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Abstract

This study examines the convergence of inflation and the formation of inflation clubs across Indian states from 2012 to 2023. The empirical findings indicate a reduction in inflation dispersion among Indian states. The convergence test using panel unit root analysis and the club convergence test suggest that inflation will eventually reach a steady state. We observe this convergence, particularly during the inflation targeting period, implying that the inflation targeting regime plays an important role in achieving inflation convergence across Indian states. This also suggests increased economic integration, improved policy effectiveness, and enhanced market efficiency in India. Additionally, our club convergence test revealed the possibility of 'conditional' convergence. Further analysis using System-GMM reached the same conclusion. Our findings highlight concerns regarding the significance of wages, as they substantially increase inflation disparity. Consequently, we recommend that policymakers take steps to eliminate wage inequality between states in India. This can be achieved by increasing investment in underdeveloped states, reducing disparities in minimum wages, and ensuring compliance with minimum wage regulations.

Keywords: Club convergence; Inflation convergence; Inflation Targeting; Regional analysis; Sigma convergence

JEL Code: E31, E50, E52, R12

Inflation convergence across Indian states

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1. Introduction

According to the optimum currency area theory, inflation rates are expected to equalize or converge across regions or countries within a monetary union due to the extensive integration of labor, product, and capital markets. Competitive markets should lead to price equalization for identical goods across different regions or countries when prices are denominated in the same currency (Rogoff, 1996). However, these theoretical assumptions often face challenges in reality, as regional disparities in inflation rates are frequently observed (Beck et al., 2009; Nagayasu, 2011; Purwono et al., 2020). These disparities may persist, even in developed areas like the European Monetary Union (EMU) and the United States, casting doubts on the practical applicability of the theory.

Despite a substantial body of empirical research in this area, mainly focused on developed areas, there appears to be a lack of similar analyses for developing areas. Inflation convergence is the tendency of inflation rates across different regions, countries, or sectors to become more similar over time. Inflation convergence has received significant attention in economic studies, with much research focusing on national levels (Busetti et al., 2007; Dridi and Nguyen, 2019). However, investigations into regional inflation convergence remain relatively scarce.

Monetary policy rules that neglect regional-level information can lead to welfare losses, especially when there are asymmetries in the transmission mechanism (De Grauwe, 2000; Gros and Hefeker, 2002). For instance, different regions may have diverse economic bases (e.g., agriculture vs. manufacturing vs. services), causing a change in monetary policy to have varying impacts depending on the dominant economic activities in each region. Consequently, such monetary policies may not be optimal and need to be addressed. In Indonesia, where inflation targeting was introduced in 2005, measures have been taken to address regional disparities. In 2008, regional inflation control teams were established at provincial and city/regency levels, complementing the central inflation control team (Purwono et al., 2020). Similarly, for India, a newcomer to the inflation targeting regime, this analysis will explore the feasibility of establishing similar regional inflation control teams to effectively address regional disparities.

In this paper, we examine the convergence of consumer price index inflation (CPII) across different states of India, covering the period between 2012 and 2023. We are considering monthly CPI data since it is regarded as an indicator of inflation in the current inflation-targeting regime. Our preliminary analysis, we examine if there is any inflation cluster across Indian states. Further, we check for sigma (σ) convergence, wherein we inspect whether there is a decline in inflation dispersion across states. However, as concerns raised by Bernard and Durlauf (1996) and Jungmittag (2006) about σ-convergence, we additionally check for convergence of inflation based on various panel unit root methods.[1] Nevertheless, the traditional techniques for checking inflation convergence have limitations, especially in the presence of heterogeneity within the economy. These methods often fail to capture individual variability and do not adequately address concerns related to sector-specific clusters or sub-groups within the entire region.[2] So, to account for heterogeneity and check for the possibility of forming clubs, we use Phillips and Sul (2007, 2009) methodology (PS) to test for club convergence.

This exploration is crucial because persistent disparities in inflation levels among regions can have profound implications, particularly on real interest rates, which, in turn, can exacerbate inflation divergence. Higher inflation in a region reduces the real interest rate (nominal interest rate minus inflation), potentially stimulating economic activity by making borrowing cheaper and increasing consumption and investment. Regions with lower real interest rates may experience faster economic growth and higher inflation, while regions with higher real interest rates may face slower growth and lower inflation, thus perpetuating or even exacerbating inflation disparities.

Conversely, inflation differentials can serve as an adjustment mechanism within regions. For example, if one region experiences higher inflation, this can lead to a reduction in demand for its goods, cooling off inflationary pressures. However, an empirical question remains whether the expansionary effects associated with a reduction in real interest rates or the contractionary effects induced by higher inflation predominate.

In this paper, we contribute to this literature in several ways. First, we examine the extent of mean-reverting behavior in regional inflation rates in the context of emerging economies like India. Further, we discuss the dynamics of overall dispersion in our sam-

[1] σ-convergence only suggests catching up process, it does not convey anything about the establishment of a steady state which panel unit root methods can estimate.

[2] σ-convergence and panel unit root tests assume that inflation will converge towards a common inflation rate, which may not be the case.

ples for CPII with a primary focus on how this dispersion has evolved over time. Our third contribution addresses the question of convergence of inflation at the regional or state level. We evaluate the presence of inflation convergence or divergence and explore the underlying reasons. To do so, we refer to methodologies used in the empirical growth literature.

Our results suggest that inflation is randomly distributed across states in India, and there is no formation of any inflation cluster. The inflation dispersion has declined, particularly after 2019. The rate of decline was higher during the inflation targeting regime compared to pre-targeting regime. However, this decline is accompanied by increased inflation across states. We further find evidence of inflation convergence using the panel unit root test and based on PS methodology, we find the formation of a single convergence club. This implies that inflation across states in India is converging towards a single steady state. [3] Moreover, we find the role of inflation targeting regime in reducing inflation dispersion across states in India.

The results obtained using PS methodology confirms the presence of conditional convergence. To test for conditional convergence, we used a variety of controls, including the relative share of agriculture, industry, and services in GDP by state. We also considered state-specific factors such as fiscal deficit ratios and wages. Given concerns about endogeneity, we use system-GMM to estimate conditional convergence, and our findings support the presence of conditional convergence. While most controls were insignificant, wages were consistently positive and significant, implying that wage disparities between states may hinder the inflation convergence process. In addition to standard controls, we used a variety of other controls such as the financial inclusion index, roadway and rail-

[3] This result is driven by the inclusion of the COVID-19 period, as multiple clubs are present in the pre-Covid period. However, for the inflation targeting regime, which runs from 2016m7 to 2023m12, we observe the formation of a single club.

way index, and temperature deviation index, and the results remained consistent. Overall, we identify a single convergence club, indicating increased economic integration and improved market efficiency across Indian states. Furthermore, we recommend that the government take initiatives to reduce wage disparities.

The remainder of the paper is organized as follows. The following Section 2 presents a brief review of the literature. Section 3 presents the methodology and data used in our analysis. Section 4 presents the results and discusses them, and finally, in Section 5, we conclude.

2. Literature review

Much research has been dedicated to studying convergence, particularly concerning economic growth, where convergence implies that poor economies will grow faster than richer ones. However, there has been a recent surge in examining convergence across various other metrics such as inflation and CO_2 emissions growth (Berk et al., 2020; Kuncoro, 2020; Marrero et al., 2021). Inflation convergence within the European Union has garnered significant attention, given it is a precondition for full membership in the European Monetary Union, as outlined in the 1992 Maastricht treaty. Similarly, in the East African Community (EAC), where there is a drive toward establishing a common currency union, studies like Kishor and Ssozi (2010) have observed increased inflation synchronization among member countries. Additionally, research by Dridi and Nguyen (2019) has also detected evidence of convergence among EAC members.

While there is a substantial literature examining convergence at the national level, particularly for countries aspiring to be part of a currency union, research at the sub-national level, such as states or regions within a country that already share a common currency, is relatively scarce. Some notable studies include Cecchetti et al. (2002), which analyzed annual city-level data to identify price divergences among 19 cities in the United States. Similarly, researchers like Yilmazkuday (2013), Yesilyurt and Elhorst (2014), and Duran (2016) have conducted convergence analyses for Turkey, while Ridhwan (2016), Purwono et al. (2020), Tirtosuharto and Adiwilaga (2013), and Kuncoro (2020) have explored the phenomenon for Indonesia. For example, Duran (2016) found that the inflation differential declined over time with no discernible cluster formation, suggesting inflation convergence for Turkey. Similarly, for Indonesia, Purwono et al. (2020) identified inflation convergence during the period from 2013 to 2018. However, such an analysis on inflation convergence is yet to be done for India.

Additionally, the construction of national indices typically involves aggregating data along sectoral and geographical dimensions. The sectoral dimension, which involves analysis at the disaggregate level has been thoroughly examined (Ibarra, 2012; Monacelli and Sala, 2009). For India Ball et al. (2016); Dua and Goel (2021) have explored the sectoral dimension by looking at disaggegate level inflation data; however, the geographical dimension has been relatively overlooked. It is essential not to underestimate this limitation, as distinctions in regional inflation could be equally significant as disparities in sectoral inflation. Benigno (2004) and Benigno and López-Salido (2006), in the context of the European Monetary Union with cross-country heterogeneity, demonstrated that optimal inflation targeting (IT) should assign greater importance to regions with more significant nominal rigidities, i.e., areas where prices and wages do not adjust immediately or frequently in response to changes in economic conditions, a similar argument can be made about the states.

Inflation disparities often arise due to multiple factors outlined in studies such as Beck et al. (2009), Ridhwan (2016), and Tirtosuharto and Adiwilaga (2013), with important implications for economic stability, policy coordination, and global economic integration. For instance, regions with subdued economic activity tend to exhibit weak inflationary pressures, leading to higher real interest rates (nominal interest rate minus inflation). This situation increases borrowing costs, reduces borrowing and spending by consumers, and diminishes investment by businesses. Consequently, economic activity remains low, exacerbating subdued conditions and potentially leading to persistently low inflation or deflation. This creates a feedback loop where weak demand keeps inflation low, maintaining high real interest rates, which further constrains economic growth and inflation, posing challenges for monetary policymakers (Yilmazkuday, 2013).

Moreover, misguided domestic policies or unforeseen developments like fiscal misalignment, excessive wage growth, or fluctuations in production input prices can fuel inflation differentials. For instance, Duarte and Wolman (2002) found that fiscal authority can affect inflation differential associated with shocks to productivity growth. By adjusting spending and taxation in response to changes in productivity, fiscal policy can either amplify or dampen inflation differentials across regions or sectors. Additionally, asynchronous business cycles across regions contribute to regional inflation disparities. When different regions are at different points in the business cycle, their varying demand pressures lead to differences in regional inflation rates. Variations in production structures can further amplify these differences by affecting the transmission mechanisms of common shocks differently across regions. Finally, nominal wage and price rigidities, characterized by sluggish adjustments to external shocks, can prolong the adjustment process and sustain inflation disparities over time (Beck et al., 2009).

Differences in inflation levels can partly arise from varying productivity growth between a country's tradable and non-tradable sectors, as noted by Yilmazkuday (2013). Their study found that, during Turkey's inflation-targeting period, regional inflation rates converged for CPI groups with non-tradable components but diverged for those with tradable components. The Balassa-Samuelson effect posits that productivity growth is typically higher in the tradable sector due to technological advancements and trade openness, leading to lower production costs and prices. Conversely, slower productivity growth in the non-tradable sector keeps production costs high, increasing prices for non-tradable goods and services. As long as this productivity differential exists, inflation disparities will persist, with lower inflation in the tradable sector and higher inflation in the non-tradable sector Busetti et al. (2007).

India, a vast and diverse country, is characterized by a wide range of geographical features across its states and union territories (UTs). From the towering Himalayas in the north to the expansive coastline along the Arabian Sea, Bay of Bengal, and the Indian Ocean, India boasts diverse landscapes. The northern states, including Jammu and Kashmir, Himachal Pradesh, and Uttarakhand, are known for their majestic mountain ranges, including the Himalayas, which are home to some of the highest peaks in the world. Moving southwards, the landscape transitions to the fertile plains of the Indo-Gangetic region, spanning states like Punjab, Haryana, and Uttar Pradesh, which are known for their agricultural productivity. Along the western coast, states like Maharashtra, Goa, and Gujarat feature scenic beaches and rocky coastlines. To the east, states like West Bengal, Odisha, and Andhra Pradesh are characterized by lush greenery, deltas, and rivers like the Ganges and the Godavari. The northeastern states, often referred to as the ”Seven Sisters,” are known for their rich biodiversity, hills, and valleys, while the island territories like Andaman and Nicobar Islands and Lakshadweep boast stunning coral reefs and pristine beaches. India, a federal union comprising 28 states and 8 union territories (UTs), exhibits a complex administrative structure reflecting its diverse cultural, linguistic, and geographical landscape. All these suggests the possibility of the presence of inflation differential across states in India.

Furthermore, the process of formation of inflation expectations, the channel through which our monetary policy operates, also depends on the characteristics of a particular region. Understanding the inflation dynamics within specific regions can assist the central bank in devising region-specific policies to achieve uniform inflation expectations across India. Additionally, managing inflation in a country as large and diverse as India poses significant challenges. While most nations are composed of various regions, the impacts of aggregate economic shocks do not necessarily unfold uniformly across these regions (Carlino and DeFina, 1999). Moreover, what holds true at the aggregate level may not apply when examined at disaggregated levels (Jha and Dhal, 2019). Therefore, investigating inflation convergence across states is crucial for India.

3. Methodology and data

3.1. Methodology

Convergence, in general, is a widely explored topic, and different methodologies have been applied to test it. In his seminal study, Baumol (1986) implemented a simple cross-sectional regression method to test the neoclassical prediction of convergence based on the equation below :

$$\log\left(\frac{y_t}{y_0}\right) = a + b\log\left(y_0\right) \tag{1}$$

where the left-hand side of the equation represents the growth rate of output over the period (0, t), and a negative value for the coefficient b is interpreted as evidence of convergence. This approach is also known as absolute or beta (β) convergence. It indicates that economies with low initial levels of output have experienced faster growth rates. This method was further extended by Barro (1991); Barro and Sala-i Martin (1992); Barro et al. (1991) for the case of panel data. Similarly, one can test for conditional convergence, which implies that economies experience convergence depending on their structural characteristics. Apart from this, there is a possibility that in the long term, the initial conditions are irrelevant, which implies for convergence to occur, the cross-section dispersion must decrease over time; this approach is known as σ-convergence.

Furthermore, various panel data approaches have been developed to test for convergence. There are two main approaches. The first one extends the cross-sectional regression method to consider panel data estimation. In contrast, the second one uses the time series definition of convergence and panel unit root estimation. As argued by Evans (1998) and Evans and Karras (1996), it is better to test for convergence using the panel data method, which combines cross-sectional and dynamic information. Because some of these determinants may be unobserved and constitute nuisance parameters, panel data methods are the only way to obtain consistent estimates.

For example, Lall and Yilmaz (2001) tested for conditional convergence by exploiting the panel data approach to examine the role of human and public capital in convergence while controlling for regional-specific effects. Similarly, Marrero et al. (2021) used the following equation to check for convergence of CO_2 emissions growth

$$\Delta \log y_{it} = \alpha_i + \tau_t + \rho \ \log(y_{i,t-1}) + \epsilon_{it} \tag{2}$$

where α_i is country fixed effect and τ_t is time fixed effect. Evidence of convergence suggests a negative relationship between the growth rate of the variable denoted as $\Delta \log y_{it}$ and the initial level of the variable denoted by $\log(y_{i,t-1})$, necessitating a negative and significant ρ parameter. Following Goldberg and Verboven (2005), we modify the Equation 2, to incorporate variables affecting inflation differentials (*Infdiff*),

$$\Delta Infdiff_{i,t} = \alpha_i + \tau_t + \rho \ Infdiff_{i,t-1} + X_{it} + \epsilon_{i,t} \tag{3}$$

where in the equation above, ρ represents an autoregressive parameter associated with the speed of convergence, $X_{i,t}$ is a vector of control variables affecting inflation differential. $\epsilon_{i,t}$ is the error term, which we assume to be independently and identically distributed (i.i.d). $Infdiff_{i,t}$ is the inflation differential, calculated by subtracting the overall mean of inflation across states from the inflation of state i. Following the price differential calculation of Goldberg and Verboven (2005) and Berk et al. (2020), we calculate the change in inflation differential ($\Delta Infdiff_{i,t}$) as the difference between inflation differential from its lagged value.

For estimation of Equation 3, we use 2-step System-GMM estimator suggested by Arellano (1988); Arellano and Bond (1991) since the traditional methods like least squares dummy variable estimator (Hsiao, 2022) are biased as these estimators are consistent only for a large number of observations over time (Nickell, 1981). To assess the reliability of the System-GMM, we rely on the Hansen J-test, which provides p-values for testing the null hypothesis of the validity of the over-identifying restrictions. The acceptance of the null hypothesis indicates the model's validity. Additionally, we examine the reported values for Arellano-Bond test for AR(1) and AR(2) in first differences (Roodman, 2009), representing the p-values for first and second-order auto-correlated disturbances, respectively. High first-order auto-correlation is expected, while there should be no evidence of significant second-order auto-correlation.

Furthermore, within panel data estimation, the panel unit root test is used to check for convergence. This is based on the idea that when the distance between two or more time series decreases, they eventually converge to a constant or zero. The first part of the idea implies a catch-up process. However, the second part of this concept denotes the establishment of a steady state. In addition, in the second part, which is more about long-term forecasts, the steady state is unaffected by both the initial values of the economic variables and time-related shocks. Both β-convergence and σ-convergence only account for the first part of the convergence process, which is merely a snapshot taken during the adjustment process (Bernard and Durlauf, 1996; Jungmittag, 2006). Therefore, to also consider the second aspect, which is more restrictive than the first one, many studies have employed panel data unit root tests to assess inflation convergence.

For instance, Beck et al. (2009) complement a univariate approach based on the Augmented Dickey-Fuller (ADF) test with the panel unit root test developed by Levin and Lin (1993); Levin et al. (2002). Dridi and Nguyen (2019), Yilmazkuday (2013) inspected for the absence of unit root in the panel data to test for convergence. Our analysis uses different panel unit root tests to account for heteroskedascity and autocorrelated error in the presence of structural break to check for convergence. If the panel data is stationary, then it is an indicator of convergence. Fundamentally, the unit root test considers an autoregressive model, say an AR(1) process given by,

$$y_t = \alpha + \delta\ y_{t-1} + \epsilon_t \tag{4}$$

where y_t is the variable in which the presence of the unit root is tested. If ϵ_t is white noise, then for $\delta = 1$, Equation 4 represents a non-stationary random walk process. And if $|\delta| < 1$, then we have a stationary first-order autoregressive process. However, Dickey and Fuller (1979) suggested modification to the above Equation 4 by subtracting y_{t-1} from both sides of the equation what is known as a DF test, where we estimate the following regression:

$$\Delta\ y_t = \rho\ y_{t-1} + \epsilon_t \tag{5}$$

where we test for the null (H_o) of $\rho = 0$, which indicates the presence of unit root against the alternative of stationarity. Several other methods are suggested in the existing literature to test for unit root, and we use various panel unit root methods to test for inflation convergence.[4]

Additionally, we follow the PS methodology, which has been extensively used to test for club convergence. Club convergence is the tendency across states to converge to multiple equilibria depending upon the basin of attraction in which they begin.[5] The PS methodology is a non-linear time-varying factor model that accommodates individual heterogeneity and transitional dynamics. It utilizes a one-sided t-test, named log t-test, where the null hypothesis of convergence is tested against alternative hypotheses of either partial convergence within sub-groups or outright divergence. In cases where the test fails to demonstrate convergence across a panel, an algorithm is utilized to determine if convergence is occurring towards different steady states. Subsequently, it forms sub-convergent groups or clusters. This method offers advantages over established techniques like unit root, co-integration, β-convergence test and σ-convergence test and dynamic panel data methods. Notably, it addresses heterogeneous transitional dynamics, a facet often overlooked by conventional approaches. Additionally, it eliminates the need for pre-testing procedures, such as assessing the co-integration of variables, and models the long-run behavior of time series data as a non-linear time-varying factor model.

For any variable of interest, in our case, inflation following PS, we first decompose inflation according to the following equation:

$$Inf_{it} = \phi_{it}\ \mu_t \tag{6}$$

where Inf_{it} is inflation, μ_t is a growth component common to all states and ϕ_{it} is an idiosyncratic component that varies over time. It also represents the transition path of state

[4]We use panel unit root tests suggested by Levin et al. (2002), Im et al. (2003), Hadri (2000), Herwartz and Siedenburg (2008), and Karavias and Tzavalis (2014).

[5]Note that absolute or conditional convergence can occur inside each convergence club (Phillips and Sul, 2009).

i in relation to common steady state trend μ_t. Convergence to steady state occurs when the transition component converges to the same value that is $\lim_{N\to\infty}\ \phi_{it} = \phi$ for all i = 1,..., N. Phillips and Sul (2007, 2009) developed a test to identify whether ϕ_{it} converges to a common steady state through time. To do this, PS modified the Equation 6 by eliminating the trend component given by:

$$h_{it} = \frac{Inf_{it}}{N^{-1}\sum Inf_{it}} = \frac{\phi_{it}}{N^{-1}\sum \phi_{it}} \tag{7}$$

where h_{it} is the relative transition path and captures the individual's relative deviation from the common steady-state growth path μ_t. The PS method also assumes a semi-parametric model for ϕ_{it} to determine convergence clusters, given by:

$$\phi_{it} = \phi_i + \sigma_{it}\,\epsilon_{it}; \quad \sigma_{it} = \frac{\sigma_i}{L(t)t^{\alpha}}, \quad \sigma_i \geq 0, \quad t \geq 0 \text{ for all } i \tag{8}$$

where ϕ_i is fixed, ϵ_{it} is independently and identically distributed $(0,1)$, L(t) is a slowly varying function of time, and α is the speed of convergence. From Equation 8, the null hypothesis of convergence implies $\phi_i = \phi$ for all i and $\alpha \geq 0$. In contrast, the alternative hypothesis can either be divergence, which is $\phi_i \neq \phi$ for all i (or $\alpha < 0$), or club convergence, which is $\phi_i = \phi$ for some i and $\alpha \geq 0$.

For convergence, since $\lim_{N\to\infty}\ \phi_{it} = \phi$ for all i = 1,..., N, Equation 7 implies that h_{it} approaches 1 as t approaches infinity. In this scenario, the cross-sectional variance of h_{it} under the null hypothesis, denoted by ${\sigma_t}^2 = \frac{1}{N}\sum_1^{N=\infty}(h_{it}-1)^2$, must tend to zero. PS demonstrated that testing for absolute convergence is equivalent to conducting a one-sided test for the estimated coefficient b in the following log-t regression equation:

$$\log\left(\frac{\sigma_1^2}{\sigma_t^2}\right) - 2\ \log L(t) = \hat{a} + \hat{b}\ \log t + \hat{u}_t \tag{9}$$

Here, σ_1^2/σ_t^2 represents the cross-sectional variance in the initial period relative to the variance of each subsequent time period, $\hat{a}$ denotes an intercept, $\hat{b} = 2\hat{\alpha}$, and $\hat{u}_t$ is the error term. The hypothesis for testing convergence involves employing a one-sided t-test for the parameter $\hat{b}$ using HAC standard errors. The null hypothesis of absolute convergence is rejected if $t_{\hat{b}} < -1.65$, as recommended by PS. Additionally, we follow the approach of Marrero et al. (2021) since we are interested in both the sign and magnitude of the coefficient $\hat{b}$. A value of $\hat{b}$ greater than or equal to 2 implies absolute convergence, while values within the range $2 \geq \hat{b} \geq 0$ suggest conditional convergence.

3.2. Data

This section contains information about the variables used in the study.The key variable is inflation. For calculating inflation, we used the CPI data, which is provided monthly by the National Statistical Office (NSO) under the Ministry of Statistics and Programme Implementation (MoSPI). We have calculated inflation using year-on-year percentage change, i.e.,

$$\text{Inf}_{it} = \frac{P_{it} - P_{i,t-12}}{P_{i,t-12}} * 100$$

where P_{it} is the monthly CPI for state i, and Inf_{it} is the monthly inflation of state i for the period from 2012m1 to 2023m12. For annual inflation, we have taken the yearly mean of monthly inflation. As explained in methodology section, for estimating conditional convergence regression, the dependent variable ($\Delta Infdiff_{i,t}$) is the change in the inflation differential ($Infdiff_{i,t}$).

Following Beck et al. (2009); Ridhwan (2016); Cecchetti et al. (2002); Purwono et al. (2020) and based on availability of data, we considered various explanatory variables. According to Beck et al. (2009), differences in business cycle phases across regions can lead to varying inflation rates. To capture these differences, we follow Beck et al. (2009);

Ridhwan (2016) and use proxies such as the relative sizes of the agriculture, industry, and services sectors across the regions in our sample. The explanatory variables representing structural characteristics are the relative share of agriculture (rel_agri_gdp), the relative share of industry (rel_industry_gdp), and the relative share of services in total GDP (rel_services_gdp). The annual data of respective share of GDP is taken from various reports of the Handbook of Statistics on Indian States released by the Reserve Bank of India (RBI). The data is available for 31 States and UTs from 2012 to 2022.

While monetary policy centrally controls and determines the money supply uniformly across all regions within a monetary union, regional wage determination can still influence inflation differential. Furthermore, fiscal policies operate at both national and regional levels. Lagoa (2017) emphasize that inflation differentials within the Euro Area are more pronounced compared to the US due to less effective adjustment mechanisms stemming from limited wage flexibility, reduced labor mobility across countries, and constraints on transfers to crisis-hit countries. Furthermore, European treaties impose restrictions on national fiscal policies, which may hinder effective adjustment mechanisms and, in some cases, exacerbate inflation differentials. Similar to the European Union, which is an agglomeration of various countries, India at the regional level is also an agglomeration of states with a federal structure in which state governments have separate fiscal policies and labor-related rules and regulations (Sapkal, 2016). Therefore, our analysis also incorporates state-wise wage income (ln_wages) and relative fiscal deficit (rel_fis_def). The data for state-wise wages, which is the sum of self-employed wages, casual wages, and regular wages, is taken from the Periodic Labor Force Survey (PLFS), which is an annual survey conducted by the NSO under MoSPI; the dataset is available for the period from 2017 to 2022. The data for the relative fiscal deficit data, which is the ratio of state fiscal deficit to its total GDP, is taken from the Handbook of Statistics on Indian States.

Furthermore, poorly diversified household financial portfolios, as shown in Euro-Area nations, lead to greater inflation differentials than the US (Lagoa, 2017). For India, where development in financial inclusion is still needed Chakravarty and Pal (2013), this can influence inflation disparity. We include an index called FI reflecting financial inclusion within states, following the approach outlined by Sarma (2012). The index consists of several dimensions representing banking penetration, availability of banking services, and usage. For banking penetration, we consider the number of bank accounts of scheduled commercial banks as a proportion of the total state's population. For the availability of banking services, we consider the number of ATMs and bank employees per population. Finally, for the usage of banking services, we consider the volume of credit and deposits as a proportion of the state's GDP. The individual dimension index for i_{th} dimension d_i is calculated as follows:

$$d_i = \frac{A_i - m_i}{M_i - m_i} \tag{10}$$

where A_i is the actual value of dimension i, m_i is the minimum value of dimension i, and M_i is the maximum value of dimension i. Finally, the index is calculated as follows:

$$\mathrm{FI}_i = 1 - \frac{\sqrt{(1-d_1)^2 + (1-d_2)^2) + \ldots + (1-d_n)^2}}{\sqrt{n}} \tag{11}$$

where d_i represents the dimensions and FI_i is the index of financial inclusion for respective states. The data for different dimension is taken from several reports in the Handbook of Statistics on Indian States released by the RBI.

Further, (Yilmazkuday, 2013) suggests that the primary explanation for the decreased dispersion of inflation levels among cities during 2013–2018, particularly the accelerated reduction in disparities outside Java-Bali, could be attributed to the enhancement of logistic infrastructure. To address structural issues in the supply chain that may disrupt inventory stability, as suggested by Yilmazkuday (2013), and considering that the enhancement in logistics infrastructure, especially outside the Java-Bali region, has contributed to the decline in inflation dispersion among cities in Indonesia, we incorporate railway (railway_index) and roadway indices (roadway_index). These indices are constructed by dividing the total length of railway and roadways by the respective state's area. The data for the length of railways and roadways has been taken from various reports of the RBI Handbook of Statistics on Indian States.

We also consider the role of temperature deviation (dev_temp) since temperature shocks could affect prices and inflation in several ways, including a decrease in agricultural output and changes in energy demand Mukherjee and Ouattara (2021). Inflation dispersion occurs when individual factors exert asymmetric impacts across regions.

4. Results and discussion

Figure 1 depicts the average inflation rates from 2012 to 2023 across Indian states. Unlike Indonesia, where a regional divide in inflation is observed (Busetti et al., 2007), no distinct geographical pattern emerges in India. A visual inspection of the map indicates absence of inflation cluster throughout the country. While this randomness complicates interpretation, excluding Jammu and Kashmir and few north-eastern states reveals a north-south divide, with southern regions experiencing higher average inflation than their northern counterparts.

To further substantiate our claim that the inflation behavior is not clustered, we use Moran'I statistics. Moran's I statistic is widely regarded as the primary indicator of global spatial auto-correlation. It was first proposed by Moran (1948) and gained prominence through the seminal work on spatial autocorrelation by Cliff and Ord (1970).[6] The Moran's I statistics for Indian states, as shown in Figure 2 considering rook contiguity, comes out to be -0.133.[7] However, it is insignificant, suggesting absence of an inflation cluster across states in India.

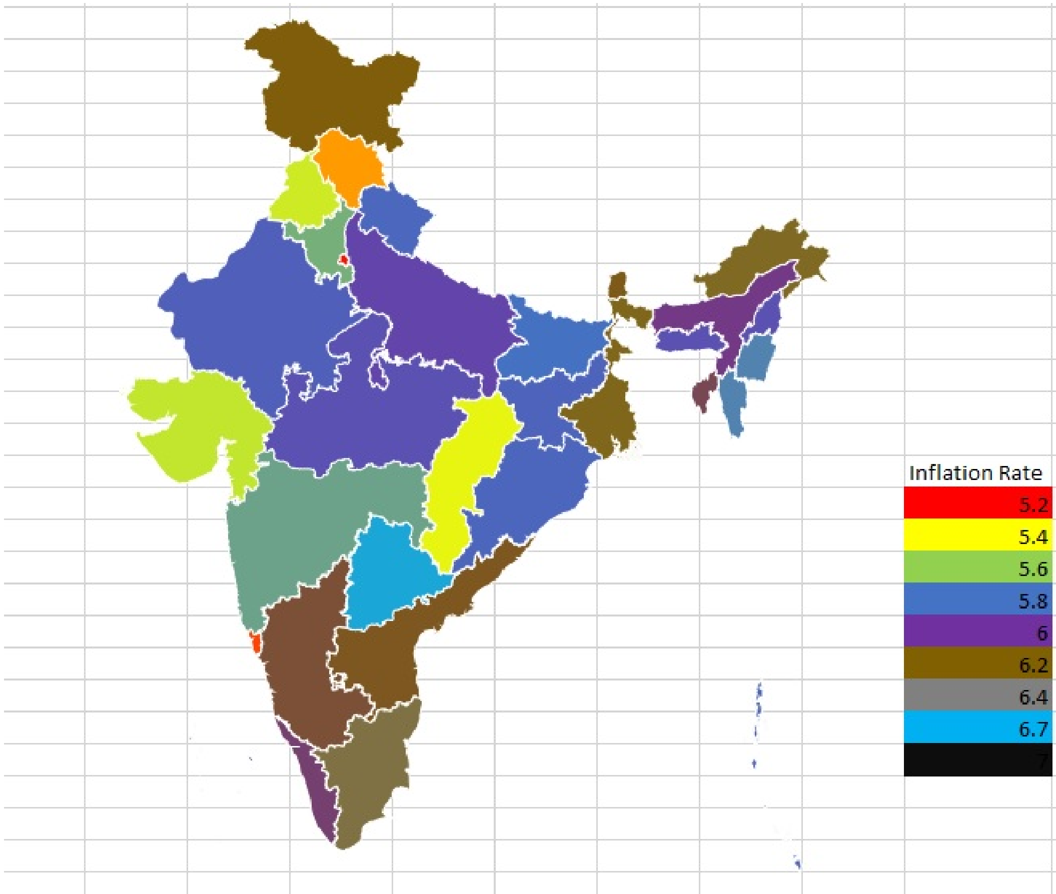

Figure 1: Average inflation of Indian states for the period 2012 to 2023

As shown in Figure 3, the monthly mean inflation of Indian states shows consistent variations, suggesting regional variation in inflation rates. We see that initially, there has been a consistent decline in the mean inflation rate, which later increased after 2020, possibly due to the impact of the COVID-19 pandemic. We further see a consistent decline

[6]Moran's I is a cross-product statistic between a variable and its spatial lag, representing the variable as deviations from its mean. Moran'I statistic has been calculated using GeoDa software.

[7]Rook contiguity refers to neighbors who share a line segment (or a boundary).

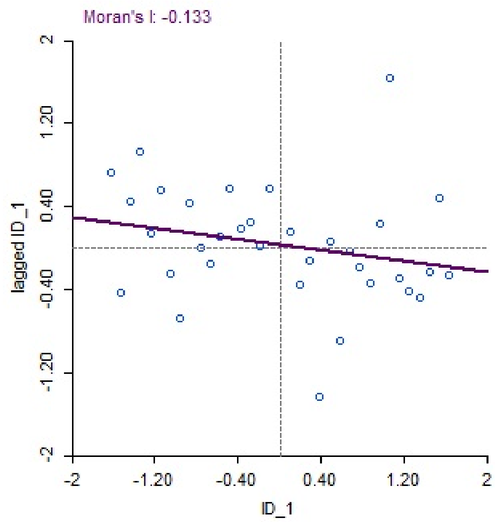

Figure 2: Moran'I statistics for average inflation

ID_1 indicates the average inflation of the time period between 2012 and 2023.

in the regional variations of the inflation rate. Figure 5 further confirms the decrease in dispersion as it can be seen that there has been a decreasing trend in cross-sectional dispersions of inflation, especially after 2018, suggesting the possibility of convergence in CPII.

Following the preliminary analysis, we start our analysis with σ-convergence since σ-convergence may not accompany β-convergence. Young et al. (2008) found that in US cities, while there is evidence of β-convergence in income, σ-convergence cannot be detected during that time period. Further, as Quah (1993) argued that σ-convergence is of greater interest, we explore whether the dispersion in the cross-section distribution has declined during the period of study. σ-convergence provides a holistic view of convergence by looking at the entire distribution of the variable across regions. It captures overall trends in equality or disparity, rather than focusing on individual growth rates relative to starting points.[8] We follow Marrero et al. (2021) to investigate σ-convergence

[8] β- convergence can sometimes be misleading if it is driven by extreme outliers or if some regions are improving rapidly while others are stagnating. σ-convergence, by focusing on overall dispersion, avoids this issue and provides a more comprehensive picture.

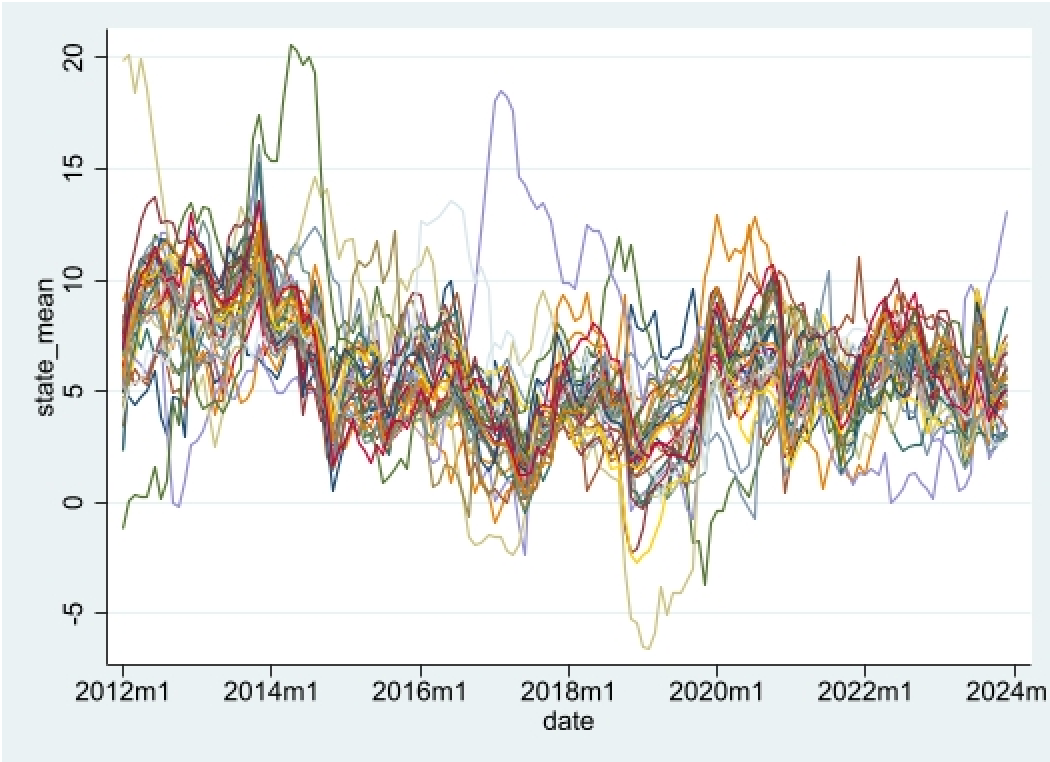

Figure 3: Monthly mean inflation of Indian states

across Indian states. First, we compute the sample variance of inflation across states at time t as

$$\sigma_t^2 = \frac{\sum_{n=1}^{N}[Inf_t - \mu_t]^2}{N}, \tag{12}$$

where Inf_t is inflation at time t, μ_t is the sample mean of inflation at time t, and N is the number of states. To ascertain whether the cross-country dispersion increases or decreases during the period, we estimate σ_t^2 using the following expression:

$$ln(\sigma_t^2) = \psi + \theta t + u_t, \tag{13}$$

where ψ is a constant, the slope θ denotes the growth rate of a linear trend, t is the time variable, and u_t is the error term. We find θ (= -.0052178) to be negative and significant, suggesting a decline in the dispersion of inflation. Overall, we find evidence of σ-convergence from 2012 to 2023. Additionally, a sub-sample analysis explores how it

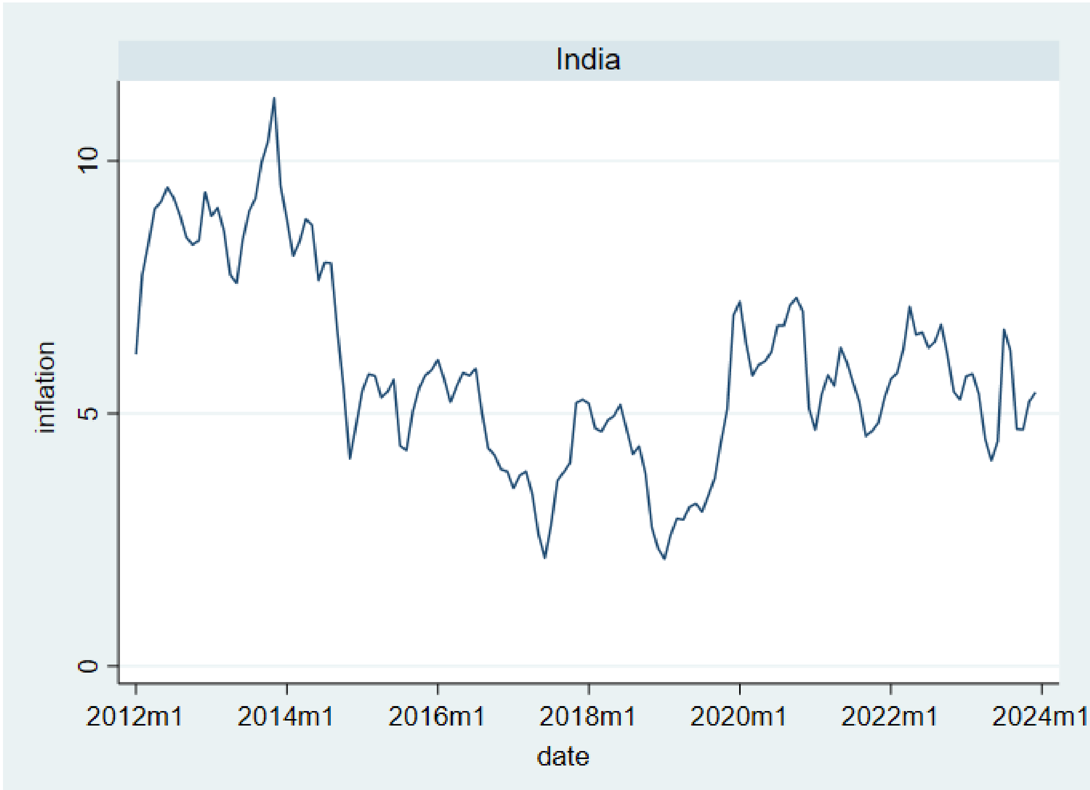

Figure 4: Monthly mean inflation of India

has progressed throughout different years. When a sub-sample analysis is considered, taking the pre-inflation targeting (IT) sample (2012m1-2016m7) and post-IT sample, we again see evidence of σ-convergence with θ being equal to -.00924 and -.0113847, suggesting a faster convergence during the post-IT period. So, overall, we find that inflation dispersion has reduced for the full sample, similar to what we see in Figure 5. However, this decline in dispersion is due to increased inflation across Indian states, as seen from Figure 3 and Figure 4.

As argued in Section 3, about the advantage of unit root estimation over σ- convergence, we now use various panel unit root tests to check for inflation convergence. We employ unit root methods suggested by Levin et al. (2002) and Im et al. (2003), both of which have the null hypothesis that "All panels contain unit roots," against the alternative hypothesis that "Some panels are stationary." Our results suggest the rejection of the null

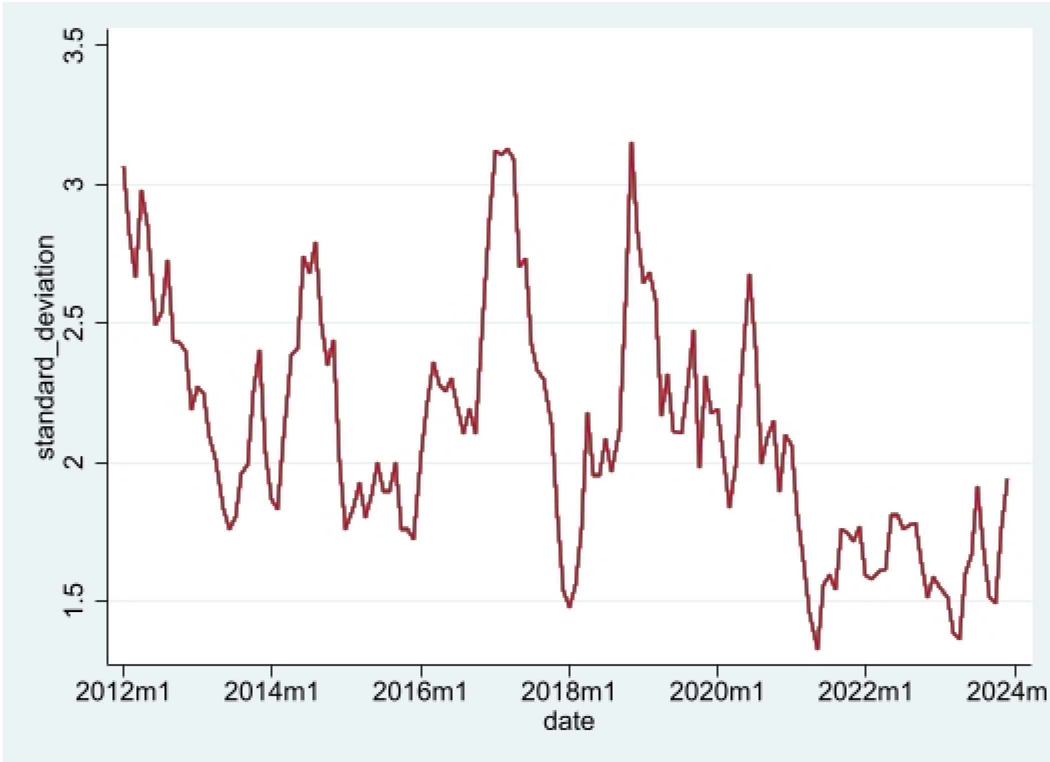

Figure 5: Year-wise cross-sectional dispersion of inflation

hypothesis. Furthermore, we test for the absence of a unit root using the Hadri (2000) LM test, which assumes cross-section dependence. In this case, the null hypothesis, "All panels are stationary," is tested against the alternative, "Some panels contain unit roots," and our results fail to reject the null. Overall, panel unit root analysis suggests the presence of convergence; however, these tests might provide misleading inferences under heteroskedasticity (Herwartz et al., 2016). Therefore, we use the Herwartz and Siedenburg (2008) unit-root test, which rejects the null of the presence of a unit root. Furthermore, considering that most of the study period lies within the IT regime, which restricts inflation within a band of 4±2 percent, we include a trend. With the inclusion of the trend, the Herwartz and Siedenburg (2008) unit-root test fails to reject the null of the presence of a unit root.

However, it is crucial to acknowledge that structural breaks can significantly impact the behavior of unit-root tests, as demonstrated by Perron (1989). Structural breaks are exogenous shocks that have lasting effects, altering model parameters. Such breaks can make stationary series appear non-stationary and may mislead unit-root tests to accept the null hypothesis of non-stationarity incorrectly. In response to this issue, Karavias and Tzavalis (2014) proposed panel-data unit-root tests that allow for structural breaks in the intercepts or both the intercepts and linear trends. Under the null hypothesis, the panel series are assumed to be unit-root processes without breaks, while under the alternative hypothesis, they are stationary around breaking means or breaking means and trends. The results suggest break date at 2021 and rejects the null hypothesis of unit root process without breaks.

Further, as mentioned in Section 3, in the case of heterogeneity, there can be a possibility of the formation of clubs; therefore, we look at the possibility of club convergence. We follow the idea of PS, wherein they consider the possibility of forming sub-convergent clubs. Our results for full sample analysis suggest the formation of a single club since t-stat = 6.2925 $>$ -1.65, as shown in Table 1. Furthermore, we can see in Table 1 that the value of the coefficient of b is less than 2, as pointed out in Marrero et al. (2021), this implies the presence of conditional convergence. In addition, our finding for inflation for the time between 2012m1 and 2020m7, i.e., before the COVID-19 pandemic, supports the creation of several clubs, as shown in Table A. Furthermore, if we restrict our sample to the time of inflation targeting, from 2016m7 to 2023m12, we find a single convergence club, implying that the inflation targeting regime has aided in the convergence of inflation across states in India.

Given the presence of conditional convergence, as pointed in the above paragraph, we further analyze the factors relevant to convergence. To do so based on existing literature,

Table 1: log t-test results

log t test:			
Variable	b-coefficient	SE	t-stat
Inf	1.1961	0.1901	6.2925

we select variables affecting inflation differentials. Table 2 presents System-GMM results. In our System GMM estimation, we have considered rel_agri_gdp, rel_industry_gdp, rel_services_gdp, rel_fis_def, ln_wages as endogenous and as suggested by Roodman (2009), we instrument it using its lagged values from lag 2 to lag 4. Moreover, the inflation lag is considered predetermined, so it is instrumented from lag 1 to lag 3. We find that the Hansen-J test does not reject the null of over-identifying restrictions. Furthermore, we find that the AR(1) row is significant, suggesting a first-order correlation, while AR(2) is insignificant, indicating no evidence of a second-order correlation.

From Table 2, we find consistent evidence of convergence since the coefficient of lagged inflation differential (L.$Infdiff_{i,t}$) is consistently negative and less than one, suggesting conditional convergence. For example, under column head M-1, the coefficient of (L.$Infdiff_{i,t}$) is -0.86 is significant at a 1 percent level. Similarly, we also find that the coefficient of ln_wages is positive and significant, suggesting that an increase in wages increases the inflation differential. Furthermore as argued in a paper by Tyagi (2023), that there exist significant wage inequality across India and there has been a rise in wage inequality across some states compared to 2004-05, this inequality can be a cause of concern as it may lead to a rise in the inflation differential. It may happen that an increase in wages increases the cost of production for goods and services. Industries or regions with higher labor intensity or reliance on sectors experiencing significant wage growth may face higher production costs. As a result, these sectors or regions may pass on the increased costs to consumers through higher prices, leading to inflationary pressures. Conversely, sectors or regions with more moderate wage growth may experience lower inflation rates, creating inflation differentials based on wage dynamics. We do not find any other variable like relative share of different sector to GDP, relative fiscal deficit, financial inclusion index, etc, to be statistically significant, suggesting no role played by these variables in affecting inflation differentials.

As shown in Table 2, we can see from Column M5-robust and Column M6-robust that our results are robust to consideration of only the credit deposit volume of states as a measure of the financial inclusion index.

Table 2: Estimation using system-GMM

VARIABLES	M1	M2	M3	M4	M5	M6	M5-robust	M6-robust
L.$Infdiff_{i,t}$	-0.86*	-0.85*	-0.84*	-0.82*	-0.89*	-0.80*	-0.86*	-0.80*
	(0.22)	(0.22)	(0.23)	(0.19)	(0.18)	(0.22)	(0.23)	(0.21)
rel_agri_gdp	-7.34	-10.08	-15.88	-18.62	-19.09	-21.70	-16.69	-21.20
	(20.37)	(15.68)	(20.12)	(22.69)	(28.06)	(22.36)	(31.08)	(21.99)
rel_industry_gdp	0.16	-0.86	-4.40	-1.36	-3.28	-6.73	0.14	-6.67
	(9.10)	(8.55)	(9.30)	(7.04)	(13.85)	(11.76)	(9.27)	(11.99)
rel_services_gdp	5.82	4.47	0.35	0.12	1.49	-4.79	4.76	-4.30
	(8.58)	(9.14)	(10.24)	(7.88)	(15.83)	(14.37)	(12.23)	(14.95)
ln_wages	0.33’	0.34’	0.33’	0.36’	0.31ˆ	0.31’	0.27 ˆ	0.30ˆ
	(0.16)	(0.15)	(0.15)	(0.14)	(0.15)	(0.13)	(0.14)	(0.15)
rel_fis_def	-12.85	-13.07	-13.16	0.59	-4.65	3.66	-4.39	-0.67
	(16.59)	(15.85)	(18.37)	(17.66)	(12.11)	(14.68)	(22.79)	(18.13)
dev_temp			-1.03	-1.07	-1.11	-0.93	-1.06	-0.96
			(0.65)	(0.67)	(0.78)	(0.83)	(0.86)	(0.87)
FI		1.84	1.59	1.61	0.93	1.51		
		(2.93)	(2.88)	(1.95)	(3.66)	(2.40)		
cre_dep_sc_bank							0.00	0.00
							(0.01)	(0.02)
highway_index				-8.39	-6.25	0.91	-6.65	0.81
				(9.33)	(13.22)	(16.66)	(16.26)	(18.57)
railway_index					-19.66	-12.80	-21.41	-21.11
					(14.84)	(17.17)	(14.08)	(40.23)
unemployment						-0.00		-0.00
						(0.01)		(0.01)
y2020	3.38*	3.05*	2.89’	1.46	1.89ˆ	1.55	2.11	2.01
	(0.75)	(0.95)	(1.11)	(1.26)	(0.95)	(1.19)	(1.39)	(1.20)
y2021	0.95	0.52	0.60	0.25	0.48	-0.18	0.84	0.37
	(0.71)	(0.97)	(0.98)	(1.00)	(1.43)	(1.33)	(1.02)	(1.10)
y2022	1.50’	1.03	1.24	0.78	1.42	0.80	1.86’	1.40
	(0.72)	(1.00)	(1.03)	(0.86)	(1.30)	(1.14)	(0.83)	(1.04)
Constant	-2.95	-3.31	0.61	-0.58	1.58	4.23	-0.26	5.33
	(7.93)	(7.22)	(8.26)	(7.04)	(10.46)	(9.26)	(11.64)	(11.30)
Observations	177	177	177	158	152	152	152	152
States and UTs	31	31	31	31	30	30	30	30
ar1p	0.0488	0.0479	0.0696	0.0958	0.0869	0.0888	0.164	0.0819
ar2p	0.558	0.587	0.862	0.953	0.735	0.902	0.855	0.895
hansenp	0.239	0.258	0.239	0.220	0.306	0.505	0.321	0.512

1. The dependent variable is the inflation differential $\Delta \log y_{it}$.
2.Superscripts *, ’, ˆ represent significance at 1 percent, 5 percent, and 10 percent, respectively.
3.rel_agri_gdp, rel_industry_gdp, rel_services_gdp, rel_fis_def, ln_wages unemployment are considered as endogenous and instrumented with lags(2,4) and L.inf_yoy_adj is considered as pre-determined and instrumented with lags(1,3) while the remaining variables are considered as exogenous.
4. We have only considered the states and union territories for which data was available.
5. ar1p and ar2p represent the p-values for the Arellano-Bond test for AR(1) and AR(2) in first differences, respectively.

5. Conclusion

This study aims to examine inflation convergence in India and its evolution over time. Generally, we do not find the formation of distinct inflation clusters among states in India. Furthermore, our analysis using multiple techniques suggests that from 2012 to 2023, inflation in India has converged and its dispersion has decreased. We identify a single convergence club rather than multiple clubs. The convergence of inflation across states indicates increased economic integration, improved policy effectiveness, and enhanced market efficiency. This can promote greater economic stability, reduce regional disparities, and standardize living conditions. For policymakers, businesses, and consumers, inflation convergence fosters a more predictable economic environment, facilitating better decision-making and planning. Additionally, our panel data analysis, while testing for conditional convergence, indicates that wages may contribute to inflation differentials between states. As highlighted in Beck et al. (2009), excessive wage growth can lead to undesirable economic outcomes. Therefore, policymakers should address this issue effectively. This can be accomplished by boosting investment in less developed states, minimizing differences in minimum wage, and ensuring adherence to minimum wage laws.

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Appendix A

Club 1	Assam, Goa, Gujarat, Haryana, Manipur, Karnataka, Sikkim, Kerala, Madhya Pradesh, Maharashtra, Nagaland, Puducherry, Punjab, Tamil Nadu Tripura Uttar Pradesh, Uttarakhand, West Bengal, Meghalaya, Mizoram, Odisha, Rajasthan, Telangana
Club 2	Delhi, Jharkhand
Club 3	Bihar, Chhattisgarh
Club 4	Andhra Pradesh, Nagaland
Non convergent Group	Arunachal Pradesh, Himachal Pradesh, Karnataka

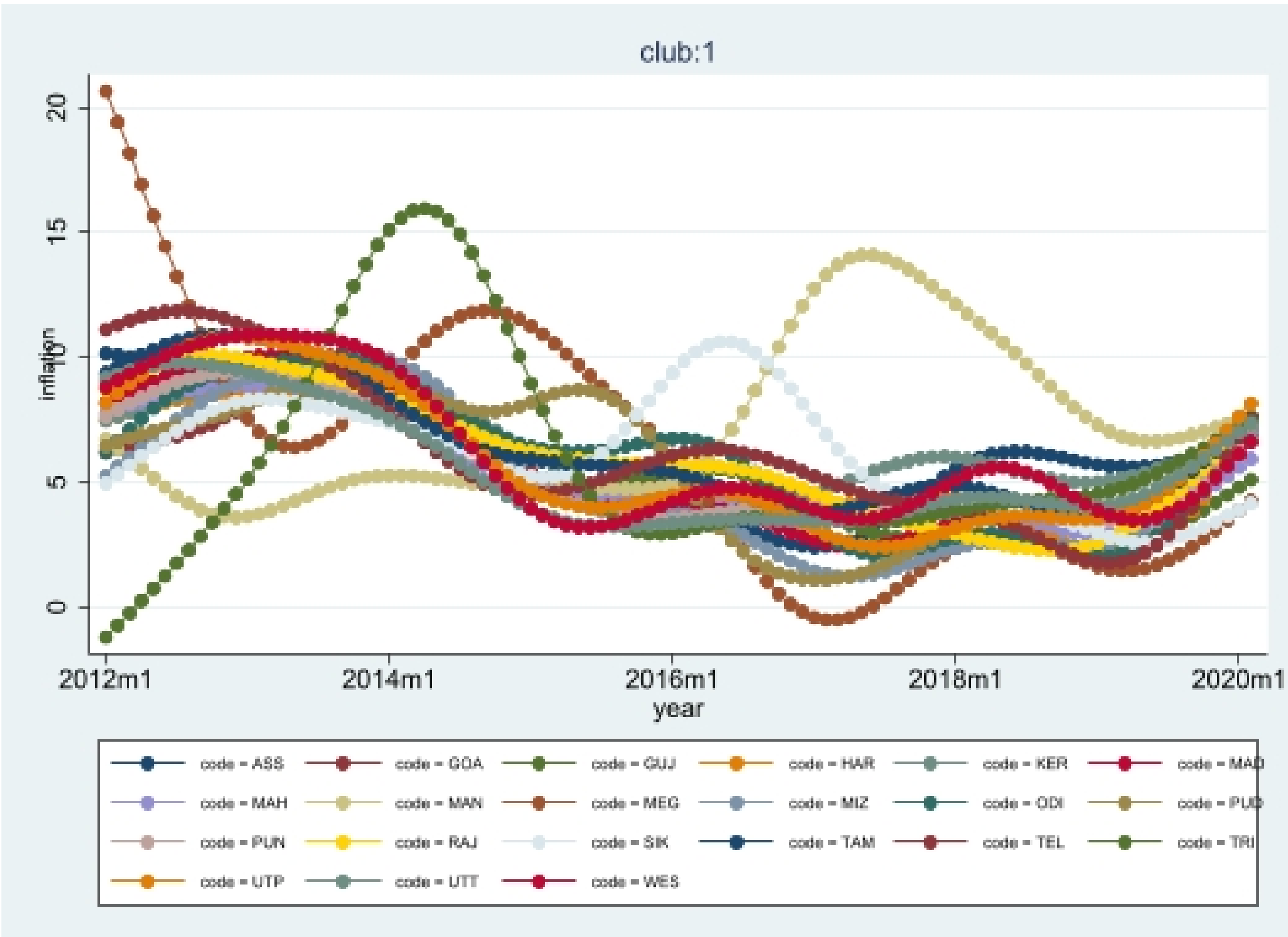

Figure 1: Club:1 formed after applying PS methodology

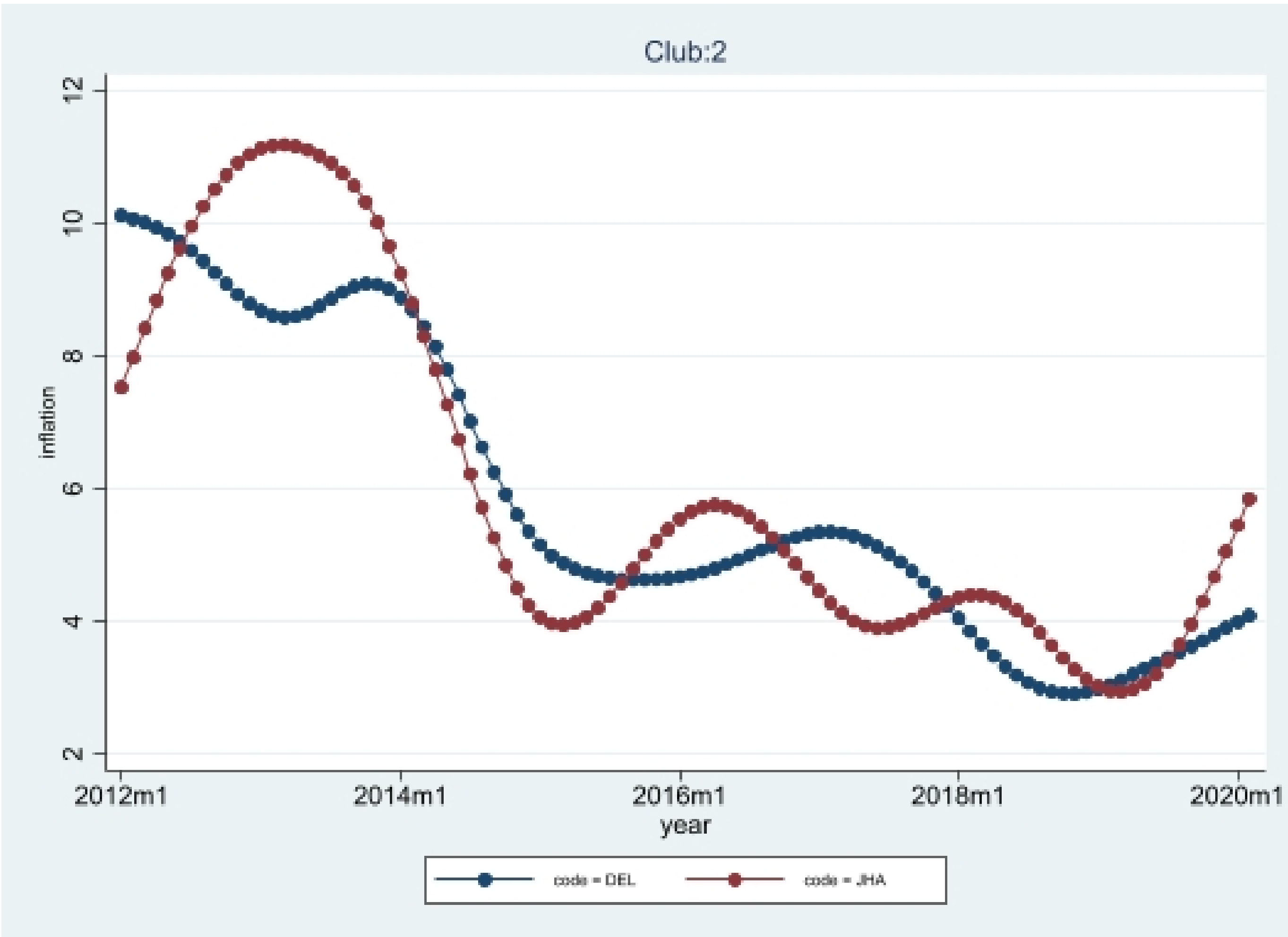

Figure 2: Club:2 formed after applying PS methodology

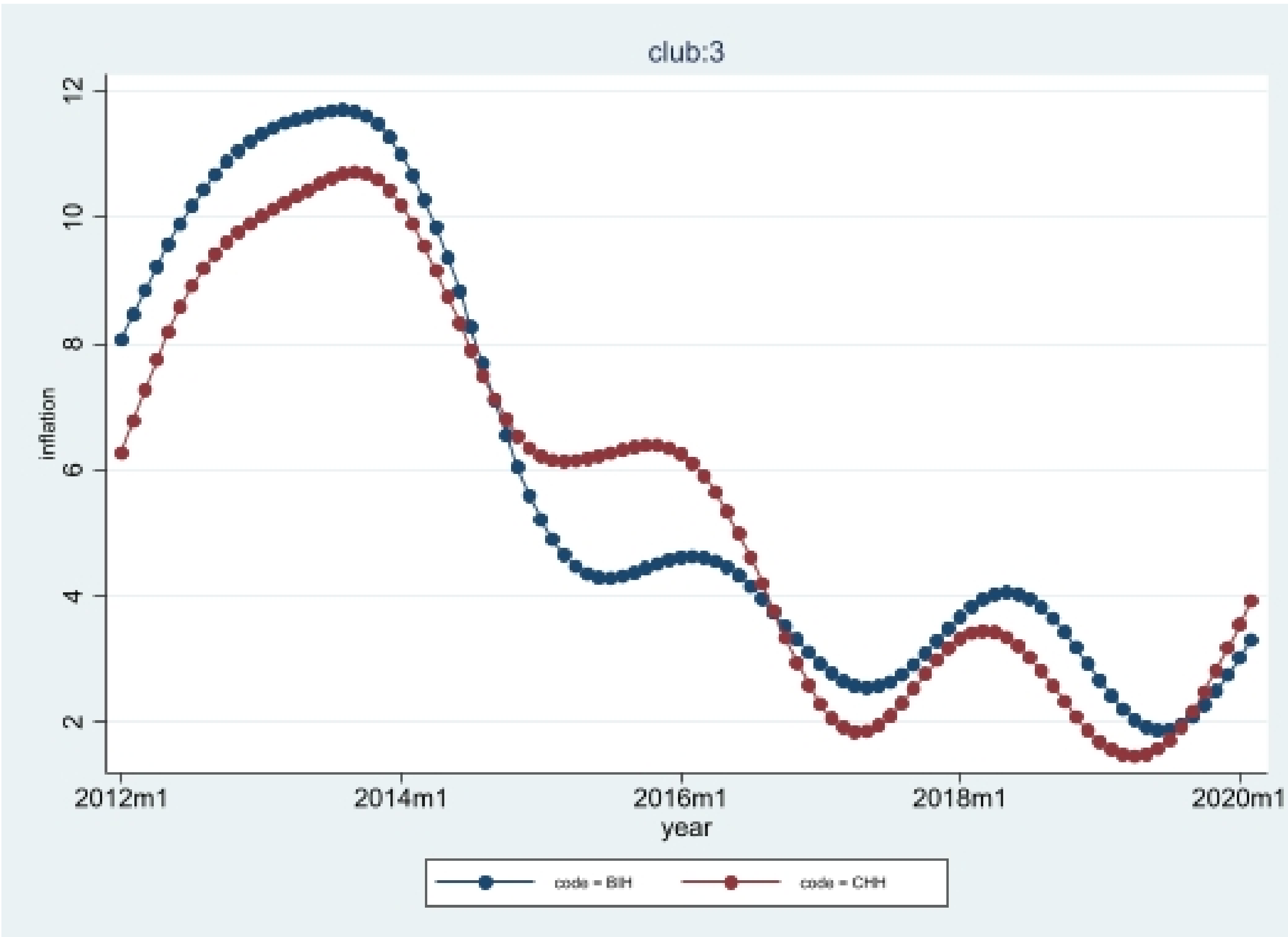

Figure 3: Club:3 formed after applying PS methodology

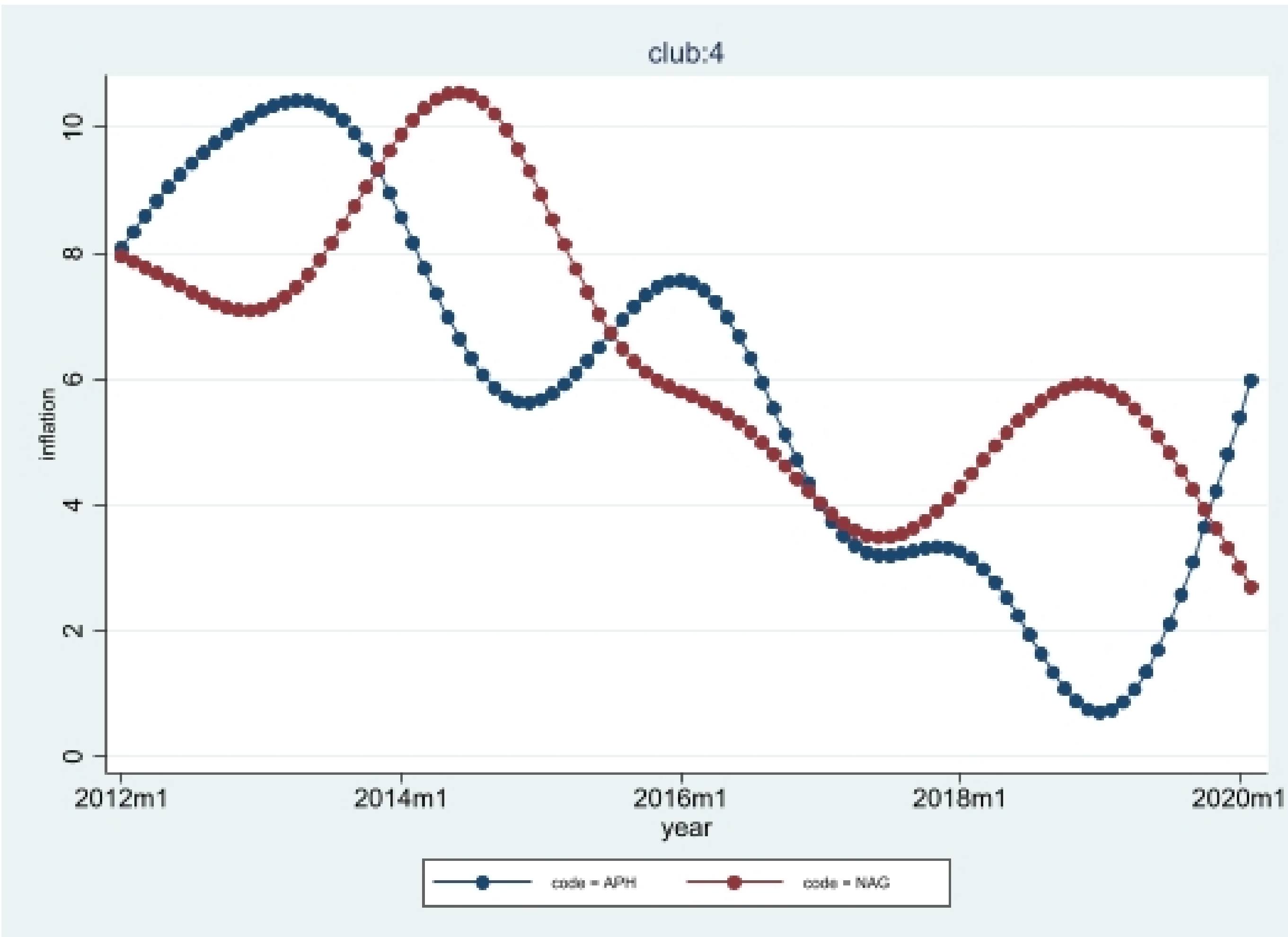

Figure 4: Club:4 formed after applying PS methodology