A Cross-Country Analysis of the Determinants of International Competitiveness in the Global Electric Vehicles Market

Adhvait Pillai

MSc Management of Technology

Faculty: Technology, Policy & Management

MOT2910: Master Thesis Project

A Cross-Country Analysis of the Determinants of International Competitiveness in the Global Electric Vehicles Market

Student Name	Student ID
A.S. Pillai	5805090

in partial fulfilment of the requirements for the degree of

Master of Science
in Management of Technology
Faculty of Technology, Policy and Management
at the Delft University of Technology

To be defended in public on August 30, 2024

Project Duration: April 07, 2024 - August 30, 2024

Graduation Committee	
1st Supervisor	Dr. Geerten van de Kaa
2nd Supervisor	Dr.ir. Maarten Kroesen
Chair	Dr. Geerten van de Kaa
Advisor	Roman Stollinger, PhD

Cover: Generated by DALL-E, (OpenAI)

An electronic version of this thesis is available at https://repository.tudelft.nl

Delft University of Technology

Acknowledgements

I would like to thank Roman Stollinger for his guidance, supportive feedback, encouraging words, and monthly intensive brainstorming sessions throughout the journey of my thesis. Next, I would like to express my sincere gratitude to Dr. Geerten van de Kaa for his insights and motivational words, along with keeping me aware of the practical matters of this process. Further, I'd also like to thank Dr Ir. Maarten Kroesen for his critical and apt feedback along with his clear communication style.

Reflecting upon the duration of my Master's thesis brings mixed feelings, countless memories, and valuable lessons to mind. It has been a challenging road, but always stimulating with the wide spectrum of opportunities provided by TU Delft and the Faculty of TPM to their students. I would like to take this opportunity to thank my parents for their unconditional support, unwavering faith, and constant inspiration. Next, I would like to thank my brother for being my sounding board and motivating me when times seemed too tough to deal with all alone. Everything I do is a tribute to the three of you and these two years away from you have made me realise how fortunate I am to call you family. This feels incomplete without thanking my maternal uncle and acknowledging the impact he's had on me ever since I was a young boy. Your constant open communication and never-ending lessons were an essential part of my self-management toolkit while living alone in a foreign country. I look back at countless conversations I've had with all of you in my moments of solitude and how they've helped me navigate the few not-so-pleasant experiences I've had here.

Thank you to my friends who've cheered me on from back home and to the ones who've helped make the Netherlands feel like home. This journey would not have been half as fun without all of you living it with me. I'd like to thank my girlfriend for her constant support, her kindness, her pep talks, and for always having context for my shenanigans during my time here.

Adhvait Pillai
Delft, August 2024

Executive Summary

The global wicked problem of the climate crisis has drawn significant interest and attention over recent years from world governments, industry leaders and researchers. In a collaborative effort to tackle this problem while maintaining economic and social development, in 2015 the United Nations developed the Sustainable Development Goals (SDGs) and countries globally committed to this initiative (United Nations Development Programme, 2024). The transport sector forms a crucial component of infrastructural development while also being a significant contributor to greenhouse gas emissions, and a sizeable share of these emissions are attributed to the use of Internal Combustion Engine Vehicles (ICEVs), dependent on petroleum fuels. The globally recognised solution to replace ICEVs as of 2024 is through electrification of the transport sector, facilitated by the use of Electric Vehicles (EVs). Given the importance and significance of this relatively emerging technology, countries across the globe have formulated various strategies and made major efforts to enhance their country's competitive positioning in the international trade of EVs.

Enhancing competitiveness in international markets in the EV sector is a viable method for nations to improve their energy security and independence from other potentially rival countries for their energy requirements. For instance, in the aftermath of the Russia-Ukraine conflict, many countries minimized ties with Russian products, despite Russia being the world's largest exporter of oil to global markets, further stressing upon the need for countries to strengthen their positions in electric mobility and EV trade, since the incumbent car companies that built their reputations on ICE vehicles have also started updating their vehicle line-ups and incorporating EVs due to the constantly evolving nature of the transport sector. Moreover, the government support through industrial policy subsidy measures directed towards their domestic industries to bolster EV production also communicates concerns about employment for incumbent ICE vehicle producers, as with the growth of adoption in any emerging technology, or EVs in this case. Hence, the continuously evolving trade competitiveness dynamics require focused research to support policymakers in recognising the factors that may have a positive or negative impact on EV export performance. This can further facilitate the introduction of effective policy measures to improve international competitiveness in a sector such as EVs, which is of paramount importance in the widespread uptake of Net-Zero technologies.

There is an abundance of research analysing different aspects of the adoption and uptake of EVs in global, national and regional settings. Additionally, the extant literature also contains works that analyse the determinants of international competitiveness in established industries such as agriculture, forestry and the automotive sector. However, there is a lack of research on the international competitiveness of countries in the EV sector. Hence, the primary objective of this study was to fill this knowledge gap by providing a cross-country, empirical analysis of the determinants of international competitiveness in the EV sector, such as technological innovation, cost-competitiveness, green industrial policy measures and endowments in critical metals required for EV manufacturing. The following main research question guided this study:

Which factors are most strongly associated with the export competitiveness of the electric vehicle industry across countries?

The study adopted an empirical, quantitative approach by utilizing econometric models to gain insight into the secondary data available for 160 countries, for the timeframe of 2017-2022, for the factors identified through key themes of the literature concerning the EV industry and international competitiveness by testing hypotheses derived from said literature. The research design included the operationalization of the variables derived from these hypotheses, collecting secondary data from recognized databases for different factors, pre-processing the data with programming software and setting up a structured panel for further econometric analysis. Specifically, fixed effects regression models were used to aid in isolating the relationships between the variables under investigation from time-invariant, unobserved country-specific effects. Further, multiple diagnostic tests were conducted to identify any abnormalities in the datasets that could distort the interpretation of the results, such as multicollinearity and heteroskedasticity, followed by the implementation of robustness checks to analyse the sensitivity of the results to different model specifications and control variables.

The results of the various econometric models and robustness checks identified the absolute levels of technological innovation, endowments in critical metals such as lithium, nickel and cobalt and industrial policy subsidy measures targeted towards the automotive sector as the most strongly associated factors with the dependent variable, i.e. EV export performance. Drawing from the interpretation of the statistical results concerning the key themes of literature on international trade, EVs and industrial policy measures, the study posited incremental policy recommendations based on the findings. Also, the study contributed to the extant literature by providing a nuanced analysis method for future econometric studies aiming to analyse the determinants of international competitiveness in high-technology industries or environmental technology sectors.

Lastly, the limitations of the study are important to acknowledge to avoid any misinterpretation of the results and to build a foundation for future research related to the research topic. Firstly, there is an absence of a factor that represents the domestic demand for the exporting nations in the analysis. Next, the study uses the industrial policy subsidy measures directed to the automotive sector as a whole, instead of the EV sector due to data availability constraints. Lastly, the negative R-squared (Between) values indicate that there are additional explanatory factors apart from the independent variables considered in this study that could be included in the analysis to strengthen the explanatory power of the variance in EV exports across countries in the regression models.

The study also reveals certain recommendations for future research regarding EV export performance. Firstly, it can serve as a foundation for future research to recognize causal factors that drive EV export performance by using advanced econometric methods such as Difference-in-Difference estimations or the Instrument Variables method. Next, the use of interaction terms can further strengthen the understanding of the interactions between the various factors that may influence export performance in the EV sector. Further, the use of the gravity model to analyse the import tariffs in the EV sector bilaterally can help gain a deeper insight into how specific import tariffs on EVs affect international competitiveness. Lastly, for a more robust analysis on the determinants of international competitiveness of the EV sector, the industrial policy subsidy measures can be operationalised using a policy intensity measure, and using updated data on EV-specific industrial policy subsidies.

Contents

List of Figures

List of Tables

List of Abbreviations

ICE	Internal Combustion Engine
EV	Electric Vehicles
GDP	Gross Domestic Product
FDI	Foreign Direct Investment
FE	Fixed Effects
RE	Random Effects
GTA	Global Trade Alert
IHS	Inverse Hyperbolic Sin Transformation

1 Introduction

1.1 Background

In the global effort to reduce greenhouse gas (GHG) emissions, the transport industry is one of the most carbon-intensive, hard-to-abate sectors. Transport emissions grew at an annual average rate of 1.7% from 1990 to 2022 (*IEA Transport - Energy System*, 2023). A large component of this sector is the Internal Combustion Engine vehicles (ICEVs), running on extinguishable energy sources like fossil fuels such as gasoline, petrol or diesel. In light of the Russia-Ukraine conflict and the Paris Agreement (UNFCCC, 2018), countries have been actively working towards improving their energy security and independence in the global context. Electric vehicles (EVs) have the potential to mitigate the severity of significant concerns including environmental pollution and reliance on fossil fuels; however, despite strong governmental promotional efforts, their market penetration is still at the nascent stage (Pamidimukkala et al., 2024). Despite this, Electric car markets are seeing exponential growth as sales exceeded 10 million in 2022. A total of 14% of all new cars sold were electric in 2022, up from around 9% in 2021 and less than 5% in 2020 (IEA, 2023).

Global EV Landscape

In the grand Zero-Emission Vehicles (ZEVs) and Low-Emission Vehicles (LCEVs) landscape, with the rise of EV adoption globally, there has been a clear increase in international competition in the EV race. This shift has intensified international competition in the EV sector. In 2022, the leading countries in terms of trade value from EV exports over imports (trade balances in EV trade) included Germany ($16.7B), China ($15.6B), South Korea ($6.06B), Belgium ($3.84B), and Mexico ($3.82B). (OEC, 2022). Notably, China is now one of the world's leading exporters of EVs, accounting for nearly 60% of global electric car sales (IEA, 2023), and exported about 20.1 billion U.S. dollars worth of battery-electric passenger cars, an increase over twice the value recorded in 2021 (W. Zhang, 2024). As for 2023, China's overall Battery-Electric Vehicle (BEV) exports rose 70 per cent in 2023, reaching $34.1 billion. The European Union (EU) is the largest recipient of Chinese BEV exports, accounting for nearly 40 per cent of them (Jcookson, 2024). The large number of European imports of Chinese EVs have caused logistical and congestion-related issues at European ports, with executives calling it the conversion of European ports to "car parks" (Alim et al., 2024). As nations continue to navigate the transition towards more sustainable transportation solutions, the dynamics of international trade in the EV industry are set to evolve further, informing the broader trends towards innovation, decarbonization of economies and maintaining leadership in such emerging technologies.

The global increase in the uptake of electric vehicles is evident through the numbers, in terms of overall market share and increased user adoption. The market share of electrified auto sales in the global market witnessed a significant increase in 2021, reaching nearly 10%, which is four times higher than the market share recorded in 2019. (Pamidimukkala et al., 2024). As pointed out by EV adoption researchers, due to electric vehicles' potential benefits for environmental protection and decreased pollution, global electric vehicle retail sales reached 6.6 million in 2021 (Shahbaz et al., 2023), which marks a threefold increase from that of 2018, nearly 2.1 million units (Irle, 2024).

In the last decade, many of the developed countries made significant strides in the diffusion and adoption of EV technology as well as its complementary technologies such as EV charging infrastructure. As of 2024, EV sales in the United States are projected to rise by 20% compared to the previous year, translating to almost half a million more sales, relative to 2023. (*IEA Transport - Energy System*, 2023). After experiencing a downturn in EV sales in 2022, Europe accounted for 25% of global electric car sales in 2023 and is projected to keep that up in 2024 (International Energy Agency, 2024a), spearheaded by Automobile giants like Germany, Belgium, Italy and France, and supported with by the Scandinavian countries which are extremely committed to climate change initiatives. This is highlighted by Norway's achievement of 91.5% EV market share, setting an unprecedented sustainable example (European Alternative Fuels Observatory, 2024). The EU remains the 2nd largest market for electric vehicles after China. (Virta, 2024). However, despite the improved uptake in EVs, the EU and the USA are laggards as compared to China in the EV race. China is at the forefront of battery technology innovation and has ample quantities of lithium reserves, as an essential component in car batteries. For instance, BYD, a Chinese firm is one of the largest EV manufacturers in the world, and

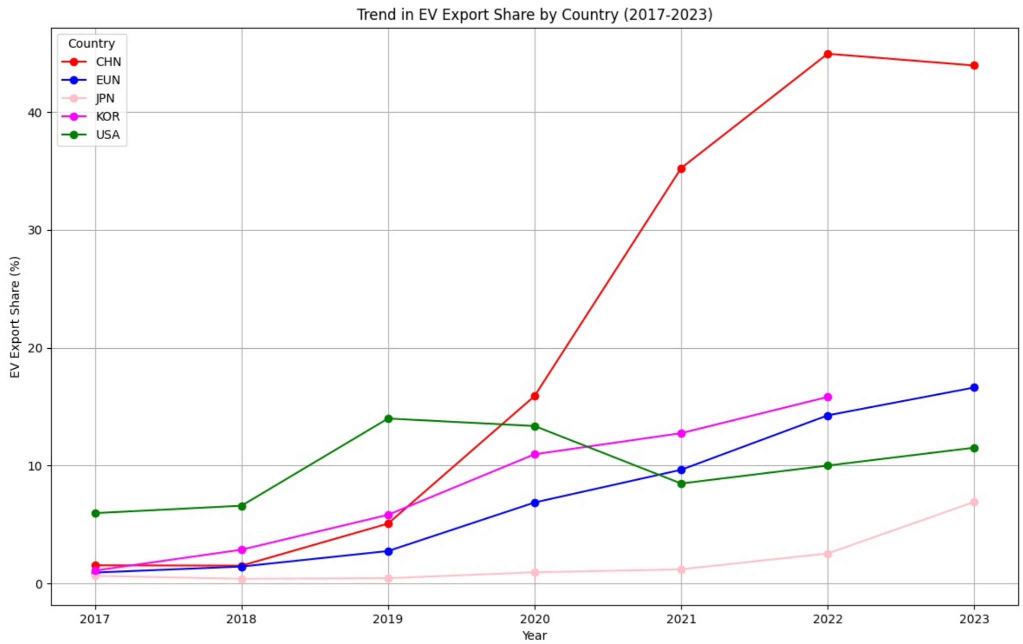


Figure 1: EV Export Share for Developed Countries* (2017-2023), Data Source: UN Comtrade Database, own illustration

Tesla, an American EV manufacturer is facing competitive pressure in European and American markets. China has, however, proven it can mount a credible vehicle export effort in the face of globally imposed trade barriers (Shivaraman, 2024), mainly since Chinese automakers have a notable cost advantage due to lower labour rates, increased scale, healthy government subsidies, and more favourable battery costs facilitated by their geographical advantage (Shivaraman, 2024). Using these strategies and advantages, Chinese EV firms pose significant threats to other top competitors, such as American and European EV firms.

In the matter of the developing countries, although slower than that of their developed counterparts, there are clear signs of increasing uptake in EVs. In 2023, India's EV sales doubled from the previous year, accounting for 2% of total passenger vehicle sales in the country (Counterpoint Technology, 2024). Sales are further projected to increase by nearly 66% in 2024 (Prasad, 2024), due to a combination of factors such as government schemes and subsidies, the introduction of affordable EV options and charging infrastructure development. In Latin America, electric car sales reached almost 90,000 in 2023, with markets in Brazil, Colombia, Costa Rica and Mexico leading the region. In Brazil, electric car registrations nearly tripled year-on-year to more than 50,000, a market share of 3% (International Energy Agency, 2024b). The trends in evolving export market shares for EVs out of automobiles are visually represented in Figure 1 and Figure 2. The data for the figures have been retrieved from the United Nations COMTRADE database.

International Policy Initiatives in the EV Sector

As countries make plans and efforts to enhance their competitive advantage in international EV trade, they have been increasingly implementing industrial policy instruments like grants and subsidies for domestic EV production, incentives for research and development leading to technological innovation, and environmental regulations to strengthen their standing in the international context. Furthermore, trade disagreements and tactical negotiations are becoming increasingly prevalent as countries aim to protect their infant EV industries while ensuring access to global markets. Additionally, countries are also trying to secure and increase production of the critical, rare earth metals required for EV manufacturing. In this context, the international competitiveness of nations in the EV market has become increasingly significant. The essence

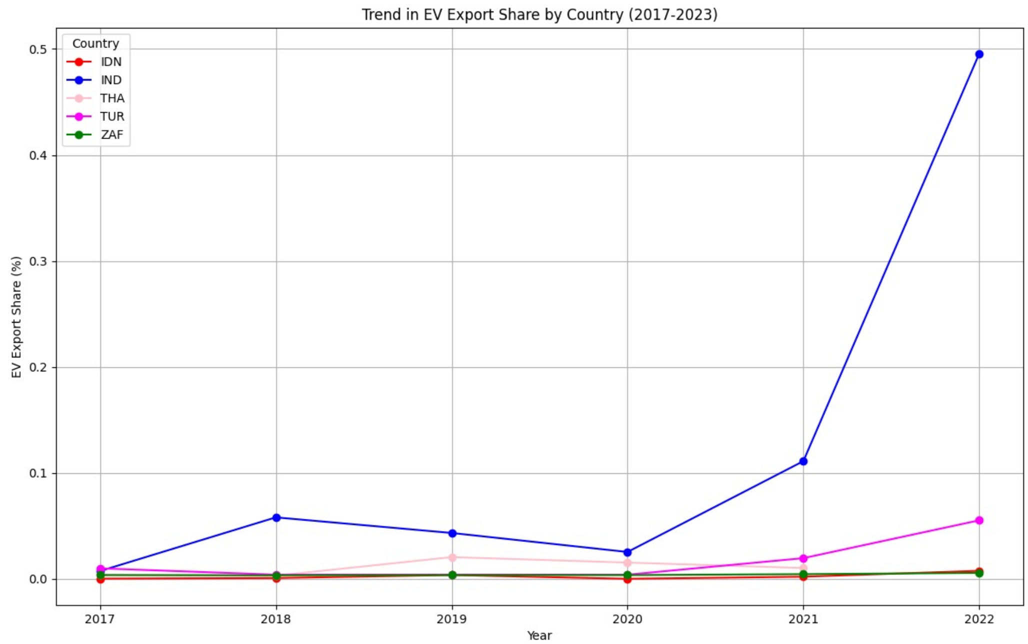


Figure 2: EV Export Share for Developing Countries (2017-2022), Data Source: UN Comtrade Database, own illustration

of this argument can be further demonstrated with some of the recent policy acts implemented by a few of the major EV exporting nations:

U.S. Inflation Reduction Act (IRA): U.S. climate policy undertook a major initiative with the passage of the Inflation Reduction Act of 2022. The $370 billion allocated to climate and clean energy investments are expected to deliver deep emission reductions across all sectors of the economy. This act including the EV supply chain, highlights the complex political-economic implications of such policy decisions on international cooperation and competition, particularly in clean energy sectors (Slowik et al., 2023). It includes a strategic initiative to stimulate the domestic EV industry and an effort to turn international trade advantages in favour of the U.S. in the global EV market. For instance, another proposal in the IRA imposed import tariffs on Chinese EVs in the U.S., making it more difficult for domestic consumers to purchase Chinese EVs, and adapt to increasing sales of American EVs. As of May 2024, the White House further increased the import tariffs on Chinese EVs from 25% to 100% (EIU, 2024), as an effort to further improve their foothold on the domestic and international EV markets.

China's New Energy Vehicles Act (NEV): China's approach to electrification is supported by its New Energy Vehicle (NEV) policy, establishing it as a front-runner in the EV industry. The policy framework, characterized by substantial subsidies, investments in battery technology, and regulatory mandates, aims to strengthen China's competitive position in the global EV trade. This aggressive policy initiative reflects China's strategic move to lead in the global shift towards electric mobility, affecting global supply chains and market dynamics(X. Zhang & Bai, 2017).

EU's Net-Zero Industry Act (NZIA): The Net-Zero Industry Act's objective is to increase the competitiveness and resilience of the EU's net-zero technology industrial base. By accelerating the development and production of net-zero technologies, the Act also aims to reduce the risk of replacing the EU's reliance on Russian fossil fuels with other strategic dependencies that might hinder the EU's access to key technologies and components for the green transition(European Commission, 2023). A key component of the NZIA is aimed at developing battery and storage technology, a crucial component of EVs. Besides, the European Critical Raw Materials Act (European Commission, 2023) was an effort to strengthen the EU's commitment to decarbonise their economy, including frameworks to solidify the supply chain for materials including ones required in Battery manufacturing and further strengthen its global engagement with reliable partners to develop and diversify investment and promote stability in international trade while strengthening legal certainty for investors. Additionally, following the USA's protectionist steps, the EU has also levied new import tariffs on Chinese EVs, with the European Commission citing the reason for this move as levelling the playing field with China, who according to them has an unfair competitive advantage of EVs through unfair subsidy schemes (European Commission, 2024).

As illustrated by the above examples, nations are directed towards ramping up domestic production but are also extremely aware of the strategic importance of maintaining a competitive advantage in international markets, by leveraging their national resources, strengthening their supply chains for critical materials, R&D initiatives and prowess, and policy instruments. The international trade of EVs is moulded by a multitude of factors, including protectionist punitive tariff policies, trade agreements, and the global supply chain of critical raw materials essential for battery manufacturing. These factors collectively impact the competitiveness of countries in the global EV landscape.

1.2 Problem Statement

The current literature consists of multiple papers that focus on the determinants of increasing EV market adoption across the world, and how different aspects affect EV uptake or sales. These include cross-country studies as well as case-study approaches for specific regions. Some of the notable research covering these aspects include (Khatua et al., 2023), (Xue et al., 2021), (Ruoso & Ribeiro, 2022), (Liu et al., 2020), (Yao et al., 2020), (Sierzchula et al., 2014) and (Mekky & Collins, 2024).
Despite the prevalence of multiple studies analysing the multitude of factors that influence EV market adoption and uptake in the global EV market, there exists a gap in research for the factors that could affect the export performance or trade competitiveness of countries, specifically in the EV industry. Furthermore, studies have been conducted to measure trade performance or competitiveness for specific sectors such as the solar energy sector (Groba, 2014) or the automotive sector as a whole (Judit & Zsófia, 2018). But, there's a lack of research on the constantly evolving dynamics of EV-focused trade performance.

The Role and Challenges of Industrial Policy: Industrial Policy is defined as the part of economic policy which seeks to alter the structure of an economy in such a way that it encourages resources to move into specific sectors that are perceived as desirable for future development (Altenburg & Rodrik, 2017). However, it is a tool that has been constantly argued over amongst economists over the last few decades. The primary arguments have been regarding the effectiveness of industrial policy instruments in bolstering domestic production and development in specific industries versus the arguments categorizing industrial policy efforts as direct rent-seeking behaviour on the part of politicians, as a way to increase tax revenues for National governments. The U.S. Inflation Reduction Act, China's New Energy Vehicles Act and the EU's Net-Zero Industry Act as described in subsection 1.1 can be categorized as industrial policy acts, to improve the competitiveness of their respective domestic EV industries in the context of global EV trade. However, there is a lack of empirical research on the effects of industrial policy acts on specific sectors, including EVs, mainly due to the difficulty in identifying and measuring such industrial policy acts. These issues of measurement mean that there is a lack of a picture of global industrial policy practice. This presents a bottleneck for policymakers and social scientists studying questions surrounding real-world application and activity (Juhász et al., 2022).

As explained above, the rapidly evolving trade competitiveness dynamics in the international EV environment require focused research, to support policymakers in identifying factors that positively improve export performance as well as factors that negatively impact it. This can enable policymakers to shape effective measures to improve export performance in an emerging sector such as EVs, which is extremely important from the perspective of widespread adoption of Net-Zero technologies, and also from the perspective of maintaining national energy security and independence. Additionally, from the perspective of academia, the research gap is significant in this area, and it could develop a foundation for future studies aiming to explore trade dynamics in critical industries, using a multidimensional approach with a focus on environmental sustainability and technological innovation.

1.3 Research Objective

The primary objective of this study is to analyze the determinants of international export competitiveness across countries in the context of the Global EV market. This research aims to explore the determinants of international trade competitiveness in the electric vehicle (EV) industry through comprehensive empirical analysis. The study focuses on a multitude of factors such as technological innovation, macroeconomic conditions, the role of governments (industrial policy instruments), and resource availability(endowments), implementing panel data regression to assess their impact on export performance. The main objectives include providing insights and directions to inform policy suggestions and contributing to both academia as well as practical knowledge bases. Lastly, it seeks to support strategic decision-making processes for EV industry stakeholders and investors by recognizing the key drivers of international competitiveness. The ultimate goal is to foster a deeper understanding of global trade dynamics in the EV sector, supporting strategies that enhance competitiveness and promote sustainable development.

1.4 Research Questions

Following the research objective, the main research question and sub-research questions were developed. The main research question of this study is,

Which factors are most strongly associated with the export competitiveness of the electric vehicle industry across countries?

Further, the research question is divided into multiple sub-research questions that help direct the focus of the theoretical background into the different core factors most strongly associated with export performance in the EV sector, as follows -

SQ1 - How does the rate of technological innovation, indicated by patent filings, relate to the export performance in the EV sector of different countries?

SQ2 - What is the relationship between labour productivity in the EV industry and the export performance of countries in the international EV market?

SQ3 - How do the endowments and presence of local suppliers of critical materials necessary for EV production, such as lithium, nickel, and cobalt, affect a nation's export performance in the EV industry?

SQ4 - In what way do industrial policy subsidy measures impact the export performance of the EV sector across countries?

1.5 Research Design Approach

This study follows a deductive research approach using a quantitative research design to analyse the determinants of international export competitiveness across countries in the Electric Vehicles industry. This research design approach suits the research objective and helps to address the research questions, specifically due to the cross-country approach with an emphasis on empirically testing the EV industry's context-specific export performance factors. The following sections explain the method of data analysis and the key variables in further detail and shed light on how they will be operationalized for econometric analysis and tests. Following these steps, the descriptive statistics for the variables are displayed and analysed, specifically to understand the outliers in the sample. Further, the different econometric models used for the empirical analysis are explained in detail, incorporating the variables that have been derived from the hypotheses.

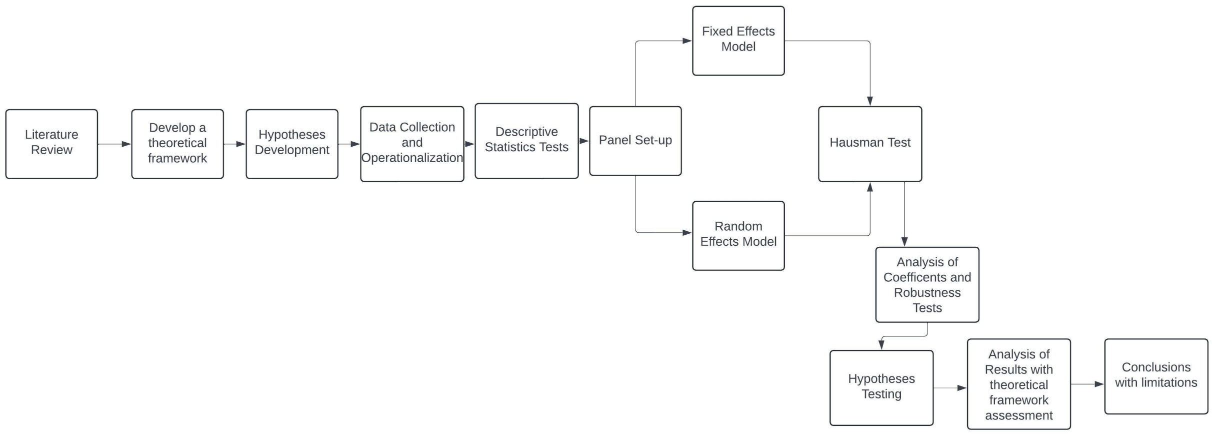


Figure 3: Research Approach, own illustration

1.6 Societal Relevance

This study aims to contribute to understanding how countries make strategic plans and efforts to mitigate the climate crisis and be on course to achieving sustainable development goals. EVs are the globally regarded strategic solution to achieve the goals of decarbonization, ecological balance, commercialization, and technology innovation in the transportation sector (Cao et al., 2021). The availability of green technologies such as EVs, both lowers social costs in the transition to a green growth path and helps achieve a satisfactory rate of material progress under that path (Rodrik, 2014). Green industrial policy supports environmentally-friendly technologies, such as EVs, and as Rodrik (2014) proposes is crucial in making EVs affordable for consumers and competitive in the automobile market. Nevertheless, governments usually support their domestic EV manufacturing firms rather than EV technology itself. This focus on domestic producers communicates concerns about employment as with any potentially disruptive technology, which in this case is about incumbent producers (of ICE vehicles) fearing job losses. Environmental policies and regulations supporting the energy transition have major implications for the labour market, creating new types of jobs while causing a shift in the types of skills required for the new roles, also leading to job losses in traditional oil, coal and gas dependent sectors (OECD, 2023). Additionally, as per ILO (2018), the green economy is projected to create nearly 24 million jobs by 2030. Hence, the inclusion of green industrial policy makes it a crucial factor in the societal relevance of this study.

Further, increasing competitiveness in the EV sector is a method for nations to enhance their energy security and reduce dependencies on other countries for their energy needs, for instance, oil and gas. This is of critical importance in the current geopolitical landscape, highlighted by the consequences of the Russia-Ukraine conflict. Russia is the world's largest exporter of oil to global markets and the second largest crude oil exporter behind Saudi Arabia (International Energy Agency, 2022). In the aftermath of the conflict, multiple economies decided to impose sanctions on Russian imports, even though the EU is highly dependent on Russia's oil and gas supplies. This is an instance that highlights the urgent need for countries to improve energy security and enhance competitiveness in electric mobility. As explored further in section 2, this research effort tries to identify the major factors associated with export competitiveness in the EV sector, trying to emphasize the role of technological innovation, natural endowments in critical metals and the steps governments have taken to improve their competitive positions in international markets through policy means.

1.7 Practical Context

There are substantial benefits to adapting to EVs instead of ICE vehicles in terms of emission savings. Countries aiming to secure their energy needs have made strategic efforts to reduce the prices of EVs through subsidies and improve EV charging infrastructure with substantial investments for faster consumer adoption of the technology. However, being a relatively new technology, EVs face competition not just from firms across the globe specialising in electric mobility, but also from incumbent car manufacturers that have secured significant market shares in the global automobile market. For instance, an American EV manufacturer like Tesla has had to compete with established automobile giants like Volkswagen and Hyundai. These firms in turn face competition from cost-competitive Chinese EV firms such as BYD and the innovative company from South Korea, Kia. Simultaneously, European Automakers such as BMW, Mercedes and Audi have also made massive strides in updating their vehicle lineups based on the changing consumer demand and in alignment with the Sustainable Development Goals. The Indian automobile giant, Tata has made remarkable developments in making EVs affordable and appealing to the masses of the country. In terms of developing countries, nations like India, Thailand and Turkey have been making considerable advancements in their domestic automobile markets, but are still not major competitors in EV trade, as highlighted by Figure 2. However, with the speed at which China has emerged as an EV export giant over the last decade, the dynamic EV export market still has scope to take shape as a relatively nascent industry.

Figure 4: Lithium Triangle Satellite Image, Source: Earthbeat (2024)

EV battery demand is projected to grow four and a half times by 2030, and by nearly 7 times as compared to 2023 as per IEA (2024). Due to the limited reserves of critical elements like Lithium, nations have tried to secure the procurement of such metals with countries abundant in them. China is the third largest miner of lithium globally after Australia and Chile The Northern Miner Group (2024), but the Chinese Government tends to secure the reserves for its firms to maintain competitive advantage in the global context. In light of this, American and European automakers have been targeting the South American Lithium Triangle, consisting of Argentina, Chile and Bolivia which holds up to 58% of the lithium reserves in the world, as per , to ensure sufficient supply of the crucial raw material. The differences in technological innovation and features compel domestic consumers of a country to buy imported EVs, which is not favourable to domestic EV firms.

To enhance export advantage in the global EV market, countries have also deployed strategic industrial policies towards this sector, as highlighted by the U.S. Inflation Reduction Act which imposes punitive import tariffs on Chinese EVs in hopes of boosting domestic EV producers. As discussed previously, the EU has also followed suit and claimed that the import tariffs on Chinese EVs in the EU countries have been imposed to level the playing field with the cost-effective Chinese vehicles which have impacted the European Automobile sector in current times. Given this intensified competitive environment, countries have invested in research and development, strategic partnerships, trade agreements, global value chains for raw materials and investments in hopes of bolstering production and uptake of EVs and is worth investigating with a quantitative approach to gain some insight on the rapidly evolving EV sector.

1.8 Management of Technology Relevance

The programme in MOT educates students as technology managers, analysts of technological markets (either as scientists or consultants), and entrepreneurs in highly technology-based, internationally-oriented and competitive environments for a variety of industrial sectors (TU Delft, 2024). Given the objectives of the program, analysing the determinants of international trade competitiveness, specifically in a high-technology sector such as Electric Vehicles exemplifies the practical application of MOT principles. It integrates some core concepts elaborated in the MOT curriculum such as technological innovation, international trade economics, national trade balances and market structures. The research aligns with TU Delft's MOT pillars of technological innovation management and strategy, delving into how technological advancements and policy instruments can influence a nation's competitive advantage in the technologically intensive EV sector, addressing the core objectives of the MOT curriculum to foster leaders who can navigate and shape the technological futures of industries and economies globally.

1.9 Reading Guide

The report structure follows the sequence shown in the Research Approach Diagram (subsection 1.5). **Chapter 2** presents the key themes of literature used to derive the theoretical framework, from which the hypotheses are developed. Next, **Chapter 3** elaborates on the quantitative research methods used along with sampling, data and the variables employed. **Chapter 4** presents the results of the quantitative analysis, addressing the research questions, followed by which **Chapter 5** discusses the interpretation of the results along with the contributions to literature and the limitations of the study. Lastly, **Chapter 6** concludes the study and presents the academic and policy implications of the study, with a discussion on the scope for future research.

2 Literature Review and Theoretical Background

2.1 Overview on Literature Review Structure

In this chapter, the essential subjects of the research area required to achieve the research objective (subsection 1.3) have been discussed. These include the directions into which the research will be driven. These research areas have been derived from reviewing key themes from the extant literature and investigating their relevance in the context of international trade competitiveness and export performance in the EV industry. Firstly, this chapter discusses the approach followed for the literature review, extracting from competitiveness literature and how export performance, an indicator of success in international markets, has been conceptualised to derive testable hypotheses to enable quantitative analysis.

According to existing understanding, there is an absence of a study that empirically analyses the determinants of export competitiveness, specifically in the EV sector. This is comprehended to be the case due to the relative newness of the global EV market, and there has been a larger focus among researchers on more established industries like the agriculture, forestry, automotive and steel industries. Such studies that focus on EVs do so more for EV uptake and adoption with a cross-country, quantitative research approach. Additionally, very few such studies were found for high-technology industries, with a sector-specific focus and empirical methodology, for the determinants or factors of export competitiveness. As a consequence of these factors, the literature review for this study was conducted by exploring such studies in general determinants of export competitiveness and methodologies in different industries, backed with studies focusing on the EV industry and competition in different countries, and supported by industry reports and grey literature. Additionally, the commonly explored determinants in sector-specific export competitiveness studies were also drawn from, especially high-technology industries and green technologies. Some of these are technological innovation levels, labour cost and output, industrial policy interventions and the role of governments, endowments and macroeconomic conditions. These factors are further explored in detail in (subsection 2.3).

Based on these key themes, hypotheses were developed for empirical testing, by operationalising independent variables connected to each of the hypotheses. This aids in narrowing down the focus of the study and provides a good way to quantitatively observe the various themes across extant literature concerning export performance in the EV sector.

2.2 Competitiveness

Competitiveness is a term of interest for policymakers, firms and economic researchers. It is a multi-faceted concept whose understanding comes from economics, management, history, politics and culture (Waheeduzzaman & Ryans, 1996), and the relevance of this competitiveness changes with time and context. (Chaudhari & Ray, 1997). Across economic as well as management literature, competitiveness has been broadly defined at three levels: the national level, the industry level and the firm level. Given the number of stakeholders and varying underlying perspectives, multiple efforts have been taken to provide critical reviews of competitiveness, such as Bhawsar & Chattopadhyay (2015) and Chaudhari & Ray (1997), that categorise the different streams of competitiveness literature at different levels.

At the national level, the recognition of the concept of competitiveness began in the 1980s, when U.S. competitiveness was being challenged by the rise in international competition from countries like Japan (Chen et al., 2016). One of the first, commonly acknowledged definitions was provided by Michael Porter, through his Diamond Model to explain the competitiveness of nations, in which he theorises that a nation's competitiveness is dependent on its industries and their capacities to innovate and upgrade, as further explained by a country's factor conditions, demand conditions, related and supporting industries and firm structure, strategy and rivalry, and supported by government policy and chance (exogenous shocks) that support the system of national competitiveness but do not create it (Porter, 1990). Further, Krugman (1994), another notable contributor to contemporary competitiveness literature questioned the notion of national competitiveness and proposed that the term was often misinterpreted and wrongly used when applied to national economies. He further argued that on a national level, competitiveness is dependent on a country's internal factors such as productivity, rather than relative advantage in international trade. These two arguments profess that competitiveness is dependent on long-run productivity. However, Laura D'Andrea Tyson defined competitiveness as, "The ability to produce goods and services that meet the test of international competition while the citizens enjoy a standard of living that is both rising and sustainable"(Tyson, 1992). This definition stresses upon international performance as well as a nation's standard of living, providing a balanced perspective between external and internal economic criteria.

Definitions of competitiveness at the industry and firm level are interlinked and similar (Chen et al., 2016), and hence discussed together. At the firm level, competitiveness is defined as the capability of a firm to sustainably fulfil its double purpose i.e. meeting customer requirements at profit (Chikán, 2008). A slightly different view was proposed by Barney (1991), i.e. the Resource-Based View, which claims that a firm's competitiveness is a combination of a firm's resources and its ability to use them. Subsequently, multiple researchers further explored the resource-based view for firms focusing on different methodologies and combinations of resources. For example, Prahalad & Hamel (1990) propose that a firm's competitiveness depends on price and performance attributes of current products in the short-run and on the firm's ability to build at low cost and faster than competing firms in the long run. At the industry level, Momaya (1998) defines competitiveness as the extent to which a sector satisfies the needs of customers from the right combination of product price, quality and innovation; along with offering returns on investment and addressing the needs of its employees or internal stakeholders. Given the scope and focus of this study, international competitiveness at the industry level is paid attention to and is considered the overarching level of competitiveness in consideration, specifically for the EV industry.

2.2.1 Measures of International Competitiveness

As briefly discussed in (subsection 2.3), competitiveness is understood in many different and sometimes disputed ways. With respect to international competitiveness, "Export competitiveness has been widely regarded as one of the mediums for achieving global competitiveness"(Paul & Dhiman, 2021), further explained and testified by works such as Asteriou et al. (2016), Caporale et al. (2018) and Gnangnon (2019). Essentially, this understanding of competitiveness is about success in international markets. Henceforth, this aspect of competitiveness is explored in this study.
There are multiple measures of export performance across the extant literature, including dollar values of exports, export quantities and trade balances. A comprehensive literature review on determinants of export performance Beleska-Spasova (2014) identifies export sales volume and export sales ratio among the most commonly used financial indicators as measures of competitiveness. This is further backed by studies such as Axinn (1988); Lado et al. (2004) which explains export sales volume by destination based on a company's export marketing strategy; and Blonigen (2016) uses export values to study the impact of industrial policy in the steel industry on export competitiveness.

Another popularly recognized way to operationalize export performance is Revealed Comparative Advantage (RCA), as used in studies such as Judit & Zsófia (2018) in the context of the automotive industry, Madiyarova et al. (2018) in the context of Kazakhstan in multiple sectors and Obadi (2017) for measuring comparative advantage of Yemen in the export market of the USA. Revealed Comparative Advantage is defined as a measure used in international trade to identify the relative advantage or disadvantage of a certain country in a certain class of goods or services, as evidenced by trade flows (Balassa, 1965). It is calculated by comparing the share of a country's exports of a specific good or service to the share of its total exports, relative to the global share of that good or service in total global exports. Balassa's index is implemented to measure revealed comparative advantage, as a popular choice across literature. This index was proposed by Bela A. Balassa in 1965 to investigate the structure of exports for industrial goods and was called the coefficient of 'revealed comparative advantage' (RCA) (Balassa, 1965).

2.3 Key Themes and Determinants

2.3.1 Technological and Cost Competitiveness Factors:

The extant literature that links technology factors, labour productivity and costs(wages) and export performance at the country level has multiple theoretical foundations and approaches. Joseph Schumpeter (1976) introduced the concept of "creative destruction", which is the process by which innovations in technology lead to disruption and replacement of outdated technologies, business models and products. He further argued that this process is what drives economic growth, with the reallocation of resources for more productive applications, and firms that innovate more gain a competitive advantage, enabling them to dominate the market. This concept was further elaborated upon by works such as Nelson & Winter (1982), which argued that firms with advanced technological capabilities are better positioned to achieve and sustain competitive advantage. This includes both investing in and acquiring innovative technologies as well as the knowledge and skill to utilize them efficiently. Further building upon Schumpeterian concepts, Aghion & Howitt (1998) posited that continuous innovation is crucial for sustained economic growth.

Similarly, Posner (1961) proposed that one of the main sources of advantage for a country is its relative technological position when posed against its competitors. Multiple researchers studied this relationship and further developed the technology-gap theories, which emphasized that the main source of international competitive advantage was the widespread technological asymmetries between countries which relate to the capability of some countries to produce innovative commodities (i.e. commodities which other countries are not yet capable of producing, irrespective of relative costs) and to use process innovations more efficiently or more quickly thus reducing input coefficients, which eventually provides the nations superior in technological innovation with a temporary monopoly in that industry until the competing nations catch up with them. These aspects were studied and tested in detail notably by Soete (1981), Fagerberg (1988), and Dosi et al. (1990), identifying a strong, positive link between the level of technological innovation and higher export market shares. Additionally, Bahar et al. (2019) finds a positive and statistically significant correlation between the number of patents as a measure of technological innovation and export growth. Dosi et al. (2015) propose a framework derived from the technology gap theories, essentially as an export performance model, further specified as sectoral trade performance as a function of both technological absolute advantage (Ti,j) and variable costs (Ci,j):

$$X_{ij} = f(T_{ij}, C_{ij}) \tag{1}$$

- $X_{i,j}$ is an indicator of international competitiveness.
- $T_{i,j}$ represents an indicator of technological levels in sector i for country j.
- $C_{i,j}$ represents a proxy for variable costs, typically labour costs.

Based on this approach, for this study, labour productivity, reflecting the output per labour unit can serve as an effective measure of international cost competitiveness. It encompasses the efficiency and cost-effectiveness of production processes, which are crucial for maintaining competitive pricing in international markets. This is because a higher labour productivity, or a higher output per worker capturing process innovations and thereby improving production efficiency could lead to lower unit labour costs, making products more cost competitive, importantly in price-sensitive sectors. This approach is in line with the Ricardian Theory of comparative advantage, which states that countries should specialize in producing goods for which they have a lower opportunity cost compared to other nations (Ricardo, 1817). This indicates that cost competitiveness plays an important role as countries with lower costs of production can produce goods efficiently and trade them internationally, with the lower production costs being transferred to lower prices in international markets. Further argued by the Hecksher-Ohlin model, Heckscher & Filip (1919); Ohlin & Gotthard (1933) countries will export goods that proactively use their cheap factors of production in which they are abundant, including labour. This model highlights that cost advantages derived from a country's factor endowments play a driving role in that country's export performance. Further, Porter (1980) identifies cost leadership, or the ability of a firm to be the most cost-efficient producer in an industry as a path to competitive advantage.

There is a contrast in these key themes of literature. As discussed, some theoretical foundations justify that technological innovation and capabilities are the drivers of international competitiveness, whereas others claim that cost competitiveness is the primary driver of success in international markets. Firms that try to leverage technological progress and innovation as their instrument to gain competitive advantage often utilize their profits to fund Research and Development (R&D) or to acquire new technologies that can help them stay ahead of the competition, whereas firms that focus on competing based on lower prices spend on improving productivity and optimizing their supply chains for lower production costs, in order to achieve economies of scale (Krugman, 1994). Based on these contrasting streams of literature, concerning this study, the following have been hypothesized:

H1 : ***Higher levels of technological innovation in a country are positively associated with higher export performance in the EV sector.***

H2 : ***Higher output per worker in a country is positively associated with higher export performance in the EV sector.***

2.3.2 Endowments

The role of a country's endowments or availability of resources in shaping its export performance has received interest in economic literature. For the case of the EV industry, this is of particular importance due to a major component of the technology, i.e. car batteries being heavily dependent on critical metals such as lithium, nickel and cobalt. Lithium is an essential component in the production of electric vehicles EVs, specifically in the batteries that power them (Harish, 2023). Nickel is an important metal used in the production of EVs due to its ability to enhance the performance and longevity of EV batteries; Cobalt is an essential metal used in the production of EVs due to its ability to enhance the performance and safety of EV batteries (Harish, 2023). Analysis by Jones et al. (2020) indicates that for EVs, demand in 2030 for cobalt, lithium and nickel is projected to increase by 39.6, 19.6 and 4.7 times, consumption levels in 2015, respectively (Jones et al., 2020).
Some of the extant literature linking a country's natural endowments and export performance offers a rationale for how such countries may exploit their access to such materials to enhance international competitiveness in this sector. The Heckscher-Ohlin (H-O) model proposes that countries will export goods that intensively use their abundant and relatively cheap factors of production. With regards to critical metals, nations with significant reserves of these resources are positioned to hold a competitive advantage in industries that rely heavily on these inputs, such as the EV industry (Heckscher & Filip, 1919),(Ohlin & Gotthard, 1933). A closely interlinked aspect of the availability of these critical metals is the presence of reliable value chains through the presence of local suppliers with high geographical proximity. This is in alignment with Porter (1990), who posits in his Diamond Model that the presence of related and supporting industries is a key determinant for nations to gain competitive advantage in a sector, by facilitating local competition which in turn drives innovation for differentiation of solutions, further supported by knowledge exchange due to proximity. The presence of local suppliers also aids firms in terms of cost savings due to lower transportation costs and bulk procurement. Hence, countries abundant with critical metals can utilize their access to these essential raw materials and their supply chains to enhance their competitiveness in technology-intensive sectors such as EVs, depending on whether they manage these resources effectively and utilize complementary assets such as technology and human capital.

The existence of competitive industries producing goods that are intermediate inputs such as lithium mining to sectors of a yet small sector such as the EV sector could help the latter to develop and become an exporter industry (Bahar et al., 2019). Bahar et al. (2019) also conclude that supplier linkages explain export growth for developed economies, indicated by the positive and statistically significant regression coefficient obtained in a regression model with the dependent variable as export growth. Additionally, an empirical study on the determinants of revealed comparative advantage (a measure of export competitiveness) finds a positive and statistically significant relationship between factor endowments represented by GDP per capita and export competitiveness in the case of the European Ham trade sector (Torok & Jambor, 2016). Hence, the availability of critical materials, like lithium, nickel and cobalt in the context of EVs is further explored in the context of export competitiveness in this study. The expected association between the availability of the critical materials required for battery production and EV export competitiveness is expected to be positive. Drawing from these perspectives, the following hypotheses have been developed:

H3 : ***Greater endowments and robust value chains for critical metals like lithium, nickel and cobalt are positively associated with export performance in the EV sector.***

2.3.3 Industrial Policy: The Role of Government Interventions

As discussed with a few examples in subsection 1.1 and subsection 1.2, industrial policy being strategically implemented by national governments is increasingly being identified as an important factor in improving a country's position in international markets. This emergence has been backed and argued against in contemporary literature, specifically in studies that focus on analysing the effect of such government interventions and the creation of conducive environments in countries for better export performance. Additionally, industrial policy is also being used to mitigate climate risks and boost the energy transition by targeting these interventions towards critical sectors, including the transport sector through supporting the EV industry. (Rodrik, 2014) argues that industrial policy interventions have a vital role to play in transforming the global economy towards the green path. (Altenburg & Rodrik, 2017) shed further light on this premise, highlighting how strategic policy measures can significantly catalyze a nation's industrial base, specifically in high-technology sectors like EVs. These instruments include a mix of direct financial support through subsidies and grants and indirect incentives such as tax breaks and credits, infrastructure investments along with import tariffs and public procurement, which collectively enhance a nation's export performance by supporting domestic industries. These arguments are derived from the infant industry argument, which is empirically studied in the context of export activity, by Harrison & Rodríguez-Clare (2010).

Industrial policy interventions are found to be positively correlated with an industry's revealed comparative advantage by Evenett et al. (2024), who also stresses the importance of the need for nations to strike a balance between fostering their infant industries and maintaining trade relationships. Works such as those by Sierzchula et al. (2014) have identified a positive influence of policies including purchase subsidies, tax credits, and expenditure on building better-charging infrastructure, on the uptake and production of electric vehicles. These policies enhance domestic markets and prepare firms for international competition by scaling up production and lowering costs. Further, (Bown, 2023) delves into the analysis of trade disputes and tariff measures implemented in the EV industry and specifically sheds light on how the US Inflation Reduction Act affects the EV supply chain, and how the subsidies may lead other countries to change their climate policies, especially out of concern over reduced industrial competitiveness. Countries have also used direct protectionist measures to protect their domestic EV industries. For instance, China has long used a variety of export restrictions on inputs including some critical minerals to take advantage of its supply-side market power, thereby supporting its downstream, using industries relative to their foreign competitors Kowalski & Legendre (2023). Further, a study by Khan & Azam (n.d.) on the impact of industrial policy on export performance in Pakistan finds positive and statistically significant associations between industrial policy interventions such as R&D expenditure and industrial expenditure and export performance. They also find that import tariffs negatively influence export performance. Overall, drawing from the arguments made above, the association between the implementation of industrial policy instruments and export performance is expected to be strong and positive, and the hypothesis to be tested is:

H4 : Higher number of industrial policy interventions in the automotive sector of a country are positively associated with export performance in the EV sector.

2.4 Knowledge Gap

As explored above, there is a rich body of literature concerning technological innovation and cost competitiveness factors, resource endowments, and industrial policies' impacts on export performance. However, a knowledge gap exists in sector-specific research, specifically dealing with the nascent and rapidly growing EV industry. The current literature is abundant in theoretical and empirical analyses but often overlooks the unique and nuanced factors affecting EV sector-specific trade, which is a brilliant example of the impending green transformation. This oversight shows the requirement for detailed exploration into whether technological advancements, availability of critical metals, and targeted industrial policies interact within the global perspective on industrial export competitiveness exactly how researchers have theorized or whether the data speaks differently. Furthermore, as best known, there is a lack of such studies employing econometric analysis that is as comprehensive in terms of the factors included, informed by different strands of literature on international competitiveness, green industrial policy and EVs.

Additionally, research that sheds light on the interaction between various policy instruments and their combined effects on cultivating innovation, lowering costs for domestic industries, and increasing international competitiveness in the EV sector with a cross-country analysis, is relatively low in quantity. The literature seldom addresses strategies for effectively utilising natural resource endowments without succumbing to the resource curse, particularly in a context where these resources are critical to the production of EVs.

This gap is significant, given the strategic importance of the EV industry in achieving economic and environmental goals. Identifying the determinants of export competitiveness with a specific focus on the EV sector with a methodical, empirical approach is critical for informing effective policies in the future, and strategic industry support in the face of global market shifts.

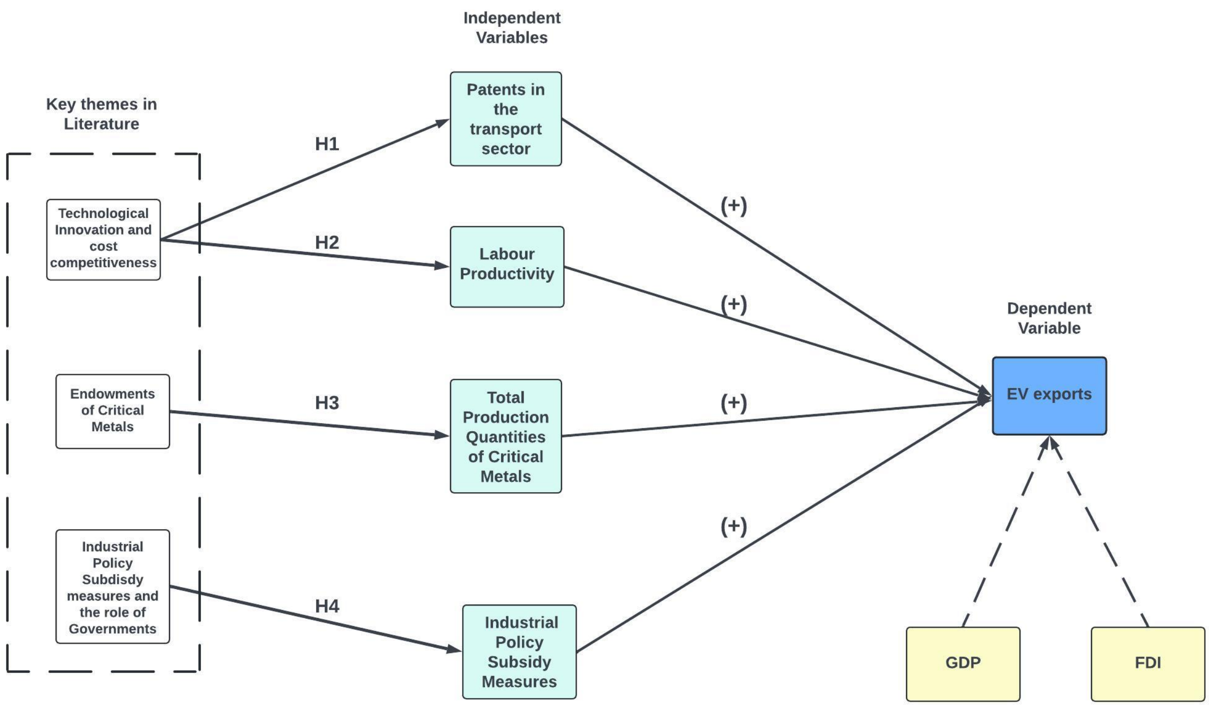


Figure 5: Theoretical Framework Conceptualization, own illustration

3 Methodology

This chapter begins with elaborating upon the need and suitability of the research methods chosen for this study followed by discussing the econometric models used for statistical analysis. Further, it sheds light upon the variables and their appropriate operationalization implemented to test the main hypotheses derived in section 2, and the approach used to select the sample of countries for investigation. Lastly, the descriptive statistics of the dataset have been presented followed by multiple diagnostic tests conducted to identify potential inconsistencies in the dataset or econometric models.

As discussed in the research approach (1.5), this study follows a quantitative research design to analyse the determinants of international export competitiveness across countries in the Electric Vehicles industry, using panel data regression. This methodology was chosen due to its ability to incorporate both cross-sectional data as well as time-series variations, presenting a nuanced analysis by controlling for unobservable variables that vary across entities but are constant over time. Further, it also factors in the time dimension of the data for more dynamic analyses (J. Wooldridge M, 2011). The methodology is particularly valued for its capacity to provide insights into complex behavioural relationships across different entities (such as countries or firms) and over time, making it highly relevant for studies on export competitiveness and other economic phenomena that vary both across entities and over time (J. Wooldridge M, 2011). These features of the chosen methodology enable a cross-country analysis of the global EV industry in terms of export performance, with the ability to gain an understanding of the relationships between each factor and the international competitiveness measurement metric chosen. This further facilitates the joint investigation of the various hypotheses drawn from different strands of literature, as explained in detail in section 2. Panel data regression enables testing multiple hypotheses concerning a dependent variable together, which makes it apt for this study, while also enabling the inclusion of control variables. The software tools chosen to implement the panel data and to run the various statistical tests are Python and MS Excel. Using these tools, the data was collected, structured, pre-processed and set up in a panel, for all countries from 2017-2022.

3.1 Econometric Models

Econometric models are known for their ability to characterize relationships among aspects of economic behaviour and hence are often used to understand how economic and political decisions may influence different sectors across countries (*Econometric models | Rand*, n.d.). Additionally, econometric models can also account for cross-country heterogeneity in technological industry characteristics (Ciccone & Papaioannou, 2019), which makes it apt for this study. The initially chosen econometric models for this study are the fixed effects regression model and the random effects regression model. The final model is chosen based on the results of the Hausman test, further discussed in subsection 3.2.

Fixed Effects Model (FE):

The FE model is used to analyze the effects of the independent variables on the dependent variables, i.e. asinh(EV exports) while controlling for the unobservable, time-invariant characteristics specific to each country. The FE model is particularly useful for analyzing changes within the sample countries over time (J. Wooldridge M, 2011). The mathematical equation for the FE model is:

$$\text{asinh(EV exports}_{it}) = \beta_0 + \beta_1 asinh(PATit) + \beta_2 asinh(\lambda it) + \beta_3 asinh(Q_(Cr.Met.)it) + \beta_7 asinh(IPit) + \beta_8 log(GDPit) + \beta_9 asinh(FDIit) + \alpha_i + \epsilon_{it} (2)$$

where

- $asinh$ is the functional form of the variables or the inverse hyperbolic sin transformation.
- $(EVexports)_{it}$ is the export value in EVs for country i at time t.
- PAT_{it} is the number of patents in the transport sector for country i at time t.
- β_0 is the intercept term, $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients for the independent variables, which measure the impact of these variables on the dependent variable.

- λ_{it} is labour productivity, $Q(Cr.Met._{it})$ is the total production quantities of lithium, nickel and cobalt for country i at time t.
- IP_{it} is the number of financial grants, state loans and trade financing in the automotive sector for country i at time t.
- $log(GDPpit)$ represents the log transformed values of GDP for country i at time t.
- α_i is the unobserved country-specific effect (time-invariant) for country i. In the FE model, this effect is treated as fixed and is removed from the model through transformation or inclusion as dummy variables
- ϵ_{it} is the error term for country i at time t.

The functional transformation chosen, i.e. the IHS transformation and the rationale behind using it for the variables has been explained further in subsection 3.3, following the definitions of all the variables. Further, the control variable GDP's values have been transformed using the logarithmic function instead of the IHS transformation due to the lack of zeros in the variable, eliminating the need for a function that can incorporate zeros in the results. However, the other control variable, FDI contains negative values which need to be addressed and hence requires the IHS transformation.

Random Effects Model (RE):

This model assumes that individual country effects are random and uncorrelated with the independent variables (J. Wooldridge M, 2011). The mathematical equation for the RE model is similar to Equation 3.1, except that instead of the unobserved country-specific time-invariant factors for a country (α_i), it captures the individual, specific characteristics affecting the dependent variable, asinh(EV exports). Unlike in the FE model, μ_i or the random effects variance, is assumed to be randomly distributed and uncorrelated with the regressors.

For both models, mention robust inference statistics to avoid heteroskedasticity after understanding it.

3.2 Hausman Test

Another crucial step in the analysis is conducting the Hausman test to determine the appropriateness of the FE versus RE models. The test evaluates the null hypothesis that the preferred model is RE against the alternative hypothesis that FE is more appropriate, based on whether the unique errors (country-specific effects) are correlated with the regressors in the model Hausman (1978). Running both models before conducting the Hausman test follows a methodologically rigorous approach. It allows to assess the consistency of the estimates under different assumptions about the unobserved effects.

H0: The individual effects are uncorrelated with the regressors in the model, i.e. the random effects model is the better fit.

HA: The individual effects are correlated with the regressors in the model, i.e. the fixed effects model is the better fit.

Based on the results of the Hausman test, the most appropriate model is picked for further analysis, followed by which the regression coefficients for each independent variable such as the number of patents, labour productivity, production quantities and industrial policy instruments, will be analyzed for the impact on the dependent variable- log(EV exports), adjusting for the control variables GDP, and FDI. This structured approach to data analysis ensures that the study's findings are robust, reliable, and relevant to policymakers, industry stakeholders, and academic researchers interested in improving export competitiveness in the EV sector.

3.3 Variables and Operationalization

Dependent Variable

This study aims to analyse the determinants of international trade competitiveness which will be represented as the independent variables, as explained in subsection 3.3. The dependent variable for this study must be a measure of export performance that can be uniform and comparable across the large sample set of countries. There are multiple measures of export performance across the extant literature, including dollar values of gross exports, export quantities, trade balances, revealed comparative advantage indices, etc. The measure chosen to operationalize export performance for this study is the dollar values of exports in EVs, or EV exports. This approach has been implemented widely across the literature, used in studies such as: Bano & Scrimgeour (2011) analysing New Zealand's export performance in Kiwifruits uses export values as the measure of export performance; Hchaichi & Ghodbane (2014) empirically analysing international competitiveness of firms in African countries implements export values as an indicator of international competitiveness; a comprehensive literature review on the determinants and measures of export performance by Beleska-Spasova (2014) categorizes export sales volume as a widely used measure of export performance; and a study by Blonigen (2016) analysing the impact of industrial policies on export performance in the steel sector also uses logged values of exports as the dependent variable.

Export values as a measure of export performance are convenient to quantify and are a good standardized measure for comparability, which enables empirical analysis in quantitative models with multiple countries and time-series data. Lastly, Gnangnon (2019) highlights that export values are a good measure of success in international markets, capturing both demand conditions and capabilities for supply.

Independent Variables

The independent variables have been derived from the theoretical background, as explored in the theoretical framework (Figure 5). The independent variables are operationalized versions of the factors identified from the theoretical framework, as represented in 5. The data collection for this study involved sourcing empirical data from reliable international databases and industry reports to examine the relationships between technological innovation, labour productivity, critical metals' availability, industrial policy subsidy interventions and countries' export values in the EV sector.

- ***Technological Innovation:*** The method to operationalize technological innovation levels in each country for this study has been identified as the number of patents granted in the transport sector. This approach was used by Dosi et al. (2015) as a way to quantify the number of product innovations in their study. Patent data was sourced from the World Intellectual Property Organization (WIPO) platform, by using advanced queries to filter and extract patents granted in the Transport Sector, using the PATENTSCOPE feature on the platform.
- ***Labour Productivity:*** Labour Productivity, or the output per unit of labour input, is used as a key indicator of international cost competitiveness. Labour productivity data was procured from the International Labour Organization (ILOSTAT) DATABASE, focused on the output per worker in dollar values within the manufacturing sector.
- ***Endowments and Linkages:*** The endowments in this case are the availability of critical materials, which are metals such as lithium, nickel and cobalt. In this study, this aspect is operationalised using the total production quantities of lithium, nickel and cobalt per year, for each country in the sample. The production quantities of critical metals required for EV battery production such as lithium, nickel and cobalt were sourced from the World Mining Data webpage, by filtering for the required raw minerals and obtaining quantities in units of metric tonnes, for each country considered in the sample.
- ***Industrial Policy instruments:*** Industrial Policy interventions have been agreed upon as difficult to identify, categorize and empirically analyse in extant, quantitative research work. However, certain solutions have been identified to mitigate this problem. The work of Juhász et al. (2022) uses a contemporary approach to identify industrial policy interventions. This was done by implementing a machine learning algorithm, with a text-based approach on a large dataset of trade flows from the Global Trade Alert database (GTA), to categorize the trade flows as different forms of industrial policy acts by matching two key criteria for labelling as these interventions, based on theoretical definitions

and frameworks proposed in earlier economic literature. The results identified 7 different categories of industrial policy interventions, out of which financial grants, state loans and trade financing will be used in this study, given the data availability, constraints and maintaining enough of a differentiator between both types of interventions. In the context of the EV sector, the industrial policy subsidies given out by governments pertaining to the automotive industry are the method of operationalization chosen for the econometric analysis.

Control Variables

- ***Gross Domestic Product (GDP):*** The inclusion of GDP addresses the economic size effects of each country under study, used as a control variable. By controlling for GDP, this study aims to isolate the effects of the aforementioned primary variables on export competitiveness, ensuring that the observations won't be confounded by the general economic status of the sample countries.
- ***Foreign Direct Investment (FDI):*** FDI inflows (and outflows incorporated with a negative sign) are also included as a control variable to account for the investment across borders which could affect industrial development of the EV sector for a host country due to another trading partner, and could possibly affect the exports of EVs.

Functional transformations

Functional transformations are often used in econometric studies, especially when the datasets used for the analysis consist of high variability in the distribution. For this study, given the size of the dataset and the number of countries being considered, the features may differ substantially, making comparability a problem. For instance, the sample contains a country like China whose EV exports in 2022 were in the range of $20 billion (United Nations & World Bank, 2024), but it also consists of countries such as Andorra, whose EV exports for 2022 are in the range of $0.5 million (United Nations & World Bank, 2024). Lastly, as elaborated further in subsection 3.4, the sample also consists of countries that are not exporters of EVs which translates to EV export values as 0s. The functional transformation used for this study is the inverse hyperbolic sin (IHS) transformation.

The IHS transformation is a well-known functional transformation in extant quantitative literature employing panel data regressions as their statistical method. It is frequently applied in econometric studies to transform right-skewed variables that include zero or negative values (Aihounton & Henningsen, 2019). Further, the advantage it has over another commonly used transformation in such studies, i.e. the logarithmic transformation (log), is that logged values of the variables exclude the zeros in the sample, whereas the IHS transformation facilitates the inclusion of the zeros in the sample while also reducing the variability in the dataset for better comparability, thus ensuring completeness of the analysis. It has been applied in works such as those of Bellemare et al. (2013) to study the impact of commodity price volatility on the welfare of rural households in developing countries. The mathematical function of the IHS transformation is represented by Equation 3

$$arcsinh(x) = log(x + \sqrt{x^2 + 1}) \tag{3}$$

The dependent and independent variables have been transformed using the IHS function to incorporate a large number of zeros, whereas the control variable GDP has been transformed using the log transformation due to the lack of zeros as it captures the general economic output for each country. However, the other control variable FDI has been transformed using IHS again, due to the presence of negative values, making the log transformation unfit for this variable. Table 1 summarizes the dependent, independent and control variables with their definitions and the sources used to build the dataset.

Table 1: Definition of Variables and Data Sources

Variable	Definition	Abbreviation	Source
Dependent variables			
EV export performance	EV export values	IHS(EV exports)	UN Comtrade, via World Integrated Trade Solutions
Independent variables			
Technological innovation levels	Number of Patents Granted in Transport Sector	IHS(PAT)	World Intellectual Property Organization (WIPO)
Labour productivity	Output per worker	IHS(λ)	International Labour Organization (ILOSTAT)
Endowments in Critical Metals	Total Production Qtys. of lithium, nickel and cobalt	IHS(Q.Cr.Met.)	World Mining Data
Industrial Policy instruments	Number of Financial Grants, State Loans and Trade Financing in Automotive Sector	IHS(IP)	Global Trade Alert database (GTA)
Control variables			
Gross Domestic Product	Economic size effects	log(GDP)	World Development Indicators (WDI)
Foreign Direct Investment	FDI inflows	IHS(FDI)	World Development Indicators (WDI)

The data collection involved a systematic approach to extract the latest available secondary data for the time frame considered for the study, enabling consistent comparability across countries. This included downloading datasets, extracting relevant data for the dependent and independent variables, and structuring data in a comprehensible format. Attention was given to the quality of the data, its completeness, and the period covered, to include a diverse set of countries with varying levels of involvement in the EV market. This structured approach to data collection is designed to gather comprehensive and reliable datasets that will aid the empirical analysis of the determinants of export competitiveness in the global EV industry, facilitating a robust examination of the proposed research questions.

3.4 Sampling Strategy

Due to the empirical and data-driven nature of this study, the sampling strategy chosen is mainly informed by the availability of data, a form of convenience sampling. Given the data constraints, the countries included in the analysis were those for which complete data on EV exports, followed by technological innovation, labour productivity, critical material availability, and all other variables of interest could be obtained. Further, the missing values for certain variables were computed by extrapolation and minor assumptions based on trends from previous years or future years. Hence, the selection of countries was contingent upon the availability of reliable datasets for the determinants. The number of countries in the models is 162 and the complete list of countries can be referred to in Appendix A. This is slightly different from the sampling strategy followed in multiple cross-country EV adoption studies, such as Khatua et al. (2023), Ruoso & Ribeiro (2022) and Sierzchula et al. (2014) to name a few, which generally consider the top 10 to top 20 ranked countries in terms of EV uptake. The sampling approach used in this study helps avoid a selection bias by including the non-EV-exporting countries in the sample which helps prevent the analysis from being skewed towards just the successful cases and neglecting the contexts where EV exports are absent or minimal.

Generalizability

Additionally, this approach also increases the generalizability of the findings due to the large dataset, since larger datasets in quantitative research are typically associated with higher levels of generalizability than such research that uses smaller datasets (Ercikan, 2009).

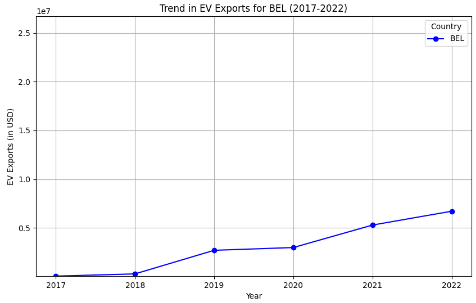
Statistical Power

As mentioned above, along with higher generalizability, the statistical power of the research is also positively correlated with the sample's size (Suresh & Chandrashekara, 2012). This further justifies the use of the relatively large dataset of countries in this study.

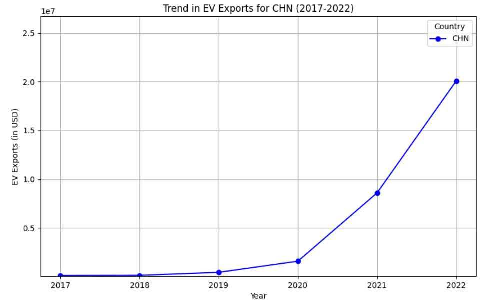
Limitations of Sampling Strategy

Acknowledging the inherent limitations of this sampling strategy, it is important to note that the reliance on data availability may introduce a bias, as not all countries might be equally represented. This potential bias is a recognized limitation of the study. Further, although larger sample sizes are positively correlated with statistical power, it is important to recognize that statistical significance does not necessarily equate to scientific meaning (Suresh & Chandrashekara, 2012). Hence, there is a recognition of the expected results drawn from the key themes of literature from which the hypotheses have been derived, to infer scientific meaning from the statistical results obtained in this study.

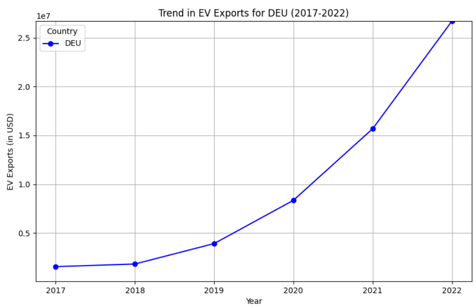
Figure 6 display the trends of EV exports across 2017 to 2022 for the major exporters of EVs in this time frame. The overall increase in exports of EVs is evident from the figure, indicating that the time frame chosen for the study is of importance and is worth investigating further.



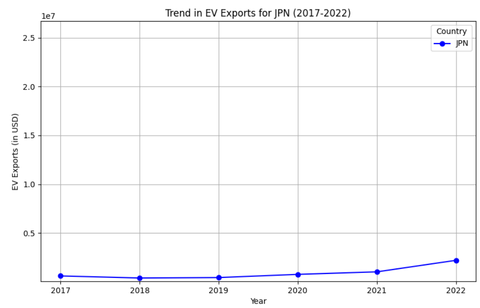
(a) Belgium



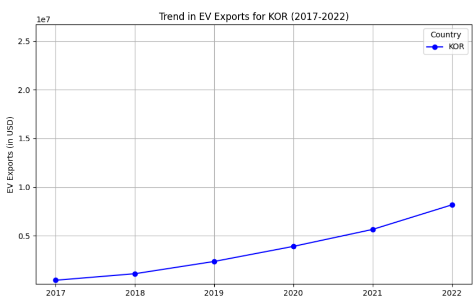
(b) China



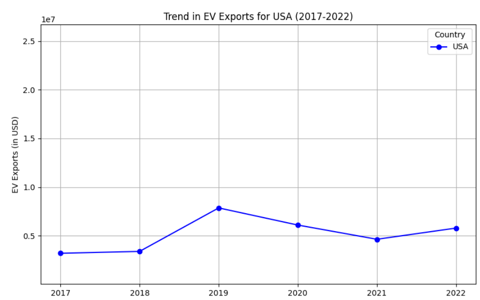
(c) Germany



(d) Japan



(e) South Korea



(f) USA

Figure 6: Trend in EV Exports for Major Exporter Countries (2017-2022), Data Source: United Nations & World Bank (2024), own illustration

The following table provides the number of EV exporting countries for each year considered in the sample. The numbers demonstrate a clear rise in the number of EV exporters from 2017 onwards, providing further justification for the sampling time frame chosen for further analysis.

Table 2: EV Exporter Countries from 2017-2022

Year	**No. of EV Exporter Nations**
2017	52
2018	56
2019	65
2020	68
2021	79
2022	76

Descriptive Statistics

The descriptive statistics for the dependent variable, the independent variables and the control variables are provided. This generates the first overview of the data distribution including means, standard deviations, minima and maxima, to facilitate a preliminary comprehension of the dataset and identify any anomalies in the set of countries. Table 3 displays the descriptive statistics for the dependent, independent and control variables.

Table 3: Descriptive Statistics of Variables with Functional Transformation

Variable	Count	Mean	Min	Max	Median	Std
IHS(EV exports)	960	3.62	0.00	17.79	0.00	5.02
IHS(PAT)	960	1.95	0.00	10.74	0.00	2.77
IHS(Q(Cr.Met.))	960	1.73	0.00	14.98	0.00	4.00
IHS(IP)	960	0.12	0.00	4.36	0.00	0.47
IHS(λ)	960	11.11	8.11	13.10	11.26	1.03
IHS(FDI)	960	6.45	-13.38	13.56	7.78	5.14
log(GDP)	960	24.81	19.19	30.88	24.74	2.15

As can be observed, the dependent variable i.e. IHS(EV exports) reports a mean of 3.62, with the maximum value ranging up to roughly 17.8 and a median value of 0, indicating a skewed distribution with most of the values being closer to 0, which further highlights that EV exports are concentrated amongst a few countries in the dataset. Next, the absolute value of patents in the transport sector (with the IHS transformation, IHS(PAT)) shows a mean of 1.95 and ranges from 0 to nearly 10.8, indicating that a large number of countries have low levels of technological innovation in the transport sector in the time frame chosen, with a few outliers driving up the average. This highlights the high variation in absolute levels of technological innovation amongst the countries in the sample, specifically in the transport sector. Furthermore, the production quantities of the critical metals required for battery production have a low average value of 1.73, but a maximum value of approximately 15 which shows that while the the norm for this variable for the majority of countries in the sample is low levels of production quantities, a few countries have very high levels of production quantities of lithium, nickel and cobalt. The Industrial Policy variable IHS(IP) and the control variable for economic size effects, IHS(GDP) do not show much dispersion and their upper and lower limits are relatively closer to their means, i.e. 0.12 and 24.81 respectively. Additionally, the relatively low standard deviation for the mean for GDP indicates that a large number of countries in the sample have transformed GDP in similar ranges, with a few exceptions with very high or very low values. Further, the labour productivity, representing the output per worker also has a high mean of 11.11 considering the upper and lower limits along with a relatively low standard deviation of 2.15, indicating that the worker efficiency, further capturing process innovations is considerably consistent within the sample. Lastly, the control variable FDI also includes a high number of negative values, indicated by its lowest value of -13.4. Also, its highest value is 13.56, and the standard deviation is substantial which signifies that some countries have high net inflows while some have significant outflows.

Overall, the occurrence of zeros as medians for multiple variables, namely EV exports, patents, production quantities and industrial policy subsidies connotes that a large fraction of countries may have underdeveloped capabilities in the time frame selected, for these key aspects which could be associated with lower competitiveness in the EV trade sector. However, descriptive statistics do not help in inferring associations between the independent variables and the dependent variable. For this purpose, the panel data regression is implemented, as discussed above in subsection 3.1.

3.5 Diagnostic Tests

Multicollinearity occurs when the multiple linear regression analysis includes several variables that are significantly correlated not only with the dependent variable but also with each other. Multicollinearity makes some of the significant variables under study to be statistically insignificant (Shrestha, 2020). There are multiple ways to detect multicollinearity in extant literature; for this study, two methods are applied to check for multicollinearity in the variables: correlation coefficients and variation inflation factors.

Correlations

Table 2. displays the Pearson's correlation coefficient matrix for the different independent variables, to check for underlying collinearity between them.

Table 4: Pearson's R Correlation Matrix for Independent Variables

	IHS(PAT)	**IHS(IP)**	**IHS(Q(Cr.Met.))**	**IHS(λ)**	**log(GDP)**	**IHS(FDI)**
IHS(PAT)	1.00	0.5	0.14***	0.56	0.73	0.2***
IHS(IP)	0.5	1.00	0.21	0.17***	0.41***	0.16***
IHS(Q(Cr.Met.))	0.14***	0.21	1.00	-0.03***	0.31	0.15***
IHS(λ)	0.56	0.17***	-0.03***	1.00	0.46	0.07***
log(GDP)	0.73	0.41***	0.31	0.46	1.00	0.33
IHS(FDI)	0.2***	0.16***	0.15***	0.07***	0.33	1.00

*This table presents the Pearson's R correlation matrix for the given variables, including significance levels. The matrix is useful for examining the relationships between the independent variables. Significance levels: * : p less than 0.10, ** : p less than 0.05, *** : less than 0.01.*

As can be observed, no correlation coefficients are above 0.8 which is a preliminary indication for the absence of severe multicollinearity in the model.

Variation Inflation Factors

Next, to confirm the absence of multicollinearity among the independent variables, the Variation Inflation Factor(VIF) method was implemented.

Table 5: Variation Inflation Factor (VIF) Results

Variables	**VIF**
IHS(PAT)	2.91
IHS(IP)	1.40
IHS(Q(Cr.Met.))	1.18
IHS(λ)	1.54
log(GDP)	2.64
IHS(FDI)	1.14
constant	407.11

None of the VIF values is greater than 10, which confirms the absence of multicollinearity (Chatterjee & Price, 1992) in the independent variables for the models.

Heteroskedasticity

Heteroskedasticity is the condition in a regression model where the variance of the error terms is not constant across all observations (Mills, 2014), or independent variables in this case. When heteroskedasticity is present in the dataset, it indicates a bias in the standard errors of the regression coefficients, which could further lead to biased testing of hypotheses with inaccurate t-tests and F-tests used to determine the significance of the coefficients (J. M. Wooldridge, 2010). Heteroskedasticity occurs for multiple reasons. Variables which are important to include in the model are omitted (J. M. Wooldridge, 2010), errors in measuring the independent variables (*Heteroskedasticity: Definition, Overview & Example*, 2023), and the presence of outliers in the sample which can disproportionately affect the variance of the residuals in the sample (Alih & Ong, 2015).

The Breusch-Pagan test proposed by Breusch & Pagan (1979), is implemented to check for heteroskedasticity in regression models. The hypotheses used for this purpose are:

H0: Homoskedasticity is present, i.e. the variance of the residuals is constant.

HA: Heteroskedasticity is present, i.e. the variance of the residuals is not constant.

The results of the test have been displayed and analysed further in Table 6. Additionally, an outlier analysis is conducted to identify the extreme values in the dataset of countries that could be distorting the results of the econometric models, leading to misinterpretation of the analysis. Further, in case the null hypothesis is rejected and the presence of heteroskedasticity is confirmed, the robust covariance estimator is used to correct the standard errors for each variable in the model as explored further with the econometric models in section 4.

Heteroskedasticity Test Results

The Breusch-Pagan test was used to check for heteroskedasticity in the variables. The results of the test have been displayed in Table 6. As can be observed, the p-value for the Lagrange Multiplier Statistic is less than 0.05, indicating that the null hypothesis can be rejected, or that heteroskedasticity is present. Additionally, the F-value and the F p-value provide additional confirmation of heteroskedasticity, with the F p-value being less than 0.05 thereby confirming the results of the Lagrange Multiplier Statistic.

Statistic	**Value**
Lagrange Multiplier Statistic	13.747
p-value	0.033
F-value	2.308
F p-value	0.032

Table 6: Breusch-Pagan Test for Heteroskedasticity

Further, the outliers have been identified and analysed in detail after the baseline regression models and can be referred to in subsubsection 4.2.1.

4 Empirical Results

This chapter displays and explains the empirical results found based on the different econometric models described in subsection 3.1, starting with a discussion on the Hausman test results followed by the regression results including the fixed effects model and the analysis of said results concerning the hypotheses developed from the theoretical framework (Figure 5). Lastly, robustness checks are conducted to verify the sensitivity of the results to some of the assumptions made while constructing the models.

4.1 Hausman Test Results

As explained in subsection 3.2, the Hausman test is carried out to determine the better fitting model out of the Fixed Effects and Random Effects models. The test evaluates the null hypothesis that the preferred model is RE against the alternative hypothesis that FE is more appropriate, based on whether the unique errors (country-specific effects) are correlated with the regressors in the model (Hausman, 1978). Table 7 shows the results for the Hausman test, with a p-value less than 0.05 (at a confidence level of 5%), which points to reject the null hypothesis and suggests the Fixed Effects model as the better fitting model for this analysis.

Table 7: Hausman Test Results for Dependent Variable: *IHS(EV exports)*

Statistic	**Value**
Chi2 Statistic	32.09
P-value	1.57e-05

Hence, the results of the study focus solely on the fixed effects regression models as they were identified to be the better fitting models for the dataset used, and the results for the random effects model are displayed in Appendix C for reference.

4.2 Regression Analysis

Table 8 displays the results for multiple panel regression models with a step-by-step introduction of the independent variables and control variables for the dependent variable, i.e. IHS(EV exports). All models are fixed effects regressions, i.e. all models control for unobservable, time-invariant country-specific effects which aids in isolating the relationships between the main variables under study and reducing omitted variable bias from the models. Additionally, this step-by-step introduction of independent variables aims to explain how the main model, Model(F) is constructed as it includes all independent and control variables. Further, this presentation also helps to ensure the robustness of the statistical results being analysed.

The regression estimations in Table 8 increase in Adjusted R-squared values on moving from 0.0025 for Model(A) to 0.0476 for Model(F), indicating that Model(F) is the most suitable in terms of goodness of fit. Moreover, the F-statistic is statistically significant at the 5% confidence interval for Models(A) through (G), which indicates that the models are statistically significant overall and at least one of the variables in each model has a statistically significant regression coefficient estimation, warranting further investigation into the models. Further, the IHS transformation is implemented in all models which enables the interpretation of the regression coefficients as elasticities (Bellemare et al., 2013), as implemented by MacKinnon & Magee (1990) and Pence (2006).

Model (D) is the regression model which contains all independent variables without the control variables. In Model(D), the signs of the regression coefficients are almost all as predicted by the theoretical framework (Figure 5). As can be observed, the model suggests that a 1% increase in the number of patents in the transport sector is associated with an approximate increase of 0.42% in EV exports, pointing to a positive and statistically significant association between technological innovation levels of a country measured by the absolute value of patents and the export performance of that country in the EV sector. On the introduction of the control variable for economic size, i.e. log(GDP), the IHS(PAT) coefficient remains statistically significant and very close in value, with the same positive sign. This is a testament to the robustness of this result, which increases even further in the main model (F) with the introduction of the IHS(FDI) control variable to nearly 0.45, statistically significant at a 5% confidence interval when controlling for the various economic standards of the large number of countries in the sample.

Table 8: Regression Models for EV exports with a step-by-step Introduction of Independent Variables

	(A)	(B)	(C)	(D)	(E)	(F)
IHS(PAT)	0.4369**	0.4320**	0.4151**	0.4175**	0.4398**	0.4468**
	(0.2071)	(0.2064)	(0.2047)	(0.2040)	(0.1979)	(0.1976)
IHS(IP)		0.5153*	0.5618**	0.5484**	0.4375*	0.4392*
		(0.2783)	(0.2412)	(0.2374)	(0.2282)	(1.4169)
IHS(Q(Cr.Met.))			0.1046**	0.1009**	0.0802**	0.0802**
			(0.0313)	(0.0310)	(0.0319)	(0.0318)
IHS(λ)				1.5225	-1.8845	-1.8041
				(1.2490)	(1.4030)	(1.4169)
log(GDP)					3.0341***	3.0040***
					(0.7385)	(0.7347)
IHS(FDI)						-0.0140
						(1.4169)
Constant	2.7703**	2.7200**	2.5663**	-14.3441	-51.7773**	-51.8482**
	(0.4098)	(0.4097)	(0.4104)	(13.8428)	(16.2886)	(16.3671)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	960	960	960	960	960	960
Entities	160	160	160	160	160	160
R-Squared (Within)	0.0087	0.0139	0.0246	0.0275	0.0528	0.0535
R-Squared (Between)	0.3853	0.4110	0.3961	0.5822	-0.3131	-0.2771
Adjusted R-Squared	0.0025	0.0077	0.0185	0.0214	0.0468	0.0476
F-test	7.035***	5.61***	6.7020***	5.6325***	8.8655***	7.4873***
Covariance Type	Robust	Robust	Robust	Robust	Robust	Robust

*This table presents the regression coefficients for the dependent variable: IHS(EV Exports), with the standard deviations for each coefficient below in brackets(). Significance levels: * : p less than 0.10, ** : p less than 0.05, *** : less than 0.01.*

It can hence be inferred that higher levels of technological innovation in the transport sector are positively associated with a higher EV export performance, and there is evidence to accept **H1**.

Next, the industrial policy variable, IHS(IP) also shows a positive and statistically significant (with a p-value less than 0.05) coefficient estimation close to 0.55, starting from model(D) without controls. However, on the introduction of the GDP variable and both GDP and FDI variables as seen in model(E) and model(F) respectively, the coefficient progressively decreases in value as well as statistical significance to 0.45, now at the 10% confidence interval. This essentially means that a 10% increase in government-issued industrial policy subsidy measures specifically financial grants, state loans and trade financing targeted towards the automotive sector from 2017 to 2022 are associated with a 4.5% increase in export performance in the EV industry while controlling for time-invariant factors and economic size as well as external investment into the domestic EV industry. This provides strong statistical support in favour of accepting **H4**.

Furthermore, in terms of the IHS(Q(Cr.Met.))variable, model(D) indicates that a 1% increase in the production quantities of critical metals such as Lithium, Nickel and Cobalt is linked with an increase of 0.1% and a 0.08% in EV export performance with and without the control variables respectively. The sign of the coefficient remains uniform across all models, with a slight reduction in magnitude upon the introduction of the economic size effects control. This points to the understanding that although the production quantities and supply chain efficiency play a key role in association with EV export performance, the economic size effects of a nation could be contributing to its capability to produce these critical metals, which in turn affects EV exports. This can be further supported by the argument that countries with better economic performance are likely to be associated with having more efficient supply chains and the necessary capital to mine as well as process these essential materials. Hence, this robust statistical result supports the acceptance of **H3**.

Additionally, the cost-competitiveness indicator, IHS(λ) was statistically insignificant across all models, which indicates no association between labour productivity and EV export performance. This points towards the rejection of **H2**, indicating that cost may not be a significant driver of international competitiveness in the EV sector. However, this could also be explained by the relatively short duration of analysis which may not be enough to capture the variances in changing levels of production efficiency, and generally, an increase in production efficiency is facilitated by sustained investment towards process innovations by firms.

The log(GDP) control variable shows a regression coefficient of a high magnitude of 3.03, statistically significant at the 5% confidence interval. This confirms that the inclusion of log(GDP) to control for disproportionate economic sizes of the countries in the sample was crucial to isolate the effects of independent variables under study, on EV export performance. However, the inclusion of GDP drastically reduces the R-squared (between) from 0.58 in model(D) to -0.27 in model(F). This indicates that the extent to which the models account for differences in the dependent variable, IHS(EV exports) between countries decreases from approximately 5.28% in model(D) to model (F). A plausible explanation for this is the inclusion of the GDP control variable causes over-fitting of the model(F), which can distort the results and lead to inaccurate conclusions about the regression estimations. Another reason for this could also be due to the presence of heteroskedasticity, but this has been mitigated by using a robust covariance estimator for all models. Another set of regression models without outliers has been developed and can be referred to in subsection 4.3.

Contrarily, the R-squared (Within) increases from nearly 0.028 to approximately 0.054, which indicates that the extent to which the models explain the variance in IHS(EV exports) within each of the countries over the chosen period of 2017 to 2022, increases from nearly 2.8% to 5.4% on the inclusion of the control variables. These postulates suggest that the model(F) is better equipped to capture the temporal effects of the independent variables within countries than accounting for the difference of country-specific effects.

4.2.1 Outlier Analysis

As explained in subsection 3.5, one of the significant contributors to heteroskedasticity in the regression models is the presence of outliers, i.e. extreme values in the sample that distort the standard errors of the regression estimates. A graphical representation of the outliers is presented in Figure 7.

Residuals are the differences between predicted values and observed values in statistical analysis. A method popular in econometric studies for outlier identification is by analysing studentized residuals, a form of standardized residuals, which are the residuals divided by their standard errors (Blatná, 2006). The values of studentized residuals that do not fall in the range of -2 to 2 are highly likely to be outliers, as per Blatná (2006).

The figure plots the standardized residuals of the observations versus the dependent variable, IHS(EV exports). The standardized residuals not falling in the range of -2 to 2 are marked as outliers, as can be observed from the graph. The analysis indicates that there are roughly 65 observations which are most likely to be outliers. This consists of 41 countries and different year observations. The list of outliers (country and year) can be found in Appendix D.

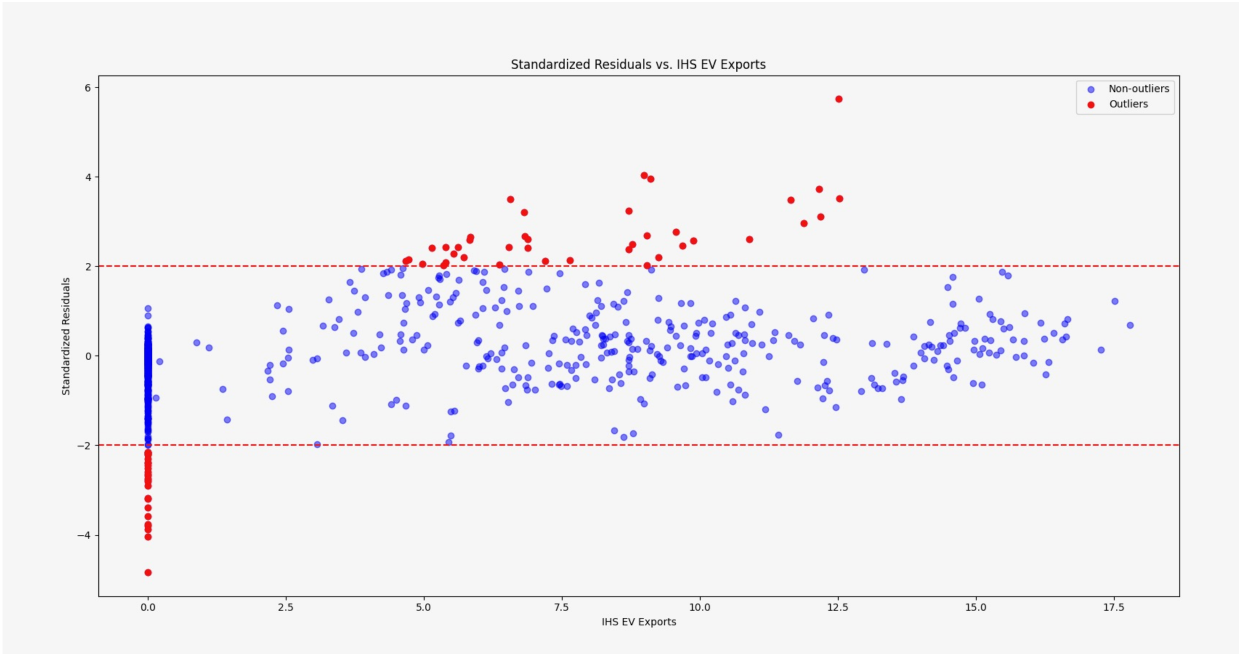


Figure 7: Standardized Residuals for Outlier Identification, own illustration

4.3 Robustness Tests

A common exercise in empirical studies is a "robustness check", where the researcher examines how certain "core" regression coefficient estimates behave when the regression specification is modified by adding or removing regressors. If the coefficients are plausible and robust, this is commonly interpreted as evidence of structural validity (Lu & White, 2014). Following this approach, robustness tests are conducted for this study to ensure that the results are not sensitive to the choice of model specifications or the presence of specific outliers in the sample of countries.

4.3.1 Innovation Intensity Indicator

The results for the baseline models used for the fixed effects regression coefficient estimates in Table 8, specifically for the patents, industrial policy and production quantities variables maintain similar magnitudes and the same mathematical signs across all models. They also remain statistically significant upon the introduction of other variables, which further solidifies the evidence of robustness in the empirical findings. However, the IHS(PAT) variable utilizes the absolute value of the number of patents granted in the transport sector in each country as the independent variable to operationalize the levels of technological innovation in the EV sector. Table 9 displays the results of an alternate set of regression models, incorporating a patent intensity measure instead of the absolute value of patents. The patent intensity measure for each country is defined by:

$$PatentIntensity = (AbsoluteNo.of Patents * 10^9)/GDP \quad (4)$$

Table 9: Regression Models for EV exports with a Patent Intensity Measure

	(G)	(H)	(I)	(J)	(K)	(L)
IHS(PAT/GDP)	0.6305	0.6670	0.6739	0.7288	0.7479	0.7624
	(0.4668)	(0.4707)	(0.4728)	(0.4669)	(0.5032)	(0.5045)
IHS(IP)		0.5379*	0.5857**	0.5726**	0.4643**	0.4663**
		(0.2832)	(0.2448)	(0.2409)	(0.4643)	(0.2311)
IHS(Q(Cr.Met.))			0.1079**	0.1041**	0.0838**	0.0839**
			(0.0316)	(0.0314)	(0.0323)	(0.0322)
IHS(λ)				1.6071	-1.7489	-1.6743
				(1.3010)	(1.4588)	(1.4749)
log(GDP)					2.9901**	2.9625**
					(0.7327)	(0.7347)
IHS(FDI)						-0.0125
						(0.0212)
Constant	3.5071**	3.4380**	3.2443**	-14.6109	-51.4798**	-51.5467**
	(0.1089)	(0.1168)	(0.1252)	(14.4548)	(0.0020)	(116.6944)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	960	960	960	960	960	960
Entities	160	160	160	160	160	160
R-Squared (Within)	0.0022	0.0078	0.0192	0.0225	0.0471	0.0477
R-Squared (Between)	0.0593	0.1054	0.1102	0.3843	-0.2007	-0.1683
Adjusted R-Squared	-0.0041	0.0015	0.0131	0.0163	0.0411	0.0417
F-test	1.7556	3.1343***	5.2119***	4.5757***	7.8515***	6.6212***
Covariance Type	Robust	Robust	Robust	Robust	Robust	Robust

*This table presents the regression coefficients for the dependent variable: IHS(EV Exports), with the standard deviations for each coefficient below in brackets(). Significance levels: * : p less than 0.10, ** : p less than 0.05, *** : less than 0.01.*

The patent intensity measure serves as an indicator of technological innovation intensity rather than absolute levels of technological innovation as measured by patents. IHS(PAT/GDP) does not have a statistically significant regression coefficient across model(G) to model(L), unlike the results estimated in the baseline models Table 8. This is interpreted to be the case because countries with a larger economic output or larger economic scales are highly likely to have a larger number of world-class institutions, more capital for research funding and a larger population, which in turn could be the reason for the larger absolute number of patents. In other words, higher EV export performance associated with a higher number of absolute patents in the transport sector could plausibly be due to size effects, rather than the differences in the levels of intensity of technological innovation across the countries in the sample.

4.3.2 Handling Outliers

An additional robustness test was conducted using the regression models but excluding the outliers identified in subsection 4.2. Table 10 displays the results of the fixed effects regression with the variables as used in the baseline model, excluding the outlier observations from the dataset. The list of countries and the corresponding years that have been categorized as outliers as discussed in subsubsection 4.2.1 can be referred to in Appendix D. Furthermore, the functional transformation used is the logarithmic function instead of the IHS function to ensure robustness of the results to the transformations used earlier. Due to the large number of zeros in the dataset, a minor adjustment was made to the logarithmic transformation by adding a small constant to facilitate the safe transformation of the zeros and to include them as zeros in the regression models instead of dropping those observations. This is represented mathematically by the expression: **log(1+x)** and can be found in the python codes included in Appendix B.

Table 10: Regression Models for EV exports without Outliers

	(M)
log(PAT)	0.2575**
	(0.1472)
log(IP)	0.3814
	(0.2861)
log(Q(Cr.Met.))	0.0734**
	(0.0236)
log(λ)	0.0490
	(0.6447)
log(GDP)	1.8219**
	(0.4081)
IHS(FDI)	-0.0178
	(0.0119)
Constant	-42.8341**
	(9.1302)
Year FE	Yes
Observations	895
R-Squared (Within)	0.0839
R-Squared (Between)	0.4088
Adjusted R-Squared	0.0777
F-test	11.1620**
Covariance Type	Robust

*This table presents the regression coefficients for the dependent variable: IHS(EV Exports), with the standard deviations for each coefficient below in brackets(). Significance levels: * : p less than 0.10, ** : p less than 0.05, *** : less than 0.01.*

The preliminary analyses suggest an improvement in explanatory power as compared to the baseline models (Table 8), indicated by the increases in R-squared parameters. For instance, the R-squared (Within) for model(M) is nearly 0.084, which means that model(M) explains approximately 8.4% of the variance in EV export performance within countries while controlling for temporal and unobserved effects, as compared to Model(F) which explains close to 5.4% of the variance in the dependent variable with the same control measures. Moreover, even the extent to which the models account for the differences in EV export performance between countries increases from -0.28 in Model(F) to roughly 41% in Model(M). Lastly, the Adjusted R-squared is also increased on the removal of outliers, providing higher goodness of fit. This confirms that the distortion of the R-squared(between) to an unexpected negative value in the baseline model(F) was likely due to the extreme values present in the dataset, or due to misspecifications in the IHS transformation used. Moreover, the F-statistic is statistically significant for Model(M) and warrants analysing the coefficients for the independent variables.

Concerning the independent variables, the regression coefficients for the log-transformed absolute number of patents and the production quantities of the critical metals required for EV manufacturing retain the same signs as in the baseline models. Model(M) suggests that a 1% increase in the number of patents in the transport sector is associated with a 0.26% increase in logged EV exports, which is lower than the association noted in Model(F). This points to the inference that a sizeable portion of the absolute number of patents was concentrated amongst some of the outliers leading to a slight exaggeration of the effect of patents on export performance. Next, log(Q(Cr.Met.)) is confirmed to be a robust factor linked with EV export performance. It is the only independent variable that remains positive in directionality and statistically significant from Model (A) to Model(M), insensitive to time-invariant effects as well as economic size effects and unaffected by the influence of extremities in the sample. A 10% increase in the production quantities of Lithium, Nickel and Cobalt is associated with a 1.1% increase in EV export values.

Additionally, the industrial policy variable, log(IP) does not remain statistically significant on the exclusion of the extreme values, which points to the interpretation that the initial results may have been driven by specific cases of industrial policy's effects on EV exports. Also, the variable used does not capture the intensity of the government interventions by incorporating a policy intensity measure which leads to an insufficient capture of the effectiveness or nuances of each industrial policy subsidy in the context of those specific countries.

5 Discussions

This chapter highlights the key findings from the econometric analyses with a broader lens, in terms of the extant literature and the study's practical implications. It starts with a broader interpretation of the key findings from section 4 and summarizes them. Next, the academic contributions of this study have been mentioned, followed by a connection to current affairs in the EV industry as a testament to the study's practical significance. Lastly, the limitations of this research effort have been discussed in detail.

5.1 Key Findings

The econometric analysis provided a systematic method to statistically analyse theoretical concepts and findings from the different streams of literature explored in section 2 in the context of the global EV industry.

Technological and Cost Competitiveness Factors

The measure used for quantifying the technological innovation levels of the countries was the absolute number of patents, capturing the product and process innovations in the transport sector from 2017 to 2022. The various regression models with different specifications reveal mixed results regarding this factor. Firstly, a 1% increase in absolute number of patents is associated with a 0.45% increase in the IHS transformed EV export values, which was updated to 0.26%, statistically significant on the exclusion of the extreme values that could have created a bias in the reported estimation due to a high concentration of patents amongst the outliers. However, this is also an indicator of the estimation's low sensitivity to outliers which does indicate that the absolute degrees of technological innovation in a country are positively linked with its export performance in the EV sector.

However, the patent intensity measure was statistically insignificant in models(G) to (L), which indicates the levels of technological innovation intensity are not correlated with international competitiveness in the EV sector. Both these findings point to the fact that countries with scale effects are observed to perform better than countries without them, due to the higher likeliness of countries with higher economic output and economies of scale to have greater volumes of research output and the accessibility to expenditure for innovations in the transport sector.

Labour productivity was found to be statistically insignificant across all regression models, which provides robust evidence to underplay the role that cost competitiveness plays in exports of this high-technology sector. However, an alternate interpretation of these results is also likely due to the lack of change in labour productivity in the short period of 5 years, since a measurable increase in manufacturing efficiency at a national level takes significant policy upgrades and also depends on the macroeconomic strategies specific to each country, based on appropriate wage-setting mechanisms. This points to the requirement of analysis with a larger time frame setting the boundary conditions of research.

In closing, in terms of the widely disputed and contrasting streams of literature regarding technological and cost competitiveness factors, this study posits that the absolute levels of technological innovation are likely to be a larger driver of international export competitiveness in the EV industry rather than cost competitiveness, in alignment with the Schumpeterian chains of thought as well as the works of Soete (1981), Fagerberg (1988) and Dosi et al. (1990) which stress on the importance of advanced technological capabilities to maintain competitive advantage.

Industrial Policy Measures

The number of industrial policy subsidy measures, specifically state loans, financial grants and trade financing targeted towards the automotive sector were found to be positively linked with export performance in the EV sector and were robust to the inclusion of the patent intensity measure but were later identified as sensitive to outliers in the sample since the regression coefficient was statistically insignificant in model(M) (Table 10). This indicates that the effects of government intervention with industrial policy efforts are more efficiently implemented or with higher vigour in select countries in the sample. While this finding aligns with Evenett et al. (2024)'s inference of a positive correlation between industrial policy interventions and export performance, it applies selectively. However, the temporal effects of the implementation of industrial policies can vary significantly depending on a government's alignment and misalignment of industrial policy with innovation to achieve green transformation (Narassimhan et al., 2023), and countries that initially gained a first mover advantage due to alignment of innovation and industrial policy in the EV sector may have lost this advantage due to evolving political strategies and preferences (Narassimhan et al., 2023). Moreover, the effectiveness of industrial policy can also vary with the institutional soundness of different countries. For instance, a comparative study conducted by Coulter (2023) finds that countries with robust institutions tend to implement more effective industrial policies due to more efficient utilization of resources and that the level of government involvement in industrial policy implementation also varies with countries. These postulates are an explanation for the fact that the regression estimations including the outliers found industrial policy subsidy measures to be positively linked with EV export performance. In contrast, the estimation excluding the outliers did not. These nuances require further exploration and case-specific analysis and interpretation. Lastly, the sensitivity of the results for this variable could also possibly be due to the method of operationalisation of the variable as the industrial policy subsidy measures for the entire automotive sector, due to the data constraints on EV-specific industrial policy subsidy measures.

Another component of industrial policy that has received interest from the extant literature and has been of relevance in the current geopolitical scenario is import tariffs. Hence, a regression model with the average of import tariffs imposed by each country on the rest of the world for each year was deployed and can be referred to in the Appendix C. However, due to this method of operationalization for the tariff variable, the regression coefficient was found to be unusual and unexpected in magnitude and sign. The main contributor to the nature of this result is that the aggregation of the percentages of import tariffs imposed by a single country on the rest of the world does not capture the nuances of the various types of trade agreements and partnerships that countries have with each other. For instance, the EU countries have free trade agreements amongst themselves but not necessarily outside of the EU, which gets inefficiently captured in the model. Furthermore, keeping the magnitude aside, the sign of the coefficient is also unexpected but could be explained by the notion of countries imposing retaliatory tariffs against the countries that may have initiated the strategy, which could rebound on the initiator and affect export performance in the EV sector. Hence, the negative sign could indicate that import tariffs on the rest of the world can have a self-defeating effect on raising the EV export performance of the exporting countries.

Endowments and Linkages

The production quantities of critical metals are found to have a strong and significant association with EV export performance, as illustrated by the statistically significant positive regression coefficients in the baseline models, the patent intensity measure model and the model without the outlier observations. This is the most robust finding from the econometric analyses. As suggested by Heckscher & Filip (1919) and Ohlin & Gotthard (1933), countries with substantial reserves of critical metals which are available to them in abundance and at lower costs are in pole position to hold a competitive advantage in exports of EVs. Additionally, the quantitative results for this factor are inline with Bahar et al. (2019)'s indication of how countries thriving in the production of intermediate raw materials such as lithium, nickel and cobalt can help a nascent sector like the EV sector to gain strong dominance in international markets.

Furthermore, this variable was also a proxy for the presence of local suppliers and value chains of the critical metals in exporting countries. In terms of this aspect, the association found is inline with Porter (1990)'s Diamond Model, which posits that the presence of related and supporting industries for a sector is a key factor for a nation to gain a strong foothold in international markets for industries such as EVs. The related and supporting industries in this case is the mining of the critical metals required for battery manufacturing, potent electromagnets and EV chassis, which are all essential components of EV production. Additionally, the result also provides supporting empirical evidence in favour of Bahar et al. (2019)'s inference on how reliable supplier linkages are an explanatory factor for growth in EV exports in developed economies.

5.2 Contributions to Literature

This study makes a contribution to the extant literature concerning the determinants of sector-specific export performance by providing a unique econometric approach, driven by secondary data. Previous studies have analysed the export competitiveness of specific countries as studies, or the impact of a particular industrial policy on the exports of a single nation like China or South Korea, and multiple cross-country econometric studies on EV adoption and uptake. However, this study provides empirical evidence to reveal the quantitative relevance of four determinants of export performance for EVs, as suggested by the different streams of literature. Furthermore, the cross-country nature of this study along with the econometric models chosen for the analysis help in isolating the effects of the identified determinants on international competitiveness in the global EV market, while controlling for country-specific, time-invariant and unobserved effects. There is a lack of cross-country sector-specific export performance studies, especially for high-technology industries and even lower for environmentally-friendly technologies, and this study fills this knowledge gap by focusing on a critical industry for the future, the EV industry. This is highly relevant due to the global shift towards sustainable energy technologies, especially in the hard-to-abate transport sector. Moreover, this paper also examines the impact of green industrial policies on the export performance of EVs implementing a quantitative research design and can serve as a tool for future academic research in this subject.

5.3 Limitations

The recognition of the limitations of this study is important to acknowledge to ensure that the interpretation of the results is not misleading. Also, the limitations of this study drive the various areas for future research in this context. The study discusses a multitude of factors that could affect EV export performance, but there is no direct indicator of domestic demand for the exporters which could be another important factor worth investigating. This is because domestic demand can catalyse production and hence potentially enhance export performance. Intertwined with the demand factor are institutional and socio-economic factors that could be important to include in the analyses, but were left out due to the excessive broadening of the scope of research.

In terms of the methodology adopted for the study, while the IHS transformation used for the variables has its merits and is a useful solution to handle a dataset consisting of zeros or negative values, it could lead to a slight misinterpretation of the results due to its handling of values smaller in magnitude (McKenzie, 2023). Further, the operationalization of the industrial policy factor captures the specific nuances of the various subsidy measures to a decent level, but still incompletely. This is due to the lack of quantitative data available on industrial policies for all countries as discussed in subsection 1.2 due to the ambiguity in the categorization of policies as industrial policies or other forms of policies. Additionally, there was a lack of data regarding the industrial policy subsidy measures directly targeting EVs instead of the automotive sector on the whole, which could have facilitated a more EV-specific quantification of the factor. Furthermore, the relatively low R-squared (within) values indicate that the inclusion of more factors in the model could improve the explanatory power of the models. Also, the model was unable to gain a comprehensive explanation of the relationship between import tariffs imposed by exporters on the rest of the world and export performance due to the way the measure was aggregated using the average, which doesn't enable analysing the import tariffs bilaterally between countries. Furthermore, the instrument used as a measure of the level of technological innovation in countries, i.e. patents is a widely used innovation indicator in econometric literature for this purpose. However, patents do not necessarily capture all innovative activity in a high-technology sector. There is also an abstract and unquantifiable level of non-patented innovation in the EV sector that is not captured by this measure. Moreover, the absolute number of patents in an industry also depends on the propensity to patent, which varies substantially across different sectors Arundel & Kabla (1998).

Lastly, although the models account for the production quantities of the critical metals, they lack consideration of the dimension of global value chains for these raw materials. Global value chains and trade partnerships for lithium need to be explored further to understand how countries with an abundance of lithium position themselves in international markets, and whether they prioritise exporting the metal or using it to develop their home EV industries.

6 Conclusion

The main objective of this study was to analyze the determinants of international competitiveness in the global EV market with a cross-country approach, to gain insights on the extent to which the commonly linked factors as indicated by the extant literature are related to export performance in the EV sector. This study was guided by the following main research question:

Which factors are most strongly associated with the export competitiveness of the electric vehicles industry across countries?

In an attempt to answer this main research question and the sub-research question, the study was initiated by a literature review focusing on the key themes of international competitiveness academia, followed by delving into streams of literature linked with export competitiveness such as technological innovation factors, cost-competitiveness aspects, industrial policy subsidy measures towards the automotive sector and endowments in critical metals required for EV production. Following this, a conceptual framework was created and falsifiable hypotheses were developed to quantitatively investigate the research areas further.

Next, based on the hypotheses, independent variables were operationalised for econometric analysis and the relevant secondary data was collected from reliable databases. The collected data was studied further and the descriptive statistics helped understand the central tendency and dispersion of the data. Next, several diagnostic tests helped in identifying any multicollinearity and heteroskedasticity amongst the variables which could have distorted the interpretation of the results. Followed by this, the econometric analyses enabled the joint investigation of the multiple hypotheses and deploying the fixed effects regression model to control for time-invariant, unobserved country-specific effects. This model also accounts for other important variables that may have been omitted in the analyses, and provides regression estimates of the different inverse hyperbolic sin transformed independent variables, to interpret the elasticises of the coefficients with respect to the dependent variable, i.e. EV exports, including controls for economic size and the influx of foreign investment in the countries.

The baseline models provide a foundational understanding of the relationships, which is further strengthened by implementing two robustness checks: one with a patent intensity measure and one without the outliers. Out of the multitude of factors analysed, the most robust results point to the inference that the absolute levels of technological innovation, endowments of critical metals such as lithium, Nickel and Cobalt and the presence of industrial policy subsidy measures targeted towards the automotive sector are the most strongly associated factors related to international competitiveness in the EV sector.

6.1 Implications

6.1.1 Theoretical Implications

The study posits a novel approach to comprehending the export performance for high-technology sectors such as the EV sector. It fills a gap in extant literature by recognizing certain key determinants of export competitiveness across countries, providing empirical justification and support on factors drawn from streams of literature like technological and cost competitiveness, endowments and linkages, and green industrial policy measures.

Further, by integrating the Heckscher-Ohlin model (Heckscher & Filip (1919), Ohlin & Gotthard (1933)) and the technology-gap theories, the study blends traditional economic theories with EV context-specific factors to gain an understanding on the export performance for this sector. It solidifies the theoretical foundation required for studies exploring endowments' relevance in high-technology exports.

Moreover, the study's use of econometric models such as the Fixed Effects regression model which facilitates the isolation of the effects the identified factors have on export performance while controlling for country-specific, geographical or institutional effects which do not vary temporally has added further to the abundant use of econometric methods in international trade literature. Lastly, by a cross-country comparison, the study lays out a thorough perspective of the global EV market, identifying certain patterns and disproportions in export competitiveness for the EV sector.

6.1.2 Policy Implications

For policymakers, this study has incremental insights in terms of enhancing their country's positioning in the global EV market. Firstly, the study highlights the requirement of targeted industrial policy subsidy measures towards the EV sector, but with careful consideration of the forms and implementation of these measures over announcements. For instance, the debates about China gaining an unfair advantage in EV trade supported by unrestricted subsidy measures towards domestic EV manufacturers may have led to the retaliatory import tariffs imposed by the USA and the EU. Even though these measures may boost China's EV export performance, they could cause international tensions and trade disputes if not used precariously and have a self-defeating effect on export performance in the long run. This reinforces the need for a balanced approach towards industrial policies, to enable increased international competitiveness in the EV sector, without instigating trade disputes internationally.

Further, the study also recommends that governments implement policy measures that enable the development and nurturing of local supplier networks and reinforce the linkages between mining and EV producers for critical metals required for EV production. This is highlighted by the over-dependence of the USA and the EU on Asian imports for procurement of critical metals such as lithium (Manthey, 2023), due to the lack of robust supply chains for critical metals in these countries, which could thereby lower EV export performance and needs attention from policymakers.

Apart from their access to abundant supplies of lithium through natural endowments and robust linkages, China is also a world leader in battery technology (Jameel, 2024), which further drove up Chinese EV exports and helped China emerge as one of the leading EV exporters in the world over the last decade. In this context, the findings of the study indicate that policies which can boost research output such as research grants and tax incentives coupled with sustained investment directed towards innovation in EV technology can be beneficial to improve EV export performance.

6.2 Future Research

Based on the limitations and the results from the study, a few recommendations for future research have been developed.

Firstly, the results of the study indicate that advanced econometric methods such as the Instrument variables method or the Difference-in-Difference approach can help in identifying causality between the factors identified to have statistically significant associations with international competitiveness in the EV sector. This could aid in the development of strategies for policy-makers to enhance their country's competitive positioning in EV exports. Further, the use of interaction terms in the econometric analyses is recommended to gain more insight on the interplay between the factors that have been studied, concerning EV export performance.

Additionally, a measure such as R&D expenditure or intensity can be used as a marker of the levels of technological innovation in a country to capture the intensity of investments in boosting innovation performance in the EV sector. An alternative to this is implementing the number of green patents as a marker of technological innovation in the EV sector as done by Zhao et al. (2024), which utilizes the proportion of EV-related patents in total patents to measure the degree of transformation from ICE vehicles to EVs in the automobiles market.

Furthermore, the global value chains for critical metals are of evergreen interest in extant literature, and an additional layer of analysis could be provided to this research area by including the import values of metals like Lithium as an explanatory variable in a model that aims to explore the factors ahead in an econometric manner. Moreover, the impact of industrial policy measures on EV export dynamics can be analysed individually, to comprehend the most important types of industrial policies required for this purpose instead of a combined perspective to inform future directions for policy-makers. Case-specific approaches for different countries can also enrich this notion further. Lastly, as mentioned in the limitations of this study (subsection 5.3), the import tariffs that exporters impose on their trading counterparts can be analysed bilaterally, for a more nuanced understanding of the influence they may have on EV export performance. A recommendation for this purpose is implementing the gravity model as done by Matsumura (2021) to analyse the determinants of bilateral trade flows for environmental goods, and by Gnutzmann-Mkrtchyan & Hugot (2022) to estimate the impact of import tariffs changes on bilateral trade and welfare.

References

Aghion, P., & Howitt, P. (1998). *Endogenous Growth Theory*. Cambridge, MA: MIT Press.

Aihounton, G. B. D., & Henningsen, A. (2019). *Units of Measurement and the Inverse Hyperbolic Sine Transformation.* Copenhagen. Retrieved from https://hdl.handle.net/10419/211087

Alih, E., & Ong, H. C. (2015). An outlier-resistant test for heteroscedasticity in linear models. *Journal of Applied Statistics*, *42*(8), 1617–1634. Retrieved from https://doi.org/10.1080/02664763.2015.1004623 doi: 10.1080/02664763.2015.1004623

Alim, A. N., Wright, R., Campbell, P., & Li, G. (2024, 4). *European ports turned into 'car parks' as vehicle imports pile up.*

Altenburg, T., & Rodrik, D. (2017). *Green Industrial Policy: Accelerating Structural Change towards Wealthy Green Economies.*

Arundel, A., & Kabla, I. (1998, 6). What percentage of innovations are patented? empirical estimates for European firms. *Research Policy*, *27*(2), 127–141. doi: 10.1016/S0048-7333(98)00033-X

Asteriou, D., Masatci, K., & Pilbeam, K. (2016, 11). Exchange rate volatility and international trade: International evidence from the MINT countries. *Economic Modelling*, *58*, 133–140. doi: 10.1016/J.ECONMOD.2016.05.006

Axinn, C. (1988). EXPORT PERFORMANCE: DO MANAGERIAL PERCEPTIONS MAKE A DIFFERENCE? *International Marketing Review*, *5*, 61–71.

Bahar, D., Rosenow, S., Stein, E., & Wagner, R. (2019, 5). Export take-offs and acceleration: Unpacking cross-sector linkages in the evolution of comparative advantage. *World Development*, *117*, 48–60. doi: 10.1016/J.WORLDDEV.2018.12.016

Balassa, B. (1965, 5). Trade liberalisation and "revealed" comparative advantage¹. *The Manchester School*, *33*(2), 99–123.

Bano, S., & Scrimgeour, F. (2011). *New Zealand Kiwifruit Export Performance: Market Analysis and Revealed Comparative Advantage.* Hamilton, New Zealand.

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*, 99–120.

Beleska-Spasova, E. (2014). Determinants and measures of export performance: Comprehensive literature review. *Journal of Contemporary Economic and Business Issues*, *1*, 63–74.

Bellemare, M. F., Barrett, C. B., & Just, D. R. (2013). The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. *American Journal of Agricultural Economics*, *95*(4), 877–899. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1093/ajae/aat018 doi: https://doi.org/10.1093/ajae/aat018

Bhawsar, P., & Chattopadhyay, U. (2015). Competitiveness: Review, Reflections and Directions. *Global Business Review*, *16*(4), 665–679. Retrieved from https://doi.org/10.1177/0972150915581115 doi: 10.1177/0972150915581115

Blatná, D. (2006). OUTLIERS IN REGRESSION.. Retrieved from https://api.semanticscholar.org/CorpusID:17248646

Blonigen, B. A. (2016, 9). Industrial Policy and Downstream Export Performance. *The Economic Journal*, *126*(595), 1635–1659.

Bown, C. (2023). Industrial policy for electric vehicle supply chains and the US-EU fight over the Inflation Reduction Act. *SSRN Electronic Journal*.

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, *47*(5), 1287–1294. Retrieved from http://www.jstor.org/stable/1911963 doi: 10.2307/1911963

Cao, J., Chen, X., Qiu, R., & Hou, S. (2021, 11). Electric vehicle industry sustainable development with a stakeholder engagement system. *Technology in Society*, *67*, 101771. doi: 10.1016/J.TECHSOC.2021.101771

Caporale, G. M., Spagnolo, F., & Spagnolo, N. (2018, 12). Exchange rates and macro news in emerging markets. *Research in International Business and Finance*, *46*, 516–527. doi: 10.1016/J.RIBAF.2018.06.007

Chatterjee, S., & Price, B. (1992, 1). Regression analysis by example (2nd ed.). *Biometrical Journal*, *34*(6), 734.

Chaudhari, S., & Ray, S. (1997, 1). *The Competitiveness Connundrum: Literature Review and Reflections.* Retrieved from https://ideas.repec.org/p/iim/iimawp/wp01423.html

Chen, J., Sousa, C., & He, X. (2016). The determinants of export performance: a review of the literature 2006-2014. *International Marketing Review*, *33*, 626–670.

Chikán, A. (2008, 6). National and firm competitiveness: A general research model. *Competitiveness Review: An International Business Journal incorporating Journal of Global Competitiveness*, *18*, 20–28. doi: 10.1108/10595420810874583

Ciccone, A., & Papaioannou, E. (2019, 5). *Estimating Cross-Industry Cross-Country Interaction Models Using Benchmark Industry Characteristics.*

Coulter, S. (2023). Implementing industrial policy: The experiences of five countries. *Industrial Policy, The Economic Key Ideas*, 45–92.

Counterpoint Technology. (2024, 4). *India EV sales forecast to rise 66% in 2024.* Retrieved from https://www.eetindia.co.in/india-ev-sales-forecast-to-rise-66-in-2024/

Dosi, G., Grazzi, M., & Moschella, D. (2015, 12). Technology and costs in international competitiveness: From countries and sectors to firms. *Research Policy*, *44*(10), 1795–1814. Retrieved from https://linkinghub.elsevier.com/retrieve/pii/S0048733315000888 doi: 10.1016/j.respol.2015.05.012

Dosi, G., Pavitt, K., & Soete, L. (1990). *The Economics of Technical Change and International Trade*. Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy. Retrieved from https://EconPapers.repec.org/RePEc:ssa:lembks:dosietal-1990

Earthbeat. (2024, 1). *In South America's 'lithium triangle,' indigenous people defend sacred sites.* Retrieved from https://www.ncronline.org/earthbeat/justice/south-americas-lithium-triangle-indigenous-people-defend-sacred-sites

Econometric models | Rand. (n.d.). Retrieved from https://www.rand.org/topics/econometric-models.html

EIU. (2024, 5). *US tariffs on Chinese evs will be a double-edged sword.*

Ercikan, K. (2009). Limitations in sample-to-population generalizing. In *Generalizing.* Qeios.

European Alternative Fuels Observatory. (2024). *Norwegian EV market surges to 91.5% market share, setting a sustainable example.* Retrieved from https://alternative-fuels-observatory.ec.europa.eu/general-information/news/norwegian-ev-market-surges-915-market-share-setting-sustainable-example

European Commission. (2023). *The Net-Zero Industry Act: Accelerating the transition to climate neutrality.* Retrieved from https://single-market-economy.ec.europa.eu/industry/sustainability/net-zero-industry-act_en

European Commission. (2024, 6). *Questions and Answers on the pre-disclosure of duties on imports of subsidised electric cars from China*.*

Evenett, S., Ruta, M., Martín, F., & Jakubik, A. (2024, 1). The Return of Industrial Policy in Data. *IMF Working Papers*(001), 1.

Fagerberg, J. (1988, 6). International competitiveness. *The Economic Journal*, *98*(391), 355.

Gnangnon, S. K. (2019, 6). Effect of multilateral trade liberalization on export performance in developing countries: Does aid for trade matter? *Review of International Business and Strategy*, *29*, 117–138. doi: 10.1108/RIBS-09-2018-0079

Gnutzmann-Mkrtchyan, A., & Hugot, J. (2022). Gravity-Based Tools to Assess the Impact of Tariff Changes: An Application to Armenia. *Asian Development Review*, *0*(0), 1–38. Retrieved from `https://doi.org/10.1142/S0116110524500057` doi: 10.1142/S0116110524500057

Groba, F. (2014). Determinants of trade with solar energy technology components: evidence on the porter hypothesis? *Applied Economics*, *46*(5), 503–526. Retrieved from `https://doi.org/10.1080/00036846.2013.857005` doi: 10.1080/00036846.2013.857005

Harish, N. (2023). *The future of critical metals in electric vehicles: Impact of the exponentially increasing number of electric vehicles on the supply of Critical Metals* (Doctoral dissertation, Delft University of Technology, Delft). Retrieved from `http://resolver.tudelft.nl/uuid:f387f2ca-b300-4acb-b5f7-3acaf4824ffa`

Harrison, A., & Rodríguez-Clare, A. (2010). Chapter 63 - Trade, Foreign Investment, and Industrial Policy for Developing Countries*. In D. Rodrik & M. Rosenzweig (Eds.), *Handbooks in economics* (Vol. 5, pp. 4039–4214). Elsevier. Retrieved from `https://www.sciencedirect.com/science/article/pii/B978044452944200001X` doi: https://doi.org/10.1016/B978-0-444-52944-2.00001-X

Hausman, J., A. (1978, 11). Specification tests in Econometrics. *Econometrica*, *46*(6).

Hchaichi, R., & Ghodbane, S. B. (2014). Empirical analysis of determinants of international competitiveness. *International Journal of Business and Social Science*, *5*.

Heckscher, & Filip, E. (1919). *The effect of foreign trade on the distribution of income*.

Heteroskedasticity: Definition, Overview & Example. (2023, 2).

IEA. (2023). *Global EV Outlook 2023 – analysis.* Retrieved from `https://www.iea.org/reports/global-ev-outlook-2023`

IEA. (2024). *Global EV Outlook 2024.* Retrieved from `https://www.iea.org/reports/global-ev-outlook-2024`

IEA Transport - Energy System. (2023, 7). Retrieved from `https://www.iea.org/energy-system/transport`

ILO. (2018). *24 Million Jobs to Open up in the Green Economy.*

International Energy Agency. (2022). *Russian supplies to global energy markets.* Retrieved from `https://www.iea.org/reports/russian-supplies-to-global-energy-markets`

International Energy Agency. (2024a). *Electric car registrations and sales share in China, United States and Europe, 2018-2023.*

International Energy Agency. (2024b). *Global EV Outlook 2024.*

Irle, R. (2024, 2). *Global EV sales for 2018 – final results.*

Jameel, A. (2024, 4). *China's Electric Vehicle Leadership: Abdul Latif Jameel®.* Retrieved from `https://alj.com/en/perspective/how-china-rose-to-lead-the-world-in-electric-vehicles/`

Jcookson. (2024, 2). *China has become an electric vehicle export behemoth. how should the US and EU respond?* Retrieved from `https://www.atlanticcouncil.org/blogs/new-atlanticist/china-has-become-an-electric-vehicle-export-behemoth-how-should-the-us-and-eu-respond/`

Jones, B., Elliott, R. J., & Nguyen-Tien, V. (2020, 12). The EV revolution: The road ahead for critical raw materials demand. *Applied Energy*, *280*, 115072. doi: 10.1016/J.APENERGY.2020.115072

Judit, N., & Zsófia, J. (2018). Competitiveness in global trade: The case of the automobile industry. *Economic Annals*, *63*(218), 61–84.

Juhász, R., Lane, N., Oehlsen, E., & Pérez, V. (2022, 8). The Who, What, When, and How of Industrial Policy: A Text-Based Approach.

Khan, K., & Azam, A. (n.d.). *The Impact of Industrial Policy on Export Performance in Pakistan* (Unpublished doctoral dissertation). Pakistan Institute of Development Economics, Islamabad.

Khatua, A., Ranjan Kumar, R., & Kumar De, S. (2023, 4). Institutional enablers of electric vehicle market: Evidence from 30 countries. *Transportation Research Part A: Policy and Practice*, *170*, 103612. Retrieved from https://linkinghub.elsevier.com/retrieve/pii/S0965856423000320 doi: 10.1016/j.tra.2023.103612

Kowalski, P., & Legendre, C. (2023). *Raw materials critical for the green transition: Production, international trade and export restrictions.* Paris.

Krugman, P. (1994). Competitiveness: A dangerous obsession. *Foreign Affairs*, *73*, 28–44.

Lado, N., Martínez-Ros, E., & Valenzuela, A. (2004, 6). Identifying successful marketing strategies by export regional destination. *International Marketing Review*, *21*, 573–597. doi: 10.1108/02651330410568024

Liu, L., Zhang, T., Avrin, A. P., & Wang, X. (2020, 11). Is China's industrial policy effective? An empirical study of the new energy vehicles industry. *Technology in Society*, *63*, 101356. doi: 10.1016/J.TECHSOC.2020.101356

Lu, X., & White, H. (2014, 1). Robustness checks and robustness tests in applied economics. *Journal of Econometrics*, *178*(PART 1), 194–206. doi: 10.1016/J.JECONOM.2013.08.016

MacKinnon, J. G., & Magee, L. (1990). Transforming the Dependent Variable in Regression Models. *International Economic Review*, *31*(2), 315–339. Retrieved from http://www.jstor.org/stable/2526842 doi: 10.2307/2526842

Madiyarova, D., Amirbekova, A., & Syrlybayev, M. (2018). Comparative advantages of Kazakhstan assessed by the Balassa Index: consistently competitive exports are limited to raw materials with low added value. *Journal of Business and Retail Management Research*, *12*(3).

Manthey, E. (2023, 9). *Global electric vehicle supply chains struggle to keep up as demand continues to surge.* Retrieved from https://www.fastmarkets.com/insights/global-electric-vehicle-supply-chains-struggle-as-demand-surges/

Matsumura, A. (2021). Gravity analysis of trade for environmental goods focusing on bilateral tariff rates and regional integration. *Asia-Pacific Journal of Regional Science*, *5*(2), 477–511. Retrieved from https://doi.org/10.1007/s41685-020-00189-x doi: 10.1007/s41685-020-00189-x

McKenzie, D. (2023). *Interpreting treatment effects on an inverse hyperbolic sine outcome variable and alternatives.* Retrieved from https://blogs.worldbank.org/en/impactevaluations/interpreting-treatment-effects-inverse-hyperbolic-sine-outcome-variable-and

Mekky, M. F., & Collins, A. R. (2024, 3). The Impact of state policies on electric vehicle adoption -A panel data analysis. *Renewable and Sustainable Energy Reviews*, *191*, 114014. doi: 10.1016/J.RSER.2023.114014

Mills, T. C. (2014). Heteroskedasticity. In *Analysing economic data: A concise introduction* (pp. 219–230). London: Palgrave Macmillan UK. Retrieved from https://doi.org/10.1057/9781137401908_15 doi: 10.1057/9781137401908{_}15

Momaya, K. (1998, 6). Evaluating International Competitiveness at the Industry Level. *Vikalpa*, *23*, 39–46. doi: 10.1177/0256090919980206

Narassimhan, E., Myslikova, Z., & Gallagher, K. S. (2023, 12). Strategies for green industrial and innovation policy–an analysis of policy alignment, misalignment, and realignment around dominant designs in the EV sector*. *Environmental Research Letters*, *19*(1).

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change.* Cambridge, MA: Harvard University Press.

Obadi, S. (2017). Competitive advantage of Yemeni export in the US market. *Open Access Library Journal*, *4*(9), 1–9.

OEC. (2022). *Electric motor vehicles (HS: 870380) product trade, exporters and importers.* Retrieved from `https://oec.world/en/profile/hs/electric-motor-vehicles`

OECD. (2023). Job Creation and Local Economic Development 2023: Bridging the Great Green Divide. *Job Creation and Local Economic Development*. Retrieved from `https://www.ilo.org/resource/news/24-million-jobs-open-green-economy-0`

Ohlin, & Gotthard, B. (1933). Interregional and international trade.

Pamidimukkala, A., Kermanshachi, S., Rosenberger, J. M., & Hladik, G. (2024, 1). Barriers and Motivators to the Adoption of Electric Vehicles: A Global Review. *Green Energy and Intelligent Transportation*, 100153. doi: 10.1016/J.GEITS.2024.100153

Paul, J., & Dhiman, R. (2021, 5). Three decades of export competitiveness literature: systematic review, synthesis and future research agenda. *International Marketing Review*, *38*, 1082–1111. doi: 10.1108/IMR-12-2020-0295/full/html

Pence, K. M. (2006). The Role of Wealth Transformations: An Application to Estimating the Effect of Tax Incentives on Saving. *Contributions in Economic Analysis & Policy*, *5*.

Porter, M. E. (1980). *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. New York: Free Press.

Porter, M. E. (1990). *The Competitive Advantage of Nations*. New York: Free Press.

Posner, M. (1961, 10). International Trade and Technical Change. *Oxford Economic Papers*, *13*(2), 323–341.

Prahalad, C., & Hamel, G. (1990). The Core Competence of the Corporation. *Harvard Business Review*, *68*, 79–90.

Prasad, N. (2024, 4). *India's EV market to grow 66% in 2024, likely to represent nearly one-third of PV sales by 2030.* Retrieved from `https://www.livemint.com/industry/energy/indias-ev-market-to-grow-66-in-2024-likely-to-represent-nearly-one-third-of-pv-sales-by-2030-11712674882925.html`

Ricardo, D. (1817). *Principles of Political Economy and Taxation* (P. Sraffa & M. Dobb, Eds.). London: Cambridge University Press.

Rodrik, D. (2014, 9). Green industrial policy. *Oxford Review of Economic Policy*, *30*(3), 469–491.

Ruoso, A. C., & Ribeiro, J. L. D. (2022, 12). The influence of countries' socioeconomic characteristics on the adoption of electric vehicle. *Energy for Sustainable Development*, *71*, 251–262. doi: 10.1016/J.ESD.2022.10.003

Schumpeter, J. A. (1976). *Capitalism, Socialism and Democracy* (1st ed.). London: Routledge.

Shahbaz, M., Siddiqui, A., Siddiqui, M., Jiao, Z., & Kautish, P. (2023). Exploring the growth of sustainable energy Technologies: A review. *Sustainable Energy Technologies and Assessments*, *57*, 103157. Retrieved from `https://www.sciencedirect.com/science/article/pii/S2213138823001509` doi: https://doi.org/10.1016/j.seta.2023.103157

Shivaraman, S. (2024, 6). *China has an EV advantage but can it maintain its edge?*

Shrestha, N. (2020, 6). Detecting Multicollinearity in Regression Analysis. *American Journal of Applied Mathematics and Statistics*, *8*, 39–42. doi: 10.12691/ajams-8-2-1

Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. (2014, 5). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194.

Slowik, P., Searle, S., Basma, H., Miller, J., Zhou, Y., Rodriguez, F., . . . Pierce, L. (2023). Analyzing the impact of the Inflation Reduction Act on electric vehicle uptake in the United States. *Energy Innovation and International Council on Clean Transportation*.

Soete, L. (1981, 12). A general test of technological gap trade theory. *Weltwirtschaftliches Archiv*, *117*(4), 638–660.

Suresh, K., & Chandrashekara, S. (2012). Sample size estimation and power analysis for clinical research studies. *Journal of Human Reproductive Sciences*, *5*(1), 7–13.

The Northern Miner Group. (2024, 5). *Ranked: The world's largest lithium producers in 2023.* Retrieved from `https://www.mining.com/web/ranked-the-worlds-largest-lithium-producers-in-2023/`

Torok, A., & Jambor, A. (2016, 6). Determinants of the revealed comparative advantages: The case of the European ham trade. *Agricultural Economics (Zemědělská ekonomika)*, *62*. doi: 10.17221/177/2015-AGRICECON

TU Delft. (2024). *MSC Management of Technology.* Retrieved from `https://www.tudelft.nl/onderwijs/opleidingen/masters/management-of-technology/msc-management-of-technology`

Tyson, L. D. (1992). *Who's Bashing Whom? Trade Conflict in High-Technology Industries*. Peterson Institute for International Economics.

UNFCCC. (2018, 11). Paris Climate Change Conference. In *Cop21.* Paris: UNFCCC. Retrieved from `https://unfccc.int/documents/184656`

United Nations, & World Bank. (2024). *UN COMTRADE Database.* Retrieved from `https://wits.worldbank.org/`

United Nations Development Programme. (2024). *Sustainable development goals.* Retrieved from `https://www.undp.org/sustainable-development-goals`

Virta. (2024, 6). *The Global Electric Vehicle Market in 2024.*

Waheeduzzaman, A., & Ryans, J. (1996, 6). Definition,perspectives, and understanding of international competitiveness: A quest for a common ground. *Competitiveness Review: An International Business Journal incorporating Journal of Global Competitiveness*, *6*, 7–26. doi: 10.1108/eb046333

Wooldridge, J., M. (2011). *Econometric analysis of cross section and panel data*. Cambridge, Mass: MIT Press.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

Xue, C., Zhou, H., Wu, Q., Wu, X., & Xu, X. (2021, 3). Impact of Incentive Policies and Other Socio-Economic Factors on Electric Vehicle Market Share: A Panel Data Analysis from the 20 Countries. *Sustainability*, *13*(5), 2928.

Yao, J., Xiong, S., & Ma, X. (2020, 7). Comparative Analysis of National Policies for Electric Vehicle Uptake Using Econometric Models. *Energies*, *13*(14), 3604.

Zhang, W. (2024, 1). *China: Annual export value of electric vehicles for passengers by type 2022.* Retrieved from `https://www.statista.com/statistics/1201560/china-annual-electric-vehicles-for-passengers-export-value-by-type/`

Zhang, X., & Bai, X. (2017, 4). Incentive policies from 2006 to 2016 and new energy vehicle adoption in 2010–2020 in China. *Renewable and Sustainable Energy Reviews*, *70*, 24–43. doi: 10.1016/J.RSER.2016.11.211

Zhao, Y., Jian, Z., & Du, Y. (2024, 1). How can China's subsidy promote the transition to electric vehicles? *Renewable and Sustainable Energy Reviews*, *189*, 114010. doi: 10.1016/J.RSER.2023.114010

Appendices

A Sample of Countries

Table 11: List of Country Names and Country Codes

Country Name	Country Code
Angola	AGO
Albania	ALB
Andorra	AND
United Arab Emirates	ARE
Argentina	ARG
Armenia	ARM
Australia	AUS
Austria	AUT
Azerbaijan	AZE
Burundi	BDI
Belgium	BEL
Benin	BEN
Burkina Faso	BFA
Bulgaria	BGR
Bahrain	BHR
Bahamas	BHS
Bosnia and Herzegovina	BIH
Belarus	BLR
Belize	BLZ
Bermuda	BMU
Bolivia	BOL
Brazil	BRA
Barbados	BRB
Brunei	BRN
Botswana	BWA
Central African Republic	CAF
Canada	CAN
Switzerland	CHE
Chile	CHL
China	CHN
Côte d'Ivoire	CIV
Cameroon	CMR
Congo (Kinshasa)	COD
Congo (Brazzaville)	COG
Colombia	COL
Comoros	COM
Cape Verde	CPV
Costa Rica	CRI
Cuba	CUB
Cayman Islands	CYM
Cyprus	CYP
Czech Republic	CZE
Germany	DEU

Continued on next page

Table 11 – *Continued from previous page*

Country Name	Country Code
Dominica	DMA
Denmark	DNK
Dominican Republic	DOM
Algeria	DZA
Ecuador	ECU
Egypt	EGY
Spain	ESP
Estonia	EST
Ethiopia	ETH
Finland	FIN
Fiji	FJI
France	FRA
Gabon	GAB
United Kingdom	GBR
Georgia	GEO
Ghana	GHA
Gambia	GMB
Guinea-Bissau	GNB
Greece	GRC
Greenland	GRL
Guatemala	GTM
Guyana	GUY
Hong Kong	HKG
Honduras	HND
Croatia	HRV
Hungary	HUN
Indonesia	IDN
India	IND
Ireland	IRL
Iran	IRN
Iceland	ISL
Israel	ISR
Italy	ITA
Jamaica	JAM
Jordan	JOR
Japan	JPN
Kazakhstan	KAZ
Kenya	KEN
Kyrgyzstan	KGZ
Cambodia	KHM
Kiribati	KIR
South Korea	KOR
Kuwait	KWT
Laos	LAO
Lebanon	LBN
Libya	LBY
Sri Lanka	LKA
Lesotho	LSO
Lithuania	LTU

Continued on next page

Table 11 – *Continued from previous page*

Country Name	Country Code
Luxembourg	LUX
Latvia	LVA
Macao	MAC
Morocco	MAR
Moldova	MDA
Madagascar	MDG
Maldives	MDV
Mexico	MEX
North Macedonia	MKD
Mali	MLI
Malta	MLT
Myanmar	MMR
Montenegro	MNE
Mongolia	MNG
Mozambique	MOZ
Mauritania	MRT
Mauritius	MUS
Malawi	MWI
Malaysia	MYS
Namibia	NAM
Niger	NER
Nigeria	NGA
Nicaragua	NIC
Netherlands	NLD
Norway	NOR
Nepal	NPL
New Zealand	NZL
Oman	OMN
Pakistan	PAK
Panama	PAN
Peru	PER
Philippines	PHL
Palau	PLW
Papua New Guinea	PNG
Poland	POL
Portugal	PRT
Paraguay	PRY
French Polynesia	PYF
Qatar	QAT
Romania	ROU
Russia	RUS
Rwanda	RWA
Saudi Arabia	SAU
Sudan	SDN
Senegal	SEN
Singapore	SGP
El Salvador	SLV
Slovakia	SVK
Slovenia	SVN

Continued on next page

Table 11 – *Continued from previous page*

Country Name	**Country Code**
Sweden	SWE
Eswatini	SWZ
Seychelles	SYC
Togo	TGO
Thailand	THA
Timor-Leste	TLS
Tunisia	TUN
Turkey	TUR
Tanzania	TZA
Uganda	UGA
Ukraine	UKR
Uruguay	URY
United States	USA
Uzbekistan	UZB
Vietnam	VNM
Samoa	WSM
Yemen	YEM
South Africa	ZAF
Zambia	ZMB
Zimbabwe	ZWE

B Python Codes for Statistical Tests

```python
import pandas as pd
import numpy as np
from linearmodels.panel import PanelOLS

# Input Dataset
data = pd.read_excel('/Users/adhvaitpillai/Desktop/Independent Variables/ThesisPanelwithGDP.xlsx'
    )
data = data.set_index(['country_codes', 'year'])

# Functional transformations
data['ihs_IP'] = np.arcsinh(data['IP'])
data['ihs_Total_Production_Qtys'] = np.arcsinh(data['Total Production Qtys.'])
data['ihs_patents'] = np.arcsinh(data['patents'])
data['ihs_LP'] = np.arcsinh(data['LP'])
data['ihs_ev_exports'] = np.arcsinh(data['EV_exports'])
data['ihs_FDI'] = np.arcsinh(data['FDI'])
data['log_GDP'] = np.log1p(data['GDP'])

data['constant'] = 1

# Different model specifications for parsimonius regression models
model_specs = [
    ['constant', 'ihs_patents'],
    ['constant', 'ihs_patents', 'ihs_IP'],
    ['constant', 'ihs_patents', 'ihs_IP', 'ihs_Total_Production_Qtys'],
    ['constant', 'ihs_patents', 'ihs_IP', 'ihs_Total_Production_Qtys', 'ihs_LP'],
    ['constant', 'ihs_patents', 'ihs_IP', 'ihs_Total_Production_Qtys', 'ihs_LP', 'log_GDP'],
    ['constant', 'ihs_patents', 'ihs_IP', 'ihs_Total_Production_Qtys', 'ihs_LP', 'log_GDP', '
        ihs_FDI']
]

# Fixed effects model
results = []
for spec in model_specs:
    model = PanelOLS(data['ihs_ev_exports'], data[spec], entity_effects=True)
    result = model.fit(cov_type='robust')
    results.append(result)

# Collect results
result_dict = {}
for i, result in enumerate(results):
    n = result.nobs
    p = len(spec) - 1  # minus one for the constant
    rsquared = result.rsquared
    rsquared_adj = 1 - (1 - rsquared) * ((n - 1) / (n - p - 1))

    model_name = f'Model {i+1}'
    result_dict[f'{model_name} Coef.'] = result.params
    result_dict[f'{model_name} Std. Err.'] = result.std_errors
    result_dict[f'{model_name} P-value'] = result.pvalues
    result_dict[f'{model_name} No. of Observations'] = result.nobs
    result_dict[f'{model_name} R-squared'] = rsquared
    result_dict[f'{model_name} R-squared (Within)'] = result.rsquared_within
    result_dict[f'{model_name} R-squared (Between)'] = result.rsquared_between
    result_dict[f'{model_name} Adj. R-squared'] = rsquared_adj
    result_dict[f'{model_name} F-statistic'] = result.f_statistic.stat
    result_dict[f'{model_name} F-test p-value'] = result.f_statistic.pval
    result_dict[f'{model_name} No. of Entities'] = result.nentity


combined_results = pd.DataFrame(result_dict)

```

```
output_file_path = '/Users/adhvaitpillai/Desktop/Independent Variables/
    Finalfixed_effects_results_with_pvalues_observations_adjustedrsquared.csv'
combined_results.to_csv(output_file_path)

print(f"Results have been saved to {output_file_path}")
```

Python Code: Fixed Effects Regression

```
import pandas as pd
import numpy as np


data = pd.read_excel('/Users/adhvaitpillai/Desktop/Independent Variables/ThesisPanelwithGDP.xlsx'
    )
data = data.set_index(['country_codes', 'year'])


data['ihs_IP'] = np.arcsinh(data['IP'])
data['ihs_Total_Production_Qtys'] = np.arcsinh(data['Total Production Qtys.'])
data['ihs_patents'] = np.arcsinh(data['patents'])
data['ihs_LP'] = np.arcsinh(data['LP'])
data['ihs_ev_exports'] = np.arcsinh(data['EV_exports'])
data['ihs_FDI'] = np.arcsinh(data['FDI'])
data['log_GDP'] = np.log1p(data['GDP'])


variables = ['ihs_IP', 'ihs_Total_Production_Qtys', 'ihs_patents', 'ihs_LP', 'ihs_ev_exports', '
    ihs_FDI', 'log_GDP']

descriptive_stats = data[variables].describe()
medians = data[variables].median()
descriptive_stats.loc['median'] = medians

print(descriptive_stats)

descriptive_stats.to_excel('/Users/adhvaitpillai/Desktop/Independent Variables/
    descriptive_statistics.xlsx')
```

Python Code: Descriptive Statistics

```
import pandas as pd
import numpy as np
from linearmodels.panel import PanelOLS


data = pd.read_excel('/Users/adhvaitpillai/Desktop/Independent Variables/
    ThesisPanelwithGDPWITHOUTOUTLIERS.xlsx')
data = data.set_index(['country_codes', 'year']
data['log_IP'] = np.log1p(data['IP'])
data['log_Total_Production_Qtys'] = np.log1p(data['Total Production Qtys.'])
data['log_patents'] = np.log1p(data['patents'])
data['log_LP'] = np.log1p(data['LP'])
data['log_ev_exports'] = np.log1p(data['EV_exports'])
data['ihs_FDI'] = np.arcsinh(data['FDI'])
data['log_GDP'] = np.log1p(data['GDP'])
data['constant'] = 1

```

```
model_specs = [
    ['constant', 'log_patents'],
    ['constant', 'log_patents', 'log_IP'],
    ['constant', 'log_patents', 'log_IP', 'log_Total_Production_Qtys'],
    ['constant', 'log_patents', 'log_IP', 'log_Total_Production_Qtys', 'log_LP'],
    ['constant', 'log_patents', 'log_IP', 'log_Total_Production_Qtys', 'log_LP', 'log_GDP'],
    ['constant', 'log_patents', 'log_IP', 'log_Total_Production_Qtys', 'log_LP', 'log_GDP', '
        ihs_FDI']
]

results = []
for spec in model_specs:
    model = PanelOLS(data['log_ev_exports'], data[spec], entity_effects=True)
    result = model.fit(cov_type='robust')
    results.append(result)

result_dict = {}
for i, result in enumerate(results):
    n = result.nobs
    p = len(spec) - 1
    rsquared = result.rsquared
    rsquared_adj = 1 - (1 - rsquared) * ((n - 1) / (n - p - 1))

    model_name = f'Model {i+1}'
    result_dict[f'{model_name} Coef.'] = result.params
    result_dict[f'{model_name} Std. Err.'] = result.std_errors
    result_dict[f'{model_name} P-value'] = result.pvalues
    result_dict[f'{model_name} No. of Observations'] = result.nobs
    result_dict[f'{model_name} R-squared'] = rsquared
    result_dict[f'{model_name} R-squared (Within)'] = result.rsquared_within
    result_dict[f'{model_name} R-squared (Between)'] = result.rsquared_between
    result_dict[f'{model_name} Adj. R-squared'] = rsquared_adj
    result_dict[f'{model_name} F-statistic'] = result.f_statistic.stat
    result_dict[f'{model_name} F-test p-value'] = result.f_statistic.pval

combined_results = pd.DataFrame(result_dict)


output_file_path = '/Users/adhvaitpillai/Desktop/Independent Variables/
    LOGGEDRobustnessCheckwithoutOutliers.csv'
combined_results.to_csv(output_file_path)

print(f"Results have been saved to {output_file_path}")
```

Python Code: Robustness Check without Outliers

C Additional Regression Models

Table 12: Random Effects Regression Results

	(M)
IHS(PAT)	1.0237***
	(0.0930)
IHS(IP)	0.4872*
	(0.2933)
IHS(Q(Cr.Met.))	0.0236
	(0.0298)
IHS(λ)	0.8391**
	(0.1652)
log(GDP)	0.3080**
	(0.1160)
IHS(FDI)	-0.0205
	(0.0208)
Constant	-15.3021***
	(3.0331)
Year RE	Yes
Observations	960
R-Squared (Within)	0.0123
R-Squared (Between)	0.7731
Adjusted R-Squared	0.3666
F-test	93.5262***
Covariance Type	Robust

Table 13: Regression Models with Import tariffs

	(K)
IHS(PAT)	0.4147**
	(0.1885)
IHS(IP)	0.3234
	(0.2043)
IHS(Q(Cr.Met.))	0.0582*
	(0.0309)
IHS(λ)	-0.8517
	(1.3563)
IHS(Tariffs)	-18.5123**
	(2.1795)
log(GDP)	2.0808**
	(0.6935)
IHS(FDI)	0.0027
	(0.0203)
Constant	1.3477
	(16.3321)
Year FE	Yes
Observations	960
R-Squared (Within)	0.1263
R-Squared (Between)	-9.5025
Adjusted R-Squared	0.1199
F-test	16.3747**
Covariance Type	Robust

D Outlier Observations

Table 14: Outlier Observations in Panel

Country Name	Country Code	Year
Andorra	AND	2018
United Arab Emirates	ARE	2017
Armenia	ARM	2019
Armenia	ARM	2022
Bahrain	BHR	2021
Belarus	BLR	2022
Bolivia	BOL	2022
Brazil	BRA	2022
Barbados	BRB	2021
Brunei	BRN	2021
Colombia	COL	2017
Colombia	COL	2018
Costa Rica	CRI	2022
Cyprus	CYP	2020
Cyprus	CYP	2021
Cyprus	CYP	2018
Dominican Republic	DOM	2021
Ecuador	ECU	2017
Georgia	GEO	2022
Indonesia	IDN	2020
Ireland	IRL	2021
Ireland	IRL	2017
Ireland	IRL	2018
Iceland	ISL	2021
Iceland	ISL	2017
Iceland	ISL	2018
Israel	ISR	2020
Jordan	JOR	2022
Jordan	JOR	2017
Kyrgyzstan	KGZ	2022
Kuwait	KWT	2017
Lebanon	LBN	2020
Sri Lanka	LKA	2020
Macau	MAC	2022
Macau	MAC	2021
Morocco	MAR	2022
Morocco	MAR	2021
Morocco	MAR	2020
Morocco	MAR	2017
Morocco	MAR	2018
Mexico	MEX	2022
North Macedonia	MKD	2019
Malta	MLT	2017
Malaysia	MYS	2022
Namibia	NAM	2019
Oman	OMN	2022
Panama	PAN	2020
Poland	POL	2022

Table 14 – Continued from previous page

Country Name	Country Code	Year
Poland	POL	2018
Poland	POL	2017
Poland	POL	2019
Poland	POL	2020
Poland	POL	2021
Russia	RUS	2022
Saudi Arabia	SAU	2021
Singapore	SGP	2017
El Salvador	SLV	2021
Ukraine	UKR	2021
Ukraine	UKR	2020
Vietnam	VNM	2022
Vietnam	VNM	2021
Vietnam	VNM	2020
Vietnam	VNM	2017
Vietnam	VNM	2018
Vietnam	VNM	2019