Do Special Economic Zones reduce household inequality in India?

A Spatial Econometric Analysis

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Abstract: The study investigates into the effect of Special Economic Zones (SEZs) on expenditure inequality between the Indian households. In specific, it is important to understand the impact of place-based industrialization on poverty and inequality in emerging market economies, which is rare in the existing literature. Earlier studies have mainly focused on growth, industrial performance and changes in structure following such industrialization efforts. Exploiting the household-level data from the Consumer Pyramid Household Survey (CPHS) database for the period 2014-2019, the spatiotemporal regression method is employed to show how the presence of SEZs across Indian districts impact the spatial household expenditure inequality, after controlling for household- and other district-specific characteristics. With evidence pointing to clustering of SEZs in districts, particularly in the coastline of districts of India, the inequality in annual real per-capita expenditure between the Indian households at the district-level is found to be spatial dependent. The spatiotemporal model estimates provide nuanced evidence on SEZs significantly lowering within-district inequality in expenditures between the households, though the spillover effect in the neighboring districts is found to be limited. The observed impact can be explained with larger employment in SEZ-driven ancillary sectors on account of presence of SEZs across Indian districts.

Keywords: Special Economic Zones, Expenditure inequality, Spatial econometrics, Spillovers.

JEL Classification No.: D12, C23, E21, O12, O25, P36.

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Introduction

Place based industrialisation policies and industrial clusters[*] like Special Economic Zones (SEZs) have gained worldwide prominence, especially after globalisation[†]. While advanced economies target SEZs to induce development of backward regions, these zones in emerging market economies, including India, are meant to attract FDI, promote exports, and thereby foster economic development (Chakraborty et al., 2017). While numerous policies and schemes with a large range of features have been implemented through an approach of managed cluster for promoting industrialization in India,[‡] the distinguishing feature of the Indian SEZ policy is to provide benefits to both developers and units operating within the SEZ jurisdictions.[§] Economists have long debated the potential benefits and distortions associated with the spatially targeted programs, including SEZs (Glaeser & Gottlieb 2008). Aggarwal (2010) explores the rationale for the establishment of SEZs which can bring agglomeration benefits, push the economy towards higher growth trajectory through localized spillover effects. A plethora of empirical studies has assessed the effects of various strategies towards industrialisation, including SEZs (see, for example, Wang, 2013; Busso et al. 2013; Brussevich, 2020; Alder et al., 2016; Frick & Rodriguez-Pose, 2023; among others). The findings of these studies however vary depending on the country and time period of study. In the Indian context, as well, the findings similarly vary. For instance, Hyun & Ravi (2018) show that Indian SEZs not only benefit firms located within them but also produce positive spillover effects in terms of expansion of economic activities. On the contrary, Gorg & Mulyukova (2024) find no discernible positive effect on the productivity growth of the Indian firms operating within the SEZs. As regards to socio-economic development, Alkon (2018) find evidence of no local spillovers from SEZs. Again, Anwar & Carmody (2016) find that land acquisitions for the establishment of SEZs in India have aggravated poverty and widened the gap between the rich and the poor. In a recent work,

[*]The term 'industrial cluster' was introduced and popularised by Porter (1990).

[†]According to World Investment Report 2019, there are nearly 5,400 Special Economic Zones operating across 147 economies, bringing a new wave of industrial policies and a response to increasing globalisation through internationally competitive investment.

[‡]Examples of managed cluster approach-based policies in India include National Manufacturing Policy (2011), Scheme for Integrated Textile Parks (SITP), Mega Leather Cluster (MLC), Mega Food Park (MFP), Micro and Small Enterprise-Cluster Development Programme (MSE-CDP), among others.

[§]For other distinctive features of SEZs in comparison to other cluster-based policies and schemes in India, please see detailed discussions in chapter 7 of Mukherjee et al. (2016).

Aggarwal & Kokko (2021) find that SEZs lead to rising rural poverty in Andhra Pradesh, India. However, to the best of our knowledge, studies on the effect of SEZs on Indian household expenditures are rare. This paper investigates into the impact of SEZs on expenditure inequality between the Indian households. The study is all the more important in the context of SDG 10 on "Reducing Inequality".

There is a widespread consensus among economists that economic development is often accompanied by increase in inequality (see for example Fawaz et al., 2012; Rubin & Segal, 2015; Ndjobo & Otabela, 2023, etc.). The spatial diffusion of economic activities and regional economic disparities have gained paramount importance on both theoretical and empirical forefront (see for example Anselin, 1998; Rey & Le Gallo, 2009; Combes et al., 2011; Rey & Smith, 2013; Márquez et al., 2019; Panzera & Postiglione, 2020, among others)[*]. Kanbur & Venables (2005) show increasing trends in spatial income inequality and other social indicators in many transition economies including India. The underlying mechanism of inter-regional trade, factor mobility, diffusion of technology are observed to be the driving forces for such spatial interactions (Lin et al., 2013).[†]

There is a large body of literature on different dimensions of inequality in India. Some of these include Dutta (2005), Das (2012), Khurana et al. (2020), Kijima (2006), Chamarbagwala (2006), Mehta & Hasan (2012), Sarkar & Mehta (2010), Subramanian & Jayaraj (2013), Chancel & Piketty (2019), among others. In a recent work, Bharti et al. (2024) find that the income and wealth concentrations have reached highest historic levels at the top-end of the respective distributions (top 1%) between 2014-15 and 2022-23 in India. However, Himanshu (2019) suggested that inequality has gained comparatively lesser attention among the policymakers compared to poverty.

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[*] The detailed explanations of the theoretical models of convergence and divergence of economic growth is given in Wei (2015). As regards to regional inequality, Gezici & Hewings (2004) suggested that cultural, institutional and productivity factors might have significant influence on neighbors' regions and the level of inequality in a region may not be independent from others.

[†]Williamson (1965) find that diffusion of income generating factors leads to subsequent slowing down and eventual decline in regional income inequality overtime, though initially, unequal natural resource endowments is attributable to concentration of incomes in certain geographical regions.

Here it is important to understand the factors that determine income/expenditure inequality.[*] The effect of economic growth on income differentials has been analysed within the ambit of Kuznets' inverted-U-hypothesis (Kuznets, 1955). While some studies find significant empirical support for the hypothesis (see for example Ahluwalia, 1976; Jha, 1996; Mushinski, 2001; Cheng & Wu, 2017; etc.), others find insignificant results (see for example Frazer, 2006; Sato et al., 2009; Lind & Mehlum, 2010; Angeles, 2010; etc.). On the other hand, the mechanisms of credit market imperfections, political economy factors, social instability and savings rate are analysed to discuss the effect of income inequality on economic growth (Perotti, 1996; Barro, 2000; etc.). While both political economy approach and social unrest theories predict that income inequality aggravates economic growth (see for example Perotti, 1993; Persson & Tabellini, 1994; Alesina & Rodrik, 1994; Benhabib & Rustichini, 1996; Alesina & Perotti, 1996; etc.), the savings rate theory suggests that income inequality spurs economic growth (see for example Kaldor, 1955; Bourguignon, 1981; etc.).[†] In contrary, the theories of credit-market imperfections do not present an unifying effect (Banerjee & Newman, 1993; Galor & Zeira, 1993; Aghion & Bolton, 1997; Aghion et al., 1999; Barro, 2000; Ezcurra, 2007; etc.). Some of the empirical studies show negative impact of income inequality on economic growth (Persson & Tabellini, 1994; Keefer & Knack, 2002; Easterly, 2007; Ezcurra, 2007; Herzer & Vollmer, 2012; among others) while others find positive effect (Li & Zou, 1998; Forbes, 2000; Bleaney & Nishiyama, 2004; etc.).[‡] Among a few notable empirical studies, Fawaz et al. (2014) points to the presence of endogeneity between economic growth and income inequality which needs to be accounted for identifying the true effect.[§]

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[*] The empirical exercise in this study considers expenditure inequality rather than income inequality on account of the fact that, most often, economists refer to consumption rather than income to study inequality in the standard of living as it is a better measure of households' welfare (see for example, Friedman, 1957; Kakwani, 1993; Attanasio & Pistaferri, 2016, among others).

[†] See for example, Cook (1995), Bourguignon (1981), among others. Stiglitz (1969) suggests that total savings in an economy is independent of income and wealth distribution if saving is a linear function, but independence disappears under non-linearity of saving function.

[‡]Castells-Quintana & Royuela (2017) state that income inequality can have both positive and negative effects on economic growth, and thus emphasized on the complexity of the relationship. Moreover, this complexity is more pronounced in developing countries.

[§]In fact, Acheampong et al. (2023) suggest that the causal relationship between income growth and income inequality has not been adequately explored in the existing literature.

Among other factors, financialization, urbanisation and sectoral shares of GDP can also affect income or expenditure inequality as evident from a large segment of the extant literature. The theoretical models of Galor & Zeira (1993) and Banerjee & Newman (1993) find a negative impact of financialisation on inequality, whereas a non-linear effect is reported in the findings of Greenwood & Jovanovic (1990). Empirical studies like Clarke et al. (2006), Tomaskovic-Devey & Lin (2013), Kus (2012), Van Arnum & Naples (2013), Barradas & Lagoa (2017), Brei et al. (2018) find evidence of aggravating income inequality on account of financialisation, whereas Beck et al. (2007), Agnello et al. (2012), Alvarez (2015), Aslan et al. (2017), Neaime & Gaysset (2018) find evidence of declining income inequality with rapid increase in financialisation. The level of urbanisation is also found to have either linear or non-linear impact on inequality. Some scholars also argue that the relationship between urbanization and income inequality could either be positive or negative (see for example Jones & Kone, 1996; Siddique et al., 2014). In this regard, Kanbur & Zhuang (2013) uncover that while urbanization had increased income inequality in the Philippines, Indonesia and India, it had rather reduced income inequality in China. Moreover, few other studies find evidence to support the inverted U-shaped relationship between urbanization and income inequality proposed by Kuznets (see Liddle, 2017; Wu & Rao, 2017; Sagala et al., 2014; among others). Again, though the effect of overall economic growth on income inequality has been extensively studied, the impact of sectoral GDP shares on inequality is not sufficiently explored[*]. Gordón & Resosudarmo (2019) find significant positive impact of both manufacturing and services shares of GDP and negative effect of agricultural GDP on income inequality. In stark contrast, Villanthenkodath et al. (2023) find evidence that shares of industrial and services sectors' output decrease income inequality in high income countries, whereas agricultural share improves income distribution in middle- and low-income countries.

Demographic characteristics like population ageing and education have also been identified as major determinants of income inequality in a growing body of empirical literature. Again, cross-country empirical evidence suggests equivocal conclusion on the impact of population ageing on inequality (see for example Lam & Levison, 1992; Cameron, 2000; Zhong,

[*]Raeskyesa (2020) found reduction in income inequality on account of rise in the share of agricultural GDP. Similar findings have been reported by Ha et al. (2019) in the context of developing countries. Conversely, Sulemana et al. (2019) found negative impact of rising share of manufacturing GDP on income inequality in sub-Saharan Africa.

2011; Gutsafsson & Johansson, 1999; Beiwen & Juhasz, 2012; Liu, 2014; etc.). Again, a handful of studies presents inconclusive causal relationship between education and economic inequality (see for example Becker & Chiswick,1966; Knight & Sabot, 1983; Checchi, 2004; Dabla-Norris et al., 2015; Ram, 1989; Castelló-Climent & Doménech, 2014; Tasseva, 2021; etc.). In fact, Coady & Dizioli (2017) opines that ignoring the potential reverse causality between the two would likely to generate biased results.

The above review of the existing literature identifies various determinants which are found to affect income distribution. Studies identifying the factors affecting household income distribution in India is however anecdotal. In addition, empirical studies on explicitly assessing the impact of SEZs on household expenditure inequality are rare. Against this backdrop, our contribution to the existing literature is threefold. Firstly, we intend to study the spatiotemporal dynamics of consumption expenditure inequality in the context of emerging market economies like India using a nationally representative Consumer Pyramid Household Surveys (CPHS) database, provided by the Centre for Monitoring Indian Economy (CMIE). Secondly, we instigate to use spatiotemporal models to study the impact of SEZs on expenditure inequality between the households at the district level. The novelty of the paper also stems from the finding that expenditure inequality between the Indian households in SEZ-districts has significantly declined on account of establishment of SEZs, while the spillover effects on expenditure inequality in the neighboring districts is found to be insignificant.

The remainder of the paper is organised as follows. Section 2 presents some stylised facts on operational SEZs and household expenditure inequality in India. Section 3 provides an explanation of the empirical methodology and a brief description of the econometric model used in the study. Major sources of the data as well as brief descriptions of the variables are given in Section 4. Section 5 reports the robust empirical results. Section 6 provides an explanation of the econometric findings. Lastly, conclusion with insightful policy implication is provided in Section 7.

Stylised Facts

Stylized facts on operational SEZs in India

Operational SEZs are observed to have clustered particularly along the coastline of peninsular India (see Figure 1). While, the southern states of Tamil Nadu, Karnataka, Telangana, Andhra Pradesh, Kerala and western states like Maharashtra and Gujarat collectively account for more than 75% of the operational SEZs in India, the northern land-locked states like Punjab and Uttar Pradesh have limited number of SEZs. Even, the north-eastern states do not have any operating SEZ. This pattern of spatial distribution of SEZs clearly indicates inter-state SEZ-led industrialisation disparities in India.* More importantly, SEZs are found to be concentrated in few districts within the states and are in close proximity to each other (see Figure 1-2), which can potentially generate agglomeration/localisation economies through labour market pooling, sharing of inputs and outputs, knowledge and technological spillovers, etc. (Aggarwal 2012). Such spatial distribution of SEZs across districts are likely to have impact on household income inequality.

Figure 1: Distribution of operational SEZs in India in 2019

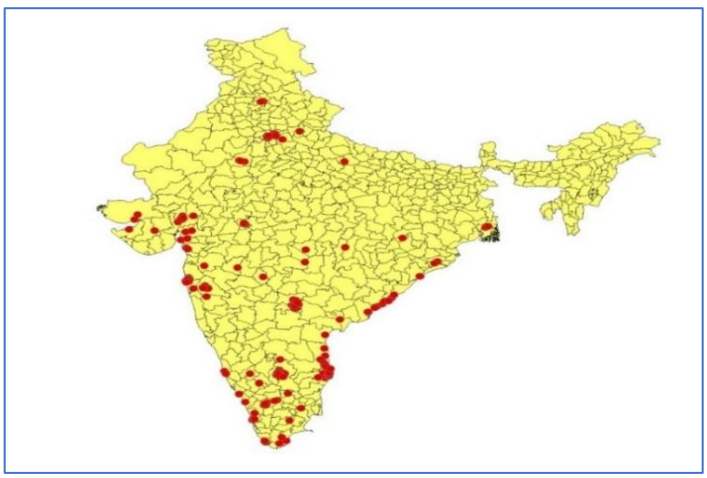
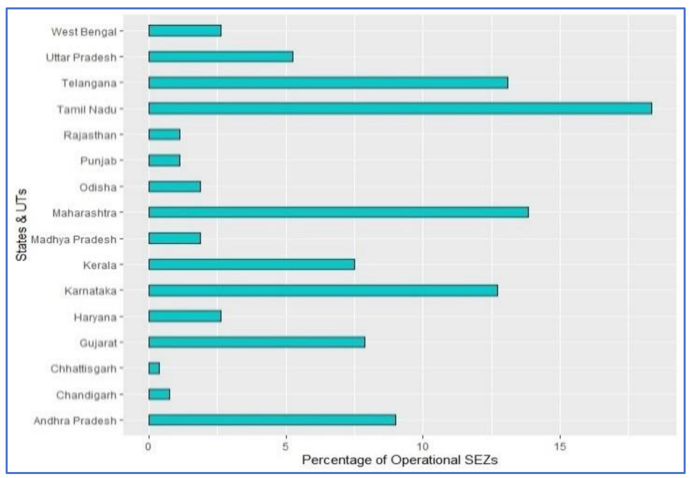


Figure 2: State-wise Distribution of SEZs in 2019 (in %)



Source: Authors' calculation based on the data obtained from 'Special Economic Zones in India' website, Ministry of Industry and Commerce, Government of India.

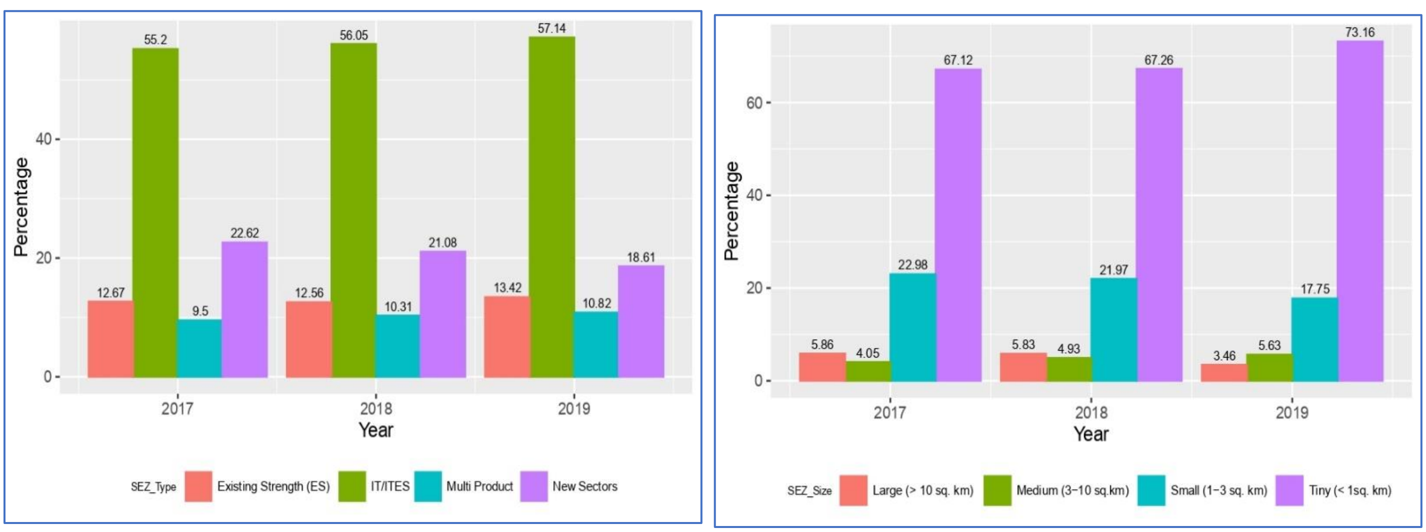
The number of SEZs proliferated since the enactment of SEZs Act in 2005, which opened the door for investment by private players in SEZs. Compositionally, Indian SEZs differ from

* In fact, Majeed et al. (2024) highlight the evidence of rising inter-state industrialisation disparities in India where the southern states benefit from their locational advantages as opposed to northern states.

other place-based policies in the world (including SEZs) in two key ways based on minimum size requirement and industry of operation.*

Following Jenkins et al. (2014)†, classifications of operational SEZs based on size and industry denomination for the period 2017-2019 are shown in Figure 3. More than 55% of the operational SEZs belong to IT/ITES industry, which falls under the category of Producer Services (PS) sector.‡ While the share of SEZs in New Sector category declined from 2017 to 2019 by 4.01 percentage point, both the Existing Sector and Multi-Product SEZs shares increased merely between 2017 and 2019. Approximately 90% of the operational SEZs are in India is found to be tiny and small in size. Moreover, the share of medium-sized SEZs increased while that of large-sized SEZs decreased marginally. This categorisation of Indian SEZs is likely to have implications on SEZ performance and henceforth, on direct and spillover effects on different economic outcomes. For instance, Gorg & Mulyukova (2024) find differential productivity growth of SEZ- and non-SEZ firms in the vicinity depending on the size and industry of operation of Indian SEZs.

Figure 3: Composition of SEZs according to Industry and size categories



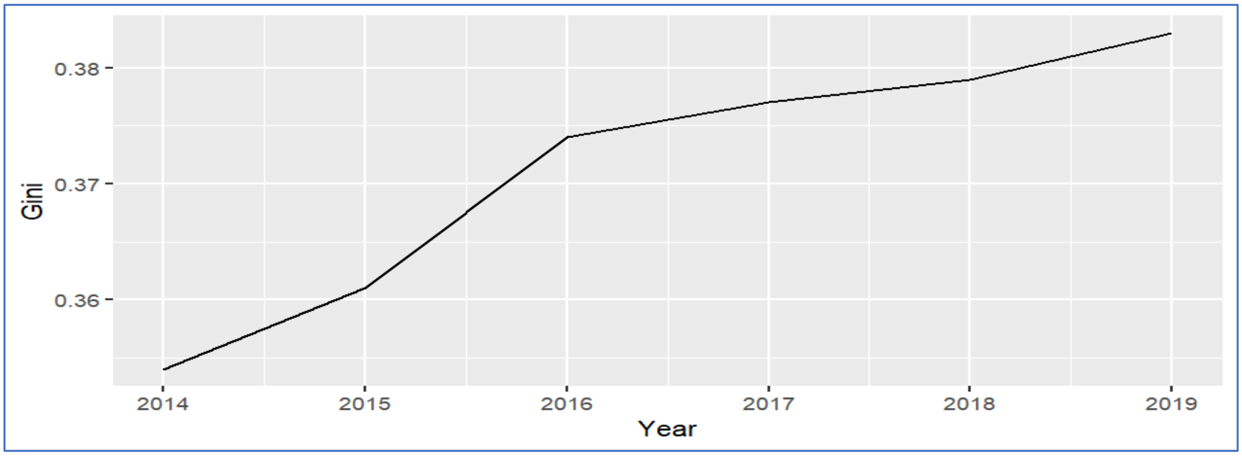
Source: Authors' calculation based on the data obtained from 'Special Economic Zones in India' website, Ministry of Industry and Commerce, Government of India.

* Moreover, according to Hyun & Ravi (2018), 70% of the SEZs are private sector or joint sector initiatives.
† Existing sector comprises of textiles, apparels, pharmaceuticals, gems & jewellery and footwear. New Sectors include food processing, power, engineering goods, electronics, minerals, automotives etc.
‡ See Fan et al. (2023) for the sub-sector classifications of services sector into producer and consumer services.

Stylized facts on spatiotemporal dynamics of expenditure inequality in India

Disparities in expenditure between Indian households is found to have widened over the sample period, as evident from Figure 4. This corroborates with the findings of some recent empirical studies in the context of India (see for example, Kapoor & Duggal, 2022; Bharti et al., 2024; Chancel & Piketty, 2019, etc.).

Figure 4: Dynamics of household expenditure inequality for the period 2014-2019



Source: Authors' calculation on the basis on data obtained from the CPHS database, CMIE.

Apart from increasing household expenditure inequality at All-India level, the spatial dependence of high inequality is observed at a disaggregated district-level. Districts of industrialized southern states, like Maharashtra, Gujarat, Tamil Nadu, Karnataka experienced higher concentration of inequality over the period 2014-2019. In fact, the global Moran's statistics for the Gini measure of household expenditure inequality is found to be positive and significant (Table 3 and Figure 2).

Table 1: Global Moran's statistic for the Gini measure of household expenditure inequality at the district-level from 2014 to 2019 *

Year	2014	2015	2016	2017	2018	2019
Global Moran's I	0.0882	0.0770	0.0728	0.0996	0.0734	0.0999
z-statistic	2.1869**	1.8585**	1.8339**	2.4680***	2.2088**	3.0287***

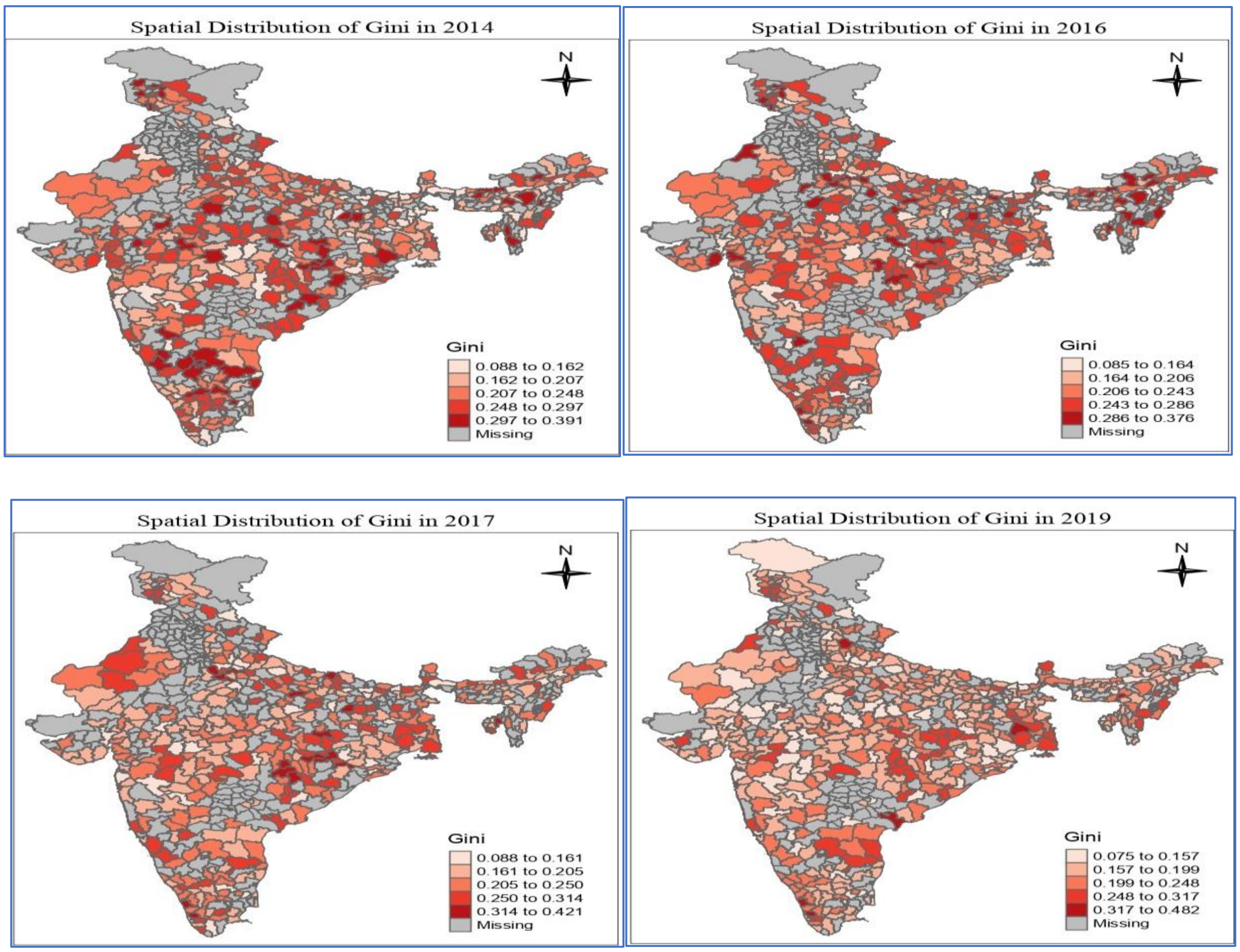
* The annual data on households' expenditure (including both food and non-food items) are available for 417 districts in 2014, 416 districts in 2015, 414 districts in 2016 and 2017, 490 districts in 2018 and 492 districts in 2019.

No. of observations	417	416	414	414	490	492

Source: Authors' calculation on the basis of the data obtained from the CPHS database, CMIE.

Note: Inference is drawn on the basis of 999 permutations and normalized queen weights are used. ***, ** and * indicate p-values <1%, <5% and <10%, respectively.

Figure 5: Spatial Distribution of Gini measure of household expenditure inequality at the district-level for selected sample years



Source: Authors' computation on the basis of data obtained from CPHS database.

High temporal dependence and comparatively low spatial dependence (though significant) of household expenditure inequality at the district-level, as evident from the above stylized facts justify the use of time-space recursive model on account of achieving long-run equilibrium with high spatial dependence. On empirical ground, the classic and robust LM lag tests conducted on the residuals of dynamic non-spatial panel model point to the rejection of no autocorrelation in spatial lag. Again, the classic and robust LM error tests are found to be significant, rejecting the null of no spatial error autocorrelation. The evidence on simultaneous presence of spatial lag and spatial error autocorrelations indicates the appropriateness of the spatial Durbin model. Similar conclusion is drawn from the results of the LR tests as well. Thus, it is imperative to estimate the spatial Durbin model.

Table 2: Diagnostic tests for spatial model specifications

Spatial Panel Diagnostic tests	Contiguity Weights Matrix	Inverse Distance Weights Matrices	
	Queen Weights	Cut-off distance (160 km)	Cut-off distance (200 km)
LM lag panel test	9.183*** [0.002]	23.911*** [0.001]	25.794*** [0.000]
LM lag robust panel test	6.142** [0.041]	3.612** [0.04]	6.432** [0.003]
LM error panel test	12.643*** [0.000]	24.778*** [0.000]	28.642*** [0.000]
LM error robust panel test	9.602*** [0.002]	4.479** [0.030]	9.271*** [0.002]
LR test for SAR	76.821*** [0.004]	74.725*** [0.002]	68.912*** [0.003]
LR test for SEM	83.214** [0.032]	74.364** [0.021]	64.321** [0.026]

Source: Authors' estimation on the basis of data obtained from the CPHS database, CMIE.
Note: Figures in square brackets are p-values. '***', '**' and '*' indicate p-values <1%, <5% and <10%, respectively. Queen weights are used.

Empirical Methodology

A large body of growing empirical literature have assessed the spillover effects of various place-based industrialisation policies including SEZs on various socio-economic indicators like productivity growth of firms, wage structure etc. (see for example Wang, 2013; Busso et al. 2013; Brussevich, 2020; Alder et al., 2016; Frick & Rodriguez-Pose, 2023; Gorg & Mulyukova, 2024; Hyun & Ravi, 2018; Alkon, 2018, among others). However, the findings of these studies are found to vary depending on the country and time period of study. Thus, it is pertinent to study the spillover impact of SEZs on income/expenditure distribution in Indian context. The evidence for spatial dependence in expenditure inequality is a prerequisite for employing spatiotemporal econometric method for assessing both direct and spillover effects.

Spatial Autocorrelation tests

The most widely used measure of spatial dependence (or autocorrelation) is the Moran's I statistic which indicate whether a variable exhibits significant spatial dependence at a pre-specified spatial scale (Getis, 2008). While global Moran's statistic provide evidence on overall spatial association, local Moran's statistic identifies the impact of specific locations (Anselin, 1995).

$$Global\ Moran's\ I = \left(n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x}) \right) \Bigg/ \left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right) \ldots \ldots (1)$$

$$(Local\ Moran's\ I)_i = n \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y}) \Bigg/ \sum_{i=1}^{n} (y_i - \bar{y})^2 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

where x_i and x_j are the values of the variable of interest for locations i and j respectively, $\bar{x}$ is the mean value, n is the number of observations and w_{ij} is the pre-specified spatial weights matrix summarizing the neighborhood structure across space.

Spatial weights matrix

Spatial weights specification is the prerequisite for analyzing spatial dependence (Anselin et al., 2014). Spatial arrangements of variables are modelled using either contiguous borders or by measuring distances between spatial units. The most widely used contiguous weight matric is the queen weights where two spatial units are treated as neighbors if they share common border or common vertex.[*] For the computation of the distance-based neighbor weights, the weights matrices based on inverse distances between all possible pairs of i^{th} and j^{th} spatial units with cut-off distances is used to control for the distance-decay effect, confirming the Tobler's law[†].

[*] There are two other types of contiguous weights, one being the Rook weights and another being the Bishop weights.

[†] Tobler's law states that "everything is related to everything else, but near things are more related than distant things."

Queen-based contiguity weights and inverse-distance weights based on two different cut-off distances (160 kms and 200 kms)[*] are used for robustness check of the estimates.

Dynamic panel model without spatial effects

The most widely used estimation method for non-spatial dynamic panel models is the Arellano & Bond (1991) 'Difference-GMM' (Diff-GMM) and the Arellano & Bover (1995) and Blundell & Bond (1998) 'System-GMM' (Sys-GMM). The Diff-GMM estimator potentially corrects for the dynamic panel bias caused by the OLS estimation (Nickell, 1981). However, it suffers from the weak instrumentation problem in small samples if the endogenous variables follow random walk processes (Blundell & Bond, 1998). Sys-GMM estimator, on the other hand, is devoid of such limitation.[†] The consistency of the Sys-GMM estimator requires validation of the instruments which is ascertained by testing the correlation between the instruments and the estimated residuals using Sargan/Hansen J test of over-identification (Blundell & Bond, 1998).[‡] The rule of thumb for achieving a consistent Sys-GMM estimator is to keep the number of instruments sufficiently less than the number of groups within the panel (Roodman 2009). Condition for the absence of second-order serial correlation in the first differenced residuals also needs to be satisfied by applying the Arellano & Bond (1991) test for ensuring the consistency of the results.[§] Moreover, the Sys-GMM estimator of the time-lagged dependent variable must lie between the fixed effects estimator and the pooled OLS estimator which are biased downward and upward, respectively (Bond, Hoeffler & Temple, 2001). Moreover, the two-step Sys-GMM estimation alongside Windmeijer (2005) finite-sample correction strategy helps to improve the efficiency of the estimates as opposed to one-step estimation.

The regression specification for the estimation of the benchmark non-spatial dynamic panel model used in the study is as follows:

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[*] The minimum threshold distance is chosen following the max-min criterion to avoid the problem of isolates. The minimum threshold distance in our case is 160 kms. Another weights matrix used is with cut-off distance of 200 kms.

[†] Both Diff-GMM and Sys-GMM estimations are more robust to measurement errors compared to cross-section regressions.

[‡] See Roodman (2006) for further details.

[§] By construction, the test for AR (1) process in first difference usually rejects the null hypothesis, which is expected since $\Delta\varepsilon_{it}$ is mathematically related to $\Delta\varepsilon_{it-1}$ via the shared ε_{it-1} term.

$$Gini_{it} = \theta_0 + \tau Gini_{i,t-1} + \theta_1\, Sez\_la_{it} + \theta_2\, Ln\_inc_{it} + \theta_3\, Sq\_ln\_inc_{it} + \theta_4 Fin\_inc_{it} + \theta_5 Sq\_Fin\_inc_{it} + \theta_6 Depr_{it} + \theta_7 Lt\_edu_{it} + \theta_8\, Prop\_rc_{it} + \theta_9\, Prop\_ps_{it} + \alpha_i + \mu_t + \varepsilon_{it} \quad \text{.. (3)}$$

where i refers to district and t indicates year. α_i, μ_t denotes district-specific, year-specific effects and ε_{it} denotes the idiosyncratic error term.

Overview of Spatiotemporal models and related estimation strategies

Non-spatial dynamic panel models are biased in presence of spatial dependence (LeSage & Pace, 2009). Among the set of spatial models, it is important to choose the appropriate one. Anselin (1988) and Anselin et al. (1996) develop two classic Lagrange Multiplier (LM) tests to check for the presence of spatial lag effect and spatial error effect (Classic LM-lag & Classic LM-error) and their robust versions (Robust LM-lag and Robust LM-error)[*], respectively as well.[†] Moreover, according to LeSage & Pace (2009, Chap. 6), firstly, the spatial panel Durbin model can be estimated and consequently Likelihood Ratio (LR) tests or Wald tests can be applied to check whether it can be boiled down to a spatial lag or a spatial error model.[‡]

The spatial dynamic panel model has gained attention since the last decade (Zheng et al., 2013). Estimations of non-spatial dynamic model or spatial non-dynamic model are likely to produce biased estimates (Elhorst, 2012). Anselin et al. (2008) categorise spatiotemporal models into four variants. The specifications are as follows:

$$Y_t = \rho WY_{t-1} + \beta X_t + \mu + \alpha_t \iota_N + \varepsilon_t \quad \text{(4)}$$

$$Y_t = \tau Y_{t-1} + \rho WY_{t-1} + \beta X_t + \mu + \alpha_t \iota_N + \varepsilon_t \quad \text{(5)}$$

$$Y_t = \tau Y_{t-1} + \delta WY_t + \beta X_t + \mu + \alpha_t \iota_N + \varepsilon_t \quad \text{(6)}$$

$$Y_t = \tau Y_{t-1} + \delta WY_t + \rho WY_{t-1} + \beta X_t + \mu + \alpha_t \iota_N + \varepsilon_t \quad \text{(7)}$$

[*] These two tests are 'robust' because the existence of one type of spatial dependence does not bias the test for other type of spatial dependence, which is not the case for the classic versions of these tests.
[†] Note that the test results should satisfy the condition that Classic LM spatial lag + Robust LM spatial error = Classic LM spatial error + Robust LM spatial lag.
[‡] Likelihood Ratio (LR) tests require estimation of all the three models (SAR, SEM and SDM) whereas Wald tests require estimation of the SDM only. This is popularly known as the 'specific-to-general' approach for the search of model specifications.

where (4), (5), (6) and (7) are ‘pure-space recursive’, ‘space-time recursive’, ‘space-time simultaneous’ and ‘space-time dynamic’ models respectively.

The results of the spatial diagnostic tests (see Table 4) points to the appropriateness of the spatial Durbin model[*]. In this case, inclusion of either spatially lagged explanatory variables (WX_t) and/or space-time lagged explanatory variables (WX_{t-1}) lead to identification problems in both space-time simultaneous and space-time dynamic models.[†] On the contrary, inclusion of space-time lagged explanatory variables will cause identification problems[‡] in pure space recursive and space-time recursive models whereas inclusion of spatially lagged explanatory variables will not (Anselin et al., 2008). Again, Lee & Yu (2016) find that the omission of relevant Durbin terms result to significant biases, while including irrelevant Durbin terms cause no loss of efficiency.

Apart from the above empirical perspective, intuitively, space-time recursive model is useful to study the phenomena of spatial diffusion (Anselin et al., 2008; LeSage & Pace, 2009). As the literature suggests, regional income inequality tend to be correlated overtime. Spatial dependence particularly arises from diffusion processes overtime rather than instantaneously (LeSage & Pace, 2009). Impact of SEZs on household expenditure inequality is likely to get channelised through increasing opportunities for employment and consequently through income growth of labors. However, migration decisions of households from non-SEZ to SEZ districts involve benefits of getting jobs and costs associated with migration. This decision-making requires time to gather information, creating delays in the decision-making process and thus, spatial dependence is likely to take time for manifestation[§] (Elhorst, 2001). Again, LeSage &

[*] The Spatial Error Model does not require a theoretical framework which can make it problematic on substantive grounds (Fingleton & Lopez-Bazo, 2006; Franzese & Hays, 2007). Again, McMillan (2012) criticize the overuse of SAR model and SEM which can lead to misspecification issues relating to space. Elhorst (2010) points to the limitation of SAR model as the ratio between marginal impacts of changes in explanatory variables in a region on the dependent variables in other regions (spillover effects) and own region (direct effects) is the same for all explanatory variables in case of SAR model, which is unlikely to hold in most applied settings. Also, the empirical evidence in favor of a spatially lagged dependent variable can be misleading, since it can pick up the interaction effects among explanatory variables which are erroneously omitted from the model (Corrado & Fingleton, 2012).

[†] The explicit inclusion of WY_t in both time-space simultaneous and time-space dynamic models along with WX_t will result to biased estimates as the impact of the latter (WX_t) is already present in the former (WY_t).

[‡] The effects of (WX_{t-1}) is already captured by WY_{t-1} terms.

[§] Another key observation is that regions are not isolated due to factor mobility (Rodriguez-Pose, 2017).

Pace, (2009) refer to space-time recursive model as an appropriate spatiotemporal model in presence of high temporal dependence alongside low spatial dependence which lead to long-run equilibrium with high spatial dependence. Thus, the use of time-space recursive model is justified in the current context.

The space-time recursive model with spatial interaction effects among the explanatory variables and allowing for some explanatory variables to be endogenous other than time-lagged and space-time lagged dependent variables usually takes the form as follows:

$$Y_t = \tau Y_{t-1} + \rho W Y_{t-1} + \theta Z_t + \pi W Z_t + \beta X_t + \gamma W X_t + \mu + \alpha_t \iota_N + \varepsilon_t \text{ .... (8)}$$

where Y_t denotes an $N \times 1$ vector consisting of one observation of the dependent variable for every spatial unit $(i = 1,2, \dots, N)$ in the sample at a particular point in time $(t = 1,2, \dots, T)$. Z_t is an $N \times K_1$ matrix of endogenous explanatory variables and $K_1 \times 1$ vectors of θ and π as parameters of the corresponding endogenous variables. X_t is an $N \times K_2$ matrix of exogenous explanatory variables associated with the $K_2 \times 1$ parameter vectors β and γ. The spatial weights matrix W is a non-negative $N \times N$ matrix describing the spatial arrangement of cross-sections in the sample, where W is row-normalized and diagonal elements are set to zero as no cross-section can be viewed as its own neighbor. A vector or matrix with subscript $t-1$ denotes its serially lagged values and the same pre-multiplied by W denotes its spatially lagged values. τ and ρ are the parameters associated with the time lagged dependent variable and space-time lagged dependent variable, where ρ is termed as the lagged SAR (Spatial Autoregressive) coefficient. $\mu = (\mu_1, \mu_2, \dots, \mu_N)$ is a vector of spatial fixed effects and α_t is the coefficient of a time-period fixed effects, one for each year (except one to avoid perfect multicollinearity), while ι_N is an $N \times 1$ vector of ones. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{Nt})$. If $\rho \geq 0$, then stationarity condition for the time-space recursive model requires $|\tau| < 1 - \rho$, while if $\rho < 0$, the model is stable when $|\tau| < 1 - \rho r_{min}$, where r_{min} is the most negative purely real eigenvalue of W after it is row-normalised. The control for time-period fixed effects is crucial since most variables tend to move together in different cross-sections over time resulting to overestimation of ρ, if not accounted for.

The interpretation of the spillovers is one of the advantages of considering interaction effects among the explanatory variables (Elhorst, 2014). Moreover, LeSage & Pace (2009) show that the long-term marginal effects of the expected value of the dependent variable with respect to the k[th] explanatory variable Z_k and X_k, respectively in spatial unit 1 up to N take the forms:

$$\left[\frac{\partial E(Y_t)}{\partial z_{1kt}} \cdots \frac{\partial E(Y_t)}{\partial z_{Nkt}}\right] = \left(I_N - \frac{\rho}{1-\tau}W\right)^{-1}\left(I_N \frac{\theta_k}{1-\tau} + W\frac{\pi_k}{1-\tau}\right) \ldots \quad (9)$$

$$\left[\frac{\partial E(Y_t)}{\partial x_{1kt}} \cdots \frac{\partial E(Y_t)}{\partial x_{Nkt}}\right] = \left(I_N - \frac{\rho}{1-\tau}W\right)^{-1}\left(I_N \frac{\beta_k}{1-\tau} + W\frac{\gamma_k}{1-\tau}\right) \ldots \quad (10)$$

Since W is row-normalized, the long-term direct and spillover effects respectively simplify to,

$$\frac{\theta_k(1-\tau)}{\left(1-\rho(1-\tau)\right)} = \frac{\theta_k}{1-\tau-\rho} \text{ and } \frac{\pi_k(1-\tau)}{(1-\rho(1-\tau))} = \frac{\pi_k}{1-\tau-\rho} \ldots \quad (11)$$

$$\frac{\beta_k(1-\tau)}{\left(1-\rho(1-\tau)\right)} = \frac{\beta_k}{1-\tau-\rho} \text{ and } \frac{\gamma_k(1-\tau)}{(1-\rho(1-\tau))} = \frac{\gamma_k}{1-\tau-\rho} \ldots \quad (12)$$

indicating that the long-term direct and spillover effects can be obtained from their short-term counterparts by multiplying them by the factor $1/(1-\tau-\rho)$.

The regression specification for the estimation of the space-time recursive model used in the study is as follows:

$$Gini_{it} = \theta_0 + \tau Gini_{i,t-1} + \rho \sum_{j=1}^{N} W_{ij} Gini_{i,t-1} + \theta_1\, Sez\_la_{it} + \theta_2\, Ln\_inc_{it} + \theta_3\, Sq\_Ln\_inc_{it} +$$
$$\theta_4 Fin\_inc_{it} + \theta_5 Sq\_Lin\_inc_{it} + \theta_6 Depr_{it} + \theta_7 Lt\_edu_{it} + \theta_8\, Prop\_rc_{it} + \theta_9\, Prop\_ps_{it} +$$
$$\gamma_1 \sum_{j=1}^{N} W_{ij}\; Sez\_la_{it} + \gamma_2 \sum_{j=1}^{N} W_{ij}\; Ln\_inc_{it} + \gamma_3 \sum_{j=1}^{N} W_{ij}\; Sq\_Ln\_inc_{it} + \gamma_4 \sum_{j=1}^{N} W_{ij}\; Fin\_inc_{it} +$$
$$\gamma_5 \sum_{j=1}^{N} W_{ij}\; Sq\_Fin\_inc_{it} + \gamma_6 \sum_{j=1}^{N} W_{ij}\; Depr_{it} + \gamma_7 \sum_{j=1}^{N} W_{ij}\; Lt\_edu_{it} + \gamma_8 \sum_{j=1}^{N} W_{ij}\; Prop\_rc_{it} +$$
$$\gamma_9 \sum_{j=1}^{N} W_{ij}\; Prop\_ps_{it} + \alpha_i + \mu_t + \varepsilon_{it} \ldots \quad (13)$$

Anselin (2001) and Elhorst (2003) provide detailed survey of the different spatiotemporal models and suggest econometric strategies for estimation. Elhorst (2008) analyzes the finite sample performance of various estimators (Spatial MLE, Spatial Dynamic MLE and GMM) for spatial dynamic panel model with only exogenous variables. His Monte Carlo study shows that Spatial Dynamic MLE has a better performance in terms of bias reduction and root-mean-squared errors (RMSE), although the Spatial MLE results to smallest bias for the spatial lag coefficient. Based on this, Elhorst (2008) proposes two mixed estimators where the spatial lag dependent variable is estimated using spatial MLE and the rest by using either GMM or Spatial Dynamic MLE. Though this mixed Spatial MLE/Spatial Dynamic MLE estimator depicts superior performance in terms of bias reduction and RMSE in comparison to Spatial MLE/GMM, the latter offers more robustness on practical grounds when number of observations (N) is substantially large relative to number of time points (T) in a panel set-up. The main caveat for applying these estimation methods is that when some explanatory variables are endogenous, no instrumental treatment is applied to control for other potential endogenous variables. In particular, extended-GMM can correct for the endogeneity of the spatial lag and the time-lagged dependent variable as well as other potentially endogenous explanatory variables, apart from controlling for measurement errors, weak instruments, time-invariant individual specific effects. Again, the Monte Carlo simulation done by Kukenova & Monteiro (2009) indicates spatial system GMM as a dominant estimation method in terms of unbiased criterion. Additionally, RMSE decays at a faster rate as N or T increases and standard error accuracy is acceptable in case of spatial system GMM.

The above overview of different estimation techniques in the context of spatiotemporal models clearly suggest the appropriateness of the system-GMM estimation in space-time recursive models.

Data sources and Variables' description and Sample size

Brief overview of the data source

Consumer Pyramid Household Survey (CPHS) is a nationally representative household survey database covering approximately 98.5% of India's population (Mishra et al., 2022).[*] The panel survey provides information on household demographics[†], incomes and expenses[‡], asset

[*] CPHS provides the data in four separate modules, namely People of India$_{dx}$, Aspirational India$_{dx,}$ Income Pyramids$_{dx}$ and Consumption Pyramids$_{dx.}$

[†] The demographic module of the CPHS has information on the age, sex, religion, education levels and occupations of all members of the households and the households' caste, religion, and domicile.

[‡] The CPHS collects month-wise recall data on household income from different sources like wages, interests, profits, etc., and money spent on approximately 80 different goods and services (including food, health, education, utility bills, recreation, remittances, EMIs, etc.).

holdings and borrowings. It collects data three times a year at four months interval (each called as 'wave') since 2014 following stratified multi-stage random sampling method and using villages and towns of Census 2011 as Primary Sampling Units (PSUs) and households as Ultimate Sampling Units (USUs). The survey covers around 102 Homogeneous Regions (HRs)[*] representing 28 states and roughly 514 districts.[†] Approximately, on average, 63,430 rural and 110,975 urban households are surveyed in each wave of the survey.[‡] However, the sample has evolved overtime with drop-out households and new households being added.[§] To adjust for large differences in the number of households in a district, sampling weights are used to avoid improper representation of households at the district level.

Variables' descriptions

The data on district-wise distribution of operational SEZs along with their notified land areas (in sq.km and/or hectares) in India are available from the 'Special Economic Zones in India' website, officially maintained by The Ministry of Commerce and Industry, Government of India. The notified land areas of all the operational SEZs are aggregated at the district-level for each sample year to arrive at the proportion of district land area operating under the SEZ jurisdiction. Household nominal per-capita annual expenditure is calculated from the CPHS database for the period 2014-2019 and is further deflated by using aggregate Consumer Price Index (CPI) – Combined series (2012 base) available from the Ministry of Statistics and Program Implementation (MoSPI) to arrive at the household real per-capita annual expenditure. Subsequently, Gini measure of inequality between household real per-capita expenditure is computed at the district-level.

Variable for capturing the extent of financialization in districts is computed by calculating the proportion of household heads having registered bank accounts. Furthermore, district-level annual real per-capita income of households is computed to use it as a proxy for economic

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[*]A Homogeneous Region is a set of neighboring districts within a state that has similar agro-climatic conditions, relatively similar urbanisation levels and relatively similar female literacy and are of a similar size in terms of households as per the 2011 Census.
[†]Data is not available for North-eastern states like Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland and Sikkim and Union territories of Andaman & Nicobar Islands, Dadra & Nagar Haveli, Diu & Daman, Lakshadweep.
[‡] Urban areas are oversampled in CPHS and account for 63.8 per cent of the sampled households.
[§] For further details, see Bhattacharya & Sinha Roy (2021).

growth. Additionally, proportion of households with dependent heads*, proportion of households belonging to reserved castes†, proportion of households with household heads working in the primary sector‡ and proportion of household heads not completing the matriculate education are computed for the districts to control for other household demographic characteristics. To account for the possible endogeneity of variables relating to economic well-being and educational levels of households, district-level unemployment rate§ and proportion of households completing higher education** are respectively used as instruments in the empirical exercise. The detailed explanations and the summary statistics of all the concerned variables are given in Table 3 and Table 4, respectively.††

Table 3: Data sources and variables' descriptions and symbols

Type of variables	Variables' symbol	Variables' description
Dependent variable	Gini	Measure of expenditure inequality between the households at the district level
Core explanatory variable	Sez_la	Proportion of land area in a district operating under the jurisdiction of SEZs
Control variables	Ln_inc	Natural logarithm of annual real per capita income of the households at the district level
	Sq_Ln_inc	Square of natural logarithm of annual real per capita income of the households at the district level
	Fin_inc	Proportion of population in a district having bank accounts
	Sq_Fin_inc	Square of proportion of population in a district having bank accounts
	Depr	Proportion of population in a district whose age is less than 15 years and greater than 64 years
	Lt_edu	Proportion of population in a district who have completed less than matriculate education
	Prop_rc	Proportion of population in a district who belong to the reserved caste
	Prop_ps	Proportion of population in a district who are employed in

* We have taken the standard definition of the dependency rate from the glossary of World Development Indicators (WDI) definitions.

† Population of reserved caste implies population belonging to SC/ST and OBC castes.

‡ Primary sector includes agriculture and allied activities, poultry farming, animal husbandry, vermiculture, fruits and vegetable farming, crop plantation and cultivation, fishing and forestry including wood cutting.

§ Unemployed individual is the one who is willing to do job, but not getting it (involuntarily unemployed).

** People with higher education implies those who are either pursuing or have completed graduation, post-graduation, MPhil and/or Ph.D.

†† Though urbanization is found to be relevant predictor of inequality in the literature, this variable is omitted from the model specification because of considerable reduction in the sample size.

		the primary sector
Instrument variables (used in GMM estimation)	Unemp_r	Proportion of unemployed population in a district
	Gt_edu	Proportion of population in a district who are pursuing or have completed higher education

Source: Authors' definitions based on the data obtained from the CPHS database and data on SEZs obtained from the 'Special Economic Zones in India' website, Ministry of Commerce and Industry database, Government of India.

Table 4: Summary Statistics

Variables	No. of Obs	Mean	Standard Deviation	Min	Max
Gini	2244	0.3254	0.0495	0.0868	0.7219
Sez_la	2244	0.0002	0.0014	0.0000	0.0261
Ln_inc	2244	14.8821	1.3140	9.3432	18.4812
Sq_Ln_inc	2244	223.2004	37.8805	87.2954	341.5212
Fin_inc	2244	0.6628	0.2142	0.0062	1.0000
Sq_Fin_inc	2244	0.4852	0.2675	0.00004	1.0000
Depr	2244	0.2558	0.0499	0.0741	0.4682
Prop_rc	2244	0.6646	0.2086	0.0000	1.0000
Lt_edu	2244	0.6483	0.1294	0.0000	1.0000
Prop_ps	2244	0.2559	0.2265	0.0000	0.9796
Unemp_r	2244	0.5920	0.0642	0.2467	1.0000
Gt_edu	2244	0.1148	0.0687	0.0000	0.4114

Source: Authors' calculations on the basis of data obtained from CPHS database and SEZs database obtained from the Ministry of Commerce and Industry database, Government of India.

Sample size for estimation

The estimation sample consists of a common set of 374 districts over a period 2014-2019, representing a balanced panel of 2244 observations on households aggregated at the district-level. The motivating reason for using a balanced panel of districts for applying the spatial econometric exercise stems from the fact that estimation strategies for unbalanced spatial panels is at its nascent but growing stage[*].

[*] See Yesilyurt & Elhorst (2017) for detailed discussion on the concerned issue.

Empirical Results

Table 5: Dynamic Panel Model Results

Variables	POLS	LSDV	DIFF-GMM	SYS-GMM
Gini_{t-1}	0.5589***	0.1567***	0.2445***	0.3551***
	(21.52)	(6.15)	(3.83)	(6.60)
Sez_la	-0.1994	-17.5442	-17.3791	-1.1930**
	(-0.48)	(-0.30)	(-0.82)	(-1.81)
Ln_inc	0.0015	0.0611***	0.0961***	0.0674**
	(0.12)	(3.08)	(2.84)	(2.13)
Sq_Ln_inc	0.0042	-0.0017**	-0.0036**	-0.0023**
	(0.10)	(-2.49)	(-2.07)	(-2.17)
Fin_inc	0.0931***	0.0959***	0.0268	0.0764**
	(4.19)	(3.74)	(0.73)	(2.56)
Sq_Fin_inc	-0.0934***	-0.0989***	-0.0380	-0.0888***
	(-5.27)	(-4.71)	(-1.32)	(-3.43)
Depr	0.0732***	0.0591	-0.0129	0.2441***
	(3.33)	(1.63)	(-0.18)	(2.79)
Lt_edu	-0.0372***	-0.0229	-0.1632	-0.2845***
	(-3.75)	(-0.92)	(-1.14)	(-2.72)
Prop_rc	-0.0028	0.0074	-0.0129	0.0259*
	(-0.61)	(0.39)	(-0.28)	(1.71)
Prop_ps	-0.0014	-0.0062	-0.0042	0.0382**
	(-0.26)	(-0.67)	(-0.20)	(2.22)
Constant	0.0493	-0.3643**		-0.3336
	(0.53)	(-2.51)		(-1.46)
No. of observations	1,870	1,870	1,496	1,870
No. of groups		374	374	374
No. of instruments			35	40
AR (1)			-2.91	-5.31
			[0.004]	[0.000]
AR (2)			-1.32	0.39
			[0.186]	[0.696]
Hansen			20.75	28.71
			[0.474]	[0.276]

Source: Authors' estimations on the basis of data obtained from CPHS database and SEZ data taken from The Ministry of Commerce and Industry database, Government of India.

Dependent variable: Gini of expenditures between the households at the district level.

Notes: POLS and LSDV denotes pooled OLS and fixed effects estimations. DIFF-GMM and SYS-GMM denote two-step Difference GMM and two-step System GMM, respectively. The t-statistics are reported in the parentheses. The explanatory variables Ln_inc, Sq_ln_inc and Lt_edu are treated as potential endogenous regressors. The second- and higher order temporal lags of the endogenous variables as well as that of the external set of instruments are used as instruments in the regression. The t-statistics are computed based on Windmeijer (2005) standard errors. Hansen is the test of over-identifying restrictions; AR (1) and AR (2) are the tests for first-order and second-order serial correlations in the first-differenced residuals.

Table 5 shows the results of the dynamic panel data models without spatial effects. The results of the pooled OLS and LSDV models are reported to check the consistency of the dynamic panel model results obtained by using the Diff-GMM and Sys-GMM estimation. Notably, all the four models are found to be stationary since $|\tau| < 1$. Sys-GMM appears to be consistent as the estimate of the time lagged dependent variable ($Gini_{t-1}$) strictly lie in between that of the pooled OLS and LSDV estimates. Both the Hansen-J test as well as the AR (2) test fail to reject the null hypotheses of valid instruments and no second-order serial correlation respectively. Accordingly, the lags of all the potential endogenous regressors (Gini_{t-1}, Ln_inc, Sq_Ln_inc, Lt_edu) starting from $(\mathrm{t}-2)$ are used as internal instruments. In addition, second- and higher order lags of Unemp_r, Sq_Unemp_r, Gt_edu are employed as external instruments, respectively. A one-unit change in lagged-expenditure inequality between the households in a district is explaining about 0.36 unit of inequality in the current year, providing significant evidence of temporal dependence. The expansion of SEZs is found to be welfare-enhancing suggesting that an increase in the land area operating under the jurisdiction of SEZs is likely to bring about a significant decline in between-household expenditure inequality by 1.19 units. Nevertheless, the dynamic panel model results are obvious to be somewhat biased as there is evidence of spatial dependence in inequality. Accordingly, the estimated results of the most-suited Time-Space Recursive model are reported in Table 7.

Since $\rho > 0$, the stationarity condition for the time-space recursive model (Table 7), $|\tau| < 1-\rho$, is satisfied for all the models with different spatial weights. The null hypothesis of zero second-order serial correlation is also accepted with considerably large p-values. Accordingly, the lags of all the potential endogenous regressors (Gini_{t-1},$\mathrm{W} * \text{Gini}_{\mathrm{t}-1}$, Ln_inc, W*Ln_inc, Sq_Ln_inc, W*Sq_Ln_inc, Lt_edu, W*Lt_edu) starting from $(\mathrm{t}-2)$ are used as internal instruments. In addition, second- and higher order lags of Unemp_r, W*Unemp_r, Sq_Unemp_r, W*Sq_unemp_r, Gt_edu and W*Gt_edu are employed as external instruments, respectively. The Hansen test cannot reject the null that instruments and residuals are uncorrelated. Moreover, Roodman's (2009) rule of thumb that the number of instruments should be considerably less than the number of groups is also satisfied. These two criteria collectively imply that the set of instruments are valid for all the model specifications.

The following Table (Table 6) shows the results of the time-space recursive Durbin model. Expenditure inequality is found to be strongly correlated overtime, the coefficient estimates for the time-lagged dependent variable being large, positive and highly significant across all models. The estimates of the time-lagged inequality measure strictly fall between that of pooled OLS and LSDV, signifying that the Sys-GMM estimation models are consistent. There is robust evidence of persistent inequality between the households' expenditure as indicated by the significance of the estimates of Gini_{t-1}. In addition, the past levels of expenditure inequality between the households in the neighboring districts are positively affecting the expenditure inequality between the households in a particular district. In fact, the short-term significant spillover effect of inequality is 0.2091 while in long-term the effect is found to be 0.9107 which is sufficiently large and significant. Since τ dominates ρ in terms of both magnitude and significance, the significance levels of long-term effects (both direct and indirect) are comparable with those of the short-term effects, respectively. A one-unit increase in the land area operating under SEZs in a district is significantly reducing the expenditure inequality between the households in that district by 0.2937 units in the short-term and by 1.2792 units in the long-term, both being significant at 5% level. This establishes the fact that the welfare-enhancing effect of presence of SEZs on reducing inequality are more effectively realized overtime rather than instantaneously. The Kuznets' hypothesis also holds true with respective significant positive and negative coefficients associated with *Ln_inc* and its squared term. Moreover, the per-capita real income of the households in the neighboring districts is positively affecting the income of the households in a particular district. The effect of financialization on expenditure inequality is found to be non-linear inverted-U shaped indicting that with increase in access to financialization, inequality first increases and thereafter starts declining. The expenditure inequality increases with increase in dependency ratio. However, the associated spillover effects turn out to be insignificant. As the proportion of less educated people in a district increases, expenditure inequality significantly increases in the same district, but not in the neighboring districts.

Table 6: Space-Time Recursive Model Results

	Contiguity Based Weights Matrix			Inverse Distance Weights Matrices					
	Queen weights			Cut-off distance (160km)			Cut-off distance (200km)		
Variables	POLS	LSDV	SYS-GMM	POLS	LSDV	SYS-GMM	POLS	LSDV	SYS-GMM
$Gini_{t-1}$	0.8543***	0.3563***	0.5613***	0.6508***	0.3447***	0.6361***	0.7464***	0.3403***	0.6573***
	(21.06)	(6.06)	(5.42)	(20.88)	(5.63)	(3.72)	(20.65)	(5.47)	(4.15)
$W * Gini_{t-1}$	0.0323	0.0302	0.2091***	0.2029	0.3627	0.2206**	0.1872	0.3639	0.2130**
	(0.45)	(0.85)	(3.89)	(0.53)	(0.68)	(2.06)	(0.50)	(0.73)	(2.42)
Sez_la	-0.2893**	-0.8182**	-0.2937**	-0.1113**	-0.8812**	-0.4662***	-0.1104**	-0.4101**	-0.3706**
	(-2.69)	(2.99)	(-2.59)	(-2.27)	(3.13)	(-2.79)	(-2.24)	(2.97)	(-2.36)
W*Sez_la	0.3612	0.3926	-0.2417	0.5187	0.5327	0.7361	0.1913	0.4622	0.5211
	(0.36)	(1.46)	(0.99)	(0.04)	(0.29)	(0.55)	(0.15)	(0.21)	(1.09)
Ln_inc	0.0025	0.0496**	0.0373**	0.0011	0.0543**	0.0796**	0.0016	0.0546***	0.0456**
	(0.20)	(2.46)	(2.40)	(0.09)	(2.70)	(2.13)	(0.13)	(2.72)	(2.74)
W*Ln_inc	0.0051	0.0203	0.2175**	0.0806	-0.7443	0.1849**	0.0664	-0.7957*	0.1778***
	(0.55)	(1.22)	(2.06)	(1.54)	(1.64)	(2.17)	(1.34)	(1.87)	(2.20)
Sq_Ln_inc	-0.0022	-0.0031*	-0.0011**	-0.0077	-0.0015**	-0.0026**	-0.0061	-0.0014**	-0.0014***
	(0.47)	(-1.94)	(-2.12)	(-1.18)	(-2.05)	(-2.09)	(0.14)	(-2.08)	(-2.53)
W*Sq_Ln_inc	-0.0057	-0.0172	-0.0504**	-0.0057	-0.0319	-0.0121***	-0.0054	-0.0311**	-0.0112***
	(-1.26)	(-0.54)	(-2.56)	(-1.22)	(-1.02)	(-2.71)	(-1.19)	(-2.22)	(-2.74)
Fin_inc	0.0935***	0.0903***	0.0792***	0.0950***	0.0887***	0.1068***	0.0902***	0.0829***	0.1043***
	(4.21)	(3.49)	(2.94)	(4.33)	(3.43)	(3.64)	(4.11)	(3.21)	(3.68)
W*Fin_inc	0.0015	0.0639	0.0669	0.4628	0.2207	0.9962	0.6129	0.1334	0.8213
	(0.61)	(0.54)	(0.67)	(0.97)	(1.30)	(1.65)	(0.46)	(1.75)	(1.45)
Sq_Fin_inc	-0.0952***	-0.0959***	-0.0817***	-0.0948***	-0.0953***	-0.1031***	-0.0909***	-0.0908***	-0.0996***
	(-5.37)	(-4.51)	(-3.72)	(-5.45)	(-4.49)	(-4.45)	(-5.21)	(-4.28)	(-4.39)
W*Sq_Fin_inc	-0.0029	-0.0143	0.0381*	-0.2401	-0.7381*	-0.5569	-0.3365	-0.8406**	-0.4937
	(-0.37)	(-0.15)	(1.95)	(-0.66)	(-1.74)	(-1.19)	(-0.85)	(2.17)	(-1.12)
Depr	0.0744***	0.0505	0.0823**	0.0713***	0.0658*	0.0767*	0.0716***	0.0687*	0.0687***
	(3.28)	(1.38)	(2.35)	(3.14)	(1.81)	(1.94)	(3.12)	(1.90)	(2.05)
W*Depr	0.0067	0.0367	0.1045*	0.3602	0.5708	0.1717**	0.5032	0.6141	0.1692**
	(0.67)	(0.19)	(1.81)	(0.84)	(0.65)	(2.28)	(1.02)	(0.74)	(2.77)

Lt_edu	-0.0392*** (-3.76)	-0.0217** (-2.86)	-0.0450** (-2.09)	-0.0389*** (-3.75)	-0.0231** (-2.92)	-0.0841*** (-2.84)	-0.0421*** (-3.89)	-0.0213** (-2.85)	-0.0651*** (-2.66)
W*Lt_edu	-0.0082 (-0.16)	-0.0826 (-0.64)	0.0832* (1.91)	-0.3378 (-1.39)	-0.8359 (-1.44)	-0.3646 (-0.79)	-0.3608 (-1.60)	-0.7711 (-1.42)	-0.2048 (-0.53)
Prop_rc	-0.0048 (-1.00)	0.0062 (0.33)	0.0121 (-0.06)	-0.0038 (-0.81)	0.0077 (0.41)	0.0019 (0.27)	-0.0040 (-0.85)	0.0085 (0.45)	0.0022 (0.33)
W*Prop_rc	0.0271 (0.29)	0.08176 (0.89)	-0.0081 (-0.54)	0.1033 (0.95)	0.1614 (0.35)	-0.0537 (-0.34)	0.1086 (0.48)	0.2905 (0.64)	-0.0304 (-1.20)
Prop_ps	0.0022 (0.39)	0.0856** (2.92)	0.0136** (2.19)	0.0013* (2.05)	0.0785* (1.95)	0.0955** (2.31)	0.0011* (2.20)	0.0606** (2.98)	0.0104** (2.57)
W*Prop_ps	0.0072 (0.29)	0.0253 (0.55)	0.0453 (1.46)	0.0738 (0.65)	0.3997* (1.83)	0.2359** (2.55)	0.0421 (0.39)	0.4597** (2.22)	0.2917** (2.17)
Constant	0.0767 (0.82)	-0.6742** (-2.77)	-0.4777 (-0.23)	0.0541 (0.56)	-0.8331* (-1.91)	-0.4649* (-1.72)	0.0552 (0.59)	-0.9978* (-1.96)	-0.2413 (-1.18)
No. of observations	1,870	1,870	1,870	1,870	1,870	1,870	1,870	1,870	1,870
No. of groups		374	374		374	374		374	374
No. of instruments			108			108			108
AR (1)			-6.01*** [0.000]			-4.96*** [0.000]			-7.91*** [0.000]
AR (2)			0.43 [0.665]			0.23 [0.817]			0.28 [0.780]
Hansen			90.11 [0.253]			75.79 [0.421]			99.34 [0.107]

Source: Authors' estimations on the basis of data obtained from CPHS database and the SEZ data obtained from The Ministry of Commerce and Industry, Government of India.

Dependent variable: Gini of expenditures between the households at the district level.

Note: POLS and LSDV denotes pooled OLS and fixed effects estimations. SYS-GMM denotes two-step System GMM. District-specific fixed effects and year-fixed effects are controlled for in LSDV and SYS-GMM estimations. The explanatory variables Ln_inc, WLn_inc, Sq_ln_inc, WSq_ln_inc, Lt_edu and WLt_edu are treated as potential endogenous regressors. Figures in parentheses are t-statistics computed based on Windmeijer (2005) standard errors. Figures in square brackets are p-values. '***', '**' and '*' indicate p-values <1%, <5% and <10%, respectively. Hansen is the test of over-identifying restrictions; AR (1) and AR (2) are the tests for first-order and second-order serial correlations in the first-differenced residuals.

The demographic factor of social caste of the people does not adequately explain variations in inequality between their expenditures. The employment in the primary sector activities like agriculture and allied activities tend to significantly enhance the disparity in the expenditures between the households, though the spillover effect is insignificant.

1. Discussion and Policy Implications

Table 7: Employment shares in Ancillary sectors (in %) in SEZ districts vis-à-vis non-SEZ districts

	2015	2016	2017	2018	2019
SEZ Districts	36.01	36.58	37.39	37.46	39.33
Non-SEZ Districts	34.15	34.70	35.69	36.29	36.88

Source: Authors' calculations on the basis of data obtained from CPHS database.

The proclaimed objectives of SEZs in India are to generate additional economic activities, to promote export of goods and services, to facilitate both domestic and foreign investments, to create ample employment opportunities and to develop infrastructural facilities. All these objectives associated with such place-based policy of SEZs can trigger structural transformation in the Indian economy (Galle et al., 2023). However, this would invariably depend on the type, size and locations of SEZs. SEZs can create significant employment, both within and outside SEZs and indirect effect of SEZs can be manifested in ancillary and induced employment opportunities generated in sectors of the economy affected by the operations of SEZs (Aggarwal, 2007). As more than 55% of the operational SEZs in India is based on IT/ITES, it is likely to generate employment of skilled workforce. However, Fan et al. (2023) point out that the ICT industry inclusive of IT/ITES accounts for less than 1% of total employment in 2011 in India. Thus, the increase in skilled labor employment due to expansion of SEZs will have negligible impact on overall employment and hence on incomes of the majority of Indian households. The manufacturing SEZs (including the already existing and new sectors SEZs) which comprise of mainly textiles, apparels, pharmaceuticals, leather, food processing etc., are also likely to trigger skilled employment as these have transformed to medium- to- high-skilled labor-intensive industries complimented with rising capital intensities (Goldar, 2000; Das & Kalita, 2010; Kapoor, 2015). In addition, the SEZs have acted as a catalyst in creating employment for other categories of labors in ancillary sectors like utilities (water & electricity), transport, construction, administration, hotels & restaurants, real estate, healthcare, education, banking & insurance etc., which belongs to the consumer services sector contributing to almost 55% of the services sector workers in India in 2011 (Fan et al., 2023). In fact, our findings from CPHS data reveal that employment in these ancillary sectors is found to be two percentage point greater in SEZ districts compared to non-SEZ districts and has increased overtime (see Table 7). The creation of these additional employment opportunities can be attributable to inequality reducing effects of SEZs. Again, as most of the SEZs in India are localized in urban outskirts and peripheries of the metropolitan cities and in areas with already existing industrial clusters (Banerjee-Guha, 2008; Hyun & Ravi, 2018), the SEZ-driven increase in ancillary sector employment caters to the consumption basket of local urban middle class residents enhancing their welfare gains. Again, Galle et al. (2023) reflects that SEZs in India have enhanced newer avenues of employment without any relocation of economic activities from far-distant places. All these factors instigate the process of structural change on account of establishment and expansion of SEZs which can potentially lead to reduction in expenditure inequality between the households within Indian districts. However, we observe insignificant inter-district spillover effects of SEZs on mitigating expenditure inequality between the households which corroborates with the findings of Hyun & Ravi (2018) and Galle et al. (2023) who found that SEZs in India have not affected economic activities beyond 5-10 kms radius outside the SEZs and their results are comparable up to a level of geographical aggregation, a district, which of prime interest to political and administrative authorities. The plausible explanation for such insignificant spillover effects from SEZs could be due to traditionally low level of labor mobility across space and comparatively smaller size of SEZs in India. These findings have severe policy implications on the ground that SEZs of other industry denominations particularly of labor-intensive manufacturing sectors should be promoted to generate employment for larger pool of unskilled labor force which could potentially bring larger uniformity in income distributions among the households. Also, SEZs with proper lbor training facilities should be set up in rural areas to relocate agricultural labor force to newer job opportunities thereby increasing productivity of agricultural sector.

Conclusion

In recent times, inequality with spatial consideration has increasingly gained importance among policymakers (Rey & Le Gallo, 2009; Shorrocks & Wan, 2005). Spatial interactions that exist among the neighboring regions through the channels of inter-regional trade, factor mobility, diffusion of technology and knowledge are reality (Lin et al., 2014). Empirical literature indicates that the effects of structural transformation on income distribution is still a debatable issue. Special Economic Zones (SEZs) have evolved as managed industrial clusters[47] in India, traditionally focusing on exports (Mukherjee et al. 2016). However, the socio-economic impact of SEZs on potential economic outcomes have long been debated (Glaeser& Gottlieb, 2008). In the context of India, there is mixed evidence on the effects of SEZs on different economic parameters (Hyun & Ravi, 2018; Alkon, 2018; Galle et al., 2023). Moreover, no explicit study has yet been conducted on the effects of SEZs on household inequality. Against this backdrop, our novel objective is to study the spatiotemporal dynamics of inequality in India and the impact of establishment and expansion of SEZa on expenditure inequality between the households at the district level using spatiotemporal model of estimation and exploiting the panel CPHS database. This study finds relevance for India where there is evidence of rising inequality in different episodes (Kijima, 2006; Chamarbagwala, 2006; Mehta & Hasan, 2012) and with 'Reducing Inequality' being a major SDG goal. The stylized facts reveal that the assignment of SEZs is non-random in terms of their locations and are specific to few industry denominations and sizes. The global Moran's statistic signifies spatial dependence in expenditure inequality between the households which requires proper instrumentation. The spatial diagnostic tests point to the appropriateness of Spatial Durbin Model (SDM). The results from the most suitable time-space recursive model with Durbin terms indicates that the past levels of household expenditure inequality in the neighboring districts are found to be positively and significantly affecting expenditure inequality in a particular district which provide evidence of diffusion phenomenon of economic activities (Williamson 1965). In fact, the effect is found to be more pronounced in the long-term. A one-unit increase in the land area operating under SEZs in a district is significantly reducing the expenditure inequality between the households in that district by

[47] The term 'industrial cluster' was introduced and popularised by Porter (1990) in *The Competitive Advantage of Nations*.

0.2937 units in the short-term, however, the effect is more nuanced in the long-term. This establishes the fact that the welfare-enhancing effect of presence of SEZs on reducing inequality are more effectively realized overtime rather than instantaneously. The effect is economically intuitive as the establishment and expansion of SEZs generate potential employment in ancillary activities which commensurate with the enhancement of employment in consumer services sectors in India. However, the spillover effects from SEZs to neighboring districts are insignificant as the effects from SEZs increasingly attenuates within 5-10 kms surrounding the SEZs.

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