India's Steady State Equilibrium Inflation: A Revisit

*by R. K. Sinha^*

The article tracks the stochastic transition of inflation over the period 2014 to 2022, which coincides with the de-facto adoption of inflation targeting by the Reserve Bank followed by its formal institution in 2016 and the experience thereafter including the pandemic-induced era. It finds that the long-run steady state equilibrium level of inflation could be around 4.3 per cent based on the pre-pandemic data. The same may appear to have edged up marginally in the pandemic period, which is likely to be transient and may glide to lower trajectories in due course once macroeconomic conditions normalise globally.

Introduction

In the process of achieving an acceptable and desirable level of inflation, while the policy stance of the Reserve Bank has been the most prominent and guiding factor, there are other domestic and global macroeconomic factors as well, which have been impacting the inflation path. Frequent shocks drag inflation away from its central tendency and disturb smoothness of the inflation trajectory in the short-to-medium term. These shocks are positive (favourable) as well as negative (adverse). The positive shocks (such as the international crude oil price crash) have aided at times in bringing headline inflation down while the adverse shocks (such as sudden and unprecedented rise in the prices of select food items, especially cereals and vegetables, and crude oil price jump), drag inflation out of the normal trajectory in the short run. Notwithstanding vulnerability to these supply shocks, the sustained effort of the Reserve Bank through its policy stance played a vital role in bringing the inflation to 4 per cent mark during the pre-COVID period[1] adding to Flexible Inflation Targeting's (FIT's) credibility.

In the presence of various shocks, it has always been a pertinent question as to what has been the trend inflation[2] in India in the post-FIT period, and where it would hover in the long run under a steady state equilibrium. Against this backdrop, a preliminary exercise of the likely central tendency of the long run inflation was carried out by Reserve Bank revealed that the long run steady equilibrium level of inflation could be settling to around 4 per cent with an upward bias (RBI, 2017). The study tracked transitions of inflation through Markov chains through suitable transition probability matrices (TPMs) using the limited data available. An update on this was also analysed and discussed subsequently, which corroborated the findings of the earlier study (Sinha, 2018).

A recent study by Behera and Patra (2020) estimated the trend inflation through a New Keynesian Phillips curve (NKPC) using a longer series of inflation observed from 2007 to 2020 (prior to the emergence of the COVID pandemic). Before estimating the NKPC model with pre-specification of regimes, a Markov switching regression with unknown regimes was estimated to understand the current regime of inflation. The key findings indicated two regimes in India's recent inflation history – a high inflation regime of 9.4 per cent during 2007-2014 and a low inflation regime of 4.0 per cent during 2015-2020 (prior to COVID). The probability weighted estimate of trend inflation in the latter regime was estimated at 4.2 per

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[1] The emergence of the COVID-19 pandemic and the subsequent Ukraine war led to surges in inflation far from the target point across the globe, including the advanced economies.

[2] Trend inflation is the permanent or the underlying component of inflation to which actual inflation converges after a shock. Alternatively, this is referred to as steady state inflation (Ascari and Sbordone, 2014). In this article, we use trend inflation and steady state (or steady state equilibrium) inflation interchangeably.

cent. The real time filtered and smoothed posterior estimate-based weighted average trend inflation in Q1:2019 was estimated at 4.1 per cent. It was found that the smoothed probability weighted estimates of trend inflation eased steadily from 2009 to reach 4.3 per cent in Q1 of 2020.

With the availability of long series CPI-C based inflation data now, we revisit the steady state equilibrium of inflation and extend the earlier preliminary study (RBI, 2017) and examine the transient changes in the trajectory of inflation from the pre-COVID to post-COVID period. We find the steady state equilibrium of inflation in the pre-COVID era to be broadly in line with the findings of Behera and Patra (2020), which followed an alternate approach. The long-run equilibria for both the sets of data (pre- and post-COVID) indicate 20-40 bps lower levels as compared to the respective observed data recorded in the respective periods.

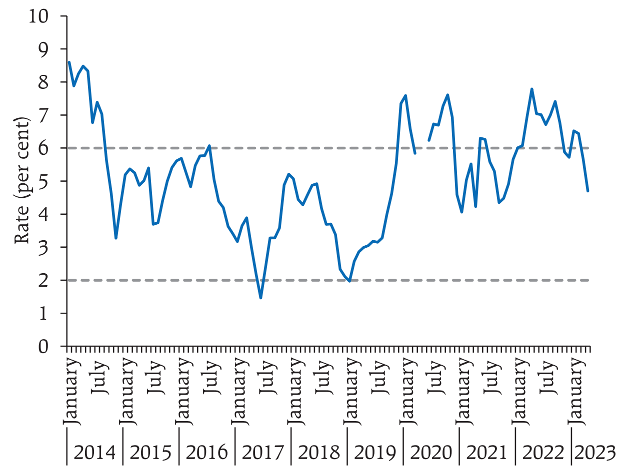
The article is divided into four sections. After the introductory section, the stylised facts are covered in the second section. The third section covers the methodology adopted in the study. The last section concludes the article with some key takeaways from the study.

II. Key Stylised Facts

The CPI-C based inflation rate (y-o-y) witnessed a decline from mid-2014 aided by easing of price pressures in a broad-based manner. The inflation dipped below 6 per cent in September 2014 from its several double-digit prints of the previous year 2013, and remained within the target band till November 2019, breaching only on three occasions[3] during a long period of 63 months (Chart 1).

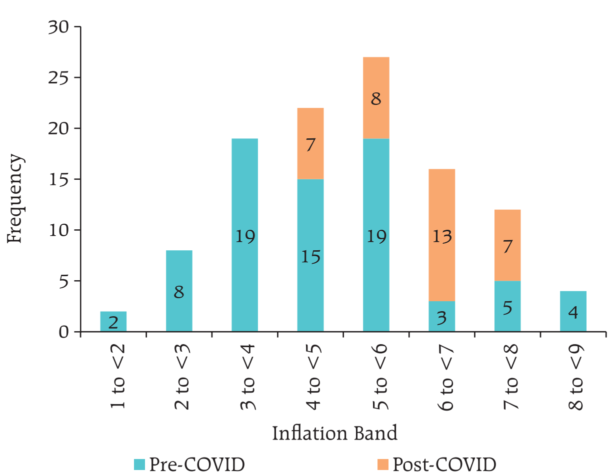
Inflation in several economies, including advanced countries, hovered in double-digits for several months after the emergence of the COVID pandemic followed by the Ukraine war. India could keep its inflation contained in single-digit levels with the highest recording at 7.79 per cent (April 2022). The average overshoot of the upper threshold, in case of a breach, has been relatively low (79 basis points) since the beginning of the pandemic. The lowest inflation in the post-COVID period has been

Chart 1: Time-series of CPI-C Inflation



Note: Inflation prints for April and May 2020 are not included. These were not published routinely by MoSPI due to pandemic-induced economy-wide lockdowns and were imputed subsequently.
Source: Ministry of Statistics and Programme Implementation (MoSPI).

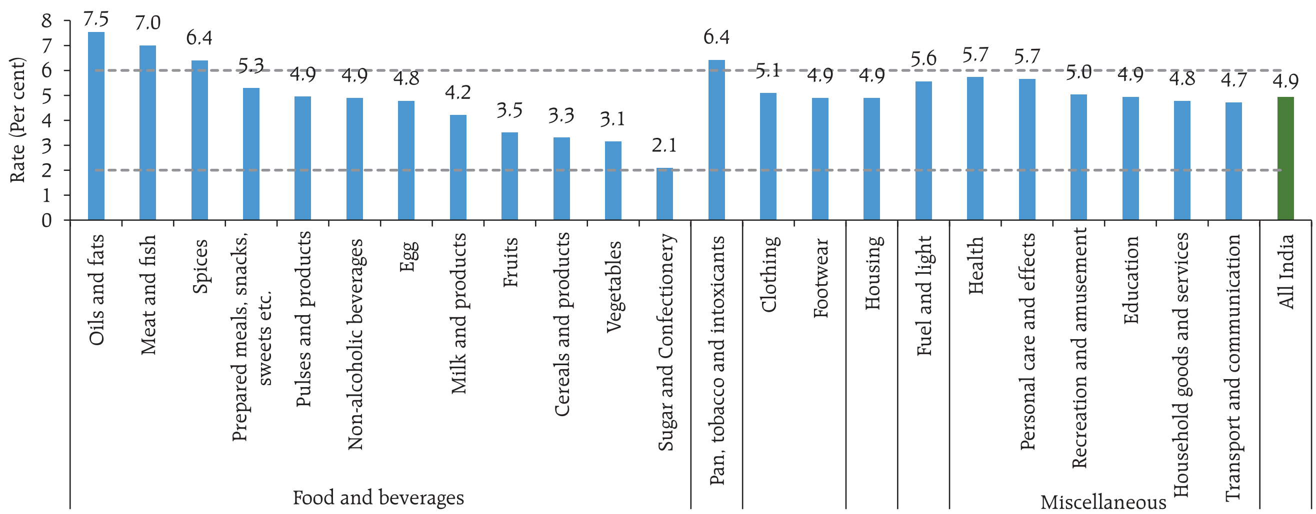
Chart 2: Frequency Distribution of CPI-C Inflation



Note: The Pre-COVID and Post-COVID periods pertain to January 2014 to March 2020 and June 2020 to April 2023, respectively.
Sources: MoSPI; and Author's calculations.

[3] Inflation breached the lower threshold two times (1.46 per cent in June 2017 and 1.97 per cent in January 2019), and the upper threshold once (6.07 per cent in July 2016). Noticeably, out of these three breaches, two were minuscule (just 3 and 7 basis points).

Chart 3: CAGR of CPIC-C Components (2014-2022)



Note: The CAGR is calculated as the growth over eight years (by taking the average index in the calendar year 2022 over the average index in the calendar year 2014).
Source: Author's calculations.

at 4.06 per cent recorded in January 2021 (Chart 1 and Chart 2).

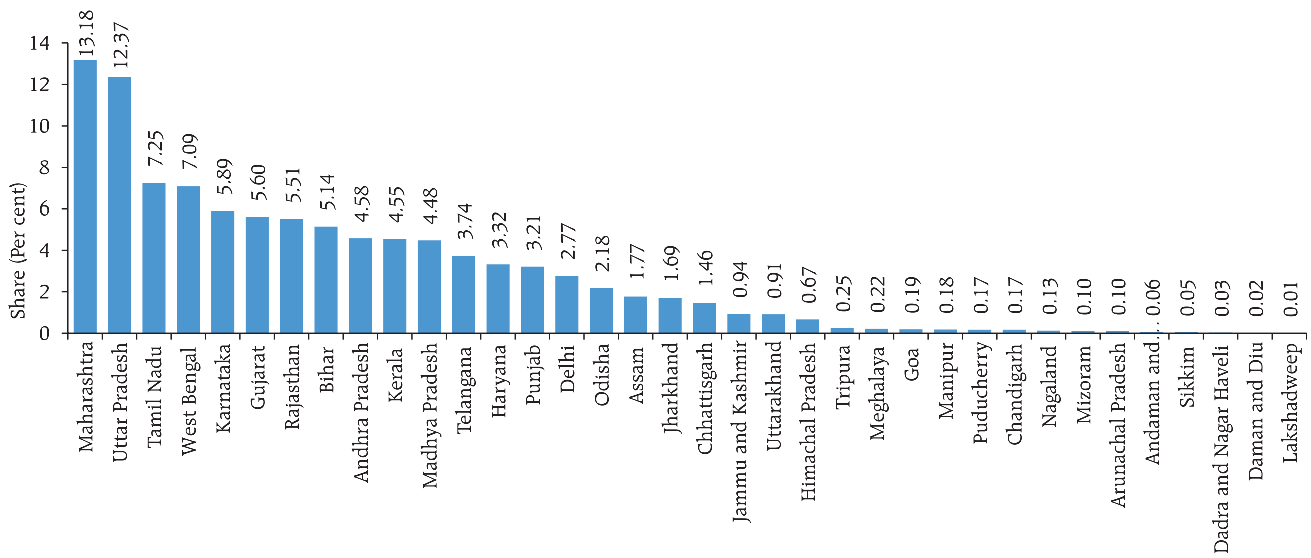
The average inflation over a longer period *viz.*, 2014 to 2022 across the components of CPI-C indicates large variations in some product sub-groups, especially in 'food and beverages' *viz.* 'meat and fish', 'oils and fats' and 'spices' at a higher side with a compound annual growth rate (CAGR) of above 6 per cent. In contrast, the CAGR of 'sugar and confectionery' remained lowest, slightly at above 2 per cent (Chart 3).

The variation in CAGRs of the sub-products are reflective of the relative demand for and supply of these products and their intra-year and inter-year variations may represent several generic and specific shocks in the economy. The CAGRs of inflation across States and Union Territories (UTs) have remained in greater sync during the period. The weights (share) of States appeared to have concentrated amongst the top few States, *e.g.*, the top six States, collectively cover more than 50 per cent of weight in the CPI-C basket (Chart 4).

The MoSPI publishes higher levels of disaggregated data of inflation for the larger 22 States/UTs. These cover granularity – by area (rural and urban), by product groups (*viz.* 6 groups – 'food and beverages', 'pan and tobacco', 'clothing and footwear', 'housing', 'fuel and light' and 'miscellaneous') and by product sub-groups (total 23 sub-groups). The smaller 14 States/UTs, which have individual weights of less than or equal to 0.25 per cent do not have the information at the product sub-group levels. The granular level weights have been taken from CSO (2015). The set of 22 larger States/UTs can be considered to be a proxy for the aggregate CPI-C, as they comprise 98.30 per cent of the aggregate CPI-C of India. It is observed that the compilation of aggregate inflation from the disaggregate (granular) level inflation may have some divergence with the published aggregate inflation prints due to methodological/aggregation issues (Das and George, 2023).

The rest of the analysis in this section and subsequent sections is based on the dataset of 22 large States/UTs. Further, the analysis incorporates appropriate probability-weighted distributions in the

Chart 4: Relative Weight of States/UTs in CPI-C Basket



Source: MoSPI; and Author's calculations.

computations as exhibited in the Tables and Charts barring one Table (Annex Table A1), which is a simple demonstration of unweighted count of transitions.

As the prime objective of this study is to track monthly transitions of annual inflation from one level to another at the most granular level[4], the granular level inflation data of larger States are considered. Based on this disaggregation of data, the gradual decline in the share[5] of products having high inflation (above 6 per cent) till mid-2017, touching a trough of 13.75 per cent in June 2017, appears to be an important contributor in bringing the CPI-C inflation down and containing it in the desired corridor comfortably. Interestingly, the share of products with inflation between 2 per cent and 6 per cent peaked at around 58 per cent (58.87 per cent in May 2017 and 57.18 per cent in June 2017) during this period reflecting moderate inflation across the board (Chart 5).

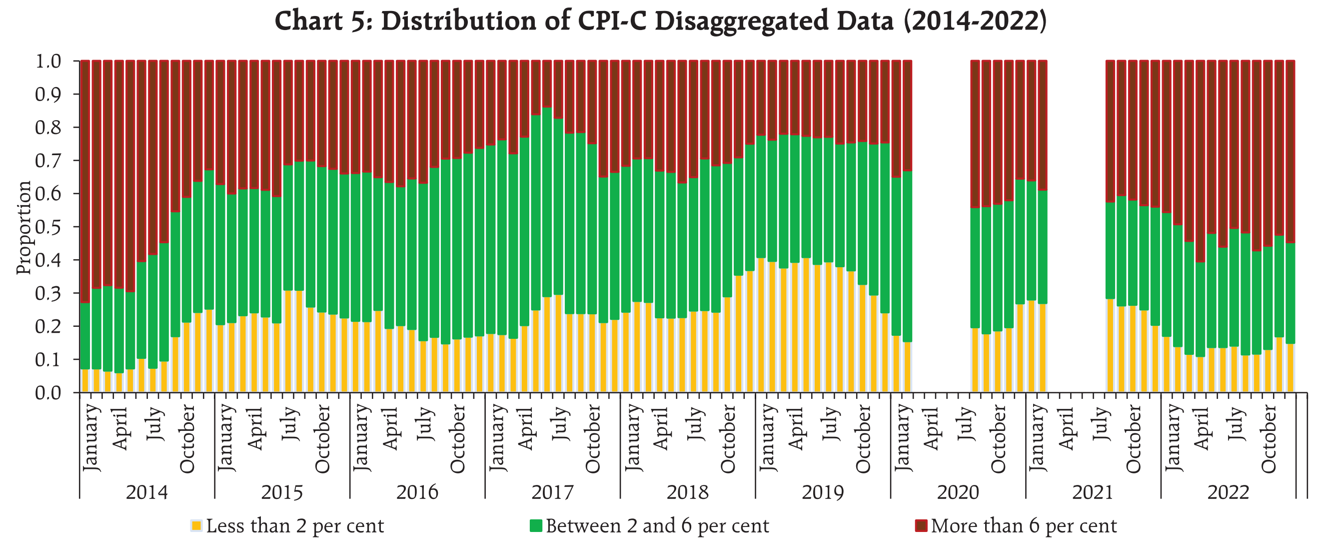
Inflation has generally risen with the rise in the share of products having high inflation across the months. However, the relationship does not appear to be linear and rather a log-linear relationship exhibits a better association (Chart 6).

It may be noted that the relative share of products in the high and low inflation bands is expected to offset each other to some extent, in addition to their joint impact with the inflation profile of products in the moderate band of 2 per cent to 6 per cent. The crucial value is indeed not just the share but the conditional distributions in these strata.

The conditional mean, *i.e.*, the average value given that it is in a particular band, has bigger relevance for both the tails, as these are unbounded. As an illustration, the high inflation at 7.35 per cent recorded in December 2019, was driven by a very high conditional mean of higher band (inflation above 6 per cent), *i.e.*, the right tail. This, at 21.98 per cent, happens to be an all-time peak during the months

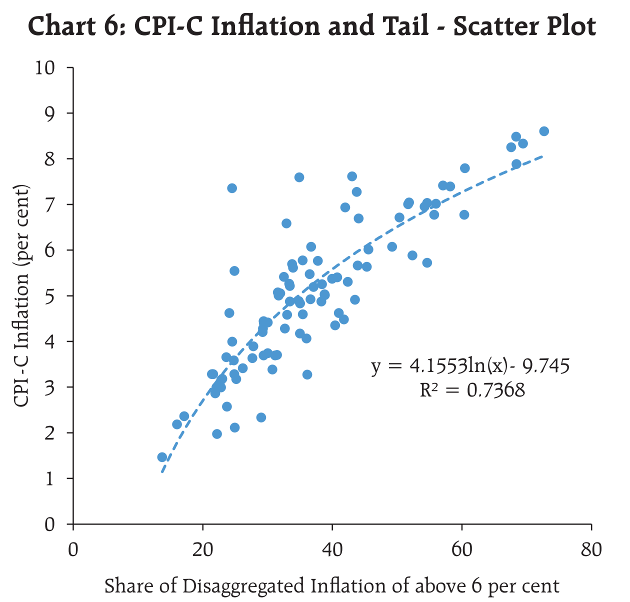
[4] The MoSPI also publishes item-level inflation for all 299 items, as used to construct the CPI-C. However, this is not published by area or by States/UTs. Accordingly, the overall granularity of the larger States is much higher covering 990 (=2*22*23 - 22) data points. The Sub-group 'Housing' is not applicable for Rural areas and, accordingly, is neither available for the States nor for the aggregate CPI-C, and accordingly is not available.

[5] The share incorporates the appropriate weights of the respective product sub-groups, and not just simple averages, in order to represent CPI-C the way it is compiled.

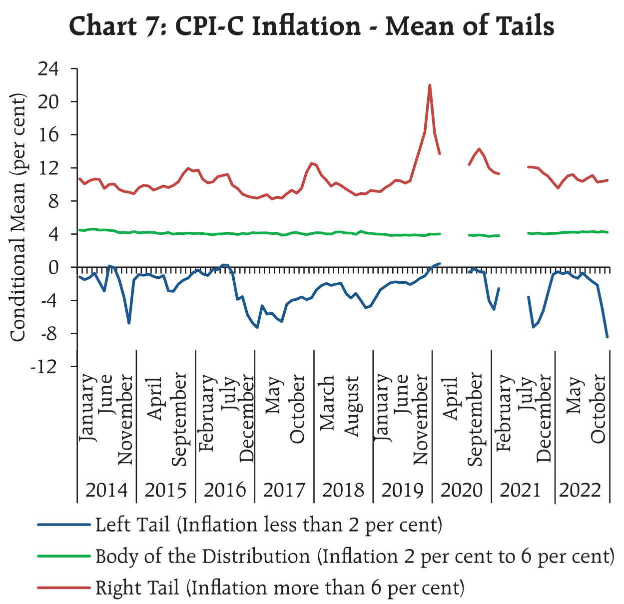


Note: Adequate granularity of data (either index or rates or both) is not available from March 2020 to July 2020 and again from March 2021 to July 2021 due to the first and second waves of COVID. Accordingly, these incomplete data points were discarded from the study and for all the subsequent Charts/Tables, wherever applicable.
Source: Author's calculations.

of 2014 to 2022. Surprisingly, while the positive and negative shocks, in terms of share of left tail (24.18 per cent) and right tail (24.55 per cent), were able to offset each other in December 2019, the spread[6] of their conditional means was quite different from the target of 4 per cent. This was otherwise also quite different from the average profile[7] of other months (Chart 7).



Source: Author's calculations.

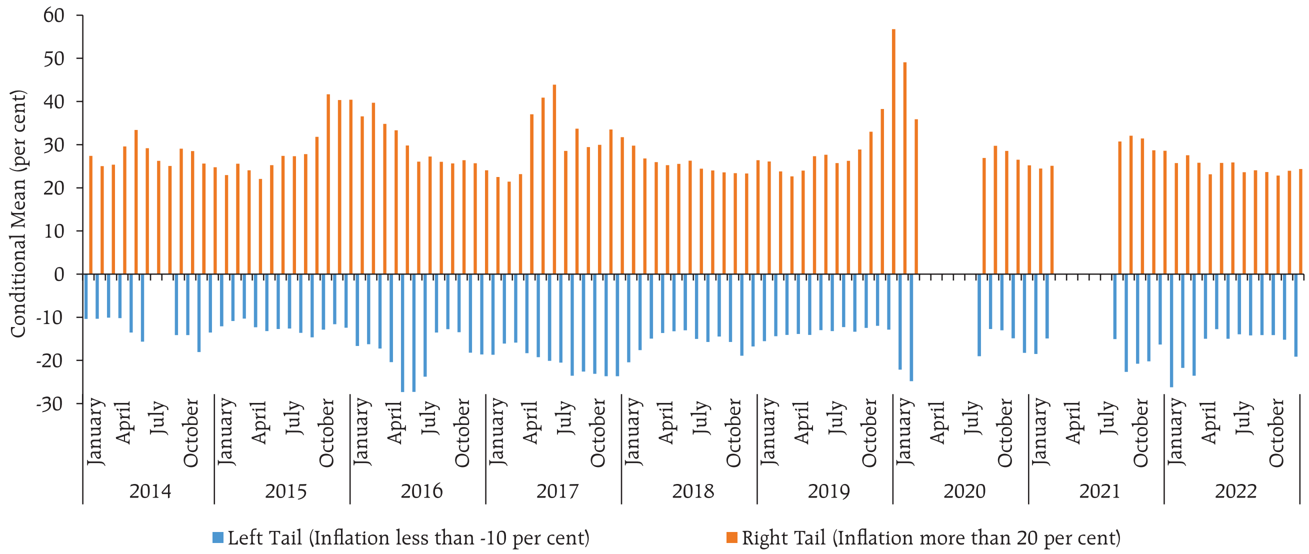


Source: Author's calculations.

6 The spread (distance) of the conditional mean of the right tail from 4 per cent was at 17.98 per cent in December 2019, while it was only -4.24 per cent for the left tail, which had a conditional mean of -0.24 per cent.

7 Based on the simple average of the 98 observed months under the study period, the conditional means of the left tail and right tail are computed as –2.50 per cent and 10.61 per cent, respectively, while it is 4.10 per cent for the body of the distribution.

Chart 8: CPI-C Inflation - Mean of Extreme Tails



Source: Author's calculations.

Due to the high importance of tails in the inflation disaggregated data, their extreme values were also investigated. These extreme tails demonstrate the vulnerability of inflation prints when the positive and negative shocks fail to offset each other, in terms of their decomposed asymmetric contributions in shaping the final single print of CPI-C inflation (Chart 8).

III. Methodology

A stochastic process is a family or set of ordered random variables. It is a model for a time-dependent random phenomenon. It is a collection of random variables X(t), one for each time t in some set J. The same is denoted as {X(t)}. The set of values that the random variable X(t) are capable of taking is called the state space of the process. A stochastic process is said to be stationary or strictly stationary, if the joint distributions of $X(t_1)$, $X(t_2)$, $X(t_3)$, …….., $X(t_n)$ and $X(k+t_1)$, $X(k+t_2)$, $X(k+t_3)$, …….., $X(k+t_n)$ are identical for all t_1, t_2, t_3,…….., t_n and $k+t_1$, $k+t_2$, $k+t_3$,…….., $k+t_n$ in J and for all integers n. That is to say that the statistical properties of the process remain unchanged as time elapses. The statistical properties pertain to probabilities, expected values, variance *etc.* The failure of any of these conditions to hold could be used to show that the process is not stationary.

A continuous stochastic process $\{X(t), t \geq 0\}$ is said to be a first-order Markov process, if for a set of time points $t_0 < t_1 < t_2 \ldots. < t_n$, the conditional distribution of the random variable $X(t_n)$ can be defined in terms of only $X(t_{n-1})$. That is the history of the process prior to time t_{n-1} is assumed to be irrelevant to the value taken by the variable at time t_n. Formally, the stochastic process {X(t)} is a Markov, if for all time points $t_0 < t_1 < t_2 \ldots. < t_n$,

$$\text{Prob.}\,[\,X(t_n) \leq x_n \mid X(t_k) \leq x_k\,;\, k = 0, 1, 2, 3, \ldots., n-1]$$

$$= P\,[\,X(t_n) \leq x_n \mid X(t_{n-1}) \leq x_{n-1}]$$

where, Prob. is the probability, x_0, x_1, x_2, x_3, ……., x_n belong to a set of real numbers.

A discrete-time first-order Markov process described by a sequence of random variables X(t), t = 0, 1, 2, 3, …, with discrete state space is referred to as a first-order Markov chain or simply as a Markov chain.

We define the stationary probability distribution of a Markov chain with transition probability matrix P if the following conditions hold for all j in S:

1. $\pi_j = \sum \pi_i \, p_{ij}$
2. $\pi_j \geq 0$
3. $\sum_{j \in S} \pi_j = 1$

These three conditions can together be represented in a matrix equation, $\pi P = \pi$.

where, π is a row vector, thus, $\pi = (\pi_1, \pi_2, \pi_3, \ldots \pi_n)$

The meaning of this is if we take π as our initial probability distribution, that is,

$P[X_0 = i] = \pi_i$

Then, the distribution at time 1 is again given by π:

$P[X_1 = j] = \sum_{i \in S} P[X_1 = j / X_0 = i] \, P[X_0 = i]$

$= \sum_{i \in S} p_{ij} \, \pi_i = \pi_j$

The same is valid for all times $n \geq 1$. The probability distribution of π is invariant. If the chain ever reaches the distribution π at some time, say, n, that is, $P[X_n = i] = \pi_i$ for all values of i, then the distribution of X_t will be π for all subsequent times $t \geq n$. This is because the transition matrix will remain unchanged. With this, the statistical properties of the process will not change over time and the Markov chain will have a stationary process.

A Markov chain may or may not have a stationary probability distribution. Also, if it has a stationary probability distribution, it may not necessarily be unique. However, if a chain is having a finite space, it must have the existence of at least one stationary distribution. In practice, the transition probabilities (p_{ij}, the probability of transition from i^{th} state to j^{th} state in one step for all i and j) are not available. However, these could be estimated from the empirical data. For example, let $x_1, x_2, x_3, \ldots, x_N$ are the observations available from the empirical data. Let,

n_{ij} = number of times t ($1 \leq t \leq N\text{-}1$) such that $x_t = i$ and $x_{t+1} = j$

$n_{i.}$ = number of times t ($1 \leq t \leq N\text{-}1$) such that $x_t = i$

In fact, n_{ij} is the observed number of transitions from the i^{th} state to the j^{th} state, and $n_{i.}$ is the observed total number of transitions originating from the i^{th} state.

With this, the transition probabilities could be estimated as:

Est. $p_{ij} = n_{ij} / n_{i.} = n_{ij} / \sum n_{ij}$ (summation over j)

As an extension to the above methodology, we develop a weighted count concept to differentiate a transition of a particular product sub-group across States/UTs and Areas (Rural/Urban) having different weights in the CPI-C basket. This ensures that the transitions through granular data represent aggregate inflation. Accordingly, we now define it as:

Let $w_{g,s,a} * n_{ij}$ be the (weighted) number of moves from the i^{th} state (an inflation band) to j^{th} state (an inflation band) in a one-step period (one month) for a granular category - g^{th} product-group (total 23) of a^{th} area (either Rural or Urban) in the s^{th} State/UTs (total 22).

let p_{ij} be the corresponding (weighted) probability, which can be estimated by equating to:

$p_{ij} = w_{g,s,a} * n_{ij} / \sum_j (w_{g,s,a} * n_{ij})$, where the denominator is the sum of terms (row marginal totals) in the i^{th} state (an inflation band).

Also, $\sum_j p_{ij} = 1$ for any state i.

Let $P = \{p_{ij}\}$ be the matrix of such probabilities and let π be the row vector of $1 \times i$. This will convert P into a stationary solution, which can be obtained by solving the equation $\pi P = P$.

The present article attempts to build a simple stochastic process for the transition of CPI-C using the observed (empirical) data as discussed in the introductory section. The transitions of inflation at the granular level are analysed through the stochastic process to derive the long-run steady state of headline inflation. The study uses Markov chains (as defined above) to carry out the exercise. The Markov chains assume discrete state space and discrete time. The discrete-time spaces are considered as "months", in line with the frequency of CPI-C inflation data. The discrete state spaces are considered as various inflation bands.

The granular dataset of 22 States/UTs is used, as discussed in the second section, to the fullest to investigate every transition. A transition requires pair-wise inflation data for two consecutive months. It may be noted that the data of a particular month is used twice, one for destination (previous month to current month) and the other for origin (current month to next month). However, due to a structural break in the time series leading to the non-availability of complete data from March to July of each year 2020 and 2021, some of the pairs of consecutive months are not available and so are discarded from the study. This way, some of the months are utilised only once (such as February 2020 is used for transition only as a destination), while some others (such as March 2020) are discarded.

We now define our states (*viz.* the CPI-C inflation bands) in five broad categories, extreme low (EL), low (L), middle (M), high (H) and extreme high (EH) with sub-levels of 10 bands each for the low, middle and high bands. This results in 32 bands for inflation (Table 1).

It may be noted that the tolerance band for inflation for Reserve Bank is 2 per cent to 6 per cent, *viz.* bands M03, M04, M05 and M06, in the above-defined classification. However, it may be mentioned that it is meant for the CPI-C All India (Aggregate) inflation and not for its components/granularity. Nevertheless, these bands for the granular data may be useful for policy analysis.

Based on the classification of bands, we track the monthly transitions of the annual inflation at the granular level with appropriate weights assigned to them. Once the transitions from one band to another band for each category of granular-level data are compiled, the transition probability matrix (TPM) of size 32-by-32 is constructed. The same is done for the Pre-COVID, Post-COVID and combined period for the valid pair[8] of consecutive months. The statistical

Table 1: Bands for CPI-C Inflation

Inflation (j) (Broad Levels)	Band Codes (Sub-Levels)	State Number
Extreme Low (EL)	EL ($j < -10$)	1
Low (L)	L01 ($-10 \le j < -9$)	2
	L02 ($-9 \le j < -8$)	3
	L03 ($-8 \le j < -7$)	4
	L04 ($-7 \le j < -6$)	5
	L05 ($-6 \le j < -5$)	6
	L06 ($-5 \le j < -4$)	7
	L07 ($-4 \le j < -3$)	8
	L08 ($-3 \le j < -2$)	9
	L09 ($-2 \le j < -1$)	10
	L10 ($-1 \le j < 0$)	11
Middle (M)	M01 ($0 \le j < 1$)	12
	M02 ($1 \le j < 2$)	13
	M03 ($2 \le j < 3$)	14
	M04 ($3 \le j < 4$)	15
	M05 ($4 \le j < 5$)	16
	M06 ($5 \le j < 6$)	17
	M07 ($6 \le j < 7$)	18
	M08 ($7 \le j < 8$)	19
	M09 ($8 \le j < 9$)	20
	M10 ($9 \le j < 10$)	21
High (H)	H01 ($10 \le j < 11$)	22
	H02 ($11 \le j < 12$)	23
	H03 ($12 \le j < 13$)	24
	H04 ($13 \le j < 14$)	25
	H05 ($14 \le j < 15$)	26
	H06 ($15 \le j < 16$)	27
	H07 ($16 \le j < 17$)	28
	H08 ($17 \le j < 18$)	29
	H09 ($18 \le j < 19$)	30
	H10 ($19 \le j < 20$)	31
Extreme High (EH)	EH ($j \ge 20$)	32

[8] The data from January 2014 to December 2022 has 95 valid pairs of consecutive two months, for which granular data is available. This includes 73 pairs for the Pre-COVID period and 22 pairs for the Post-COVID period.

characteristics of this granular level observed data exhibit clear distinction in the Pre-COVID and Post-COVID periods, in line with the CPI-C Aggregate data (Table 2).

The observed data highlight a shift in the inflation trajectory after the emergence of the COVID pandemic and the subsequent Ukraine war. The evolution of the probability density function of CPI-C inflation at a granular level since 2014 is provided in the Annex, which exhibits how the density is re-shaped after the incoming of every 6-monthly new (incremental) data – both during the pre-COVID and post-COVID periods. The skewness of the density function of the increamental dataset decreased consistently during

Table 2: Probability Density Function (PDF) of Observed Data

Band	Pre-COVID		Post-COVID		Combined	
	Mid-Point	PDF	Mid-Point	PDF	Mid-Point	PDF
EL (j < -10)	-16.787	0.02483	-18.451	0.02483	-17.198	0.02483
L01 (-10 ≤ j < -9)	-9.518	0.00382	-9.504	0.00250	-9.515	0.00349
L02 (-9 ≤ j < -8)	-8.541	0.00379	-8.450	0.00146	-8.531	0.00322
L03 (-8 ≤ j < -7)	-7.453	0.00376	-7.491	0.00272	-7.461	0.00350
L04 (-7 ≤ j < -6)	-6.480	0.00463	-6.510	0.00278	-6.485	0.00417
L05 (-6 ≤ j < -5)	-5.465	0.00568	-5.494	0.00401	-5.470	0.00527
L06 (-5 ≤ j < -4)	-4.471	0.00701	-4.506	0.00622	-4.479	0.00681
L07 (-4 ≤ j < -3)	-3.492	0.00941	-3.418	0.00517	-3.481	0.00836
L08 (-3 ≤ j < -2)	-2.489	0.01397	-2.501	0.01143	-2.492	0.01334
L09 (-2 ≤ j < -1)	-1.496	0.02006	-1.515	0.01620	-1.500	0.01911
L10 (-1 ≤ j < 0)	-0.507	0.02832	-0.494	0.02004	-0.505	0.02628
M01 (0 ≤ j < 1)	0.500	0.04658	0.544	0.04165	0.510	0.04537
M02 (1 ≤ j < 2)	1.536	0.06263	1.520	0.04727	1.533	0.05883
M03 (2 ≤ j < 3)	2.524	0.08532	2.531	0.07453	2.526	0.08265
M04 (3 ≤ j < 4)	3.510	0.11637	3.510	0.08650	3.510	0.10899
M05 (4 ≤ j < 5)	4.499	0.11660	4.488	0.09480	4.497	0.11122
M06 (5 ≤ j < 6)	5.491	0.10950	5.498	0.08463	5.492	0.10335
M07 (6 ≤ j < 7)	6.474	0.08870	6.492	0.08567	6.478	0.08795
M08 (7 ≤ j < 8)	7.473	0.06270	7.476	0.07198	7.474	0.06499
M09 (8 ≤ j < 9)	8.467	0.04859	8.467	0.05997	8.467	0.05140
M10 (9 ≤ j < 10)	9.475	0.03373	9.474	0.04677	9.475	0.03695
H01 (10 ≤ j < 11)	10.473	0.02480	10.471	0.03839	10.472	0.02816
H02 (11 ≤ j < 12)	11.478	0.01608	11.473	0.02800	11.476	0.01903
H03 (12 ≤ j < 13)	12.461	0.01049	12.479	0.02443	12.469	0.01394
H04 (13 ≤ j < 14)	13.489	0.00813	13.461	0.01844	13.477	0.01067
H05 (14 ≤ j < 15)	14.485	0.00586	14.518	0.01588	14.501	0.00834
H06 (15 ≤ j < 16)	15.486	0.00492	15.468	0.01238	15.478	0.00676
H07 (16 ≤ j < 17)	16.481	0.00442	16.438	0.00935	16.463	0.00564
H08 (17 ≤ j < 18)	17.401	0.00379	17.476	0.00871	17.434	0.00501
H09 (18 ≤ j < 19)	18.465	0.00260	18.416	0.01041	18.437	0.00453
H10 (19 ≤ j < 20)	19.451	0.00254	19.467	0.00723	19.459	0.00370
EH (j ≥ 20)	32.003	0.02035	26.962	0.03564	30.164	0.02413
Mean (Per cent)		**4.66**		**6.16**		**5.03**

Note: The probability density function of the disaggregate and aggregate inflation data would be different though the central tendency derived from these two datasets would be the same or comparable. However, other statistical moments of the data (*viz.* standard deviation, skewness and kurtosis) may differ significantly. For example, the standard deviation of the granular data would be higher than that of the aggregate data.
Source: Author's calculations.

2014 and 2015, together with the lowering of inflation. The distribution turned more peaked (leptokurtic) subsequently (during 2016 and H1:2017) with more concentrated values around the central tendency coupled with generally lower extreme values at each end. The frequency of extreme low values increased significantly in H2:2018, which helped aggregate inflation to moderate. The frequency of high extreme values surged in H1:2020, prior to the emergence of COVID. In the post-COVID period, an overall right-ward shift in the inflation distribution is consistently observed with varied intensity coupled with remarkable changes in the densities at extreme ends (Annex Chart A1).

To derive the long-run stationary distribution (LRSD), implementation of a large-sized matrix was possible due to the availability of a large number of observations in the dataset as we chose the highest order of granularity, yielding in a good representation of 1,024 (=32*32) cells in the matrix. As mentioned earlier, we have 990 observations for each of the valid pairs of observations leading to 94,042 observations[9]. The transition matrix for these observations (simple/unweighted count) for the combined period is provided (Annex Table A1) for ready reference for easy demonstration.

It is interesting (and logical) to see that the probability from one extreme band (say, EL) to another extreme band (say, EH) in one month is very unlikely. The *vice-versa* is also true.

As evident from the Table, there are tiny number of observations of such cases. Accordingly, in a short period of one month, the inflation (y-o-y) is unlikely to either surge or fall drastically.

To better visualise the transitions, we collapse the 32-by-32 matrix into a much smaller matrix (of 3-by-3). It is observed that the persistency of inflation has reduced in the Post-COVID period as compared to the Pre-COVID period in case of low and moderate inflation, while it has increased at a high level. Further, the extreme shifts in transition *i.e.*, from Band A to Band C and also from Band C to Band A have also increased in the Post-COVID phase (Table 3).

Using the above persistency levels of inflation bands in the granular data, the long-run (steady state) mean reversion time of the high inflation band (Band C) appeared to have reduced considerably from the pre-COVID period (3.20 months) to Post-COVID period (2.05 months), which is compensated by an increase in the same for the other two bands. The mean reversion time for Post-COVID indicates that if a transition moves out from band C (either to band A or band B), it is expected to come again to this band (*viz.* band C) quicker (in around two months), which was 3.20 months for the Pre-COVID era (Table 4).

Based on the transition matrix [P], we can derive a stationary distribution (steady state equilibrium), which is the long-run stationary distribution (LRSD) following these transitions, by solving the set of

Table 3: Persistence of Inflation (Transition Probability Matrix)

Pre-COVID				Post-COVID			
Band	A	B	C	Band	A	B	C
A	0.8456	0.1365	0.0179	A	0.8058	0.1723	0.0220
B	0.0760	0.8322	0.0918	B	0.0719	0.7938	0.1343
C	0.0143	0.1298	0.8559	C	0.0190	0.0822	0.8988

Source: Author's calculations.
A: Inflation below 2 per cent B: Inflation within 2 per cent to 6 per cent C: Inflation above 6 per cent

[9] Eight pairs of observations were missing in the granular dataset, and accordingly, were discarded from the study resulting in 94,042 observations instead of 94,050.

Table 4: Mean Reversion Time (in Months)

Band	Pre-COVID	Post-COVID
A	4.0607	5.7720
B	2.2642	2.9483
C	3.2043	2.0510

Source: Author's calculations.
A: Inflation below 2 per cent
B: Inflation within 2 per cent to 6 per cent
C: Inflation above 6 per cent

equations π P = π, where π is a 1*32 row vector and P is a 32*32 matrix. The transpose of the row vector π for these three datasets represents the LRSD (Table 5).

Table 5: Forecasted Probability Density Function (PDF) of LRSD

Band	Pre-COVID	Post-COVID	Combined
EL (j < -10)	0.02456	0.03079	0.02595
L01 (-10 ≤ j < -9)	0.00388	0.00297	0.00369
L02 (-9 ≤ j < -8)	0.00384	0.00153	0.00337
L03 (-8 ≤ j < -7)	0.00378	0.00309	0.00357
L04 (-7 ≤ j < -6)	0.00473	0.00276	0.00425
L05 (-6 ≤ j < -5)	0.00583	0.00385	0.00538
L06 (-5 ≤ j < -4)	0.00717	0.00629	0.00694
L07 (-4 ≤ j < -3)	0.00968	0.00458	0.00848
L08 (-3 ≤ j < -2)	0.01480	0.01086	0.01373
L09 (-2 ≤ j < -1)	0.02141	0.01340	0.01938
L10 (-1 ≤ j < 0)	0.03081	0.01723	0.02723
M01 (0 ≤ j < 1)	0.05126	0.03703	0.04769
M02 (1 ≤ j < 2)	0.06911	0.04334	0.06261
M03 (2 ≤ j < 3)	0.09392	0.07076	0.08870
M04 (3 ≤ j < 4)	0.12582	0.08444	0.11649
M05 (4 ≤ j < 5)	0.12225	0.09583	0.11694
M06 (5 ≤ j < 6)	0.10993	0.08949	0.10631
M07 (6 ≤ j < 7)	0.08454	0.09243	0.08725
M08 (7 ≤ j < 8)	0.05633	0.07810	0.06158
M09 (8 ≤ j < 9)	0.04218	0.06471	0.04740
M10 (9 ≤ j < 10)	0.02783	0.04917	0.03273
H01 (10 ≤ j < 11)	0.01962	0.03995	0.02416
H02 (11 ≤ j < 12)	0.01275	0.02832	0.01610
H03 (12 ≤ j < 13)	0.00846	0.02502	0.01195
H04 (13 ≤ j < 14)	0.00662	0.01757	0.00898
H05 (14 ≤ j < 15)	0.00485	0.01477	0.00700
H06 (15 ≤ j < 16)	0.00381	0.01191	0.00559
H07 (16 ≤ j < 17)	0.00370	0.00830	0.00472
H08 (17 ≤ j < 18)	0.00314	0.00788	0.00417
H09 (18 ≤ j < 19)	0.00230	0.00944	0.00390
H10 (19 ≤ j < 20)	0.00222	0.00625	0.00314
EH (j ≥ 20)	0.01888	0.02793	0.02059
Estimated Mean (Per cent)	**4.31**	**5.92**	**4.67**

Source: Author's calculations.

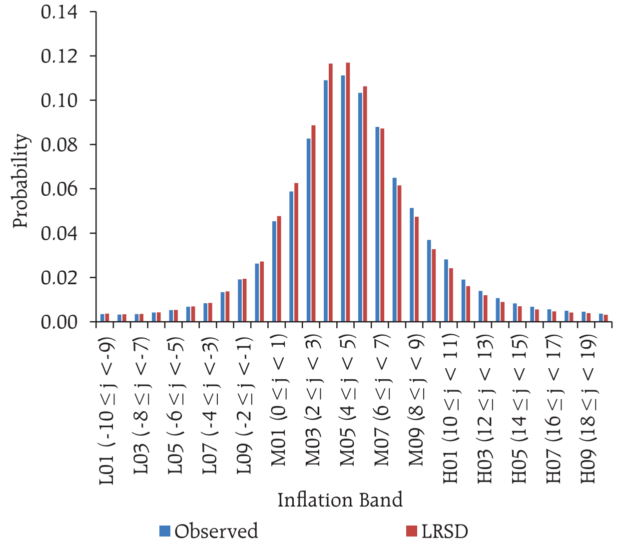
From Table 2 and Table 5, we observe that the long-run steady-state level of inflation would likely be lower than the observed levels, as is seen consistently across the datasets. This signals that the steady state is closer to the mandated target inflation of RBI, as compared to the observed data.

It may be noted that the Pre-COVID dataset is expected to be more robust being longer in series and does not cover one-off episodes of severe events such as COVID and war. Still, we observe a drop of 20-40 basis points in the inflation rate going forward if the current and past transitions hold and other underlying assumptions and conditions continue to prevail.

The nature of the shift (change) in the probability density function from the observed to the LRSD is also worthy of investigation. For example, in the case of the Pre-COVID dataset, although, the shift is small in magnitude, like in the full (combined) dataset (Chart 9), there is an indication of transitions moving towards the central value (Chart 10).

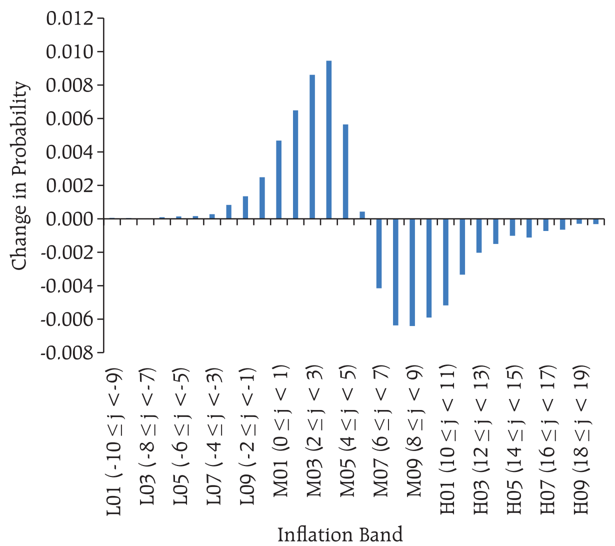
The forecasted probability density of LRSD indicates that the frequency of observations may be slightly more around the central tendency (inflation

Chart 9: PDF of Observed and LRSD



Source: Author's calculations.

Chart 10: Shift (Change) in PDF



Source: Author's calculations.

0 per cent to 6 per cent) from the observed granular data, which could be compensated with reduced observations in the high inflation bands.

IV. Conclusion

Inflation in India surged since the emergence of the COVID pandemic and the subsequent Ukraine war and became a major policy concern. With the pandemic impact waning, and the supply chains are easing, however, the long-run steady state level for inflation using stochastic transitions at the micro-level data shows a tendency of inflation to tread slowly towards its central value. This study shows that the inflation long-run steady state equilibrium level could be around 4.3 per cent based on the pre-pandemic datasets. The marginal uptick in steady state inflation observed during the pandemic period is likely to be transient and steady state inflation may revert to lower trajectories going forward. The precise speed of the recovery and normalisation of business conditions coupled with evolving situations may dictate how much and how soon the inflation glides onto a lower trajectory.

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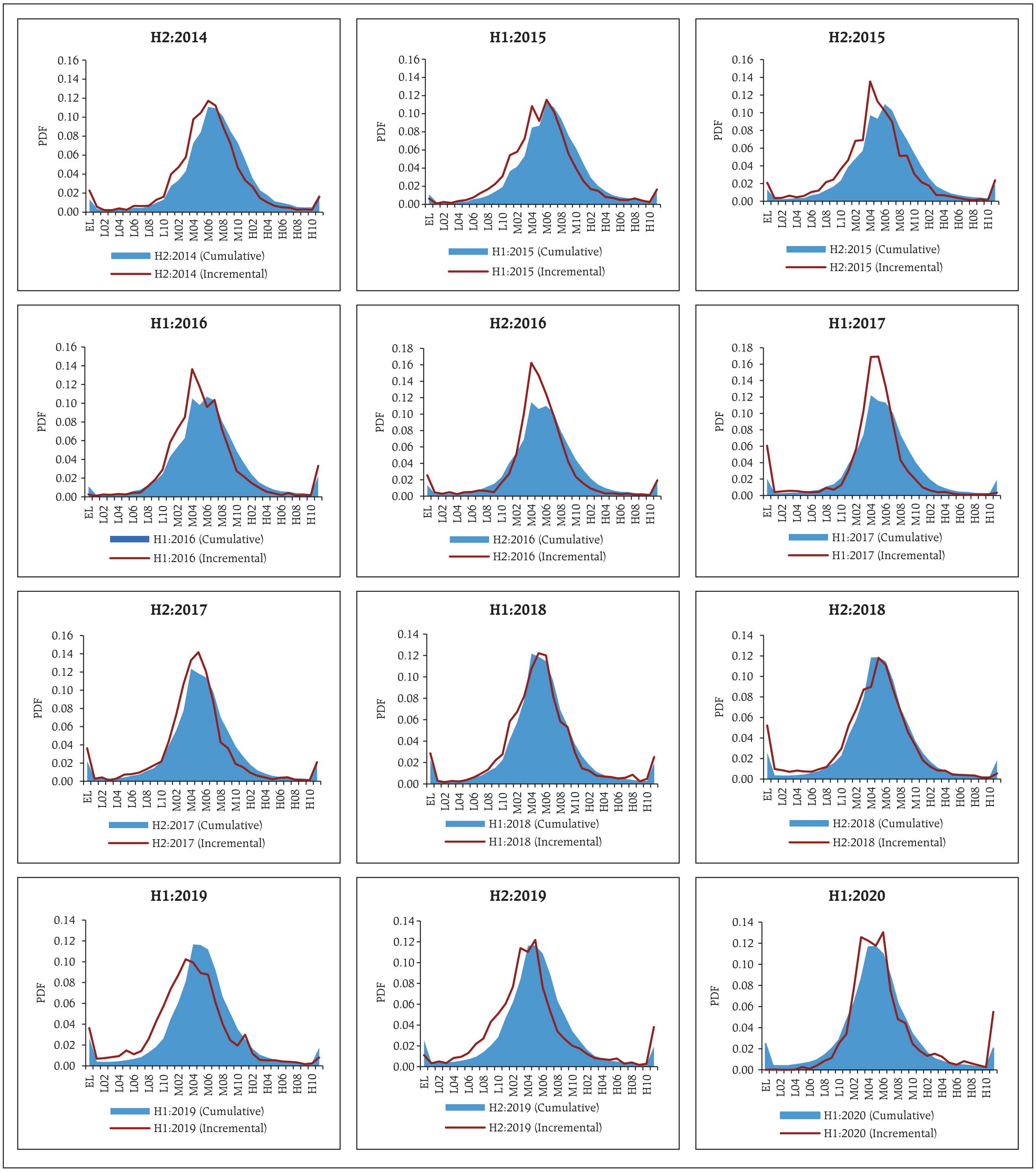
Annex

Annex Table A1: Transition Probability Matrix (Count-wise) – Combined Period

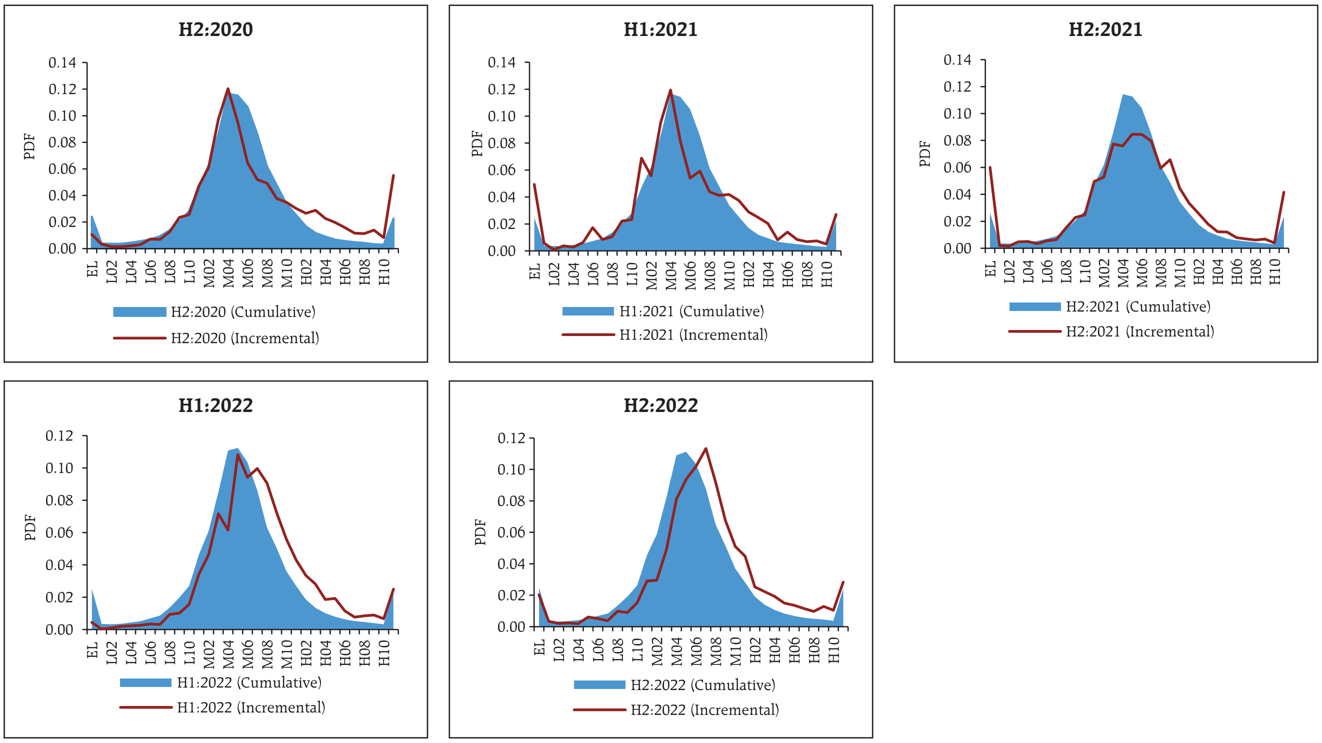
		To the Next Month																															
	Bands	EL	L01	L02	L03	L04	L05	L06	L07	L08	L09	L10	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	H01	H02	H03	H04	H05	H06	H07	H08	H09	H10	EH	Total
From the Current Month	EL	1785	121	87	64	49	33	34	20	27	14	10	10	12	10	5	6	7	8	3	1		4		3	2	2			1			2	2320
	L01	120	54	43	33	30	20	17	12	7	4	2	4	2	2	1	3		2	2		1										1	1	361
	L02	88	50	60	38	33	33	17	15	10	5	7	3	4	2	7	3	2	3															380
	L03	66	28	36	67	66	49	30	23	10	9	9	4	4	6	2	6	3		1			1			1			1	1				423
	L04	53	27	38	45	76	77	60	37	32	11	18	6	8	7	7	7	3	1	2		1	2				1		1	1				521
	L05	40	14	30	43	63	105	108	61	54	32	16	21	11	8	8	3	8	3	2	3	2			1	2							1	639
	L06	32	14	15	33	47	97	144	136	99	55	34	22	18	21	8	12	5	4		4	1	2	1	1						1		3	809
	L07	23	10	14	18	36	61	108	205	193	115	75	49	24	22	19	12	8	2	5	2	3		2	1	1	1		1	1				1011
	L08	20	5	10	15	33	45	91	176	363	303	180	115	63	48	14	16	14	9	7	2	4	1	2	1	1		1				2	2	1543
	L09	16	2	6	8	18	27	53	108	286	508	416	184	114	55	46	24	16	14	8	6	4	4	5	5	2	1	2	1	2				1941
	L10	14	8	7	7	12	15	36	65	166	372	724	651	270	107	64	39	27	19	12	9	2	3	1	3	4	1	1				2	1	2642
	M01	14	6	5	6	10	15	28	40	100	218	633	1609	960	397	164	93	48	24	11	12	12	2	7	3	2	1	2	1	1		2		4426
	M02	9	3	6	8	6	13	21	34	65	125	249	972	2564	1318	483	171	101	47	18	16	13	6	5	5	2	2	2	1		2		4	6271
	M03	8	4	2	1	7	6	9	13	38	47	119	365	1346	3292	1560	478	222	95	60	27	24	9	10	4	2	2	1	4	1	1	2	2	7761
	M04	5	2	5	4	8	4	8	11	16	37	59	183	476	1592	3801	1758	522	223	92	43	28	28	15	12	2	4	8	3	1	1		9	8960
	M05	5	1	2	6	5	8	2	12	13	27	28	89	201	547	1804	3791	1738	528	203	85	40	30	12	15	5	6	6	5	2		2	7	9225
	M06	9	1	3	2	1	2	7	8	7	19	19	55	99	215	551	1821	3379	1570	521	169	82	61	17	18	11	8	7	8	1	3	2	9	8685
	M07	6	2	3	2	1	2	8	10	8	9	10	36	54	81	207	541	1629	2741	1284	448	155	62	41	22	10	10	7	7	6	4	3	11	7420
	M08	7	1		3	1	2	2	4	5	7	14	23	26	43	97	219	557	1346	2097	1029	342	141	52	34	26	21	10	4	3	3	2	8	6129
	M09	3	1	1		2	3	3	2	4	13	10	17	10	35	56	114	209	429	1044	1531	711	297	100	45	51	19	10	7	4	8	5	12	4756
	M10	3	2		1	2	1	4	2	1		6	10	11	8	29	42	70	154	393	792	1066	555	231	95	49	25	15	9	7	3	3	12	3601
	H01	6		1	2	1	3	5	3	8	2	3	6	14	10	12	31	45	73	159	276	604	752	411	187	83	42	23	11	10	11	3	13	2810
	H02	6	2	1		2	2		1	4	5	6	2	9	10	17	15	30	38	91	122	217	433	500	288	123	72	24	24	14	8	6	26	2098
	H03	2			1		2		2	3	4	1	2	3	4	10	12	20	26	36	51	99	182	291	321	203	101	68	26	26	9	5	29	1539
	H04				3		1	1	1	1	2	1	2	6	3	6	8	11	20	21	30	50	81	137	221	240	167	83	47	29	21	15	24	1232
	H05	1		1				2	4	1	3	1	3	4	6	5	8	8	7	12	15	31	34	70	100	174	185	136	82	32	26	18	39	1008
	H06							2	1	1		4		1		4	2	4	2	11	11	17	21	42	49	85	117	143	106	47	39	23	43	775
	H07				2			1	1	1	1	1	1	4	2	2	3	2	3	9	6	11	13	29	36	53	77	70	88	84	46	29	64	639
	H08	1				1		1	1	1				5	3		4	4	4	7	9	12	10	16	9	29	38	59	60	81	65	40	75	535
	H09	2		1		1			2	2		1	1	2		3	3	1	5	3	8	10	11	16	13	16	20	28	37	52	58	43	107	446
	H10			1		2							2	1	1	3	4	5	2	3	5	10	5	12	6	11	22	16	29	46	45	49	119	399
	EH	1	1					2	2	1	3	3	2	4	4	2	5	13	15	8	10	13	26	24	34	36	41	34	65	70	90	135	2093	2737
	Total	2345	359	378	412	513	626	804	1012	1527	1950	2659	4449	6330	7859	8997	9254	8711	7417	6125	4722	3565	2776	2049	1532	1226	986	756	628	523	444	392	2716	94042

Chart A1: Evolution and Stabilisation of the Probability Density Function with the Incoming of every Half-Yearly Incremental Data (2014-2022)

Pre-COVID



Post-COVID



Note: H1:2020 and H1:2021 cover only January and February of the respective year. H2:2020 and H2:2021 do not cover July of the respective year. These are not available fully at the granular level.
Source: Author's calculations.