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This paper examines the diffusion of battery electric vehicles (BEVs) in ASEAN and the United States through a comparative analysis of adoption trajectories, key determinants, and policy implications in two contrasting regional contexts. Using logistic S-curve diffusion models, complemented by panel and country-level regression analyses, the study characterises the pace and scale of BEV market development over the periods 2010–2024 for ASEAN and 2016–2022 for the United States. The findings identify public charging infrastructure as the most consistent driver of BEV adoption across both regions. However, while charging infrastructure is essential to accelerating market uptake, it does not by itself determine the long-term pace of diffusion. The analysis underscores the importance of context-specific, sequenced policy approaches tailored to countries' stages of market development and highlights the limitations of relying on snapshot adoption metrics to benchmark EV progress across jurisdictions at different stages of the transition.

Keywords: Electric Vehicle; EV Diffusion; ASEAN; USA

JEL Classification: Q55, O33, R41, L62, H23

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1. Introduction

The global automotive industry is undergoing a profound transformation in powertrain technologies, with China, the European Union (EU), and the United States (US) leading the transition towards vehicle electrification (IEA, 2024). Sales of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) have increased rapidly, rising from just 0.2% of global vehicle sales in 2013 to 20% in 2024 (IEA, 2025). These major automotive markets are expected to continue driving the shift away from internal combustion engine vehicles (ICEVs) and conventional hybrid electric vehicles (HEVs) towards electrified vehicles (xEVs), particularly PHEVs and BEVs, thereby shaping the future trajectory of the global automotive industry.

This transition is being driven primarily by national decarbonisation commitments, with BEVs and PHEVs widely regarded as the most mature and commercially viable technologies for reducing emissions from the transport sector. However, the pace of electrification varies considerably across regions. Whilst China, the EU, and the US are expected to remain at the forefront of xEV adoption, emerging markets, including ASEAN, are progressing at a more gradual pace.

According to the latest International Council on Clean Transportation (ICCT) Light-Duty Vehicle Market Report (Sen et al., 2026), the global sales share of electric passenger vehicles increased sharply from 4.5% in 2020 to 21.4% in 2024. China has consistently outperformed the global average, with EV sales increasing from 6.6% of the market in 2020 to 47% in 2024. The European Union reached a market share of 21% in 2024, whilst growth in the United States has plateaued at around 10% in recent years, likely reflecting policy uncertainty. In ASEAN, five countries – Thailand, Viet Nam, Indonesia, Malaysia, and Singapore – recorded combined sales of 233,280 electric passenger vehicles in 2024, representing approximately 1.4% of global EV sales.

Against this backdrop, this paper compares BEV diffusion in ASEAN and the United States, examining two regions that differ markedly in their stages of market development, industrial structure, and policy environment. It applies logistic diffusion models and S-curve projections to analyse BEV adoption trajectories and assesses the influence of key determinants, including fiscal incentives, supply-side policies, and the availability of public charging infrastructure.

The comparative analysis highlights the differing drivers of BEV adoption across the two regions. In ASEAN, the maturity of domestic automotive industries and manufacturing ecosystems plays an important role in shaping market development. In contrast, BEV adoption in the United States is influenced more strongly by state-level policy leadership, regulatory differences, and political factors. These contrasting experiences demonstrate that, whilst the global trend is clearly towards vehicle electrification, the pace and

pattern of diffusion remain highly dependent on local economic, institutional, and policy conditions.

The paper begins by reviewing global EV adoption trends, with particular emphasis on ASEAN and the United States. It then examines EV policy measures implemented in both regions, identifies the research gap, and presents the study's research questions. This is followed by a review of the literature on EV diffusion theory and the key determinants of BEV adoption, which informs the study's analytical framework and research objectives.

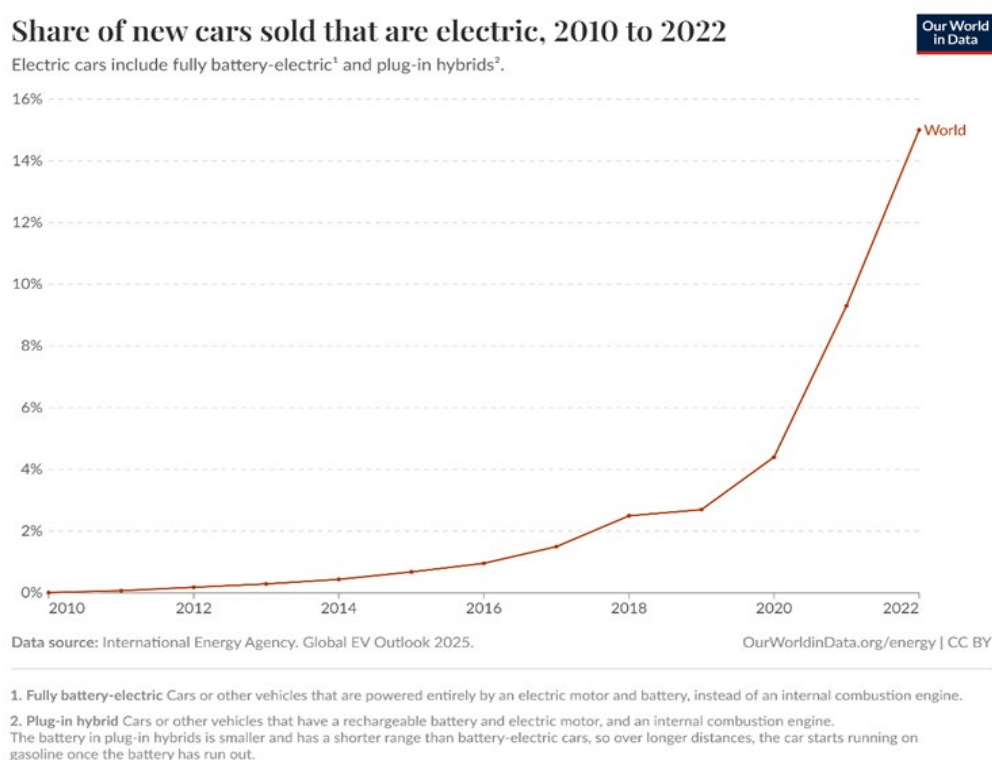
The subsequent two sections analyse BEV diffusion in ASEAN and the United States, respectively. Each section provides an overview of the regional context, describes the data and empirical methodology, and presents the modelling results and their policy implications. The paper concludes by summarising the principal findings, discussing their implications for BEV diffusion policy, and identifying lessons for future research.

1.1 Background

1.1.1 Overarching Global EV trends

The global electric vehicle (EV) sector is experiencing strong growth, though progress differs markedly across regions, with some markets nearing mass adoption while others show complacent (Hertzke et al., 2019). When it comes to passenger cars, EV penetration worldwide was minimal – below 0.1% – in 2010 and increased slowly, remaining under 1% annually until 2018.

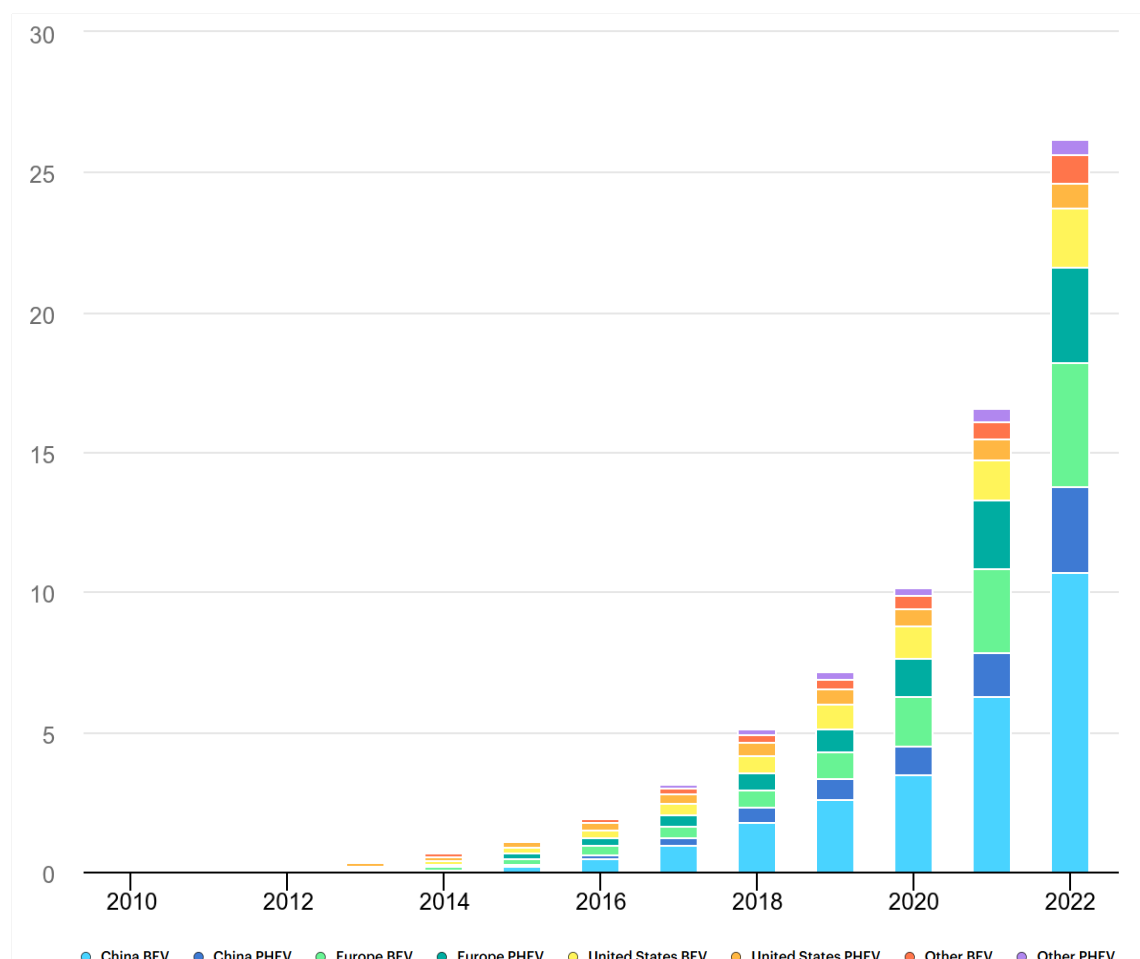
Figure 1: Share of EV sales, 2010–2022



Source: Ritchie, 2024.

From 2020 onwards, adoption accelerated markedly, with the share of EV sales almost doubling by 2022, as illustrated in Figure 1. This rapid growth was mirrored in the EV stock–total number of EVs registered—which rose substantially between 2020 and 2022.

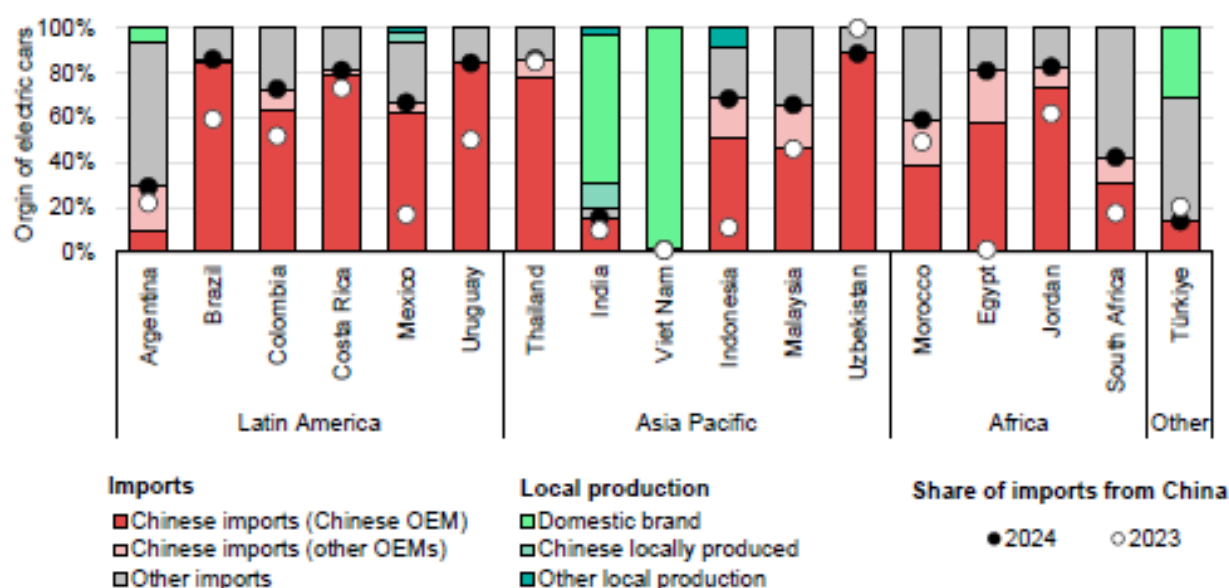
Figure 2: Global EV stock, 2010–2022



Source: IEA, 2023.

By 2025, EVs make up more than 25% of worldwide vehicle sales, with China retaining its position as the leading market (IEA, 2025). Strong fiscal incentive schemes have supported China's rapid expansion, while low-cost imports from China, combined with growing pressure to address urban air pollution, are boosting EV uptake in emerging economies, such as ASEAN. Within Southeast Asia, Thailand and Viet Nam stand out with higher levels of EV penetration (ERIA, 2023; IEA, 2025).

Figure 3: Share of total imports of China, 2023–2024



Notes: Chinese OEMs include BAIC, Geely–Volvo, GWM, GAC, BYD, Chery Automobile, JAC, Neta Auto, Seres Group, FAW, Changan, Dongfeng, Jiangling Motors, SAIC, Leap Motor, Xiaopeng, Aiyways Automobile. The domestic brands are Tata Motors, Mahindra and Mahindra (India), Togg Inc. (Türkiye), VinFast (Viet Nam), and Tito (Argentina).

Source: IEA, 2025.

Figure 3 indicates that Viet Nam stands out as the only country where electric vehicle sales are largely led by domestic manufacturers. Local brands drove a sharp increase in EV market share in 2024, nearly doubling to 17%. VinFast, a local brand in Viet Nam, has also expanded internationally, exporting to 11 countries, with the largest portions going to Southeast Asia – particularly Indonesia (44%) and Malaysia (22%) – as well as the United States (22%) (IEA, 2025).

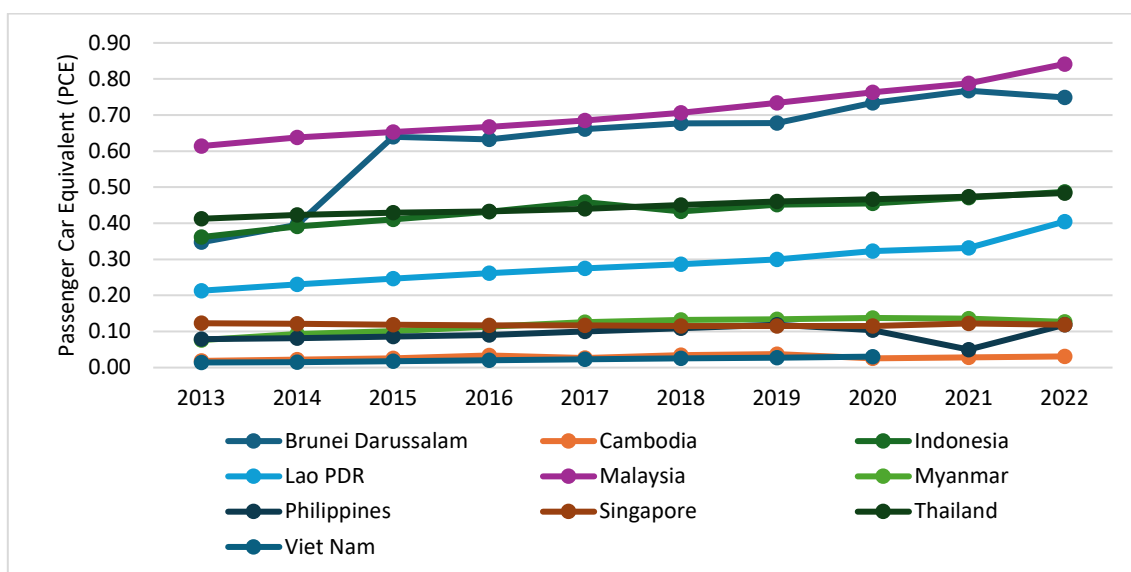
Fiscal support measures, including public subsidies, continue to play a central role in stimulating EV adoption. Gersdorf et al. (2020) described that adjustments to these incentives led to noticeable shifts in purchasing behaviour, highlighting the high price sensitivity of consumers, particularly during periods of economic downturn such as in 2019. As a result, vehicle affordability remains the dominant determinant of EV uptake, particularly within the passenger car segment (IEA, 2025). BEV offerings now exceed those of PHEVs. Over time, the composition of electric car model portfolios in China, Europe, and the United States has gradually aligned, settling at roughly two BEV models for each PHEV. Japan continues to show an even balance between BEVs and PHEVs, while globally the average tilts more strongly toward BEVs, with more than three BEV models available for every two PHEVs (IEA, 2025).

1.1.2 EV Growth in ASEAN: Current Trend, Growth, Policy, Issues, and Research Gap

The automotive sector is a pivotal part of the daily life across ASEAN, which was reflected in the region's high level of motorisation and vehicle ownership. As shown in

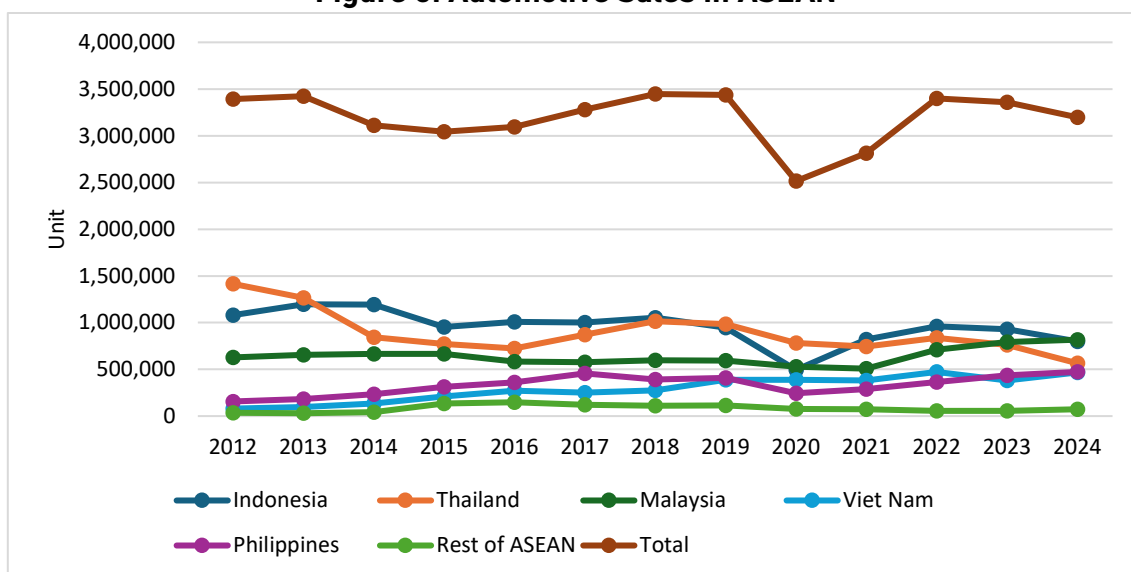
Figure 4, Malaysia and Brunei Darussalam have the highest ownership ratios, ranging between 0.7 and 0.9 passenger vehicles per person, indicating that almost every individual in the country owns a vehicle (ERIA, 2026a). These levels are followed by Indonesia and Thailand, where ownership ratios are nearing 0.5, suggesting that approximately one vehicle is owned by every two people. The mobility patterns in ASEAN are already heavily relied on private vehicles, thus the shift to electric vehicles will be crucial in determining the region's future energy consumption and transport emissions.

Figure 4: Ratio of Registered Vehicle per Population in ASEAN



Note: 1 passenger car = 1 PCE; 1 motorcycle = 0.5 PCE.
Source: ERIA, 2026a.

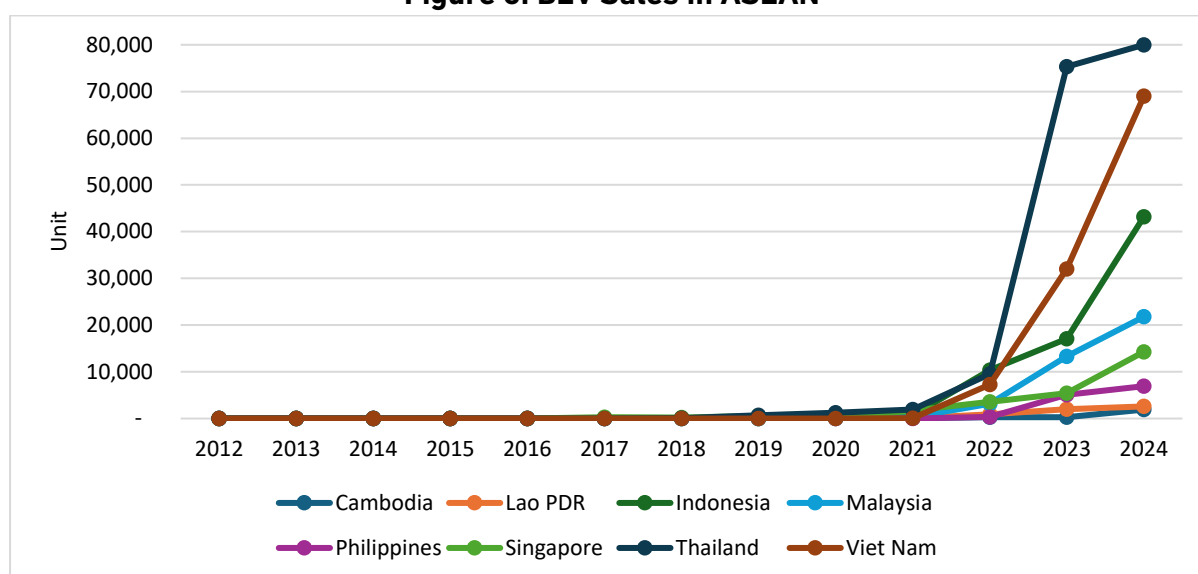
Figure 5: Automotive Sales in ASEAN



Source: ERIA, 2026a.

In contrast to the stagnation of car sales in ASEAN in the last decade as shown in Figure 5, EV market has expanded significantly over the past few years, especially since 2022. By 2024, Thailand emerged as the largest electric car market, accounting for 35% of ASEAN BEV sales (ERIA, 2026b), with cumulative sales increasing from its early market entry in 2010 to approximately 80,000 units in 2024 (CAGR: 103%). The second and third largest market in ASEAN is Viet Nam (30%) (ERIA, 2026b) and Indonesia (19%) (GAIKINDO (2025), as shown in Figure 6. Consequently, Viet Nam shows the fastest growth, with BEV sales increasing from 85 units in 2021 to 69,000 units in 2024 (CAGR: 833%). Although nascent, the EV penetration rates in ASEAN may be influenced by varying policy frameworks.

Figure 6: BEV Sales in ASEAN



Source: Authors, 2025.

Over the past few years, Governments across the region have introduced a combination of targets of ICE (Internal Combustion Engine) phase-out and EV adoption, supply-side industrial policies, non-fiscal incentives, and tax regulations to stimulate investment and for consumers, which is further elaborated on Table 1. Although these measures have accelerated electric vehicles adoption, the trend varies in ASEAN. This variation highlights the need to examine additional factors such as socioeconomics and availability of charging infrastructure in shaping EV diffusion and saturation, beyond policy alone.

Table 1: EV-related policies in ASEAN

Country	EV Target	Supply-side policy	Non-fiscal incentives	Tax regulation
Brunei Darussalam	60% EV sales by 2035			2-year excise tax incentives (until 2023) for electric and hybrid vehicles
Cambodia	30,000 electric cars and 720,000 electric scooters by 2030 40% electric cars and buses, and 70% electric motorcycles by 2050		Preferential parking for EVs in allocated parking space	- Special tax reduction from 30% to 10% for BEV import - Reduction of import tax (including custom duty, excise tax, and value added tax) from 50% to 90%
Indonesia	2,200 electric cars by 2025 15 million EVs fleet (2 million cars and 13 million motorcycles) by 2030 - Phase out ICE vehicle sales by 2050 (100% new vehicle sales to be electric) 600,000 BEV units in production in 2030		Jakarta's odd-even traffic regulation; early deployment of EVs in government vehicle fleets, along with official directives for SOEs to support the development of an integrated EV ecosystem	- BEV is exempted from sales tax on luxury goods 0% import duty for four-wheeler EVs imported in incomplete (CKD/IKD) condition - Direct purchase subsidies were announced in 2022: Rp80 million for new BEVs; Rp40 million for conventional hybrids
Lao PDR	1% EV fleet by 2025 and 30% EV fleet by 2030			
Malaysia	- EVs account for 15% of new car sales by 2030, 38% by 2040, and 80% by 2050 1.5 million EVs on the road by 2040 100% EEV (fuel efficient vehicles, hybrid, and EV) by 2030 90% local EV manufacturing	National Energy Transition Roadmap includes the strategy of incentivising investment for domestic BEV manufacturing industry and targeted subsidy for 2-wheelers purchase and leasing		- Corporate tax exemptions and 70% statutory income tax exemption for 3 years for companies involved in the manufacturing of HEV and xEVs - Road tax exemptions for zero-emission vehicles until December 2025 - Income tax relief of RM2,500 for installing, renting, or subscribing to EV charging equipment to subsidise fuel costs - BEV CBU excise duty and import tax exemption (max 10,000 units total) (2021-2022) 50% import duty and excise duty exemption for BEV (2023-2025) 100% tax exemptions for qualified CKD PHEV (2021-2022); 75% exemption for 2023-2025; and 50% exemption for 2026-2030

Country	EV Target	Supply-side policy	Non-fiscal incentives	Tax regulation
Myanmar		EV imports should obtain approval from National-Level Steering Committee, registration certificate for EV showroom, must comply with approved quotas, standards, and importers are responsible for warranties, spare parts, and after-sales service for BEV		
Philippines	- Scenario of 10% EV share by 2040: 580,600 EV in medium term and 852,100 EV in 2028 - Scenario of 50% EV share by 2040: 1,851,500 EV in medium term and 2,001,600 EV in 2028		Mandatory EV share in corporate and government entities, at least 5% of their fleet	- Income tax holiday for 4–7 years for enterprises engaged in EV-related activities - Discounted vehicle user's charge (30% for BEVs and 15% for HEVs) 100% excise tax exemption for BEVs and 50% excise tax exemption for HEVs
Singapore	- The registration of new diesel cars will be discontinued from 2025 - All new cars and taxis to be of cleaner energy by 2030			- EV early adoption incentive and Enhanced Vehicular Emissions Scheme (VES) reduce upfront EV costs by up to \$40,000 - Reduction of additional registration fee floor to \$0 for electric cars - Road tax for BEVs and HEVs based on power rating/vehicular efficiency
Thailand	30% annual local vehicle production to be BEVs by 2030 and 50% production by 2035 250,000 EVs by 2025, and 750,000 EVs by 2030	- Importers must begin BEV manufacturing in Thailand by 2024 with a production-to-import ratio of 1:1 (one produced per one imported), 1.5:1 by 2025, 2:1 by 2026, and 3:1 by 2027 - EV3.0 Policy grants subsidies up to approximately US\$4,130 per EV unit		- Import duty and excise tax reduction until the end of 2027 - Incentives and tax break schemes for carmakers to set up EV R&D centre - Up to 40% reduction in import duties for CBU BEVs priced at B2 million 8-year income tax waivers for EV 0% import duty for machinery, 1-year for material for re-export - Direct purchase subsidies of US\$1,397 to US\$2,794 per new BEV and low registry fee
Viet Nam	Phase out production and import of fossil fuel road vehicles by 2040	Producing or operating private and public transport services using electricity and renewable energy will		Registration fee exemption for BEV for the first 3 years and 50% fee reduction for the next 2 years

Country	EV Target	Supply-side policy	Non-fiscal incentives	Tax regulation
	100% road and heavy construction vehicles to use electricity or green energy by 2050	benefit preferential loans from banks		- Excise tax reduction for BEV to 1–3% until 2027 - Accessories or components imported for EV production are included in a tax incentive programme - Special consumption tax reduction - Registration fee exemption for BEV cars until 2027

Source: Authors, from various sources.

1.1.3 EV Growth in the United States: Current Trend, Growth, Policy, Issues, and Research Gap

The US electric vehicle market has expanded rapidly over the past decade but remains in a transitional and uneven phase. By 2024, EVs reached roughly 20% of new vehicle sales, driven by earlier federal policies such as the Infrastructure Investment and Jobs Act (IIJA) and the Inflation Reduction Act (IRA), which provided extensive tax credits, charging-station grants, and manufacturing incentives. These policies helped align industry expectations, reduce battery costs, and expand the national charging infrastructure. However, the landscape shifted in 2025 when federal support began to contract: funding programmes were paused, purchase incentives were weakened or rolled back, and emissions mandates entered review. This has reintroduced uncertainty for automakers, consumers, and states that had planned around long-term policy stability.

Despite federal retrenchment, state-level policy leadership has become even more central, particularly in California. California's Advanced Clean Cars II (ACC II) rule, which would require 100% zero-emission new car sales by 2035, had served as the anchor for other states, even though its federal waiver was recently overturned. The dynamics illustrate that, in moments of federal inconsistency, states remain the primary drivers of policy momentum. The overall trajectory of national EV adoption now depends more on state regulatory frameworks, market pressure, and private-sector investment than unified federal strategy.

At the market level, EV adoption in the US remains geographically and politically concentrated. Between 2012 and 2023, half of all new EV registrations came from just the 10% most Democratic-leaning counties, with one-third from the top 5% alone. California and especially the Bay Area continues to dominate adoption rates, while major counties in Texas, Ohio, and Michigan remain amongst the lowest adopters. Even as national EV sales rose to around 8% of new vehicles by 2023, the polarisation between high-adoption blue urban clusters and low-adoption red or rural regions has persisted, and in some cases intensified, over time.

This pattern reflects more than income or charging access; political ideology itself is a major predictor of adoption. Even after controlling for demographics, fuel prices, and density, Democratic vote share strongly predicts EV uptake. Importantly, the gap is not driven by knowledge differences – Republicans and Democrats are equally able to identify EV models – suggesting that cultural identity and attitudes toward climate policy play a central role. The exception is emerging EV trucks and vans, which show somewhat broader political appeal. Still, achieving federal goals of 50%+ EV sales by 2032 will require significant market expansion beyond current Democratic strongholds.

While current research focuses on policy and infrastructure in shaping EV adoption, it often does not distinguish between differences in market size and differences in diffusion speed across states. This analysis attempts to address this gap by combining logistic diffusion models with panel regressions to separately analyse these to provide a more complete understanding of cross-state heterogeneity in both the scale and dynamics of EV adoption.

1.1.4 Research Questions

Research questions of this discussion paper are the following.

- What are the current trends of the battery electric vehicle (BEV) ecosystem in emerging economies such as ASEAN and more advanced markets like the United States?
- Which key factors prominently drive EV adoption in ASEAN and the United States, and how do these drivers differ between the two regions?
- What transferable lessons from the EV adoption trends of ASEAN and the United States can inform future research and policy design to accelerate BEV uptake across diverse markets?

1.2 Literature Review

1.2.1 EV Diffusion Theories

The diffusion of technology has been a subject of scholarly discourse for several decades. Rogers (1962) was amongst the first to formalise diffusion theory, defining diffusion as the process through which an innovation is communicated over time amongst members of a social system via specific communication channels. An innovation is described as an idea, practice, or object perceived as new by an individual or other unit of adoption. In the context of electric vehicles (EVs), this definition is applicable, as EVs represent a technological innovation offering relative advantages over conventional internal combustion engine vehicles, particularly in terms of energy efficiency and emissions reduction.

Rogers (1962) further classified adopters of new technologies into five categories: innovators, early adopters, early majority, late majority, and laggards. This adopter categorisation has been widely used to explain heterogeneity in technology adoption

timing and behaviour across different social and economic contexts (Griliches, 1957; Gruber and Verboven, 2001).

In addition to Rogers' diffusion framework, the Bass model introduced by Bass (1969) has become one of the most widely applied quantitative approaches to modelling technology diffusion. Unlike Rogers' theory, which emphasises social processes and adopter characteristics, the Bass model conceptualises diffusion as the probability of first-time adoption driven by a linear function of prior adopters, capturing both innovation and imitation effects. Another commonly used approach is the Gompertz model, derived from the Gompertz function, which has been extensively employed to represent the S-shaped diffusion patterns observed in technology adoption over time (Meade and Islam, 1999; Ayyadi and Maaroufi, 2018)).

Empirically, scholars have applied Logistic, Bass, and Gompertz models to analyse the diffusion of EVs and related technologies across different regions. Fluchs (2020) employed a logistic diffusion model to forecast EV adoption in 18 European Union countries, using five additional countries as benchmarks. Nagula (2016) applied a Gompertz growth curve to assess the diffusion of fuel cell technologies in hybrid and electric vehicles in the United States. Bitencourt et al. (2021) utilised the Bass model to analyse EV diffusion in Brazil, incorporating policy-related adaptations to capture the influence of public incentives. Several studies have also compared the performance of multiple diffusion models to identify their relative strengths and limitations. For instance, Ayyadi and Maaroufi (2018) applied logistic, Bass, and Gompertz models to forecast EV market development in Morocco and evaluated the predictive performance of each model.

Given the simple yet useful method for approximation, the sigmoid S-curve models has been extensively used for different technology adoption aside from EV. However, scholars have been reporting the limitations on relying solely on the forecasting results for exact timing projections of market saturation and inflection point. Sandberg et. al. (2021) raised concerns on different prediction results from sigmoid models over the years due to the limited available data being used to fit the model, and unless there is vast amount of available data that the results should be taken carefully. Baek et al. (2025) raised similar concerns, arguing that reliable prediction of total adoption requires reaching at least two-thirds of the time to peak adoption rates. Given these limitations, the models' results shall still be useful, noting that interpretation will require certain level of caution and, where necessary, accompanied by explanation on how the model's findings should be treated.

1.2.2 Determinants of EV Adoptions

The diffusion of electric vehicles (EVs) has emerged as a central policy and market issue in the global transition toward low-carbon transport systems. While EV technologies have advanced significantly in recent years, their adoption remains uneven across countries and regions. Literature broadly agrees that EV diffusion is a multi-dimensional

process shaped by economic, technological, infrastructural, institutional, and socio-behavioural factors.

Economic and cost-related determinants

High upfront purchase costs also remain one of the most significant barriers to EV diffusion. Despite declining battery costs and improving economies of scale, EVs are still perceived as expensive relative to internal combustion engine (ICE) vehicles, particularly in price-sensitive markets (Kalthaus and Sun, 2021; Zubaryeva et al., 2012). Several studies suggest that macroeconomic conditions play an important role in shaping adoption patterns. Agan and Balcilar (2022), for example, found that countries with higher GDP per capita tend to exhibit greater uptake of sustainable technologies, including EVs. Higher income levels are generally associated with stronger purchasing power at the household level, as well as greater fiscal capacity for governments to invest in charging infrastructure and incentive schemes (Gil Ribeiro et al., 2025). Consistent with this view, Harrison and Thiel (2017) show that countries with higher GDP per capita tend to experience more rapid EV deployment. However, the relationship between income levels and EV adoption is not unequivocal. Fluchs (2020) presented contrasting evidence, demonstrating that when per capita consumption is used as a proxy for purchasing power parity (PPP), the effect of income on EV adoption is no longer statistically significant.

Closely related to income and consumption effects, the literature also presents mixed evidence on the role of urbanisation in shaping EV diffusion patterns. Zubaryeva et al. (2012) and Yang et al. (2023) found that a higher share of the population residing in urban areas, as well as greater population density, are positively associated with EV uptake. Using data from Norway's passenger vehicle market, Yang et al. (2023) show that municipalities with more urbanised populations tend to exhibit higher EV adoption rates, reflecting the advantages of shorter travel distances, greater charging infrastructure availability, and stronger policy support in urban settings. Conversely, Fluchs (2020) reported an opposing relationship, finding that a lower proportion of the population living in urban areas is associated with higher EV diffusion. This result argued that consumers in rural or suburban contexts may exhibit a stronger preference for EVs, potentially due to higher vehicle ownership rates, access to private charging facilities, or different travel patterns.

Household vehicle ownership further complements the discussion on urbanisation and EV diffusion. Priessner, Sposato and Hampl (2018) found that a higher average number of cars per household is positively associated with EV adoption, as electric vehicles are often purchased as second or third vehicles rather than as primary household cars. This relationship is particularly relevant in suburban and less densely populated areas, where households tend to own multiple vehicles and have greater access to private parking and home charging facilities.

Charging Infrastructure and Accessibility

The availability of public charging infrastructure is widely recognised as a key enabler of electric vehicle diffusion. Existing studies generally find a positive relationship between the presence of public charging stations and EV adoption, although the strength of this effect is not always uniform across vehicle types or model specifications. For instance, Kalthaus and Sun (2021) showed that while public charging infrastructure tends to support EV diffusion, its statistical significance for passenger cars varies depending on the inclusion of additional covariates. Nonetheless, concerns related to charging availability remain amongst the most critical barriers to EV adoption (Verma, Verma and Khan, 2020). Yang et al. (2023) and Zubaryeva et al. (2012) found that higher densities of public charging stations are associated with increased EV adoption rates. Focusing on Norway's mature EV market, Yang et al. (2023) further highlighted that extensive and reliable charging infrastructure plays a crucial role in mitigating operational challenges, including those arising from cold climate conditions, thereby supporting sustained EV diffusion.

Policy, Regulation, and Institutional Support

Financial incentives, particularly purchase subsidies, are widely recognised as an important policy instrument for accelerating the diffusion of electric vehicles. For battery electric vehicles (BEVs), purchase subsidies are especially effective because they directly reduce the upfront price gap relative to internal combustion engine (ICE) vehicles (Kalthaus and Sun, 2021). Similarly, based on interviews with fleet operators, Bae et al. (2022) identified financial incentives as a pivotal factor influencing the adoption of alternative fuel vehicles, particularly in contexts where upfront investment costs remain high. Other studies rank purchase subsidies amongst the most influential financial incentives for early adopters, second only to broader cost-related considerations (Verma, Verma and Khan, 2020).

However, the effectiveness of financial incentives is not uniform across vehicle segments or national contexts. Examining financial incentive schemes across EU countries, Gil Ribeiro and Silveira (2024) find that while subsidies have successfully lowered initial purchase costs for electric light commercial vehicles, they have not consistently ensured overall cost competitiveness across all markets. More broadly, the literature emphasises that EV adoption is influenced not only by incentives at the point of purchase, but also by fiscal measures applied during the vehicle usage phase, such as registration tax exemptions, circulation taxes, and other operating-cost advantages. Accordingly, Fluchs (2020) modelled purchase price advantages by jointly accounting for upfront subsidies and purchase tax regulations, alongside usage-phase tax incentives, to capture the full cost differential between EVs and conventional vehicles.

Innovativeness and investment in R&D

The diffusion of EV may also be influenced by a country's level of innovativeness and its investment in research and development (R&D) (Yang et al., 2023). Several studies

examine this relationship by linking EV adoption to indicators of technological capability and innovation orientation. Jaiswal and Zane (2022) found that R&D expenditure as a share of GDP – used as a proxy for national innovation intensity – constitutes an essential and sufficient condition for the diffusion of new technologies, including electric vehicles. In contrast, evidence on the broader innovation environment remains mixed. Fluchs (2020) assessed innovativeness using the Global Innovation Index and finds no statistically significant relationship between this indicator and the diffusion speed of battery electric vehicles across European countries.

1.2.3 Research Gap and Objectives

Global electric vehicle adoption has accelerated rapidly in recent years. Electric car sales exceeded 17 million units in 2024, accounting for approximately 20% of total new passenger car sales worldwide. By the end of 2024, the global electrified passenger car fleet reached 58 million vehicles, representing around 4% of the total passenger car stock (IEA, 2025).

Against this global backdrop, emerging markets, particularly Southeast Asia, are increasingly recognised as important growth markets for electric vehicles. According to Ember, EV sales penetration, including battery electric vehicles and plug-in hybrid electric vehicles, reached approximately 40% of total new car sales in 2025 in several ASEAN countries, notably Singapore and Viet Nam. These penetration levels exceed those observed in more established markets such as the United Kingdom at 33% and the European Union at 26%. In contrast, major automotive production hubs within ASEAN, such as Thailand and Indonesia, recorded relatively lower EV sales penetration of around 20% and 15% respectively, highlighting substantial heterogeneity in EV adoption across the region (Ember Energy, 2025).

Despite the growing importance of ASEAN in the global EV transition, empirical studies examining passenger car EV diffusion in the region remains limited and fragmented. This can be attributed to differences in economic development, levels of policy commitment, EV supporting infrastructure deployment, institutional and governance capacity, as well as the relatively early stage of EV adoption compared to developed markets (Lin et al, 2025). More importantly, there is a lack of systematic empirical analysis that jointly examines diffusion dynamics and the interaction of key determinants across ASEAN countries over time.

Table 2: EV Adoption Determinants

EV Adoption Determinants	Country
Charging station infrastructure and investment	Thailand, Indonesia, Viet Nam, Singapore, Malaysia
Battery swapping infrastructure/ facility	Indonesia
Local manufacturing capability and expansion	Viet Nam, Thailand
Fiscal incentive (for example tax reduction, tax exemption, fee exemption, tax holiday, direct subsidy/ rebate)	Brunei, Cambodia, Indonesia, Malaysia, Philippines, Singapore, Thailand, Viet Nam (see Table 1)

Source: Lin et al., 2025; Ember Energy, 2025.

While prior literature identifies several determinants that are conceptually associated with EV adoption – such as charging infrastructure deployment, fiscal incentives, and domestic manufacturing capacity (Table 2), few studies quantitatively assess how these factors influence EV diffusion rates in a comparative, regional framework.

Therefore, this study seeks to address these gaps by providing a comprehensive, multi-country analysis of passenger car BEV diffusion in ASEAN. It contributes to literature in three main ways. First, it applies diffusion theory to empirically characterise EV adoption trajectories across ASEAN using logistic diffusion models. Second, it moves beyond descriptive analysis by identifying the key determinants of EV diffusion through panel regression analysis at both the regional and country levels. Third, by combining diffusion modelling with econometric analysis, this study offers new insights into how infrastructure, policy, and market conditions jointly shape EV adoption patterns across heterogeneous ASEAN contexts.

2. Electric Vehicle Diffusion in ASEAN Countries

2.1 Introduction

This chapter examines the diffusion of battery electric passenger vehicles (BEVs) across eight ASEAN countries over the period 2010–2024, using EV sales as the primary proxy for adoption. This time frame is selected to reflect the relatively nascent stage of EV technology deployment in the ASEAN region. BEV diffusion patterns and rates are first analysed using the technology diffusion framework proposed by Rogers (1962), with robustness checks conducted using the Bass and Gompertz models. Beyond presenting S-curve projections derived from these logistic diffusion models, the chapter also identifies the key determinants of EV diffusion at both the regional and country levels through panel regression analysis.

2.2 Data and Methodology

2.2.1 Data

This empirical study used annual data from eight Southeast Asian countries over the period 2010–2024. The selection of countries is based on the significance of EV sales, which serves as a proxy for the level of adaptation to battery electric vehicle (BEV) technology. The data were manually collected from various sources for the purpose of this research. In several countries, such as Malaysia, Singapore, and Thailand, BEV technology has already been adopted in the early 2010s, whereas in other countries such as Indonesia, the Philippines, and Viet Nam, BEV adoption only became noticeable within the last five years.

Apart from electric vehicle technologies in general, this report explicitly focuses on battery electric vehicles (BEVs). The analysis examines the adoption patterns on country level, also to gain insight on its relation to several influencing factors. Following the approach of Fluchs (2020) in analysing the diffusion of electric mobility in the EU and beyond, this study adopts a saturation level of 50% of total current vehicle stock, acknowledging that not all vehicles will be replaced by BEVs, as alternative powertrain technologies, such as fuel cells, are also likely to play a role in the future.

Government incentives are widely recognised as a key determinant of electric mobility diffusion. To capture the role of government incentives in the model, variables such as tax regulations, supply-side policies, and other non-financial incentives are included. However, given the substantial variation in policy frameworks across countries, the policy variables are quantified using binary indicators (0 and 1). Singapore is designated as a special case in the analysis, reflecting the presence of purchase price advantages.

Several existing studies examine this relationship by linking EV adoption to indicators of socio-economic situation, including technological capability and innovation orientation. Therefore, the model in this study accounts for key socioeconomic and structural characteristics, including innovative capacity, measured by the Global Innovation Index (GII). Over the past decade, all countries exhibit fluctuating trends in innovativeness. Singapore consistently records the highest GII scores amongst ASEAN Member States, while Malaysia and Viet Nam follow at a moderate distance on average.

To reflect the role of societal consumption behaviour in EV adoption, the model includes household and NPISHs final consumption expenditure per capita, measured in purchasing power parity (PPP) terms at constant 2021 international dollars, sourced from the World Development Indicators (WDI). According to the WDI, this indicator represents the market value of all goods and services consumed by households including durable and non-durable goods as well as services and serves as a proxy for overall living standards and consumption capacity. In addition, the analysis incorporates the proportion of the population living in houses as an economic–demographic factor that may influence EV purchasing behaviour. Data on the population living in houses is compiled from various sources and derived by calculating the number of households and

dividing it by the average household size. This variable reflects potential access to private residential space and charging facilities, which may facilitate EV adoption.

On the demographic side, the model includes urban population to examine the relationship between EV diffusion and residential location. These indicators are mainly obtained from the World Development Indicators (WDI). This inclusion is based on the assumption that more developed infrastructure in urban areas, such as denser charging networks, better road connectivity, and stronger policy support, can lower adoption barriers and serve as a motivation for the transition to EV.

In addition to socioeconomic and demographic factors, the model considers infrastructure-related determinants, such as public charging availability and electricity prices, which directly affect the operational feasibility and cost attractiveness of EV ownership. Public charging infrastructure is included as an indicator of charging accessibility; however, due to data limitations, the analysis does not distinguish between individual public charging points and public charging stations and instead relies on aggregated public charging data. Electricity prices are incorporated to reflect the running cost of EVs relative to conventional vehicles. Nevertheless, cross-country comparability remains limited, as electricity tariff structures differ substantially across countries. In particular, countries such as Indonesia and Thailand apply regulated or tiered electricity pricing schemes based on consumption levels or user categories, which may not fully reflect the marginal cost faced by EV users. Table 3 depicts the descriptive statistics of all variables utilised in the study and its description.

Table 3: Descriptive Statistics of Variables in the ASEAN analysis

Variable	Description	Min	Max	Mean	Median	Std Dev	Type	Unit
bev_sales	Number of BEV sales (vehicle registration)	0.00	80.00	4.08	0.01	13.70	Continuous	Thousand Units
bev_stock	Number of BEV stock	0.00	168.87	6.50	0.03	22.95	Continuous	Thousand Units
tax_reg	Availability of tax regulation on BEV	0.00	1.00	0.18	0.00	0.39	Binary	-
sp_pol	Availability of supply-side policy on BEV	0.00	1.00	0.15	0.00	0.36	Binary	-
non_fin	Availability of non-fiscal incentives on BEV	0.00	1.00	0.22	0.00	0.42	Binary	-
consumption_pc	Household final consumption expenditure per capita (PPP constant)	2.55	31.76	10.48	6.64	8.17	Continuous	Thousand US\$
innovation_index	Global innovation index score	19.90	66.43	37.97	36.20	10.90	Continuous	-
people_in_houses	Number of populations living in houses	0.28	245.78	63.56	30.26	75.48	Continuous	Million Persons
urban_pop	Number of populations living in urban areas	2.94	167.84	42.58	31.38	45.43	Continuous	Million Persons
elec_price	Electricity price	0.05	0.70	0.20	0.15	0.15	Continuous	US\$/kWh
pub_charge	Number of public charging available	0.00	11.47	0.62	0.00	1.80	Continuous	Thousand Units

Source: Authors.

2.2.2 Empirical Models

This study derives mainly from the logistic model, deriving from the Rogers (2003) technology diffusion theory. The study is divided into 2 steps: 1) Forecasts of BEV diffusion, and 2) Examining the determinant's effect on EV diffusion. The logistic model followed the formula as follows:

$$y_{it} = \frac{y_i^*}{1 + \exp(-a_i - b_i t)}$$

Where y_{it} is defined as the number of registered BEV in country i in year t . y_i^* denotes the total BEV market potential, in which in this study is exogenously defined as 50% of the current vehicle stock of each country. The parameter y_i^* is also defined as the asymptote of the S-curve. a_i and b_i are the parameters that are estimated, into the historical data of registered BEV to predict the future number of BEV stock.

To compare the results of the forecast conducted utilising logistic model, also as a measure of robustness check, forecasting exercise is also conducted, utilising Bass and Gompertz model. The Bass model is specified as follows:

$$y_{it} = y_i^* \frac{1 - e^{-t(p+q)}}{1 + \frac{p}{q} e^{-t(p+q)}}$$

Where similar to logistic model, y_{it} indicates the cumulative adoption of BEV at time t and y_i^* indicates the constant value of maximum potential BEV adopters. Parameters p and q are estimated utilising non-linear least square, in which p is defined as coefficient of innovation and q is defined as the coefficient of imitation.

Furthermore, the Gompertz Model is specified as follows:

$$y_{it} = y_i^* e^{-ae^{-bt}}$$

Where all variables y_{it} , y_i^* , a , and b have similar definitions with the logistic model.

To understand the difference of diffusion speed between countries, a regression exercise derived from the logistic model is conducted, following the specifications underlined in Fluchs (2020) and Gruber & Verboven (2001). The model is then specified as follows:

$$y_{it} = \frac{y_i^*}{1 + \exp(-a_{it} - b_{it} t)}$$

The above model specification indicates that parameters a_{it} and b_{it} can now vary over time due to external factors that may influence these variables. The parameter a_{it} shift the logistic model horizontally while parameter b_{it} is indicated as the diffusion rate which compresses and inflates the S-curve (Fluchs, 2020).

Performing a regression towards the diffusion rate (parameter b_{it}) will need to be done by differentiating the equation to t , resulting in the following equation:

$$b_{it} = \frac{dy_{it}}{dt} \frac{1}{y_{it}} \frac{y_i^*}{(y_i^* - y_{it})}$$

The above equation is then being used to determine the diffusion rate of each country i in year t . It is then assumed that the diffusion rate depends on external factors, which can be determined as follows:

$$b_{it} = \beta_i^F + \beta Socioeconomic_{it} + \beta Incentive_{it} + \beta Infrastructure_{it}$$

Where $\beta Socioeconomic_{it}$ indicates the vector of socio-economic variables: consumption per capita, innovation index, people living in houses, and urban population; $\beta Incentive_{it}$ indicates the vector of incentive policy variables: tax regulation, non-financial, and supply policy; $\beta Infrastructure_{it}$ indicates the vector of Infrastructure related variables: public charging and electricity price; and β_i^F indicates the country-specific fixed effects that control for time-invariant heterogeneity across countries.

To assess the relative importance of these factors, the empirical analysis adopts a stepwise specification strategy. One model includes only the socio-economic variables as a baseline specification, capturing fundamental structural and demand-side conditions. Another model extends the baseline by incorporating incentive-related policy variables, allowing the incremental effect of policy intervention to be identified. Further, another model further augments the specification by adding infrastructure-related variables, which directly affect the feasibility and cost of BEV adoption.

A similar set of regressions is also conducted towards BEV sales data, to compare the effects of the determinants towards diffusion rate, which implies a long-term adoption, and BEV annual sales, which represents a short-term market expansion of BEV. The full stepwise model specification for the panel regressions is shown in Table 4.

Table 4: Panel Regression Model Specifications

Model	Specification
(1)	$b_{it} = \beta_i^F + \beta Socioeconomic_{it}$
(2)	$b_{it} = \beta_i^F + \beta Socioeconomic_{it} + \beta Incentive_{it}$
(3)	$b_{it} = \beta_i^F + \beta Socioeconomic_{it} + \beta Incentive_{it} + \beta Infrastructure_{it}$
(4)	$BEV_sales_{it} = \beta_i^F + \beta Socioeconomic_{it}$
(5)	$BEV_sales_{it} = \beta_i^F + \beta Socioeconomic_{it} + \beta Incentive_{it}$
(6)	$BEV_sales_{it} = \beta_i^F + \beta Socioeconomic_{it} + \beta Incentive_{it} + \beta Infrastructure_{it}$

Source: Authors.

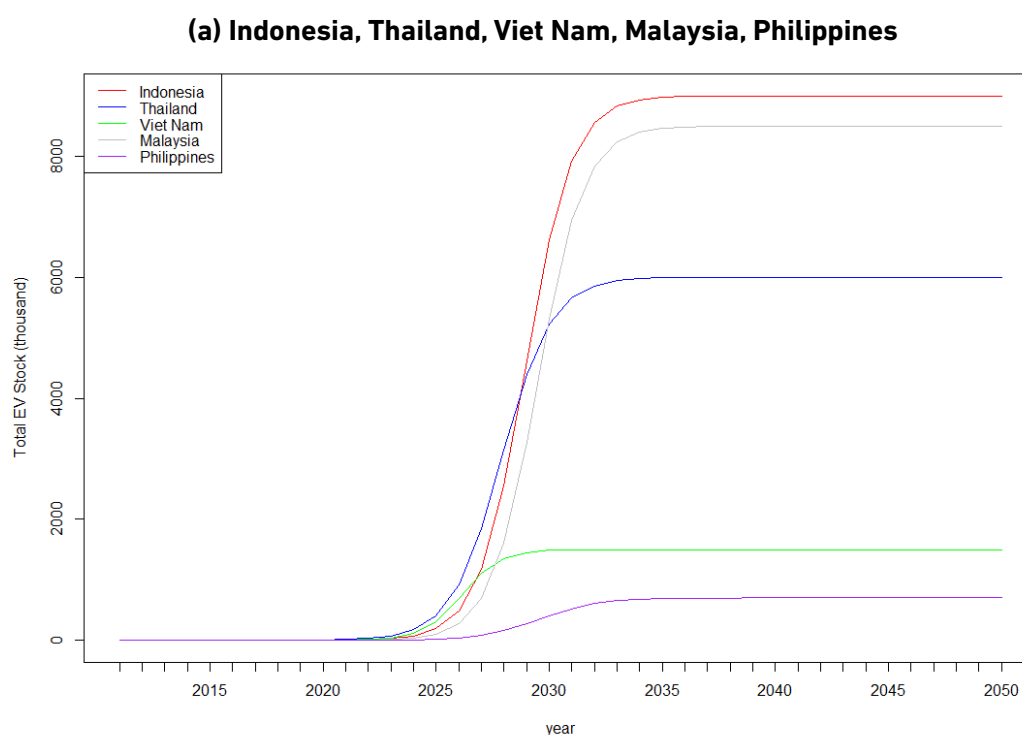
To further analyse the country specific determinants and effects of variables on EV adoption, country level regressions are conducted and undertaken.

2.3 Results

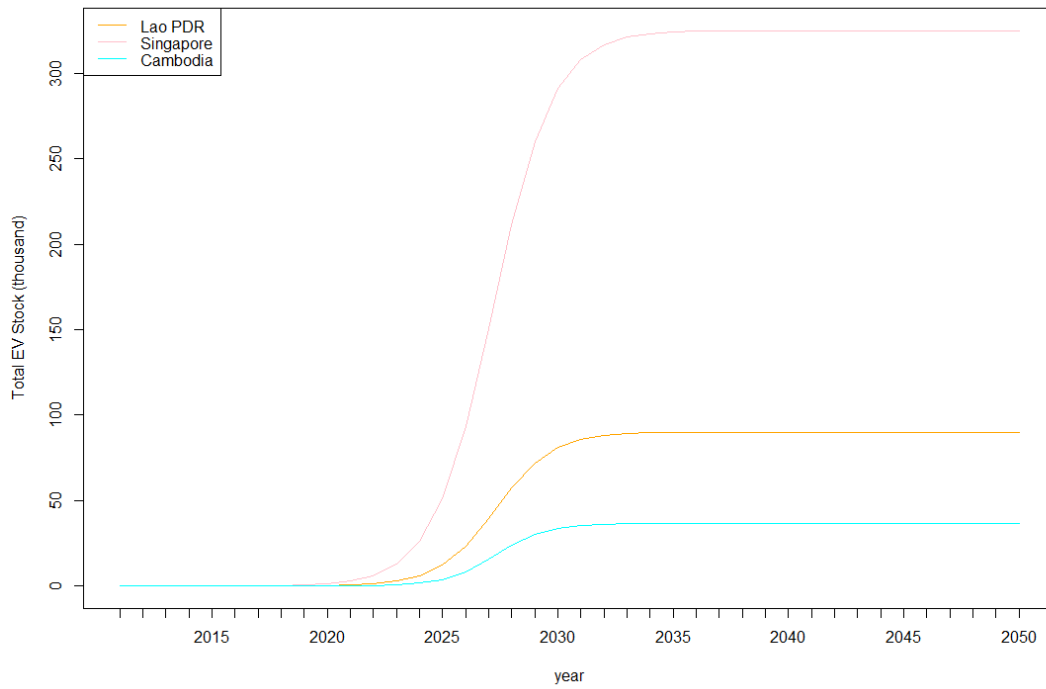
2.3.1 EV Diffusion Patterns: Logistic Model Results

Figure 7 illustrates the logistic S-curve representing the projected BEV uptake from 2010 to 2015 for selected ASEAN countries. Overall, the results suggest that EV adoption across ASEAN follows a relatively progressive diffusion path, with most countries projected to reach the assumed maximum market potential (defined as 50% of the total vehicle stock) between 2030 and 2035. Viet Nam is projected to reach market saturation earlier, before 2030, assuming that recent policy developments and supporting measures continue. In contrast, the Philippines is expected to reach its maximum potential market after 2035, indicating a comparatively slower diffusion trajectory.

Figure 7: Projection of Total Ev Stock in Selected ASEAN countries

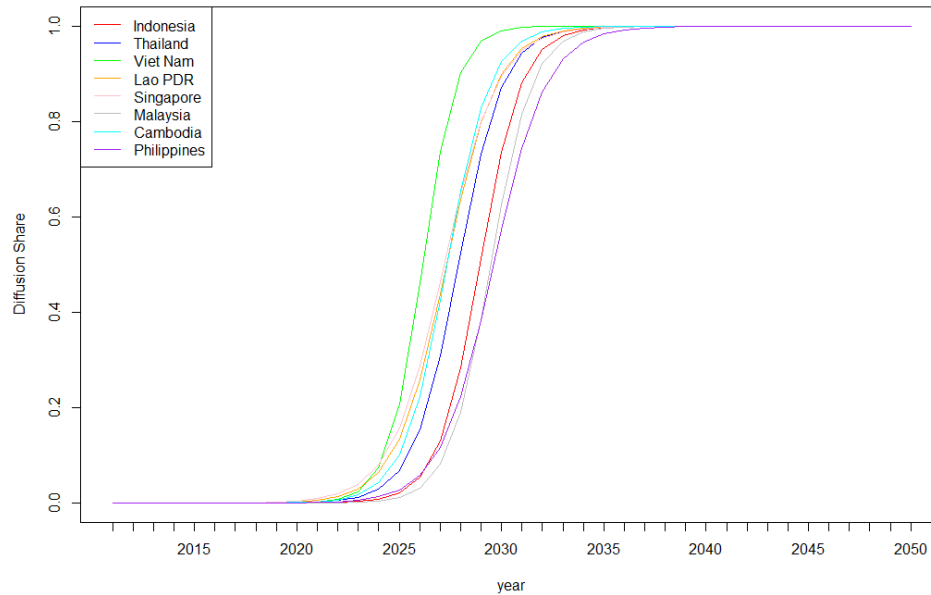


(b) Lao PDR, Singapore, Cambodia



Source: Authors.

Figure 8: Projection of EV Diffusion Share in ASEAN countries



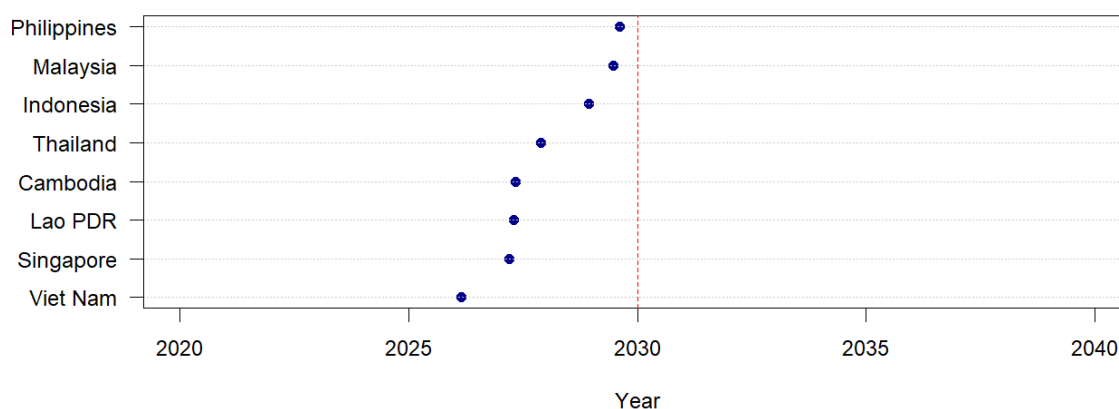
Source: Authors.

Figure 8 presents the estimated inflection points, defined as the point at which the growth rate of EV sales begins to decline, and the market reaches 50% of its total potential. The figure highlights notable differences in diffusion rates across countries. Viet Nam is projected to reach its inflection point by 2026, signalling rapid EV adoption. This is followed by Singapore, which is projected to reach its inflection point after 2027,

reflecting strong recent growth in EV uptake. Cambodia and Lao PDR are also projected to reach their inflection points relatively early, at levels comparable to Singapore. While EV sales in these countries have risen in recent years, the relatively early projected inflection points may partly reflect the modelling assumption that the maximum potential vehicle stock remains constant. In practice, the overall automotive market in these countries is still expanding, which may delay actual saturation.

Thailand is projected to reach its inflection point around 2028, followed by Indonesia and Malaysia, while the Philippines is expected to reach its inflection point between 2029 and just before 2030. Although these countries have also experienced strong recent growth in EV adoption, their projected diffusion rates remain slower compared to the leading ASEAN economies.

Figure 9: Forecasted Years of Inflection



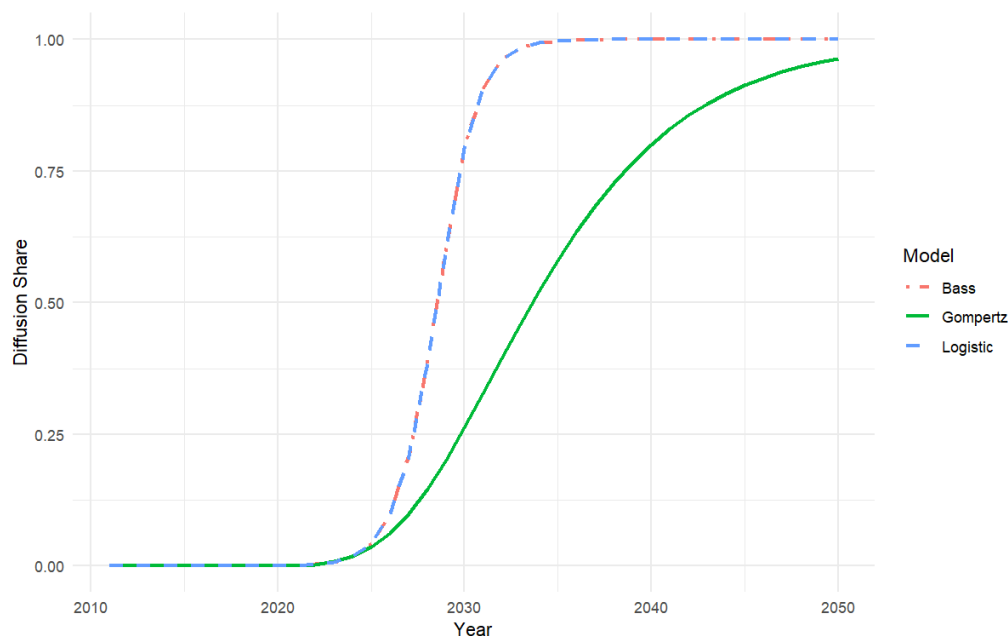
Source: Authors.

Figure 10 compares EV diffusion trajectories under three alternative models – Logistic, Bass, and Gompertz – for a subset of countries: Cambodia, Indonesia, Lao PDR, Singapore, and Thailand. These countries are included because the remaining countries did not converge across all models when estimated using non-linear least squares (NLS).

The results indicate that the Logistic and Bass models produce broadly similar diffusion paths, while the Gompertz model generates a flatter S-curve with a notably lower slope, leading to substantially different projections. Such divergence across models is common in diffusion studies, particularly for technologies such as EVs that are still at an early stage of market penetration. Previous studies also raised concerns towards the level of uncertainty and discrepancy in estimates, especially when the technology is still in early diffusion and limited data is available on the ground (Massiani and Gohs, 2015; Sandberg et.al., 2021). Nonetheless, the consistency between the Logistic and Bass model results suggests that the projections are relatively robust to model specification and historical data limitations, assuming the absence of major external shocks and the continued implementation of current policy frameworks, economic situation, and infrastructure

availability. The modelling results can also still provide some information to provide benchmarks between countries to a certain extent.

Figure 10: Comparison of EV Diffusion Curve (Cumulative of Selected Countries)



Source: Authors.

2.3.2 Determinants of EV Diffusion: Regression Model Results

This section presents the regression results for two related but conceptually distinct outcomes: (i) BEV diffusion speed, measured by the estimated diffusion parameter b_{50} , and (ii) annual BEV sales, capturing short-run market uptake. For both outcomes, three nested fixed-effects specifications are estimated. Model (1) includes baseline socio-economic structural variables; Model (2) augments the baseline with policy variables; and Model (3) further incorporates infrastructure-related variables. Country fixed effects are included in all specifications.

Table 5 reports the results for the diffusion speed parameter b_{50} , which reflects the pace at which BEVs diffuse toward a maximum potential market of 50% of the current vehicle stock.

In the baseline specification Model (1), the regression result indicates that consumption per capita and urban population emerges as statistically significant determinant with positive correlation. Innovation index also emerges as a statistically significant variable, but with a negative correlation. The number of people in houses does not display any significant relationship with diffusion speed.

After introducing policy variables in Model (2), the magnitude of significance within variable consumption per capita decreases, while urban population and innovation index

remain robust. Amongst policy variables, tax regulation shows a statistically significant correlation with diffusion speed, with positive correlation, whereas supply-side policy and non-financial incentives have no reported significance against diffusion speed.

Model (3) adds infrastructure-related variables electricity price and number of charging stations. Both variables have no reported statistical significance against diffusion speed. The variables tax regulations and supply side policy variables have shown a slight change in t-value, displaying a low level of significance of the variables against the dependent variable.

Table 5: Panel Regression Results for Diffusion Rate in ASEAN

b_50					
	(1)	(2)	(3)		
tax_reg		0.196762 *	0.18400 .		
		<i>2.1338</i>	<i>1.96890</i>		
sp_pol		0.161371	0.17417 .		
		<i>1.6503</i>	<i>1.66810</i>		
non_fin		-0.23542	-0.19927		
		<i>-1.0371</i>	<i>-0.84420</i>		
consumption_pc	0.063111 **	0.035671	0.03580		
	<i>2.8033</i>	<i>1.5537</i>	<i>1.45000</i>		
innovation_index	-0.025 *	-0.02256 *	-0.02166 *		
	<i>-2.5332</i>	<i>-2.3539</i>	<i>-2.23460</i>		
people_in_houses	0.033753	0.005328	0.00109		
	<i>0.817</i>	<i>0.1321</i>	<i>0.02610</i>		
urban_pop	0.014637 *	0.018208 *	0.02003 *		
	<i>2.3669</i>	<i>1.9891</i>	<i>2.09550</i>		
elec_price			-0.45163		
			<i>-0.99450</i>		
pub_charge			-0.0000002		
			<i>-0.01040</i>		
Country FE	YES	YES	YES		
R-squared	0.42366	0.49344	0.50526		
Adj R-squared	0.36234	0.42108	0.41476		

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

t-statistics in italics

Source: Authors.

Table 6 shows the regression results for BEV sales, to capture the short-run market uptake dynamics. The regression is conducted under similar model specifications as the regression previously conducted at diffusion speed.

In the baseline specification under Model (4), consumption per capita is positive and statistically significant, confirming that income plays a key role in enabling BEV purchases. Urban population share is likewise positive and significant, while people living in houses

When policy variables are introduced in Model (5), supply-side policies display a positive and statistically significant effect on BEV sales, while tax and regulatory measures and non-fiscal incentives remain insignificant. Urban population and people in houses remain statistically significant, meanwhile consumption per capita loses its significance once policy variables are introduced.

A markedly different pattern emerges once infrastructure variables are added in Model (6). Public EV charging availability shows a strongly positive and statistical significance, with a substantial increase in explanatory power (adjusted R-squared rises to 0.92). At the same time, consumption per capita and people in houses shows a statistically significant correlation, while urban population and supply side policies loses its significance. Electricity price shows no statistically significant correlation with the dependent variable.

Table 6: Panel Regression Results for BEV Sales in ASEAN

	bev_sales		
	(4)	(5)	(6)
tax_reg		1.21818	0.728645
		<i>0.2896</i>	<i>0.5254</i>
sp_pol		14.33333 **	0.227282
		<i>3.2102</i>	<i>0.1466</i>
non_fin		-14.6868	-2.54766
		<i>-1.4192</i>	<i>-0.7286</i>
consumption_pc	2.99974 **	1.77946 .	-1.28406 ***
	<i>2.8563</i>	<i>1.6981</i>	<i>-3.5032</i>
innovation_index	0.34407	0.52704	0.028849
	<i>0.7377</i>	<i>1.188</i>	<i>0.1979</i>
people_in_houses	-1.0791	-2.69164	1.259739 *
	<i>-0.5607</i>	<i>-1.4631</i>	<i>2.0399</i>
urban_pop	0.64151 *	1.12936 **	0.035048
	<i>2.2265</i>	<i>2.7051</i>	<i>0.2473</i>
elec_price			-4.89747
			<i>-0.7259</i>
pub_charge			0.007697 ***
			<i>23.1877</i>
Country FE	YES	YES	YES
R-squared	0.21646	0.33964	0.93134
Adj R-squared	0.1331	0.24531	0.91977

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

t-statistics in italic

Source: Authors.

Country Level to Diffusion Rate

To examine within-country dynamics over time, a multiple linear regression analysis to the diffusion rate is conducted using a consistent set of variables for all countries (Table

3). We further validated the model by testing for multicollinearity to ensure the independent variables are not highly correlated. The result shows that cars per household variable is multicollinear against other variables and therefore excluded in this analysis. Table 7 further detailed the results of country-level regression to the diffusion speed parameter b_{50} .

Table 7: Country Level Regression to Diffusion Rate

	Cambodia	Indonesia	Malaysia	Philippines	Singapore	Thailand	Viet Nam
tax_reg	1.246e-01	1.889e-01		0.0765714	-2.292e-01		4.979e-01
	<i>0.588</i>	<i>0.870</i>		<i>0.259</i>	<i>-0.564</i>		<i>1.365</i>
sp_pol			5.496e-01			1.298e-02	
			<i>2.824 *</i>			<i>0.073</i>	
non_fin		-1.565e-01					
		<i>-0.682</i>					
innovation_index	-5.035e-03	-3.289e-02	2.382e-02	-0.0390317	2.209e-03	8.325e-03	-4.548e-02
	<i>-0.254</i>	<i>-1.225</i>	<i>1.267</i>	<i>-0.899</i>	<i>0.057</i>	<i>1.576</i>	<i>-0.792</i>
consumption_pc	-6.125e-04	-2.248e-04	1.806e-05	0.0004102	7.390e-05		
	<i>-2.019</i>	<i>-1.279</i>	<i>0.560</i>	<i>2.019</i>	<i>1.090</i>		
people_in_houses			1.533e-07		-1.518e-05	-3.762e-08	1.761e-07
			<i>2.905 *</i>		<i>-1.233</i>	<i>-1.425</i>	<i>1.580</i>
urban_pop					-1.567e-08		
					<i>-0.021</i>		
elec_price	-1.029e+01	5.725e+00	-1.466e+01	2.1187577	-3.807e+00	-4.924e-01	-1.588e+00
	<i>-3.011 *</i>	<i>3.360 **</i>	<i>-1.468</i>	<i>0.955</i>	<i>-1.265</i>	<i>-1.082</i>	<i>-0.095</i>
pub_charge		-2.761e-05	-3.037e-04	-0.0004194	-2.072e-06	-2.666e-06	-4.850e-05
		<i>-0.464</i>	<i>-2.857 *</i>	<i>-1.012</i>	<i>-0.050</i>	<i>-0.085</i>	<i>-0.839</i>
R²	0.6941	0.8699	0.8508	0.5193	0.7354	0.6684	0.7354
Adj. R²	0.5717	0.7724	0.7389	0.2523	0.4708	0.4842	0.5884

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

t-statistics in italic

Source: Authors.

The regression results indicate that BEV adoption across ASEAN is driven by various variables. In Cambodia and Indonesia, electricity price has the highest statistical significance. In Malaysia, people living in houses and supply-side policy variables have a high statistical significance with a positive coefficient, whereas public charging shows a negative coefficient. In the Philippines, consumption per capita has a relatively lower statistical significance. These findings suggest that supply-side policies, consumption per capita, the number of people residing in houses, electricity prices, and the availability of public charging are deemed significant in shaping the pace of BEVs diffusion toward a maximum potential market of 50% of the existing vehicle stock across ASEAN.

Country Level to BEV sales

Other than the diffusion rate, multiple linear regression analysis and multicollinearity test were conducted on BEV sales for each country using the same set of variables outlined in Table 3. The multicollinearity test indicate that some variables needed to be excluded in a specific country, and after adjustments, multicollinearity is not present for variables such as public charging,

electricity price, and innovation index. The variables affected by multicollinearity vary by country because of data availability. For instance, cars per household is non-multicollinear only in Cambodia, Philippines, Singapore, and Thailand, while people living in houses is non-multicollinear in all countries except Cambodia, Indonesia, and Philippines.

Table 8: Country Level Regression to BEV Sales

	Cambodia	Indonesia	Malaysia	Philippines	Singapore	Thailand	Viet Nam
tax_reg	6.620e+02	30.420		1.266e+03	-1.36E+03		3.555e+03
	<i>1.931 .</i>	<i>0.018</i>		<i>0.594</i>	<i>-1.689</i>		<i>0.392</i>
sp_pol			-6.239e+02			1.28E+03	
			<i>-0.561</i>			<i>0.198</i>	
non_fin		1406.670					
		<i>1.027</i>					
innovation_index	2.018e+01	-39.769	1.056e+02	6.330e+01	-2.11E+02	3.34E+01	-1.897e+02
	<i>0.725</i>	<i>-0.192</i>	<i>0.984</i>	<i>0.320</i>	<i>-2.414 *</i>	<i>0.174</i>	<i>-0.133</i>
consumption_pc	6.531e-01		-2.468e-01	1.097e+00			
	<i>1.201</i>		<i>-1.341</i>	<i>1.235</i>			
people_in_houses			6.919e-05		2.25E-02	1.00E-03	-4.359e-06
			<i>0.230</i>		<i>0.802</i>	<i>1.044</i>	<i>-0.002</i>
urban_pop					-3.69E-03		
					<i>-2.605 *</i>		
cars_ph	6.821e+04			3.297e+04	-1.01E+04	4.095e+03	
	<i>-1.967 .</i>			<i>0.916</i>	<i>-4.16 **</i>	<i>0.228</i>	
elec_price	-6.293e+03	-26361.747	-1.085e+05	1.738e+04	-1.35E+03	-4.04E+03	5.425e+04
	<i>-1.216</i>	<i>-2.013</i>	<i>-1.903</i>	<i>1.710</i>	<i>-0.212</i>	<i>-0.244</i>	<i>0.131</i>
pub_charge		8.870	7.204e+00	-3.825e+00	1.10E+00	8.22E+00	8.675e+00
		<i>21.320 ***</i>	<i>11.870 ***</i>	<i>-2.072 .</i>	<i>12.31***</i>	<i>5.08E-05 ***</i>	<i>6.036 ***</i>
R²	0.7217	0.99	0.9898	0.5872	0.9894	0.9602	0.9276
Adj. R²	0.5671	0.9844	0.9821	0.2776	0.9789	0.9381	0.8874

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

t-statistics in italic

Source: Authors.

Regression result on Table 8 shows that public charging infrastructure is the most significant driver of BEV diffusion across ASEAN countries except Cambodia (due to multicollinearity), which may be due to the lack of well-documented charging data in Cambodia. In contrast, other variables show weaker or inconsistent effects.

Tax regulations and non-fiscal incentives have an overall positive coefficient, thus having positive effects on BEV sales, although not statistically significant. The innovation index coefficient is positive in most countries except Indonesia, Singapore, and Viet Nam, where innovation index score fluctuates despite the increase in BEV sales.

Electricity prices show a negative correlation with BEV sales in Cambodia, Indonesia, Malaysia, Singapore, and Thailand, which is expected, indicating that an increase of electricity price (as BEV fuel) will lower consumer demand. However, this trend is not shown in the Philippines or Viet Nam, which is probably because BEV sales and electricity

prices fluctuate in Philippines, while BEV sales continue to grow in Viet Nam despite rising electricity prices in 2024 after a seven-year period of price stagnation.

Overall, differences in BEV adoption across ASEAN reflect varying starting points, policy mixes, and national priorities, leading to heterogenous outcomes across countries.

Cambodia

In Cambodia, tax regulation and cars per household are statistically significant variables, albeit at a low significance level (0.1). The number of registered BEVs increased significantly from 600 units in 2023 to 2,513 units in 2024 (CamNess, 2024), showing a good response to tax incentives, such as the reduction of special, customs, excise, and value-added taxes (listed in Table 1). Additionally, as Cambodia's economy and household final consumption expenditure continue to increase, the motorisation rate is forecasted to continue to grow, which is in line with earlier studies (ERIA, 2024; World Bank, 2024).

Indonesia

In Indonesia, the development of the EV ecosystem has been primarily driven by industrialisation anchored in resource nationalism, particularly the strategic utilisation of the country's abundant nickel reserves. The regression results show that EV diffusion in Indonesia is strongly influenced by the expansion of public charging infrastructure, which emerges as the dominant determinant of adoption. Electricity prices display a negative but only weakly significant association, indicating limited yet observable consumer sensitivity to operating costs. One possible explanation is the timing of policy implementation: fiscal incentives aimed at promoting EV adoption only began to take shape between 2022 and 2023 and are scheduled to expire in 2025. Non-fiscal policy measures, meanwhile, originated with Presidential Regulation No. 55/2019, which introduced the country's first substantive incentives for accelerating battery electric vehicle deployment and gained traction in subsequent years. Another contributing factor is the geographic concentration of EV adoption, which is largely confined to two provinces – Jakarta and Bali – not sufficient to represent national-level EV adoption. Taken together, the policy assessment and EV ecosystem analysis suggest that Indonesia's EV market remains in an early, infrastructure-constrained phase, in which practical usability considerations outweigh financial or technological factors.

Malaysia

Public charging infrastructure is statistically significant in Malaysia, indicating that an increase in public charging availability is associated with higher BEV sales, as expected. Although not statistically significant, supply-side policy, electricity price, and consumption per capita shows negative coefficients. This likely reflects the indirect and delayed nature of supply-side policy, which primarily targets production capacity rather than immediate consumer adoption. Moreover, the positive coefficient on people in

houses suggests that household characteristics play an important role in BEV purchase decisions in Malaysia.

Philippines

According to the EV ecosystem data for the Philippines (see the appendix), the findings indicate that: (i) EV diffusion in the country remains at an early, emerging stage; (ii) this reflects the fact that key enabling factors – such as tax incentives, innovation capacity, household consumption, infrastructure availability, and non-fiscal policies – introduced since around 2010 and gaining momentum only after the enactment of the EV Industry Act (EVIDA) in 2022, have not yet translated into strong, measurable drivers of adoption; and (iii) the Philippines' EV ambitions are primarily linked to broader renewable energy development objectives, resulting in less stringent industrial protection and localisation policies compared to countries with abundant nickel reserves, such as *Indonesia*.

Thailand

The regression results show a strong model fit, with an R-squared of 0.9602 and an adjusted R-squared of 0.9381. Amongst the explanatory variables, public charging infrastructure is the only statistically significant determinant of EV adoption in Thailand. This finding indicates that charging infrastructure functions as a key enabler of EV diffusion by reducing range anxiety and improving the practicality of daily EV use.

According to the Electric Vehicle Association of Thailand (EVAT), by the end of 2024 Thailand had installed more than 11,000 charging points nationwide, with an approximately equal split between AC and DC chargers. Around 30% of these charging points are concentrated in Bangkok and the central region, particularly in major business districts such as Lumpini, Wang Mai, and Pathum Wan. Charging infrastructure deployment has also expanded into key provinces and major tourist destinations, including Phuket, Chiang Mai, Pattaya, and Hua Hin.

The rapid expansion of charging infrastructure reflects the cumulative impact of early-stage EV development policies and institutional arrangements implemented mainly between 2015 and 2020, particularly from 2018 onwards following the establishment of the EV charging consortium. This consortium brought together charging operators, service providers, automotive companies, and EV supply and equipment manufacturers, facilitating interoperability and co-ordinated infrastructure rollout. In parallel, both public and private actors have played significant roles in scaling up the EV charging business in Thailand (see Table 9).

Table 9: Stakeholders' Role in EV Charging Business

Business Type	Company	Driving Factor	Contributions to EV Charging
Oil and Gas Company	• PPT Plc • Bangchak • Susco • Shell • Caltex Chevron	Diversify and increase revenue from business lines beyond the oil and gas sector, support EV policies	Supporting pilot project of EV charging and charging business
Electricity State Enterprise	• Metropolitan Electricity Authority (MEA) • Provincial Electricity Authority (PEA) • Electricity Generation Authority (EGAT)	Potential of new demand and revenue, support EV policies	Launched pilot charging stations, support charging installations, partner with other agencies or automotive companies
Green Energy Companies	• Energy Absolute • GLT	Tap into emerging markets within related industries	Develop charging stations, provide EV charging system and solution
Start-ups	• Grid Whiz • EVen • EVF • The fifth element • Future Charge • Share Management	Tap into emerging markets within related industries	EV charging apps, EV charging installations, and EV charging equipment/ parts provision
Charging Operators and Automotive Companies	• BMW – Charge Now • Mercedes Benz – EQ-Electric • Nissan • MG	Increase the BEV sales and provide its supporting infrastructure	EV charging installations

Source: Authors.

In addition, supply policy variable remains statistically insignificant in the regression model. This is interesting, given that Thailand is one of the largest automotive manufacturing hubs in ASEAN and has positioned the EV industry as a key pillar of next-generation vehicle development. The result suggests that supply-side policy has not been a key driver of domestic EV adoption in Thailand.

Table 10: BOI Approved Incentive Package in 2020

Investment Package	Incentive
≥5 million Baht	8-year corporate income tax, eligible for extension for R&D investment and expenditures
<5 million Baht	3-year tax holidays, eligible for extension if: ➤ Commencement of production in 2022 ➤ Additional part production ➤ Production of ≥10,000 units in 3 years ➤ R&D investment

Source: Authors.

Table 11: Summary of EV 3.0 Policy

EV 3.0 Policy (2022–2023)			
Retail Purchase Subsidy	Import Duty Rate Reduction for Completely Built Up (CBU)		Excise Duty Rate Reduction
Specification	Specification		
Seat ≤ 10 RP ≤ B2 million	BC ≥ 10 kWh RP ≤ B2 million	BC ≥ 30 kWh RP B2–7 million	
Received Subsidy: 10 ≤ BC < 30 kWh B70,000 BC ≥ 30 kWh B150,000 (eligible for imported or locally produced)	Non-FTA Duty reduced from 80% to 40% FTA Partner Countries If preferential tariff > 40%, then the duty rate is reduced to 40% If preferential tariff < 40%, then the duty rate is exempted	Non-FTA Duty reduced from 80% to 60% FTA Partner Countries If preferential tariff > 20%, then the duty rate is reduced to 20% If preferential tariff < 20%, then the duty rate is exempted	Excise tax is reduced from 8% to 2%
	CBU import privileges require production offset. With import to local production ratio at: 1:1 by end of 2024 1:1.5 by end of 2025		

B = Thai Baht, RP = Retail Price, BC = Battery Capacity.

Source: Summarised by authors.

Table 12: Summary of EV 3.5 Policy

EV 3.5 Policy (2024–2027)			
Retail Purchase Subsidy			Tax Benefit
Retail Price	Battery Capacity	Subsidy	
< B2 million	10–50 kWh	1 st year (2024): B100,000/ unit 2 nd year (2025): B75,000/ unit 3 rd – 4 th year (2026–2027): B50,000/ unit	Excise tax reduction from 8% to 2%
	>50 kWh	1 st year (2024): B500,000/ unit 2 nd year (2025): B35,000/ unit 3 rd – 4 th year (2026–2027): B20,000/ unit	Import duty reduction up to 40% (for CBU imported in 2024–2025) For the imported CBU, manufacturers should offset the local production with import to local production ratio: 1:2 by end of 2026 1:3 by end of 2027
B2–7 million		No subsidy	Excise tax reduction from 8% to 2%

B = Thai Baht, CBU = Completely Built-Up vehicle.

Source: Summarised by authors.

This can be explained by the orientation of Thailand's EV supply policies. While recent incentive and policy packages under EV 3.0 and EV 3.5, introduced in support of the 30@30 policy, do include some demand-side elements, such as direct purchase rebates for EV buyers (see Table 9 and 10), the overall policy focus remains strongly on the manufacturing side (Table 8, 9, and 10). Major policy instruments include excise tax reductions, import duty exemptions, income tax incentives, and tax holidays, which are primarily designed to attract investment, expand production capacity, and support the EV and EV-parts manufacturing industry.

As a result, these supply-side policies are more effective in strengthening Thailand's role as an EV manufacturing and export base than in directly encouraging domestic EV uptake. In this context, the regression results suggest that charging infrastructure, rather than supply-side incentives, is the key enabler for EV diffusion in the domestic market. At the same time, Thailand's supply policy remains consistent with its broader strategy of serving both regional and global EV demand.

Viet Nam

Viet Nam has experienced a rapid rise in electric vehicle sales over the past five years, with total EV deliveries increasing sharply, reflecting rapid market formation supported by the presence of a domestic EV manufacturer. In this context, VinFast, Viet Nam's leading domestic EV manufacturer, has consistently strengthened its market presence, with deliveries in the home market nearly doubling to around 170,000–175,000 EVs in 2025, underscoring strong local acceptance and helping to anchor the broader EV ecosystem. However, the econometric results suggest that, beyond this broader market context, the expansion of public charging infrastructure is the only factor that shows a statistically significant association with EV diffusion. This finding is consistent with Hoang, Nguyen and Nguyen (2024) that highlighting structural challenges in Viet Nam's charging ecosystem, particularly the limited number of stations, weak integration with urban road networks, and the use of charging station design standards that are not fully adapted to local traffic and safety conditions. This infrastructure expansion continues to lag behind vehicle uptake, noting a classic 'chicken-and-egg' dilemma, where consumers hesitate to buy EVs due to limited public charging availability, and investors are cautious without clear demand signals. The responsibility for scaling the charging ecosystem should be shared amongst public authorities, automakers, and private investors, with effective progress requiring not only supportive policy and planning but also technological innovation by manufacturers to improve charging convenience, efficiency, interoperability, and nationwide standardisation.

Singapore

The regression results show a very high goodness of fit, with an R^2 of 0.9789, indicating that the selected variables explain most of the variation in BEV adoption in Singapore.

Several variables are statistically significant, and their coefficients reflect Singapore's distinctive approach to vehicle management and transport decarbonisation.

Car ownership (cars per household) has a negative and significant coefficient (p-value = 0.00424), indicating that BEV sales increase as overall car ownership declines. This relationship reflects Singapore's long-standing quota-based vehicle control system, most notably the Certificate of Entitlement (COE). Under this system, potential car owners must bid for a COE, the price of which has increased sharply over time. For instance, COE premiums for passenger car (category A and B) rose from around S\$18,000–19,000 in 2010 to over S\$100,000 after 2022, reaching more than S\$109,000–115,000 by the end of 2025.

In addition to COE costs, car purchases in Singapore are subject to multiple supplementary charges, including a 20% excise duty, a tiered Additional Registration Fee (ARF), and emissions-related surcharges, which together can exceed the car's base price. Within this policy environment, BEVs become relatively more attractive due to targeted incentives and rebates, which in some cases can reach up to S\$40,000 through deductions in the Additional Registration Fee (ARF). These incentives are mainly provided under the Electric Vehicle Early Adoption Incentive (EEAI) and the Vehicle Emissions Scheme (VES), both of which reward lower-emission vehicles and significantly reduce the upfront cost of fully electric cars. A more detailed assessment of the historical purchase price advantage and tax regulation differences between BEVs and petrol-based ICE vehicles in Singapore is examined separately in an ERIA Discussion Paper.

However, the negative coefficient does not imply that Singaporeans are rejecting BEVs. Instead, it reflects a broader policy objective: suppressing car ownership overall. As COEs expire after 10 years, vehicles must be deregistered and scrapped, unless owners pay the prevailing quota premium (PQP) to renew the COE. Against the backdrop of high replacement costs associated with COE renewal or purchasing a cleaner-fleet vehicle, Singapore's transport ecosystem enables residents to commute affordably, conveniently, and efficiently through public transport and active mobility (such as walking and cycling), while maintaining high punctuality and reliability. Consequently, the decision to adopt BEVs is shaped by a mobility system where private vehicle ownership is only one of several effective options.

This interpretation is reinforced by the negative coefficient on urban population (p-value = 0.03519). Singapore is already a fully urbanised, space-constrained city-state, so increases in 'urban population' effectively capture population growth under strict land and road capacity constraints. As population rises, the government further tightens vehicle control to prevent congestion and environmental degradation. This is consistent with observed trends: cars per household declined from about 0.5 in 2010 to around 0.39 in 2024, while cars per 1,000 people fell from roughly 115 to 95 over the same period (with BEVs accounting for only about 4 per 1,000 people in 2024). Hence, the negative

coefficient reflects system-wide vehicle suppression, rather than a BEV-specific deterrent.

The innovation index also shows a negative and marginally significant coefficient (p -value = 0.04651). According to the Global Innovation Index (GII), Singapore consistently ranks amongst the world's top innovators, with strong performance in high-tech manufacturing, government effectiveness, unicorn valuation, and digital activity. However, the GII does not directly capture transport-specific innovation factors relevant to BEV adoption. Over the study period, Singapore's innovation rank remains at a very high level, while its innovation scores exhibit a fluctuating and declining trend, even as BEV adoption continues to increase. This divergence in trends likely drives the negative coefficient observed in the regression. As such, the result should not be interpreted as innovation discouraging BEV uptake.

In contrast, charging infrastructure availability emerges as a positive driver of BEV adoption. The expansion of nationwide charging points reduces range anxiety and improves daily usability, making BEVs more viable within Singapore's tightly managed vehicle stock.

Overall, the regression results suggest that Singapore's BEV trajectory is shaped less by a simple substitution from ICE vehicles to BEVs, and more by a deliberate strategy to limit the total number of vehicles. While several variables exhibit negative coefficients, these primarily reflect strong vehicle suppression policies aimed at reducing congestion, managing land scarcity, and minimising environmental impacts. At the same time, Singapore adopts a multi-pathway decarbonisation strategy for land transport: electrification is promoted within a capped vehicle population, supported by extensive charging infrastructure, while public transport, walking, and cycling are actively encouraged as cleaner and more affordable alternatives. In this context, BEVs grow in share, not because more cars are added, but because they gradually replace ICE vehicles within a tightly controlled system.

2.3.3 Discussion: Interpretation of Findings and Policy Implications

The logistic S-curve forecasts presented in the earlier section reveal a notable heterogeneity in BEV adoption dynamics across ASEAN countries. In particular, lower-income economies such as Viet Nam, Lao PDR, and Cambodia exhibit faster projected diffusion trajectories than relatively higher-income countries including Thailand, Indonesia, and Malaysia. This pattern appears counterintuitive when viewed through a conventional affordability lens, as higher-income countries are typically expected to adopt new vehicle technologies more rapidly.

The ASEAN-level panel regression results help reconcile this apparent paradox by distinguishing between the determinants of diffusion speed and those of market scale. The diffusion speed (b_{50}) regressions indicate that income levels are not a robust determinant of diffusion speed once structural factors are controlled for. Instead, urban population scale and innovation index variables play a more prominent role, while

charging infrastructure does not significantly affect diffusion speed. This suggests that faster adoption in lower-income countries may reflect structural and institutional conditions rather than higher purchasing power alone.

In contrast, the BEV sales regressions show that infrastructure availability, represented by public charging, is the dominant driver of annual BEV sales. Once charging infrastructure is controlled for, higher consumption per capita is associated with lower marginal BEV sales, consistent with market maturity effects in higher-income countries. This indicates that while wealthier economies host larger BEV markets, their incremental sales growth may be slower due to earlier adoption and partial saturation.

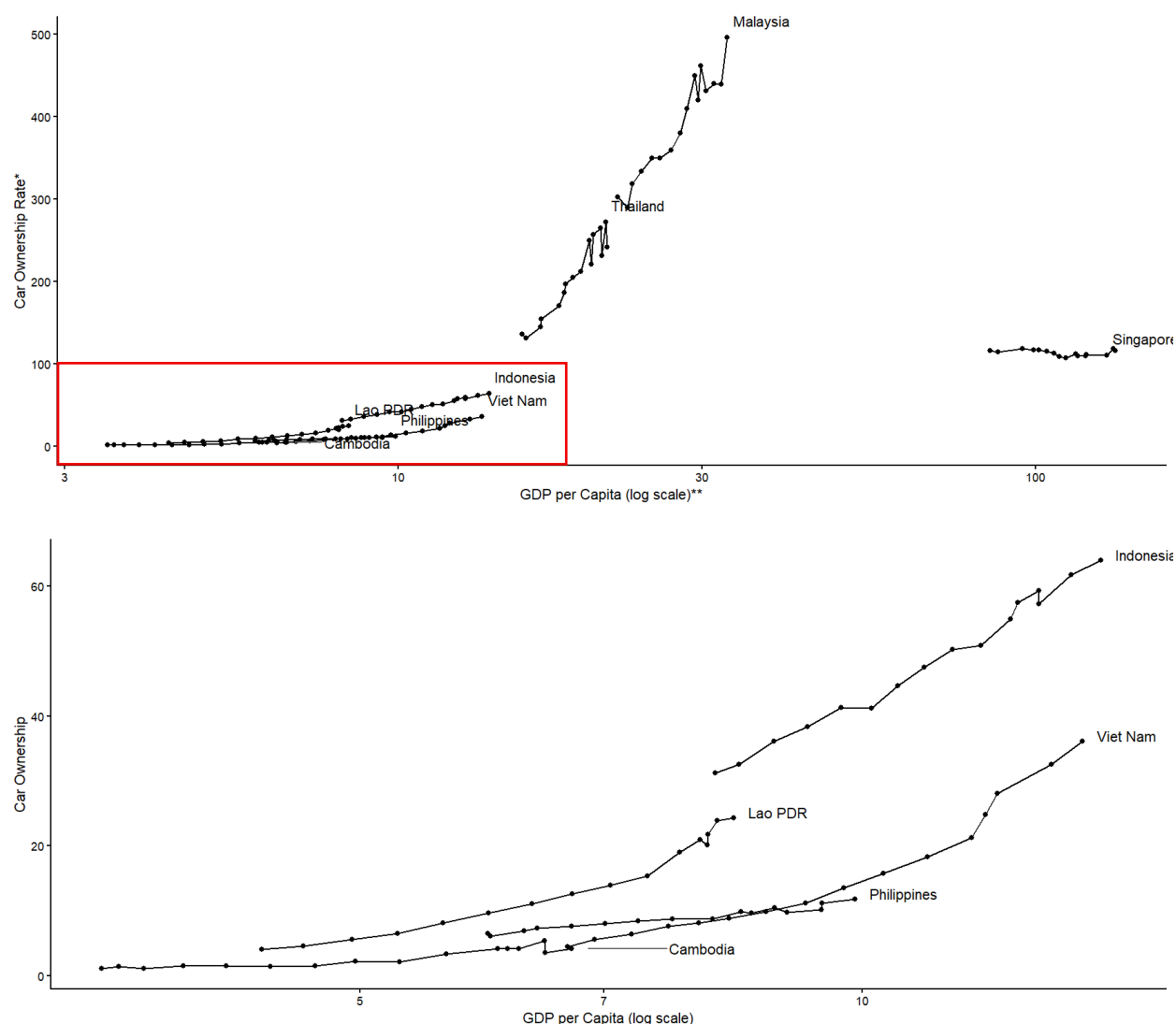
Taken together, these findings suggest that several lower-income ASEAN countries may experience faster diffusion once adoption begins, resulting in steeper S-curve trajectories despite smaller absolute market sizes. This pattern is consistent with the notion of technological leapfrogging (Sauter and Watson, 2008), whereby developing economies that lag in the adoption of incumbent technologies may transition more rapidly to newer technologies under favorable conditions. In the ASEAN context, Viet Nam, Cambodia, and Lao PDR may exhibit early indications of such dynamics, particularly Viet Nam, which has successfully developed a domestic BEV industry.

By contrast, Indonesia, Malaysia, and Thailand, while also classified as developing economies, have long-established automotive industries and extensive internal combustion engine (ICE) infrastructure. The presence of these legacy systems may create adoption inertia or 'lock-in' effects, slowing the pace of transition toward BEVs despite strong policy interest. Singapore represents a distinct case, where higher income levels, strong regulatory intervention, and rapid infrastructure deployment have jointly supported accelerated BEV adoption.

Comparing the results with the growing car ownership rate in ASEAN countries, as depicted in Figure 11, there is a correlation between the proposed lock-in effect with the growth of car ownership rate relative to growth in economic activity. Some countries that lagged in EV adoption, such as Malaysia and Thailand, have relatively higher car ownership rate. Countries such as Viet Nam, Lao PDR, and Cambodia, with lower car ownership rate, had a faster EV adoption rate as was shown in previous parts. These echoes the potential lock-in effect Indonesia, on the other hand, although had a relatively lower car ownership rate, turns to be relatively slower in adoption as well. It is notable, however, that Indonesia has a relatively mature infrastructure and is a strong manufacturing base for ICE. Philippines also has a relatively lower car ownership rate and lags behind in terms of EV adoption. In this case, theoretically, Philippines shouldn't experience a lock-in effect as it affects other countries, but the adoption of EV is still relatively slower compared to other countries. This finding calls for further study that perhaps need to look deeper on other factors that may affect this situation, particularly in Philippines. Singapore is also another unique case in ASEAN, in which the car

ownership rate remains stable despite and kept relatively low despite a very strong economic situation compared with its ASEAN peers.

Figure 11: Car Ownership Rate and Log Income per Capita of (a) ASEAN Countries, (b) Countries with Ownership rate below 100 vehicles per 1000 population



Note :

*Car Ownership Rate is defined as the total registered car per 1000 of population.

**GDP per Capita (log scale) is defined as the log of GDP per Capita in thousands of US\$, PPP constant 2021.

Source: author's calculation based on ASEANstats, WDI, Statista.

Notwithstanding these differences, historical data indicate that BEV adoption has grown rapidly across all ASEAN countries over the past five years, pointing to a strong regional outlook. The forecasting results suggest that all countries are expected to reach their inflection points before 2030 and approach market saturation before 2035, with the assumption that there will be no external shock, market saturation level remains constant, and the current historical growth trend will continue in the forthcoming years.

This is also inline to the finding from another study conducted by ERIA (2023) which analyses the tipping point of buying a passenger vehicle BEV against ICE will be around 2025–2030. However, the results came from several assumptions, including a further reduction of Lithium-Ion batteries, in which the study assumed a 75% learning rate.

Finally, country-level regression results indicate that public charging infrastructure is the only variable that consistently exhibits strong statistical significance in explaining BEV sales, mirroring the panel regression findings. Other variables do not consistently display robust significance at the country level, likely reflecting limited sample size and country-specific heterogeneity. This divergence between panel and country-level results underscores the value of panel analysis in identifying common regional drivers, while also highlighting the need for more granular, country-specific studies to better capture national transition pathways.

3. Electric Vehicle Diffusion in the United States

3.1 Introduction

Over the past decade, electric vehicle (EV) adoption in the United States has accelerated rapidly, driven by declining battery costs, technological improvements, and increasing policy support at both the federal and state levels. Despite this overall growth, EV adoption has been highly uneven across US states, reflecting differences in market conditions, infrastructure availability, and policy environments.

This analysis studies EV adoption in the United States using a combination of panel regressions and diffusion models applied to state-level data from 2016 to 2022. We employ a standard logistic diffusion framework to estimate states' diffusion speeds and saturation timing, complemented by log-linear exponential growth models that capture early-stage adoption dynamics. In addition, we examine baseline panel regressions to identify correlates of EV adoption, including charging infrastructure, vehicle market size, and economic indicators. Our results indicate that EV adoption is growing rapidly but at different speeds across the US, that most states are projected to approach saturation by the early 2040s, and that infrastructure availability is strongly associated with higher adoption levels. These findings highlight the importance of state-specific policy approaches when evaluating and promoting the adoption of EVs.

3.2 Data and Methodology

3.2.1 Data

The dataset utilised in this United States analysis is a state-year panel covering all 50 US states and the District of Columbia over 7 years (2016–2022), and the key variables are highlighted in Table 11.

Table 11: Summary of Key Dataset Variables

Variable	Description
State	US state
year	Year of observation
EV_count	Total registered electric vehicles in a given state and year
gas_count	Total registered gasoline vehicles in a given state and year
rd	R&D expenditure indicator representing share of GDP spent on R&D
station_count	Number of charging stations
real_pce	Real personal consumption expenditures, proxying for income

Source: Authors.

Data on electric vehicle count and gas vehicle count for each state and each year was obtained from the U.S. Department of Energy Alternative Fuels Data Center (U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, n.d.-b). These reported statistics account for the total number of light-duty registered vehicles for a particular year and are broken down into vehicle type: electric, plug-in hybrid electric, hybrid electric, gasoline, etc.

Data on Research and Development (R&D) expenditure was obtained from the National Center for Science and Engineering Statistics, which collects data on expenditures related to R&D (National Center for Science and Engineering Statistics, 2024). In this analysis, we specifically calculate the ratio between a state's R&D expenditure and its GDP, which provides a measure into the R&D 'intensity' within each state. This R&D intensity measurement serves as a proxy for an 'innovation index' for each state.

Data on charging station counts was also obtained from the Alternative Fuels Data Center, which provides statistics on the number of alternative fuelling stations in each state, along with the number of charging ports (U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, n.d.-a).

Finally, data on real personal consumption expenditures was obtained from the U.S. Department of Commerce Bureau of Economic Analysis, and this variable proxies for each state's income and purchasing power (U.S. Bureau of Economic Analysis, n.d.).

3.2.2 Empirical Models

The analysis proceeds in four steps:

1. Logistic diffusion models to investigate electric vehicle diffusion speed and long-run saturation levels in each state.
2. Log-linear exponential growth models to study early-stage adoption dynamics in the US

3. Model comparison and a robustness check involving a broader definition of electric vehicles which included hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs).
4. Baseline panel regressions to identify correlates of electric vehicle adoption.

The most important model in this analysis is the standard logistic diffusion model, which is utilised to capture long-run dynamics and estimate the year in which electric vehicles are saturated in each state's market. This model follows the below equation

$$EV_{it} = \frac{K_i}{1 + \exp(-(a_i + b_i t))} \quad (1)$$

Where EV_{it} denotes the number of electric vehicles in state i at time t , t is a time index measured in years, K_i is the saturation level of EV adoption in state i , a_i is a location parameter governing the timing of adoption, b_i is the diffusion speed parameter, and ε_{it} is an error term.

Recall that we previously defined the saturation level of each state's market to be 50% of the overall vehicle market.

Because electric vehicle adoption in the United States remains far from the saturation level, early-stage growth (especially regarding technological diffusion) may be well approximated by an exponential-like model, which is what is explored next. Although the logistic diffusion model is the main method used in this analysis, a log-linear exponential growth model is also used because it avoids assumptions about market size and serves as another useful approximation to diffusion dynamics. And the relevant equation for this model is below.

$$\log(EV_{it} + 1) = \alpha_i + b_i t + \varepsilon_{it}, \quad (2)$$

where EV_{it} denotes the number of electric vehicles in state i at time t , t is a time index measured in years, α_i is a state-specific intercept capturing baseline adoption levels, b_i is the state-specific exponential growth rate of EV adoption, and ε_{it} is an error term.

Then, the results of each model were compared to validate and investigate the results and their implications. Additionally, since the models above were fit to data regarding only battery electric vehicles, the final step of this analysis involved using a broader definition of the term 'electric vehicle' (which includes HEVs and PHEVs). With this 'new' definition of EVs, the two models from above were used again to study the diffusion dynamics of these vehicles in the US.

Finally, baseline panel regressions were utilised to study the relationship between the variables of interest and EV adoption. The relevant equation is shown below:

$$\text{EVCount}_{it} = \beta_1 \text{GasCount}_{it} + \beta_2 \text{RD}_{it} + \beta_3 \text{StationCount}_{it} + \beta_4 \text{RealPCE}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (3)$$

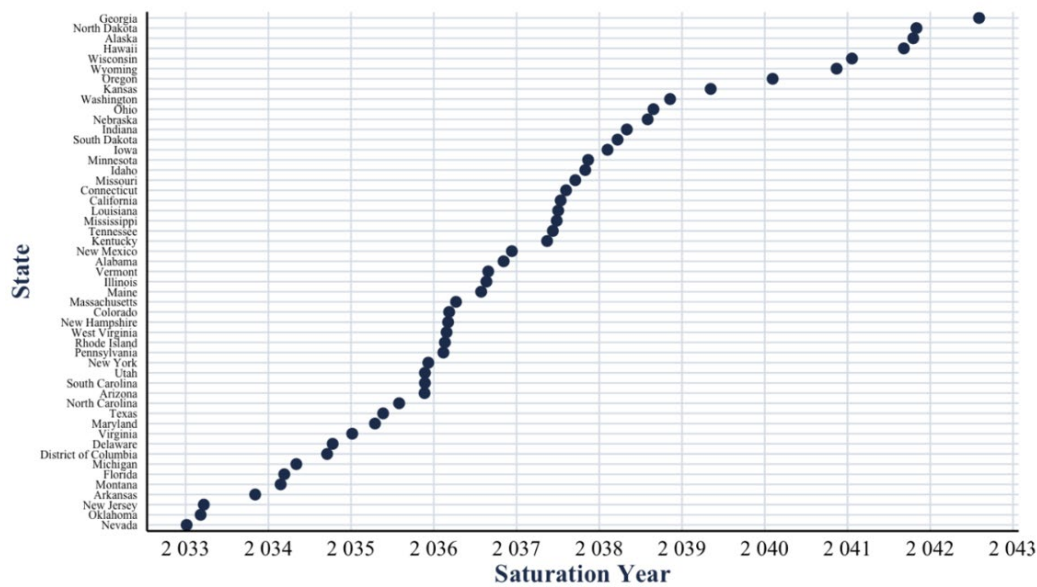
Taken together, these three modelling approaches serve complementary roles. The baseline panel regression identifies relevant aspects of adoption, the log-linear exponential model captures early-stage growth rates, and the logistic diffusion model provides a standard framework for long-run forecasting. This combination offers a more complete picture of electric vehicle adoption dynamics in the US than any single model could provide on its own.

3.3 Results

3.3.1 EV Diffusion Patterns: Logistic Model Results

The logistic diffusion model reveals substantial heterogeneity in electric vehicle adoption dynamics across the 50 US states and the District of Columbia. While the estimated saturation levels for each state are fixed (at 50% of the total market), the timing and speed of diffusion vary considerably. Most states are projected to reach 90% of their saturation levels between the mid 2030s and early 2040s, with the majority being around the late 2030s (Figure 12). This suggests that electric vehicles in the United States are likely to transition from a rapidly expanding technology to a mature market within just the next 2 decades.

Figure 12: Predicted EV Saturation Year (90%) by State



Source: Authors.

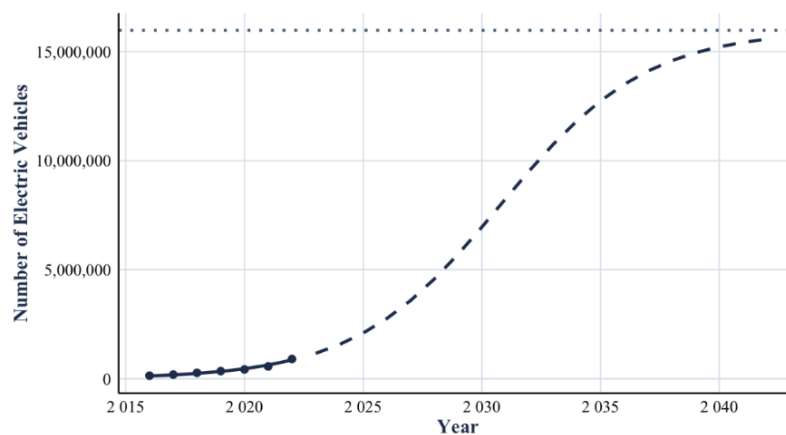
It is important to note that the dispersion in predicted saturation years across states is driven primarily by differences in diffusion speed, rather than differences in states' market sizes. States with earlier saturation years are characterised by steeper logistic curves and being later along the 'S-curve.' Conversely, states projected to reach

saturation later tend to exhibit flatter diffusion paths, indicating slower uptake over time or an earlier adoption stage. However, this does not necessarily mean that later-saturating states are predicted to achieve substantially lower long-run adoption levels. In Figure 13, the logistic curve for California is depicted, and this graph shows how far along the state of California is regarding EV adoption.

Additionally, the log-linear exponential growth model provides some more insight into the early-stage EV adoption dynamics across the US. From the logistic diffusion model, it is clear that the US is still quite in the early stages of adoption when it comes to pure EVs and relatively far from saturation. Thus, the current growth can be reasonably approximated as exponential. The log-linear exponential model is best utilised as a tool for comparing the relative adoption speeds across different states during the initial expansion of the EV market.

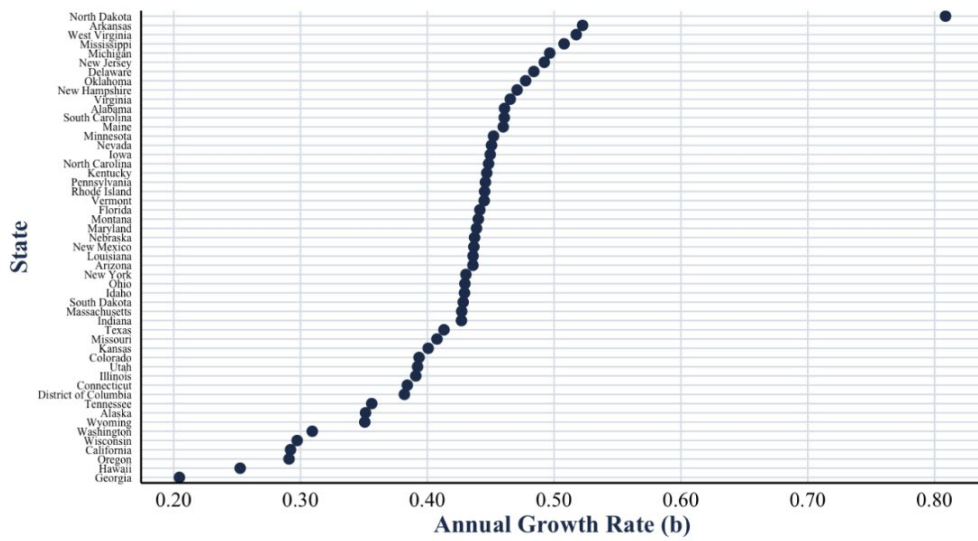
Figure 14 presents the estimated exponential growth rates obtained from the log-linear model. In particular, this figure highlights substantial heterogeneity in EV adoption across the US, with annual growth rates spanning a wide range. While most states cluster around the sample mean, several exhibit faster or slower growth. North Dakota appears to be an outlier on the right of the graph, thus suggesting that it currently has low EV penetration but a high growth rate and rapid expansion. This reflects a late but rapid entry into EV adoption.

Figure 13: EV Diffusion Graph with 20 Year Projection for California



Source: Authors.

Figure 14: Log-Linear EV Adoption Growth Rates by State



Source: Authors.

Extending the definition of electric vehicles to include hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) provides an important robustness check on the baseline results, which focus exclusively on battery electric vehicles. In the United States, PHEVs and HEVs especially account for a substantial share of overall EVs, particularly in earlier stages of adoption, and may follow different adoption trajectories due to differences in cost, infrastructure dependence, and consumer preferences.

The diffusion model estimated using total electric vehicle counts (BEVs, HEVs, and PHEVs combined) yields results that are qualitatively similar to those obtained in the initial analysis. While the inclusion of HEVs and PHEVs mechanically raises the level of adoption and shifts the diffusion curve upward, the estimated timing and shape of the diffusion process remain broadly consistent. This suggests that the main idea of substantial heterogeneity in diffusion speed across states is not driven solely by the narrow definition of electric vehicles and reflects more general dynamics in the US EV market.

3.3.2 Determinants of EV Diffusion: Regression Model Results

Table 12 presents the results from the baseline panel regressions examining correlates of electric vehicle adoption across US states. In the preferred specification with both state and year fixed effects, charging infrastructure is significantly associated with electric vehicle adoption, indicating that within a given state, increases in charging station availability over time are correlated with higher levels of electric vehicle registrations. This result is consistent with the hypothesis that greater infrastructure availability reduces barriers to adoption and facilitates the expansion of the EV market in the United States.

Table 12: Determinants of Electric Vehicle Adoption: Baseline Regressions

	(1) EV Count State FE + Year FE	(2) EV Count Year FE Only (No State FE)
Gasoline Vehicle Count	0.036* (0.016)	-0.0015 (0.0010)
R&D Expenditure	-2008.25 (2727.76)	-935.93 (757.93)
Charging Stations	41.86*** (3.30)	53.34** (9.38)
Real PCE	-0.023 (0.757)	-0.276 (0.119)
Year Fixed Effects	Yes	Yes
State Fixed Effects	Yes	No
Observations	357	357
Number of Years	-	7
Within R^2	0.839	0.924
Adjusted R^2	0.950	0.925

Notes: Standard errors in parentheses. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

EV = electric vehicle; FE = fixed effects; PCE = personal consumption expenditure; R^2 = coefficient of determination.

Source: Authors.

Gasoline vehicle counts are also positively associated with electric vehicle adoption when state fixed effects are included, suggesting that states with larger overall vehicle markets tend to have higher levels of electric vehicle adoption. One possible explanation is that states with populations more likely to purchase and use private vehicles also exhibit higher demand for EVs. In contrast, R&D expenditure and real personal consumption expenditures are not statistically significant once state and year fixed effects are included, implying that these variables do not explain substantial within-state variation in EV adoption after controlling for state-specific characteristics and common time trends over the study period.

It is important to note that these baseline regression results should be interpreted as descriptive correlations rather than true causal effects. In particular, reverse causality is a potential concern, because states experiencing rapid EV adoption may then choose to invest more heavily in infrastructure.

3.3.3 Discussion: Interpretation of Findings and Policy Implications

A central empirical finding is the strong association between charging infrastructure and electric vehicle adoption in the baseline regressions. Although establishing a causal relationship would require a separate, in-depth analysis, the results suggest that the availability of charging infrastructure plays an important role in encouraging EV adoption. From a policy perspective, this underscores the potential effectiveness of investing in charging networks, particularly in states where diffusion is progressing more slowly. Conversely, if a state experiences rapid EV adoption without a

corresponding expansion of charging infrastructure, this may constrain further market growth.

The diffusion results also suggest that policy evaluations based solely on current adoption metrics may be misleading. States with slower initial growth are not necessarily projected to exhibit substantially lower long-term EV penetration, whilst rapid early adoption does not necessarily translate into faster market saturation. Policymakers should therefore exercise caution when benchmarking states or evaluating policy programmes based solely on snapshot adoption rates.

Finally, these analyses point to the need for more targeted policy approaches. States are at different stages of the adoption process and therefore require different policy interventions. Moreover, they operate within distinct policy environments, with substantial variation in EV incentives, regulatory frameworks, and charging infrastructure. Differences in adoption dynamics are therefore likely to reflect not only underlying market conditions but also the broader policy environment.

States such as California, which exhibit relatively rapid early-stage adoption and steep diffusion trajectories, may benefit most from policies that support continued market expansion, particularly through the timely deployment of charging infrastructure. In contrast, states at earlier stages of diffusion may benefit more from measures that reduce initial barriers to consumer adoption. By tailoring policy instruments to both a state's position along the diffusion curve and its broader policy environment, policymakers can more effectively accelerate EV adoption.

4. Conclusion and Lessons Learnt

This study examines battery electric vehicle (BEV) adoption in ASEAN and the United States within the broader context of the global transition towards low-carbon transport. Although both regions have experienced rapid growth in BEV uptake in recent years, they remain at different stages of market diffusion and exhibit considerable variation in adoption trajectories across countries and states. ASEAN's BEV market is generally at an earlier stage of diffusion, with adoption patterns still evolving, whereas the United States exhibits a more mature but uneven market characterised by significant cross-state disparities. By analysing these two regions jointly, the study demonstrates that early adoption signals, diffusion dynamics, and structural drivers can differ substantially across markets, underscoring the need for context-specific interpretation of BEV adoption trends.

Based on the modelling exercises undertaken for ASEAN and the United States, five key findings emerge.

1. Early market penetration does not necessarily translate into faster long-term market diffusion.

Early BEV adoption is not a reliable indicator of earlier market saturation, and vice versa. In ASEAN, countries such as Thailand and Malaysia, which experienced relatively early BEV uptake, are projected to reach market saturation more slowly than Viet Nam, where adoption began later but is projected to accelerate more rapidly. A similar pattern is observed in the United States, where California, despite being the pioneer in EV adoption, is projected to follow a flatter S-curve, indicating slower long-term diffusion than might be expected. These findings suggest that comparisons of adoption rates across countries, states, or regions should be interpreted with caution, as snapshot adoption indicators do not necessarily reflect long-term market trajectories.

2. Logistic diffusion models provide useful benchmarking insights but should not be interpreted as precise forecasts.

The logistic modelling exercise estimates when BEV markets may approach saturation, defined in this study as BEVs accounting for 50% of the current vehicle stock. However, these projections should be interpreted with caution. Previous studies have shown that estimating long-term diffusion from relatively early adoption data is subject to considerable uncertainty. The projections are therefore more useful as comparative benchmarks for assessing the relative pace of market development across jurisdictions than as precise predictions of future market outcomes.

3. Public charging infrastructure is the strongest and most consistent driver of BEV market uptake, but not necessarily of long-term diffusion.

Regression analyses for both ASEAN and the United States indicate a strong positive relationship between the availability of public charging infrastructure and annual BEV sales. In ASEAN, both the panel regression and individual country regressions show that charging infrastructure remains a significant determinant of BEV adoption even after policy incentive variables are included. These findings suggest that widespread and accessible charging infrastructure is a prerequisite for accelerating BEV market uptake. However, charging infrastructure is not strongly associated with the estimated long-term diffusion speed, implying that it primarily acts as a catalyst for initial market adoption rather than determining the ultimate pace of market diffusion.

4. Economic development alone does not explain differences in BEV adoption.

The findings suggest that higher levels of economic development do not necessarily correspond to higher levels of BEV adoption. Within ASEAN, some economies with relatively lower income levels and less mature automotive industries exhibit stronger BEV uptake than wealthier countries. Moreover, the diffusion modelling indicates that ASEAN countries are, on average, projected to reach market saturation earlier than many US states. ASEAN markets are generally projected to reach the study's saturation threshold between 2030 and 2035, whereas US states are projected to reach comparable

levels between 2033 and 2043. These differences may reflect technological leapfrogging in emerging markets and lock-in effects associated with established vehicle markets in more mature economies. Further research is required to investigate these dynamics in greater depth.

5. BEV policies should be tailored to local market conditions rather than following a one-size-fits-all approach.

The considerable variation in BEV adoption across countries and states suggests that policy design should reflect local market conditions, institutional settings, and stages of market development. ASEAN Member States have implemented diverse combinations of fiscal incentives, non-fiscal measures, and industrial policies, yet this study does not find a consistent statistical relationship between the policy variables included in the analysis and observed BEV adoption. This may partly reflect limitations in the available data and the simplified representation of policy measures in the modelling exercise. Future research should therefore examine the effectiveness of individual policy instruments in greater detail, particularly those that directly reduce the purchase price of BEVs or improve their overall affordability.

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Appendix

Appendix A. Global Innovativeness Index (GII) in ASEAN

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010 ^a	66.43	53.85	33.20	43.71	33.80	35.30	38.28	n/a
2011	59.64	44.05	36.71	37.63	29.00	27.80	25.46	n/a
2012	63.50	45.90	33.90	36.90	29.00	28.10	23.40	20.20
2013	59.41	46.90	34.80	37.63	31.20	32.00	28.10	n/a
2014	59.24	45.60	34.90	39.28	29.90	31.80	28.70	n/a
2015	59.36	46.00	38.30	38.10	31.10	29.80	30.40	n/a
2016	59.16	43.40	35.40	36.51	31.80	29.10	27.90	n/a
2017	58.69	42.70	38.30	37.57	32.50	30.10	27.00	n/a
2018	59.83	43.00	37.90	38.00	31.60	29.80	26.70	n/a
2019	58.37	42.70	38.80	38.63	36.20	29.70	26.60	n/a
2020	56.61	42.40	37.10	36.68	35.20	26.50	21.50	20.60
2021	57.80	41.90	37.00	37.20	35.30	27.10	22.80	20.20
2022	57.30	38.70	34.30	34.90	30.70	27.90	20.50	17.40
2023	61.50	46.00	35.90 ^b	37.10	32.20	30.30	19.90	n/a
2024	61.20	41.00	36.20 ^b	36.90	31.10	30.60	22.00	n/a
Average	59.40	44.27	36.18	37.36	32.04	29.73	25.95	19.60

Note: All GI data are retrieved from Brás, 2022, except for a = areppim, n.d., and b = TheGlobalEconomy.com, n.d.

Source: Brás, 2022; areppim, n.d.; TheGlobalEconomy.com, n.d.

Appendix B. Consumption per capita in ASEAN (US\$)

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010	24,400.61	11,127.23	3,685.69	8,036.01	4,460.00	4,580.00	2,545.08	n/a
2011	24,843.63	11,684.61	3,941.74	8,132.66	4,620.00	4,750.00	2,776.30	n/a
2012	25,144.15	12,446.01	4,103.11	8,675.09	4,850.00	4,950.00	2,899.91	n/a
2013	25,436.77	13,121.97	4,253.26	8,706.57	5,030.00	5,160.00	3,051.41	n/a
2014	26,013.78	13,798.76	4,420.43	8,706.71	5,220.00	5,370.00	3,169.10	n/a
2015	27,030.97	14,377.74	4,640.14	8,892.37	5,500.00	5,570.00	3,300.63	n/a
2016	27,581.82	14,952.40	4,984.81	9,107.36	5,780.00	5,780.00	3,401.81	n/a
2017	28,406.99	15,705.74	5,240.72	9,348.96	6,070.00	6,010.00	3,579.09	3,186.70
2018	29,504.53	16,672.89	5,556.15	9,747.02	6,360.00	6,260.00	3,728.39	3,197.10
2019	30,124.47	17,670.28	5,882.29	10,112.86	6,610.00	6,520.00	3,806.20	3,224.50
2020	26,102.96	16,748.37	6,237.11	10,017.16	6,230.00	6,290.00	3,679.86	3,250.00
2021	29,169.05	16,852.53	6,206.64	10,065.53	6,220.00	6,370.00	3,537.28	3,260.30
2022	30,944.17	18,536.12	6,293.93	10,686.01	6,690.00	6,640.00	3,672.69	n/a
2023	30,906.83	19,160.87	6,744.46	11,424.88	7,000.00	6,910.00	3,791.90	n/a
2024	31,759.93	19,894.83	6,931.95	11,934.26	7,270.00	7,200.00	3,835.37	n/a
Average	27,824.71	15,516.69	9,572.90	5,890.67	5,860.67	5,890.67	3,385.00	1,074.57

Source: World Bank (n.d.)

Appendix C. People Living in Houses in ASEAN

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010	284,911.00	26,618,952.60	6,088,453.30	67,599,000.00	87,739,500	200,491,200	12,549,500	n/a
2011	290,394.00	29,151,420.00	5,837,209.30	67,526,092.55	90,480,000	204,750,000	12,657,300	n/a
2012	300,150.00	29,820,070.00	6,060,052.22	67,244,147.17	93,090,000	209,336,400	12,663,800	n/a
2013	281,450.00	29,069,410.00	6,078,895.08	67,368,201.75	95,700,000	214,578,000	12,987,360	n/a
2014	299,808.00	31,149,630.00	6,386,842.11	67,283,218.44	97,875,000	218,509,200	13,332,120	n/a
2015	297,560.00	30,326,880.00	6,787,061.99	67,402,241.45	99,963,000	223,095,600	13,352,519	n/a
2016	283,336.00	29,599,136.00	7,042,888.28	67,310,213.88	103,095,000	227,354,400	13,648,954	n/a
2017	285,285.00	29,974,395.00	7,082,459.46	67,424,205.25	105,705,000	231,285,600	13,800,512	n/a
2018	283,143.00	30,260,615.00	8,135,581.70	63,948,324.23	108,315,000	236,199,600	15,266,377	n/a
2019	292,560.00	30,448,640.00	8,365,531.56	60,224,158.72	110,490,000	240,786,000	15,228,323	n/a
2020	299,592.00	31,291,647.20	8,834,244.79	59,231,574.83	114,796,500	239,080,800	15,332,469	n/a
2021	287,700.00	32,099,360.00	8,981,065.69	58,261,412.23	115,275,000	242,272,800	15,464,848	n/a
2022	280,984.00	32,051,990.00	9,104,563.12	57,408,887.18	117,885,000	245,784,000	15,572,723	n/a
2023	278,388.00	33,751,220.00	9,451,953.14	54,234,031.68	109,620,000	241,634,400	15,944,565	n/a
2024	283,731.00	34,597,480.00	9,666,238.86	n/a	111,360,000	245,145,600	17,280,000	6,038,736.00
Average	288,599.47	30,680,723.05	7,593,536.04	59,497,713.96	104,092,600	228,020,240	14,338,758	6,038,736.00

Source: Authors' calculation by multiplying the number of households by the average household size.

Number of households: HelgiLibrary, n.d.; statista, 2022; OpenDOSM, 2024; Department of Statistics Singapore, 2025; Lao Statistics Bureau, n.d.

Average household size: Global Data Lab, n.d.; Lao Statistics Bureau and United Nations Children's Fund (UNICEF), 2025; Department of Statistics Singapore, 2025

Appendix D. Urban Population in ASEAN

Year	Country							
	Singapore ^a	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010	5,076,732	20,320,384	26,601,234	30,076,202	43,671,546	122,940,838	2,942,777	1,904,312
2011	5,183,688	20,882,645	27,495,952	30,844,842	44,724,734	126,219,363	3,042,128	1,970,392
2012	5,312,437	21,438,811	28,421,328	31,555,235	45,792,230	129,573,696	3,143,998	2,038,093
2013	5,399,162	22,006,091	29,371,952	32,263,554	46,856,101	132,928,149	3,248,700	2,107,181
2014	5,469,724	22,585,297	30,359,692	32,961,669	47,829,383	136,260,119	3,356,342	2,177,659
2015	5,535,002	23,178,796	31,382,614	33,643,727	48,743,065	139,573,034	3,466,487	2,251,889
2016	5,607,283	23,791,400	32,439,440	34,330,176	49,605,425	142,869,697	3,579,880	2,330,753
2017	5,612,253	24,411,363	33,514,669	35,010,812	50,472,435	146,129,010	3,693,661	2,411,997
2018	5,638,676	25,024,183	34,567,483	35,651,638	51,346,882	149,350,859	3,806,285	2,495,101
2019	5,703,569	25,617,837	35,592,811	36,256,070	52,243,300	152,553,180	3,923,374	2,579,855
2020	5,685,807	26,149,183	36,622,770	36,845,215	53,135,486	155,657,888	4,052,917	2,666,057
2021	5,453,566	26,636,053	37,646,783	37,415,128	53,931,057	158,554,689	4,187,222	2,753,135
2022	5,637,022	27,136,733	38,642,203	37,940,098	54,676,670	161,537,679	4,320,041	2,841,582
2023	5,917,648	27,650,017	39,619,045	38,438,241	55,477,513	164,698,646	4,455,286	2,931,630
2024	6,036,860	28,162,033	40,592,000	38,930,064	56,316,242	167,836,195	4,592,262	3,022,926
Average	5,551,295	24,332,722	33,524,665	34,810,845	50,321,471	145,778,869	3,720,757	2,432,171

Source: World Bank, n.d.; ^a Department of Statistics Singapore, 2025.

Appendix E. Rate of Urbanisation in ASEAN (%)

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010	100%	71%	30%	44%	45%	50%	20%	30%
2011	100%	72%	31%	45%	46%	51%	21%	31%
2012	100%	72%	32%	45%	46%	51%	21%	31%
2013	100%	73%	32%	46%	46%	52%	21%	32%
2014	100%	74%	33%	47%	46%	53%	22%	32%
2015	100%	74%	34%	48%	46%	53%	22%	33%
2016	100%	75%	35%	48%	46%	54%	23%	34%
2017	100%	75%	35%	49%	47%	55%	23%	34%
2018	100%	76%	36%	50%	47%	55%	23%	35%
2019	100%	77%	37%	51%	47%	56%	24%	36%
2020	100%	77%	37%	51%	47%	57%	24%	36%
2021	100%	78%	38%	52%	48%	57%	25%	37%
2022	100%	78%	39%	53%	48%	58%	25%	38%
2023	100%	79%	39%	54%	49%	59%	26%	38%
2024	100%	79%	40%	54%	49%	59%	26%	39%
Average	100%	75%	35%	100%	47%	55%	23%	34%

Source: Authors' calculation, based on World Bank, n.d.

Appendix F. Cars Per Household in ASEAN

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010	0.510	0.092	0.024	0.222	0.002	0.140	0.006	n/a
2011	0.517	0.179	0.030	0.245	0.001	0.150	0.008	n/a
2012	0.525	0.267	0.031	0.286	0.001	0.160	0.008	n/a
2013	0.517	0.355	0.034	0.327	0.001	0.160	0.008	n/a
2014	0.500	0.441	0.037	0.352	0.001	0.170	0.008	n/a
2015	0.470	0.523	0.041	0.372	0.001	0.180	0.012	0.073
2016	0.437	0.590	0.049	0.392	0.001	0.190	0.011	0.080
2017	0.424	0.654	0.057	0.416	0.001	0.190	0.018	0.087
2018	0.416	0.718	0.058	0.444	0.001	0.200	0.020	0.106
2019	0.405	0.781	0.067	0.471	0.001	0.210	0.026	0.114
2020	0.71	0.827	0.076	0.490	0.040	0.210	0.020	0.119
2021	0.417	0.869	0.099	0.505	0.020	0.220	0.020	0.123
2022	0.415	0.933	0.098	0.524	0.050	0.220	0.017	0.136
2023	0.401	1.004	0.191	0.565	0.060	0.240	0.020	0.137
2024	0.389	1.074	0.201	n/a	0.060	0.260	0.014	n/a
Average	0.486	0.620	0.073	0.401	0.016	0.193	0.014	0.097

Source: Authors' calculation based on car passenger car from ASEANstats (n.d.) and Number of households in Appendix C.

Appendix G. Number of Public Charging Station and Point in ASEAN

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010								
2011								
2012								
2013								
2014					1			
2015					2	15		
2016	25	29			4	22		
2017	51	31			9	31		
2018	106	43			19	45		
2019	218	196			30	65		
2020	450	287			49	93		
2021	636	509		2,285	78	534		
2022	900	900		3,739	125	1,400	7	27
2023	1,990	2,020	4,900	9,694	200	2,704	18	44
2024	13,825	3,354	6,100	11,467	992	5,104	21	34

Source: Dharmawan, Kumara, and Budiastira 2021; CamNess, 2024; Lokesh and Min, 2017; The Business Times, 2020; Channel News Asia, 2024; SM Strategic Research, 2023; SBR, 2025.

Appendix H. Electricity Price in ASEAN (US\$/kWh)

Year	Country							
	Singapore	Malaysia	Viet Nam	Thailand	Philippines	Indonesia	Cambodia	Lao PDR
2010	0.23	0.09	0.05	0.12	0.58	0.18	0.23	0.04
2011	0.25	0.10	0.06	0.12	0.57	0.14	0.22	0.04
2012	0.28	0.09	0.07	0.11	0.60	0.15	0.23	0.04
2013	0.25	0.09	0.07	0.11	0.57	0.16	0.22	0.04
2014	0.23	0.09	0.07	0.11	0.56	0.18	0.21	0.04
2015	0.18	0.09	0.07	0.1	0.50	0.20	0.21	0.04
2016	0.15	0.09	0.07	0.1	0.44	0.19	0.19	n/a
2017	0.17	0.08	0.08	0.1	0.47	0.22	0.19	n/a
2018	0.19	0.09	0.08	0.1	0.49	0.23	0.18	n/a
2019	0.19	0.10	0.08	0.1	0.48	0.23	0.15	0.09
2020	0.18	0.10	0.08	0.1	0.42	0.30	0.14	0.08
2021	0.17	0.09	0.08	0.1	0.42	0.36	0.13	0.08
2022	0.20	0.09	0.08	0.08	0.40	0.36	0.13	0.05
2023	0.19	0.09	0.08	0.08	0.46	0.36	0.12	0.04
2024	0.19	0.09	0.09	0.7	0.47	0.36	0.12	0.03

Source: CEIC Data, n.d.-a; CEIC Data, n.d.-b; ERIA, 2020; Vietdata, 2023; EAC, 2024; EMA, 2024.