Place-based Policies, Structural Change and Female Labor: Evidence from India's Special Economic Zones *

Johannes Gallé † Daniel Overbeck ‡ Nadine Riedel § Tobias Seidel ¶

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Abstract

This paper quantifies the local economic impact of special economic zones (SEZs) established in India between 2005 and 2013. Using a novel dataset that combines census information on the universe of Indian firms with geo-referenced data on SEZs, we find that the establishment of SEZs increased local manufacturing and service employment, with positive spillovers up to 10 km from the SEZ area. The analysis shows that the gains in manufacturing and service employment were accompanied by a decline in agricultural labor, especially for women, suggesting that the policy contributed to structural change. In further analysis, we document that significant local employment effects occur across different types of SEZs: privately and publicly run zones, and SEZs with different industry designations.

Keywords: Economic development, female labor, place-based policy, spillovers, structural change, Special Economic Zones
JEL: O23, O53, R12, R58

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†Mercator Research Institute on Global Commons and Climate Change & Ruhr University Bochum
‡University of Mannheim
§University of Münster, CESifo & Oxford University Centre for Business Taxation
¶University of Duisburg-Essen, CESifo & CRED

1 Introduction

An increasing number of less-developed countries have implemented Special Economic Zones (SEZs) to foster economic development. According to UNCTAD's World Investment Report (UNCTAD, 2019), the total number of SEZs worldwide increased from 500 in 1995 to about 5,400 in 2018 - with the vast majority of the new zones being located in developing economies. While their specific design can differ, SEZs have in common that they are set up in a clearly defined geographic area where physically present firms have access to lower tax and tariff rates or cost-saving bureaucratic procedures (World Bank, 2008). Their establishment can thus be understood as a place-based policy.

The literature on place-based policies is primarily set in developed economies (e.g. Neumark and Simpson, 2015; Criscuolo et al., 2019a; Grant, 2020). Evidence on the effects of SEZs in developing or transitional countries is still scarce (e.g. Duranton and Venables, 2018).[1] This is an important gap in the literature as experiences with place-based policies in developed countries can hardly be transferred to less-developed economies for various reasons. First, developing countries are characterized by significantly lower institutional quality than their developed country counterparts, which may limit the efficiency of local transfer programs and place-based policies (Becker et al., 2013; Farole and Moberg, 2014). Second, formal firms operating in developing countries often face substantially higher tax and bureaucratic burdens than firms in developed countries (Gordon and Li, 2009). Place-based policies that reduce administrative burdens and grant tax exemptions might hence create steeper location incentives. Finally, SEZs in developing countries also differ in purpose and structure from SEZs in the developed world. Among others, they often target exporting firms, for example by offering tariff exemptions for input goods – a feature that is hardly prevalent in developed economies and a clear distinction from other place-based policies that target lagging regions through transfers or tax cuts.

This paper contributes to the growing literature on place-based policies by evaluating the economic and spatial effects of SEZs that were established after the Special Economic Zones Act in 2005 (SEZ Act, 2005) in India. The policy provided a uniform legal framework for developing and doing business in SEZs and granted firms within SEZs generous tax and tariff exemptions. India was ranked as one of the least business-friendly countries in the *Ease of Doing Business Index* (World Bank, 2005) at the time and the SEZ Act was initiated to improve this situation and create new economic activity. Using a newly compiled data set on the establishment of 147 SEZs between 2005-2013, we show that the SEZ Act led to a substantial increase in non-agricultural employment in SEZ-hosting municipalities.[2] The policy also induced positive employment effects in neighboring locations up to 10km. The rise in local manufacturing and service employment was mirrored

[1] An important exception is the growing literature on Chinese SEZs (Lu et al., 2019, 2022; Wang, 2013; Alder et al., 2016). Other papers on place-based policies in developed countries include Gobillon et al. (2012), Busso et al. (2013), Kline and Moretti (2014) and Ehrlich and Seidel (2018).

[2] We use *municipality* as a collective term for villages and towns in India.

by a decline in agricultural work, especially by women. We interpret this pattern as an indication for local structural change from the primary sector towards better-paying jobs in non-agricultural industries. Additional analyses suggest that the establishment of SEZs led to a genuine increase in non-agricultural employment rather than a relocation of jobs.

Methodologically, we identify the effects of SEZs on local employment based on census data in a spatial difference-in-differences (DiD) framework. The estimator compares changes in the economic outcomes in municipalities where SEZs were established with municipalities in the same region without SEZs. To this end, we define 5km-distance bins around each SEZ up to a radius of 50km and determine the spatial gradient of the SEZ-effect without parametric restrictions. The main empirical identification concern is that SEZs are not randomly allocated in space, but that their location systematically correlates with the economic trajectories before SEZ-establishment.[3] In the parlance of DiD design, there might be a violation of the common trend assumption.

We address this concern in two ways: First, we examine baseline differences between treated and other municipalities. While such differences are absorbed in DiD designs if time-constant, we also allow outcome trajectories to differ in municipalities' pre-treatment characteristics. In a complementary analysis, we use matching techniques to reduce the imbalance in pre-treatment characteristics of treated and other municipalities in the estimation sample. Second, we run placebo tests, where we draw on census data prior to SEZ establishment to show that employment outcomes did not develop systematically differently between SEZ-hosting municipalities, their neighbors and municipalities in further distance prior to SEZ establishment. This further corroborates the plausibility of the common trend assumption. As census rounds are infrequent, we also show that parallel pre-trends between treated and reference municipalities hold when we proxy economic activity by annual nightlight data, which allows for a more detailed picture in the immediate lead-up to SEZ establishment.

Our empirical analysis builds on a novel data set that combines census data with georeferenced data on SEZs for the period 1998-2013. In the main model, we draw on employment information from the 2005 and 2013 waves of the Economic Census and on population information from the 2001 and 2011 waves of the Population Census, which cover the universe of firms and households in India, respectively. We, moreover, identify the location of all SEZs and the date when they went into operation from newspaper articles, official statistics by the Ministry of Commerce and Industry as well as from minutes of the Central Board of Approval and match them with their hosting municipality using the India Village-Level Geospatial Socio-Economic Data Set (Meiyappan et al., 2018). Having identified the SEZ-hosting municipality allows us to add rich granular census information like municipal employment by sector and gender and the number of firms (Asher et al.,

[3] Note that we restrict our data to municipalities within a 50km radius of an SEZ. Even if SEZ developers condition the location of SEZs on regional economic outcomes, it is – e.g. due to land restrictions (Levien, 2012; Parwez and Sen, 2016) – hardly feasible to precisely target SEZs to specific subareas. This dampens concerns that the location of SEZs across sample municipalities correlates with outcome trends in our data.

2021). Our final sample includes almost 50K Indian municipalities with a total population of 146M people in 2011.

Our baseline results uncover a sizable effect of SEZ-establishments on local employment in manufacturing and services. In SEZ-hosting municipalities, employment growth over the 8-year time frame between 2005 and 2013 is estimated to exceed employment growth in reference locations – defined as municipalities in the 20-25km distance bin – by 52 percentage points (*pp*). To put this sizable effect into perspective, note that India experienced high overall employment growth in this time period and municipalities are mostly small entities with average non-farm employment of 290 workers (median of 41). Our findings indicate that the policy also contributed to local economic development beyond the boundaries of SEZ-hosting municipalities up to a distance of 10km. In the first distance bin around SEZs (< 5km), non-agricultural employment growth is 22*pp* higher than in the reference location after SEZ-establishment; in the second distance bin (5-10km), it is 16*pp* higher. For municipalities in a distance of 10-50km from an SEZ, we find no significant difference in employment trajectories relative to the reference location.

In additional analyses, we show that the SEZ policy reduced the number of workers in the agricultural sector: SEZ municipalities experienced a 17*pp* lower agricultural employment growth than reference locations. This pattern suggests that the SEZ Act contributed to a local transition from an agrarian-based towards an industrial and service economy. This transition is widely considered to be one of India's main development challenges (Sud, 2014) as productivity in the agricultural sector is low: the 50-60% of Indian workers employed in agriculture contribute only 18% to GDP (World Bank, 2023a,b). The drop in agricultural work is centered around marginal employment (i.e. employment of 183 days per year or less) and hence around the least-paying jobs in the agricultural sector. This further supports the interpretation that SEZs created better employment opportunities for local workers. This finding connects well with previous research that has emphasized the importance of sectoral shifts from agriculture to more productive industries as a key driver of economic development (McMillan et al., 2014; Eichengreen and Gupta, 2011; Gollin et al., 2014). A back-of-the-envelope calculation suggests that the decrease in agricultural employment amounts to around one third of the increase in non-agricultural employment.

Moreover, we find that the decline in agricultural employment was in particular driven by female workers. Men experienced a weaker and statistically insignificant drop in agricultural work. One possible explanation for the latter finding is that men own most agricultural land in India (Agarwal et al., 2021), which might limit their responsiveness to alternative job opportunities. Female non-agricultural employment in SEZ municipalities went up markedly after SEZ establishment: the growth rate of female manufacturing workers in SEZ-hosting municipalities exceeded that in reference municipalities by 55*pp*. The policy hence contributed to better employment opportunities for women in the secondary sector. Female employment in services increased only marginally (and insignificantly) in turn, while male employment went up to a similar extent in manufacturing and services.

The finding on gender effects resonates well with observers' expectation that SEZ policies would generate new and better jobs for women (World Bank, 2011; Bacchetta et al., 2009; Rama, 2003). And it connects to recent literature that has documented rising shares of female employment caused by free-trade policies in many countries (Ozler, 2000; Bussmann, 2009). We also consider SEZs' effect on female employment to be of particular relevance as women in India – similar to other less developed countries – are a vulnerable group in the labor market: Gender discrimination is a prevalent and long-standing phenomenon, and unemployment rates among women are significantly higher than among men (Klasen and Pieters, 2015; Srivastava and Srivastava, 2015).

Finally, we offer two further insights. The first concerns the impact of SEZ policies on the formal and informal sector. Our empirical analysis draws on census data that allows us to observe the universe of Indian manufacturing and service firms and to proxy for formal and informal firms. We show that smaller, informal entities – which, despite accommodating over 90% of the Indian workforce, are ignored in many previous studies – also respond strongly to SEZ establishment and contribute significantly to the aggregate creation of non-agricultural jobs by SEZs. Ignoring these firms hence underestimates the local employment impact of SEZs and other place-based policies. In further analyses, we exploit that India hosts a variety of SEZs, which differ in two key dimensions: there are zones that are developed by private and public developers respectively and zones with different industry denominations. Our analysis shows that SEZs of different types exert broadly comparable effects on overall local employment (while the industry composition of the new employment can naturally differ). Finally, we combine our estimates with official statistics on foregone tax revenues. This tentatively suggests that the SEZ scheme supported job creation at relatively low fiscal costs.

Beyond the referenced literature so far, our study relates closely to research on the spatial economic effects of place-based policies. Most existing work is set in developed countries (Neumark and Simpson, 2015; Neumark and Kolko, 2010; Gobillon et al., 2012; Busso et al., 2013; Ehrlich and Seidel, 2018). Evidence on the effects of SEZs in less-developed countries is scarce – with studies on SEZs in China being the notable exception (e.g. Lu et al., 2019, 2022; Wang, 2013). While offering valuable insights, it is unclear whether these Chinese experiences translate to other countries. Chinese SEZs were established during a time when China transitioned from a central planning to a market economy. The country's institutional context at that time differed from many other less developed economies. In particular, the high degree of government intervention in the economy stands out (Bosworth and Collins, 2008; Farole and Moberg, 2014). As SEZs were granted more free market-oriented economic policies and flexible governmental measures compared to the planned economy elsewhere, incentives for firms to locate inside SEZs might have been steeper than in other countries.[4] Observers have thus raised concerns that results from existing studies may not be externally valid for other countries (The Economist, 2015). The World Bank Group writes: "Extracting wide-ranging policy implications from [...] [such] analysis remains risky" (World Bank, 2017). This calls for evidence for other countries. We fill this gap and augment the evidence on China by documenting a sizable SEZ-effect on local employment in India, another leading emerging economy, which has firmly embraced SEZ policy.[5]

A comprehensive overview of the history and development of the Indian SEZ experience is offered by Mukherjee et al. (2016). An earlier working paper by Hyun and Ravi (2018) mostly relies on nightlight intensity and sample survey data to assess the effect of SEZ establishment on economic development within broad SEZ-hosting districts in India.[6] We offer the first granular analysis based on census data and deliver novel insights on the channels through which SEZs shape local economic outcomes as well as the geographical and social dispersion of economic growth. Previous empirical work on the economic consequences of other regional and local public policies in India has studied distinctively different programs, namely preferential tax policies for industrially backward districts (Hasan et al., 2021; Abeberese et al., 2024), state-level tax incentives (Chaurey, 2017; Shenoy, 2018), rural road construction programs (Asher and Novosad, 2020a). The latter policies aimed at reducing spatial disparities by targeting lagging regions or improving the infrastructure network. SEZ policies differ from these interventions in terms of objectives and instruments. They aim to promote exports and investments, mostly in non-lagging regions (SEZs are often located close to urban areas or transport infrastructure like ports), target internationally active firms (by granting tax and tariff benefits to exporters and importers) and contrary to other place-based policies allow for a bottom-up approach, where private developers can develop and run SEZs. The effectiveness of these policies and agglomeration dynamics may differ, rendering it difficult to apply lessons from prior research to the SEZ policy.

To the best of our knowledge, we are also the first to empirically link SEZ establishment to sectoral shifts from agriculture to manufacturing and services. This adds to the

[4]Other SEZ-related benefits, in part, overlap: Investors in China and India are e.g. granted special tax cuts when locating in SEZ areas. One particularity, in turn, of the Indian scheme is that SEZs can be developed bottom-up by private investors. Our evidence suggests that these private SEZs induce significant local employment effects.

[5]Our estimated employment effects for directly affected municipalities are quantitatively broadly comparable to those measured in China (e.g., Lu et al., 2019; Wang, 2013). Other studies on place-based policies in China include Koster et al. (2019) who find 10-15% higher firm productivity following the opening of science parks in Shenzhen. Chen et al. (2019) document a decline in TFP by 6.5% due to closures of development zones. Jia et al. (2020) explore China's Great Western Development Programme finding no evidence for employment or wage effects, but higher local GDP through physical investment. Also note that prior research for China finds little evidence for SEZ spillovers to neighboring jurisdictions (Lu et al., 2019), while we find statistically significant and quantitatively relevant spillover effects in a more granular spatial setting in India.

[6]Alkon (2018) focuses mainly on infrastructure effects of SEZs at the sub-district level. Another paper by Görg and Mulyukova (2024) uses a sample of large Indian firms to study the effect of SEZs on exporting behavior and factor productivity.

literature on structural change and economic growth (Kline and Moretti, 2014; McMillan et al., 2014; Gollin et al., 2014; Laitner, 2000). For India, Eichengreen and Gupta (2011) identify the sectoral shift from agriculture to services as a key driver of economic growth; Blakeslee et al. (2022) study the effects of a land-rezoning program in Karnataka on local sectoral shifts. Previous work in other countries has mostly focused on the role of trade liberalization and international integration for structural change, see e.g. Uy et al. (2013) for Korea and McCaig and Pavcnik (2013) for Vietnam.

The results on changes in female employment in agriculture, manufacturing and services further inform the extensive literature that has documented the positive effects of female labor force participation and empowerment for economic development as summarized, for example, by Duflo (2012) and World Bank (2012) in general and by Das et al. (2015) for India. According to statistics by the International Labour Organization, India features a comparably low female labor force participation rate of around 25%. Policies, which create labor market opportunities for women, may hence come with high socio-economic returns. Our paper contributes to this line of research by connecting novel gender-specific labor market effects with the place-based policy literature.

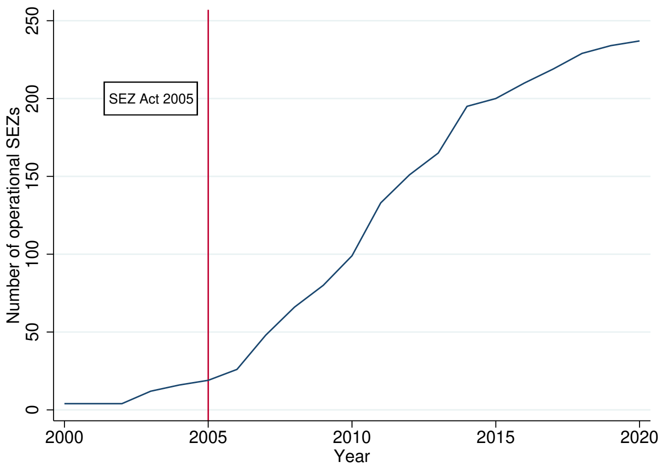
The remainder of the paper is organized as follows. Section 2 describes the institutional background. Section 3 presents the empirical methodology. Section 4 introduces the construction of our data set and descriptive statistics. We discuss our findings in Sections 5 and 6. Section 7 offers a back-of-the-envelope calculation on the cost effectiveness of the policy before we conclude.

2 Institutional background

In the 1960s, India became one of the first countries to establish export-processing zones which were later relabeled as SEZs in the early 2000s. But for long, SEZs were rare in the country. Between the 1960s and the 1990s, only seven SEZs were established by the central government. This changed drastically when the Indian government implemented the Special Economic Zones Act in 2005, allowing for private investments in SEZs and a much more flexible environment than the precedent framework in which all zones were owned and managed exclusively by the central government. Until 2020, the number of operational SEZs, i.e. zones with at least one active company, increased markedly to 240 of which more than 90% were established under the SEZ Act (see Figure 1).

Against the background of India's economy being highly regulated and poorly integrated into the global economy (World Bank, 2005), the main goals of the SEZ Act were to (i) generate additional economic activity, (ii) promote exports of goods and services, (iii) promote investment from domestic and foreign sources, (iv) create employment oppor-

Figure 1: Operational SEZs in India



Notes: This figure plots the cumulative sum of operational SEZs in India by year. SEZs are defined as being operational as soon as one firm commenced with its production. The individual SEZ data are obtained from the Indian Ministry of Commerce and Industry. The date of operation is sourced from newspaper articles and administrative records.

tunities, and (v) develop local infrastructure facilities (SEZ Act, 2005).[7] To achieve these goals, the SEZ Act provided a uniform legal framework for developing and doing business in these specially designated areas. Firms in SEZs, moreover, enjoyed various administrative and fiscal benefits. On the administrative side, there was so-called "single-window clearance", that is, all approvals were issued by a single authority.[8] Businesses in SEZs, moreover, received a 100% income-tax exemption on export income for the first five years of operation, which reduced to a 50% exemption for the following five years. Thereafter, SEZ firms received a tax benefit of 50% on reinvested profits for a final period of five years. SEZ business units were, furthermore, exempted from sales and service taxes and, until 2012, from the Minimum Alternate Tax (MAT), a minimum tax on profits of 18.5%. SEZ firms also benefited from duty-free imports and domestic procurement of goods and services. Note that SEZs were treated as being outside of the domestic tariff area (DTA), so that goods that were produced in the SEZ and sold into the DTA were considered as imports to the Indian market. In consequence, companies in the DTA had to pay import tariffs if they purchased goods from a SEZ company. In turn, goods and services supplied by DTA companies to SEZ units were considered as exports from the DTA and exempted from any taxes and tariffs. Hence, the flow of goods from DTA into SEZs was subject to no taxes or tariffs, but not vice versa.

Applications for establishing a SEZ were assessed by the Central Board of Approval. One of the main criteria for an approval by the board was that SEZ developers were

[7]Mukherjee et al. (2016) conducted a survey of 145 businesses from 32 SEZs and asked for their motivation to locate in SEZs. Duty-free imports, ease of exports, tax holidays, single window clearance and ease of business were mentioned as the most important reasons.

[8]According to the World Bank's Enterprise survey in 2022, 12.1% of IT-firms mentioned "business licensing and permits" to be their biggest obstacle to doing business.

in the rightful possession of sufficiently large parcels of land depending on the industry denomination. For example, multi-product zones required a minimum contiguous area of 10 square kilometers while sector-specific zones such as IT zones required only 0.1 square kilometers. After the formal approval by the board, the proposal to develop the SEZ was recommended for notification to the Ministry of Industry and Commerce, which officially declared the designated area as an SEZ area.

3 Empirical approach

To identify the causal economic impact of SEZs across space, we draw on two economic census waves (2005 and 2013) and implement a difference-in-differences-style analysis comparing changes in outcome variables between municipalities that host an SEZ and municipalities in the same region without an SEZ before and after the treatment, i.e. the start of the SEZ Act in 2005.[9] To this end, we group municipalities in 5km-distance rings around their closest SEZ up to 50km.[10] This allows us to non-parametrically study the spatial effects of the policy. Municipalities outside of the 50km radius around an SEZ are dropped from the analysis. The main analysis relies on a spatial difference-in-differences model of the following form:

$$\ln(y_{it}) = \sum_{d=0, d\neq 5}^{10} \beta_d (D_{[d_i=d]} \times POST_t) + \boldsymbol{\eta}' (\mathbf{X}_i \times POST_t) + POST_t + \alpha_i + \varepsilon_{it}, \qquad (1)$$

where y_{it} represents outcomes like employment or the number of firms in municipality i in year t. $D_{[d_i=d]}$ indicates whether a municipality i is in distance bin d to an operational SEZ in the post-treatment year. $d_i = 0$ indicates SEZ-hosting municipalities, $d_i = 1$ SEZ-neighboring municipalities within a 5km-distance to the SEZ, $d_i = 2$ municipalities in a 5-10km distance etc. up to 50km. Distance bin $d = 5$ (distance of 20-25km) is omitted and serves as the reference category. We interact the distance dummy with a post-reform dummy $POST_t$. The model further includes municipality fixed-effects, α_i, and additional control factors, $\mathbf{X}_i \times POST_t$, which are specified in further detail below. ϵ_{it} is the error term. The β_ds are the parameters of interest capturing differences in outcome trends in municipalities in distance bin d relative to municipalities in the reference category. In the

[9] The prior literature on place-based policies has also pursued identification strategies, where locations that are targeted by a given policy are compared with locations that were considered but not finally picked for treatment (see e.g. Greenstone et al. (2010)). Approaches along these lines are, unfortunately, not feasible in our setting, as documentations from meetings of the SEZ Board of Approval (http://sezindia.nic.in/cms/boa-minutes.php) show that the vast majority of SEZ applications are approved. Another strategy that has been pursued in prior literature is to compare treated municipalities with municipalities that are selected for treatment in the future. Again, this is not viable in our setting as a substantial part of these potential control SEZs are located within close geographic proximity of SEZs that became operational by 2013.

[10] There are some municipalities within these 50km radii of our SEZs that are also within a 50km radius to an SEZ established before the SEZ Act in 2005. Excluding them from the sample does not change our estimation results.

baseline specification, we cluster standard errors at the district level to account for spatial correlation. In additional specifications, we cluster at the level of the "closest SEZ groups" comprising all municipalities whose d_i is determined by the same SEZ and apply Conley (1999) standard errors.

Note that the concentric ring analysis allows us to capture the spatial effect of the policy. The choice of the reference category is arbitrary and anchors the interpretation of the coefficient estimates for β_d as the effect of the SEZ on the *relative* economic development of municipalities in radius d to the reference municipalities. Prior research has shown that the spillover effects of place-based policies tend to be very local (Ehrlich and Seidel, 2018; Einiö and Overman, 2020). Our results suggest that the same holds true for SEZs in India. If we were willing to assume that the reference municipalities in 20-25km distance are unaffected by the policy, the β_ds can be interpreted as the effect of the SEZ policy on the treated municipalities.

The main threat to our empirical identification strategy and to obtaining unbiased estimates for β_d is the violation of the conditional mean independence assumption. If SEZ developers systematically place SEZs in areas whose outcome trends differ from other municipalities, conditional mean independence is violated – or in the parlance of DiD design – there is a violation of the common trend assumption.[11]

We address this concern in two ways. First, we explore differences in the baseline characteristics of treated and other municipalities. While differences in municipal baseline characteristics are absorbed by α_i if time-constant, these characteristics might also correlate with changes in economic outcomes.[12] We thus control for municipal baseline characteristics interacted with the post-treatment dummy, $\mathbf{X}_i \times POST_t$. The vector $\mathbf{X}_i$ models differences in municipality size (dummy variables for the quartiles of the population distribution), employment structure (a dummy variable indicating that there are formal firms in the locality), industry composition (dummy variables for the dominant industry measured by employment share), distance to key infrastructure (airports, ports, highways, railroad, power plants) and to the next urban center. Under the assumption, that $\mathbf{X}_i$ is randomly drawn from all factors influencing SEZ locations, obtaining similar estimates for β_d with and without the control variables $\mathbf{X}_i \times POST_t$ mitigates the concern that locational differences cause a bias (Altonji et al., 2005).

In a complementary line of inquiry, we turn to matching techniques to reduce imbalances in the characteristics of treated and other municipalities. We employ coarsened exact matching (CEM), that is we temporarily coarsen the data based on the observed $\mathbf{X}_i$

[11] In particular, unbiasedness relies on the following assumption:

$$\mathbf{E}[\varepsilon_{it}|D_{[d_i=d]} \times POST_t, \mathbf{X}_i \times POST_t, POST_t, \alpha_i] = \mathbf{E}[\varepsilon_{it}|\mathbf{X}_i \times POST_t, POST_t, \alpha_i] \tag{2}$$

That is, conditional on α_i, $POST_t$ and $\mathbf{X}_i \times POST_t$, the regressor of interest $D_{[d_i=d]} \times POST_t$ and the error term ε_{it} are mean-independent.

[12] One potential example are differences in the proximity of municipalities to the Golden Quadrilateral National Highway in India whose construction was completed in 2013.

using automated binning strategies and define unique observations of the coarsened data, each of which is a stratum. Treated and control municipalities are then exactly matched on these strata. Observations whose strata do not contain at least one treated and one control observation are dropped and weights are used to compensate for the different strata sizes (Iacus et al., 2012). Importantly, and contrary to many other matching strategies, coarsened exact matching does not only account for imbalances in means, but also for imbalances in higher moments and interactions (Iacus et al., 2012; Blackwell et al., 2009).

The second strategy to further corroborate the common-trend assumption is twofold. First, we use the Census waves in 1998 and 2005 to run placebo regressions for the pre-treatment period. If running the spatial difference-in-differences model in Eq. (1) on data prior to SEZ introduction reveals no differential outcome trends between treated and control units, this supports the common-trend assumption. Second, as census data are available only infrequently, we augment our analysis by annual nightlight data that have been shown to serve as a good proxy for economic activity and are widely used in the literature (Henderson et al., 2012). This allows us to test for differential outcome pre-trends between SEZ-treated municipalities and reference municipalities in the years directly leading up to treatment.

While our main analysis follows a classic two-by-two difference-in-differences approach (tracking economic outcomes between two censuses), the nightlight data allow us to model the staggered implementation of SEZs in an event study analysis. To obtain unbiased estimates in this setting in the presence of heterogeneous and dynamic treatment effects, we rely on the estimator proposed by Callaway and Sant'Anna (2021), which – similar to other estimators in the literature – ensures that already-treated units are not used as a control group for later-treated units.[13] The model compares the evolution of employment outcomes of municipalities treated by SEZs with reference municipalities (in a distance of 20-25km). It reads:

$$\ln(nl_{it}) = \sum_{k=-5, k\neq -1}^{5} \theta_k \mathbf{1}[t - T_i = k] + \gamma_t + \alpha_i + \epsilon_{it}, \tag{3}$$

where nl_{it} denotes the average nightlight intensity in municipality i in year t and T_i denotes the year in which the SEZ related to municipality i became notified. α_i and γ_t denote municipality and year fixed effects, respectively. The θ_ks can therefore be interpreted as the dynamic treatment effects (in relative time k) of SEZs on municipal nightlight intensity.

4 Data

Data on SEZs. We compiled information on all 147 Indian SEZs that were established under the SEZ Act and became operational until 2013 from various sources. Data on the

[13] Other estimators, e.g. Sun and Abraham (2021), yield similar results to the ones presented below.

name of the SEZ, whether the SEZ was privately or publicly developed, its location, size, industry type and date of notification are readily available from the Ministry of Commerce and Industry.[14] We georeference each SEZ at the municipality-level or, if available, even at its exact location. We verify our strategy by comparing our SEZ coordinates with a subsample of officially georeferenced SEZs that is accessible at the development commissioner's website of the Visakhapatnam SEZ.

A key variable for our empirical analysis, the start of operation of a zone, was not directly accessible and had to be hand-collected from newspaper articles, official statistics by the Ministry of Commerce and Industry as well as from minutes of the Central Board of Approval. We define the date of operation as the earliest date available, where we find at least one firm in the SEZ that went into operation. Figure 2 illustrates the geographical location of SEZs.

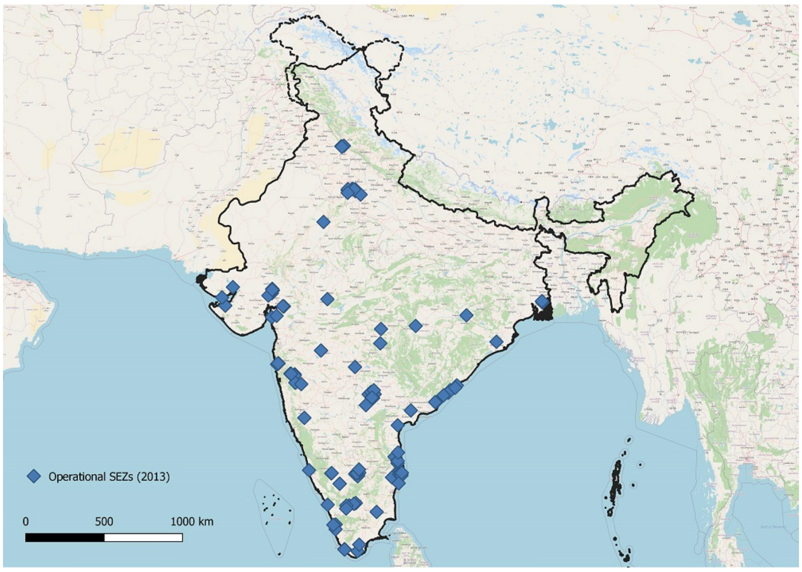
Link to municipal data. Using GIS techniques, we spatially join the georeferenced SEZ data with the India Village-Level Geospatial Socio-Economic Data Set (Meiyappan et al., 2018), which provides the administrative boundaries of every municipality in India based on the Population Census of 2001. To identify SEZ-hosting municipalities and municipalities in close proximity to SEZs, we approximate the area of the SEZ based on the geo-coordinates and information on the SEZ's area which by the SEZ Act is required to be contiguous (SEZ Act, 2005). As information on precise SEZ boundaries is unavailable, we assume SEZs to be circular. Based on the total area, we then calculate the radius of the zone and consider all municipalities that fall within this radius as SEZ-hosting municipalities (see Appendix A for details). The geo-referencing further allows us to compute distances from sea ports, airports, railway networks, highways, cities or power plants that we will use as control variables in the empirical analysis.[15]

Data on outcome variables. Having information on the start of operation of each SEZ and knowing their hosting municipalities, we finally use both the *Economic Census* and the *Population Census* to add economic variables like employment, population and the number of firms. The *Economic Census* contains the population of all non-agricultural (i.e. manufacturing and service) firms in India including the informal sector. We can draw on three repeated cross-sections of data for the years 1998, 2005 and 2013. We link municipalities across the three Economic Census waves by using the time-consistent municipality identifiers provided by the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (Asher et al., 2021, SHRUG). For every non-agricultural firm in India, the Economic Census contains information on employment (total and separate by gender), a firm's industry code and its host municipality. We disregard public administration employment and employment in international organizations. The Economic

[14] http://sezindia.nic.in/index.php.

[15] We retrieved data on the geo-coordinates of these infrastructure facilities as follows: Airports from the WFP SDI-T Logistics Database (https://data.humdata.org/dataset/global-logistics), Ports from the World Port Index (https://msi.nga.mil/Publications/WPI), Power Plants from the Global Power Plant database (https://datasets.wri.org/dataset/globalpowerplantdatabase), railways and roads from the Digital Chart of the World (https://www.soest.hawaii.edu/pwessel/dcw).

Figure 2: Geographical distribution of operational SEZs

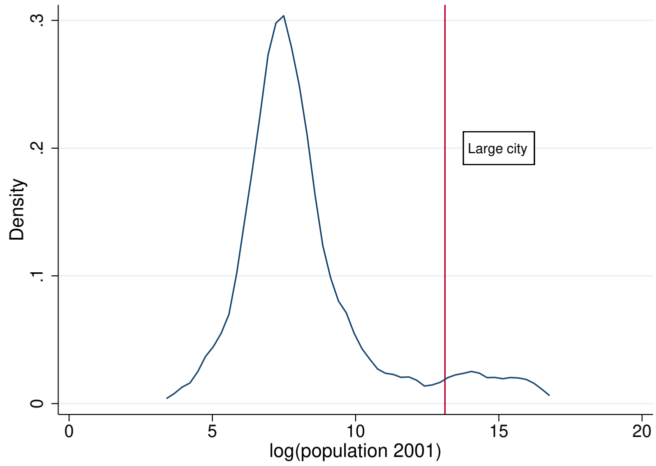


Notes: This figure plots the location of all SEZs in India that were established under the SEZ Act 2005 and became operational until 2013.

Census for 2013 lists 58.5 million firms employing 131.3 million workers. We collapse each Economic Census round to the municipality level and calculate the municipalities' number of firms, total employment, employment by gender and by industry as well as employment for small and large firms, defined as firms with less than 10 employees and firms with 10 employees or more, respectively.[16] The latter distinction is of particular importance as firm size in India discontinuously impacts firm formality. While firms of all sizes may decide to operate outside the formal sector, all firms with less than 10 employees are by official statistics classified as informal, reflecting that they are subject to a light regulatory burden under Indian law (NCEUS, 2009). For example, they do not need to register with official statistics, are exempted from social security taxes and subject to light bureaucratic procedures (Amirapu and Gechter, 2020; Mehrotra, 2019). We will show below that these small, informal firms employ the majority of Indian workers - ignoring them in empirical analyses hence implies that aggregate employment effects of place-based policies can be severely underestimated. We thus consider it to be a decisive advantage of our census data that it provides a complete picture of economic activity, accounting for formal and informal firms as well as for manufacturing and service entities.

[16] We use the concordance tables provided by the Ministry of Statistics and Programme Implementation to harmonize industry codes across time. While the Economic Census of 2013 uses the National Industry Classification (NIC) of 2008, the Economic Censuses of 2005 and 1998 use the NIC codes of 2004 and 1987, respectively. We match the three-digit NIC-04 Codes to three-digit NIC-08 codes and aggregate them to one digit NIC-08 codes for our analysis. In cases of industry splits across industries, we assign the industry code, that has a higher employment share according to the Economic Census of 2013. Hence, while the harmonization of industry codes is not entirely time consistent, note that most of the industry splits are between NIC-04 and NIC-08 are within the same one-digit industry.

Figure 3: Size distribution of SEZ-municipalities



Notes: Large cities are defined as $> 500K$ population.

We further complement the data with three waves of the *Population Census* containing a repeated cross-section of data for the years 1991, 2001 and 2011. The data contain information on the total population, literacy and infrastructure facilities such as number of schools, road access or electricity for every municipality in India. Most importantly, the Population Census contains information on persons working as cultivators or agricultural laborers, which are not covered by the Economic Census. As the last wave of the Population Census was 2011, we restrict the sample to municipalities in 50km radii of SEZs which became operational up to 2011 for analyses based on Population Census variables. Finally, we use annual information on average nightlight intensity matched to the municipality level (NOAA, 2013; Asher et al., 2021).

Descriptive statistics. Figure 3 illustrates that the majority of SEZ-hosting municipalities are relatively small as measured by their inhabitants in 2001. There are a few SEZs in India's leading cities – defined as cities with more than 500K inhabitants in 2001 – which we take out of our base analysis as effects related to SEZ establishment in these metropolitan areas are difficult to detect in the data. Since it concerns few observations, this sample restriction is not decisive for any of the results presented in this paper.[17]

The final sample comprises 49,669 municipalities with a total population of 146M people according to the latest Population Census in 2011. As shown in Appendix A.2, the average municipality employs 290 non-agricultural employees with a median of 41 workers and accommodates 3,061 residents. On average, there are 70 (220) female (male) non-agricultural workers per municipality and 189 (330) female (male) agricultural workers. Small informal firms with less than 10 workers account for about two thirds of average municipal employment.

[17] We show in Appendix B that the estimated SEZ effects do not change when large cities are included.

Table 1: Pre-treatment location characteristics

	Mean values and standard deviations (in brackets)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(6)-(1)
	0km	0-5km	5-10km	10-15km	15-20km	20-25km	25-30km	30-35km	35-40km	40-45km	45-50km	Difference
log distance to city (km)	3.808	3.645	3.712	3.658	3.749	3.806	3.861	3.952	4.035	4.108	4.159	-0.002
	(1.011)	(0.909)	(0.874)	(0.808)	(0.838)	(0.763)	(0.699)	(0.651)	(0.594)	(0.549)	(0.536)	(0.066)
log distance to power plant (km)	3.718	3.652	3.699	3.531	3.733	3.753	3.816	3.896	3.925	3.929	3.939	0.035
	(0.750)	(0.774)	(0.784)	(0.851)	(0.769)	(0.798)	(0.767)	(0.752)	(0.753)	(0.776)	(0.765)	(0.068)
log distance to airport (km)	4.519	4.395	4.431	4.370	4.607	4.618	4.701	4.783	4.796	4.825	4.855	0.099
	(1.350)	(1.264)	(1.193)	(1.052)	(1.053)	(1.016)	(0.970)	(0.917)	(0.881)	(0.838)	(0.810)	(0.088)
log distance to port (km)	4.459	4.756	4.842	4.753	5.046	4.960	5.025	5.102	5.087	5.143	5.126	0.501
	(1.327)	(1.345)	(1.273)	(1.277)	(1.175)	(1.132)	(1.138)	(1.117)	(1.080)	(1.094)	(1.058)	(0.097)
log distance to railway (km)	1.735	2.002	2.073	2.020	2.112	2.156	2.220	2.316	2.382	2.461	2.467	0.421
	(1.153)	(1.153)	(1.085)	(1.054)	(1.068)	(1.084)	(1.116)	(1.116)	(1.092)	(1.114)	(1.148)	(0.093)
log distance to highway (km)	1.941	2.151	2.312	2.419	2.553	2.618	2.733	2.863	2.954	3.014	3.063	0.677
	(1.290)	(1.228)	(1.150)	(1.062)	(1.118)	(1.112)	(1.116)	(1.062)	(1.047)	(1.040)	(1.055)	(0.096)
log population in 2001	7.643	7.428	7.204	7.257	7.115	7.092	7.088	7.044	6.997	6.980	6.949	-0.551
	(1.432)	(1.220)	(1.098)	(1.063)	(1.098)	(1.071)	(1.034)	(1.049)	(1.079)	(1.080)	(1.079)	(0.093)
Formal employment share in 2005	0.222	0.135	0.110	0.102	0.105	0.0995	0.0873	0.0745	0.0735	0.0715	0.0687	-0.122
	(0.310)	(0.235)	(0.214)	(0.204)	(0.215)	(0.211)	(0.192)	(0.178)	(0.176)	(0.174)	(0.167)	(0.018)

Notes: This table reports the mean values and their standard deviations for municipalities in the respective distance bins relative to SEZs. The last column shows the differences between the control group (column 6) and SEZ-hosting municipalities (column 1). *Distance* measures the distance in kilometers to the closest respective amenity. *City* denotes municipalities with a population of more than 500K. *Formal employment share in 2005* denotes the share of of formal employment (i.e. in firms with more than 10 employees) in total municipal employment. Standard deviations in brackets.

With respect to ownership, 77% of the SEZs in our 2005-2013 sample were developed by private companies versus 23% by public bodies. In terms of industry denomination, 57% are IT zones, followed by engineering (12%), pharmaceutical (9%) and multi-product zones (9%). The average SEZ covers 1.76 square kilometers, but the size varies systematically by industry denomination. IT-zones, on average, cover 0.25 square kilometers, multi-product SEZs 14.02 square kilometers.[18]

As we compare municipalities across space, Table 1 provides an overview of locational characteristics by distance bin, mostly in logs as they enter our estimation. The last column shows differences between the reference locations and SEZ-hosting municipalities. There are no significant differences between the two groups with respect to proximity to large cities, airports and power plants, but SEZ-hosting municipalities tend to be closer to other infrastructure facilities such as railways or highways compared to reference locations. Further, municipalities with an SEZ tend to be larger in terms of population and are characterized by a higher formal employment share. We ensure that these differences in locational characteristics are not driving our estimation results by interacting all depicted covariates with the post-treatment dummy according to Eq. (1).

5 Baseline results

In this section, we will present estimation results for the models specified in Section 3. In the following, we will show that SEZ establishment increased local manufacturing and service employment in India (Section 5.1), illustrate that SEZs generated genuinely new

[18] Based on a self-compiled firm-level dataset that we describe in Appendix B.3, we further observe that about 65% of SEZ firms are privately owned by Indians and about 25% belong to a company group. Private firms owned by foreigners only account for about 10% of SEZ firms.

jobs, rather than inducing relocation of jobs in space (Section 5.2) and present evidence that relates SEZs to structural change (Section 5.3). In the appendix, we furthermore document that SEZ establishment did not improve local infrastructure provision (which was another goal of the SEZ Act as outlined in Section 2).

5.1 Employment effects

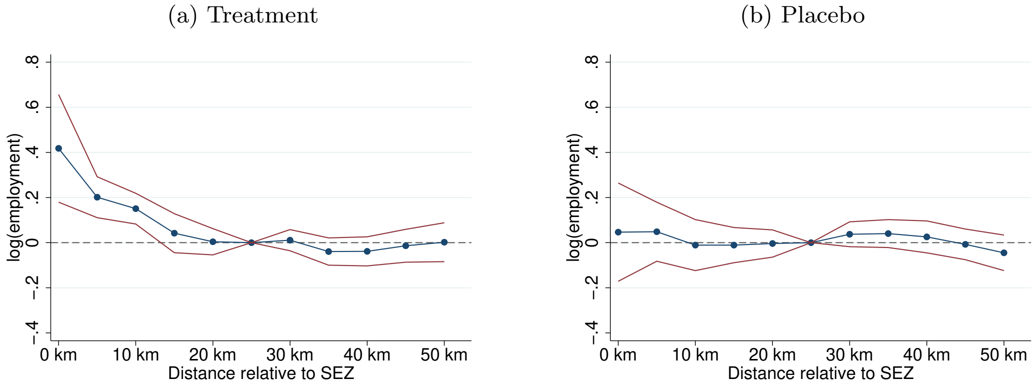
Using the log of municipalities' manufacturing and service employment as the dependent variable, Figure 4 (a) presents estimation results of the spatial model in Eq. (1) by plotting the coefficients $\hat{\beta}_d$ with the corresponding 95%-confidence intervals for all distance bins. We find a sharp difference in the employment growth of SEZ-hosting municipalities and reference locations between 2005 (the year of the SEZ Act) and 2013. SEZ-hosting municipalities and direct neighbors significantly gained employment relative to municipalities in further distance to the SEZ, suggesting that SEZs had a strong impact on local economic activity. Quantitatively, the point estimate suggests that SEZ establishment increased employment growth in SEZ-hosting municipalities by $52pp$ $(= (e^{0.418} - 1) \times 100)$ relative to the reference municipalities.[19] Employment growth in municipalities in the <5km distance bin and the 5-10km distance bin increased by $22pp$ and $16pp$, respectively, indicating substantial positive spillovers to adjacent regions. For more distant municipalities, the estimates for β_d turn out to be small and statistically insignificant, suggesting that employment changes between municipalities in further distance to the SEZ did not differ systematically. The magnitude of the estimated employment response is fairly large, but not implausible given the high general employment growth in India between the 2005 and 2013 Census waves and the relatively small sizes of our sample jurisdictions. The average SEZ municipality in the sample hosts only 3,139 non-agricultural employees prior to treatment, so the estimated relative effect translates into moderate absolute values. We show in Appendix B.1 that these results are robust to using alternative distance bin classifications, alternative standard error clustering, including municipalities up to a distance of 200km, including large cities in the sample, re-estimating Eq. (1) without the control vector $\mathbf{X}_i \times POST_t$ or applying coarsened exact matching to reduce the imbalance between treated and other municipalities. We further show that the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) – a public employment program that was enacted in 2005 – does not act as a confounder in the analysis.

Figure 4 (b), moreover, presents estimates of a placebo test that reruns the spatial difference-in-differences analysis for the pre-treatment period 1998-2005. Evidently, all estimated coefficients are close to zero and statistically insignificant which supports the common trend assumption of our spatial difference-in-differences design.

Given the 7-year gap between the censuses prior to treatment, we augment our data

[19] As Eq.(1) includes municipality fixed effects, β_d is the difference between changes over time in $\ln(y)$ for municipalities in distance band d relative to changes over time in $\ln(y)$ for municipalities in the reference distance band. Thus, it captures percentage point differences in growth rates of y.

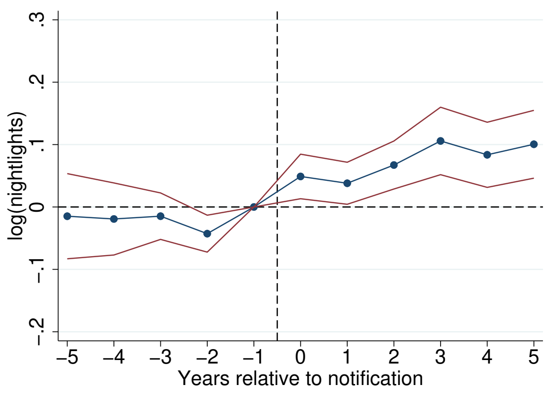
Figure 4: Spatial difference-in-differences model



Notes: The dots indicate the estimated parameters $\hat{\beta}_d$. Each subscript d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Red lines indicate 95%-confidence intervals. Panel (a) refers to specification Eq. (1), panel (b) depicts the placebo test, where we rerun the analysis for the pre-treatment period 1998-2005. Standard errors are clustered at the district level. Employment data are based on the Economic Census for 1998, 2005 and 2013.

by annual nightlight information to more granularly assess outcome trends in treated and control municipalities in the years leading up to treatment. Estimates based on Eq. (3) are presented in Figure 5. We define municipalities up to 10km as treated (as they feature positive employment effects in the base analysis) and compare their nightlight outcomes to those in reference municipalities in a 20-25km distance radius. Treatment time is set to the year of SEZ notification by the board of approval, reflecting that SEZ construction – and hence nightlight intensity – plausibly emerges from SEZ notification onward. Figure 5 shows that nightlights developed in parallel between treated and reference municipalities in the years prior to treatment, which corroborates the common trend assumption and the causal interpretation of our baseline estimates. Intuitively, the effect of interest is largest

Figure 5: Nightlights in event study



Notes: Event study estimates for 10km-regions around SEZs, municipalities in 20-25km distance serve as controls. The figure plots the $\hat{\theta}_k$ as estimated from Eq. (3) following Callaway and Sant'Anna (2021). Endpoints are binned. Red lines indicate 95%-confidence intervals. Standard errors are clustered at the district level.

for manufacturing SEZs, whose production sites emit relatively much nightlight and tend to be located in rural areas with low underlying nightlight levels (making it easier to detect changes in nightlight intensity), see Appendix B.2.

5.2 Job relocation or genuinely new employment?

An important aspect to understand is the extent to which the policy has generated *new* economic activity, relative to a mere relocation of manufacturing and service employment in space (Kline and Moretti, 2014; Criscuolo et al., 2019a; Ehrlich and Seidel, 2018). Relocation can, in principle, be the sole driver behind the estimated employment effects. To rebut this concern, we suggest three pieces of evidence.

First, our baseline estimates show a stark picture in the sense that employment growth differs strongly between SEZ-hosting municipalities and their neighbors in distance circles up to 10km, while there is no significant difference between the employment growth of municipalities in further distance from the SEZ (10-50km). For this pattern to be consistent with relocation of economic activity, relocation costs must be invariant in space, i.e. additional employment must have been sourced from municipalities in distance radii of 10-50km at about equal rates, irrespective of their precise distance to the SEZ. This is at odds with existing empirical evidence, which shows a rather stable inverse relation between geographic distance and relocation costs (Bodemann and Axhausen, 2012; Rossi and Dej, 2020). Note that extending the distance radius to 200km from SEZs does not change this pattern (see Appendix B.1).

Second, we explore whether the additional employment or the number of firms in SEZ municipalities and their direct neighboring jurisdictions in distance bands of up to 10km systematically correlate with changes in employment or the number of firms in municipalities in further distance. If the strong relative employment increase in SEZ-hosting municipalities and jurisdictions in close proximity to an SEZ (less than 10km distance) reflects relocation, we expect that larger employment increases in SEZ municipalities and surroundings are associated with stronger employment declines in jurisdictions in further distance (> 10km). We run a regression model of the following form:

$$ln(y_{i,t}) = \beta_0 + \beta_1 ln(y_{i,t}^{0-10}) + POST_t + \alpha_i + \epsilon_{it}, \quad (4)$$

where $y_{i,t}$ measures non-agricultural employment or the number of firms in municipalities in a distance of more than 10km to their closest SEZ while $y_{i,t}^{0-10}$ depicts either variable in SEZ-municipalities and its neighbors up to 10km. We run this regression separately for each distance bin $> 10km$.

The estimates for β_1 on employment are reported in the upper panel of Table 2. The columns reflect specifications for neighboring municipalities in different distance bins (Specification (1) comprises municipalities in a distance between 10-15km from an SEZ; Specification (2) municipalities in a distance between 15-20km etc.). Throughout all spec-

Table 2: Outcome changes in SEZs vs distant municipalities

	Distance to SEZ							
	10-15km	15-20km	20-25km	25-30km	30-35km	35-40km	40-45km	45-50km
Employment ($\leq$ 10km)	-0.021	-0.031	-0.023	-0.027	-0.000	0.057	0.009	0.019
	(0.047)	(0.039)	(0.048)	(0.029)	(0.046)	(0.038)	(0.043)	(0.046)
Firms ($\leq$ 10km)	0.008	-0.039	-0.039	-0.030	-0.009	0.034	-0.015	-0.011
	(0.055)	(0.039)	(0.038)	(0.030)	(0.044)	(0.036)	(0.042)	(0.041)
Observations	6,940	7,864	9,070	10,556	11,656	12,334	13,054	13,534
Municipality fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Regression results from Eq. (4). The upper panel depicts the effects of employment within a 10km radius around a SEZ on employment in municipalities in further distance bins. The lower panel reruns this specification using the number of firms as the dependent variable. Standard errors are clustered at the district level. Years included: 2005 and 2013. *** p<0.01, ** p<0.05, * p<0.1.

ifications the β_1-estimate turns out small and statistically insignificant, corroborating the notion that the observed baseline findings reflect a genuine increase in local non-agricultural economic activity rather than relocation of economic activity in space. Similar results emerge if we use the number of firms as the measure of economic activity (see the lower panel of Table 2).[20]

In Appendix B.3, we also show in a back-of-the-envelope calculation that, even if we take the negative (and statistically insignificant) coefficient estimates for some distance bins as depicted in Table 2 at face value, the estimates suggest that only around 1% of the observed employment gain in SEZs and neighboring jurisdictions up to 10km relates to relocation from municipalities in further distance. This points to genuine increases in aggregate economic activity through SEZ establishment rather than relocation across space, which is consistent with prior findings in the literature (Ehrlich and Seidel, 2018; Criscuolo et al., 2019a).

One remaining concern may be that some of the firms located in SEZs belong to larger firm groups, which may be active throughout India, including locations outside of the 50km radius accounted for in the above analyses. If firms relocate economic activity from other group locations to SEZ areas, it may hence not be captured in our prior analyses. To address this point, we undertake a third analysis, where we compile a firm dataset for India (see Appendix B.3 for details), which allows us to identify SEZ firms and other corporations within the same firm group. We use this data to first show that most firms, which are active in SEZs (> 60%) are standalone Indian companies, limiting the scope for relocation. We, furthermore, use this data to construct firm groups and determine the impact of entering an SEZ on firm activity of treated company groups *outside of* SEZ areas – specifically, outside of the 50km radius reflected in our baseline analysis. The effect

[20] Note that the number of municipalities per bin increases mechanically with distance to SEZs. Thus, the number of sourcing municipalities becomes larger relative to the number of potentially receiving municipalities (municipalities in <10km from an SEZ). Nevertheless, relocation would still imply that the estimated coefficients β_d decline in distance d.

is identified by comparing the development of firm activity of companies outside of SEZ areas that belong to groups, which enter an SEZs, to the development of firms in company groups without SEZ connection. Event study estimates suggest that the economic activity of these treated and non-treated firms emerged in parallel prior to the implementation of the SEZ Act in 2005. After 2005, we find no indication for a reduction of sales, profits, assets, or the total wage bill of treated firms versus non-treated firms – which rejects that economic activity is relocated within company groups towards SEZ areas. If anything, we observe an *increase* in economic activity of treated firms outside of SEZ areas after the group entered an SEZ. This – as discussed in more detail in the appendix – is consistent with existing evidence in the literature, which suggest that economic activities at different firm group locations are complements rather than substitutes (see e.g. Desai et al., 2009, Becker and Riedel, 2012, Chodorow-Reich et al., 2024). See Appendix B.3 for details.

5.3 Structural change and migration

If genuinely new jobs were created, then a natural follow-up question is who took up these jobs. We explore two channels: structural change and regional migration.

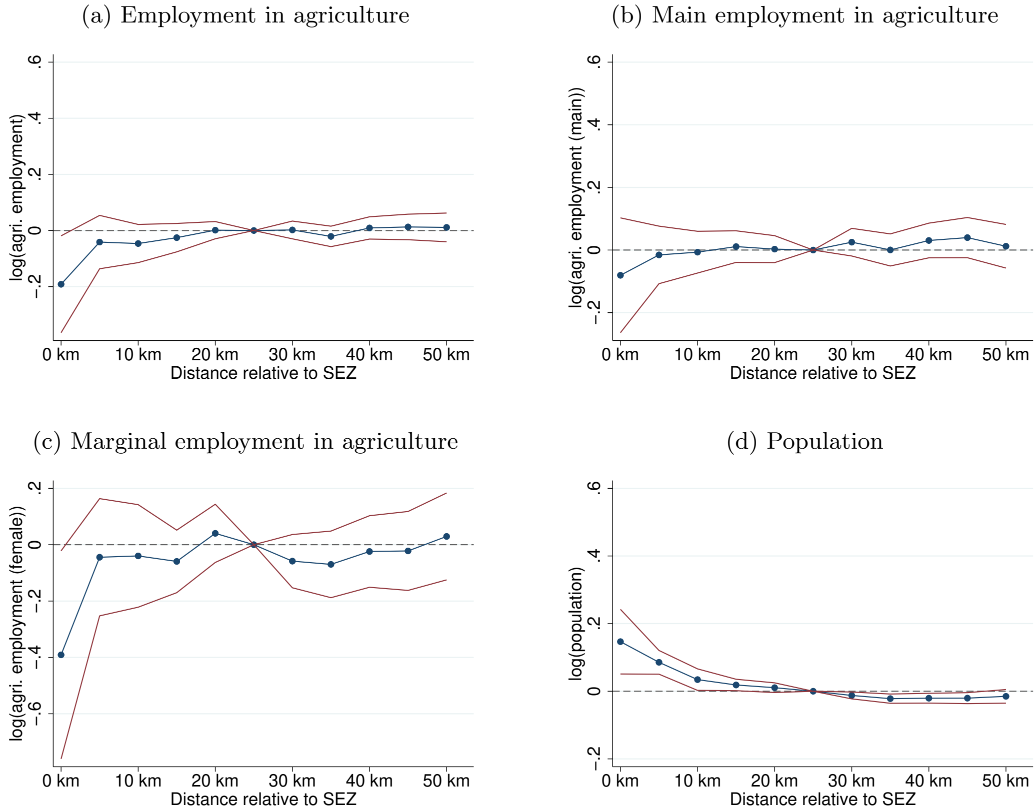
India is characterized by a large agricultural sector that accommodates about half of the working population, mostly in low-productivity jobs and in marginal employment relationships (International Labour Organization, 2013). Managing the transition from an agricultural to a manufacturing and service economy is widely believed to be one of the country's top challenges (Binswanger-Mkhize, 2013) and a promising avenue to higher-paid jobs and economic growth (McMillan et al., 2014; Eichengreen and Gupta, 2011; Gollin et al., 2014). We test whether SEZs contributed to this transition.

Specifically, we ask whether the documented increase in local non-agricultural employment in SEZ-areas is paralleled by a decline in agricultural employment. Based on the population census, we assign agricultural employment to municipalities following the procedure outlined in Section 4 and then rerun our baseline model in Eq. (1) using the log of the number of agricultural workers as the dependent variable. Panel (a) of Figure 6 indicates that the number of workers in the primary sector declined in SEZ municipalities after SEZ establishment. Quantitatively, the drop amounts to 17*pp* (p-value: 0.03). Neighboring municipalities up to 10km also experience a negative, but smaller effect.[21]

We can go one step further and split up the overall reduction of agricultural jobs into main and marginal employment. As shown in panels (b) and (c) of Figure 6, SEZs in particular led to a reduction in marginal agricultural employment – that is, in the number of agricultural workers that are employed for less than 183 days per year. Quantitatively, their number declined by 33*pp* (p-value: 0.04) in SEZ-municipalities relative to municipalities in the reference category. The point estimate for the response of the number of main agricultural workers is close to zero, in turn. It is thus the least attractive jobs in

[21] Data on agricultural employment come from the Population Census that is available for 1991, 2001 and 2011.

Figure 6: Sources for local non-agricultural employment growth



(a) Employment in agriculture

(b) Main employment in agriculture

(c) Marginal employment in agriculture

(d) Population

Notes: The dots indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (1). Each d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Panel (a) depicts results for agricultural employment. Panels (b) and (c) show results for main and marginal agricultural employment, respectively. Panel (d) depicts results for total municipal population. Red lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. All panels are based on the Population Census for the years 2001 and 2011.

the agriculture sector, which drop off the market. In Appendix B.4, we further show in a back-of-the-envelope calculation that the decline in agricultural employment explains about one third of the increase in non-farm jobs. We also provide additional evidence for employment increases in low-skilled services and manufacturing. Although we cannot follow individual workers across space and jobs, these results provide novel evidence in line with a transition from agricultural to low-skilled non-farm employment.

The result adds to a growing literature on structural change in less developed countries, which has documented large differences in productivity between agriculture and non-agriculture sectors and across regions (e.g. Gollin et al., 2009), stemming from various frictions (e.g. imperfect transport infrastructure (Asher and Novosad, 2020b), rural insurance networks (Munshi and Rosenzweig, 2016) or social norms that stigmatize migration (Beegle et al., 2011)). While the SEZ policy did not directly eliminate or lower these frictions, local productivity gains in non-agricultural employment in SEZs areas, related to agglomeration advantages (e.g. Combes and Gobillon, 2015) or the location of high-productivity (multinational) firms (see e.g. Alfaro-Urena et al., 2022), may have induced worker movements across sectors and regions, consistent with our findings.

Turning to the second channel, workers may be sourced from outside of the SEZ-municipality. While we have shown above that there is little evidence for net job relocation in space, workers might migrate towards SEZ-municipalities, resulting in higher local population growth. The pronounced population growth in India provided an ideal environment for such an effect. In our sample frame, the population increased from 127M to 146M between 2001 and 2011. Panel (d) of Figure 6 shows that population growth in SEZ areas was systematically higher than in control jurisdictions and there is indication of SEZ-induced population gains in neighboring areas. In principle, the difference in population growth might also reflect differences in fertility rates (e.g. triggered by higher income opportunities in SEZ areas). Given that we study a rather short time frame, we consider this explanation to be of second-order importance at best.[22]

6 Heterogeneous effects

In this section, we shed light on heterogeneous treatment effects by gender (6.1), firm size (6.2) and zone characteristics (6.3) to explore the anatomy of the employment response.

6.1 Employment effects by gender

Female workers are a particularly vulnerable group in the Indian labor market as unemployment rates among women tend to be high and discrimination is a long-standing phenomenon (Klasen and Pieters, 2015; Srivastava and Srivastava, 2015). Against this background, providing better income opportunities to women by integrating them into the formal labor market would be an important effect of the policy. One presumption proponents of the SEZ-policy have expressed is that additional jobs in manufacturing or services would be sourced from the unused female workforce or from women being employed marginally in the agricultural sector and that women might be the main beneficiaries of such policies (e.g. Bacchetta et al., 2009; Rama, 2003; Brussevich and Dabla-Norris, 2020). These hopes were further spurred by rising female employment shares in export-oriented industries in many less-developed countries (Ozler, 2000; Bussmann, 2009).

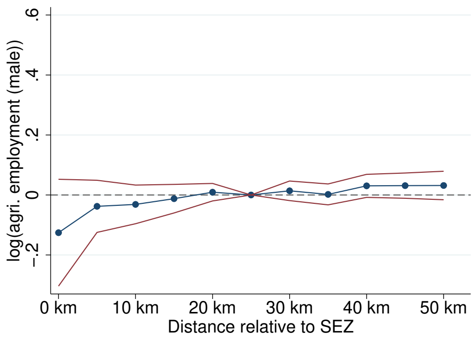
Our data allow us to split up employment effects by sector and gender. Panels (a) and (b) in Figure 7 reveal that in particular female employment declined in the agricultural sector ($-29pp$, p-value: 0.001) relative to reference municipalities, while the effect on men was closer to zero and statistically insignificant. An explanation for this gender effect

[22] Employment growth in manufacturing and services could also be associated with higher labor-force participation or lower unemployment. As related data are unavailable at the municipality level, we can explore neither of these underlying sources empirically. Workers could, on top of that, also commute from neighboring locations to SEZ areas. Commuting is rather uncommon in India, however, as public transport networks are not well developed and services tend to be infrequent. Census data for 2011 suggests that only around 18% of the Indian workforce travels more than 10km to work (own calculation based on the Population Census 2011).

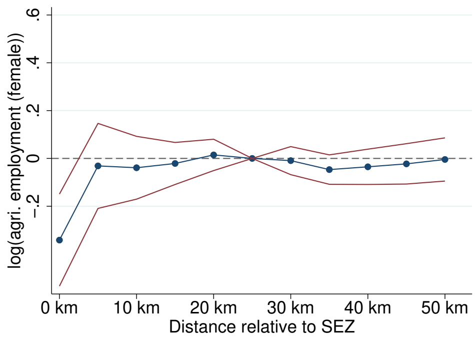
might be that only about 15% of agricultural businesses are owned by women rendering them more responsive to new job opportunities in manufacturing (Agarwal et al., 2021). Moreover, our data reveal that female workers account for 59% of marginally employed agricultural workers such that non-agricultural jobs might offer an appealing alternative for many. The decline of female employment in agriculture is paralleled by a pronounced increase of female workers in manufacturing by 55*pp* (which just fails to gain statistical

Figure 7: Employment effects by gender

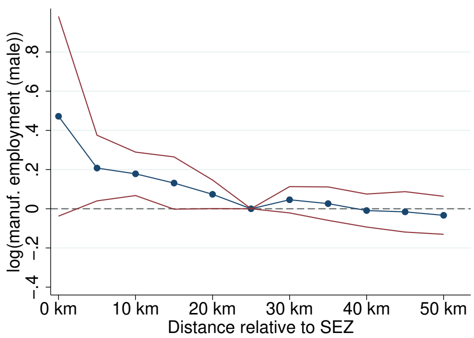
(a) Agricultural: Male



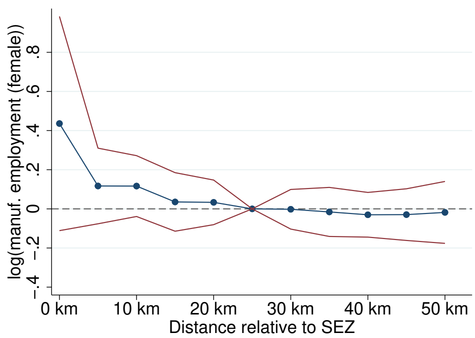
(b) Agricultural: Female



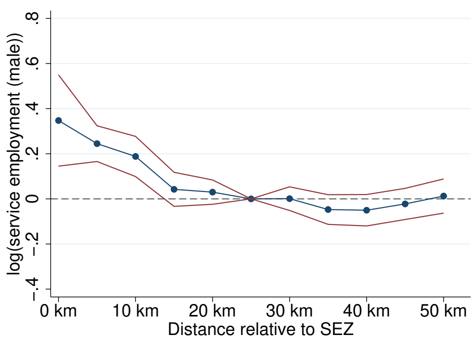
(c) Manufacturing: Male



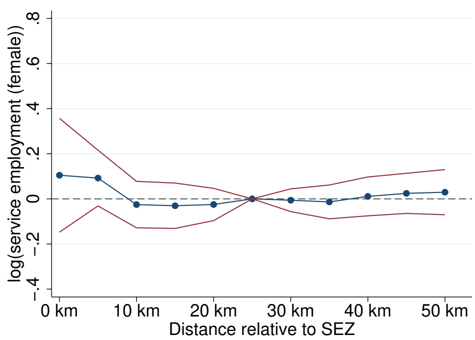
(d) Manufacturing: Female



(e) Services: Male



(f) Services: Female



Notes: The dots indicate the estimated parameter $\hat{\beta}_d$ according to Eq. (1). Each d refers to a distance on the horizontal axis e.g. the coefficient at 0km refers to $d = 0$. Red lines indicate 95% confidence intervals. Standard errors are clustered at the district level. Panels (a)-(d) are based on the Economic Census for the years 2005 and 2013. Panels (e)-(f) are based on the Population Census for the years 2001 and 2011.

significance at conventional levels, p-value: 0.118, panel (d)), but a much smaller and insignificant effect in services. Male employment, in contrast, rises in both manufacturing (60*pp*, p-value: 0.069) and services (41*pp*, p-value: 0.001) as can be seen from panels (c) and (e). As high-skill-intensive IT-zones play a quantitatively important role within the service industry in our sample, it is plausible that additional employment is taken up by skilled workers rather than being drawn from the predominantly low-skilled agricultural sector. A potential source of skilled-workers could be regional migration (see panel (d) of Figure 6).

In sum, we conclude that employment changes in agriculture, manufacturing and services point in the same direction for men and women. The decline in agriculture appears more pronounced for women, the increase in services is higher for men.[23] The sectoral shifts are hence centered around female employment (see Section 5.3).

6.2 Employment effects by firm size

Our data further allow us to decompose the overall employment effect by firm size. While some elements of the SEZ-policy (e.g. tariff-related benefits or lighter regulations) mainly target large firms, others – e.g. the corporate tax holidays provided – are equally attractive for smaller entities. Smaller and informal firms may also find it attractive to co-locate in or close to SEZs if they are connected to other (exporting) firms through input-output links. In the following, we assess the impact of SEZ establishment on employment in firms with more or less than 10 workers, where the latter are classified as informal by official statistics in India (NCEUS, 2009). Our analysis hence provides indication as to what extent studies underestimate aggregate employment responses to local policies if the focus is on the formal sector only. Second, distinguishing between small and large firms is also of interest as firm size correlates with economic outcomes like worker productivity and workers' wages (Idson and Oi, 1999; Oi and Idson, 1999) and with firms' fiscal contributions (LaPorta and Shleifer, 2014; McCaig and Pavcnik, 2021).[24]

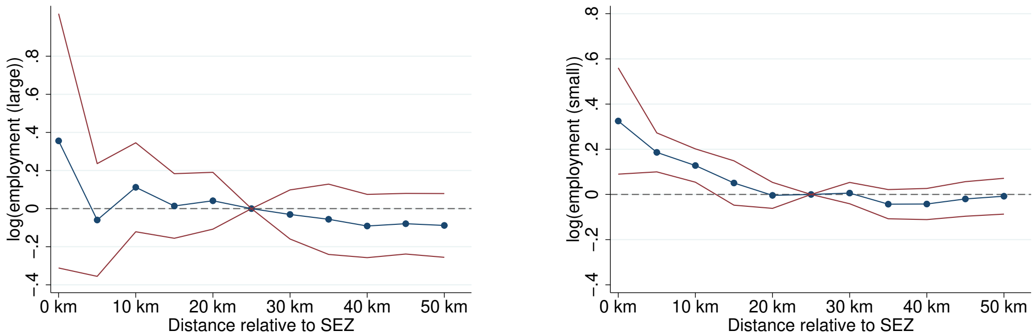
Panels (a) and (b) of Figure 8 report employment responses separately for large (more than 10 workers) and small firms (up to 10 workers), respectively. We find a strong, but insignificant effect for large firms of 53*pp* and a somewhat smaller, but significant employment gain of 38*pp* for small firms. The insignificant estimate for large firms likely relates to the relatively small number of large firms per municipality (which lowers the statistical power of the analysis). Complementary, we show in Appendix B.5 that the SEZ-policy has stimulated entry of small informal firms, especially in areas outside SEZs. Small informal firms are hence found to add significantly to the observed positive local

[23] Only the estimates for services are statistically significantly different from each other.

[24] Note that productivity and wages of small firms in the manufacturing and service sector are arguably still higher than wages in agriculture, especially in comparison with marginal agricultural work (workers would otherwise not switch jobs). Fiscal contributions also correlate with firm size as small firms are exempt from certain insurance and social security tax payments and, in general, show weaker tax compliance behavior than larger entities (LaPorta and Shleifer, 2014; McCaig and Pavcnik, 2021).

Figure 8: Employment effects by firm size

(a) Large firms (b) Small firms



Notes: A firm classifies as small if it employs not more than 10 workers. The dots indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (1). Each d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Red lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. All panels are based on the Economic Census for the years 2005 and 2013.

economic effect induced by SEZ establishment.

6.3 Zone characteristics

One feature of the small existing literature on the spatial effects of SEZs is that studies largely assume SEZs to be homogeneous entities (e.g. Wang, 2013; Lu et al., 2019). This is at odds with real-world settings (World Bank, 2008). Zones in India differ in two key dimensions: First, there is heterogeneity in zones' main industry denomination. There are IT, pharma, engineering, apparel or manufacturing zones (the latter are tabbed 'multi-product zones'). Zones further differ in whether they are developed and run by a private or a public body. In this section, we assess how these characteristics shape the impact of SEZs on local economic activity.

Public vs. private SEZs. As depicted in panel (a) of Figure 9, more than two thirds of the zones that went into operation during our sample period were developed and run by a private entity. While privately developed zones do not systematically differ from their publicly developed counterparts in terms of area size (see panel (b)), they tend to be located in larger and more prosperous areas (as determined by host municipalities' employment and nightlight intensity, see panels (c) and (d)).[25] This is consistent with public developers putting a stronger emphasis on creating new employment in less prosperous regions compared to private developers, who primarily seek to maximize profits.

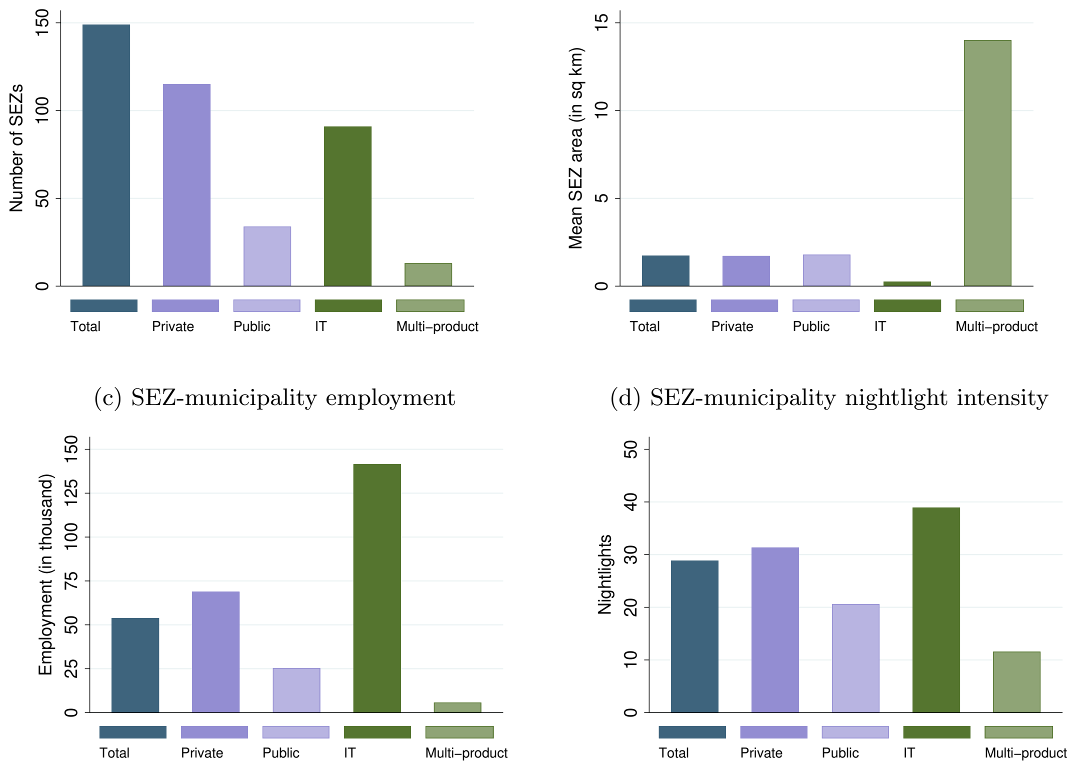
There are also reasons to believe that the local employment impact of public and private SEZs may differ. On the one hand, public bodies have less incentives to run projects efficiently (see e.g. Megginson and Netter, 2001) and the optimal size of publicly

[25] Consistent GDP data are, unfortunately, not available at the level of Indian municipalities. Henderson et al. (2012) show that nightlights are a reasonable proxy for economic development and income growth at subnational levels.

Figure 9: SEZ characteristics by industry and ownership

(a) Number of SEZs

(b) Mean SEZ area



(c) SEZ-municipality employment

(d) SEZ-municipality nightlight intensity

Notes: SEZ-municipality characteristics are based on the year 2005. Authors' own calculations based on SEZ information from the Ministry of Industry and Commerce, the Economic Census and DMSP-OLS Nighttime Lights Time Series provided by the National Oceanic and Atmosphere Administration (NOAA).

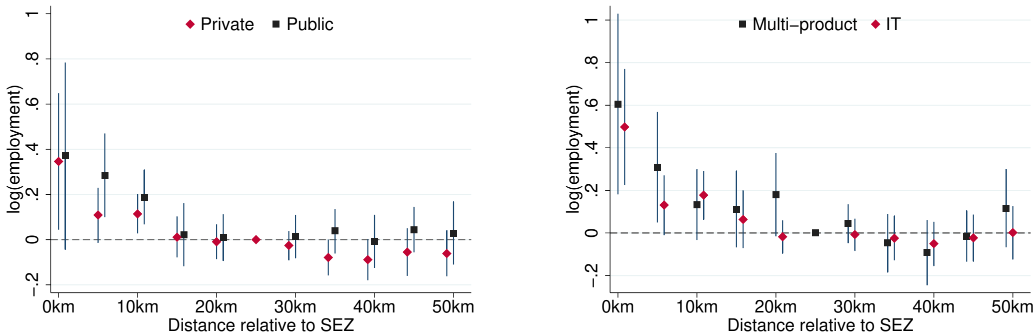
developed zones may therefore, ceteris paribus, be smaller than the optimal size of private zones. On the other hand, public zones may exert stronger local employment effects as public developers often pursue employment goals when designing SEZs, while private developers first and foremost aim for profit maximization. To test for effect heterogeneity along these lines, we estimate a model of the following form:

$$\begin{aligned} ln(y_{it}) = &\sum_{d=0,d\neq 5}^{10} \beta_d D_{[d_i=d]} \times POST_t + \sum_{d=0,d\neq 5}^{10} \theta_d D_{[d_i=d]} \times POST_t \times priv.developer_i \\ &+ POST_t \times priv.developer_i + \boldsymbol{\eta}' \left(\mathbf{X}_i \times POST_t \right) + POST_t + \alpha_i + \epsilon_{it}, \end{aligned} \tag{5}$$

where the variable definitions correspond to Eq. (1) and $priv.developer_i$ is a dummy variable indicating that the closest SEZ to municipality i is developed by a private developer. One challenge when estimating Eq. (5) is that SEZs do not only differ in their status of being developed by a private or public body, but also in their industry denomination. If the industry denomination correlates systematically with private and public development status and with SEZs' local employment impact, estimates of θ_d may be confounded. Descriptive statistics indeed suggest that the fraction of IT zones is, for example, larger

Figure 10: Employment effects by zone type (CEM)

(a) Public vs. private SEZs (b) IT- vs. multi-product SEZs



Notes: The plotted coefficients are estimated according to Eq. (5). In panel (a) (panel (b)), black squares depict the effects of public (multi-product) SEZs on employment in the respective distance bins ($\hat{\beta}_d$). Red diamonds show the effects for private (IT) SEZs ($\hat{\beta}_d + \hat{\theta}_d$). Each d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Black lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. Regressions include municipality and year fixed effects. Observations are re-weighted using coarsened exact matching over designated industry (ownership-type) and with *private* (*IT*) as the treatment category. For the purpose of giving a comprehensive picture of the full set of SEZ location choices the IT-sample includes also large municipalities. Employment data are based on the Economic Census for the years 2005 and 2013.

among private than among public SEZs. We draw on exact matching to address this concern. In the base analysis, we match observations according to the industry class of the closest SEZ located in distance d_i from municipality i to balance differences in industry denomination across SEZs developed and run by private and public entities.

Panel (a) of Figure 10 plots the effects of SEZs on local employment conditional on industry denomination and separately for public and private SEZs (β_d and $\beta_d + \theta_d$ in Eq. (5)). It is evident that the effects do not differ systematically between publicly and privately developed SEZs. If anything, employment effects are larger in publicly developed zones, but the effects are not statistically different from each other. In Appendix B.1, we report additional results where we re-estimate Eq. (5), first, without matching and, second, applying coarsened exact matching and accounting for SEZ's industry denomination *and* the area size of the SEZ relative to the area of its hosting municipality (Iacus et al., 2012; Blackwell et al., 2009). The latter variable is coarsened based on the default autocut algorithm as in Blackwell et al. (2009). All specifications yield similar results.

Sector-specific effects. The impact of SEZs on local economic activity may also hinge on SEZs' industry denomination. In the following, we will in a first step compare IT and multi-product (i.e. manufacturing) zones. Testing for effect heterogeneity in this dimension again comes with the challenge that industry denomination might correlate with other zone characteristics like the type of developer and zones' size relative to the size of the host municipality. Our data indeed suggest that IT-zones tend to be hosted by systematically larger jurisdictions than multi-product zones. This is intuitive since

IT-firms demand high-skilled labor, which can be found predominantly in big cities.[26] Furthermore, the minimum area size requirement for IT-zones is substantially smaller than for other zone types, facilitating the establishment of IT-SEZs in areas where land is scarce and costly. Multi-product SEZs are, in turn, observed to be located in smaller municipalities at the coast, reflecting their need for proximity to physical infrastructure such as ports for exporting manufactured goods.

We apply coarsened exact matching to account for these features by estimating a model similar to Eq. (5) where we replace $priv.developer_i$ by an industry identifier $multiproduct_i$. In panel (b) of Figure 10, we match zones by developer type (private vs. public body). In Appendix B.1, we present additional results, where we match on zones' size relative to the host municipality. Across both specifications, point estimates are somewhat higher for multi-product zones in some distance bins, but are never statistically different from IT-zones. Similar conclusions emerge for other industries (pharma, engineering, apparel), see Appendix B.1. This suggests that the aggregate local employment effects are comparable across SEZs of different type.

Note that the existence of (privately-developed) SEZs with different industry denominations, which also exert comparable local employment effects, suggests that different SEZ features – tax cuts for export income, tariff reductions and ease of regulatory burden – have pull and attract firms to SEZ areas. In Appendix B.1, we substantiate this point by showing that IT and manufacturing firms substantially differ in relevant underlying characteristics – the regulatory burden (which is particularly high for firms in the IT sector), import intensity (which is particularly high for firms in manufacturing) and export intensity (which is broadly comparable for firms in manufacturing and IT) – and that there is within-industry selection of firms with high export and import-intensity into SEZ areas.

7 Has the SEZ policy been cost-effective?

We finally draw on a simple back-of-the-envelope calculation to obtain an understanding whether the Indian SEZ-policy has been cost-effective. The exercise relates net employment changes to the fiscal expenditures of the program (Criscuolo et al., 2019a; Lu et al., 2019). Information on foregone revenues is taken from the Indian Ministry of Finance, which monitors the SEZ-policy and publishes foregone revenues as the total amount of income tax concessions claimed by SEZ-firms and SEZ-developers (Ministry of Finance, 2015). For the years 2006-2013, these concessions amounted to INR 596.2 billion, equivalent to USD 9.85 billion based on 2013 purchasing power parity (PPP) exchange rates.[27] Our baseline estimates suggest that the policy, in the aggregate, created 1.25 million new

[26] Note that we include municipalities with more than 500K inhabitants when studying heterogeneous effects across industries since a significant share of IT-SEZs is located in large cities.

[27] For 2006, official statistics only include the aggregate income tax concessions for all incentive programs in India. We approximate the SEZ-related foregone revenues in 2006 by extrapolating the share of SEZs in total revenue loss for 2007 (where the revenue losses were split up by incentive programs) to 2006.

jobs (see Appendix B.3 for details).[28] This translates into revenue costs of INR 475,158 (USD 7,853, PPP) per newly created job. The ratio between workers' wages and fiscal costs per job is 0.72 if jobs are created for the eight years we study and workers earn the Indian minimum wage ($3,562$ INR per month). If we additionally account for the decrease in agricultural employment and assign a value of INR 50 per day as agricultural income (Saini et al., 2020), we retrieve a ratio of 0.62. These estimates are within the broad range of prior studies on place-based policies (Chodorow-Reich, 2019; Criscuolo et al., 2019a). Note, however, that the latter are largely set in the developed world, limiting comparability with our findings.[29] For India, most existing studies fail to report program costs. An exception is Chaurey (2017), who shows that tax concessions granted to firms in two Indian states created employment at much higher fiscal costs than the SEZ program studied in our paper.[30]

While these back-of-the-envelope estimates offer a valuable benchmark, caveats need to be kept in mind. They include that the foregone revenues calculated by the Indian Finance Ministry abstract from firms' behavioral response to the SEZ policy by assuming that all foregone taxes would have been paid under the counterfactual and by abstracting from spillovers to other tax bases.[31] More broadly, note that our bang-for-the-buck estimates follow the spirit of several prior papers on place-based policy interventions (e.g. Lu et al., 2019 and Criscuolo et al., 2019b) but do not directly speak to the welfare implications of the SEZ policy (e.g. accounting for sectoral or regional migration costs and productivity shifts induced by the policy (Combes and Gobillon, 2015)). We consider analyses in this direction to be a fruitful avenue for future research.

8 Conclusion

This paper has studied a highly prevalent type of place-based policy in less-developed countries: the establishment of Special Economic Zones. While the number of SEZs in the developing world has increased steeply over recent decades, there is hardly any evidence on their effectiveness in fostering local economic development. A notable exception are studies on SEZs in China. But given the particularities of the Chinese institutional context, there

[28] One concern might be that SEZ-induced employment effects may systematically differ across municipalities of different size, which may potentially bias the estimate for the specified aggregate employment response. Note that, if we split the set of municipalities with less than 500K inhabitants into four equally-sized bins and run our regression model separately in each subset of municipalities before aggregating, this yields very similar estimates for the aggregate employment effect (1.24 million new jobs).

[29] Information on the minimum wage is taken from: https://countryeconomy.com/national-minimum-wage/india, Last retrieved: June 21, 2023. Also note that the minimum wage only binds in the formal sector. But prior evidence for India shows that it also shapes informal wages (Kar and Khattar, 2023).

[30] Chaurey (2017) estimates that the tax incentives created 33,000 jobs and that the (upper bound of the) fiscal cost to taxpayers were INR 66 billion. This yields fiscal costs per newly created job of INR 2 million. The SEZ policies assessed in our study hence created jobs at less than a quarter of the tax costs.

[31] We also do not observe workers' wages but have to rely on the approximation by the minimum wage. Moreover note that our estimates on the aggregate employment gain comprise the SEZ-related employment responses in larger urban areas, which are challenging to estimate and are more likely to include a margin of error (see Appendix B.3 for a more detailed discussion).

is scepticism in the policy domain that the Chinese experience extends to SEZs in other countries (see e.g. World Bank (2017); African Development Bank (2016)).

We add to the literature by studying the local economic impact of SEZs in India. The empirical analysis relies on granular census information and on hand-collected data on the location and characteristics of SEZs. We use a transparent empirical identification design to document that the SEZ Act stimulated quantitatively important non-agricultural employment growth in SEZ-hosting municipalities and their close neighbors. Additional analyses suggest that genuinely new non-agricultural jobs were created (rather than jobs being relocated in space). We furthermore shed light on the anatomy of the response: We present evidence consistent with workers migrating towards SEZ areas to take up the new jobs. And we document that SEZ establishment stimulated sectoral transition from the primary sector to manufacturing and services. This sectoral shift centers around local female employment and may thus have added to the empowerment of women. Last but not least, the positive local employment effects emerge across different types of SEZs: privately and publicly run zones and SEZs with different industry denominations. Overall, we interpret our findings to dispel the general pessimism about zone programs in developing countries outside of China.

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Appendix

A Data

This appendix complements Section 4 in the main paper providing more information on the data compilation process (Section A.1), descriptive statistics (Section A.2) and the geographic location of SEZs by industry (Section A.3).

A.1 Data compilation procedure

Figure A.1 illustrates each individual step implemented in QGIS 3.10. to arrive at the municipality sample.

Figure A.1: Automated workflow in QGIS 3.10 to obtain final municipality sample

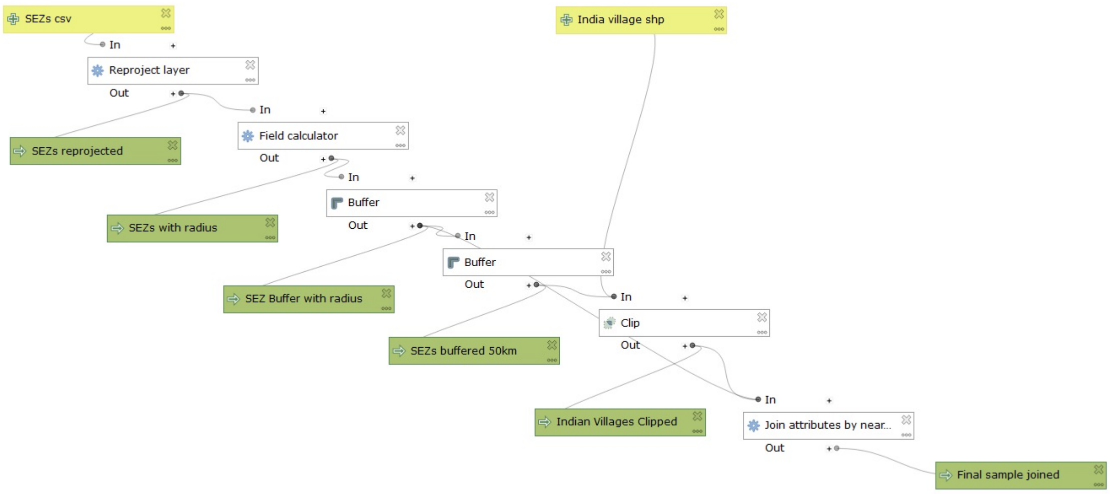
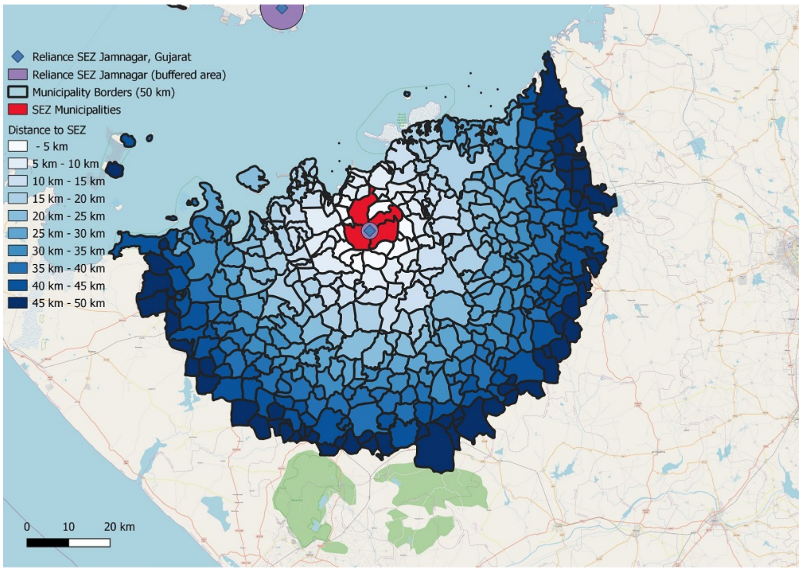


Figure A.2: Mapping municipalities into distance bins around SEZs



Notes: This figure illustrates the procedure of mapping municipalities into distance bins using the"Reliance SEZ" in Jamnagar (Gujarat) as an example.

Figure A.2 illustrates the procedure for the Reliance SEZ in Jamnagar, where the red-colored polygons correspond to municipalities, whose administrative borders intersect with the SEZ-area. We consider these municipalities as municipalities that contain an SEZ. The blue-shaded polygons illustrate neighboring municipalities, classified by their distance to their closest SEZ ("Reliance SEZ" in the example above). The light blue color indicates municipalities which are within a 5km distance to their closest SEZ; darker blue colors indicate municipalities in a distance of 5-10km, 10-15km etc. to the closest SEZ (up to 50km).

A.2 Descriptive statistics

Table A.1 summarizes the baseline sample, i.e. excluding large cities with a population larger than 500K.

Table A.1: Descriptive statistics

	Mean	*SD*	*Median*	*# Municipalities*	*# Obs.*
Economic Census					
- Non-agricultural employment	290.0	2,457	41	49,669	140,386
- Male non-agricultural employment	220.2	1,967	30	49,669	140,386
- Female non-agricultural employment	69.77	573.2	8	49,669	140,386
- Non-agricultural employment (large firms)	87.68	1,518	0	49,669	140,386
- Non-agricultural employment (small firms)	202.3	1,337	36	49,669	140,386
- Manufacturing employment	113.0	1,307	7	48,093	96,186
- Service employment	211.3	1,637	34	48,093	96,186
- Number of firms	115.6	692.1	23	49,669	140,386
Population Census					
- Agricultural employment	520.1	793.4	303	42,910	127,868
- Male agricultural employment	330.6	501.2	194	42,910	127,868
- Female agricultural employment	189.5	333.5	93	42,910	127,868
- Main agricultural employment	433.9	706.7	240	42,654	85,308
- Marginal agricultural employment	117.9	223.8	42	42,654	85,308
- Population	3,061	15,224	1,043	42,910	127,868

Notes: Small and large firms are classified according to the 10-worker rule. Marginal workers (as opposed to main workers) work less than 183 days a year. Information on main and marginal workers is only available for the years 2001 and 2011. Information on sector employment (Manufacturing, Services) is only available for the years 2005 and 2013. The sample consists of all municipalities which are located within a 50 km radius of one of the 147 SEZs and observed for at least two consecutive rounds in the economic census. Municipalities with more than 500K inhabitants are excluded.

Table A.2 summarizes additional information on SEZs.

Table A.2: Descriptive statistics SEZ-level data

	Mean	*SD*	*Median*	*N*
- Year of notification	2007	1.17	2007	147
- Year of operation	2010	2.07	2010	147
- Developing time (in years)	2.67	1.76	3	147
- Area sq. km	1.76	7.40	0.27	147
- Private SEZ	0.77	0.42	1	147
- Public SEZ	0.23	0.42	1	147
- IT SEZ	0.57	0.50	1	147
- Multiproduct SEZ	0.09	0.29	1	147
- Pharma SEZ	0.09	0.29	0	147
- Engineering SEZ	0.12	0.32	0	147
- Apparel SEZ	0.05	0.23	0	147

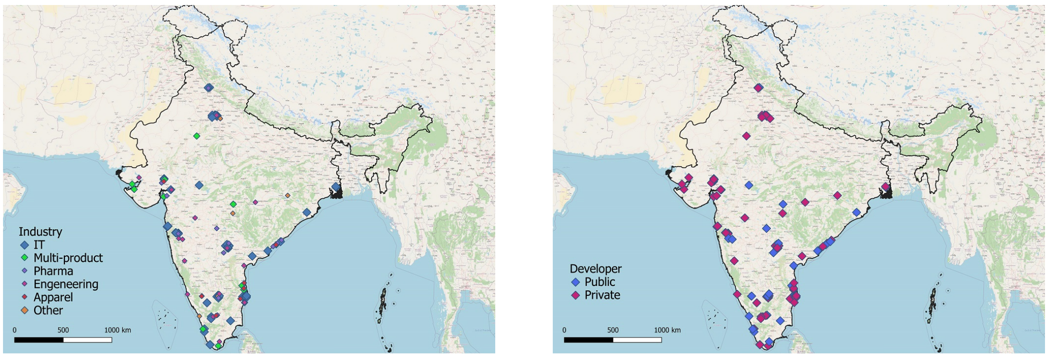
Notes: Authors' own calculations based on sources described in the main text. Private implies that the SEZ was established by a private body. Year of operation denotes the year in which the SEZ initialized its operation. Sample includes all SEZ that became operational until 2013.

A.3 Geographical location of SEZs by industry and developer

The maps in Figure A.3 show the geographic distribution of different types of SEZs (IT, multi-product and public/private, respectively) across India.

Figure A.3: Geographical location of SEZs by industry and developer

(a) SEZs by industry (b) SEZs by developer



Notes: Panel (a) plots the location of all SEZs in India that were established under the SEZ Act 2005 and became operational until 2013 by their industry designation. Panel (b) plots the location of all SEZs in India that were established under the SEZ Act 2005 and became operational until 2013 by their type of developer.

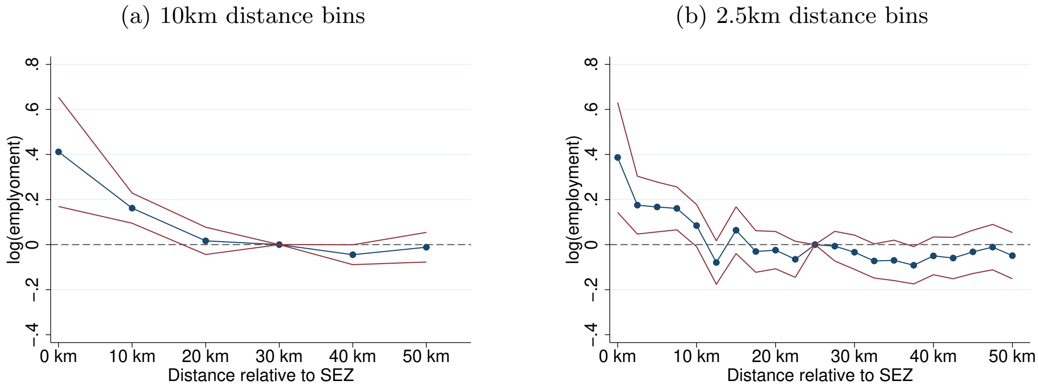
B Results

This appendix complements Section 5 of the main paper. We present additional robustness checks for our baseline results (Section B.1), further details on the nightlights event study (Section B.2), the relocation analysis (Section B.3) and the structural change analysis (Section B.4) and show additional results for outcomes like infrastructure (Section B.5)

B.1 Robustness

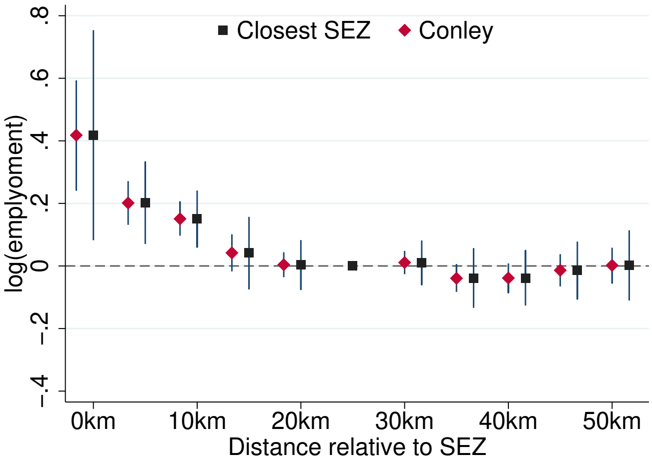
Baseline results. We check the robustness of our baseline results with regard to (1) alternative distance bin classifications (Figure B.1), (2) alternative standard error clustering (Figure B.2), (3) including municipalities up to a distance of 200km (Figure B.3), (4) including large cities (Figure B.4), (5) estimating our baseline model without additional controls and with CEM matching (B.5, panels (a)-(b) and (c)-(d) respectively).We find that none of these modifications alter the conclusions derived in Section 5.

Figure B.1: SEZ effect on employment (10km and 2.5km distance bins)



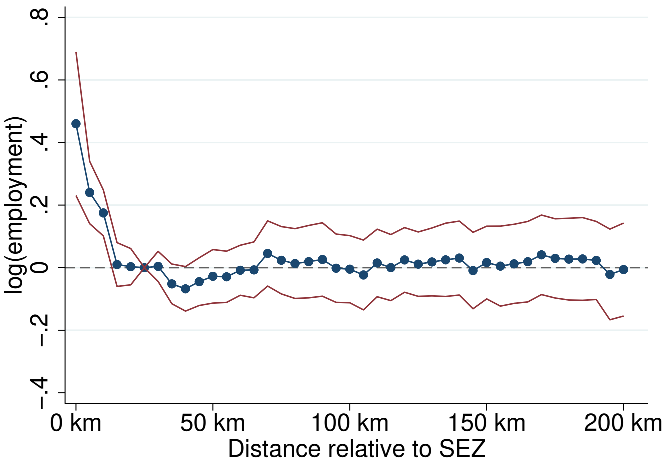
Notes: In this figure, distance bins are redefined as spreading 10km (panel (a)) and 2.5km (panel (b)). The dots indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (1). Red lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. Employment data are based on the Economic Census for the years 2005 and 2013.

Figure B.2: SEZ effect on employment (SE clustered by closest SEZ and Conley)



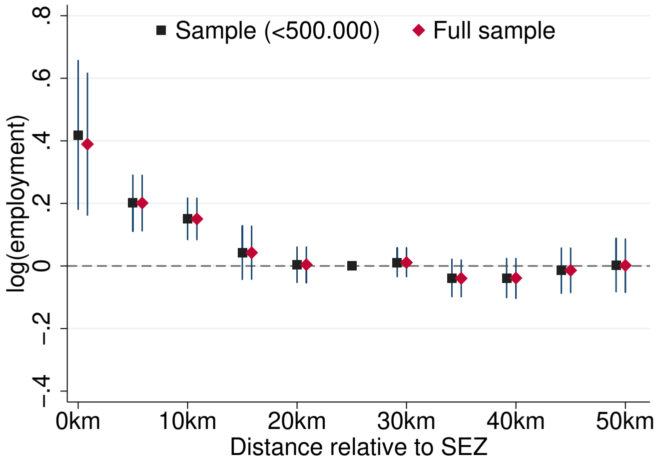
Notes: The dots indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (1). Each d refers to a distance on the horizontal axis e.g. the coefficient at 0km refers to $d = 0$. Red diamonds show the effects for when using Conley standard errors (Conley, 1999) with a distance cut-off at 30km. Black squares depict the results when clustering by closest SEZ. Red lines indicate 95%-confidence intervals. Employment data are based on the Economic Census for the years 2005 and 2013.

Figure B.3: SEZ effect with 200km radius



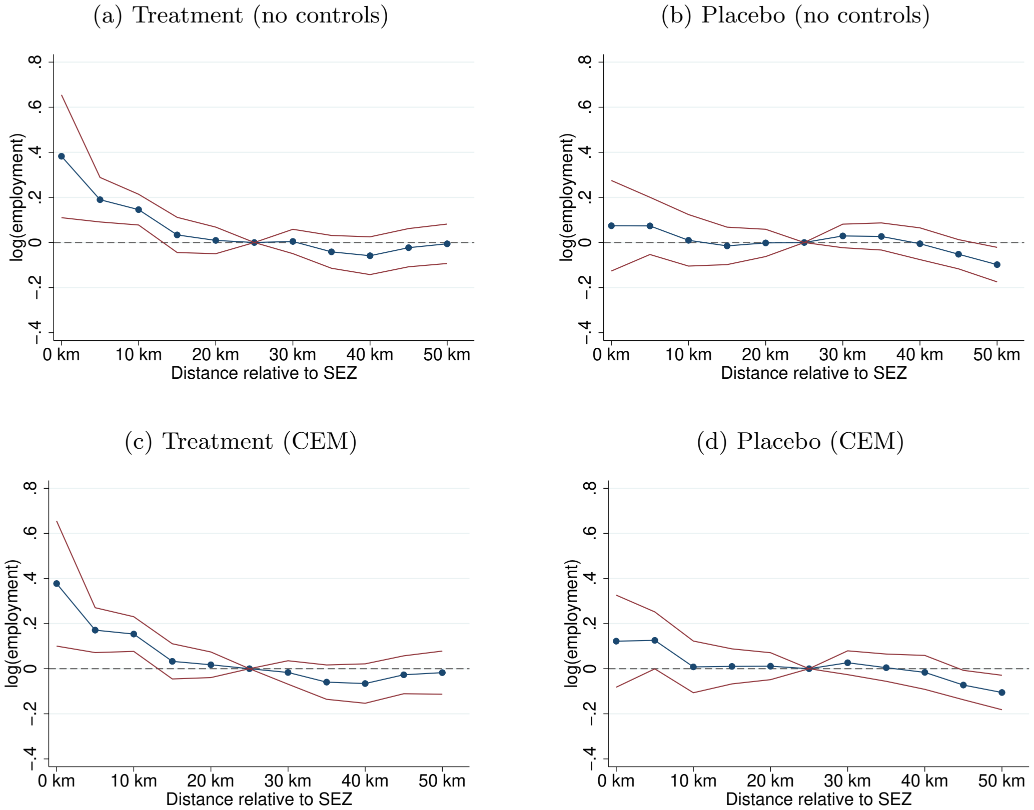
Notes: The dots indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (1). In this figure, the radius drawn around SEZs has been increased from 50km to 200km. Red lines indicate 95%-confidence intervals. The standard errors are clustered at the district level. Employment data are based on the Economic Census for the years 2005 and 2013.

Figure B.4: SEZ effect on employment with and without large cities



Notes: The squares and diamonds indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (1). Black squares depict the effects of SEZs on employment in small municipalities (baseline), i.e. $\leq$ 500K ($\hat{\beta}_d$). Red diamonds show the effects including large municipalities, i.e. $> 500K$ ($\hat{\beta}_d + \hat{\theta}_d$). Each subscript d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Black lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. Employment data are based on the Economic Census for the years 2005 and 2013.

Figure B.5: Spatial difference-in-differences model



Notes: The dots indicate the estimated parameters $\hat{\beta}_d$. Each subscript d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Red lines indicate 95%-confidence intervals. Panel (a) refers to specification Eq. (1) without the controls $\boldsymbol{\eta}' (\mathbf{X}_i \times POST_t)$, panel (c) is based on coarsened exact matching (CEM). The panels in the right column depict the respective placebo regressions. Standard errors are clustered at the district level. Employment data based on the Economic Census for 1998, 2005 and 2013.

We, moreover, explore whether the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), a public work program enacted in 2005 and thus in parallel to the SEZ policy, may act as a confounder in our analysis. MGNREGA guarantees at least 100 days of wage employment per year for unskilled manual work. If no job is found, the government pays transfers to workers who applied. At least one member of every household is eligible for this program. We provide three pieces of evidence, which suggest that our findings are not affected by the MGNREGA program.

First, MGNREGA was implemented at the district level while our analysis uses variation at the municipality level. Districts in India are large spatial units. On average, a district accommodates around 900 municipalities and has a radius of 63.6km (determined based on shapefiles that capture the 641 districts from the Population Census 2011). Our main empirical identification stems from within-district variation: the distance of SEZ-municipalities to reference location is only 25km. This setup makes it unlikely that effects from the MGNREGA program bias our estimates.

Second, MGNREGA provided jobs in the public sector, with a focus on the maintenance and the construction of infrastructure (roads, wells, etc.). As documented in Figure B.13, we find no indication that infrastructure construction emerged differentially between SEZ-locations and reference municipalities, again speaking against MGNREGA acting as a confounder in the analysis.

Third, we explicitly control for MGNREGA takeup in our empirical analysis.[32] Specifically, we compute the total number of person-days under MGNREGA in district k at time t relative to the total district population ($MGNREGA_{kt}$) and use this variable as an additional control.[33] The specification reads:

$$\begin{aligned}\ln(y_{it}) = &\sum_{d=0,d\neq 5}^{10} \beta_d (D_{[d_i=d]} \times POST_t) + \boldsymbol{\eta}' (\mathbf{X}_i \times POST_t) + POST_t \\ &+ \xi \times MGNREGA_{kt} + \alpha_i + \varepsilon_{it},\end{aligned} \tag{6}$$

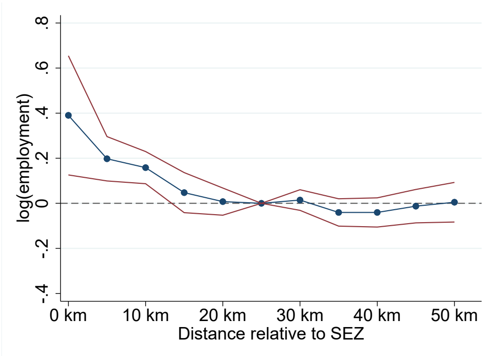
where the other variables are defined as in our main specification. The results are shown in Figure B.6 and resemble our baseline estimates. This corroborates that MGNREGA does not act as a confounder in our analysis.

[32] We added to each district information on MGNREGA take-up which has been made publicly available by Clement Imbert. The data was retrieved from LINK, last accessed: 19th April, 2024. Also note that, we ran additional specifications, where we estimated our baseline model separately for urban and rural municipalities, following the observation that MGNREGA was targeted at rural areas only. The results point to a negative (positive) effect of SEZ establishment on marginal agricultural (non-farm) employment in rural places, while there is no significant effect in urban areas. The latter finding reflects a lack of statistical power, however, as the number of urban municipalities in our data is small.

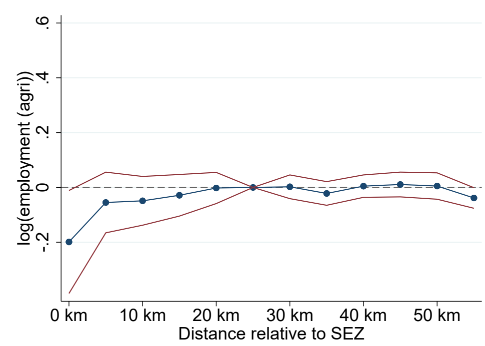
[33] For the year 2005, we assign the number of person-days under MGNREGA in 2006 (the first year after the MGNREGA policy was enacted). Note, moreover, that the number of person-days under MGNREGA is normalized on district population in 2001 (drawn from Census data).

Figure B.6: Baseline, when controlling for log($MGNREGA_{kt}$)

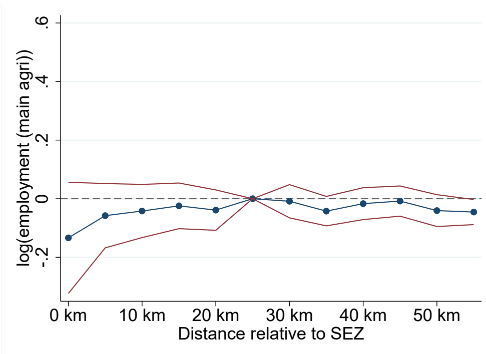
(a) non-agricultural employment



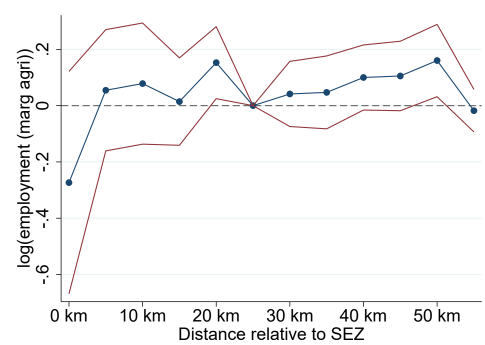
(b) agricultural employment



(c) main agricultural employment



(d) marginal agricultural employment



Notes: The dots indicate the estimated parameters $\hat{\beta}_d$ according to Eq. (6). Each d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Panel (a) depicts results for non-agricultural employment. Panels (b) - (d) show results for agricultural employment, respectively. Red lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. $MGNREGA_{kt}$ measures the ratio of person-days for in year t relative to the population at the district level in 2001.

Heterogeneous zone characteristics. In this part, we test whether the impact of SEZs on local employment hinges on the characteristics of the SEZ: the developer (public vs. private body) and the zone's industry denomination.

Table B.1 presents estimates of Eq. (5) – where we compare privately and publicly developed zones – with and without reverting to matching. The results are similar to the baseline findings in Section 6.3. If anything, the point estimates suggest that employment effects are more pronounced for publicly developed zones, but the estimated effects are not statistically different from each other.

Next, we assess whether zone's industry denomination shapes SEZ's local employment effect, again in specifications with and without matching. The point estimates in Figure B.7 and Table B.2 indicate that multi-product zones have a higher local employment effect than other SEZs, but we cannot rule out statistically that they are different from employment effects of SEZs with other industry denominations.

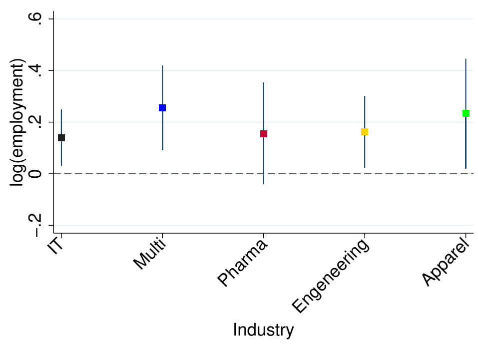
Table B.1: Employment effects by developer

	(1)	(2)	(3)	(4)	(5)	(6)
			Employment			
Matching	None		Industry		Industry & size	
Distance bins	*Private*	*Public*	*Private*	*Public*	Private	*Public*
0km	**0.314****	**0.549*****	**0.382*****	**0.411****	**0.369****	**0.400****
	(0.159)	(0.209)	(0.146)	(0.180)	(0.150)	(0.158)
0-5km	**0.125****	**0.357*****	**0.130****	**0.266*****	**0.122****	**0.263*****
	(0.056)	(0.080)	(0.056)	(0.089)	(0.056)	(0.089)
5-10km	**0.120*****	**0.202*****	**0.121*****	**0.191****	**0.121*****	**0.200****
	(0.040)	(0.064)	(0.040)	(0.076)	(0.041)	(0.077)
10-15km	**0.025**	**0.061**	**0.027**	**0.021**	**0.021**	**0.017**
	(0.051)	(0.063)	(0.051)	(0.072)	(0.052)	(0.070)
15-20km	**-0.009**	**0.030**	**-0.007**	**0.012**	**-0.015**	**0.012**
	(0.039)	(0.046)	(0.038)	(0.045)	(0.042)	(0.045)
20-25km	–	–	–	–	–	–
25-30km	**-0.023**	**0.070***	**-0.022**	**0.034**	**-0.028**	**0.033**
	(0.032)	(0.038)	(0.032)	(0.043)	(0.032)	(0.043)
30-35km	**-0.091****	**0.051**	**-0.092****	**0.074***	**-0.088****	**0.080****
	(0.040)	(0.059)	(0.040)	(0.042)	(0.040)	(0.040)
35-40km	**-0.075***	**0.024**	**-0.078***	**0.024**	**-0.079***	**0.028**
	(0.044)	(0.058)	(0.044)	(0.050)	(0.044)	(0.051)
40-45km	**-0.054**	**0.055**	**-0.057**	**0.074**	**-0.057**	**0.067**
	(0.051)	(0.043)	(0.050)	(0.045)	(0.051)	(0.046)
45-50km	**-0.069**	**0.123****	**-0.073**	**0.072**	**-0.076**	**0.084**
	(0.049)	(0.054)	(0.048)	(0.067)	(0.048)	(0.065)
Observations	92,980	92,980	92,954	92,954	91,960	91,960
R-squared	0.899	0.899	0.919	0.919	0.919	0.919
Municipality fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

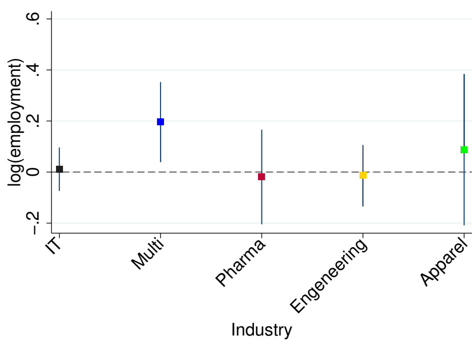
Notes: Regression results based on Eq. (5) contrasting employment effects of public and private SEZs. Columns (1)-(2) report results without matching. In columns (3)-(4), we match on industries as in Figure 10. Columns (5)-(6) show results when municipalities are matched according to SEZ-industry and SEZ-area relative to municipality area. Employment data are based on the Economic Census for the years 2005 and 2013. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Figure B.7: Employment effects by SEZ industry

(a) 0-10km (incl. SEZ municipalities):



(b) 10-20km:



Notes: The plotted coefficients refer to $\hat{\beta}_d + \theta_d$ based on a variant of Eq.(5) as explained in section 6.3. Panel (a) depicts results for municipalities up to 10km away from their closest SEZ (incl. SEZ-municipalities). Panel (b) illustrates results for municipalities that are 10-20km away from their closest SEZ. Straight lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. For the purpose of giving a comprehensive picture of the full set of SEZ location choices across industries the industry sample includes all municipalities. Employment data are based on the Economic Census for the years 2005 and 2013.

Table B.2: Employment effects by SEZ industry

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment					
Matching	None		Developer		Developer & size	
Distance bins	*Multi*	*IT*	*Multi*	*IT*	Multi	*IT*
0km	**0.625*****	**0.420*****	**0.544****	**0.416*****	**0.641***	**0.413*****
	(0.186)	(0.157)	(0.210)	(0.157)	(0.348)	(0.157)
0-5km	**0.324*****	**0.114**	**0.280****	**0.112**	**0.239****	**0.106**
	(0.117)	(0.075)	(0.122)	(0.075)	(0.113)	(0.076)
5-10km	**0.139***	**0.168*****	**0.119**	**0.165*****	**0.077**	**0.164*****
	(0.075)	(0.057)	(0.075)	(0.057)	(0.083)	(0.057)
10-15km	**0.164**	**0.061**	**0.103**	**0.061**	**0.040**	**0.056**
	(0.124)	(0.067)	(0.088)	(0.067)	(0.083)	(0.068)
15-20km	**0.157***	**-0.011**	**0.171***	**-0.012**	**0.097**	**-0.012**
	(0.092)	(0.038)	(0.093)	(0.038)	(0.071)	(0.038)
20-25km	–	–	–	–	–	–
25-30km	**0.020**	**-0.002**	**0.039**	**-0.001**	**-0.006**	**0.000**
	(0.046)	(0.039)	(0.042)	(0.039)	(0.042)	(0.039)
30-35km	**-0.024**	**-0.016**	**-0.039**	**-0.015**	**0.007**	**-0.015**
	(0.057)	(0.053)	(0.065)	(0.053)	(0.065)	(0.053)
35-40km	**-0.044**	**-0.041**	**-0.075**	**-0.039**	**-0.111****	**-0.038**
	(0.062)	(0.052)	(0.069)	(0.052)	(0.052)	(0.052)
40-45km	**0.030**	**-0.014**	**0.005**	**-0.012**	**-0.030**	**-0.011**
	(0.048)	(0.058)	(0.051)	(0.059)	(0.065)	(0.058)
45-50km	**0.155****	**0.005**	**0.127***	**0.007**	**0.112**	**0.012**
	(0.073)	(0.061)	(0.076)	(0.061)	(0.078)	(0.061)
Observations	51,202	51,202	51,202	51,202	50,414	50,414
R-squared	0.898	0.898	0.898	0.898	0.899	0.899
Municipality fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: Regression results based on Eq. (5) with $industry_i$ instead of $priv.developer_i$ as an identifier. CEM is applied with IT being the treatment category. Columns (1)-(2) report the results without matching. Columns (3)-(4) show results when municipalities are matched according to SEZ developer (public or private) as in Figure 10. Columns (5)-(6) report results when municipalities are matched according to SEZ-developer and SEZ-area relative to municipality area. The sample includes all municipalities. Employment data are based on the Economic Census for the years 2005 and 2013. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

The fact that zones with different industry denomination emerged in the wake of the 2005 SEZ Act (often developed by private investors) illustrates that firms with different underlying characteristics seem to reap benefits from locating within SEZs. SEZs in India offer various advantages to firms within their borders – most importantly, tax cuts on export income, benefits from being outside of the Indian tariff area as well as lighter regulation and less bureaucracy. The heterogeneity in zone denominations suggests that all of these factors may have pull and may be instrumental in attracting firms to SEZ areas.

To dig deeper and substantiate this claim, we draw on rich firm-level data on Indian companies, the so-called Prowess database, which is described in detail in Appendix B.3. This data is matched to firms, which are active in SEZs, obtained from various publicly available lists (e.g. SEZ-developer webpages and members directory of the export promotion council), see Appendix B.3 for further details. Based on this data, we determine the export intensity (measured by the value of firms' exports relative to overall sales), import intensity (measured by the value of firms' imports relative to overall sales) and the level of consultant fees (which serve as a proxy for the regulatory burden faced by the firms[34]) for firms in different industries (IT vs. manufacturing) and, within these industries, for firms in and outside of SEZ areas.

The findings are presented in Figure B.8. They point to pronounced differences in underlying characteristics of IT and manufacturing firms and (within sectors) of firms within and outside of SEZ areas. Panel (a) suggests that both IT firms and manufacturing firms engage in export activity to a relevant extent, with rates being somewhat higher among IT firms. We further observe that firms in SEZs feature a higher export intensity than firms outside of these zones – consistent with firms with high-export intensity, which benefit over-proportionally from tax reductions on export income, selecting into SEZ areas. Panel (b) shows that the import intensity starkly differs across IT and manufacturing firms: While imports make up less than 1% of sales for IT firms, this ratio stands at about 17% for manufacturing firms located in SEZs; and somewhat lower at 6% for manufacturing firms outside of SEZs. This suggests that manufacturing firms, contrary to their IT counterparts, find it attractive to locate in SEZ areas for tariff-related reasons (while both types of firms, to some extent, reap benefits from low tax rates on export income). And, again, consistent with firms' incentives, there seems to be selection of particularly import-intensive entities into SEZ areas within the manufacturing sector. Panel (c) presents analogous evidence for consultancy fees, which serve as a proxy for firms' regulatory burden. We compare the costs between SEZ- and non-SEZ firms as well as between IT and manufacturing firms. On average, IT firms spent about five times as much on consultancy fees as their counterparts in the manufacturing sector, suggesting that they benefit overproportionally from a lighter regulatory burden within SEZs.[35]

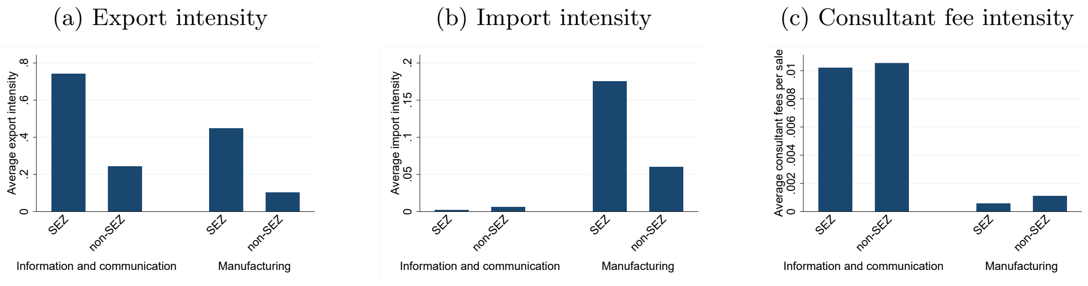
In sum, the descriptive evidence in Figure B.8 suggests that SEZ-benefits likely differ quite pronouncedly across IT and manufacturing industries. The fact that zones with different industry denomination emerged endogeneously and that the establishment of these zones is associated with broadly similar local treatment effects (i.e. impacts on local economic activity) serves as tentative evidence that different types of SEZ-benefits have

[34]The idea is that firms subject to tighter regulation outsource a larger fraction of regulatory compliance work thus reporting higher consulting fees. It would have been ideal to combine information on external consultancy fees with information on internal costs incurred to comply with government regulations, but this information is not available, unfortunately.

[35]Similar evidence emerges from other data sources like the World Enterprise Survey, where firms are asked about their biggest obstacle to doing business. In the IT sector, 12.1% of firms state "business licensing and permits", which is significantly more than in any other sector besides construction. In manufacturing, only 4.3% state this to be the case. Also note that Panel (c) does not point to a within-industry selection of firms with particularly high regulatory costs towards SEZ areas. This may relate to a lack of intra-firm variation in regulatory burdens or to the imperfect nature of consultancy fees as a proxy for firms' regulatory and bureaucracy costs.

pull and contribute to the attractiveness of SEZs for corporate activity.

Figure B.8: Industry characteristics



Notes: The figure depicts the export-intensity (exports over sales), import-intensity (imports over sales) and consultant fee intensity (consultant fees over sales) of firms in the IT and manufacturing industry, outside and inside of SEZs. SEZ firms are identified via fuzzy name matching. For details on the data, see Appendix B.3.

B.2 Event study and nightlights

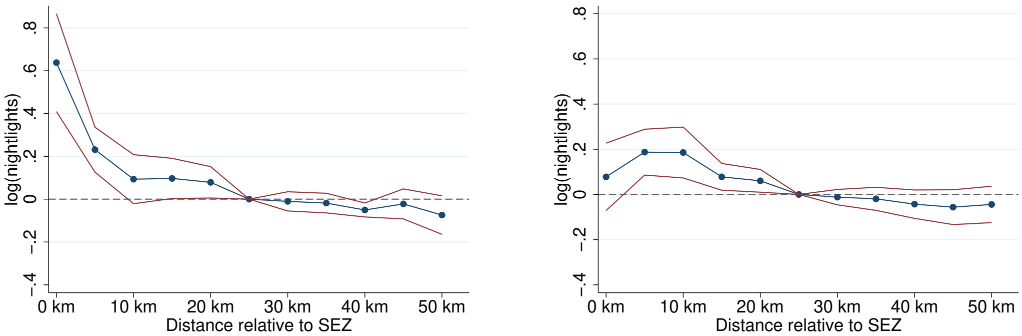
This appendix complements Section 5.1 in the main paper, where we present event study regressions based on annual nightlight data to corroborate the common-trend assumption.

Figure B.9 reestimates our baseline spatial difference-in-differences model with nighlight data, differentiating between multi-product and IT SEZs. The exercise confirms our baseline estimates and shows a positive treatment effect for SEZ hosting municipalities and municipalities in close proximity. Intuitively, the effect is particularly pronounced for multi-product SEZs, which, first, tend to be dominated by manufacturing firms with a high nightlight intensity and, second, tend to be located in more rural areas with low underlying nightlight intensity (making it easier to identify nightlight effects).

Figure B.10 presents event study estimates for the impact of multiproduct SEZs on nightlight emissions. It compares municipalities treated by SEZs to reference locations as defined in the main text. The figure shows that nightlights emerged in parallel prior to SEZ establishment. After SEZ establishment, nightlight intensity increased significantly in treated relative to reference SEZs.

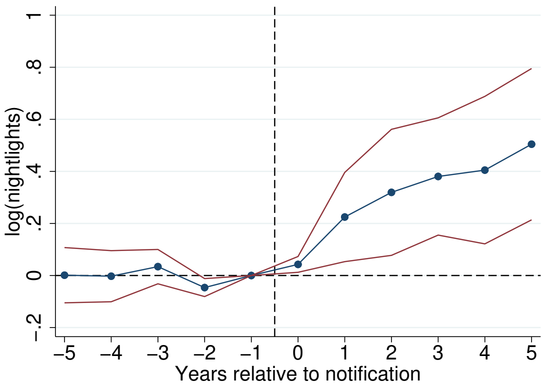
Figure B.9: SEZ effect on nightlights by SEZ-industry

(a) Multi-product SEZs (b) IT SEZs



Notes: The dots indicate the parameters $\hat{\beta}_d$ as estimated by (1) Each subscript d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Red lines indicate 95%-confidence intervals. Panel (a) depicts the effect of multi-product SEZs on municipal nightlight intensity. Panel (b) depicts the effect of IT-SEZs on municipal nightlight intensity. Standard errors are clustered at the district level. Employment data based on the Economic Census for 1998, 2005 and 2013.

Figure B.10: Nightlights in event study for multi-product SEZs



Notes: Event study estimates for municipalities hosting multi-product SEZs, municipalities in 20-25km distance serve as controls. The figure plots the $\hat{\theta}_k$ as estimated from Eq.(3) following Callaway and Sant'Anna (2021). Endpoints are binned. Red lines indicate 95% confidence intervals. Standard errors are clustered at the district level.

B.3 Aggregate employment effects and relocation of economic activity

This appendix complements Section 5.2 in the main paper in two ways. First, we do a back-of-the-envelope calculation to obtain a rough idea about the magnitude of the aggregate employment effect of SEZs (in levels). Second, we offer robustness checks that explore whether and to what extent SEZs establish new economic activity or trigger relocation of economic activity in space. The two questions are intertwined as relocation of economic activity dampens the aggregate employment effect of the SEZ policy.

1. Back-of-the-envelope: Aggregate non-farm employment gain and aggregate relocation: In this subsection, we quantify the number of jobs that were established by SEZs in total within our sample frame. The analysis draws on our baseline estimates in panel (a) of Figure 4. They suggest that, for municipalities with a population below 500K, employment increased by 52%, 22%, and 16%, respectively, in SEZ-municipalities and municipalities in distance bins of 0-5km and 5-10km. Drawing on the average pre-treatment employment levels in SEZ-municipalities with less than 500K inhabitants in our sample of municipalities (3,139) and the indicated distance bins (574 and 439, respectively) and the total number of such municipalities per distance bin (152; 1,264 and 2,390), the aggregate effect of SEZs on municipalities within a 10km radius amounts to 575,598 additional workers ($= 0.52 \times 3,139 \times 152 + 0.22 \times 574 \times 1,264 + 0.16 \times 439 \times 2,390$).

We augment this number by the effects of SEZs on municipalities with a population of more than 500K, which are excluded from our baseline sample.[36] For these municipalities the estimated effect of SEZs on employment is smaller and estimated at 5% for SEZ-hosting municipalities, 7% for municipalities in a 0-5km distance and a small negative effect of -3% in municipalities in a 5-10km distance from SEZs. Again, considering the average pre-treatment employment levels in SEZ-municipalities with more than 500K inhabitants (666,796), the two closest distance bins (1,233,342 and 280,455, respectively) and the total number of such municipalities per distance bin (12; 4; 7), the aggregate effect of SEZs on municipalities within a 10km radius amounts to 680,102 additional workers.

Thus, overall employment in 10km radii around SEZs increased by about 1.25 million, which corresponds to an employment increase by 7.3% relative to the pre-treatment year 2005. Note that official statistics quantify the increase of employment within SEZs at 0.94 million over our period of study 2005-2013. Taken at face value, this suggests that 3/4 of the estimated net employment increase accrues within-SEZ municipalities and 1/4 of it reflects spillovers to surrounding regions (including SEZ municipalities themselves).[37]

In a second step, we use a back-of-the-envelope calculation to strengthen our argument in the main text that the observed estimates plausibly reflect the creation of new economic activity rather than job relocation in space. The results in Table 2 of the main text do not show any indication that the expansion of employment in SEZ areas correlates with declining employment paths in neighboring municipalities in further distance ($>$ 10km, which would serve as 'source jurisdictions' in case of job relocation). The point estimates are small and statistically insignificant.

For distance rings smaller than 30km, the coefficient estimates nevertheless turn out negative. To obtain a notion of the quantitative relevance of these point estimates, we take the estimated 7.3% employment increase within a 10km-radius (see above), and calculate

[36] We estimate the separate effect for large municipalities using interaction terms in a variant of Eq. (5).

[37] Figures are accessible via the Indian Export Promotion council: https://www.epces.in/facts-and-figures.php#hpgallery-6, last accessed: June 26th, 2022. Furthermore, one concern might be that SEZ-induced employment effects may systematically differ across municipalities of different size, which may potentially bias the specified aggregate employment response. Note that, if we split the set of municipalities with less than 500K inhabitants into four equally-sized bins and run our regression model separately in each subset of municipalities before aggregating, this yields very similar estimates for the aggregate employment effect (1.24 million new jobs).

the aggregate employment decrease across municipalities in 10-30km distance rings from SEZs as implied by the point estimates in the first row of Table 2. We again evaluate the estimated coefficients at the average pre-treatment employment (624; 370; 310 and 226) and account for the number of municipalities (4,178; 4,334; 4,788 and 5,524) for the 10-15km, 15-20km, 20-25km and 25-30km distance bin, respectively. The total job loss calculated for these jurisdictions is 16,524 jobs, which is thus minuscule relative to the aggregate employment gain in SEZ areas (1.25 million workers).

As a word of caution, note, however, that the aggregate employment response calculated above hinges significantly on the response determined for SEZs in larger urban areas. This response is more difficult to determine than the response of smaller municipalities (see our discussion in the main text) and involves more uncertainty. Note that even if we abstract from SEZ-related job creation in larger urban areas altogether, the number of relocated jobs is still small relative to aggregate employment creation in SEZ-areas, namely 2.9% ($= 16,524/575,598$). The bang-for-the-buck estimates in Section 7 change in turn. The costs per job created then are higher: 1,034,792 INR (17,118 USD in ppp per job) and the ratio of workers' wages to fiscal costs drops to 0.4.

2. Firm-level data. The data we use in the paper contains information about economic outcomes (e.g. employment), aggregated at the level of towns and villages. While this allows for a fine geographical resolution, information on firm-level characteristics is limited. To overcome this limitation to some extent, we constructed a firm-level dataset that offers more detailed information on the characteristics of firms located in SEZ areas.

To construct the dataset, we, first, retrieved the names of firms which are active in SEZs from various publicly available lists (e.g. SEZ-developer webpages and members directory of the export promotion council).[38] Second, we purchased the Prowess database compiled by the Centre for Monitoring of the Indian Economy (CMIE). Prowess contains detailed information on about 50,000 Indian firms, covering more than 70% of national industrial output from the organized sector, and it is widely used in empirical work (Goldberg et al., 2010; Stiebale and Vencappa, 2018; Barrows and Ollivier, 2021). Within this database, we identify SEZ firms through a *fuzzy matching* of firm names as appearing in the publicly available lists. With our procedure, we are able to identify 782 firms in the Prowess database that are active in SEZs. We believe that this data provides complementary information that is helpful in the context of our paper.

Prowess comes with two main drawbacks. First, it does not include disaggregated information on plant activity and plant locations (firm addresses are for entities' main location). The data is hence not well suited to model the spatial location of economic activity (contrary to the census data used in the main analysis). Second, the informal

[38] As an example, see here for the SEZs firm names in the members directors of the export promotion council on export oriented units and Special Economic Zones: https://www.epces.in/members-directory.php.

economy is not well represented in the Prowess data. As a convincing assignment of all (formal and informal) economic activity to a geographic entity is central for the credibility of our results, we cannot build on Prowess in the main empirical analysis, but the dataset is still helpful to generate additional insights.

Specifically, we use the data in two key ways in our analysis: First, we rely on the firm-level information to model key characteristics of SEZ firms (their export intensity, import intensity and external consultant fees), which shape firms' benefits from being active in an SEZ (see Appendix B.1 for details). Second, we use this data to augment the relocation analyses presented in the main text by assessing if firms relocate corporate activity within company groups towards SEZ areas. If relocation takes place from entities outside of the 50km radius, related relocation of corporate activity would not be captured in the relocation analysis presented in Section 5.2 of the main paper.

Specifically, we assess if entering an SEZ is associated with a reduction of economic activity at other locations of the same firm group outside of SEZ areas (defined as any group entity apart from the SEZ firm). The main analysis accounts for all firms, which belong to the same company group as the SEZ firm but are located outside of the 50km radius accounted for in our baseline analysis (where similar result patters emerge when we account for all non-SEZ firms in company groups with connections to an SEZ area, including entities within the 50km radius). The evolution of balance sheet items like sales, assets, profits, and the total wage bill is compared to firms in company groups without SEZ activity. Formally, we run the following regression:

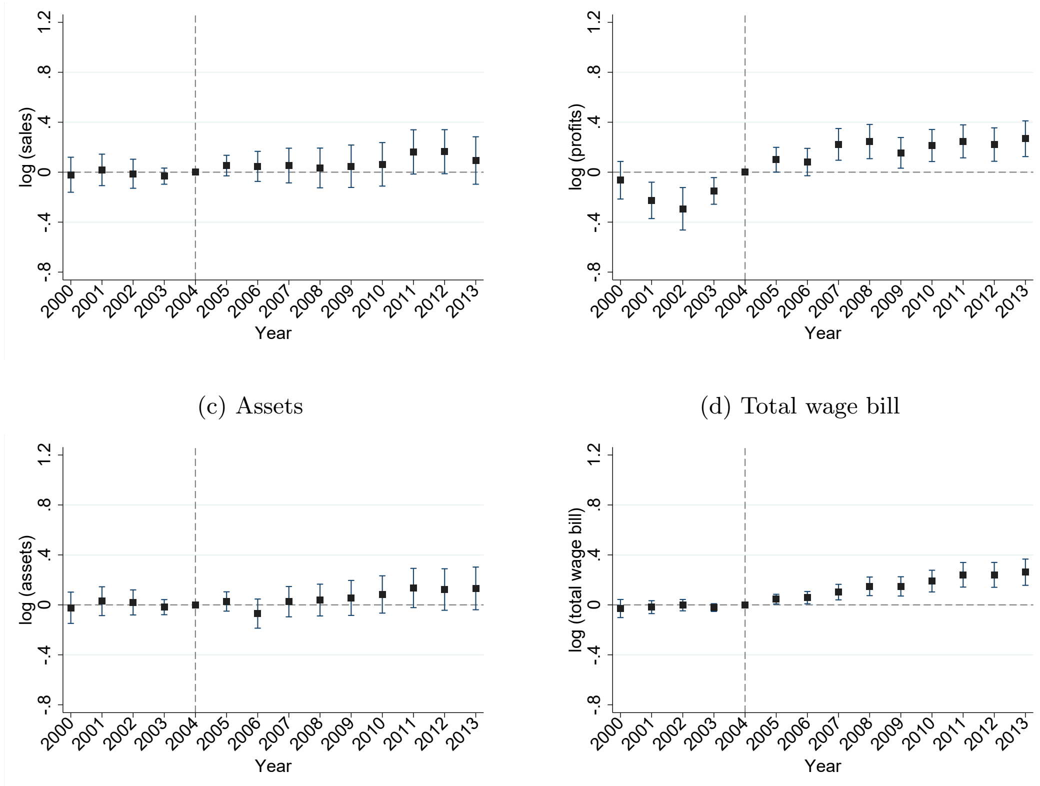
$$\ln(y_{it}) = \sum_{k=2000, k\neq 2004}^{2013} \theta_k \mathbf{1}[t=k] + \gamma_t + \alpha_i + \epsilon_{it}, \tag{7}$$

where y_{it} denotes balance sheet information of firm i in year t. α_i and γ_t denote firm and year fixed effects, respectively. The θ_ks capture differences in the outcomes of interest across treated firms (belonging to groups that enter an SEZ) to control firms (belonging to groups without SEZ connection) across time, accounting for the time frame from 2000 to 2013, where the pre-SEZ reform year 2004 serves as base category.

The results are presented in Figure B.11. The figure shows that firm outcomes emerged in parallel prior to the enactment of the SEZ policy. There is no indication for a drop in firm activity after companies entered SEZs at group locations outside of the SEZ area. This speaks against the notion that economic activity was shifted into SEZs across longer distances. On the contrary, the estimates point to an increase in economic activity at these locations after treatment, which is consistent with prior evidence, documenting that firm activity at different group locations are complements rather than substitutes (see e.g.

Desai et al., 2009, Becker and Riedel, 2012, Chodorow-Reich et al., 2024).[39]

Figure B.11: Intra-Group Relocation of Economic Activity (> 50km)



(a) Sales

(b) Profits

(c) Assets

(d) Total wage bill

Notes: The figure determines the impact of SEZ establishment on non-SEZ firms within the same company group, comparing firms in groups that establish entities in an SEZ with company groups that have no SEZ activity. The sample is restricted to firms that are located beyond 50km from the closest SEZ entity within the same group. Only geocoded firms are included. 95% confidence intervals are displayed.

B.4 Structural change

This appendix complements Section 5.3 in the main paper. First, we calculate the aggregate reduction in agricultural employment and extend the back-of-the-envelope calculation from Appendix B.3, comparing this reduction to the observed increase in aggregate non-farm employment (in levels). This allows us to determine the fraction of the non-agricultural employment gain that is sourced from workers, who were previously employed in agriculture. The decline of agricultural employment is also a relevant ingredient for the cost-effectiveness calculation in Section 7. Second, we provide evidence for pronounced employment gains in low-skilled service industries in SEZ areas and surroundings, which further supports the narrative that low-skilled workers transit from agriculture to non-farm

[39] If group locations are e.g. connected through input-output-linkages, expanding investment at one group location is associated with higher investments at other group locations. Equivalently, the cost reductions may imply that it becomes more attractive for multinational firms to operate in India, which might enhance real economic activity at Indian group locations inside and outside of SEZs.

sectors.

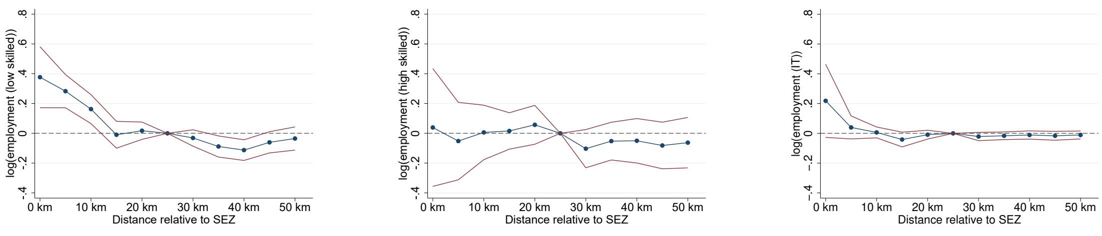
1. Aggregate decline in agricultural employment: In our baseline sample of municipalities with a population below 500K, agricultural employment decreased by 17%, 4%, and 5%, respectively, in SEZ-municipalities and municipalities in distance bins of 0-5km and 5-10km. Drawing on the average pre-treatment agricultural employment levels in SEZ-municipalities with less than 500K inhabitants in our sample of municipalities (777), the indicated distance bins (571 and 532, respectively) and the total number of such municipalities per distance bin (152; 1,264 and 2,390), the aggregate negative effect of SEZs on municipalities within a 10km radius amounts to 112,521 less agricultural jobs ($= -0.17 \times 777 \times 152 - 0.04 \times 571 \times 1,264 - 0.05 \times 532 \times 2,390$). To account for the effect in large municipalities, too, we estimate effects separately and follow the same aggregation procedure as in the base analysis. Note, however, that the estimated effects for this sample should be interpreted with caution as they are based on a small sample of large municipalities. The decrease in agricultural jobs in large municipalities amounts to 291,740 ($= -0.45 \times 31377 \times 12 - 0.68 \times 22916 \times 4 - 0.65 \times 13181 \times 7$). Overall, our back-of-the-envelope calculation suggests that SEZs reduced agricultural employment by 404,262 jobs. Comparing this figure to the estimated increase in non-agricultural employment from Appendix B.3, we find that around every third new non-agricultural job (32%) is sourced from the agricultural sector.

Note that similar findings emerge when we refine the analysis and allow for heterogeneity in the effect of SEZs on municipalities of different size. In particular, we again divide the sample of municipalities with less than 500,000 inhabitants into four equally sized subsamples according to population quartiles. We then reestimate our baseline model in these subsamples and rerun the aggregation exercise above for each of the four samples and for large municipalities in addition. We do so for non-agricultural employment as well as for agricultural employment. This leaves the ratio of the aggregate agricultural employment decrease and the non-agricultural employment increase unchanged, at 32.2%.

2. Characteristics of new employment. We also shed light on the type of jobs that emerged in and around SEZs. We turn to the Economic Census for this exercise, which contains detailed 3-digit industry codes. As the industry classification changed within our sample frame, we use the concordance tables provided by the Ministry of Statistics and Programme Implementation to harmonize the National Industry Classification (NIC) of 2008 – which is used in the Economic Census of 2013 – and the NIC codes of 2004 and 1987 – which is used in the Economic Censuses of 2005 and 1998. In cases of industry splits, we assign the industry code, which has a higher employment share according to the Economic Census of 2013. We draw on this data to classify industries in the service sector into low-skilled industries (e.g. restaurants) and high-skilled service industries (e.g. information technologies, communication, or management). The evidence is presented in Figure B.12. The figure suggests that employment in industries classified as 'low-skilled' increases pronouncedly, see panel (a). Employment in industries classified as 'high-skilled' shows small, but insignificant increase, in turn, see panel (b). An exception is employment in the IT-sector, which – albeit high-skilled – rises strongly after SEZ establishment, likely reflecting the importance of this worker group for SEZ activities. In sum, the evidence supports the narrative that the decline in (marginal) agricultural employment reflects that lower-skilled workers transitioned from the agricultural sector to lower-skilled service jobs (additionally to manufacturing).

Figure B.12: Service employment (high- vs. low-skilled)

(a) Low skilled (b) High skilled (excl. IT) (c) IT employment only



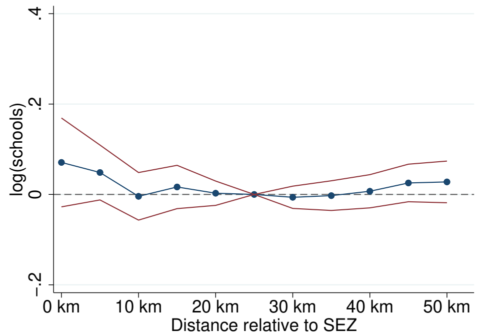
Notes: We characterize industries as low-skilled or high-skilled based on on the National Industry Classification (NIC) 2008 as follows: NIC codes IT: 581-639. NIC codes high skilled: 641-750. NIC codes low skilled: 451-563. The dots indicate the estimated parameters $\hat{\beta}_d$. Each subscript d refers to a distance on the horizontal axis, e.g. the coefficient at 0km refers to $d = 0$. Red lines indicate 95%-confidence intervals. Standard errors are clustered at the district level. Employment data are based on the Economic Census for 2005 and 2013.Red lines indicate 95%-confidence intervals.

B.5 Additional outcomes

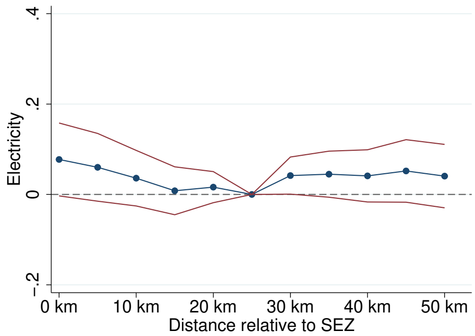
Local public goods. In this section, we explore whether the SEZ Act led to higher provision of local public goods, e.g. streets or electricity infrastructure, that benefited local residents (which was one goal of the SEZ policy, see Section 2). The population census allows us to shed some light on local public good provision. We observe the number of schools in each municipality and whether a municipality had access to any kind of electricity or to a paved road, respectively. Re-estimating Eq. (1) with these different dependent variables does not point to any SEZ-induced improvements in electricity and road access. The number of schools slightly increased in treated municipalities after SEZ establishment (relative to municipalities in further distance). This positive effect vanishes, however, when we normalize the number of schools on population size. Finally, we find no effect on local literacy rates, see Panel (d).

Figure B.13: SEZ effect on local infrastructure and literacy

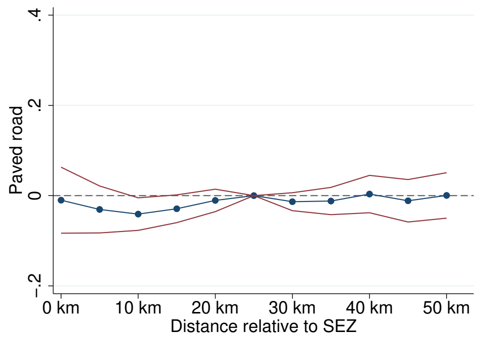
(a) Number of schools: 2001-2011



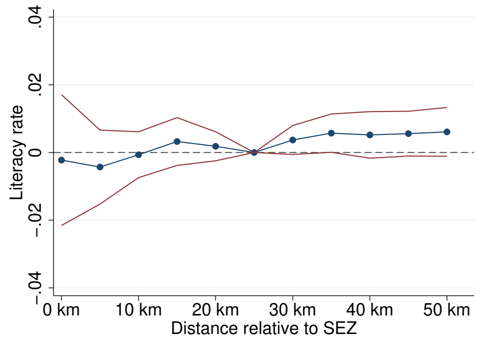
(b) Electricity: 2001-2011



(c) Paved road access: 2001-2011



(d) Literacy: 2001-2011



Notes: The dots indicate the estimates for $\hat{\beta}_d$ as estimated according to Eq. (1). Each d refers to a distance on the horizontal axis e.g. the coefficient at 0km refers to $d = 0$. Panel (a) depicts results for the number of schools. Panel (b) depicts results for electricity access. Panel (c) depicts results for paved road access. Panel (d) depicts the results for the literacy rate. Red lines indicate 95% confidence intervals. The standard errors are clustered at the district level. Data are based on the Population Census for the years 2001 and 2011. Hence, only municipalities that are within 50km of SEZs that became operational until 2011 are included.

Firm entry. We have shown in the main part of the paper that the SEZ Act led to more employment in SEZ-hosting and neighboring municipalities. This part complements these insights by exploring the extensive margin, that is the change in the number of firms through entry or exit. We show in Column (1) of Table B.3 that the policy led to a strong positive response at the extensive margin in SEZ-hosting municipalities and their neighbors up to 10km. The placebo regressions in Column (2) point to no differences in pre-treatment trends. We further document in Columns (3)-(6) that the increase in the number of firms was primarily driven by male firm ownership and by small firms.

Table B.3: SEZ effect on firm entry

Distance bins	(1) *Total*	(2) *Placebo*	(3) *Male*	(4) *Female*	(5) *Large*	(6) *Small*
0km	**0.296*** **	**-0.100**	**0.390*** **	**0.094**	**0.063**	**0.314*** **
	(0.112)	(0.106)	(0.114)	(0.147)	(0.219)	(0.116)
0-5km	**0.204*** **	**0.002**	**0.260*** **	**0.108**	**-0.176**	**0.210*** **
	(0.045)	(0.061)	(0.057)	(0.092)	(0.107)	(0.045)
5-10km	**0.142*** **	**-0.024**	**0.176*** **	**0.099**	**-0.049**	**0.144*** **
	(0.035)	(0.059)	(0.044)	(0.077)	(0.123)	(0.037)
10-15km	**0.056**	**0.001**	**0.078**	**0.009**	**-0.156**	**0.059**
	(0.049)	(0.040)	(0.053)	(0.052)	(0.101)	(0.051)
15-20km	**-0.009**	**-0.010**	**0.032**	**-0.001**	**-0.032**	**-0.010**
	(0.027)	(0.028)	(0.030)	(0.046)	(0.058)	(0.028)
20-25km	–	–	–	–	–	–
25-30km	**-0.005**	**0.023**	**0.006**	**-0.037**	**-0.111** **	**-0.008**
	(0.025)	(0.028)	(0.033)	(0.037)	(0.056)	(0.025)
30-35km	**-0.058* **	**0.047**	**-0.057**	**-0.009**	**-0.094**	**-0.060* **
	(0.032)	(0.034)	(0.038)	(0.048)	(0.081)	(0.033)
35-40km	**-0.056* **	**0.027**	**-0.063**	**-0.007**	**-0.144* **	**-0.058* **
	(0.032)	(0.030)	(0.039)	(0.053)	(0.079)	(0.033)
40-45km	**-0.024**	**-0.002**	**-0.034**	**0.025**	**-0.125* **	**-0.025**
	(0.035)	(0.035)	(0.042)	(0.057)	(0.068)	(0.036)
45-50km	**-0.008**	**-0.044**	**-0.015**	**0.031**	**-0.183** **	**-0.009**
	(0.037)	(0.037)	(0.042)	(0.060)	(0.072)	(0.037)
Observations	92,926	84,120	85,216	36,888	16,712	92,828
R-squared	0.905	0.900	0.883	0.841	0.842	0.904
Municipality fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: Regression results from Eq. (1) with the number of different types of firms as the dependent variable. Column (1) reports the estimated effects on total firm count. Column (2) reports the placebo results. Columns (3)-(6) report the results for male owned-, female owned-, large- and small firm count. Data are based on the Economic Census for the years 1998, 2005 and 2013. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.