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Evaluating the Economic Impact of Special Economic Zones on GDP per Capita in China: A Difference-in-Differences Approach

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Abstract. This study investigates the economic impact of Special Economic Zones (SEZs) on GDP per capita (GDPc) in China using a Difference-in-Differences (DiD) approach. By comparing cities designated as SEZs with those that were not, the analysis assesses the effect of SEZ policies implemented at different times. The results indicate that SEZs have a robust, positive, and significant impact on GDPc, with earlier treated cities experiencing a higher positive effect than later treated ones. This underscores the importance of timely policy implementation in maximizing economic benefits. Robustness checks, including two-way fixed effects and state-specific linear time trends, reinforce the reliability of the findings. However, the study acknowledges several limitations, such as the potential weakening of the parallel trends assumption over time, the use of a binary treatment variable, and the specific context of China's SEZ policy which may limit generalizability. Future research should address these limitations by exploring continuous treatment variables, incorporating additional control variables, and conducting comparative studies in different contexts. Despite these limitations, the findings provide valuable insights into the economic effects of SEZs and contribute to the broader understanding of regional economic development policies.

Keywords: Special Economic Zones (SEZs), GDP per capita (GDPc), Difference-in-Differences (DiD), Economic Impact, Regional Development, China, Policy Implementation, Fixed Effects, Robustness Check, Comparative Studies

1. Introduction

In the late 1970s and early 1980s, China began a profound shift from a closed, centrally planned economy to a more open and market-oriented one. This transition was marked by the introduction of outwardly-oriented development policies designed to stimulate economic growth and integration into the global economy [8]. One of the most pivotal aspects of this transformation was the establishment of Special Economic Zones (SEZs). SEZs are designated areas within a country that possess special economic regulations different from other areas in the same country. These regulations tend to be conducive to and attract foreign direct investment (FDI), promote trade, and boost economic growth. The first SEZs in China were established in 1980 in the cities of Shenzhen, Zhuhai, Shantou, and Xiamen. These zones were strategically chosen due to their coastal locations, which facilitated easier access to international markets [2]. Following the initial success of these SEZs, the Chinese government expanded the program. In 1984, the State Council approved 14 additional coastal cities, including major hubs such as Shanghai, Tianjin, and Ningbo, to operate under similar economic policies. The establishment of these zones allowed these cities to implement more flexible government measures, reduced taxation, and increased support for foreign and private enterprises. Further expansions occurred in subsequent years, with Hainan and Kashgar being granted SEZ status in 1988 and 2010, respectively.

Gross Domestic Product per capita (GDPc) is a critical economic metric that represents the average economic output per person in a given area. It is calculated by dividing the Gross Domestic Product

(GDP) of a region by its population, providing insight into the standard of living and economic health of a population. The introduction of SEZs in China provides an excellent natural experiment for studying the economic impacts of such policies. SEZs, by fostering favorable business conditions, are expected to boost local GDPc through increased investment, employment, and productivity [10]. Numerous studies have examined the impact of SEZs on various economic outcomes in China. For instance, Song et al. empirically investigated the effect of SEZs on foreign direct investment (FDI) using a time-varying Difference-in-Differences (DiD) specification [6]. They concluded that SEZs significantly attract FDI by improving institutional quality and fostering local economic conditions. Their findings suggest that place-based policies, such as SEZs, are effective tools for regional economic development. Similarly, Wu et al. explored the relationship between SEZs and innovation in China [9]. Utilizing a DiD model, they discovered that SEZs positively influence innovation, as evidenced by increases in patent applications, grants, and citations. This indicates that SEZs not only contribute to immediate economic gains but also enhance the long-term innovative capacity of the regions.

While existing literature extensively covers the direct economic impacts of SEZs, there remains a gap in understanding the nuanced differences in economic outcomes between early and later established SEZs. Additionally, there is limited research on the long-term effects of SEZ policies on GDPc across different regions and time periods. This study aims to fill these gaps by employing a Difference-in-Differences (DiD) approach to analyze the impact of SEZs on GDPc in China, comparing cities that received SEZ designation at different times and examining the robustness of these effects over an extended period.

2. Methodology

The analysis was conducted using STATA, a statistical software that allows for robust data analysis and regression modeling. A Difference-in-Differences (DiD) specification was employed to assess the impact of opening up cities, SEZs in China's GDPc. The DiD approach is particularly suitable for evaluating policy interventions as it helps control for time-invariant unobserved heterogeneity by comparing the changes in outcomes over time between a treatment group (cities that became SEZs) and a control group (cities that did not) [1]. The basic assumption for the DiD model is the parallel trends assumption, which posits that in the absence of the treatment (SEZ policy), the difference in GDPc between the treated and control cities would have followed the same trend over time. This assumption allows us to attribute any post-treatment divergence in trends to the impact of the SEZ policy. The DiD model used in this study can be expressed in three different specifications to improve robustness and account for various factors:

Model 1: Naive Regression

$$\mathrm{GDPc}_{ct} = \alpha + \beta \mathrm{SEZ}_{ct} + \varepsilon_{ct} \tag{1}$$

In this model, GDPc_{ct} represents the GDP per capita in city c at time t, and SEZ_{ct} is a dummy variable that equals 1 if the city c has been designated as an SEZ by time t, and 0 otherwise. The coefficient β captures the treatment effect of the SEZ policy on GDPc.

Model 2: Two-Way Fixed Effects (TWFE)

$$\mathrm{GDPc}_{ct} = \alpha + \beta \mathrm{SEZ}_{ct} + \sum \delta_k \mathrm{City}_{kc} + \sum \gamma_j \mathrm{Year}_{jt} + \varepsilon_{ct} \tag{2}$$

This model includes city fixed effects (δ_k) to control for time-invariant characteristics of the cities and year fixed effects (γ_j) to control for common shocks over time. The inclusion of these fixed effects helps to remove omitted variable bias, ensuring a more accurate estimation of the treatment effect.

Model 3: State-Specific Linear Time Trends

$$\mathrm{GDPc}_{ct} = \alpha + \beta \mathrm{SEZ}_{ct} + \sum \delta_k \mathrm{City}_{kc} + \sum \gamma_j \mathrm{Year}_{jt} + \sum \vartheta_k \mathrm{City}_{kc} \, x \, t + \varepsilon_{ct} \tag{3}$$

In this specification, state-specific linear time trends (ϑ_k) are introduced to account for differential pre-treatment trends across cities. This model assumes that in the absence of the treatment effect, GDPc in city k would deviate from common year effects by following a linear trend. The primary focus of our study is the estimation of the coefficient β of the DiD regressor SEZ_{ct}. A significant and positive β would suggest that the SEZ policy has a positive effect on GDPc.

In summary, Model 1 provides a basic estimate of the treatment effect but may suffer from omitted variable bias. Model 2 controls for unobserved heterogeneity across cities and common time shocks, offering a more robust estimate. Model 3 further accounts for potential differential trends in GDPc across cities, providing the most rigorous estimate of the treatment effect.

For this analysis, data were sourced from the statistical yearbooks of various provinces and cities in China. The dataset comprises information on GDPc and several control variables, including the number of health institutions (Health), total government spending (Government Expenditure), and total private savings (Private Savings). The data cover 30 provinces and cities over the period from 1978 to 1995 [4]. The treatment group includes cities designated as SEZs, while the control group consists of cities that were not.

3. Pre-treatment check

The identifying assumption for this analysis is that the control group (CG) would have followed a similar trend as the treatment group (TG) if there had been no treatment. If there were expectations about the establishment of the SEZs, it might lead to ex-ante non-comparability and biased estimates between the TG and CG [7]. To verify the common trend assumption between the treatment and control groups, a pre-trend check was conducted using graphical observation and a balance test. The TG, indicated in Figure 1A, refers to the cities that were treated in 1980, while the CG comprises the remaining untreated cities. It is evident that the trends for both TG and CG were similar before 1980. However, starting in 1980, the TG grew faster than the CG. In 1984, more cities were treated, and they were subsequently included in the TG. Figure 1B shows a common trend for both groups before 1984, after which the trend line for TG becomes steeper. This graphical analysis suggests that the pre-trend for both the treatment and control groups is parallel.

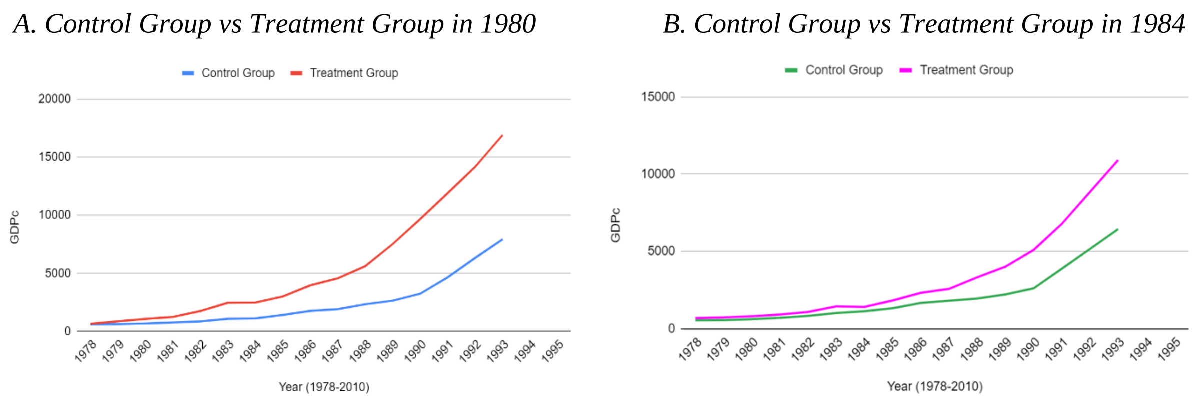

Figure 1. Control Group vs Treatment Group

Additionally, a balance test was conducted on GDPc and control variables for both TG and CG. Table 1 below shows that all variables displayed insignificant t-test results with p-values higher than 0.1, indicating no statistically significant differences between the group means in this balance test.

Table 1. Pre-treatment Balance Test for Treated and Control Groups

Variables	Treated	Control	Difference	P-value
Ttest GDPc, by(alltreated)	485.74	714.55	228.81	0.21
Ttest Health, by(alltreated)	5991.00	1610.83	-4380.17	0.11
Ttest Savings, by(alltreated)	12.59	10.54	-2.06	0.77
Ttest Government Expenditure, by(alltreated)	20.39	8.92	-11.47	0.15

4. Results

The coefficient within the traditional DiD estimator does not distinguish between different treatment timings and may be inaccurate. This can be observed in Table 2, where the estimated treatment effect is insignificant.

Table 2. Regression Results for the Impact of SEZ Treatment GDPc

	GDPc
Total_treat	269.3 (0.8)
_Cons	2595.0*** (15.77)
N	518

t statistics in parentheses

*p < 0.05, **p < 0.01, ***p < 0.001

Goodman-Bacon's decomposition approach separates the results into three groups: Earlier vs. Later Treated, Later vs. Earlier Treated, and Treated vs. Untreated. Figure 2 illustrates this separation, with the untreated group (12 cities) shown as the bottom line, the early-treated group (4 SEZs) as the upper line, and the late-treated group (14 coastal cities) as the middle line. This decomposition corrects for bias caused by different treatment timings and allows for a clearer understanding of the effect of SEZ policies [5]. The weights from each estimate are derived from the size of each city and the variance of treatment, such as the timing of the treatment within the subsample window. Disaggregating into components accounts for the effect of receiving treatments at different times, allowing for a comparison of the effects on earlier-treated and later-treated cities. The following discussions are based on the Bacon decomposed 2x2 models shown in the figure below.

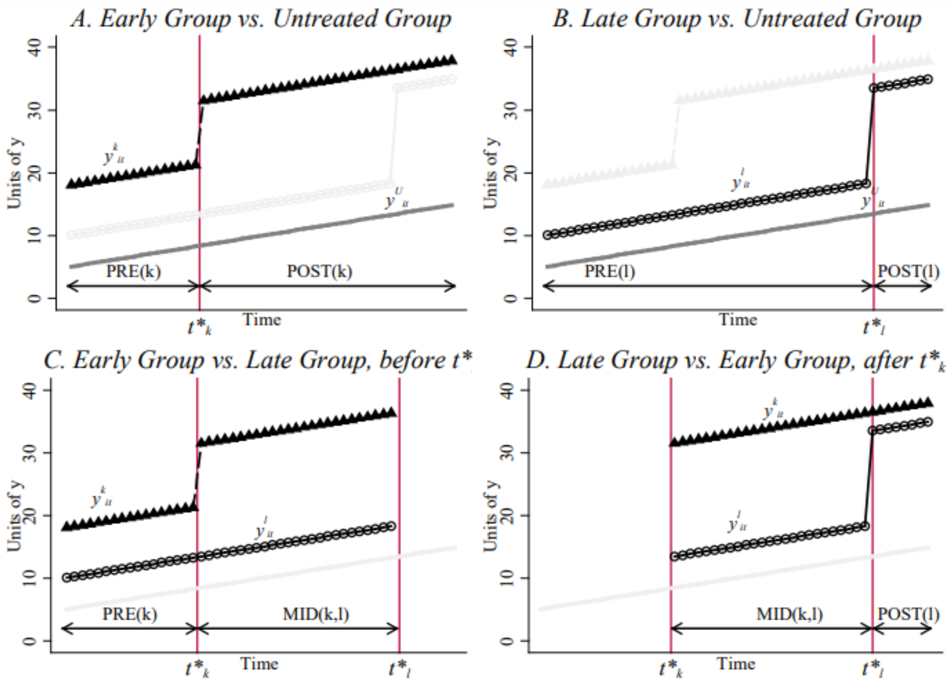

Figure 2. Difference-in-Differences with Variation in Treatment Timing [3]

In Figure 2A, the early group, consisting of 4 SEZ cities (TG), is compared with the untreated group of 12 cities (CG) over the period from 1978 to 1995. In Figure 2B, the late group of 14 coastal cities (TG) is compared with the same untreated group of 12 cities (CG) over the same period. Figure 2C presents a comparison between the early group of 4 SEZ cities (TG) and the late group of 14 coastal cities (CG) during the earlier period from 1978 to 1984. Finally, Figure 2D shows the comparison between the late group of 14 coastal cities (TG) and the early group of 4 SEZ cities (TG) over the period from 1980 to 1995. These comparisons illustrate the differential impacts of SEZ policies implemented at different times on the GDP per capita of these cities.

4.1. Naive Regression

Naive regressions were conducted using data from 1978-1995. In table 3, Columns 1 and 2 compared the effect of the early-treated group (TG) with the untreated group (CG). The results suggest that early-treated cities experienced an average higher GDPc of 3439.8 compared to unreated cities. Both results are robust and significant. Columns 3 and 4 show the comparison between the late-treated group (TG) and the untreated group (CG). The results indicate that late-treated cities have an average higher GDPc of 886 compared to untreated cities. The difference between Column 1 and Column 2, Column 3 and Column 4 is that Column 2 and Column 4 were clustered at the city level, indicating that observations are correlated within cities but independent between cities. Lastly, Column 5 shows the regression result between the treated group (12 coastal + 4 SEZ) and the untreated group, indicating that early-treated cities experienced an average higher GDPc of 3051.3 compared to the control group cities.

Table 3. Regression results comparing early-treated and late-treated cities vs. untreated control group cities from 1978-1995

	1	2	3	4	5
	Early vs Control	**Early vs Control (Clustered at city level)**	**Late vs Control**	**Late vs Control (Clustered at city level)**	**Treated vs Never-Treated**
Early_treat2	3439.8*** (4.54)	3439.8** (3.02)			
Late_treat			866.7** (2.46)	866.7* (1.85)	
Early_treat					3051.3** (2.78)
_Cons	460.6*** (9.12)	460.6*** (6.31)	556.4*** (15.26)	556.4*** (6.46)	600.1*** (6.06)
City FE	No	No	No	No	No
Year FE	No	No	No	No	No
Robust	Yes	Yes	Yes	Yes	Yes
Cluster	No	Yes	No	Yes	Yes
Observations	286	286	448	448	518
R-squared	0.182	0.182	0.202	0.202	0.123

t statistics in parentheses

*p < 0.10, ** p < 0.05, *** p < 0.001

In Table 4, Columns 1 and 2 compare early-treated (TG) and late-treated (CG) from 1978-1984. The insignificant results suggest that early-treated and late-treated groups share similar characteristics, contrary to expectations. Columns 3 and 4 compare the late-treated (TG) with the early-treated (CG) from 1980-1995. The negative and significant results indicate that the late-treated group has an average lower GDPc of 3311 compared to the early-treated group, possibly due to SEZ cities having more time to grow since 1978.

Table 4. Regression results comparing early-treated vs late-treated cities between 1978-1984 and 1980-1995

	1	2	3	4	5
	Early vs Late	**Early vs Late (Clustered at city level)**	**Late vs Early**	**Late vs Early (Clustered at city level)**	**Regression2**
	1978-1984		**1980-1995**		
Time_treatc	337.2 (1.4)	337.2 (1.19)			
Time_treated			-3311.0*** (-3.57)	-3311.0** (-2.52)	
Early_treat					3051.3** (2.78)
_Cons	734.0*** (5.99)	734.0*** (4.16)	959.1*** (6.71)	959.1*** (3.99)	600.1*** (6.06)
City FE	No	No	No	No	No
Year FE	No	No	No	No	No
Robust	Yes	Yes	Yes	Yes	Yes
Cluster	No	Yes	No	Yes	Yes
Observations	113	113	271	271	518
R-squared	0.0571	0.0571	0.228	0.228	0.123

t statistics in parentheses

*p < 0.10, ** p < 0.05, *** p < 0.001

4.2. Two-Way Fixed Effects (TWFE)

The inclusion of fixed effect estimators in Model 3 removes omitted variable bias by measuring changes within cities over time. In Table 5, Column 1 compares early-treated vs. never-treated from 1978-1995, showing a significantly greater impact of 2823.2 for the early-treated group. The result is consistent with the naive regression results. Similarly, Column 2 compares late-treated vs. never-treated from 1978-1995, indicating that the late-treated group has a significantly greater impact of 832.6 compared to the never-treated group. Column 3 compares early-treated vs. late-treated from 1978-1984, yielding an insignificant estimate due to the restricted time period, which reduces the number of observations. Column 4 compares the late-treated group and early-treated from 1984-1995. The late-treated is considered as TG while the early-treated is the CG, as the treatment status only changed for the late-treated from 1984-1995. Results remain negative and significant, suggesting that the early-treated group has a stronger effect than the late-treated group. Comparing Columns 1 and 2 (both covering 1978-1995 data), the late-treated GDPc is still relatively lower than the early-treated even with the FE estimators, raising the question: Does being treated early in 1978 generate higher returns than being treated in 1984? Such observations require the assumption of heterogeneous treatment, which opposes the initial assumption and will be excluded.

Table 5. Decomposed 2x2 Regression Results Comparing Early Treated, Late Treated, and Untreated Cities

	1	**2**	**3**	**4**
	Early vs Control	**Late vs Control**	**Early vs Late**	**Late vs Early**
Early_treat2	2823.3** (2.73)			
Late_treat		832.6** (3.08)		
Time_treatc			214.7 (1.45)	
Time_treated				-3366.2*** (-5.35)
_Cons	2007.7*** (7.62)	2050.5*** (18.03)	912.6*** (24.63)	5573.9*** (14.59)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust	Yes	Yes	Yes	Yes
Cluster	No	No	No	No
Observations	286	448	113	271
R-squared	0.715	0.786	0.885	0.808

t statistics in parentheses

*p < 0.10, ** p < 0.05, *** p < 0.001

To investigate the insignificant result from Column 3, the time restriction was removed, comparing the effect of early-treated with late-treated using data from 1978-1995, as shown in Table 6. The result becomes significant at the 10% confidence level, suggesting that treatment takes time to manifest, and the 1978-1984 period may be too short for the treatment effect to fully appear.

Table 6. Regression Results Comparing Early Treated vs Late Treated Cities After Removing Time Restriction

	Early Treated
Time_treatc	2118.4* (2.26)
_Cons	2873.2*** (12.61)
City FE	Yes
Year FE	Yes
Robust	Yes
Cluster	No
Observations	302
R-squared	0.787

t statistics in parentheses

*p < 0.05, **p < 0.01, ***p < 0.001

4.2.1 Two Way Fixed Effects (TWFE) with Control Variables

The TWFE model was re-estimated using the same comparison groups, incorporating control variables: savings, health, and government expenditure. As shown in Table 7, the first two regressions remain significant and positive, indicating robust estimates. The last column remains significantly negative, suggesting that the GDPc of early-treated cities is higher on average compared to later-treated cities. The third column in Table 7 remains insignificant, possibly due to a smaller period of observations.

Table 7. Two-Way Fixed Effects Regression Results with Control Variables

	1	**2**	**3**	**4**
	Early vs Control	**Late vs Control**	**Late vs Early**	**Early vs Late**
Early_treat2	3577.8** (2.38)			
Late_treat		1971.2** (3.08)		
Time_treatc			46.86 (0.6)	
Time_treated				-3295.5** (-2.31)
_Cons	-4407.2 (-1.48)	-3453.9* (-1.88)	1049.7** -4.51	5254.9** -2.85
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust	Yes	Yes	Yes	Yes
Control Variables	3	3	3	3
Observations	123	135	14	56
R-squared	0.89	0.918	0.999	0.95

t statistics in parentheses

*p < 0.10, ** p < 0.05, *** p < 0.001

4.3. State-Specific Linear Time Trend with Control Variables

Changes occurring after treatment, such as the migration of human capital and businesses from untreated to treated cities, may render the control group an unreliable counterfactual. To address this, Model 3 was utilized, which includes an additional state-specific linear time trend to control for annual changes within cities. The analysis which includes city fixed effects, year fixed effects, and state-specific linear time trends, demonstrates consistent and significant treatment results across most of the different models. Additionally, there is a gradual improvement in R-squared values, as shown in Table 8.

Table 8. State-Specific Linear Time Trend Regression Results with Control Variables

	Early vs Control	**Late vs Control**	**Early vs Late**	**Late vs Early**
Coefficient	16783.4*** (7613300.35)	4528.7*** (3336227.1)	321.6*** (13325.59)	-21989.1*** (-5998927.86)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State Specific	Yes	Yes	Yes	Yes
Control Variables	3	3	3	3
Observations	123	135	14	138
R-squared	0.133	0.312	1	1

t statistics in parentheses

*p < 0.10, ** p < 0.05, *** p < 0.001

5. Limitations

5.1. Weakening of Parallel Trends Assumption

In a long-term Difference-in-Differences (DiD) study, expanding the time horizon can weaken the parallel trends assumption due to the increasing presence of confounding factors. As the study period extends, external factors such as changes in national policies, economic conditions, and global market dynamics may influence the results, potentially leading to biased estimates.

5.2. Binary Treatment Variable

The SEZ and opening-up policies are gradual processes that unfold over time. However, this study assumes a binary treatment variable (0 or 1) to indicate whether a city is designated as an SEZ. This simplification overlooks the continuous and evolving nature of policy implementation. A continuous treatment variable could provide a more nuanced understanding of the varying intensities and durations of SEZ impacts on economic growth.

5.3. External Validity

The external validity of the findings is specific to the context of China's SEZ policy. The results may not be directly generalizable to other countries or regions with different economic conditions and policy environments. Comparative studies in different contexts would be valuable to understand the broader applicability of SEZ policies.

6. Conclusion

The establishment of SEZs has a robust, positive, and significant impact on GDPc in China. The results consistently show that cities treated earlier with SEZ designation experience a higher positive impact compared to those treated later. This suggests that the early implementation of SEZ policies provides a more substantial and enduring boost to economic growth. The analysis using DiD models demonstrates that SEZs are effective tools for fostering regional economic development. The positive effects observed in early-treated cities underscore the importance of timely policy implementation in maximizing economic benefits. Furthermore, the robustness checks, including two-way fixed effects and state-specific linear time trends, reinforce the reliability of the findings.

The study's findings emphasize the critical role of policy timing in economic development. Early-treated cities not only enjoyed immediate economic benefits but also sustained higher growth rates over time, indicating that prompt policy action can lead to compounding positive effects. This highlights the strategic advantage of early policy adoption and implementation, which can set the foundation for long-term economic resilience and prosperity. Moreover, the robustness of the results across different model specifications and control variables strengthens the conclusion that SEZs have a significant impact on economic performance. The consistent positive effects observed across various robustness checks provide confidence in the validity of the findings and suggest that SEZs are a powerful policy tool for economic enhancement.

In summary, while the study provides robust evidence of the positive impact of SEZs on GDP per capita in China, it also highlights the need for careful consideration of methodological limitations and the dynamic nature of policy implementation. Future research should address these limitations by exploring continuous treatment variables, incorporating additional control variables, and conducting comparative studies in different contexts. Despite these limitations, the findings contribute valuable insights into the economic effects of SEZs and provide a strong foundation for further research in this area. The results underline the importance of SEZs as an effective mechanism for driving economic growth, and they offer practical implications for policymakers aiming to design and implement similar initiatives in other developing regions.

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References

[1] Chen, H., Wang, Y., Hu, Y., Xu, Z., Wu, C., & Li, Y. (2023, September 23). Identifying environmental information disclosure manipulation behavior through machine learning: A comparative analysis of recognition models. In *2023 IEEE 6th International Conference on Information Systems and Computer Aided Education (ICISCAE)* (pp. 1052-1059).

[2] Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from China's National Trunk Highway System. *Journal of Development Economics, 107*, 38-48. https://doi.org/10.1016/j.jdeveco.2012.10.009

[3] Goodman-Bacon, A. (2019). So you’ve been told to do my difference-in-differences thing: A guide [Ebook]. Retrieved May 21, 2024, from https://cdn.vanderbilt.edu/vu-my/wp-content/uploads/sites/2318/2019/10/09023516/so_youve_been_told_dd_10_9_2019.pdf

[4] National Bureau of Statistics of China. *China statistical yearbook*. Retrieved from https://www.stats.gov.cn/sj/ndsj.htm

[5] Qian, Y., Li, Y., Hao, Y., Yu, T., & Hu, H. (2023). Greenhouse gas control in steel manufacturing: Inventory, assurance, and strategic reduction review. *Carbon Research, 3*(1), 27.

[6] Song, Y., Deng, R., Liu, R., & Peng, Q. (2020). Effects of Special Economic Zones on FDI in emerging economies: Does institutional quality matter? Sustainability, 12(20), 8409. https://doi.org/10.3390/su12208409

[7] Song, Z., He, Q., & Shen, L. (2020). The impact of Special Economic Zones on regional economic development: Evidence from China. *China Economic Quarterly International*, 1(1), 100-115. https://doi.org/10.1016/j.ceqi.2021.11.004

[8] Wang, Y., Hao, Y., Hou, Y., Quan, Q., & Li, Y. (2023). Optimizing scope 3 emissions in the automotive manufacturing industry: A multidisciplinary approach. *Carbon Research*, *3*(1), 49.

[9] Wu, M., Liu, C., & Huang, J. (2021). The special economic zones and innovation: Evidence from China. China Economic Quarterly International, 1(4), 319-330. https://doi.org/10.1016/j.ceqi.2021.11.004

[10] Xiao, P., & Li, Y. (2023). Dose response assessment of silica exposure and poisoning of construction workers. *Environmental Pollutants and Bioavailability*, *35*(1), 2190489.