Journal of Economics, Technology and Business (JETBIS)
Volume 4, Number 4 April 2025
p-ISSN 2964-903X; e-ISSN 2962-9330

THE EFFECT OF GOVERNMENT-BORNE VALUE ADDED TAX (VAT) INCENTIVES ON ELECTRIC CAR SALES IN INDONESIA

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KEYWORDS:
Indonesia, Tax Incentives, Battery-Based Electric Motor Vehicles, Electric Cars, VAT DTP

ABSTRACT
Micro, Small, and Medium Enterprises (MSMEs) serve as vital contributors to economic resilience, particularly in developing nations like Indonesia. However, the COVID-19 pandemic has disrupted their sustainability, demanding strategic frameworks for recovery. This study aims to formulate effective development strategies for MSMEs in East Java by integrating SWOT analysis with the Analytical Network Process (ANP). The research adopts a qualitative-quantitative approach, employing expert judgment to identify internal and external factors affecting MSMEs, followed by pairwise comparisons to evaluate interdependencies among these factors using ANP. The results identify the most critical strategies, emphasizing increased digital literacy, innovation, and collaboration with stakeholders. The integration of SWOT and ANP offers a robust methodological advancement by capturing complex interrelationships among strategic factors, overcoming the limitations of traditional AHP-based approaches. The study's findings provide actionable insights for policymakers and business practitioners to guide MSMEs through post-pandemic recovery and sustainable growth. These implications extend the applicability of strategic management tools in volatile economic contexts and enrich the decision-making toolkit for MSME development.

INTRODUCTION

The rising levels of Greenhouse Gases (GHGs), particularly carbon dioxide (CO_2), have significantly contributed to global warming, threatening both ecosystems and human well-being (Dube et al., 2018). Indonesia, a major GHG emitter (International Energy Agency, 2023), has committed to achieving net-zero carbon emissions by 2050 through its Nationally Determined Contributions (NDCs) (Khalifa et al., 2022), targeting key emission sectors such as waste, energy, IPPU, and agriculture. With the energy sector responsible for over 60% of emissions—largely from fossil fuels—the government has prioritized reducing transportation-related emissions by promoting battery-based electric vehicles. This effort is formalized through Presidential Regulation Number 55 of 2019, which introduced the term Battery-Based Electric Motorized Vehicle (KBLBB) to denote Battery Electric Vehicles (BEVs), aiming to curb fossil fuel dependence (Fullarton, 2018). According to Sanguesa et al. (2021), electrified vehicles include BEVs, Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicles (FCEVs), with

BEVs relying solely on battery power and xEVs encompassing all types that utilize electric technology.

A Life Cycle Assessment (LCA) evaluates the environmental impact of a product across its entire life cycle, whereas the well-to-wheel (WtW) approach focuses specifically on emissions from fuel extraction to vehicle operation (Ansari, 2021; Eva et al., 2021). Hawkins et al. (2013) found that electric vehicles (EVs) using Europe's current electricity mix can lower global warming potential by 10% to 24% over 150,000 km compared to gasoline or diesel cars. This supports global efforts to adopt EVs for reducing greenhouse gas emissions. In Indonesia, the government targets two million EV units by 2030 to cut CO_2 emissions by 6.42 million tons annually (of Energy & Resources, 2022). However, adoption remains slow, with only 68,000 EVs in circulation—about 0.04% of total vehicles (Aszhari, 2023)—despite targets of 400,000 units by 2025 and 1 million by 2035 (Roadmap of the Ministry of Industry, Permenperin Number 28 of 2023). BEV sales reached only 17,051 units by the end of 2023, even with a boost during the 2022 G20 Summit (Yuniza et al., 2021).

Price remains a major barrier to electric vehicle (EV) adoption in Indonesia, as conventional cars are typically priced below IDR 300 million, whereas most electric cars exceed IDR 600 million (Sidabutar, 2020), contributing to a higher Total Cost of Ownership (TCO) for Battery Electric Vehicles (BEVs) compared to Internal Combustion Engine Vehicles (ICEVs) (Riyanto et al., 2019). TCO, which includes purchase, operational, and maintenance costs, plays a key role in consumer decision-making (Danielis et al., 2018). Price reductions have been identified as the most influential factor in shifting consumer intentions toward EV purchases (Cecere et al., 2018). In response, the Indonesian government has implemented various fiscal incentives since 2019, including exemptions from the Sales Tax on Luxury Goods (PPnBM) and the Motor Vehicle Name Return Duty (BBNKB) (Fitriya, 2024), as regulated by the Minister of Home Affairs Number 6 of 2023. Battery-based electric vehicles are also exempt from the Motor Vehicle Tax (PKB) and BBNKB at a rate of zero percent, applicable to both imported (CBU) and locally assembled (CKD) units but excluding converted EVs. Additionally, Government Regulation Number 73 of (2019) provides pure EVs with a zero percent Tax Imposition Basis (DPP) for PPnBM, while Plug-in Hybrid Electric Vehicles (PHEVs) face tariffs of five percent initially and eight percent later.

Despite the introduction of various incentives since 2019—including exemptions from Motor Vehicle Name Return Duty (BBNKB), Motor Vehicle Tax (PKB), and Sales Tax on Luxury Goods (PPnBM)—electric car prices in Indonesia remain relatively high, contributing to low ownership rates, with only 3,193 units registered by the end of 2021, representing just 3.95% of the battery-based electric car population. To further boost demand, the government introduced additional fiscal incentives through Government-Borne Value Added Tax (VAT) (DTP), as outlined in PMK Number 38 of 2023 and extended by PMK Number 8 of 2024, which reduce VAT from 11% to 1% for electric cars with a Domestic Content Level (TKDN) of at least 40%, a threshold that will rise to 60% by 2027. This VAT incentive, effective from April 2023 to December 2024, applies to cars whose total cost includes not just the base price but also taxes, administrative fees, and other associated costs—collectively referred to as the 'on-the-road' (OTR) price (Agustini et al., 2022).

The Wuling Cloud EV price simulation highlights the significant effect of fiscal incentives on reducing the on-the-road (OTR) price of electric vehicles in Indonesia. Starting from a base price of

IDR 400,000,000, taxes raise the total to IDR 562,000,000; however, government incentives—such as a 10% Government-Borne VAT (VAT DTP), and exemptions from PPnBM, PKB, and BBNKB—reduce the price to IDR 404,000,000. Including administrative fees and the SWDKLLJ contribution, the final OTR price becomes IDR 404,818,000, reflecting a 7.98% price reduction due to VAT DTP. This reduction is anticipated to drive higher Battery Electric Vehicle (BEV) adoption, as evidenced by the rise in sales from 25 units in 2019 to 17,051 units in 2023. However, empirical evidence on the direct impact of VAT DTP on BEV sales in Indonesia remains limited, necessitating further analysis to evaluate the policy's effectiveness and explore other contributing factors. A literature review on Google Scholar reveals no specific research on this topic within the Indonesian context, emphasizing a gap that this study aims to address.

Previous research on VAT incentives by Hardman et al. (2017) in nine countries (Canada, China, France, Germany, Japan, the Netherlands, Norway, the United Kingdom, the United States) showed that VAT exemptions are effective, but not intended for premium-class electric vehicles. Premature removal of incentives can negatively impact sales of plug-in electric vehicles (PEVs). Therefore, incentives should be designed with a long-term perspective. On the other hand, Clinton & Steinberg (Cecere et al., 2018) found that tax credit incentives had no significant effect on BEV purchases, which may be attributed to limited temporal variation in vehicle attributes.

Until now, electric car sales in Indonesia have yet to meet projected growth. This study is important because it provides new insights into the influence of VAT DTP incentives on electric car sales in Indonesia. The results of this research are expected to be a reference for the government in making effective tax policies. This study aims to analyze the influence of the Government-Borne Value Added Tax (VAT DTP) incentive policy on electric car sales in Indonesia. The main focus of this study is to examine the effectiveness of the DTP VAT incentive policy in encouraging an increase in electric car sales.

This research provides insight into the effectiveness of VAT incentives and aids policymakers in making informed decisions regarding future incentives to increase sales of electric cars in Indonesia. Furthermore, it also contributes to the existing literature on the implementation of electric cars and the role of government incentives in shaping consumer behavior. This study introduces a novel integration of SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis with the Analytical Network Process (ANP) to evaluate and prioritize strategies for MSME development in Indonesia's post-COVID-19 context. While previous studies have applied SWOT or ANP independently or combined SWOT with AHP (Analytical Hierarchy Process) for strategic decision-making (Sari et al., 2017; Nugroho et al., 2019), this research differentiates itself by employing ANP to handle the interdependence among SWOT factors, which AHP fails to capture. The use of ANP allows for a more dynamic and realistic strategic prioritization, accommodating the complexity of MSME operational environments in the pandemic recovery phase. Additionally, the application of this integrated approach to MSMEs in East Java provides fresh empirical insights into region-specific post-pandemic recovery strategies, which are currently underrepresented in the literature (Harjanti & Sularso, 2019; Firdaus & Yusuf, 2020).

RESEARCH METHOD

This study employs a quantitative approach, combining two analysis methods, namely Difference-in-Differences (DID) and Propensity Score Matching (PSM), to assess the impact of the VAT DTP incentive policy on electric car sales in Indonesia. The data used is electric car sales panel data from January 2022 to September 2024, sourced from the Indonesian Motor Vehicle Industry Association (Gaikindo, 2024). This data includes various electric car models that are eligible for the DTP VAT incentive (treatment group) and those that are not (control group). The Difference-in-Differences (DID) method was used to isolate the causal effects of the policy by comparing sales changes between treatment and control groups before and after policy implementation in April 2023. The DID regression equations employed are

$$Sales_{it} = \alpha + \beta_0\, beforeafter_{it} + \beta_1\, treatmentppndtp_{it} + \beta_2\, beforeafter_{it} \times treatmentppndtp_{it} + \beta_3\, X_{it} + \varepsilon_{it}$$

where Salesit represents EV sales for model i in month t, $beforeafter_{it}$ is a time dummy indicating the period after (1) or before (0) policy implementation, $treatmentppndtp_{it}$ denotes whether model i is in the treatment (1) or control (0) group, $beforeafter_{it} \times treatmentppndtp_{it}$ is the interaction term capturing the policy's differential impact on the treatment group, X_{it} is a vector of control variables (price, segmentation, brand, promotion), α is the intercept, β0, β1, β2, and β3 are coefficients, and ϵ_{it} is the error term

Meanwhile, Propensity Score Matching (PSM) aims to mitigate selection bias in electric vehicles circulating post-policy implementation. PSM matches incentivized vehicles with non-incentivized vehicles based on similar characteristics, such as price, battery capacity, and market segmentation. The effect of the policy was measured using the Average Treatment Effect on the Treated (ATT) with the formula:

$$ATT = E\,[Y_i|D_i=1] - E\,[Y_i|D_i=0]$$

Information:

- ATT: Average Treatment Effect on the Treated
- E: Expectations or expectations value
- Y_i: Hasil (outcome) individu i
- $D_i = 1$: Individuals i receive treatment (treated group)
- $D_i = 0$: Individual i does not receive treatment (control group) Explanation:

- $E[Y_i \mid D_i = 1]$: Mean results in the treatment group
- $E[Y_i \mid D_i = 0]$: Average results in the control group
- $E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0]$: The mean difference in outcomes, reflecting the impact of treatment on the treatment group.

In this context, Yi represents the outcome variable, specifically sales, for individual *i*. The variable D_i is a binary indicator, where D_i=1 denotes membership in the treatment group and D_i=0 denotes membership in the control group.

To validate the results, robustness tests such as parallel trend tests, placebo tests, and the addition of control variables were carried out. The dependent variable in this study is the number of electric car sales transformed into its natural logarithm (ln_sales) for variance stabilization. The primary independent variables include the time dummy and the treatment dummy, while the control variables include price (ln_price), vehicle type, car brand, and promotional activities.

By combining DID and PSM, this study aims to provide a more precise estimate of the impact of the VAT DTP incentive policy on electric car sales, while minimizing selection bias and isolating the policy effect from other factors influencing the market. The results of the study are expected to provide effective policy recommendations to foster the adoption of electric cars in Indonesia.

RESULTS AND DISCUSSION

Descriptive Analysis

Effective April 1, 2023, the electric car incentive program with Government-Borne VAT applies to the sale of certain electric cars. To support the battery-based electric vehicle program, the government implemented this policy to promote a transition from fossil energy to electric energy and increase public interest in purchasing battery-based electric cars. This policy requires the government to pay VAT owed on certain four-wheeled electric cars and buses. The government will bear VAT of up to 10% of the selling price of four-wheeled electric cars and buses, so people only need to pay 1%.

Regression analysis was simulated using electric car sales data published by Gaikindo (2024) This simulation aimed to compare the sales impact between electric cars receiving and not receiving Government-Borne VAT incentives. The data comprised wholesale monthly sales data from manufacturers to distributors from January 2022 to September 2024. The study employed the DID-PSM method in the STATA17 data processing program, distinguishing between vehicle groups that received incentives and those that did not, and using the period of April 2023, when the incentives took effect, as the baseline month.

Table 1. Descriptive Statistics of Electric Car Sales (Average Sales in Units per Month)

Particulars	BEV		DID		PSM	
	Units Receiving VAT Incentive (Treatment/T)	Units Not Receiving VAT Incentive (Control/C)	T	C	T	C
Observations	498	843	219	441	126	126
Mean Sales (Units per Month)	84.34	15.42	51.37	3.87	84.92	28.91
Standard Deviation	211.57	75.93	177.35	14.67	169.29	119,42
Minimum Value	0	0	0	0	0	0
Maximum Value	2060	961	2060	207	1556	847

Source: Gaikindo (2024), processed by the author

Descriptive statistics are used to describe the object of research through several categories of data details, which reveal the characteristics of the data that has been processed. Table 1 presents descriptive statistics of research data, including the average sales of analytical units, both those affected by the DTP VAT incentive policy and those who do not receive incentives.

Of the 105 electric car (BEV) models available on the market from January 2022 to September 2024, a total of 1,341 observations were collected, with 498 units receiving the VAT DTP incentive and 843 units not receiving it. Units that receive incentives show a much higher average monthly sales of 84.34 units per model, compared to units without incentives which only average 15.43 units per model per month. This shows that VAT DTP incentives can increase sales volume.

The BYD Atto 3 Superior Extended Range model, which does not receive incentives, reached the highest sales with 961 units in August 2024. The Wuling Air EV Long Range model, which received incentives, recorded the highest sales with 2,060 units in December 2022. Although the average sales of units with higher incentives were high, there was a high variability in this group, reflected in a greater standard deviation (211.57) than units without incentives (75.93). This pattern is also observed in descriptive statistics for the DID and PSM methods.

This suggests that the impact of VAT DTP incentives on sales can vary significantly between units of analysis. The much higher maximum sales in the incentive group also indicates the presence of superior car models that are highly responsive to incentive policies. Further analysis is needed to understand the factors influencing the variation in the antamodel response in the group with the incentive. Based on the descriptive data in Table 4, it can be seen that there is a change in the average sales of electric vehicles after the policy is implemented. For all electric cars (BEV), average sales increased from 35.78 units per model per month before policy to 38.97 units per model per month after policy. In the DID method, the average sales increased from 27.73 to 30.94, and in the PSM method, the average sales were recorded at 56.92 after the policy.

Table 2. Descriptive Statistics of Electric Car Sales per Unit per Month, Before and After the Policy

Description	BEV		DID		PSM	
	Before Policy	After Policy	Before	After	Before	After
Observation	339	1.143	338	322	n.a	252
Average Sales	35.78	38.97	27.73	30.94	n.a	56.92
Standard deviation	184.19	125.51	163.25	100.48	n.a	148.87
Minimum grade	0	0	0	0	n.a	0
Maximum value	2060	1556	2060	857	n.a	1556

Source: Gaikindo (2024), processed by the author

This shows that VAT incentive policies contribute to driving an increase in average electric vehicle sales across the various analysis groups. This increase indicates that there is public interest in electric vehicles, especially those that receive VAT incentives. However, the data also shows variations in sales spreads. The standard deviation on all BEVs decreased from 184.19 units per month to 125.51 units per month, indicating a decrease in sales variation between vehicles. In the DID method, the standard deviation also decreased from 163.25 units per month before policy to 100.48 units per month after policy, which may indicate that sales have become more even among the analyzed electric cars. In the PSM method, the standard deviation was recorded at 148.87 units per month and there was no data before the policy because the baseline was after April 2023, when the policy began to take effect. This shows that the variation in sales was quite stable in the vehicles analyzed after the policy was implemented.

In addition, the maximum value of sales has also changed. In all BEVs, the maximum value dropped from 2,060 units per month before the policy to 1,556 units per month recorded by the Wuling Binguo EV car in January 2024 after the policy. This decline indicates that although average sales increased, no vehicle model recorded very high sales figures after the policy. This could be due to a change in consumer focus on certain vehicle models that meet the standards to get VAT incentives, as well as changes in marketing strategies by electric vehicle manufacturers. This data provides an initial overview of the effectiveness of incentive policies, but further analysis is needed to ascertain their significance to the electric vehicle market.

Table 3. Descriptive Statistics of Analysis Units, VAT Incentives DTP (Units/Months)

DTP VAT Incentive Analysis Unit		Number of Observations	Average Sales	Standard Deviation
BEV	Before	483	89.01	291.12
	After	894	82.71	175.97
DID	Before	97	27.73	163.25
	After	122	30.94	100.49
PSM	Before	n.a	n.a	n.a
	After	126	84.92	169.29

Source: Gaikindo (2024), processed by the author

Based on the analysis of unit sales that receive Government-Borne Value Added Tax (VAT DTP) incentives, Table 5 shows descriptive statistics before and after the implementation of the VAT DTP policy. In the unit of analysis of all electric cars (BEV), the average sales before policy was 89.01 units per month with a standard deviation of 291.12 units per month. After the policy was implemented, the average sales decreased slightly to 82.71 units per month with a smaller standard deviation, which was 175.97 units per month. This average decline can indicate a decrease in demand or a shift in purchasing focus in certain segments.

In the DID analysis unit, average sales increased slightly from 27.73 units per month before policy to 30.94 units per month after policy, with standard deviation decreasing from 163.25 units per month to 100.49 units per month. This shows that once the policy is implemented, sales become more stable, although the average increase is not significant. Meanwhile, in the PSM analysis unit, there was no data before the policy, but after the policy was implemented, the average sales were recorded at 84.92 units per month with a standard deviation of 169.29 units per month. This data provides an idea that VAT DTP incentives have a diverse influence on different units of analysis, with a significant impact on sales stabilization in some groups, while others show less positive trends. Further analysis is needed to understand the market dynamics and the factors that affect the effectiveness of these policies.

The analysis of descriptive statistical data was then continued with a more in-depth discussion.

At this stage, the difference in average sales of each type or specification of vehicles that receive the VAT DTP incentive facility will be explained. Overall, which is summarized in the following table.

Table 4. Average Sales Comparison per Month per Brand

Type	Before / After	Obs	Mean	Std Dev	Min	Max	Growth (Mean)
Hyundai Ioniq5	Before	63	45,52	105,08	0	560	96%
	After	81	89,24	197,66	0	857	
Wuling AirEV	Before	33	260,36	524,93	0	2.060	-56%
	After	63	114,05	129,74	0	452	
Wuling BingouEV	Before	6	0	0	0	0	12.100%
	After	45	121,04	281,57	0	1556	
Wuling CloudEV	Before	0	0	0	0	0	32.700%
	After	9	327	255,07	0	597	
Chery Omoda A5	Before	0	0	0	0	0	41.000%
	After	9	410,11	229,96	0	755	
Morris Garage (MG)	Before	9	0,22	0,66	0	2	19.718%
	After	63	43,60	88,79	0	332	
Neta	Before	12	15,08	35,45	0	100	18%
	After	27	17,92	33,71	0	111	
Hyundai New Kona EV	Before	15	1,33	4,64	0	18	632%
	After	63	9,74	28.15	0	166	

Source: Gaikindo (2024), processed by the author

Based on the results of the analysis of sales data in Table 6, it can be seen that the vehicle type with the most significant growth is the Chery Omoda E5, which recorded an average increase in monthly sales of 41,000%. Before the incentive policy was implemented, the average monthly sales of this type were only 1 unit, but after the policy took effect, the figure jumped sharply to 410.11 units. This extraordinary growth shows that incentive policies have a very positive influence on this type of vehicle.

On the other hand, Wuling Air EV experienced a significant decrease in average monthly sales, with a negative growth rate of -56%. Before the policy was implemented, the average monthly sales of this type reached 260.36 units, but it decreased to only 114.05 units after the policy. This indicates that not all vehicle types benefit positively from incentive policies, and certain variants actually experience a decline in performance.

In addition, types such as Wuling Cloud EV and Wuling Bingou EV, which previously had no sales, showed a huge surge after the policy was implemented, with average growth of 32,700% and 12,100%, respectively. This data shows that incentive policies are successfully driving sales on new models that were not previously available on the market.

However, for Morris Garage (MG) vehicles, although the average monthly sales increased from 0.22 units to 43.60 units, the calculated growth of 19,718% was still smaller than that of types such as the Chery Omoda E5 or Wuling Cloud EV. This reflects the diversity of impact of incentive policies, which are highly dependent on the type of electric vehicle being analyzed.

Based on the results of panel data processing, a visualization of the trend of average sales movements was carried out by comparing the analysis units that received the Government-Borne VAT (VAT DTP) incentive with the units that did not receive the incentive. Furthermore, the average movement of these sales in the period before and after the policy is implemented. A visualization of this trend can be seen in Figure 1. Gaikindo data states that wholesale sales from manufacturers to distributors of electric cars in the country of the Battery Electric Vehicle type began in 2019 amounting to 125 units.

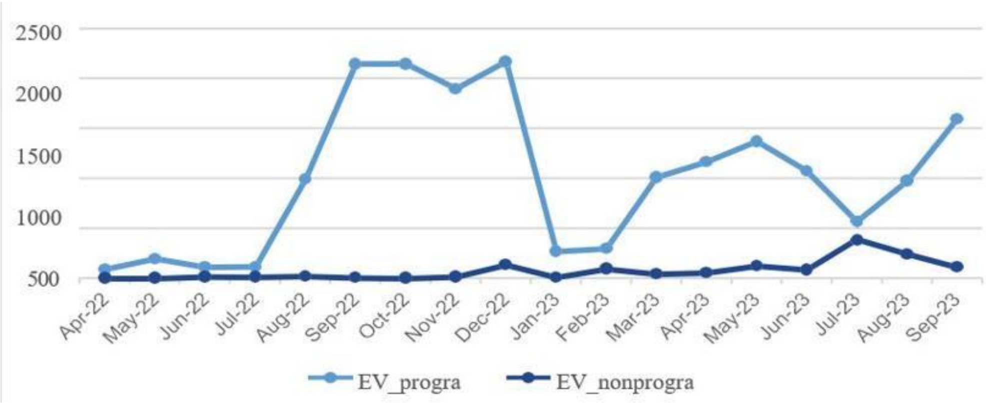

Figure 1. Electric Car Sales (Units/Month): Comparison between Included and Excluded in the VAT DTP Program in Indonesia

Source: (Gaikindo, 2024) (processed)

Electric car sales in Indonesia have increased significantly in 2022. Figure 3. shows that sales of programmatic electric cars (which receive incentives) are much higher than sales of non-programmatic electric cars (which do not receive incentives) throughout the period April 2022 to September 2023. There is a considerable gap between the two groups. To quantitatively analyze the impact of VAT incentive policies on electric car sales, Difference-in-Differences (DID) and Propensity Score Matching (PSM) regression analysis were used.

Estimation Results by Difference-in-Differences (DID) Method

Following data collection, regression equation estimation was performed in accordance with the methodology. DID was applied to assess sales changes by comparing changes before and after incentive policies across each dataset group. In this model, the logarithm of sales was used as the dependent variable to mitigate potential heteroscedasticity, yielding more robust estimates.

To more accurately identify policy effects, the Difference-in-Differences (DID) method was employed, focusing on the coefficient of interaction between the dummy time variable and the treatment variable. In this case, the interaction coefficient was represented by the DID variable, reflecting the difference in impact between the treatment and control groups over two different time periods. The estimation results derived from the analysis are presented in Table 7, which displays the results of the Difference-in-Differences (DID) regression. The analysis was conducted on four models: (1) Model 1: Sales rate without control variable, (2) Model 2: Sales rate with control variable, (3) Model 3: Sales logarithm without control variable, and (4) Model 4: Sales logarithm with control variable.

The sales data included 660 observations during the period from January 2022 to September 2024. The analysis was performed using Stata software 17. Model 1, which analyzes sales rates without control variables, shows that the Difference-in-Differences (DID) variable is insignificant (coefficient = -0.148). This indicates that the interaction between the treatment and the period after the treatment policy does not have a significant effect on the sales rate.

Table 5. The Effect of DTP VAT Incentives on Electric Car Sales: DID Estimated Results

	(1)	(2)	(3)	(4)
VARIABLES	Model 1: Sales Rate Without Control	Model 2: Sales Levels With Control	Model 3: Sales Log Without Control	Model 4: Sales Log With Control
treatment	47.52***	110.1***	0.452***	1.639***
	(14.79)	(26.14)	(0.139)	(0.229)
post	1.977	1.108	0.266***	0.211**
	(1.368)	(2.258)	(0.0997)	(0.0995)
DID	-0.148	-3.824	0.427**	0.453***
	(16.72)	(16.71)	(0.202)	(0.175)
First mover	No	759.3***	No	9.160***
		(174.8)		(1.290)
Promotional events	No	0.1921**	No	0.0857*
		(9.106)		(0.0427)
price/ln price	No	-395.5***	No	-5.000***
		(90.59)		(0.720)
5.Toyota	No	733.5***	No	8.784***
		(169.1)		(1.362)
7.Mini	No	769.9***	No	8.882***
		(180.7)		(1.488)
11.Hyundai	No	115.4***	No	2.053***
		(22.09)		(0.376)
12.DFSK	No	-107.6***	No	-1.585***
		(25.02)		(0.335)
14.Nissan	No	-88.57***	No	-0.0366
		(26.98)		(0.402)
2.hatchback	No	436.8***	No	4.850***
		(106.8)		(0.870)
3.crossover	No	374.6***	No	4.087***
		(91.90)		(0.752)
4.compact	No	303.9***	No	4.394***
		(64.09)		(0.544)
5.crossSUV	No	-621.7***	No	-6.734***
		(146.8)		(1.203)

	(1)	(2)	(3)	(4)
VARIABLES	Model 1: Sales Rate Without Control	Model 2: Sales Levels With Control	Model 3: Sales Log Without Control	Model 4: Sales Log With Control
Constant	2.826***	-2,899***	0.475***	-36.14***
	(0.813)	(665.6)	(0.0659)	(5.287)
Observations	660	660	660	660
R-squared	0.032	0.166	0.0671	0.347
Adj. R-squared	0.0289	0.152	0.0642	0.336

Robust standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1 Source: Author's Review, STATA17 (2024)

Model 2 adds control variables, such as first_mover (defined as a dummy variable that is worth 1 if the car brand is Wuling, which is considered to have a first-mover advantage in the electric car market because it came early and has built a reputation and customer base, and 0 for other brands), event_promosi (the number of promotions made), price (price), the brand, and the type of car. In Model 2, the effect of DID remained insignificant (coefficient = -3.824). However, the treatment significantly increased sales by 110.1 units ($p < 0.05$). The first_mover variable also showed a significant increase in sales, which was 759.3 units ($p < 0.05$). Event_promosi had a significant positive effect on sales; each additional one promotional unit increased sales by 0.1921 units ($p < 0.05$). On the other hand, price has a significant negative effect on sales; Each one-unit increase in price decreased sales by 395.5 units ($p < 0.05$). There is significant variation in the influence of the brand and type of car on sales. Brands such as Toyota and Mini have a great positive impact, while DFSK and Nissan brands have a negative impact.

Next, the Model 3 and Model 4 analyze the natural logarithm of the sale. Model 3, which did not include control variables, showed that DID had a significant effect on sales (coefficient = 0.427; $p < 0.05$). This value, when exponential, shows an increase in sales of 53.3%. The treatment and the period after the treatment also significantly improved the sales logarithm, by 57.1% and 30.5% respectively ($p < 0.05$). Model 4 adds a control variable into Model 3. The results showed that the impact of DID became greater and remained significant (coefficient = 0.453; $p < 0.05$), indicating an increase in sales of 57.3%. The treatment had a very significant positive impact, which was 413% ($p < 0.01$). Event_promosi also had a significant positive effect, with sales increasing by 8.9% for each additional unit of promotion ($p < 0.1$). Price, in the form of a natural logarithm (ln_price), shows a significant negative effect. An increase of 1 unit of natural logarithmic price decreased sales by 99.3% ($p < 0.05$), indicating high sensitivity to price changes. Controls for the brand and type of car also have a significant impact. Brands like Toyota and Mini provide a huge increase in the sales logarithm, while DFSK shows a significant negative impact.

The results of the analysis showed that the use of the natural logarithmic model provided more in-depth information regarding the relative change in sales (in percentage), while the rate model was better for understanding the absolute change in units sold. The combination of treatment, event_promosi, and control variables such as price, brand, and car type, significantly affects car sales. Models with controls (Model 2 and Model 4) produce more accurate and informative estimates than models without controls.

These findings have several practical implications for the marketing strategy of car companies. First, the first-mover advantage has proven to be important, as shown by Wuling's success. Companies that enter the market early and build a strong brand have a greater chance of gaining significant market share. Second, the treatment provided, such as incentive programs and marketing campaigns, has been shown to be effective in increasing sales. Companies need to evaluate and optimize the program. Third, promotions have a significant positive impact, so the allocation of sufficient resources for effective promotional activities, such as advertising, public relations, and special events, is essential. Fourth, consumers are very sensitive to price changes, so pricing strategies must consider the value offered, competitor prices, and market conditions. Fifth, brand strength, such as Toyota and Mini, positively impacts sales, so companies need to build and maintain brand equity. Finally, there are significant variations in the influence of brands and car types on sales, so companies need to understand consumer preferences in different market segments and adjust marketing strategies. By paying attention to these factors, car companies can develop more effective marketing strategies to increase sales and market share.

DID analysis was carried out using the natural logarithm of sales (sales logs) as a dependent variable. This is done to overcome the potential heteroscedasticity in the data and resulting in more robust estimates. These results are consistent with previous research, such as a study conducted by Gallagher and Muehlegger (2011), which showed that fiscal incentives can be effective in driving the adoption of clean energy technologies by providing direct support to consumers. In addition, these findings are in line with the Clinton study (2019) which stated that long-term fiscal incentives can create market stability and increase consumer confidence in environmentally friendly vehicles. With the effectiveness of incentive policies proven through significant improvements to the sales log model.

The regression results of the four models confirm that the VAT incentive policy has a significant positive impact on electric car sales, especially after considering the control variables. Model 4 showed the strongest results, with a 57.3% increase in sales in the treated group compared to the control group. This shows that price factors, promotional events, and car-brand/type characteristics contribute to strengthening the impact of VAT incentives on sales. Governments need to maintain or improve these fiscal incentive policies, while electric car manufacturers can leverage competitive pricing strategies, effective promotions, and vehicle type development to continue to drive the adoption of electric vehicles.

Estimation Results by Propensity Score Matching (PSM) Method

Because several types of electric cars are circulating in the Indonesian market after the VAT DTP policy was enforced in April 2023, and do not have the same characteristics for the DID method. The next step is to calculate the propensity score using logistic regression with relevant covariate variables, and match based on the propensity score to create a balance between the treatment groups and control. The PSM is used to evaluate the effect of the VAT DTP incentive policy on electric car sales since the policy baseline in April 2023. The analysis was carried out using two models, namely using sales level (number of sales) and sales log (natural logarithm of sales).

Figure 4 of common support shows the distribution of propensity score between the treated and untreated groups in the analysis of the impact of VAT incentives on electric car sales. The propensity score is estimated using price, segment, and battery covariates. There was significant overlap between the two groups in the propensity score range of about 0.4 to 0.6, indicating that matching could be adequately performed within that range.

However, a small number of observations in the treated group were outside the common support (off support), especially at a propensity score above 0.6. This shows that a small portion of the treated group 's data did not have a suitable partner in the untreated group and needed to be excluded from the analysis to obtain a more valid estimate of the Average Treatment Effect on the Treated (ATT).

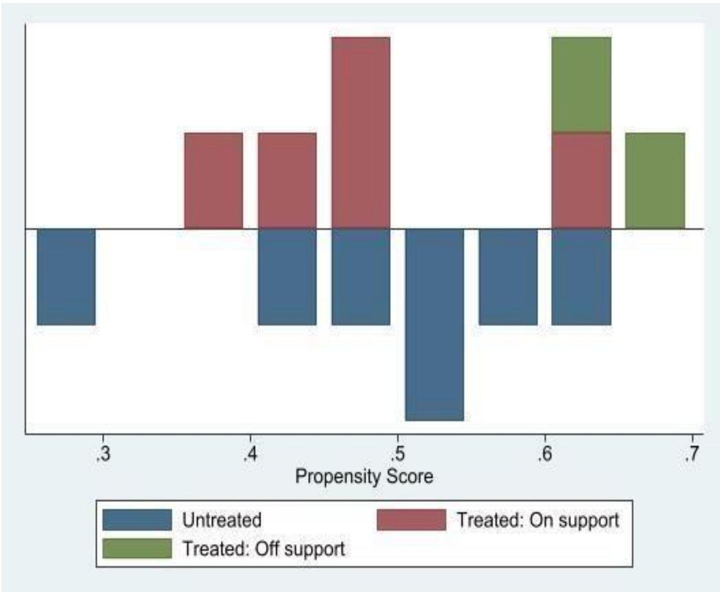

Figure 2. Distribution of Propensity Score and Common Support for the Analysis of the Impact of VAT Incentives on Electric Car Sales
Source: Author's Review, STATA17 (2024)

Although there were observations outside of common support, overall, these results suggest that the propensity score model is good enough for most of the data and can be used for subsequent follow-up analysis.

The results of the analysis in Table 8 show a statistically significant Average Treatment Effect on the Treated (ATT) in both models. In the sales level model, the ATT of 74.77 shows that the treatment (VAT DTP incentive) increases the average sales of electric cars by 74.77 units. Meanwhile, in the sales log model, because the outcome variable used is the natural logarithm of sales, the ATT coefficient obtained (0.622) needs to be transformed back to its original scale so that it can be interpreted meaningfully. The transformation is done by calculating exp(coefficient), which in this case is exp (0.622) = 1.86. This means that the treatment was associated with a 1.86-fold increase in sales, or 86%, compared to the control group. This result is also significant with a z-value of 2.12 and a p-value of 0.034.

Table 6. PSM Estimation: The Impact of the DTP VAT Incentive Policy on Electric Car Sales

	(1)	(2)
VARIABLES	Level sales	Log_sales
r1vs0.treatment	74.77***	0.622**
	(20.11)	(0.293)
Observations	252	252

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's review, STATA17 (2024)

Both models show a significant positive effect of incentive policies on electric car sales, although the magnitude of the effect differs between the two models. This is in line with research conducted by Sun & Tian (2023) which states that subsidized vehicles have characteristics comparable to non-subsidized vehicles, thus allowing for comparisons of control groups (without treatment). This result is significant with a z-value of 3.72 and a p-value of 0.000. more accurate in the effect of the policy. The PSM conducted in this study has ensured the covariate balance between the treatment and control groups, thereby reducing the potential for selection bias and strengthening the validity of the treatment effect estimate.

CONCLUSION

The Indonesian government's Government-Borne VAT (DTP) incentive policy, which applies only to electric cars with a minimum Domestic Component Level (TKDN) of 40% approved by the Ministry of Industry, aims to boost domestic EV production and reduce reliance on imports. Using Propensity Score Matching (PSM), the policy was found to significantly increase electric car sales by an average of 74.77 units ($p < 0.001$), while the sales log model showed a 1.86-fold increase in the treatment group. A Difference-in-Differences (DID) analysis further confirmed a significant impact when using log-transformed sales data, with a 1.57-fold (57.2%) increase in sales ($p < 0.05$), demonstrating that the log model provided more accurate estimates. These findings align with previous research by Li et al. (2017) and Jenn et al. (2018), underscoring the effectiveness of long-term fiscal incentives. However, factors like vehicle price, brand, promotional events, and specifications also play key roles in consumer adoption. Therefore, future research should explore the combined influence of fiscal and non-fiscal factors using multivariate or structural equation modeling to better understand consumer behavior and guide integrated EV policy strategies in Indonesia.

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