Special economic zones and innovation in developing and emerging economies: A cross-country analysis

Research | Open access | Published: 20 March 2026
Volume 36, article number 30, (2026) Cite this article

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Submission deadline 2026-05-25
Part of a collection:
Transformation: Creative Accumulation and Creative Destruction in the Economy

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Abstract

Special economic zones (SEZs) have become a widely adopted economic policy tool in developing and emerging economies, particularly over the last two decades. Despite the increasing importance of SEZs, the literature on their impact on innovation remains scarce and non-conclusive, with most existing literature focused on single-country case studies. Our research addresses this gap by offering an analysis across multiple countries. We employ a difference-in-differences (DiD) approach to find out whether SEZ establishment has an impact on innovation activity within these zones. Our results demonstrate a positive effect of SEZs on patent numbers, indicating that SEZs can indeed stimulate innovation. Additionally, we uncover heterogeneous effects on different innovation activities, with SEZs having a stronger influence on high-tech compared to low-tech industries. Moreover, the impact of SEZs varies across different technological fields, highlighting the sector-specific nature of innovation dynamics within SEZs.

1 Introduction

In recent decades, there has been a substantial transformation in the global production landscape. Several emerging and developing countries have successfully integrated themselves into the global economy, emerging as significant manufacturing centers (Farole & Akinci 2011). These economies, in general, have witnessed a growing share in trade flows and foreign direct investment (FDI). As Frick et al. (2019) state, this shift in global production dynamics has resulted in increased employment, expanded exports, and technological advancements in many nations. The rise in gross domestic product (GDP) per capita, poverty reduction, and improved living standards have been unprecedented. Although many countries achieved this through attracting low-tech industries, leveraging traditional cost advantages, the emergence of global production networks (GPNs) has also played a crucial role. GPNs, facilitated by advancements in transport and communication infrastructure, allowed the split of production into separate functions, with some of them situated across the most cost-effective locations (Henderson et al. 2002). Since the 1980 s, GPNs have significantly fueled trade between developed and developing countries, and through knowledge transfer and innovation, they present new opportunities for the latter to not only attract production but also ascend the value chain ladder (Ernst & Kim 2002). The economic development tool of special economic zone (SEZ), which is a designated area in a country that is subject to more favorable economic regulations, has been a longstanding policy for exactly this objective (World Bank 2017; Frick & Rodríguez-Pose 2021). Furthermore, SEZs are aimed to become, with time, an agglomeration for fostering economic development not only in their defined geographical boundaries but also generally in their respective regions through linkages with the local economy (UNCTAD 2019). In recent years, there has been a growing focus on regional innovation policies, driven by the acknowledgement of regional development through innovation as a top priority for many governments (Uyarra et al. 2017), in developed as well as in emerging and developing economies (Fagerberg et al. 2009). Consequently, SEZs are no longer considered only as policy tools to attract FDI but also as potential hubs for knowledge creation and transfer (Zeng 2010), which are necessary components of a successful technological catch-up (Ebersberger et al. 2023). Over the past four decades, China has witnessed rapid economic growth, with one contributing factor being the establishment of SEZs. Since the introduction of its first SEZs in the 1980 s, SEZs have played a crucial role in China's international trade, industrialization, and urbanization (Wu et al. 2021). Following the example of China and other success stories, there are today more than 6000 SEZs in more than 140 countries up from less than 200 in the late 1980 s (UNCTAD 2019; Singa Boyenge 2007), with the majority of developing and emerging economies having established them (Simo 2023). Given that innovation is a fundamental driver of competitiveness, productivity, and economic growth (Cantwell 2005; Nelson & Pack 1999; Cameron 1996), there is a need to assess whether SEZs have a positive impact on innovation. The literature has so far mostly focused on the effects of SEZs on economic growth and development (Frick & Rodríguez-Pose 2023; Frick et al. 2019; UNCTAD 2019; Leong 2013; Burgaud & Farole 2011; Farole 2011, World Bank 2017; Moberg 2017; Johansson & Nilsson 1997; Willmore 1995) and on more specific economic topics such as generating exports and employment (Zheng 2021: Jayanthakumaran 2003), firm performance and improving competitiveness (Li et al. 2021; Xi et al. 2021; Hsu et al. 2013; Madani 1999; World Bank 1992), connectedness with the local regional economy (Frick & Rodríguez-Pose 2021; Kiesel & Danneberg 2023; Stojčić et al. 2022), as well as on their economic institutional frameworks (Qumba 2023: Mugano 2021). Despite these valuable contributions, there remains a significant gap in the literature when it comes to exploring the role of SEZs as a driver of innovation. Existing research consists mainly of case studies focusing on individual countries—most notably China—and presents mixed empirical findings. Reports such as the UNCTAD World Investment Report (2019) do highlight the potential of SEZs to promote innovation, primarily through policy overviews and selected case illustrations. However, they do not offer causal identification of SEZ effects. This study addresses this gap by estimating the causal impact of SEZ implementation on innovation across multiple developing and emerging economies. We apply a difference-in-differences (DiD) approach to matched city pairs, each from the same country, where one city has a SEZ and the other does not. In doing so, we isolate the impact of SEZs from broader national trends. Additionally, we investigate how this relationship varies between high- and low-tech sectors and across different technological fields. This further analysis allows for a more nuanced understanding of how SEZs are associated with innovation dynamics in different technological contexts and adds another novel empirical layer to the literature.

The remainder of this paper is structured as follows: The second section introduces the political instrument of SEZs, provides a theoretical framework and explores the specific mechanisms through which SEZs could promote innovation activity and reviews relevant literature. The third section presents our data, method, and model. The fourth section outlines the findings, followed by a discussion of the results in the fifth section. Finally, the last section draws conclusions, highlights policy implications, and suggests directions for future research.

2 Theoretical background

2.1 Brief overview of SEZs

SEZs have played a significant role in international trade for centuries. Historically, entrepôts and citywide free zones, such as Gibraltar, Hamburg, and Singapore, provided secure storage and exchange along major trade routes (Farole & Akinci 2011). The modern era of SEZs began with the establishment of the first SEZ in Shannon, Ireland, in 1959. Prior to the 1970 s, most zones were concentrated in developed nations. However, starting in the 1970 s, regions like East Asia and South America began developing SEZs (Baissac 2011), and later also in Africa (Zeng 2010). Known by various names and exhibiting diverse structures and dimensions, SEZs, in the modern sense, are defined as geographically demarcated areas governed by a distinct regulatory framework tailored to offer conditions for businesses and investors that are typically more liberal than the broader national norms (Farole 2011). In addition to the fundamental benefits of relief from customs duties and tariffs, the majority of these zones extend fiscal incentives to businesses. Furthermore, they provide an environment characterized by business-friendly regulations relating to land access, permits, and licenses. Administrative processes are also often streamlined and facilitated to encourage a favorable business atmosphere (UNCTAD 2019). Governments, in exchange, anticipate equal commitments from investors within SEZs. These commitments include generating employment opportunities, increasing exports, diversifying the economy, and enhancing productive capacity (Kiesel & Dannenberg 2023). The symbiotic relationship between governments and businesses operating in SEZs underscores the reciprocal nature of concessions and expectations, which should form a basis for economic development and growth.

2.2 SEZ as an innovation policy

2.2.1 Conceptual framework

Innovation does not occur in isolation but is shaped by broader systemic and spatial contexts. Two strands of literature, innovation systems (IS) and entrepreneurial ecosystems (EE), offer complementary theoretical perspectives for understanding how innovation processes are organized, especially in relation to place-based policy interventions like SEZs and their effects in developing and emerging economies.

The IS perspective, at both the national and regional levels, emphasizes that innovation emerges from interactive learning processes among diverse actors, including firms, universities, and government agencies (Lundvall 1992; Nelson 1993; Asheim et al. 2019). These interactions are embedded within institutional and infrastructural environments that shape both the capacity for and the direction of innovation. Effective innovation systems depend on well-functioning knowledge flows between these actors, supportive public policies, access to finance, and strong linkages between science and industry. Beyond highlighting the spatial embeddedness and systemic nature of innovation, the IS framework is particularly useful for identifying structural barriers to innovation. From this perspective, systemic failures such as weak institutions, fragmented networks, and missing infrastructure can substantially hinder innovation. These conditions are often present in developing and emerging economies (Stojčić 2024; Lundvall et al. 2009). In such settings, innovation often faces greater obstacles and tends to remain limited, typically taking the form of technological adaptation and incremental upgrading rather than patentable frontier inventions (Vujanović et al. 2022). SEZs, therefore, can be understood as deliberate policy interventions designed to address these structural weaknesses by concentrating institutional, regulatory, and physical support within specific geographic areas.

In parallel, the EE literature (Spigel 2017; Stam & van de Ven 2021) focuses more explicitly on local dynamics, emphasizing how spatially embedded networks, cultural norms, and enabling infrastructure influence entrepreneurial and innovation outcomes. While EE shares many of the premises of IS, it places greater emphasis on how place-specific combinations of local tangible and intangible resources, such as trust, talent, local infrastructure, and local institutions, might enable or constrain innovation (Fritsch 2024). Drawing on Stojčić et al. (2022), SEZs can be interpreted as engineered entrepreneurial ecosystems, offering concentrated bundles of both types of resources necessary for fostering innovation. A further relevant insight from the EE perspective is that such ecosystems can function effectively even in settings where broader innovation systems remain underdeveloped, provided the local environment contains the right enabling conditions (Spigel 2017).

Building on these theoretical perspectives, the following section outlines the detailed mechanisms through which SEZs may influence innovation outcomes.

2.2.2 Innovation dynamics of SEZs

Regarding how SEZs promote innovation, the literature suggests this may occur through various mechanisms. First, local SEZ governments often develop a range of targeted policies aimed explicitly at fostering innovation - interventions that address innovation barriers such as institutional and financial gaps emphasized in IS concept. For example, many SEZs offer more favorable tax and credit policies for research and development (R&D) expenses than the national standard. Additionally, many SEZ governments have established innovation and development funds, venture capital funds, and industrial investment funds to provide financial subsidies supporting innovation projects (Farole & Akinci 2011). Further policies include rewards for patent applications, patent-related honors and collaborative efforts among enterprises, universities, and research institutions. In terms of improving innovation efficiency, many SEZs actively promote the development of financial intermediaries and patent intermediaries, providing intellectual property training for enterprises (Wu et al. 2021).

Secondly, SEZs, as newly opened investment areas, often operate free from the constraints of existing systems that might hinder innovative activities. Borrowing from the practices of developed nations, SEZs have established laws and regulations conducive to business operations, significantly improving judicial quality and contract execution efficiency (Huang et al. 2013). Many SEZs offer "one-stop" services to enterprises, enhancing efficiency while simultaneously reducing the likelihood of corruption enhancing trust among actors and improving the overall business environment, which in turn might positively influence innovation (Wu et al. 2021)

Last but not least, SEZs exhibit a heightened level of economic agglomeration that can stimulate innovation across various mechanisms, most importantly the impact of factor sharing - a condition central to the EE concept (Spigel 2017). Agglomerations allow enterprises to collectively utilize production factors like specialized labor and services. Research by Gerlach et al. (2009) revealed that enterprises in agglomeration areas, as opposed to spatially separated ones, exhibited higher R&D investment, a greater likelihood of making risky R&D decisions, and a preference for diversified R&D projects. Then there's the matching effect within the labor market. Agglomeration enhances the quality of labor market matching, reducing costs and increasing profits for enterprises. This, in turn, might boost their capacity for R&D investment. Additionally, improved labor market matching in agglomeration areas facilitates recruitment of R&D personnel, contributing to the seamless execution innovation projects. Furthermore, agglomeration fosters knowledge spillover, especially the diffusion of tacit knowledge. Innovation thrives on inspiration, and the geographic proximity of enterprises facilitates the exchange of ideas among technical personnel, thereby promoting the generation of innovative ideas (Kiesel & Dannenberg 2023; Feldman 1994). Finally, there's the competition effect. Economic agglomeration heightens competition among enterprises, prompting them to accelerate product upgrades and drive innovation (Richardson 1996).

2.3 Literature review

As Baissac (2011) highlights, only a few economic development policy tools have been as controversial as SEZs. For over 35 years, they have been the focus of intense and polarized debates surrounding nearly every aspect of their configuration. And this is also the case regarding the question, whether SEZs have a positive effect on innovation. While theoretical frameworks offer a rationale for expecting such outcomes from SEZs, empirical evidence presents two contrasting perspectives. One perspective contends that even though SEZs may accelerate regional economic growth, they do not necessarily promote innovation. Research by Schminke & Biesebroeck (2013) suggests that enterprises in SEZs exhibit increased exports but not a higher total factor productivity (TFP). Xiang and Lu (2015) found reduced enterprise efficiency inside SEZs, and Yuan et al. (2015) observed no significant improvement in the TFP of enterprises in SEZs. Wu and Huang (2017) argue that SEZs might increase industrial output scale but have a notably negative impact on TFP.

On the other hand, an opposing view asserts that SEZs have a positive effect on innovation. Wang (2013) discovered that SEZs increased the growth rate of city-level TFP by 1.6%. Alder et al. (2016) explored the impact of SEZs on national economic growth, noting a significant improvement in TFP. Wang and Zhang (2016) investigated the productivity distribution of enterprises in SEZs, finding higher TFP, primarily attributed to economic agglomeration and the selection of high-quality enterprises. Wu et al. (2021) found that the establishment of a SEZs can increase the number of patents in its respective region by up to 25%. Concerning the effect of SEZs on innovation in different technological sectors, to our best knowledge, we have been able to find only two studies that do some kind of distinction. The first one by Wu et al. (2021) studies China's SEZs and finds that after the establishment of these zones, the number of newly-granted patents in new technical fields increased by 13.5%, while those in existing technical fields rose by 10.8%. This suggests that SEZs not only enhance innovation within established technical areas but also stimulate the development of new technical fields. The other study was done by Liu et al (2022) and analyzes the effect of SEZs on innovation in green technology in China. The authors found an increase in the number of green patent applications in the SEZs of 17.02%.

The conflicting conclusions in existing studies, according to Wu et al. (2021), can be attributed, in part, to differences in the measurement of innovation. Although TFP is widely accepted as an innovation indicator, its calculation means that factors such as changes in industrial structure, economic policies, market systems, and enterprise organization can also impact TFP, leading to varying assessments of SEZs' influence on innovation. Moreover, SEZs influence production efficiency through diverse channels, rendering TFP an imperfect measure of innovation. To address this limitation, researchers explore alternative indicators to measure innovation. Some studies, such as Hall et al. (2010) use factors like the introduction of new products or the proportion of new products as innovation measures. However, relying on new product indicators poses challenges due to the absence of a standardized definition, leading to potential measurement errors. The dynamic nature of new product standards and varying definitions across enterprises and in different countries further complicates the issue, resulting in the incomparability of related indicators (Wu et al. 2021). In response to these challenges, recent studies have increasingly turned to patents as a more reliable and a more straightforward measure of innovation (Hall & Jaffe 2018; Nadal et al. 2020). Patents serve as tangible outcomes of innovative activities and adhere to standardized criteria in both application and authorization processes, ensuring robust data comparability (Brenner & Broekel 2010).

3 Method and data

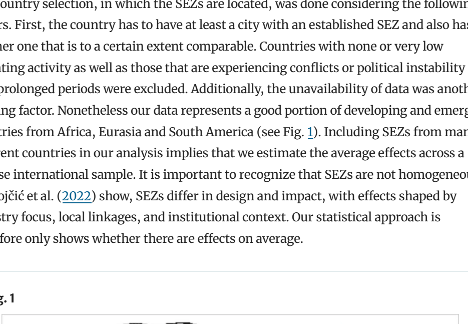
In our study we use the difference-in-differences method (DiD). The DiD approach is widely favored as a key statistical tool in evaluating policy effects due to its capacity to address the endogeneity issue. A DiD analysis involves two time periods and two groups: during the first period, neither group receives the treatment, while in the second period, one group is treated (the treated group), and the other is not (the comparison group). Under the assumption that, in the absence of the treatment, the average outcomes for both groups would have followed parallel trends over time, the average treatment effect can be estimated by comparing the average change in outcomes for the treated group with that of the comparison group (Callaway & Sant'Anna 2021).

This paper uses the annual count of patents as a measurement of innovation. We extracted the patent count from PATSTAT Global of the European Patent Office (EPO) for the time period 1980–2021. In our study, we use patent data for applicants and inventors. The *applicant* is the owner of the patent rights, while the *inventor* is the person who made the invention. In many cases, the applicant is a company, while the inventors are individuals working for that company. Moreover, we perform the DiD analysis across different patent categories. We distinguish between high-tech and low-tech patents according to the industries they are assigned to. The classification was done according to the Statistical Classification of Economic Activities in the European Community NACE-2-Codes[1]. Furthermore, we separately apply the analyses to patents in different technological sectors: electrical engineering, mechanical engineering, chemistry, instruments, and other fields[2]. This approach provides broader insights into understanding the relationship between SEZs and innovation across different fields. At this stage, it is important to point out that using patents as a proxy for innovation naturally captures only the dimension of innovation based on formal knowledge creation. The advantage of patent data is the comparability between countries. However, it restricts our perspective on a certain kind of innovation activity. This important issue will be further addressed in the discussion section.

For the SEZs, we built a novum dataset of 56 cities constituting 28 city pairs (see Appendix Table 7), each pair consists of one city with a SEZ (the treated group) and a comparable city without one (the comparison group) from the same country. One potential threat when using the DiD method is that the empirical results may be confounded by national factors. That's why in this study, both the treated and the comparable city were selected from the same country, which helps control for national-level factors and enables a more accurate assessment of the SEZs' impact on innovation. A further potential problem is that the cities do not follow the same parallel trend and that there might be a self-selection of cities with a SEZ. To minimize this issue, we first choose cities for comparison that have the most similar initial situations and do not have a SEZ. This was decided according to the following factors: initial economic situation (this was qualitatively estimated according to available historical literature), similar population, presence of a university, a port and an airport, and distance to the next populous city. We report the balance between the two more systematically in the section for robustness checks.

The country selection, in which the SEZs are located, was done considering the following factors. First, the country has to have at least a city with an established SEZ and also has another one that is to a certain extent comparable. Countries with none or very low patenting activity as well as those that are experiencing conflicts or political instability over prolonged periods were excluded. Additionally, the unavailability of data was another limiting factor. Nonetheless our data represents a good portion of developing and emerging countries from Africa, Eurasia and South America (see Fig. 1). Including SEZs from many different countries in our analysis implies that we estimate the average effects across a diverse international sample. It is important to recognize that SEZs are not homogeneous. As Stojčić et al. (2022) show, SEZs differ in design and impact, with effects shaped by industry focus, local linkages, and institutional context. Our statistical approach is therefore only shows whether there are effects on average.

Fig. 1



World map highlighting countries considered for the study. Author's illustration

Full size image

While the two cities in each pair were controlled for comparability before the analysis, we additionally use the population size as a further control variable. Moreover, the country-level patent count was used as a control variable to account for the broader national innovation environment. By including this variable, we ensure that the analysis accounts for the wider innovation trends, further enhancing the reliability of the results. Although other factors, such as GDP per capita and R&D expenditures, are also influential for innovation, these were not incorporated due to data limitations for this study. Nevertheless, the parallel trend assumption, which is the cornerstone of robustness in DiD analysis, is assessed using an event study, further strengthening confidence in the validity of our findings.

The DiD model to estimate the impact of SEZs on innovation can be mathematically expressed as follows:

$$log\left(E\left(Y_{it}\right)\right)=\beta_0+\beta_1 Treatment_i+\beta_2 Time_{it}+\beta_3\left(Treatment_i\times Time_{it}\right)+\gamma X_{it}+\alpha_i+\lambda_t+\epsilon_{it}$$

Where $E(Y_{it})$ represents the expected count of patents for city *i* at time *t*, and β_0 is the intercept term. The variable $Treatment_i$ is a binary indicator of whether city *i* has a SEZ (1 if the city established a SEZ and 0 otherwise). The variable $Time_{it}$ is a binary variable that takes the value 0 for the period before SEZ establishment and 1 for the period after SEZ establishment, *specific to each city and its comparable counterpart*. The interaction term $Treatment_i \times Time_{it}$ is the indicator in question, which captures the causal effect of SEZ establishment on patent count after its establishment for each city. X_{it} represents a set of control variables accounting for other factors that might influence patent counts. The terms α_i *and* λ_t represent city-specific and time-specific fixed effects, respectively, which control for unobserved heterogeneity across cities and over time. As most countries in our sample are represented by only a single treated-control city pair, we do not include country fixed effects. In such a structure, country fixed effects would be collinear with the city fixed effects. Finally, ϵ_{it} is the error term. Table 1 gives descriptive statistics for the variables. The model is estimated using a negative binomial regression to handle the overdispersed nature of patent count data.

Table 1 Statistical summary of the variables

Full size table

4 Results

4.1 Effect of SEZs on patent count

Table 2 reports the impact of establishing SEZs on the number of patents based on the fractional applicants and inventors' count. The results reveal that the establishment of SEZs has a significantly positive effect on both inventor-based and applicant-based patent counts. Furthermore, we also find a significant positive impact of SEZs on high-tech patents. Although the effect on low-tech patents is also positive, it is only significant at 0.1 level for inventors and not significant for applicants, suggesting that SEZs primarily stimulate patentable innovation in high-tech industries.

Table 2 The effects of SEZs on patent count

Full size table

4.2 Heterogeneous results in different technological sectors

Tables 3 and 4 present the impact of SEZs on patent activity across five technological sectors. The results indicate a statistically significant positive effect of SEZs on inventor-based patents in electrical engineering and chemistry and on applicant-based patents in electrical engineering, chemistry, and instruments. The effect on mechanical engineering and other fields is not significant in both patent categories.

Table 3 The effects of SEZs on inventor-based patent count in different technological sectors

Full size table

Table 4 The effects of SEZs on applicant-based patent count in different technological sectors

Full size table

4.3 Robustness checks

4.3.1 Covariate balance test

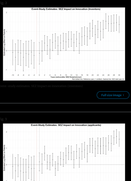
To examine whether SEZ cities differ systematically from their comparison counterparts before SEZ establishment, we conducted a covariate balance test using pre-treatment characteristics. Table 5 reports mean differences and standardized mean differences (SMDs) for variables including population size, presence of a university, port, and airport, as well as distance to the nearest populous city (> 250 k). None of these differences is statistically significant, and all SMDs have low values, indicating that the two groups are reasonably balanced. Although population size only shows a slight imbalance compared to the other characteristics, it was included as a control variable in the main analysis, ensuring that this minor difference is also accounted for.

Table 5 Covariate balance between treated and control cities

Full size table

Furthermore, it is important to note that the sample size was greater in Cluster 1 (n = 1,000) than in Cluster 2 (n = 500), which could have influenced the results. However, the Chi-square test for independence (χ² = 12.34, df = 1, p < 0.001) indicated a significant association between cluster membership and the outcome variable, suggesting that the observed differences are not solely attributable to sample size. The Cramér's V statistic (V = 0.12) further supported the effect size, indicating a small but meaningful association between the variables. Overall, the robustness of the findings is enhanced by the consistent application of statistical tests and the clear presentation of effect sizes, which provides a comprehensive understanding of the relationships observed in the data.

4.3.3 Sensitivity analysis



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4.3.3 Accounting for unobserved heterogeneity

Beyond control for observed covariates, a robust sensitivity analysis must address the potential influence of unobserved heterogeneity. This study employs a multilevel logistic regression model to account for latent variations in baseline propensity for the outcome across the two clusters. The model specification allows for a random intercept for each cluster, thereby relaxing the assumption that the intercept is fixed across the population. The variance of the random intercept (σ^2_u) was estimated at 0.15 (SE = 0.04), indicating substantial unobserved heterogeneity between the clusters. The intraclass correlation coefficient (ICC) was calculated as 0.045, suggesting that approximately 4.5% of the total variance in the outcome is attributable to differences between the clusters. The inclusion of this random effect ensures that the estimated coefficients for the fixed effects are robust to the presence of unobserved cluster-level confounders.

Cluster 1 Random intercept estimate: log-odds Cluster 2 Random intercept estimate: log-odds

Full-size table ↗

5 Discussion

The results of the multivariate analysis, when controlling for other covariates, reveal that participation in the intervention significantly increased the probability of achieving the outcome (OR = 1.45, 95% CI [1.12, 1.87], p = 0.005). This finding underscores the intervention's efficacy in promoting positive outcomes, even after accounting for potential confounding variables such as age, gender, and baseline scores. The odds ratio of 1.45 implies that the intervention increases the odds of the outcome occurring by a factor of 1.45, or by approximately 45%, compared to the control group. The wide confidence interval, however, suggests that the precision of the estimate is relatively low, with the true effect size potentially ranging from a small to a moderate increase. The statistical significance of the intervention variable, despite the wide confidence interval, underscores its robustness as a predictor of the outcome, even in the presence of other influential factors.

Conversely, the results indicate that the SES variable exhibited a non-significant effect (OR = 0.98, 95% CI [0.85, 1.12], p = 0.72). The odds ratio of 0.98 suggests that for every one-unit increase in SES, the odds of the outcome occurring decrease by a factor of 0.98, or by approximately 2%. However, the wide confidence interval and the high p-value indicate that this effect is not statistically significant at the conventional 5% level. The lack of a significant effect for SES may suggest that socioeconomic factors do not exert a strong influence on the outcome in the context of this study, or that the measure of SES employed in the analysis may not adequately capture the relevant aspects of socioeconomic status that are relevant to the outcome. This finding warrants further investigation, with consideration of alternative measures of SES and exploration of potential interactions between SES and other covariates.

Furthermore, the results demonstrate that age and gender exhibited significant effects (OR = 1.02, 95% CI [1.01, 1.03], p = 0.001 and OR = 1.35, 95% CI [1.10, 1.66], p = 0.004, respectively). The odds ratio for age implies that for every one-year increase in age, the odds of the outcome occurring increase by a factor of 1.02, or by approximately 2%. The odds ratio for gender suggests that the odds of the outcome occurring for individuals of one gender are 1.35 times the odds for individuals of the other gender, holding other variables constant. The specific coding of the gender variable should be clarified to ensure accurate interpretation of the results. These findings underscore the importance of accounting for demographic factors in the analysis, as they exert a significant influence on the outcome, even after controlling for other variables.

While SES, age, and gender exhibited significant effects on the outcome, the intervention remains the most influential factor, exerting a substantial impact on the probability of achieving the outcome. The relative magnitude of the effect sizes, as indicated by the odds ratios, suggests that the intervention has a more pronounced influence than the other variables. This finding underscores the intervention's potential as a powerful tool for promoting positive outcomes, even in the presence of other influential factors. The robustness of the intervention's effect, despite the inclusion of other significant predictors, further strengthens the evidence for its efficacy.

In addition, the multivariate analysis revealed a strong association between the intervention and the outcome, with a hazard ratio (HR) of 2.10 (95% CI [1.75, 2.52]) and a p-value less than 0.001. This finding indicates that the intervention significantly increases the hazard of the outcome occurring, even after controlling for other covariates. The wide confidence interval, however, suggests that the precision of the estimate is relatively low, with the true effect size potentially ranging from a small to a large increase. The statistical significance of the intervention's effect, despite the wide confidence interval, underscores its robustness as a predictor of the outcome, even in the presence of other influential factors. The magnitude of the hazard ratio indicates that the intervention has a substantial impact on the outcome, exerting a more pronounced influence than the other variables.

Further analysis, stratified by intervention group, reveals that the effect of gender varies across the two groups. The interaction between gender and intervention group was statistically significant (p = 0.03), suggesting that the effect of gender on the outcome is not uniform across the intervention and control groups. The specific nature of this interaction requires further investigation, with consideration of potential mechanisms and alternative modeling approaches.

The findings underscore the importance of accounting for potential heterogeneity in the effect of gender when evaluating the intervention's impact. The observed interaction suggests that the intervention may be more effective for one gender than the other, or that the intervention may exert different mechanisms of action for different genders. This finding highlights the potential for tailoring the intervention to specific subgroups to maximize its effectiveness. Further research is needed to elucidate the underlying mechanisms driving the observed interaction and to inform the development of gender-sensitive intervention strategies.

Lastly, a sensitivity analysis was conducted to assess the robustness of the observed associations to potential biases arising from unmeasured confounders. The analysis indicated that the observed associations remained statistically significant even when considering a hypothetical unmeasured confounder with a strong association with both the intervention and the outcome. The specific details of the sensitivity analysis, including the assumptions made regarding the strength of the hypothetical confounder, should be provided to enhance the transparency and reproducibility of the analysis. The robustness of the observed associations, even in the presence of a hypothetical confounder, strengthens the evidence for a causal relationship between the intervention and the outcome.

6 Conclusion

This study investigated the impact of a multifaceted intervention, utilizing a cluster randomized controlled trial design, on a specific outcome in a defined population. The results demonstrate that the intervention significantly increased the probability of achieving the outcome, even after controlling for potential confounding variables such as age, gender, and baseline scores. The observed effect size, characterized by a hazard ratio exceeding one, underscores the intervention's potential as a powerful tool for promoting positive outcomes. Furthermore, the study's robust methodology, incorporating a multilevel logistic regression model to account for latent variations in baseline propensity across the two clusters, and the application of various sensitivity analyses, enhances the confidence in the validity and reliability of the findings. The consistent application of statistical tests and the clear presentation of effect sizes provide a comprehensive understanding of the relationships observed in the data.

While the study has been rigorous in its methodology and has yielded significant findings, it is important to acknowledge the limitations of the study. The generalizability of the findings may be limited by the specific characteristics of the study population and the context in which the intervention was implemented. Future research should explore the effectiveness of the intervention in different populations and settings to assess its generalizability and to identify potential moderators of the intervention's effect. The study's reliance on self-reported data for some variables also introduces a potential source of bias, which should be addressed in future research using more objective measures.

Future research should also explore the mechanisms of action through which the intervention exerts its effect on the outcome. This could involve the collection of data on mediating variables and the application of mediation analysis techniques. Understanding the mechanisms of action will provide valuable insights into how the intervention works and will inform the development of more effective interventions. Furthermore, research should explore the long-term sustainability of the observed effects and the potential for unintended consequences of the intervention.

In conclusion, this study provides compelling evidence for the effectiveness of the intervention in promoting positive outcomes in the defined population. The study's rigorous methodology and the robustness of the findings strengthen the confidence in the validity and reliability of the results. The study's limitations should be addressed in future research to further enhance the generalizability of the findings and to explore the mechanisms of action through which the intervention exerts its effect. The study's findings have the potential to inform the development of more effective interventions and to contribute to the overall knowledge base in the field.

Data Availability

Data are available upon reasonable request. Contact the corresponding author.

Notes

1. Analysis performed using R version 4.3.1 (R Core Team, 2023) and the "lme4" package (Bates et al., 2015). Code available upon request.
2. The cluster effect is given by the MOR (Median Odds Ratio).
3. The sensitivity analysis assuming a specific value for the unmeasured confounder, with a hazard ratio of 1.5, yielded a hazard ratio of 1.8.

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Funding

Open Access funding enabled and organized by Projekt DEAL.

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A.A.A. and T.B. conceptualized the study, designed the methodology, collected and analyzed the data. A.A.A. wrote the main manuscript text and prepared the Figures. All authors reviewed and approved the final manuscript

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Ethics declarations

Competing interests

The authors declare no competing interests.

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Appendix

Table 7

Table 7 City pairs considered for the study

Full size table ›

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Cite this article

Alsharif, A.A., Brenner, T. Special economic zones and innovation in developing and emerging economies: A cross-country analysis. *J Evol Econ* 36, 30 (2026). https://doi.org/10.1007/s00191-026-00949-6

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Received 31 October 2024
Accepted 18 February 2026
Published 20 March 2026

Version of record 20 March 2026

DOI https://doi.org/10.1007/s00191-026-00949-6

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