ... (2)}$$

where, P_t is the price index and W_t is the nominal wage rate at time period t. Therefore, $\Delta logP_t$ and $\Delta logW_t$ represent price inflation and wage inflation, respectively, at time period t. Further, u_t indicates the unemployment rate at time period t, α_p and α_w are the constants, and ϵ_{pt} and ϵ_{wt} are the error terms. Substituting (2) in (1) gives us the 'Phillips curve', *i.e.*, the relationship between inflation and unemployment (Blanchard, 1998).

The wage-price relationship, as shown in equation (2), is very important as it not only spells out the labour market conditions prevailing in the economy but also helps to understand the macroeconomic linkages between nominal wages and prices in the presence of other economic factors. This paper primarily focusses on estimating equation (2) in the Indian context.

The empirical literature shows that real wages generally fall during years of high inflation (Dornbusch and Edwards, 1992). Braumann and Shah

(1999) finds a strong U-shaped pattern in real wages during a high inflation period of 1992–96 in Suriname. A sharp decline in real wages generally results during many inflationary episodes (Braumann, 2001). Kessel and Alchian (1960), however, argues that though the inference that inflation causes a decline in real wages appears to be common in the literature, it is extremely tricky to employ this idea as a tool of analysis for understanding observed movements in time series data on prices and wages. Real wages could also be affected by real factors like relative supplies of labour and capital, the quality of the labour force, the pattern of final demand in the economy and the state-of-the-art. According to Kessel and Alchian (1960; Pg. 43): *"For any time series of real wages, there exists a fantastically difficult problem of imputing changes in the level of real wages to one or the other of two classes of variables, i.e., real or monetary forces. Only if one is able to abstract from the effects of real forces can one determine the effect of inflation upon an observed time series of real wages".* In the Indian context, it has been found that the dynamics of rural wage and inflation are not straightforward and that there are a number of macroeconomic factors that have their roles to play in explaining the relationship between the two (Goyal and Baikar, 2014).

The high growth phase in rural real wages during 2007-08 to 2012-13 led researchers to revalidate the relationship between wages and prices in the Indian context. A few studies provided period-wise analyses of the wage-price interplay.[3] Monthly data on wages for rural unskilled labourers and inflation based on consumer price index of rural labourers (CPI-RL) from May 2001 to February 2011 show the existence of a bi-directional causality between wage inflation and price inflation (RBI, 2012). Nadhanael (2012) shows that from July 2000 to June 2007, money wages adjusted to prices. The elasticity of money wages with respect to prices was estimated at above 0.9, indicating that wages were almost identically getting adjusted to changes in prices, thereby keeping real wages almost unchanged. Thus, there was a limited scope of a wage-price spiral. However, for the period from July 2007 to November 2012, wages were found to be a long-term

[3] Boyce and Ravallion (1991), in the context of Bangladesh, demonstrated the interlinkages between agricultural wage rates and food prices both in the long-run as well as in the short-run.

determinant of inflation. Guha and Tripathi (2014) finds that wages of rural unskilled labourers have a significant and positive impact on agricultural wages. However, the feedback mechanism from agricultural wages and non-agricultural unskilled wages to food prices was found to be weak. Using a general equilibrium framework, Jacoby (2015) finds that nominal wages for manual labour across rural India responded positively to higher agricultural prices. In particular, wages rose faster in the districts that grew more of the crops that experienced comparatively faster increase in prices over the period 2004–05 to 2009–10. The study used National Sample Survey Office (NSSO) wage data and also noted that the increase in rural wages may lag behind the increase in consumer prices. Goyal and Baikar (2014) finds that the spread of MGNREGS did not raise wages, but the sharp jump associated with wage indexation, which itself is a response to high food prices, did. Gulati and Saini (2013), using multiple factors to explain food price inflation during 1995–96 to 2012–13, finds that apart from fiscal deficit and global food prices, wages had a higher contribution to recent food inflation. The study also indicates that MGNREGS would set a wage floor in many informal sector activities.

With respect to the determinants of wages, one of the earliest studies on determinants of real wage rates in India was Bardhan (1970). Based on rural wage data from both the Employment and Unemployment Survey Rounds of the NSSO and Agricultural Wages in India (AWI), published by the Ministry of Agriculture, the study concludes that in the Indian context, the bargaining strength of agricultural labourers might be at least as important a determinant of high real wage rates as the spread of technological progress in agriculture. Lal (1976), based on a cross-sectional regression analysis for two years, 1956–57 and 1970–71, finds that growth in agriculture led to a rise in agricultural real wages. Bhalla (1979), in a study on the state of Punjab, finds that, for the period between 1961 and 1977 there were two opposing forces that impacted the real wage rates of the agricultural labourers in Punjab. Rising farm productivity impacted real wages positively, while rising labour force and inflation, pulled real wages down. Sen (1996) finds the significance of growing rural non-agricultural employment in determining the rise in rural real wages in a majority of the Indian states between 1977–78 and 1989–90.

A number of studies finds the evidence of sticky rural wages in India. For instance, Himanshu (2005) points out the tendency of money wages to adjust to changes in agricultural productivity with a certain time lag. This has been confirmed by other studies as well (Datt and Ravallion, 1998; Lal, 1976; Tyagi, 1979). Datt and Ravallion (1998) also indicates that agricultural labour markets exhibit short-run price stickiness in wages. Ravallion (2000) concludes that in the Indian agricultural sector real wage rates do not adjust instantaneously to changes in their determinants; there is a strong serial dependence in real wage rates, which is often interpreted as wage stickiness. The study also shows that there is full indexation of nominal agricultural wages to the consumer price index of agricultural labour (CPI-AL) in the long-run but not in the short-run. Therefore, inflation is an important variable for adjustment in wages, but nominal wages do not adjust instantaneously to rise in prices.

There are a handful of studies covering the period from 2001 to 2016 which find that factors such as increase in public investment, urban spillover effect, and welfare programmes like MGNREGS have played a significant role in pushing up nominal wages, such that growth in nominal wages surpassed inflation for a couple of years (Berg *et al.,* 2012; Chand *et al.,* 2009; Himanshu and Kundu, 2016; Imbert and Papp, 2015; Pandey, 2012).

Section III
Data

Although data on rural wages are available from multiple sources – Agricultural Wages in India (AWI) published by the Directorate of Economics and Statistics, Ministry of Agriculture; Employment and Unemployment Surveys (EUS) conducted by the National Sample Survey Office (NSSO)[4]; and Wage Rates in Rural India (WRRI) brought out by the Labour Bureau, Shimla – this study uses monthly wage data from WRRI due to its extensive coverage across states as well as various agricultural and non-agricultural occupations besides availability of the data up to a more recent period.[5] However, these data are also not free of limitations.

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[4] On May 23, 2019, the Government of India announced the merger of the National Sample Survey Office (NSSO) with the Central Statistics Office (CSO) to form the National Statistical Office (NSO).

[5] For details on the various data sources on rural wages, see Himanshu (2005).

WRRI, available from 1998, is the newest series of rural wage data in India. Moreover, it is the only available data source that is useful for addressing issues like wage-price relationship as these data are available on a monthly frequency with only two to three months of lag.

The paper covers the period from January 2001 to February 2019, which provides enough number of observations for a robust time series analysis. The data for the period 1998 to 2000 were not considered in the paper due to changes in the method of aggregation, as highlighted in Nadhanael (2012). Furthermore, with a view to identify the possible major factors explaining the recent slowdown in agricultural wage growth, specifically post 2012–13, the study uses state-level monthly wage data from November 2013 to February 2019.

A major issue faced while using WRRI data was the change in the classification of occupations for collecting wage data from November 2013. Until October 2013, wage data were collected for 11 agricultural and seven non-agricultural occupations. However, from November 2013, following the recommendations of the Working Group headed by Dr. T.S. Papola, wage data are collected for 25 occupations, comprising 12 agricultural and 13 non-agricultural occupations (Table 1).[6]

According to the Working Group, the reclassification of occupations was done in order to capture changes in the occupational structure of the rural labour market. A wage series for various construction activities was also introduced in the new series, which is useful in the wake of the growing importance of the construction sector in terms of its contribution to the overall output of the economy and also absorption of rural labour. Therefore, in the new classification of rural wages some occupations were merged (*e.g.*, sowing, weeding and transplanting were merged to form a single series), some were dropped (*e.g.*, occupations like well-digging, cane-crushing and cobbler) and seven new wage categories were introduced covering both agricultural and non-agricultural occupations. For the purpose of our analysis, the study took a simple average of the first seven occupations for the period January 2001 to October 2013 and a simple average of the first

[6] See Das and Usami (2017) for further details.

Table 1: Categories of Rural Wages under WRRI

Old Wage Series (up to October 2013)	**New Wage Series (November 2013 onwards)**
Agricultural Occupations	
1. Ploughing	1. Ploughing/tilling
2. Sowing 3. Weeding 4. Transplanting	2. Sowing (including planting/transplanting/weeding)
5. Harvesting 6. Winnowing 7. Threshing	3. Harvesting/threshing/winnowing
8. Picking	4. Picking (including tea, cotton, tobacco, and other commercial crops)
9. Herdsman	5. Animal husbandry (including poultry, dairy and herdsmen)
10. Well-digging	-
11. Cane-crushing	-
-	6. Horticulture (including nursery)
-	7. Fisherman–inland
-	8. Fisherman–coastal/deep sea
-	9. Loggers and woodcutters
-	10. Packaging labourers
-	11. General agricultural labourers (including watering/irrigation, etc.)
-	12. Plant protection workers (applying pesticides, treating seeds, etc.)
Non-agricultural Occupations	
1. Carpenter	1. Carpenter
2. Blacksmith	2. Blacksmith
3. Mason	3. Mason
4. Tractor driver	4. LMV and tractor driver
5. Sweeper	5. Sweeping/cleaning
6. Cobbler	-
-	6. Weavers
-	7. Beedi-makers
-	8. Bamboo and cane-basket weavers
-	9. Handicraft
-	10. Plumbers
-	11. Electricians
-	12. Construction (for roads, dams, industrial and project construction work, and well diggers)
7. Unskilled labourers	13. Non-agricultural labourers (including porters and loaders)

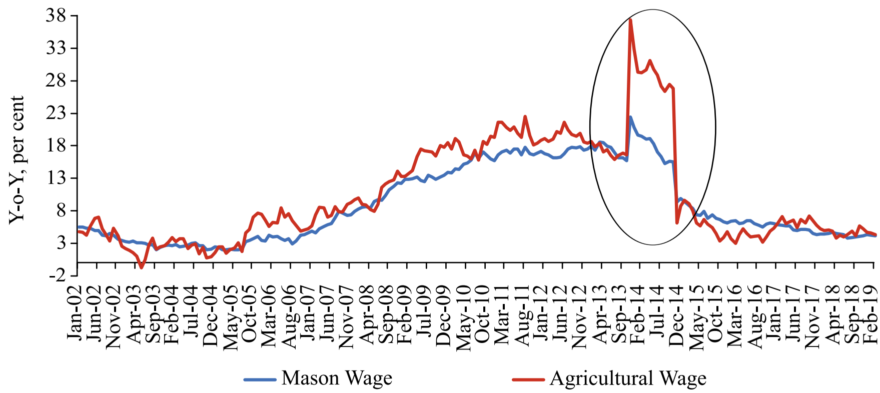
Source: Labour Bureau, Shimla, Ministry of Labour and Employment.

three occupations for the period November 2013 to February 2019 in order to construct an agricultural wage series, since these occupations are considered to be the primary agricultural operations.[7] For non-agricultural wages, mason wage was used as a proxy for construction wage. It may be mentioned that mason wage is a common category in both the new and the old wage series. Furthermore, mason wage shows a high correlation with construction wage in the new wage series.[8]

The major problem posed by the reclassification is that year-on-year (y-o-y) growth rates in wages showed a spike from November 2013 to October 2014 (Chart 1).

This spike was mainly due to the methodological changes in data reclassification, leading to a statistical break in the series (Appendix Tables A.1 and A.2). Further, in the absence of linking factors, the new and the old series could not be made comparable. Therefore, for the empirical analysis on Section V focussing on the recent years of decline in wage growth, the paper considered data for the post-break period, *i.e.*, starting from November 2013.[9]

Chart 1: Nominal Wage Growth for Mason and Agricultural Labourers



Source: Labour Bureau, Shimla, Ministry of Labour and Employment.

7 Wages corresponding to these occupations broadly follow a similar trend. Further, due to the unavailability of data on share of agricultural labourers in each of these occupations, a weighted average series of agricultural wage was not possible to generate.

8 A statistically significant correlation coefficient of 0.98.

9 In terms of year-on-year (y-o-y) growth rates, this implies that the post-break period begins from November 2014.

Section IV
Movements in Rural Wages: A Relook

Movements in rural wages during the last 15 years or so can be categorised into three distinct phases (Chart 2).

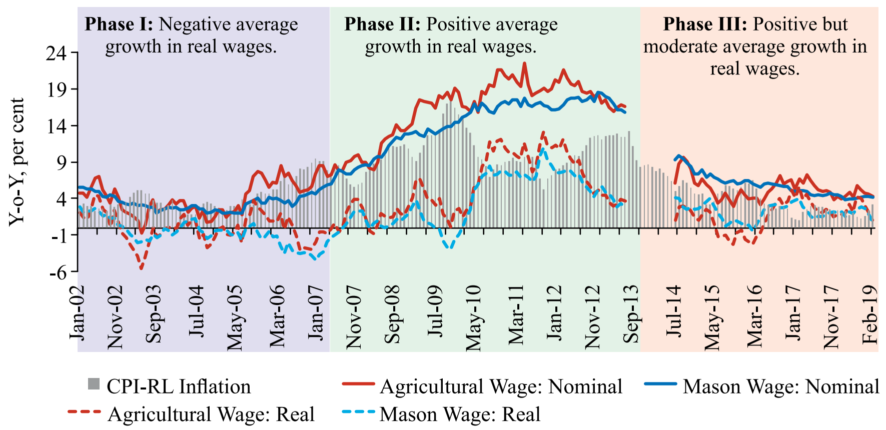
Phase I

The first phase spanned from January 2002 to September 2007, when the average growth in rural nominal wages was around 4.0 per cent, while the average rural inflation stayed around 4.5 per cent. As a result, there were extended spells when growth in real wages stayed in the negative territory. This period has been analysed quite extensively in the literature. Several authors have also termed this phase as the period of agrarian distress, a lot of which can be attributed to poor agricultural performance and lower employment opportunities outside agriculture (Abraham, 2009; Himanshu, 2006).

Phase II

This phase covers the period from October 2007 to October 2013. During this phase, the average growth in nominal agricultural and non-agricultural wages stood at around 17 per cent and 15 per cent, respectively, surpassing rural inflation which averaged at 10 per cent. Evidently, there were several months when growth in real wages reached unusually high levels.

Chart 2: Movements in Rural Wages and Inflation



Source: Labour Bureau, Shimla, Ministry of Labour and Employment.

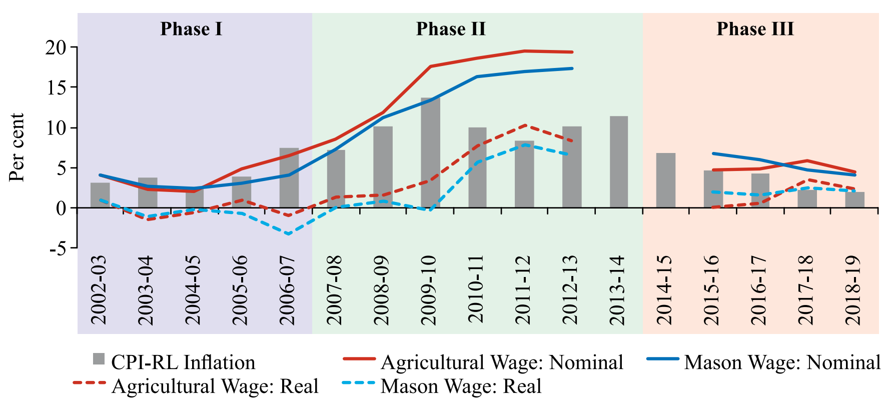
Phase III

The current phase, which began in November 2014, has seen a significant deceleration in rural wage growth. This phase is also characterised by low inflation; however, there were certain incidents when inflation surpassed growth in nominal rural wages, thereby driving real wage growth to the negative territory. For obvious reasons, such movements in rural wages after a prolonged period of boom have attracted the attention of policy researchers. Again, this phase has been labelled as a period of rural distress. However, on an average basis, rural wage growth was higher than inflation during the third phase. Average rural inflation was around 4 per cent, whereas average growth rates in nominal agricultural and non-agricultural wages were 5 per cent and 5.4 per cent, respectively.

A closer look at the annual average inflation and yearly growth in rural wages during the entire period covered in this paper brings out the following interesting points (Chart 3).

- First, nominal wage growth and inflation are closely related and, importantly, a rise (decline) in nominal wage growth is preceded by a rise (decline) in inflation.
- Second, phase-wise movements show that there have been significant shifts in the trajectories of agricultural and non agricultural wages. While the first phase was largely characterised

Chart 3: Annual Average Inflation and Rural Wage Growth



Source: Labour Bureau, Shimla, Ministry of Labour and Employment.

by an overlap between growth in agricultural and non-agricultural wages, in the second phase growth in agricultural wage has been consistently higher than that in non-agricultural wage. This divergence started showing up in the latter part of the first phase itself. In contrast, during the third phase, growth in non-agricultural wages exceeded the growth in agricultural wages for some time and thereafter it turned lower, which is somewhat similar to the pattern seen in the first phase.

Section V
Methodology and Empirical Analysis

The behaviour of rural wages relative to prices assumes importance in an emerging market economy like India where the share of rural population is about 66 per cent (as estimated by the World Bank for the year 2017). The relationship between the two plays a prime role in determining the standard of living of the rural population. A number of studies have suggested that an improvement in real rural wages leads to an alleviation of rural poverty (Datt and Ravallion, 1998; Deaton and Dreze, 2002; Radhakrishna and Chandrasekhar, 2008; Rao, 1987; Sen, 1996; Vakulabharanam, 2005). Furthermore, the connection between wages and prices has received prominent attention in inflation-targeting economies. Acute changes in the labour market conditions may have far reaching implications for inflation (BIS, 2017). The link between labour market and inflation is traditionally seen through the transmission mechanism whereby an increase in wages leads to a rise in production costs and hence higher prices. This, in turn, may lead to demand for higher wages and a rise in inflation expectations, which could feed into the demand for higher wages, representing the second-round effect. Thus, this process could lead to a wage-price spiral. However, rise in wages accompanied by productivity gains would not necessarily be inflationary. Therefore, for an inflation-targeting central bank, growth in wages is an important macroeconomic indicator, that needs to be monitored carefully, as there are associated potential upside risks to inflation.

Against this backdrop, an attempt has been made to study: (a) the long-run and short-run dynamics of rural wages and prices in India; and (b) wage-price association with a view to obtaining information that can explain the recent slowdown in wage growth. The subsection 'Rural Wage-Price Dynamics' focusses on the short-run and long-run dynamics of wages and prices. First, this study tries to find out the lead-lag relationship between changes in wages and prices. The availability of a longer time series data for the pre-break period (January 2001 to October 2013) allowed us to look at the lead-lag relationship using a cross-correlation matrix. Since cross-correlations are indicative in nature and cannot fully capture the complicated dynamics (Knotek and Zaman, 2014), the study tried to look at the short-run and long-run dynamics between the two using cointegration method and the Vector Error Correction Model (VECM) following Boyce and Ravallion (1991) and Nadhanael (2012). It may be noted that VECM is applied in case there exists a cointegrating relationship (which is the long-run relationship) between variables. The short-run relationship between variables is then estimated in a Vector Error Correction framework, which is pretty much a Vector Autoregression (VAR) model in first differences and consists of the correction of deviation from the long-run equilibrium path from the previous period. The subsection titled 'Rural Wage Growth during Phase III: What Explains the Decline?' focusses on the more recent period (*i.e.*, phase III), with the objective of finding out the probable factors that could explain the recent deceleration in agricultural wage growth using a dynamic panel data model with Arellano–Bover/Blundell–Bond system GMM structure. When independent variables are not strictly exogenous and are correlated with their past, a dynamic panel model is considered to be appropriate. This is because an Arellano–Bond dynamic panel using GMM in first difference of the regressors corrects for endogeneity, autocorrelation and deficiencies of the fixed effect panel regression. Further, Arellano–Bover/Blundell–Bond, which is an augmented version of Arellano–Bond, allows for more instrumental variables leading to an improved efficiency of the model (Roodman, 2009).

Rural Wage-Price Dynamics

Simple correlation coefficients between growth in rural wages and rural inflation indicate positive and statistically significant association between the two during phase I (Table 2). Further, correlation between growth in agricultural wage and mason wage is also strongly positive and significant.

The association between growth in rural wages and rural inflation changed significantly in phase II (Table 2). While mason wage growth and

Table 2: Correlation Coefficients between Wage Growth and CPI-RL Inflation

Variables	Phase I (Jan. 2002–Sept. 2007)	Phase II (Oct. 2007–Oct. 2013)
1	2	3
AGWG and CPI-RL	0.58*** (0.000)	0.19 (0.113)
MASONWG and CPI-RL	0.56*** (0.000)	0.19* (0.096)
AGWG and MASONWG	0.72*** (0.000)	0.88*** (0.000)

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Note: 1. Figures in parentheses indicate p-values.
2. Here and elsewhere in the paper, AGWG is nominal agricultural wage; CPI-RL is Consumer Price Index - Rural Labourers; and, MASONWG is nominal mason wage.

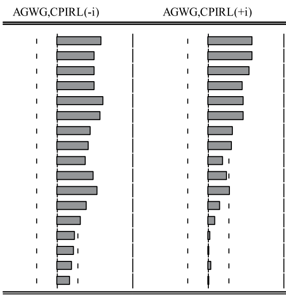
inflation showed positive correlation with a lower level of significance, correlation between agricultural wage growth and inflation turned out to be statistically not significant. However, correlation between mason wage and agricultural wage turned stronger in phase II. The weakening of correlation between wage growth and inflation indicates the increase in role of other factors in determining the surge in rural wage growth during phase II.

The study uses data for the pre-break period (January 2001 to October 2013) to examine the lead-lag relationship between seasonally adjusted quarter-on-quarter changes in rural wages and CPI-RL (Charts 4a and 4b). Cross-correlation coefficients clearly indicate that price changes generally lead wage changes in case of non-agricultural wages. However, in case of agricultural wages, changes in agricultural wages could lead changes in prices in the very short-term (as indicated by lags 1 and 2 in Chart 4a).[10]

The study uses cointegration analysis to further examine the long-run relationship between wages and inflation, and VECM to analyse the short-run dynamics. This analysis seeks to complement the literature by looking at a longer period data which brings out some interesting results.

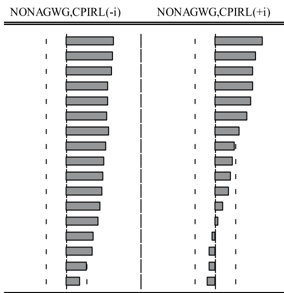
[10] Between seasonally adjusted quarter-on-quarter changes in agricultural wages and non-agricultural wages, cross-correlation coefficients suggested the former leading the latter, which is in line with expectations, given the fact that agricultural labourers are usually unskilled/semi-skilled and are generally placed at the bottom of the ladder in rural occupations. Any trigger that pushes agricultural wages up is expected to raise non-agricultural wages also under normal circumstances.

Chart 4a: Cross-correlations between Quarter-on-Quarter Change in Agricultural Wages and CPIRL



i	lag	lead
0	0.6135	0.6135
1	0.5232	0.6193
2	0.5202	0.5779
3	0.5194	0.4748
4	0.6401	0.4842
5	0.5930	0.4837
6	0.4607	0.3410
7	0.4357	0.3241
8	0.3967	0.2085
9	0.5042	0.2557
10	0.5494	0.2965
11	0.4054	0.1674
12	0.3295	0.1025
13	0.2480	0.0266
14	0.2360	0.0124
15	0.2089	0.0537
16	0.1800	0.0000

Chart 4b: Cross-correlations between Quarter-on-Quarter Change in Non-agricultural Wages and CPIRL



i	lag	lead
0	0.6575	0.6575
1	0.6540	0.5661
2	0.6356	0.5319
3	0.5853	0.5308
4	0.5847	0.5001
5	0.5816	0.4557
6	0.6028	0.3452
7	0.5622	0.2750
8	0.5390	0.2471
9	0.5212	0.2287
10	0.5056	0.2003
11	0.4807	0.1210
12	0.4480	0.0485
13	0.3883	-0.0336
14	0.3713	-0.0686
15	0.2836	-0.0777
16	0.2011	-0.1008

Note: 1. Sample period: January 2001 to October 2013.
2. The dotted lines indicate confidence bands.

The unit root tests indicate that the variables – log of agricultural wage, log of mason wage and log of CPI-RL – were non-stationary in levels and stationary in first differences, meaning that the variables are I(1) (Appendix Table A.3). Before going to the VECM analysis, pair-wise Granger causality tests were carried out to check for the existence of bi-directional causality between the variables. The results showed the existence of a bi-directional causality between changes in rural wages and prices from January 2001 to October 2013 (which is the old series) (Appendix Table A.4a). However, the results were not the same for the new wage series, *i.e.*, from November 2013 to February 2019 (Appendix Table A.4b). It may be mentioned that the Granger causality test has certain limitations, such as the results are not conditional upon the behaviour of other variables which might impact the relationship. Furthermore, results are also highly dependent on the sample period under consideration. Therefore, we checked for the existence of any cointegrating long-run relationship between the variables using Johansen cointegration test. The lag length was selected based on the Hannan-Quinn Information Criterion. The results of the tests indicate the presence of one cointegrating vector in both the cases, *i.e.*, the relationship between nominal agricultural wage and price; and the relationship between nominal non-agricultural (mason) wage and price (Appendix Tables A.5 and A.6). The model specification and estimated results, both for the cointegrating equations and the error correction equations, are given in Tables 3 and 4. The agricultural sector in India continues to be heavily dependent on monsoon.

Table 3: Results of the Vector Error Correction Model between Agricultural Wage and CPI-RL

Variables	Without Exogenous Variables		With Exogenous Variables	
	D(LAGWG)	D(LCPI-RL)	D(LAGWG)	D(LCPI-RL)
1	2	3	4	5
Error Correction Term	-0.034*** (0.004)	-0.006** (0.003)	-0.042*** (0.008)	0.003 (0.005)
D(LAGWG(-1))	-0.158** (0.079)	0.099** (0.050)	-0.151* (0.079)	0.099** (0.049)
D(LCPI-RL(-1))	-0.016 (0.125)	0.344*** (0.079)	-0.013 (0.126)	0.331*** (0.078)
Constant	0.010*** (0.001)	0.003*** (0.0007)	0.011*** (0.002)	0.001 (0.001)
MGNREGS dummy	-	-	-0.001 (0.002)	0.003** (0.001)
Rainfall departure from LPA	-	-	0.000 (0.000)	0.000 (0.000)
Observations	152	152	152	152
Adj. R-squared	0.35	0.30	0.35	0.32
Sample period: January 2001 to October 2013.				
Long-run Association between Agricultural Wage and CPI-RL				
Without Exogenous Variables	Agricultural Wage = -7.32 + 1.94***CPI-RL (0.074)			
With Exogenous Variables	Agricultural Wage = -6.92 + 1.87***CPI-RL (0.081)			

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Note: Figures in parentheses indicate standard errors.

Rainfall deviations from normal not only affect agricultural output but also the demand for both agricultural and non-agricultural labourers. Therefore, rainfall departure from the long period average (LPA) was included as an exogenous variable in the model. Further, the implementation of MGNREGS since February 2006 is an important policy measure of the government, having implications on the rural labour market and for rural wage setting. Therefore, a dummy variable for MGNREGS was included as an exogenous variable in the model. The dummy variable takes the value of 0 for pre-MGNREGS months, and 1 for post-MGNREGS months.

Table 4: Results of the Vector Error Correction Model between Non-agricultural Wage and CPI-RL

Variables	Without Exogenous Variables		With Exogenous Variables	
	D(LMASONWG)	D(LCPI-RL)	D(LMASONWG)	D(LCPI-RL)
1	**2**	**3**	**4**	**5**
Error Correction Term	-0.020*** (0.002)	-0.008*** (0.003)	-0.023*** (0.003)	-0.002 (0.005)
D(LMASONWG(-1))	0.038 (0.081)	-0.048 (0.120)	0.036 (0.082)	-0.024 (0.120)
D(LCPI-RL(-1))	0.023 (0.053)	0.330*** (0.079)	0.023 (0.054)	0.314*** (0.079)
Constant	0.007*** (0.001)	0.004*** (0.001)	0.007*** (0.001)	0.003* (0.001)
MGNREGS dummy	-	-	-0.001 (0.001)	0.003** (0.001)
Rainfall departure from LPA	-	-	0.000 (0.000)	0.000 (0.000)
Observations	152	152	152	152
Adj. R-squared	0.69	0.29	0.68	0.30
Sample period: January 2001 to October 2013.				
Long-run Association between Non-agricultural Wage and CPI-RL				
Without Exogenous Variables	Non-agricultural Wage = -6.48 + 1.90***CPI-RL (0.076)			
With Exogenous Variables	Non-agricultural Wage = -6.12 + 1.84***CPI-RL (0.076)			

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Note: Figures in parentheses indicate standard errors.

The results of the VECM analysis show that in the long-run both nominal agricultural wage and non-agricultural wage exhibit statistically significant positive relationship with price. Controlling for MGNREGS and rainfall deviations, the coefficients still remain statistically significant, though there is a marginal decline in their magnitudes (Tables 3 and 4). While the magnitudes of the long-run coefficients indicate more than full indexation of rural wages to prices, the possibility of sample bias cannot be ruled out as the average growth in nominal wages during the period under consideration was much higher than inflation. Nonetheless, the results are in conformity with the available literature (Ravallion, 2000). Furthermore, the long-run relationship between wages and prices holds given the statistically significant negative error correction terms. Any disturbance in the long-run relationship gets corrected as evident by the error correction terms in the short-run equations. However, the correction is not very quick as the magnitudes of the coefficients are small. The study could not establish the impact of prices on wages in the short-run. However, there exists a short-run relationship between agricultural wages and prices (wage impacting price) as indicated by the statistically significant coefficient of agricultural wages on prices in Table 3. The results also indicate the stickiness in nominal wages.[11]

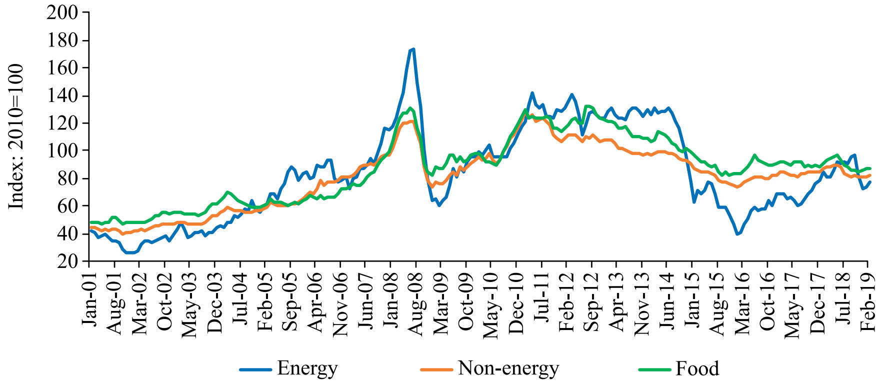
The VECM equation estimated for CPI-RL, however, indicates that in the short-run changes in agricultural wages cause changes in prices (a similar result was obtained by the cross-correlation coefficients earlier), but the impact could be quite small as suggested by the magnitude of the coefficient. Interestingly, the MGNREGS dummy turns out to be statistically significant with the expected sign, although of a small magnitude, in the short-run price equations. This indicates that the implementation of MGNREGS had a positive impact on rural prices in the short-run, which could be through the demand shock as the employment under MGNREGS provides a government guaranteed wage to the rural labourers. The error correction terms for the price equations under VECM cease to appear statistically significant when exogenous variables are introduced in the model, which implies that prices may not adjust to wages in the short-run owing to several other factors that are at play. The cross-correlation coefficients discussed earlier in the paper also indicated that changes in prices lead changes in wages and not the other way round. Serial correlation tests (VEC Residual Portmanteau Tests for Autocorrelations in Appendix Tables A.7a and A.7b; VEC Residual Serial Correlation LM Tests in Appendix Tables A.8a and A.8b) and model stability tests (CUSUM tests in Charts A.1 and A.2) showed that the models are robust.

Rural Wage Growth during Phase III: What Explains the Decline?

This section examines the role of inflation in the recent decline in rural wage growth, *i.e.*, post 2012–13. This period was marked by episodes of marginal uptick in wage growth, with a spell of negative growth in real wages (Charts 2 and 3). One could identify a mix of events happening during this phase, not only on the domestic front but also globally, most of which

[11] As evident from a statistically significant coefficient of own lag term.

Chart 5: International Commodity Prices

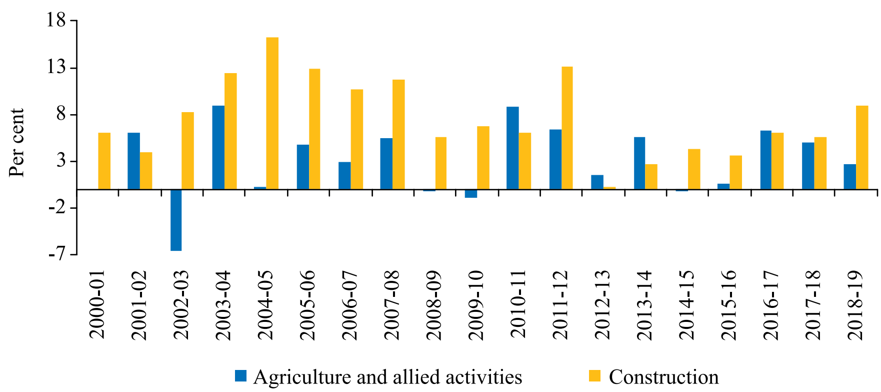


Source: World Bank Commodity Price Data (The Pink Sheet).

began around 2013-14, *viz.*, the global slowdown in growth and the collapse of international commodity prices (Chart 5).

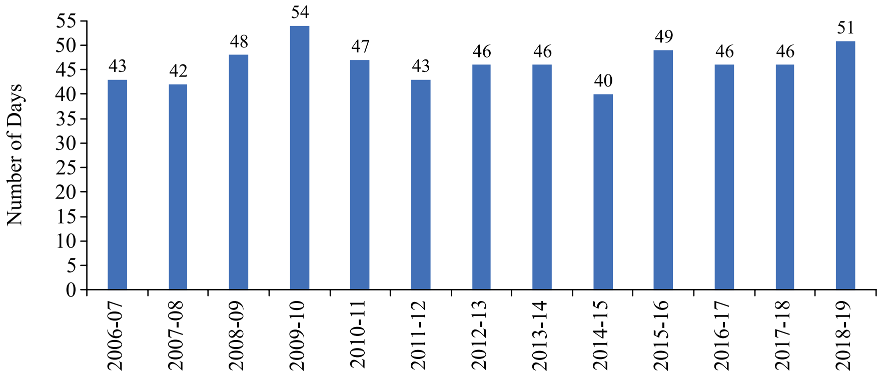
Domestically, the economy suffered two consecutive droughts in 2014-15 and 2015-16. As a result, growth in agricultural GDP turned weak. The construction sector, which grew at a fast pace during 2000-12 and was the major driver of rural non-farm employment during this period, slowed down significantly (Chart 6). These factors, along with the moderation in domestic inflation, could have suppressed rural wage growth. The employment under MGNREGS was relatively lower during this period as compared with 2008-09 to 2011-12 (Chart 7).

Chart 6: Sectoral GDP Growth



Source: Ministry of Statistics and Programme Implementation (MoSPI).

Chart 7: Average Person Days per Household under MGNREGS



Source: Ministry of Rural Development and the official website of MGNREGS.

The empirical exercise to examine the factors behind the recent slowdown in rural wage growth was undertaken using data for the period November 2013 to February 2019. The wage-price relationship was also examined for this phase, after controlling for factors like MGNREGS, construction sector slackness and rainfall deviations from normal.[12] Furthermore, the analysis was undertaken using state-level data to ensure that the sample reflects all the variabilities in the variables. A dynamic panel data analysis with the Arellano–Bover/Blundell–Bond system GMM structure was the most appropriate econometric technique available for this part of the study.[13] The explanatory variables were chosen as per the events discussed above. The

[12] The dynamics of construction sector wage seem to be much more complicated as compared with agricultural wage on account of the influence of both rural and urban macroeconomic factors. Due to data limitations, this study, did not examine the reasons behind the deceleration in construction sector wage growth during phase III.

The characterisation of the explanatory variables used in the model is as follows: rainfall departure was treated as an independent variable, MGNREGS wage was treated as a predetermined variable and CPI-RL/CPI-Rural and construction wage were treated as endogenous variables in the model.

[13] The recent literature on dynamic panel data has begun to focus on panels in which both the number of cross-sectional observations (N) and the number of time series observations (T) are large. It is obvious that the availability of data with greater frequency is a primary contributor to this growing literature. In such datasets non-stationarity becomes a concern with the increase in T. Two important techniques to estimate such dynamic panels available in the literature are mean group (MG) and pooled mean group (PMG) models. For examples, see Blackburne and Frank (2007).

In this study, however, T is only 5 years which cannot be considered as a sufficiently large time period in a macroeconomic study of this kind (although on a monthly basis N<T in our dynamic panel model). Therefore, we do not use PMG/MG estimator in this study. Further, both PMG/MG estimators are used to bring out short-run and long-run dynamics of the variables, which is not a concern in this part of the study. Such dynamics have already been tested and elaborated in the subsection titled 'Rural Wage-Price Dynamics'.

MGNREGS wage reflects some sort of a proxy for minimum wage or a government guaranteed base price for rural labour. The MGNREGS wages and rural wages are expected to be positively related. One could also expect rural agricultural wages to be positively related with construction wages, as a higher wage in the construction sector would attract unskilled labourers from agriculture, which could then drive agricultural wages up by creating a shortage of agricultural labourers. While we do not have output/unemployment rate as an explanatory variable in the model due to data limitations, construction wage could also represent, *albeit* in a limited manner, the overall health of the economy (equation (2) in section II of the paper). Furthermore, the rainfall deviation from normal level (LPA) would affect agricultural output as well as the demand for both agricultural and non-agricultural labourers. Greater the deviation of rainfall from normal, lower would be the wage. Apart from the demand aspect, we expect rainfall deviations to also reflect the associated change in agricultural productivity. Nevertheless, the literature suggests that the impact of agricultural productivity on rural wage variations has declined over the years (Himanshu and Kundu, 2016).

All variables were converted to their natural logarithms. Data for state-wise MGNREGS wage were collected from the Ministry of Rural Development and the official website of MGNREGS. Arellano–Bond tests for zero autocorrelation in first-differenced errors confirmed the robustness of the models.

The results of the regression analysis show that from November 2013 to February 2019 (new wage series) changes in rural prices had a positive and significant impact on changes in nominal agricultural wages in a contemporaneous manner (Tables 5a and 5b). The regression equations in Table 5a include CPI-RL as the measure of rural prices, while those in Table 5b include the all-India CPI-Rural index. The availability of new all-India CPI-Rural index (base 2012=100) from January 2011 allowed us to look at the impact of change in all India rural prices on agricultural wages, which was not possible with the use of CPI-RL due to its sectoral representation of CPI. The coefficient of price with lag *t-1* also suggests that wages take a month time to adjust to changes in prices. This means that the next period's real wage will not show a complete adjustment, even when the inflationary/deflationary shock is over. The results also show a positive and statistically significant impact of construction wages on agricultural wages

Table 5a: Results of the Dynamic Panel Data Models

Dependent variable: Agricultural wage						
Model	**I**		**II**		**III**	
Explanatory Variables	**Coeffi-cient**	**Z value**	**Coeffi-cient**	**Z value**	**Coeffi-cient**	**Z value**
1	**2**	**3**	**4**	**5**	**4**	**5**
Agricultural wage (t-1)	0.21	3.12***	0.21	3.50***	0.22	3.74***
Agricultural wage (t-2)	-0.07	-0.79	-0.06	-0.63	-0.09	-0.85
MGNREGS wage	0.16	2.40**	0.16	2.38**	0.16	2.38**
MGNREGS wage (t-1)	-0.01	-0.22	-0.01	-0.31	-0.005	-0.10
MGNREGS wage (t-2)	-0.04	-0.74	-0.03	-0.56	-0.04	-0.63
CPI-RL	0.31	3.33***	0.31	3.29***	0.29	3.29***
CPI-RL (t-1)	-0.16	-1.92*	-0.14	-1.70*	-0.15	-1.60
CPI-RL (t-2)	0.11	0.79	0.08	0.55	0.09	0.71
Construction Wage	0.74	9.44***	0.74	9.29***	0.75	9.85***
Construction Wage (t-1)	-0.13	-1.80*	-0.13	-1.94*	-0.15	-1.99**
Construction Wage (t-2)	0.15	1.85*	0.14	1.70*	0.17	1.80*
Rainfall Departure	-0.003	-1.65*	-0.003	-1.89*	-0.002	-1.36
Rainfall Departure (t-4)	-	-	-0.0004	-0.40	-	-
Rainfall Departure (t-12)	-	-	-	-	-0.003	-1.70*
Constant	-1.76	-3.06***	-1.74	-2.99***	-1.67	-2.78***
Arellano–Bond test for zero autocorrelation in first differenced errors (Order 2)#	Z = 0.45 [0.65]		Z = 0.27 [0.79]		Z = 0.32 [0.75]	
Wald chi^2(12;13;13)	2297.44*** [0.00]		2753.81*** [0.00]		2259.26*** [0.00]	
No. of observations	1170		1125		976	

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively; #: The null hypothesis is no autocorrelation.

Note: 1. Figures in [ ] indicate probability.

2. Sargan test of overidentifying restrictions (Null Hypothesis: Overidentifying restrictions are valid) results for models I, II and III are: chi^2 (1304) = 1421.06 [Prob. value = 0.01], chi^2 (1279) = 1453.03 [Prob. value = 0.00] and chi^2 (1140) = 1240.41 [Prob. value = 0.02], respectively. The distribution of the Sargan test is known only when the errors are independently and identically distributed. For this reason, the Sargan test does not produce a test statistic when robust standard errors are obtained in this model. The coefficients reported in the table correspond to robust standard errors. Therefore, the Sargan test results were obtained by specifying the model without the command for robust standard errors. The coefficients remained almost unchanged under both the models. We attribute the rejection of the null hypothesis under Sargan test, wherever applicable, to the possible presence of heteroscedasticity in the data generating process, thus, requiring to go for a robust standard error model (Arellano and Bond, 1991).

Table 5b: Results of the Dynamic Panel Data Models

Dependent variable: Agricultural wage						
Model	**I**		**II**		**III**	
Explanatory Variables	Coeffi-cient	Z value	Coeffi-cient	Z value	Coeffi-cient	Z value
1	**2**	**3**	**4**	**5**	**4**	**5**
Agricultural wage (t-1)	0.20	2.88***	0.20	3.24***	0.21	3.41***
Agricultural wage (t-2)	-0.08	-0.84	-0.08	-0.79	-0.10	-0.96
MGNREGS wage	0.15	1.46	0.15	1.47	0.15	1.48
MGNREGS wage (t-1)	-0.04	-0.67	-0.04	-0.69	-0.03	-0.46
MGNREGS wage (t-2)	-0.06	-1.09	-0.06	-1.17	-0.07	-1.22
CPI-Rural	0.28	2.70***	0.28	2.66***	0.27	2.83***
CPI-Rural (t-1)	-0.08	-1.14	-0.08	-1.08	-0.08	-1.16
CPI-Rural (t-2)	0.13	2.90***	0.13	2.79***	0.13	2.80***
Construction Wage	0.75	10.46***	0.75	10.36***	0.76	10.97***
Construction Wage (t-1)	-0.11	-1.58	-0.12	-1.69*	-0.14	-1.78*
Construction Wage (t-2)	0.18	2.11**	0.17	2.04**	0.20	2.07**
Rainfall Departure	-0.003	-1.58	-0.003	-1.89*	-0.002	-1.35
Rainfall Departure (t-4)	-	-	0.001	0.42	-	-
Rainfall Departure (t-12)	-	-	-	-	-0.003	-1.49
Constant	-1.54	-3.25***	-1.56	-3.30***	-1.45	-3.25***
Arellano–Bond test for zero autocorrelation in first differenced errors (Order 2)#	Z = 0.56 [0.57]		Z = 0.49 [0.62]		Z = 0.58 [0.56]	
Wald $chi^2(12;13;13)$	1736.42*** [0.00]		2045.44*** [0.00]		1971.06*** [0.00]	
No. of observations	1170		1125		976	

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively; #: The null hypothesis is no autocorrelation.

Note: 1. Figures in [ ] indicate probability.

2. Sargan test of overidentifying restrictions (Null Hypothesis: Overidentifying restrictions are valid) results for models I, II and III are: chi^2 (1304) = 1371.04 [Prob. value = 0.10], chi^2 (1279) = 1395.67 [Prob. value = 0.01] and chi^2 (1140) = 1197.89 [Prob. value = 0.11], respectively. Please see note 2 to table 5a.

and their impact is realised even with a lag of two months as indicated by the coefficient of construction wage with two months lag, which implies that not only the current period construction wage has a positive impact on agricultural wage, but construction wage with a two-period lag also impacts agricultural wages positively. This establishes the role of rural non-farm sector in driving agricultural wages. Unlike in the past, MGNREGS did not create a significant impact on agricultural wages during this period, with its coefficients not being statistically significant (when CPI-Rural index is used).

Section VI
Conclusion

The main objective of the paper is to study the relationship between rural wage growth and inflation over the past 15 years and examine the risk of a wage-price spiral to the inflation trajectory in India. Another objective of the paper is to identify the factors responsible for the recent slowdown in agricultural wage growth.

The short-run and long-run dynamics of changes in rural wages and prices were examined by studying the lead-lag relationships using cross-correlation coefficients. The paper also applied cointegration and VECM methods to analyse short-run and long-run dynamics between wages and prices. To ascertain the determinants of the deceleration in agricultural wage growth in recent years the paper used a dynamic panel data model with the Arellano–Bover/Blundell–Bond system GMM structure.

The results exhibited that, in the long-run, both nominal agricultural wages and non-agricultural wages have statistically significant positive relationship with prices. The results of the panel regression analysis showed that from November 2013 to February 2019, rural prices had a positive and significant contemporaneous impact on nominal agricultural wages. Nominal wages also displayed stickiness in the short-run. Proxied by construction sector wage, the rural non-farm sector wages demonstrated a positive and statistically significant relationship with the agricultural wage growth, indicating the role of rural non-farm sector wage behaviour in influencing agricultural wages. In terms of policy implications, weaker evidence on wage-push induced risks to the inflation trajectory and stronger evidence of inflation induced wage pressures suggest limited risk of a wage-price spiral to the price stability goal under the flexible inflation targeting framework in India.

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Appendix

Table A.1: Test Results for Statistical Break in year-on-year Growth in Agricultural Wage
Quandt-Andrews Unknown Breakpoint Test[14]

Statistic	Value	Prob.
Maximum LR F-Statistic (2014 M11)	47.241	0.000***
Maximum Wald F-Statistic (2014 M11)	94.482	0.000***
Exp LR F-Statistic	18.479	0.000***
Exp Wald F-Statistic	42.099	0.000***
Ave LR F-Statistic	1.573	0.141
Ave Wald F-Statistic	3.146	0.141
Period: January 2002 to November 2017.		

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Note: Probabilities calculated using Hansen's (1997) method.

Table A.2: Test Results for Statistical Break in Year-on-Year Growth in Non-agricultural Wage
Quandt-Andrews Unknown Breakpoint Test[15]

Statistic	Value	Prob.
Maximum LR F-Statistic (2014 M11)	24.954	0.000***
Maximum Wald F-Statistic (2014 M11)	49.908	0.000***
Exp LR F-Statistic	7.352	0.000***
Exp Wald F-Statistic	19.813	0.000***
Ave LR F-Statistic	2.080	0.057
Ave Wald F-Statistic	4.160	0.057
Period: January 2002 to November 2017.		

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Note: Probabilities calculated using Hansen's (1997) method.

Table A.3: Unit Root Test Results (Phillips–Perron Test)[16]

	LAGWG	D(LAGWG)	LMASONWG	D(LMASONWG)	LCPI-RL	D(LCPI-RL)
Adj. t-Statistic	7.326	-7.392***	6.931	-2.323**	8.376	-3.757***
P-value[#]	1.000	0.000	1.000	0.020	1.000	0.000
Sample Period: January 2001 to October 2013.						

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.
Note: #MacKinnon (1996) one-sided p-values.

Table A.4a: Pair-wise Granger Causality Test Results

Null Hypothesis	Obs.	F-Statistic	Prob.
D(CPI-RL) does not Granger Cause D(AGWG)	151	2.95	0.06*
D(AGWG) does not Granger Cause D(CPI-RL)	151	7.50	0.00***
D(CPI-RL) does not Granger Cause D(MASONWG)	151	2.90	0.06*
D(MASONWG) does not Granger Cause D(CPI-RL)	151	12.63	0.01***
Sample Period: January 2001 to October 2013.			

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Table A.4b: Pair-wise Granger Causality Test Results

Null Hypothesis	Obs.	F-Statistic	Prob.
D(CPI-RL) does not Granger Cause D(AGWG)	61	2.72	0.07*
D(AGWG) does not Granger Cause D(CPI-RL)	61	0.61	0.55
D(CPI-RL) does not Granger Cause D(MASONWG)	61	0.85	0.43
D(MASONWG) does not Granger Cause D(CPI-RL)	61	0.96	0.39
Sample Period: November 2013 to February 2019.			

***, ** & *: Represent significance at 1 per cent, 5 per cent and 10 per cent levels of significance, respectively.

Table A.5: Results of the Cointegration Tests between Agricultural Wage and CPI-RL

Series: LAGWG LCPI-RL				
Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.[$]**
None[#]	0.163	27.883	15.495	0.000
At most 1	0.007	1.030	3.841	0.310
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.[$]**
None[#]	0.163	26.853	14.265	0.000
At most 1	0.007	1.030	3.841	0.310
Sample period: January 2001 to October 2013; Sample period (adjusted): April 2001 to October 2013.				
Observations: 151 after adjustments.				

#: Denotes rejection of the hypothesis at the 0.05 level; $: Denotes MacKinnon-Haug-Michelis (1999) p-values.

Note: Both Trace and Max Eigen value tests indicate the presence of one cointegrating vector.

Table A.6: Results of the Cointegration Tests between Non-agricultural Wage and CPI-RL

Series: LMASONWG LCPI-RL				
Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.[$]**
None[#]	0.255	45.970	15.495	0.000
At most 1	0.008	1.191	3.841	0.275
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.[$]**
None[#]	0.255	44.779	14.265	0.000
At most 1	0.008	1.030	3.841	0.275
Sample period: January 2001 to October 2013; Sample period (adjusted): March 2001 to October 2013.				
Observations: 152 after adjustments.				

#: Denotes rejection of the hypothesis at the 0.05 level; $: MacKinnon-Haug-Michelis (1999) p-values.

Note: Both Trace and Max Eigen value tests indicate the presence of one cointegrating vector.

Table A.7a: VEC Residual Portmanteau Tests for Autocorrelations

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
Series: LAGWG LCPI-RL					
Null Hypothesis: No residual autocorrelations up to lag h.					
1	0.51	-	0.51	-	-
2	6.26	0.39	6.34	0.39	6
Sample period: January 2001 to October 2013.					
Observations: 152 after adjustments.					

*: df and Prob. may not be valid for models with exogenous variables.

Note: 1. Test is valid only for lags larger than the VAR lag order.

2. df is degrees of freedom for (approximate) chi-square distribution after adjustment for VEC estimation (Bruggemann, *et al.*, 2005).

Table A.7b: VEC Residual Portmanteau Tests for Autocorrelations

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
Series: LMASONWG LCPI-RL					
Null Hypothesis: No residual autocorrelations up to lag h.					
1	0.46	-	0.47	-	-
2	4.86	0.56	4.92	0.55	6
Sample period: January 2001 to October 2013.					
Observations: 152 after adjustments.					

*: df and Prob. may not be valid for models with exogenous variables.

Note: 1. Test is valid only for lags larger than the VAR lag order.

2. df is degrees of freedom for (approximate) chi-square distribution after adjustment for VEC estimation (Bruggemann, *et al.*, 2005).

Table A.8a: VEC Residual Serial Correlation LM Tests

Series: LAGWG LCPI-RL						
Null Hypothesis: No serial correlation at lag h.						
Lags	**LRE* Stat**	**df**	**Prob.**	**Rao F-Stat**	**df**	**Prob.**
1	0.51	4	0.25	1.36	(4, 286.0)	0.25
2	6.26	4	0.20	1.51	(4, 286.0)	0.20
Null Hypothesis: No serial correlation at lags 1 to h.						
Lags	**LRE* Stat**	**df**	**Prob.**	**Rao F-Stat**	**df**	**Prob.**
1	5.43	4	0.27	1.36	(4, 286.0)	0.25
2	7.03	8	0.53	0.88	(8, 282.0)	0.53
Sample period: January 2001 to October 2013.						
Observations: 152 after adjustments.						

*: Denotes Edgeworth expansion corrected likelihood ratio statistic.

Table A.8b: VEC Residual Serial Correlation LM Tests

Series: LMASONWG LCPI-RL						
Null Hypothesis: No serial correlation at lag h.						
Lags	**LRE* Stat**	**df**	**Prob.**	**Rao F-Stat**	**df**	**Prob.**
1	8.41	4	0.08	2.13	(4, 286.0)	0.08
2	4.45	4	0.35	1.12	(4, 286.0)	0.35
Null Hypothesis: No serial correlation at lags 1 to h.						
Lags	**LRE* Stat**	**df**	**Prob.**	**Rao F-Stat**	**df**	**Prob.**
1	8.41	4	0.08	2.13	(4, 286.0)	0.08
2	9.45	8	0.31	1.19	(8, 282.0)	0.31
Sample period: January 2001 to October 2013.						
Observations: 152 after adjustments.						

*: Denotes Edgeworth expansion corrected likelihood ratio statistic.

Chart A.1: VECM CUSUM Test (Series: LAGWG LCPIRL with Exogenous Variables)

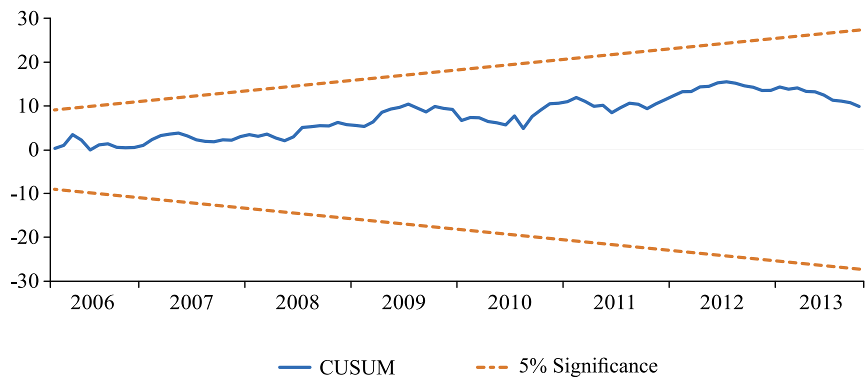
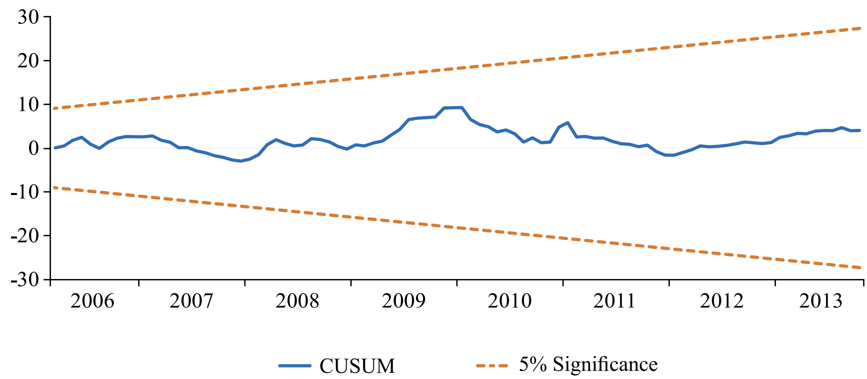


Chart A.2: VECM CUSUM Test (Series: LMASONWG LCPIRL with Exogenous Variables)



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Using Rational Expectations to Predict Inflation

Purnima Shaw*

Inflation expectations of households relate to their varying consumption baskets. This is often cited as a reason for expected inflation diverging from actual inflation, not only in India but also in other countries. As the paper finds that households' inflation expectations in India do not satisfy the statistical conditions of rationality, it aggregates inflation expectations to estimate the mean of an optimal distribution derived from the literature. These mean estimates turn out to be rational, which could be useful to generate forecasts of the headline inflation. Based on an out-of-sample performance analysis, the paper establishes that raw expectations of Indian households, when transformed into rational inflation expectations, contain forward-looking information comparable with that of the professional forecasters. In addition, the width of the confidence band for transformed expectations is much narrower than those obtained from pure time-series forecasts.

JEL Classification : C53, D84, E31

Keywords : Forecasting, inflation, rational expectations

Introduction

Households undertake future financial decisions based on their inflation expectations (Axelrod *et al.*, 2018). Financial decisions include wage negotiations, expenditure, savings and investments, among others, and these in turn form one of the important determinants of future inflation (Bullard,

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2016). Measuring and projecting inflation is one of the important aspects of conduct of monetary policy under an inflation targeting regime. Besides, gauging households' inflation expectations is also important because one of the key objectives of monetary policy is to anchor inflation expectations, which in turn can help achieve the price stability objective. Additionally, inflation expectations may also help in improving the projections of actual inflation. Hence, inflation expectations form an essential input to the central banks' policy framework.

Different measures of inflation expectations include expectations of professional forecasters, households, firms as well as market-based measures of expectations. All of these have their own advantages and disadvantages. For example, professional forecasters and market participants are well-informed and are able to provide both short-term and long-term inflation expectations. On the other hand, data on market-based expectations are available for a long time-series and are expected to contain more information than the expectations of professional forecasters. Further, there have been recent studies on extracting inflation expectations at high frequency using real-time Google Trends data (Bicchal and Durai, 2019; Guzman, 2011). Unlike household surveys, the internet-based measure does not suffer from limitations of time, cost, requirement of designing an effective interactive questionnaire, and the need for efforts in extracting the true inflation expectations of the respondents. Data extraction from Google Trends is automated and can be computed at high frequencies. Guzman (2011) used Google Trends data to estimate inflation expectations and established that these estimates outperform the low frequency measures of expectations in terms of accuracy, predictive power and rationality[1]. On the other hand, inflation expectations using search query data in Google Trends are rational and bear a long-term relationship with actual inflation in the case of India (Bicchal and Durai, 2019). However, these high frequency data may help address the data gaps and also improve inflation forecasts, but they may never work as an alternative to households' inflation expectations due to their lesser penetration and cross-sectional coverage than the latter. Thus, even with the availability of alternative measures of inflation expectations, the households' inflation expectations will remain a vital input to the central banks for policymaking.

[1] According to Muth (1961), the probability distribution of rational expectations tends towards the probability distributions of outcomes for the same information set.

The Reserve Bank of India (RBI) started conducting the Inflation Expectations Survey of Households (IESH) from September 2005. Other countries conducting such a survey at the time were the United States (US), Australia, United Kingdom (UK), New Zealand, Sweden, South Africa, the Czech Republic, and Indonesia (RBI, 2010). The survey captures household expectations on the direction of general price movement for three months-ahead and one year-ahead horizon at the aggregate level as well as for various product groups including food products, non-food products, household durables, cost of housing and the cost of services. Respondents' perception on the current inflation rate and their expectations in quantitative terms are also recorded for both horizons. The survey, being currently conducted in 18 cities in India, covers different profiles of respondents. Other details about the survey are presented in the Appendix.

There is a large amount of research on understanding the characteristics of inflation expectations and its formation, which includes Menz and Poppitz (2013), Ghosh *et al.,* (2017), Vellekoop and Wiederholt (2017) and Sharma and Bicchal (2018) among the recent ones. Since households provide their expectations about inflation in the future, as a researcher one would like to check how efficiently they can foresee inflation and, therefore, how much relevance needs to be attached to their expectations. For Brazil and Turkey, the inclusion of survey-based expectations in a state-space framework model for inflation forecasting leads to superior forecasting performance compared with forecasting models without survey expectations (Altug and Çakmaklı, 2016). On the other hand, in the Indian case, quantification of directional expectations are found to track actual inflation better than the simple average of the quantitative expectations on the future inflation rate (Das *et al.*, 2018). However, it is observed that although these estimates track inflation better than the raw responses and are comparatively much closer to the actual inflation, they are also biased and very often divergent. In light of this evidence, this paper examines the quantitative responses of Indian households' inflation expectations.

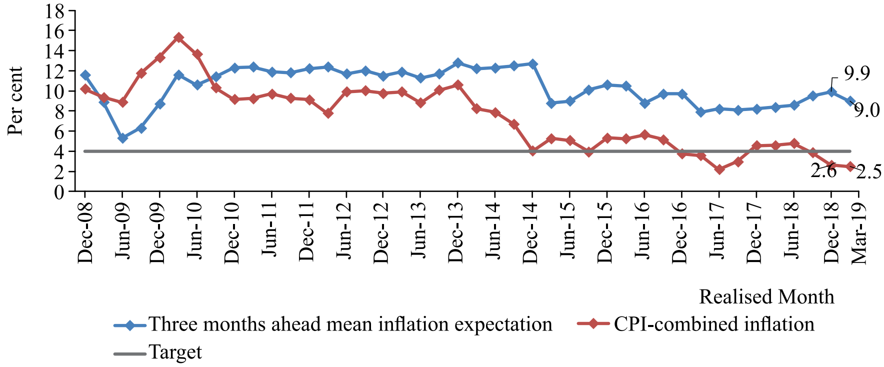
This paper utilises the idea of an optimal probability distribution discussed by Batchelor (2006). Each household is exposed to three kinds of information on inflation: the household-specific estimate based on its own consumption basket; an estimate of inflation based on its time-series history; and the policy target. Regarding the last two, Batchelor (2006) assumes that inflation at a given time point may either realise the value of the policy target with an unknown probability or realise the inflation projection based on its time-series history (subject to an error) with the remaining probability. This unknown probability is explained as the chance that the policy target will be attained and it is considered as an index of the credibility of policy. It differs across households due to various factors. If a household is rational in revealing its expectations while responding to the survey, then the distribution of the response coincides with an optimal distribution. It may be of interest to check whether households' expectations coincide with the optimal distribution, implying that they are rational. If this is true, the expectations should provide a direct inflation forecast with an acceptable error level. If not, then it can be concluded that the survey provides only the first information, *i.e.*, the household specific estimates and respondents do not make use of the remaining two pieces of information while revealing their inflation expectations. If the second statement is true, then the next question is whether household specific estimates can be aggregated in such a way that they satisfy the tests of rationality; and, third, whether this modified information can help in predicting the actual inflation.

Section II explains the behaviour of the Indian inflation expectations data and checks for their rationality using tests from the literature. Theoretical background on the deduction of optimal distribution based on the literature, as presented by Batchelor (2006) is described in Section III. This forms the basis of empirical analysis of this paper. Section IV elaborates the methodology for estimation of various parameters of optimal distribution, followed by the performance of computed mean estimates of the optimal distribution using data on inflation expectations in India. The paper concludes with remarks on the main findings.

Section II
Inflation Expectations in India

The analysis in the paper is based on data on three months-ahead mean inflation expectations of households from the IESH from September 2008. The Consumer Price Index Combined (CPIC) inflation series with base year 2012 is back-casted using the Consumer Price Index of Industrial Workers (CPIIW). The inflation expectations for the quarters for which they were expected and the quarterly averaged CPIC inflation is displayed in Chart 1. It is evident from the chart that inflation expectations in India are biased, *i.e.*, there is an almost unidirectional yet varying gap between the expectations and the actual inflation. The reason for such a bias is often alluded to variability in the components, quality and quantity of items in the consumption baskets

Chart 1: Inflation Expectations *vis-à-vis* Actual Inflation



Source: Inflation Expectations: Reserve Bank of India,
CPIC: Ministry of Statistics and Programme Implementation, CPIIW: Labour Bureau.

of the respondents. Inflation expectations of the households in the US also show an upward bias (Axelrod *et al.,* 2018). Nevertheless, the inflation expectations have decreased from the December 2014 round onwards, in line with the generally declining trend in inflation from March 2014 onwards.

Inflation expectations are said to be weakly rational if they are unbiased and form efficient inflation forecasts (Sharma and Bicchal, 2018). Using Wholesale Price Index (WPI), CPIIW and CPI Food inflation, they establish that inflation expectations in India are not weakly rational. The same tests have been performed below using the CPIC inflation. The test for unbiasedness is as follows:

$$y_t = \alpha + \beta y^e_{t-3} + \epsilon_t \qquad (1)$$

$$H_0: \begin{pmatrix} \alpha \\ \beta \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \; against \; H_1: \begin{pmatrix} \alpha \\ \beta \end{pmatrix} \neq \begin{pmatrix} 0 \\ 1 \end{pmatrix},$$

y_t = quarterly (averaged) CPIC inflation at t

y^e_{t-3} = mean inflation expectation for t made at $t - 3$, *i.e.,* t-period ahead mean inflation expectation of households, obtained from the survey conducted in t-3

ϵ_t = unexplained part of the model

The joint null hypothesis is tested using Wald test with autocorrelation-corrected standard errors using the Newey–West procedure (Newey and West, 1987). The results of this test, displayed in Table 1, indicate that inflation expectations are upward biased.

Table 1: Test for Unbiasedness of Inflation Expectations

Parameter	Estimate	Standard Error
α	1.049	5.251
β	0.622	0.451
Adjusted R-squared = 0.101		
P value for F-statistic for the joint hypothesis $\alpha = 0, \beta = 1$ is 0.000		

An alternative form of the test for unbiasedness suggested by Holden and Peel (1990) is:

$$y_t - y^e_{t-3} = \alpha + \epsilon_t$$

$$H_0: \alpha = 0 \text{ against } H_1: \alpha \neq 0 \tag{2}$$

The null hypothesis is tested using the Wald test with corrected standard errors using the Newey–West procedure. The results of this test displayed in Table 2 corroborate the results in Table 1.

The robustness of the above results is then checked by decomposing the mean squared forecast error in its bias, variance and covariance proportions following Sharma and Bicchal (2018). The bias proportion of 0.455 in Table 3 is large, indicating high systematic errors in the households' inflation expectations.

In order to test the efficiency of inflation expectations, the following test is considered:

$$y_t - y^e_{t-3} = \alpha + \sum_{j=1}^{k} \beta_j \left(y_{t-j} - y^e_{t-j-3}\right) + \epsilon_t \tag{3}$$

$$H_0: \begin{pmatrix} \alpha \\ \boldsymbol{\beta} \end{pmatrix} = \begin{pmatrix} 0 \\ \mathbf{0} \end{pmatrix} \text{ against } H_1: \begin{pmatrix} \alpha \\ \boldsymbol{\beta} \end{pmatrix} \neq \begin{pmatrix} 0 \\ \mathbf{0} \end{pmatrix},$$

$$\text{where, } \boldsymbol{\beta} = (\beta_1 \ \ \beta_2 \ \ \ldots \ \ \beta_K)'$$

k = *Number of lags to be determined using Akaike Information Criterion*

Table 2: Alternative Test for Unbiasedness of Inflation Expectations

Parameter	Estimate	P value
α	-2.867	0.002

Table 3: Decomposition of mean squared forecast error

Bias Proportion	Variance Proportion	Covariance Proportion
0.455	0.112	0.433

Table 4: Test for Efficiency of Inflation Expectations

P value for F-statistic for the joint hypothesis $\alpha = \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$	=	0.000
Adjusted R-squared	=	0.685

The joint hypothesis is tested using the Wald test and the results are reported in Table 4.

The rejection of the joint hypothesis implies that the inflation expectations are not efficient. Also, past errors committed by the households in their inflation expectations explain about 68 per cent of the information about the current error. This information remains largely unused.

It may be concluded from the above analysis that the households' inflation expectations are not weakly rational. Therefore, further tests for strong rationality are not undertaken. These results indicate that households do not make use of all the available information.

In such a scenario, the objective of this paper is to explore whether the households' inflation expectations can be aggregated in a different manner based on a theoretical framework and then verify whether this modified information turns out to be rational.

Section III
Theoretical Background

This section explains the concept of optimal distribution of inflation expectations empirically as deduced by Batchelor (2006). As explained above, households are exposed to three types of information on inflation. The first information is the household's estimate of future inflation based on its own consumption basket. Let y_{it} be the specific estimate of inflation of i^{th} household or i^{th} group of respondents for time t made at time $(t - 3)$. Let y_t be the target variable, *i.e.*, inflation at t^{th} time point. The household-specific estimate is modelled as:

$$\begin{gathered} y_{it} = y_t + u_{it}; \quad u_{it} \sim N(0,\, \tau_{it}{}^2) \\ (y_{it} | y_t) \sim N(y_t, \tau_{it}{}^2) \end{gathered} \tag{4}$$

u_{it} = unexplained part of the above model;

${\tau_{it}}^2$ = variability in the responses.

Let π_{it} be the probability that the policy target will be enforced, defined as an index of policy credibility. The probability π_{it} differs among households or group of respondents for the reasons alluded to earlier.

The second type of information is the time-series prediction of inflation for time t, denoted as y_{ht}. The third information is y_{gt}, the policy target. Inflation is modelled as:

$$\begin{aligned} y_t &= y_{gt} \quad \textit{with probability } \pi_{it}\,; \\ &= y_{ht} + u_{ht}, \quad u_{ht} \sim N(0, \tau_{ht}^{\ 2}) \textit{ with probability } (1-\pi_{it})\,; \end{aligned} \tag{5}$$

u_{ht} is the error in prediction of inflation for t^{th} time.

If a respondent is rational in his/her expectation about future inflation, then he/she should use all the above mentioned information to arrive at a statistically optimal conditional distribution based on DeGroot (1970) as given below:

$$(y_t|y_{it}) \sim N[\mu_{it}, \ \sigma_{it}^{\ 2}]\,;$$

$$\sigma_{it}^{\ 2} = \frac{V(y_{it}|y_t)\,V(y_t)}{V(y_{it}|y_t) + V(y_t)} = \frac{\tau_{it}^{\ 2}(1-\pi_{it})\left\{\pi_{it}\left(y_{gt}-y_{ht}\right)^2 + \tau_{ht}^{\ 2}\right\}}{\tau_{it}^{\ 2} + (1-\pi_{it})\left\{\pi_{it}\left(y_{gt}-y_{ht}\right)^2 + \tau_{ht}^{\ 2}\right\}};$$

$$\mu_{it} = \frac{\sigma_{it}^{\ 2}}{V(y_{it}|y_t)} y_{it} + \frac{\sigma_{it}^{\ 2} E(y_t)}{V(y_t)} = \frac{\sigma_{it}^{\ 2}}{\tau_{it}^{\ 2}} y_{it} + \frac{\sigma_{it}^{\ 2}\{\pi_{it} y_{gt} + (1-\pi_{it}) y_{ht}\}}{(1-\pi_{it})\left\{\pi_{it}\left(y_{gt}-y_{ht}\right)^2 + \tau_{ht}^{\ 2}\right\}}; \tag{6}$$

$$= w_{it} y_{it} + (1-w_{it})\{\pi_{it} y_{gt} + (1-\pi_{it}) y_{ht}\};$$

$$w_{it} = \frac{\sigma_{it}^{\ 2}}{\tau_{it}^{\ 2}} = \frac{(1-\pi_{it})\left\{\pi_{it}\left(y_{gt}-y_{ht}\right)^2 + \tau_{ht}^{\ 2}\right\}}{\tau_{it}^{\ 2} + (1-\pi_{it})\left\{\pi_{it}\left(y_{gt}-y_{ht}\right)^2 + \tau_{ht}^{\ 2}\right\}};$$

Here, μ_{it} is the posterior mean of the i^{th} group of respondents with variability $\sigma_{it}^{\ 2}$. The i^{th} group of respondents' modified inflation expectation estimate for time t given the expectations for the same time made at $(t - 3)$ is the estimate of μ_{it} with an error being the estimate of σ_{it}.

Section IV
Estimation of Parameters

The next step is to aggregate the survey-based households' inflation expectations to estimate μ_{it}, the mean of the optimal distribution using

Batchelor (2006) discussed in Section III. The estimate of μ_{it} denoted as $\widehat{\mu_{it}}$ is the estimated modified expectation of the unknown inflation for time period t given the expectations for t made at time $(t-3)$. As ${\sigma_{it}}^2$ denotes the variability in the responses around mean μ_{it}, the estimate of σ_{it} denoted by $\widehat{\sigma_{it}}$ is taken as the error estimate of $\widehat{\mu_{it}}$. The computation of $\widehat{\mu_{it}}$ and $\widehat{\sigma_{it}}$ is done using the three months-ahead mean inflation expectations made at time $(t-3)$ for time t. The expression for μ_{it} and σ_{it} involves other parameters y_{it}, τ_{it}^2, π_{it}, y_{gt}, y_{ht} and τ_{ht}^2, the estimation of which are discussed below.

- y_{it} is the specific estimate of inflation of i^{th} household or a group of respondents for time t made at time $(t-3)$. The group of respondents are considered here as cities. Hence, the estimate of y_{it}, denoted by $e[i]_t^{(t-3)}$, is considered as the i^{th} city's three months-ahead mean inflation expectation for t made at time $(t-3)$.
- τ_{it}^2 is the variability in the inflation expectations made at time $(t-3)$ for time t by the i^{th} group or category of respondents. This is estimated as:

$$\widehat{{\tau_{it}}^2} = \frac{1}{(n_i-1)}\sum_{j=1}^{n_i}\left(e[ij]_t^{(t-3)} - e[i]_t^{(t-3)}\right)^2 \qquad (7)$$

$e[ij]_t^{(t-3)}$ = three months-ahead mean inflation expectations of the j^{th} household in the i^{th} city for time t made at time $(t-3)$

n_i = number of respondent households in the i^{th} city.

- y_{gt}, the current policy target for inflation is taken as $\widehat{y_{gt}} = 4$ per cent.
- As the value for π_{it}, the index of policy credibility for time t by the i^{th} group of respondents, is not known, the proportion of survey respondents expecting inflation to be 4 per cent in the next quarter is considered as a proxy for this value. Since, quantitative inflation expectations captured in the survey are in buckets of 1 percentage points, consider,

$$I[i]_t^{(t-3)} = \frac{p[i]_{t(34)}^{(t-3)} + p[i]_{t(45)}^{(t-3)}}{2} \qquad (8)$$

$p[i]_{t(34)}^{(t-3)}$ = proportion of respondents in the i^{th} city at time $(t-3)$ expecting inflation in the range of 3 – 4 per cent for time t;

$p[i]_{t(45)}^{(t-3)}$ = proportion of respondents in the i^{th} city at time $(t-3)$ expecting inflation in the range of 4 – 5 per cent for time t;

Then, $I[i]_t^{(t-3)}$ is assumed as a proxy for π_{it}.

- The procedure followed for estimating y_{ht}, the time-series prediction of inflation for time t, based on its past realizations is explained as follows. For the purpose of modelling quarterly average inflation from March 2000, the stationarity was attained after taking first difference of the inflation series. The ARMA order was decided on the basis of correlogram of the first differenced inflation series, which indicated that there are significant spikes in the fourth and fifth lags of the autocorrelation and partial autocorrelation functions. Using the Akaike Information and Schwarz Criteria, ARIMA (5,1,5) was selected for modelling the inflation series. The residuals followed standard assumptions of a white noise process. Thus, out-of-sample three months-ahead inflation forecasts were computed for the period March 2017 to March 2019.

- τ_{ht}^2 is the variance of the errors committed in prediction of inflation, *i.e.*, y_{ht} for time t. τ_{ht}^2 is estimated as:

$$\widehat{\tau_{ht}}^2 = \{Standard\ Error(\widehat{y_{ht}})\}^2. \tag{9}$$

- The (100α) per cent Confidence Levels (CLs) of y_{ht} are:

$$\begin{aligned} Lower\ Confidence\ Level\ (LL) &= \widehat{y_{ht}} - \left(\tau_{\frac{\alpha}{2}}\sqrt{\widehat{\tau_{ht}}^2}\right); \\ Upper\ Confidence\ Level\ (UL) &= \widehat{y_{ht}} + \left(\tau_{\frac{\alpha}{2}}\sqrt{\widehat{\tau_{ht}}^2}\right); \end{aligned} \tag{10}$$

$$\tau_{\frac{\alpha}{2}}\ is\ the\ upper\ \frac{\alpha}{2}\ point\ of\ N(0,1)\ distribution.$$

- Using the above, approximate estimates of μ_{it} and σ_{it}^2 denoted by $\widehat{\mu_{it}}$ and $\widehat{\sigma_{it}}^2$ are:

$$\widehat{\mu_{it}} = \widehat{w_{it}} e[i]_t^{(t-3)} + (1-\widehat{w_{it}})\left\{I[i]_t^{(t-3)}\widehat{y_{gt}} + \left(1 - I[i]_t^{(t-3)}\right)\widehat{y_{ht}}\right\}; \quad (11)$$

$$\widehat{\sigma_{it}}^2 = \frac{\widehat{\tau_{it}}^2\left(1 - I[i]_t^{(t-3)}\right)\left\{I[i]_t^{(t-3)}\left(\widehat{y_{gt}} - \widehat{y_{ht}}\right)^2 + \widehat{\tau_{ht}}^2\right\}}{\widehat{\tau_{it}}^2 + \left(1 - I[i]_t^{(t-3)}\right)\left\{I[i]_t^{(t-3)}\left(\widehat{y_{gt}} - \widehat{y_{ht}}\right)^2 + \widehat{\tau_{ht}}^2\right\}}; \quad (12)$$

$$\widehat{w_{it}} = \frac{\widehat{\sigma_{it}}^2}{\widehat{\tau_{it}}^2}. \quad (13)$$

- These are aggregated to obtain an all-India level weighted estimate, $\widehat{\mu_t}$ with standard error $\widehat{\sigma_t}$ as given below:

$$\widehat{\mu_t} = \frac{\sum_i q_i \widehat{\mu_{it}}}{\sum_i q_i}; \quad (14)$$

$$\widehat{\sigma_t} = \sqrt{\frac{\sum_i q_i^2 \widehat{\sigma_{it}}^2}{(\sum_i q_i)^2}}; \quad (15)$$

Here the group of respondents are considered as cities and hence q_i's are taken as the city sample sizes. The (100α) per cent confidence levels for μ_t are obtained as below:

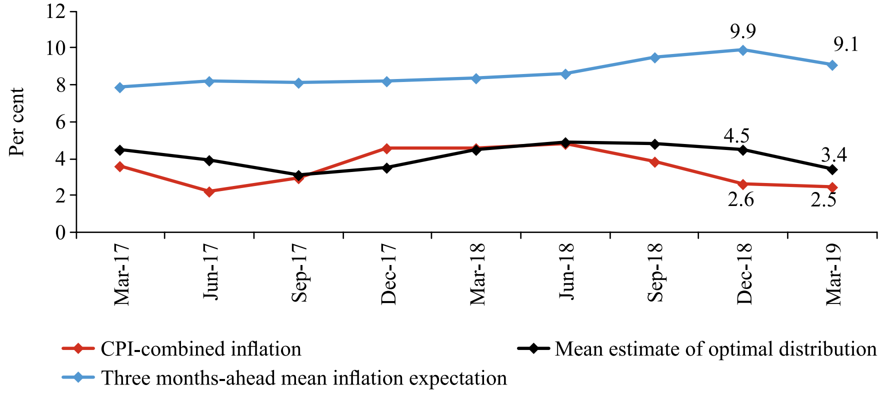
$$\begin{aligned} &Lower\ Confidence\ Level\ (LL') = \widehat{\mu_t} - \left(\tau_{\frac{\alpha}{2}}\widehat{\sigma_t}\right) \\ &Upper\ Confidence\ Level\ (UL') = \widehat{\mu_t} + \left(\tau_{\frac{\alpha}{2}}\widehat{\sigma_t}\right) \end{aligned} \quad (16)$$

Section V
Performance of Estimates

The mean estimates of the optimal distribution, their standard errors and confidence bands are computed using equations (11) – (16) considering three months-ahead mean inflation expectations from IESH data to predict inflation from March 2017 onwards to March 2019, *i.e.,* for 9 quarters. These estimates are plotted along with the mean of original inflation expectations and the CPIC inflation in Chart 2.

The next step of the analysis is to check whether the estimates pass the tests for weak rationality which were performed on the raw expectations in Section II. The two tests for unbiasedness using equations (1) and (2) and test for efficiency are performed on these 9 mean estimates of the optimal distribution (Tables 5, 6 and 8, respectively). Table 7 demonstrates the decomposition of the mean squared forecast errors for the 9 estimates.

Chart 2: Mean Inflation Expectations and New Estimates *vis-à-vis* Actual Inflation



All the results indicate that the new estimates are unbiased. Also, the errors committed earlier do not have explanatory power to explain the current error. Hence, it may be concluded that the new estimates obtained from the raw expectations using the optimal distribution are weakly rational.

Table 5: Test for Unbiasedness of Inflation Expectations

Parameter	Estimate	Standard Error
α	0.876	1.200
β	0.642	0.264
Adjusted R-squared = 0.068		
Pvalue for F-statistic for Wald Test for the joint hypothesis $\alpha = 0, \beta = 1$ is 0.151		

Table 6: Alternative Test for Unbiasedness of Inflation Expectations

Parameter	Estimate	P value
α	-0.602	0.086

Table 7: Decomposition of mean squared forecast error

Bias Proportion	Variance Proportion	Covariance Proportion
0.324	0.085	0.591

Table 8: Test for Efficiency of Inflation Expectations

Pvalue for F-statistic for Wald Test for the joint hypothesis $\alpha = \beta_1 = \beta_2 = 0$	=	0.275
Adjusted R-squared	=	0.243

The new estimates are required to be tested for sufficient and strict rationality. However, due to the limitation of only 9 out-of-sample forecasts and the fact that the tests for both sufficient and strict rationality are based on comparison of estimates with the forecasts obtained from other models, the new estimates are compared with the forecasts of the Survey of Professional Forecasters (SPF). It is observed that the new estimates derived from the optimal distribution deviate on an average by about 87 basis points in absolute terms from the actual CPIC inflation. This average deviation stood at about 95 basis points when the $\widehat{\mu_t}$'s were replaced with three months-ahead mean projections of the SPF (Chart 3). During the study period, $\widehat{\mu_t}$'s and SPF forecasts seem to compete closely in terms of average absolute deviation from actual inflation. A summary of the comparative performance based on error measures following Sharma and Bicchal (2018) is provided in Table 9.

Furthermore, 95 per cent confidence band of μ_t's are much narrower (105.5 basis points) than the range (difference between the maximum and minimum forecasts is 183.3 basis points) of three months-ahead SPF projections while both contain the actual inflation about similar number of times (Chart 4). In addition, the confidence intervals of the μ_t's when compared with that of the pure time-series projections y_{ht}'s also display gain in efficiency due to use of prior information on the inflation expectations (Chart 5).

It may also be important to check whether the inflation expectations directly help in predicting inflation in a standard time-series framework. It

Chart 3: Mean Estimate of Optimal Distribution *vis-à-vis* Actual Inflation

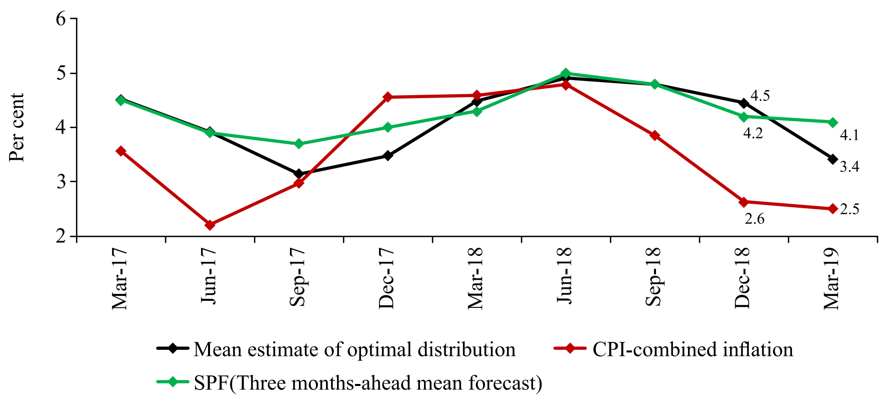


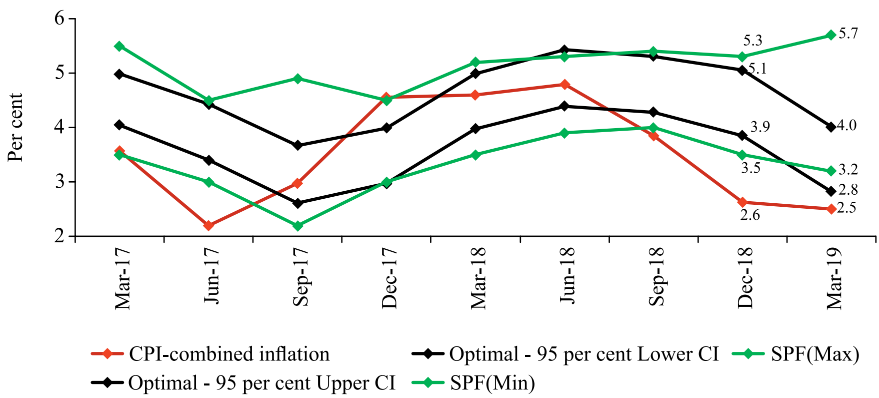
Table 9: Performance of New Estimates in Comparison with other Forecasts

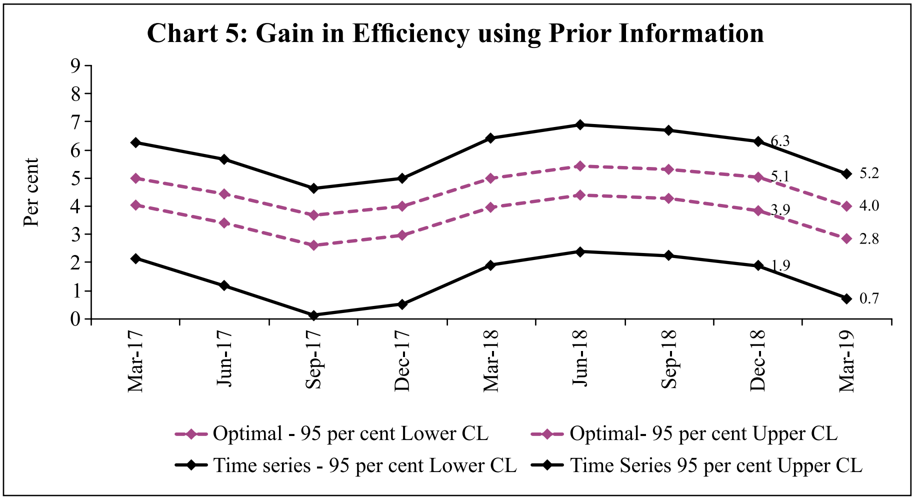
Error Measure	Mean Estimate of Optimal Distribution	SPF
Bias $=\frac{1}{T}\sum_{t=1}^{T} FE_t$	0.606	0.758
Mean square forecast error $=\frac{1}{T}\sum_{t=1}^{T} FE_t^2$	1.121	1.179
Root mean squared error $=\sqrt{\frac{1}{T}\sum_{t=1}^{T} FE_t^2}$	1.059	1.086
Standard forecast error $=\sqrt{\frac{1}{T}\sum_{t=1}^{T}(FE_t - Bias)^2}$	0.868	0.778
Mean absolute error $=\frac{1}{T}\sum_{t=1}^{T}\lvert FE_t\rvert$	0.868	0.947
Mean absolute percentage error $=\frac{1}{T}\sum_{t=1}^{T}\left\lvert\frac{FE_t}{A_t}\right\rvert$	0.299	0.331
Theil's U $=\frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_t-E_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}F_t^2}+\sqrt{\frac{1}{T}\sum_{t=1}^{T}A_t^2}}$	0.136	0.137

$FE_t = F_t - A_t$, F_t = forecast for time t; A_t = actual at time t; T = number of points for comparison

was discussed in Section II that the expectations do not help in predicting the three months-ahead actual inflation as they are not rational. However, as both the series *i.e.,* the actual inflation and the expectations, are found to be I(1) *i.e.,* integrated of order one, the same exercise may be undertaken for first differenced series for the same study period as in Section II. The results of

Chart 4: Confidence Interval of Estimates from Optimal Distribution *vis-à-vis* SPF Maximum and Minimum Projections





the empirical exercise, reported in Table 10, suggests that the coefficient of the third lag of inflation expectations is statistically significant but negative, which is counter-intuitive.

Using the equation in Table 10, the out-of-sample three months-ahead forecasts and their standard errors were generated. These forecasts, named ‘regression estimates’, are then compared with the ‘new estimates’ obtained earlier using the optimal distribution (Table 11). As the IESH is conducted only in urban areas, the new estimates and the regression estimates’ were also generated and compared for the CPI urban inflation (Table 12).

Table 10: Regression Results of Δy_t on Δy^e_{t-3}

$$\Delta y_t = c + \alpha \Delta y^e_{t-3}(-3) + \beta \Delta y_{t-1} + \epsilon_t$$

Parameter	Null	Estimate	Statistic	Decision (at 5 per cent level of significance)
c	0	-0.300	-1.359	Cannot be rejected
α	0	-0.499	-3.079	Rejected
β	0	-0.013	-0.079	Cannot be rejected
Adjusted R-squared = 0.227				
Residuals are white noise.				

Table 11: Comparison of Estimates for CPI Combined

Estimate	Average Absolute Deviation	Average Width of 95 per cent Confidence Band
New Estimates	86.8	105.5
Regression Estimates	68.9	445.9

Table 12: Comparison of Estimates for CPI Urban

Estimate	Average Absolute Deviation	Average Width of 95 per cent Confidence Band
New Estimates	71.9	98.4
Regression Estimates	64.9	468.1

It is evident from the comparison that the new estimates are more representative for CPI urban inflation as the average deviation is lower in the case of the latter. This was expected because the survey is urban-based. Comparison between the new estimates and the regression estimates for both combined and urban inflation clearly indicates that the performance of the regression estimates is better than the new estimates. However, the efficiency of new estimates is much better than that of the regression estimates as the width of the confidence interval for the latter is much wider. This was anticipated because the use of prior information makes the new estimates more efficient. Thus, it may be concluded from the above discussion that the information derived from raw expectations using optimal distribution can predict inflation more efficiently than some of the other available measures.

Section V
Conclusion

The Reserve Bank conducts a survey of households' expectations of inflation on a quarterly basis. The objective of this paper was to examine whether the outcome of these surveys can be used to predict the actual inflation and if it is possible to arrive at some transformation of expectations to obtain an alternative measure that can efficiently predict the actual inflation. It is observed that the survey results do not provide accurate information about the actual inflation. The empirical exercise in the paper suggests that households' expectations are often biased and do not pass the tests of rationality because the households do not fully incorporate the information available to them on inflation. The paper, however, finds that it is possible to derive relevant information from the inflation expectations surveys which can be used to predict the actual inflation more efficiently than some of the other available measures. To be more specific, the expectations can be aggregated to estimate the mean of an optimal distribution which can be used to predict the actual inflation. The resultant estimates were found to be rational and provided a forecast of inflation with a gain in efficiency as compared to forecasts based either on past values of realised inflation or raw expectations. The efficiency of the measure based on optimal distribution was better than even the three months-ahead mean projections of the professional forecasters as reflected in the narrower confidence interval in case of the former. The efficiency of the transformed estimates based on raw expectations was empirically confirmed when they were compared with the out-of-sample projections for the period March 2017 to March 2019. Nevertheless, the robustness of these findings needs to be further validated as more data become available in future.

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Appendix

Inflation Expectations Survey of Households (IESH)

The Inflation Expectations Survey of Households or IESH is conducted quarterly by the Reserve Bank of India (RBI) since September 2005. In addition to the quarterly rounds, two additional rounds, in November and May each year, are also being conducted since November 2016.

Till June 2018, a quota sampling procedure was followed to ensure appropriate representation of different occupational categories. The sample sizes were fixed at 500 households in metro cities and 250 in other centres. However, from September 2018 onwards, a two-stage probability sampling scheme has been implemented. Further, city-wise sample sizes have been revised in proportion to the number of households in each city as per Census 2011. Over the rounds, the coverage of the survey has been expanded and currently it covers a sample size of about 6,000 urban households in specific cities, namely Delhi, Kolkata, Mumbai, Chennai, Ahmedabad, Bengaluru, Bhopal, Bhubaneswar, Chandigarh, Guwahati, Hyderabad, Jaipur, Lucknow, Nagpur, Patna, Raipur, Ranchi, and Thiruvananthapuram.

The questionnaire consists of four blocks: Block 1 for the respondent's details like name, gender, age, category of respondent, *etc.;* Block 2 and 3 containing qualitative questions about price expectations for general and various product groups for three months and one year ahead, respectively; Block 4 containing quantitative questions on current and expected inflation rates for three months and one year ahead horizons. The response options for the questions in Blocks 2 and 3 are 'Prices will increase', 'Price increase more than current rate', 'Price increase similar to current rate', 'Price increase less than current rate', 'No change in prices' and 'Decline in prices'. For the quantitative questions in Block 4, the response options range from 'less than 1 per cent' to '16 per cent and above', with intermediate class intervals of size 100 basis points. The salient results of all the survey rounds as well as the unit-level data are available in the RBI website (www.rbi.org.in).

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Taming the Tide of Capital Flows: A Policy Guide by Atish R. Ghosh, Jonathan D. Ostry and Mahvash S. Qureshi, 472 pp., MIT Press (2018), US$ 45.

Financial globalisation has generally been argued as a means to greater economic prosperity for Emerging Markets and Developing Economies (EMDEs), subject to the effectiveness of their policy framework for enhancing resilience to vulnerabilities associated with surges and sudden stops in capital flows. Financial crises, however, have often exposed the limitations of policy frameworks, and the search for a more robust optimal framework continues. In this context, the book titled *Taming the Tide of Capital Flows*: *A Policy Guide* by three leading experts on the subject — Atish R. Ghosh, Jonathan D. Ostry and Mahvash S. Qureshi — provides a comprehensive perspective on opportunities and challenges associated with capital flows. It lucidly blends findings from exciting theoretical and empirical literature, as well as varied country-specific experiences with rich analytical insights. The book extensively deliberates upon policy measures intended to help EMDEs to contend with large and volatile capital flows in this age of financial globalisation.

Financial globalisation entails the flow of capital from capital rich nations to capital scarce ones, at times accompanied by technical know-how, leading to enhanced productivity, profitability and growth. Nonetheless, empirical evidences fail to unequivocally support these outcomes in Emerging Market Economies (EMEs). Large swings in capital flows can lead to macroeconomic imbalances and often impose serious costs on the real economy in the form of real exchange rate misalignment, credit and asset price booms, inflationary pressures, overheating and financial imbalances culminating in financial crises and large capital outflows. Such oscillations (large inflows and subsequent outflows) have also been highly unpredictable.

The macroeconomic impact of convolutions in capital flows to emerging markets, have thus become a topic of major academic and policy debate in both the group of countries- at the receiving end as well as the originating end. The authors of the book not only explain the causes and consequences of booms and busts created by surges in capital flows, but also outline the ways through which such cycles could be moderated using the right mix of instruments available with the policymakers.

The book is divided into four parts and has twelve chapters. Part I sets out the basic facts and figures about capital flows to EMEs along with a comprehensive review of the available literature on capital account liberalisation and capital controls. It also lays out the broad structure of capital flows to EMEs since the late nineteenth century. Part II takes us through a range of possible explanations for the large capital inflows to EMEs and also investigates the consequences in terms of macro-financial imbalances and balance sheet vulnerabilities. The use of different policies to cope with large capital flows in EMEs is discussed in part III. The final part provides various pragmatic choices on policy implementation for manoeuvring capital flows so as to obtain maximum benefits from capital account liberalisation.

Part I, comprising two chapters, provides a detailed introduction to the topic and a historical perspective of capital flows regulation. Following the Washington Consensus, policy prescriptions articulated by international financial institutions overwhelmingly encouraged capital account liberalisation to EMEs. The thinking on capital flows has evolved over time, taking into account opportunities and challenges under different economic conditions and different country-specific contexts, without laying down any rigid consensus. While trade in goods has been widely accepted as a tool to attain pareto optimal outcomes universally, views on trade in financial securities have become progressively more diverse. The authors have analysed capital flows in five distinct phases: pre-World War I; the interwar period; the Bretton Woods era; the adoption of generalised floating; and the aftermath of the Global Financial Crisis (GFC) of 2008. The authors emphasise that volatility in capital flows is not a new phenomenon and that it has existed as an integral part of the late nineteenth century's financial globalisation. Over time, what has changed, however, is the outlook regarding the management of capital flows. The perspective of policymakers has undergone refinements according to the needs of time. The late nineteenth century witnessed the *laissez-faire* approach, followed by structural controls contemplated at Bretton Woods, then came the free market principles and the Washington Consensus of the 1980s and 1990s. Lately, a re-examination of free market principles has started with lingering imprints of the GFC of 2008. The authors conclude that though capital flows may lead to multiple benefits to EMEs, unrestrained flows of capital could be problematic.

The authors identify US interest rates and global market uncertainty as key push factors for capital flow to EMEs and country-specific conditions such as external financing needs, growth performance, exchange rate regime, financial openness and institutional quality as the main pull factors. Capital surges have often resulted in crashes due to overheating of the economy, propelling credit booms, asset price bubbles, excessive appreciation of currency leading to loss of competitiveness and increased vulnerability of balance sheets. The authors empirically establish that the chances of some sort of financial crisis after an episode of capital surge are three to five times higher compared with a normal year in terms of size of capital flows. They suggest that such crash-landings could be avoided by timely calibration of policy tools to limit domestic credit expansion and currency overvaluation, as these factors primarily result in financial crisis. With a view to address balance sheet vulnerabilities, policies should be directed towards promoting safer types of capital inflows like Foreign Direct Investment (FDI), while capping risky inflows like other investment flows from banks and portfolio debt flows. Thus, the overall policy framework will require effective management that could ensure the right mix of capital flows as well as dampen the boom-bust cycles through the use of cyclically varying macroeconomic policies, prudential measures and capital controls.

The book moves on to discuss in detail the relevant policy framework required to deal with the consequences of large capital flows. It provides a theoretical framework that proposes rational mapping between various macroeconomic imbalances and potential policy instruments: policy interest rate for maintaining price stability; foreign exchange intervention for limiting appreciation of domestic currency; and macro-prudential measures to ensure financial stability. Since each instrument may have implications for other targets, there is a need to exercise caution while using them. Importantly, the use of one policy instrument to attain a desired target can have the potential to destabilise another macroeconomic dimension and thereby create a situation of confusion and uncertainty. The authors sensitise policymakers to be cautious in using policy instruments according to suggested mapping and suggest the use of capital controls in certain cases to manage large inflows.

The book attempts to address a more contentious issue, *i.e.,* whether policymakers in an inflation targeting (IT) framework should intervene in the foreign exchange (FX) market, and whether FX intervention is compatible with IT framework. Multiple objectives can sometimes crosscut each other, which might affect the credibility of a central bank's inflation target, as its ability to anchor expectations might be undermined. The authors, however, argue that there is no incompatibility between inflation targeting and pursuing an exchange rate objective. They show that out of three macroeconomic imbalances caused by capital flows, namely inflation, currency appreciation and credit growth, if central banks prioritise managing inflation, first using policy interest rate, and then pursue a second objective with a second tool, such an objective may not be inconsistent with inflation targeting. A careful use of multiple instruments can lead to increased welfare gains and enhanced central bank credibility as well.

Balance sheet vulnerabilities, the other kind of crisis triggered by unbridled outpouring of capital flows, may involve the piling up of an unsustainable level of liabilities leading to maturity and/or currency mismatches. The authors use a formal model to show that private agents often under-price salient risks associated with debt and borrow excessively choosing a risky liability structure, and also fail to internalise the externalities caused by them on the real exchange rate and collateral constraint for other borrowers. That is why they suggest a kind of Pigouvian tax to channelise capital inflows towards a less risky form of liability such as FDI, which can help avoid crash-landing. In practice, policymakers use both capital controls and macroprudential measures to manage large capital inflows, with country-specific approaches getting customised to historical, economic, and institutional characteristics.

The last part of the book provides an overview of the debate on the effectiveness of various policy tools in macroeconomic management and deliberates upon international spillovers, scope of international cooperation to tackle the same and, finally, offers some concrete policy advice. The authors argue that sterilised intervention can be used to alleviate the currency appreciation pressure, whereas both FX market intervention and macroprudential measures can be used to dampen excessive credit growth. Capital controls and currency-based prudential measures can be effectively employed to shift the composition of inflows towards more stable liabilities. Therefore, policymakers in EMEs should use all tools available with them to manage capital inflows. Furthermore, since capital inflows involve at least two parties across borders, there is a need for greater international coordination. Coordination between source and recipient countries aimed at containing flows could involve an 'exchange rate test' where countries, in the event of large inflows, could be expected to let their exchange rate appreciate to its multilaterally consistent equilibrium level before taking measures to curb appreciation.

The book uses rigorous theoretical, analytical and practical approaches to analyse how EMEs can reap the benefits of globalisation without facing the associated risks of financial crises, growth collapses and hurdles for the IT framework in inflation targeting economies. The authors have documented how a balanced deployment of monetary, exchange rate, macroprudential, and capital control policies can mitigate macroeconomic and balance sheet imbalances. Notwithstanding the comprehensive coverage of issues, certain aspects could have been given greater attention in the book to enhance its appeal to readers, such as threshold degree of openness, optimal level of capital flows, optimal sequencing of liberalisation of capital controls, importance of pre-conditions to liberalisation, and a matrix of factors that could determine the success or failure of any policy instrument. The suggested mapping of available policy tools to targeted macroeconomic variables, which may appear as a broad framework, needs to be tested in varied crisis events, even as countries may in practice deploy their own preferred policy mix depending on the nature of the problem capital flows pose for their macro-financial environment at any point of time. In the current context of global discussions on de-globalisation and rising trade tensions, and also considering that the outlook for both push and pull factors driving capital flows remains highly uncertain, this book is a must read for policymakers and economists to better understand the complex dynamics of capital flows and trade-offs associated with an alternative mix of policy responses.

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Misbehaving: The Making of Behavioural Economics by Richard H. Thaler, 432 pp., W. W. Norton Company (2015), US$ 27.95

Economic agents, whose actions drive macroeconomic outcomes, are often assumed to be rational, but forecasting models, in the past, that did not question this assumption of rationality, failed to predict the Great Depression of 1929, Stagflation of the 1970s and, in more recent times, the dot-com bubble of the 1990s and the Great Financial Crisis of 2008. In his book, *Misbehaving: The Making of Behavioural Economics*, Richard H. Thaler demonstrates the limitations of traditional economic models that assume completely rational but imaginary 'econs', and offers a new perspective on the way actual humans behave or rather 'misbehave'. The first example he gives is of students in his microeconomics class who were angry on receiving a score of 72 out of 100 but were perfectly fine on getting a score of 96 out of 137. This is among the long list of anomalies that he provides in the book.

Thaler became the first economist to receive the well-deserved Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel, in 2017, for "contributions to behavioural economics".

As expected, the discovery of 'misbehaviour' by economic agents and the consequences of this 'misbehaviour' for existing economic models, resulted in resistance from traditional economists. One criticism, which can be attributed to Milton Friedman, was that people may not be explicitly optimising but they often behave 'as if' they are optimising. For example, an expert billiard's player, while making a shot, does not explicitly calculate the angles and speed required to make the pocket, but nevertheless does it implicitly. Other criticisms were that people will usually behave rationally in the real world as they are aware of facing higher risks associated with irrational actions. Hence, they are more likely to rectify any irrational behaviour through learning over time. The most recurring criticism was that competitive markets, guided by the 'invisible hand', would check any misbehaviour, which in turn will lead to maximisation of welfare. Unlike the treatment of the 'invisible hand' argument in *The Wealth of Nations*, Adam Smith's other book, *The Theory of Moral Sentiments*, highlighted how 'passion' could come into conflict with rationality and it thereby laid the foundation for a behavioural approach to economics. A similar view was also adopted by John Keynes in his magnum opus *The General Theory of Employment, Interest and Money*, where he proposed investments to be driven by 'animal spirits' and not by mathematical optimisation. Yet the economists who followed Keynes, starting with Milton Friedman to Franco Modigliani and Robert Barro, assumed cleverer and more rational 'econs' who were extremely foresighted, well-versed with economic theory, completely rational and in perfect self-control, as opposed to investors who were driven by the Keynesian 'animal spirits'. Therefore, somewhere along the way, in a bid to add mathematical rigour to economic models, economics profession ignored human behaviour and transformed the subject of economics from a study of human behaviour to a study of mythical 'econs' who are completely rational, all-informative and free from all human biases.

A major part of the book focusses on how economic models, with humans back in the driving seat, should be formulated and analysed. Thaler discusses the prospect theory propounded by Daniel Kahneman and Amos Tversky, which was proposed as an alternative to the expected utility theory. It argues that people dislike losses more than they like gains though there is diminishing sensitivity to both gains and losses. The prospect theory has become a cornerstone of behavioural economics and has been instrumental in explaining many of the anomalies in traditional models.

The author combines insights from prospect theory with the way people frame choices to arrive at the phenomenon of 'myopic loss aversion', where they, in a bid to avoid short-term losses, do not undertake risk-rewarding options. This concept has been used to explain the equity premium puzzle, a phenomenon of anomalously higher historical returns on stocks over bonds. Myopic loss aversion can also be used to explain why people continue to invest in illiquid assets like real estate over more liquid assets available in financial markets, as the short-term losses in real estate are not easily perceptible and hence less painful than losses from investment in stocks.

Another example of how people tend to 'misbehave' is seen in the differential treatment of money that has been kept in real or mental baskets. One such partition that has been observed is the 'house money effect', where people partition their gains from their initial investment and are more willing to take risks on this house money. The 'house money', in combination with prospect theory, can be used to explain why business cycles get amplified.

During the boom period, people treat the existing excess gains as 'house money' and thus they take more risk-taking. Thus, investors buoyed by the initial high returns in the stock market in the 1990s and the housing market in the 2000s started taking riskier bets. On the other hand, during a downturn, when people are facing high losses, they are more likely to take more risky positions to balance off their earlier losses and thus avoid the pain associated with incurring a loss. This only leads to further losses, aggravating the crisis.

The slow resolution of non-performing assets under the Insolvency and Bankruptcy Code in India can also be attributed to what Thaler calls the 'endowment effect' and 'status quo bias', where people tend to overvalue the asset that they currently possess. Thus, the sellers of bad assets may often demand higher prices while the buyers may be willing to pay lower prices than what may be the true market price of an asset.

Thaler also discusses how people tend to view prices set by companies. People are more concerned whether a price seems fair than whether it is determined by a competitive interplay of demand and supply. People often enjoy what Thaler calls 'transactional utility', which is the difference between the prices they expect to pay and the price they end up paying. This concept is being effectively employed by retailers while announcing sales/discounts to increase the transaction utility of a customer and thereby drive up overall sales. Banks can also employ this to increase customer satisfaction, by declaring banking service charges upfront and offering better terms, if possible, later.

The latter part of the book is devoted to behavioural finance. Finance was thought to be the last domain to witness anomalies and misbehaviour, as the agents are expected to be highly rational and any misbehaviour is likely to be punished by highly competitive financial markets. Thaler, however, demonstrates that financial markets too misbehave often. He highlights, as an example, the wide fluctuation in stock prices on a daily basis, even in the absence of any underlying rationale.

In the final part of the book, Thaler discusses how behavioural economics is impacting policy-making, such as the 'Save More Tomorrow' program aimed at increasing savings for retirement and the work of the Behavioural Insights Team which is advising the U.K. government on designing policies.

Thaler makes a strong case for assigning greater importance to the behavioural approach in policymaking by respecting people's choices and emphasising the need to re-evaluate highly complex mathematical models built on the premise of sophisticated 'econs'.

In short, the book highlights that error-prone economic agents with certain biases could explain the failure of conventional economic models, but it does not elaborate on how the economic models should account for the 'misbehaving' agents. The book is an interesting read with thought-provoking real-life examples and personal experiences of the author. While reading through it, one is most likely to recognise one's own biases in behaviour in specific, real-life events of the past; however, one would also get a sense that all others around us are also subjected to rational 'misbehaviour'.

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The Third Pillar: How Markets and the State Leave the Community Behind by Raghuram G. Rajan, 464 pp., HarperCollins Publishers India (2019), ₹799.

A development model that could deliver inclusive and sustainable high growth, enhancing economic prosperity for all on a sustained basis remains largely elusive. Responding to this challenge, leading strategic thinkers in the field of economics and finance have come up with innovative ideas. A prominent feature of the extensive debate on this subject so far has been 'markets *vis-à-vis* state', not in the sense of a dichotomy between them, but more as an optimal combination of the two. While the markets are believed to ensure efficient allocation of resources that is necessary for higher economic prosperity, the state can enforce regulations enabling markets to function effectively, provide a level playing field to market participants, and undertake redistribution to address inequality. In this insightful book titled *The Third Pillar: How Markets and the State Leave the Community Behind*, Raghuram G. Rajan sheds light on the often neglected third pillar of society—the community.

The book begins with a description of the community, illustrating its benefits and shortcomings through relevant case studies. The community performs a number of roles. It gives individuals a sense of identity and belonging; it supports members in times of social and economic distress; it allows members to participate in local governance structures thereby improving the provisioning of public services while giving members a sense of control over their lives. In fact, vibrant communities can serve as a watchdog to prevent corruption and crony capitalism by mobilising protests. Notwithstanding its usefulness, the community can also be regressive if community members put too many restrictions and over-emphasise traditions to protect the power structure within the community. Thus, what is needed is the right balance between the three pillars: state, markets and community in order for society to prosper.

This book is divided into three parts. Part 1 provides a historical narrative on the evolution of the three pillars of society. It begins with a discussion on feudal society in medieval Europe, tracing developments in society till the

Great Depression. Part 2 of the book examines the interaction between the three pillars against the backdrop of the Second World War and the Information and Communications Technology (ICT) revolution. Rajan also briefly touches upon the imbalances building up in the two fastest growing large economies: China and India. In the final part of the book, he proposes solutions to restore equilibrium and balance in the three pillars.

In the first part, Rajan explains how the two pillars of society—markets and state—emerged from the community itself. The feudal community in medieval Europe encompassed both state and market. The feudal manor produced goods for self-consumption and there were no trade/market transactions. The functions of the state such as security and justice were delivered by the lord of the manor himself. Over time, with increase in trade with distant places, and with advances in military technologies and unification of territories, both the state and markets started growing, while the feudal community declined. Over a span of a few hundred years, constitutionally limited governments and free markets emerged in Europe. The feudal vassal was replaced by the commercial tenant, and parliamentary bodies dominated by propertied individuals served as a check on the powers of the state.

However, the commercialisation of agriculture had led to massive unemployment among the peasants who were forced to work in factories in the cities under terrible working conditions. As markets became dominant to the detriment of the community, the workers pushed for political representation. By the beginning of the twentieth century, male workers were eligible to vote in most countries of North America and Western Europe. The extension of suffrage re-empowered the communities. Workers also pushed the state to impose regulatory constraints on the market and provide public services like schooling and health care. Eventually liberal market democracies emerged across the developed world in the early twentieth century, with powers aptly distributed between the three pillars.

However, the onset of the Great Depression in 1929 changed the power structure between the three pillars. The enormous economic adversity caused by the prolonged slowdown turned public sentiment against markets. Market competition was blamed for the failure of small businesses and the private sector came under heavily regulated regime. Many industries were nationalised. The Great Depression, thus, marked the ascent of the state.

The developments after the Great Depression and the Second World War are analysed in the second part of the book. The Great Depression had created an anti-market sentiment and the state expanded at the cost of the markets, a trend which continued into the Second World War. The three decades after the Second World War saw spectacular growth as economies were rebuilt after the war and international trade resumed. The increased prosperity prompted governments to put in place social security benefits for the people. However, in the 1970s, growth slowed considerably. There were a number of reasons for this slowdown: increasing inflation in the United States due to spending on the Vietnam War; the breakdown of the Bretton Woods system; and the OPEC oil price shock. Also, most of the advanced economies had moved closer to the frontier of their production efficiencies, where growth is more difficult to generate. Meanwhile, the ICT revolution that started in the 1970s was changing the nature of jobs and creating inequality.

The US and continental Europe responded to the growth slowdown in different ways. While the US opted for deregulation, privatisation and trade liberalisation to give markets the upper hand, continental Europe looked more towards integrating markets to regenerate growth. Although growth picked up in the mid-1980s, it was insufficient for the government to deliver on the promises made earlier, and government debt kept increasing. The paths adopted by both the US and Europe had their own problems. In the US, while the liberalisation of markets initially brought about efficiency, market entities increasingly sought to restrict competition. Firms exploited the lax anti-trust regulation and resorted to ever-greening of intellectual property rights to preserve their monopoly power. The rise of the 'superstar' firms further exacerbated the inequalities created by the ICT revolution. Towards the beginning of this century, when it became clear that something had to be done for those left behind, the government sought to boost housing demand through cheap credit. The housing boom created a rosy picture. Housing construction generated the much-needed jobs. It also supported consumption growth, as existing homeowners took loans against the higher value of their homes. The debt-fuelled growth, however, proved unsustainable, leading to the global financial crisis of 2008.

In Europe, integration of goods, services, labour and capital markets took place through the formation of the European Union (EU). The free movement of people within the Union, however, caused dissatisfaction between citizens of different nationalities, who were from different historical backgrounds and cultural sensibilities. In addition, the adoption of a common currency without adequate discipline on government spending led to very different levels of inflation between countries in the euro area. Even while inflation was different across countries, all had the same policy interest rate as they had a common central bank. Thus, borrowing appeared very cheap in the high inflation countries, which ultimately culminated in the European debt crisis.

Rajan argues that the source of much of the problems of today, like populist nationalism and radical leftist movements, lies in the imbalance between markets, state and communities. Communities have become too weak relative to markets and the state. The ICT revolution coupled with trade liberalisation and market integration has led to the loss of middle-income jobs for the moderately educated workers in the advanced countries, while increasing the wage premium for highly educated ones. The loss/unavailability of jobs for the middle class has taken a toll on their families leading to a deterioration in the living environment for children. This has resulted in poor school performance, drug addiction and crime, which has vitiated the community environment. As still functional families move to better neighbourhoods to escape the unhealthy environment, dysfunctional communities deteriorate further. They are left with worse community institutions and less social and economic capital to support their members. Thus, economic decline leads to social decline and they reinforce each other to form a vicious cycle. The alienated individuals in dysfunctional communities then fall prey to radical left and populist nationalist ideologies that blame the corrupt elite, minorities and immigrants for the problems at hand.

Before moving on to propose solutions to this problem, Rajan turns to China and India. In China, the state has dominated markets and communities, posing a variety of problems: overcapacity in industries due to excessive investment, over-dependence on exports and large government debt. In India, on the other hand, the state faces capacity constraint in creating infrastructure, providing essential public services, enforcing regulations and clearing court cases. Thus, China needs to build a constitutionally limited state while India needs to enhance state capacity.

In the concluding part of the book, Rajan proposes ‘inclusive localism’ to rebalance the three pillars. The author describes localism as ‘the process of decentralising power to the local level so that people feel more empowered in their communities'. While empowerment of local communities will give them a sense of responsibility, markets will create competition to ensure that society remains efficient, and the state will ensure that communities do not become insular by enforcing free movement of goods and people.

Rajan argues that empowering communities would ensure that the members are well placed to adjust and absorb shocks from rapid technical changes, which require workers to develop new capabilities to participate in the job markets. Workers may also need financial support in case of economic downturns. Rajan argues that to remain relevant in times of rapid technological changes, what is needed is a solid foundation through quality school education, rather than higher education for everyone. A robust foundation would promote lifelong learning so that workers have the flexibility to move between industries as the economic environment changes. Communities are instrumental here. Research studies have found that the home environment and the socio-economic diversity of students in schools contribute significantly to learning outcomes. In this respect, communities can support learning by providing an enabling atmosphere that encourages student motivation, discipline and safety. With regard to support in times of economic distress, Rajan is of the view that the formal safety net provided by the state should be at a basic level, and that communities can supplement this, based on the needs of their members. In this way communities could provide additional buffers against market volatility.

This book has lucidly portrayed the big picture of the economy through the interplay between the three pillars of state, markets and community. A major contribution of the book lies in moving beyond the realm of traditional economics—markets and the state—by highlighting the important role of the community. Beginning with a historical perspective about the evolution of the three pillars, it elaborates upon the changing dynamics between the 'pillars' over time as significant shocks like the Great Depression and the ICT revolution hit the economy. Analysing the present situation through the lens of the three pillars, it concludes that strengthening the community is necessary to bring about balance in society. The arguments in the book are illustrated with real world examples, data and research studies, which not only lend support to the author's ideas but also make the book a delightful read. The book is engaging and thought-provoking. However, while the book offers broad solutions to rebalance the 'pillars', the devil may lie in the details. The solutions offered seem difficult to implement at times. For example, Rajan writes that when it is not possible to revive a dysfunctional community, it is better to let it die by facilitating out-migration. He writes: '…countries and communities should explore the possibility of subsidising moves by the unemployed from high-unemployment communities to elsewhere in search of employment'. The practical feasibility of such measures is questionable. Also, devolution of powers to local levels requires immense political will. As we have seen in the case of India, the process of constitutional decentralisation to create the third tier of government was a long-drawn affair. Even today, the degree to which this devolution has been successful remains a topic of debate. However, as Rajan himself acknowledges in the preface to the book, the policy prescriptions he offers are not the final word, rather they are intended to provoke debate and inspire action. In this sense, Rajan has achieved his objective, but it remains to be seen how many stakeholders draw inspiration to translate new ideas into policy actions.

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