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Navn:	Sazi Luke og Karl Constantin Rihaczek

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Is it all about the money? The drivers behind the recent Indian electric vehicle success story

M.Sc. Sustainable Finance - Master Thesis

Supervisor: Daniel Sang Kim, PhD

Authors: Sazi Luke, Karl Constantin Rihaczek

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Abstract

We show that the recent Indian electric vehicle success story has been largely driven by the available amount of liquid deposits. While we observe that the relationship between liquid deposits and the share of electric vehicles in newly registered cars consists over time, we find that the effect grows with household wealth. Furthermore, we replicate the analysis for Brazil and show that our findings regarding the relationship between liquid deposits and the share of electric vehicles also hold for another emerging market, however, at lower magnitude. Based on this, we recommend policy makers to introduce further measures aiming at an improvement of household liquidity.

1 Introduction

In the following, we will provide details on the particular importance of decarbonizing the transport sector and why the large-scale role out of electric vehicles in Emerging Markets (EMs) is necessary for achieving global net-zero. Furthermore, we will elaborate on barriers faced when implementing electric vehicles in EMs and how the usage of households' financial instruments effects their car purchasing behaviour. India's recent Electric Vehicle (EV) success story makes the country a leader in the implementation of EVs in the space of EMs and moves it into the focus of our analysis.

Climate change, emerging markets and the transport sector

As the Intergovernmental Panel on Climate Change (IPCC) points out, it has become evident that global warming is largely caused by human activity due to the emittance of Greenhouse Gases (GHGs). Resulting from global Climate Change (CC), we are witnessing more widespread and extreme climate and weather events (IPCC, 2022) which is depicted by Figure 1. The latter shows that the amount of Billion-Dollar Disaster Events in the United States of America has increased from below five to above twenty events between 1980 and 2023.

Globally, average annual anthropogenic GHG rose from 38 $GtCO_{2\text{-eq}}$ to 59 $GtCO_{2\text{-eq}}$ between 1990 and 2019 with unequal geographical and sectoral contributions (IPCC, 2022). Looking forward, EMs are of particularly high importance when designing climate adaption and mitigation measures as their population is forecasted to double between 2020 and 2050 (United Nations, 2022). Considering a high correlation between population size and travel demand (IPCC, 2022), non-action regarding transportation technologies would subsequently yield high increases in CO_2 emissions. Therefore, we deem the application of technologies with a high emission abatement potential in EMs crucial to combat CC and achieve global net-zero CO_2 emissions.

When shedding light on global sector contributions, especially the energy sector stands out with a share of 34%. This is followed by 25% of GHG emissions stemming from industry processes and the transport sector with a weight of 15% (IPCC, 2022). In India, the transport alone accounts for up to 57% of the CO_2 emissions in major cities (Ramachandra et al., 2015). The latter also plays a critical role when it comes to climate change mitigation as it currently still relies heavily on the use of fossil fuels as energy source (IPCC, 2022). When shedding light on transportation, we need to differentiate between land transport, aviation and shipping in both passenger and freight transport. During the past years, especially electromobility in land transport has offered an economically efficient way to abate CO_2 emissions (IPCC, 2022) which we will explore further as we proceed.

Current situation and future developments of electric vehicles

IPCC (2022) predicts the increase of EV usage under three scenarios, that would yield global net-zero CO_2 emissions, to be the largest compared to any other alternative transportation technology. It is forecasted that the market share of electric vehicles will reach 42.5% worldwide by 2035 while some countries such as Norway will reach a share of 50% prior to that due to strong governmental support (Rietmann et al., 2020). Further, a complete phase-out of Internal Combustion Engine (ICE) car sales over the coming 10 to 30 years has been decided by more than 20 countries, while an additional 120 countries have announced net-zero pledges. In total, these initiatives account for around 85% of the global fleet (International Energy Agency, 2023), indicating an expected boost in demand for EVs in the coming years. In EMs, this leads to EVs being established in micro mobility and light duty transport, including e-autorickshaws, e-scooters and e-bikes (Collett et al., 2021). Further, as battery technologies advance, more appliances become commercially available for heavier duty transportation such as trucks, buses and railways. Consequently, many governments have encouraged the adoption of EVs in recent years (Zhang and Fujimori, 2020).

While it is commonly agreed that the mitigation potential of EVs depends on the electricity mix of a country (Rietmann et al., 2020), resource availability (also from improved recycling processes) as well as the electricity mix used in the battery value chain, from extraction of minerals to production, and battery chemistries are also deemed important factors when decreasing the environmental impact of EVs. As technologies advance, the carbon footprint of EVs is projected to decrease in coming years. In addition, several governments and companies are also under pressure to improve the sustainability of the entire EV product value chain (European Commission, 2018).

When it comes to the appliances of EVs, one must however differentiate between High Income Countries (HICs) and EMs. Collett et al. (2021) state that in HICs EVs are mostly used as high-end private passenger cars while their appliances in EMs are mostly focused on micro-mobility. Further, we observe that the distribution of emissions across the life cycle of an ICE and an EV are different. While ICEs mainly emit tail pipe emissions, we see that EVs start their usage with a significant shortfall due to higher emissions from production that are likely recovered throughout the usage. As mentioned before, the electricity mix is a major factor when determining the break-even point between EV and ICE lifecycle emissions. The findings of Pero et al. (2018) suggest that a break-even in Europe lies around 45,000 km and give an indication that EVs will most likely overcompensate the higher production emissions in all countries. While no precise numbers are available for India, we argue that the higher emissions from the Indian electricty mix will be offset by lower emissions from the producion of smaller batteries used for Electric Two-Wheelers (E2Ws) which represent the predominant share of 70.37% in India's Q1 2023 vehicle sales (Ministry of Road Transport & Highways, 2023). Given an estimated lifecycle usage of 300,000 km for Indian cars (The Economic Times, 2020), we see that a break-even will most likely also occur in India and EVs are an effective measure to abate GHG emissions.

Barriers to a large-scale roll-out of EVs in emerging markets

Generally, Dioha et al. (2022b) state that there is no 'one-size-fits-all' solution to the implementation of EVs in EMs. Even though this might be true, there are certain barriers to the widespread implementation of EVs that have been identified by scholars.

Socio-economic challenges: Across literature, it is observable that the high upfront costs of EVs are a major obstacle to growing their sales volumes in EMs. Looking at South Africa, Moeletsi (2021) find that the main factor yielding unwillingness to switch from an ICE to an EV is the high purchase price as well as the high costs for batteries. This is confirmed by another study from Tongwane and Moeletsi (2021) that again mentions the high capital cost of EVs, but also brought up high levels of inequality leading to a shrinking target group for EVs, i.e. a disproportionally small fraction of the population owns a disproportionally large amount of capital resources and thus the number of people that can afford an EV is fairly low. Further confirmation for the lack of availability of capital for EVs in these markets is brought forward by Collett et al. (2021) and Dioha et al. (2022a). The aforementioned authors investigate the Nigerian market and conclude that the cost for EVs must drop by 40% to be a cost-effective solution under the current energy system. As shown by our research, financial constraints are the major driver of the implementation of EVs in India. On the one hand, we see that sufficient financial means to cover the acquisition cost are an important factor when purchasing an EV. On the other hand, we find that running costs of ICEs must be high to overcompensate the higher purchase prices of EVs. Consequently, our research is in line with the findings of other studies while we add to the adademic literature by quantitatively underpinning these arguements. Further, we add to previous findings that the effect of liquid deposits on the share of EVs grows with household wealth and is also existent in Brazil.

Technical characteristics of EVs and the surrounding infrastructure: Especially the charging network and underlying electricity grid are often point of discussion. Collett et al. (2021) point them out as a major difference to the appliance of EVs in EMs compared to HICs. As a temporary solution to the weaknesses of the battery technology such as the range of the car, the option of battery swaps should be explored (Rakesh Kumar and Padmanaban, 2019). Especially as electricity outages yield a security concern, i.e. the car cannot be charged in the case of an emergency (Rajper and Albrecht, 2020; Moeletsi, 2021). However, this might only be relevant when looking at countries with relatively low individual traffic as limited charging infrastructure and thus limited range does not adversely affect the willingness of people in South Africa to buy an EV (Moeletsi, 2021). The rationale behind this is that 90% of people from the sample travel less than 100 km a day on a regular basis. Contrary to that, Rakesh Kumar and Padmanaban (2019) point out that in India it is of particular importance to expand the charging infrastructure quickly to appropriately address range anxiety. Our study shows that grid outages adversely affect the implementation of EVs, and thereby confirms the findings of Rakesh Kumar and Padmanaban (2019). Similar to other scholars, we attribute this to the technical constraints that EVs are facing, i.e. limited charging infrastructure and grid outages harm the usability of EVs. Again, we contribute to previous studies by quantitatively confirming this relationship using comprehensive spacial data on night-time light radiation.

Political and fiscal support: Tongwane and Moeletsi (2021) identify policy deficiencies to foster and promote EVs in EMs. They identify a lack of clear targets, timelines and incentives that yield great uncertainty for developers and other stakeholders. As examples to improve policies in India, scholars suggest exchanging all government buses to electric buses to foster demand and offering tax exemptions for private EV holders (Rakesh Kumar and Padmanaban, 2019). A governmental incentive scheme named National Electric Mobility Mission Plan 2020 has been launched by the Government of India in 2013 (Government of India, 2023). It includes fiscal and monetary incentives that aside from tackling pollution and climate related challenges, has two interrelated objectives; namely national energy security and domestic growth of manufacturing full range EV technology (Gujarathi et al., 2018). The effect of such schemes is, however, questioned by Shetty et al. (2020) which argue that if customers are not confident in the technology, incentive schemes such as tax credits will have a minor effect on EV sales. Other authors deem these government initiatives very important for promoting EV growth within India and attribute large importance to it when it comes to determining the growth of this sector (Aijaz, 2022).

Household Finance in India

Household Finance studies how households make use of and should use financial instruments to achieve their economic objectives (Badarinza et al., 2016b). This also includes their investment and consumption decisions, e.g. which type of vehicle to acquire. While household finance is relevant on a global scale, different studies show that there are substantial differences between countries and even among different EMs (Badarinza et al., 2016a; Mehra, 2017). Therefore, we want to mainly shed light on observations for India. Nevertheless, a few general observations can be made which mostly relate to the training and education of households. While Gomes et al. (2020) find that households often face a lack of training, Campbell (2006) adds to this by stating that poorer and less educated households appear to face a higher likelihood of making financial mistakes compared to wealthier and better educated households. When looking at India, different observations can be made. Firstly, Indian households spend the largest fraction of their available means on nonfinancial assets (Mehra, 2017). The latter are mostly represented by gold and real estate. Considering gold, Indian households' gold holdings make up the largest fraction of a households' wealth compared to any other country. Considering real estate, it is found that households have high mortgage debt even when approaching retirement age indicating inter-generational transfers of liabilities (Vishwanath et al., 2020). This leads to elderly households having very little retirement savings when approaching retirement age (Badarinza et al., 2019). Considering the allocations of resources between gold and real estate, one can observe that the relative share of real estate increases with the households' level of wealth (Vishwanath et al., 2020). When looking at the financing of this spending, two observations prevail. Firstly, Indian households hold more unsecured debt compared to other countries (Badarinza et al., 2016a, 2019). Secondly, Gopalakrishnan et al. (2020) suggest that financial assets are mostly held as a transitory asset class to gain financial resources to build up physical assets. While these studies do not directly relate to the decision making related to acquiring vehicles, they still give valuable insights with regards to the wealth allocation of Indian households. We see that the latter do not maintain high liquidity levels, but have a strong preference for physical assets such as real estate or gold. In India, these assets are perceived to offer medium liquidity in the case of gold and low liquidity in the case of real estate (Bhayani and Patankar, 2016). From this, we conclude that Indian households face relatively low liquidity levels which potentially imposes financial constraints and affects decision making when acquiring expensive goods such as vehicles. Considering the latter, income and household demographics are the predominant determinants of decisions regarding private car ownership behaviour (Ramakrishnan et al., 2020; Dash et al., 2013). Besides the aforementioned factors, Gupta (2013) also raises fuel efficiency as a deciding factor for car buying decisions. Once more, this is in line with our research. We find that financial constraints are the major driver of the implementation of EVs in India. Firstly, we show that sufficient financial means to cover the acquisition cost are the most important factor when purchasing an EV. Secondly, we find that running costs in terms of petrol prices of ICEs must be high to overcompensate the higher purchase prices of EVs.

Value added through our research

As we can see from above, the decarbonization of the transport sector carries responsibility for abating 15% of global CO_2 emissions on the path to global net zero. Due to the high expected population growth in EMs particular focus should lie on these countries. As outlined, EVs regularly face different barriers when scaling in these markets. As can be seen from Figure 2, India is one country that has recently been very successful in increasing the penetration of EVs. To our knowledge, there has been no paper so far that quantitatively assesses the drivers of EV penetration in India. With our results, we contribute to closing this gap and allow drawbacks that can help other EMs in their fight against CC.

2 Theoretical framework

2.1 Background and hypothesis

In this paper, we aim to better understand the drivers behind the recent EV success story in India with particular focus on liquid deposits. Thereby, we intend to differentiate between three main driving forces: financial, environmental, and technical concerns.

As Collett and Hirmer (2021) describe, the majority of travel in Sub-Saharan Africa is based on privately-owned and unofficially run public transport vehicles, which are often referred to as *paratransit*. On the other hand, looking at the vehicles sales in India in 2021, we see that only 2.28% of car sales were compromised of heavy or medium vehicles while Two-Wheelers (2Ws) alone accounted for 70.37% of vehicle sales in India during the first five months of 2023, regardless of fuel used (Ministry of Road Transport & Highways, 2023). This is also reflected in Table 1 which displays price differences between EVs and ICEs. Firstly, the table shows again that 2Ws dominate the Indian vehicle market. Furthermore, we see that EVs are significantly more expensive than ICEs. For example when comparing the E2W and regular 2W offer from TVS Motor, we see that the electric versions are sold at an up to 62% mark-up compared to ICEs. The same trend is observable when comparing four-wheelers offered by Tata Motors. In this case the electric vehicles are up to 55% more expensive than their petrol powered counter-offer. Furthermore, India suffers from high wealth inequality. While average household wealth equals 983,010 Indian Rupees, one recognizes that we are dealing with a strongly right skewed distribution, i.e. the top 10% households measured by household wealth own 65% of wealth in India. On the other hand, the bottom 50% of households own only 6% of total wealth or 115,000 Indian Rupees per household respectively (Chancel et al., 2022). When comparing this to the prices shown in Table 1, it quickly becomes clear that the mark-up of EVs compared to ICEs imposes a constraint to most households in India.

From the above, we argue that the major user group for EVs in India will be private households that likely face strict financial constraints when purchasing new vehicles. Especially as EVs are sold at a mark-up, these constraints can become a deciding factor. As shown by literature, different ownership models for vehicles are existent in India besides proprietary ownership of a car, however, a lack of awareness and a strong preference for ownership among citizens led to a major share of vehicles being owned (Trivedi and Dave, 2022). Consequently, they must be financed by equity in the form of liquid deposits or through debt. For the purpose of this analysis, we will include bank loans as a measure of debt.

Considering the latter, Aditya et al. (2019) study the determinants and intensity of credit approvals in eastern India. They find that only half of the households in rural areas have access to credit. This is often due to people with lower asset base being excluded from regular bank financing. They suggest expanding bank branches in India and creating further awareness. From this, we see that bank financing might have been relevant for EV expansion, however, only in certain areas and parts of the society, i.e. wealthier people and areas with a high density of bank branches. For the people that do not have immediate access to debt financing, contributing equity in the form of deposits seems to be the only viable option to purchase an EV. Considering that a major burden to the EV expansion in India is the cost associated with buying one of the latter, we deem the influence of deposits crucial. Therefore, we argue that EVs will account for a larger share in newly registered vehicles in Indian states where citizens possess a greater amount of liquid deposits. This also represents our main hypothesis. Consequently, the main testable implication of our hypothesis will be the following:

Main hypothesis: The amount of liquid deposits in an Indian state affects the share of EVs in newly registered vehicles in this state.

More details on data that was used to test this implication will be provided in the next chapter.

2.2 Alternative views

Even though numbers deviate slightly, India's Ministry of Power (2023) reported a total of 5,254 operational EV charging stations in India. When looking at the current locations of these charging stations and the measures taken by the Government of India to expand the charging network, we see that the EV expansion is centered around larger cities. Given that charging infrastructure is seen as another barrier to the EV expansion in India, it could be argued that a large share of EVs is likely located in cities. As shown in the above section, the access to credit is higher if the number of bank branches in proximity is high. Taken together, most EVs might be located in areas with a higher density of banking branches and thus better access to debt financing.

Therefore, our first testable alternative implication is the following:

Alternative Prediction 1: The number of bank branches in an Indian state affects the share of EVs in newly registered vehicles in this state.

Our second alternative empirical prediction is the following:

Alternative Prediction 2: If changes in temperature in an Indian state are above the country's median, they affect the share of EVs in newly registered vehicles in this state.

Besides following a financial motivation, Indian citizens might also have environmental concerns that lead them to buying an EV. How people update their view on climate change has been examined within different recent research papers. Choi et al. (2020) argue that people have limited attention which causes them to overlook climate risk under normal circumstances as they focus on particular attention grabbing events and experiences. However, they also show that in case of an abnormal weather event, e.g. abnormally high temperature, people adapt their beliefs. On the one hand, they show that the topic "global warming" is googled more frequently during those periods. On the other hand, their findings depict that firms with high carbon emissions underperform in financial markets during the respective period. Ouadghiri et al. (2019) add to this by showing that sustainable indices outperform during the same periods. Concluding, we see that private persons adapt their beliefs based on abnormal weather events. This also means that in states where temperatures changes were particularly high, people might opt to switch to an EV to travel more sustainably.

Additionally, the current major substitution opportunities for EVs on the Indian market are petrol- and diesel-powered ICEs. Taking a closer look, we see that petrol powered ICEs had a market share of roughly 80% in 2022 while diesel vehicles had a market share of approximately 11% throughout the same period (Ministry of Road Transport & Highways, 2023). Looking at the barrier of high purchase prices for EVs, we also recognize that the opportunity cost of driving a petrol or diesel car could also have an impact on the decision for a certain vehicle class. Especially, under the light of the recently soaring energy prices (PetrolDieselPrice, 2023), the running cost for driving an ICE also went up. This might have benefitted the share of EVs. As diesel and petrol prices are highly correlated represented by a correlation coefficient of 0.96, we decided to drop diesel cars and prices from our analysis. This is mostly based on the motivation to avoid multicollinearity in our regression models and on the relatively low share of diesel vehicles. Thus, we derived our third alternative prediction:

Alternative Prediction 3: Petrol prices in an Indian state affect the share of EVs in newly registered vehicles in this state.

Last but not least, the underlying charging infrastructure is often seen as another barrier to EV expansion. As mentioned before, there are currently only few charging stations in India and data availability for the latter is problematic. Further, the ability to charge an EV always depends on the availability of the grid as long as no decentralized storage options are offered. Even though data for grid outages is not directly available either, Alam (2013) suggests that nighttime light emissions are related to grid outages in India. On the one hand, he states that variability in night lights can be used to construct a measure for power outages. Secondly, he argues that power outages are used for the purpose of demand management. Therefore, he deems it acceptable to assume that power outages are highly correlated over the day, i.e. more frequent grid outages during the night are an indicator for more frequent grid outages during the day. Consequently, our last empirical alternative prediction is the following:

Alternative Prediction 4: Variation in nighttime light radiation in an Indian state affects the share of EVs in newly registered vehicles in this state.

The data that was used for the purpose of testing these hypotheses is described in greater detail in the following chapter.

3 Data

We construct a unique panel dataset from various sources to test our Main Hypothesis and alternative predictions stated in the previous chapter. This dataset is generally based on state-level data in India and presents quarterly data. The variables included are the share of EVs in newly registered vehicles, the amount of deposits, the number of bank branches, temperature changes, petrol prices and variation in nighttime lights. The sources, descriptive statistics and adjustments to the data are presented in the following paragraphs. Further, Table 2 summarizes the descriptive statistics of all variables.

3.1 Share of electric vehicles

India's Ministry of Road Transport & Highways (n.d.) publishes data on the number of EVs in India. Among other things, they make available data on vehicle registrations on a monthly basis per state in India. Thereby, they differentiate between different fuels such as diesel, petrol or electricity. We retrieve this data for the time period between Q1 2017 and Q1 2023.

After scraping the raw vehicle registration numbers, we make several adjustments to it. Firstly, we aggregate the monthly numbers to quarterly means and delete all missing observations. This is based on the rationale that some of the explanatory variables are only published on a quarterly basis. Secondly, we convert absolute numbers of EVs in a state to the respective share in new vehicle registrations. Besides the number of EVs, we consider petrol powered ICEs in the computation of the share. Looking at the year 2022, petrol powered ICEs made up for approximately 80% of vehicle registrations in India while diesel powered ICEs and EVs accounted for 11% and 5% respectively. As previously mentioned, diesel prices are excluded from our analysis due to the high correlation between the latter and petrol prices. Given that petrol powered ICE registrations have a lot more weight in total registrations, we decide to drop diesel prices as an explanatory variable and consequently also exclude it from the computations of the EV's shares.

As depicted in Table 2, a total of 708 observations are available for the share of EVs. The data shows a mean of 1.51% and a median of 0.42% which indicates that the data is right skewed. Thus, we see that while the majority of observations lies below the mean, a lower number of observations show very high shares of EVs. This is also represented by a standard deviation of 2.34%. The mean share of EVs in each state is visualized in Figure 3. From this, we observe that some states in North India appear to have a larger share of EVs in their vehicle registrations on average. Another trend that is observable within India's EV sector is that the share of EVs increased strongly starting from Q4 2020 as shown in Figure 2. This observation motivates us to expand the analysis of our Main Hypothesis to two subsamples, i.e. prior to Q4 2020 and after Q4 2020, to check if the predicted relationship between deposits and the share of EVs holds over time. For the purposes of our analysis, we use the logarithm of the share of EVs data based on the asymmetric distribution of the data.

3.2 Deposits

The Reserve Bank of India (2023a) makes data on the deposits in India publicly available. From Q1 2017 to Q2 2022, they publish quarterly data on a state level. While the data contains details on current, savings and terms deposits, we exclude terms deposits as their maturity was not explicitly stated and longer maturities would yield a lack of liquidity for their holders which is not in line with our Main Hypothesis. The numbers are provided in crore rupees while one crore denotes 10 million.

For the purpose of our analysis, we consider nominal deposit amounts. This is based on our assumption that the EVs that count towards the share of EVs were also purchased at nominal prices. For comparability and consistency, we opt to refrain from inflation adjustments to the deposits. Furthermore, based on the magnitude of the published numbers, we convert all deposit numbers to "thousand crores", i.e. divide the original numbers by 1,000.

From Table 2, we can observe a relatively similar distribution of the observations compared to the share of EVs. Again, with a median of 195.35 thousand crores and a mean of 413.76 thousand crores, we recognize that the values are skewed to the right. This shows once more that the majority of observations lies below the mean while a relatively low number of observations lies relatively far above the mean. Moreover, represented by a standard deviation of 563.40 thousand crores, we see that there are large deviations in deposit data. Our total sample consists of 704 observations. Looking at Figure 4, we observe a consistent upward trend in nominal deposits between Q1 2017 until the end of our sample period. Further, Figure 5 depicts that the Indian state Maharashtra shows a particularly high mean number of deposits per state. This is likely based upon its capital Mumbai which hosts large parts of India's financial industry. Due to the skewed distribution, we use the logarithm of the original data for the purpose of our analysis.

To test how the relationship between the share of EVs and liquid deposits evolves across different wealth groups, we obtain data on population and household size to compute liquid deposits per household. India's Ministry of Health & Family Welfare (2019) published an update of their original population projections from 2011 in 2019 on a state and year level (2011 to 2036). When comparing these numbers to actual numbers for 2019, the average absolute deviation is 5.45% (Statistics Times, 2020). Secondly, Global Data Lab (n.d.) publishes panel data on the average number of persons in an Indian household on a state and year level. We use these numbers to compute the estimated number of households. General trends show that the Indian population increased continously while the average number of people in a household decreased over time. The descriptive statistics of the latter are presented in Table 2 in thousand households. As one can expect, there are large differences in the number of households across states. While the mean number in a state across years is 8,648, we observe a standard deviation of 10,911 and a median of 3,783. As this data is not used as an explanatory variable in our models but solely to build sub-samples, no logarithms were taken even though we observe a right skewed distribution. While we refrain from using these estimates for our regression models, we deem it inevitable to consider differences between wealth groups to address causality. The reasons for us to exclude the data from our regression models are twofold. Firstly, the number of households is based on multiple estimates which raises the issue of reliability. Furthermore, the data is only available on a yearly basis. For the sub-sample analysis, we assume that the number of households is constant throughout a given year because we can not identify intra-yearly patterns in the number of households.

3.3 Banks

Additionally to data on deposits, we retrieve quarterly data for bank branches from Reserve Bank of India (2023b) to test our Alternative Prediction 1. The values are available for the time period from Q2 2015 to Q2 2022 on a state level. This equates to 928 observations. India's Reserve Bank thereby differentiates between banked centers with different numbers of offices. As we assume that every office offers the service to apply for a loan, we consider the total number of offices for our analysis. The numbers provided are actual numbers and thus do not need to be converted. We only change the banking branches data cosmetically for the purpose of our analysis.

From Table 2 we observe that the mean and median number of banking branches in a state is 4,310 and 2,925 respectively. However, based on a lower coefficient for skewness than for the amount of deposits and the share of EVs, we continue with the original data. Similar to the deposits, we also observe a rather high standard deviation of 4,292 banking branches. From this, we can also see that there are substantial differences among the states' financial infrastructure.

3.4 Changes in Temperature

Deutscher Wetterdienst (2023) publishes vast amounts of climate data variables for a total of 4,592 weather stations worldwide. Thereof, 60 stations are located in India. Among others, the published numbers consist of data for temperature and precipitation. Unfortunately, there are great differences in data availability among the different variables and not every state is covered by a weather station. The uncovered states are mostly clustered in the north east of India.

We retrieve monthly data for all weather stations between Q1 2017 and Q4 2022. From this data, we then extract the relevant stations in India and map them to the state that they are located in. Based on our Alternative Hypothesis 2, we investigate the impact of changes in temperature on the share of EVs. Consequently, we compute the changes in temperature. For some states, multiple weather stations reported data. In these cases, we choose to use mean changes in temperature. Next, we aggregate monthly observations to quarterly data using means. To test our hypothesis, we further split up the changes in temperature into states where changes in temperature are above and below the country's median temperature change. Thereby, we want to isolate states with relatively large and small temperature changes from each other.

Looking at the descriptive statistics in Table 2 and based on 506 observations, the mean change in temperature was 3.22% while the median is represented by -3.24%. Further, a standard deviation of 33.64% is observable. Thereby, the relatively low number of observations stems from the limited number of reporting weather stations, i.e. for some states no data was available. The standard deviation which seems high at first sight is based on cyclical weather patterns over the year. While the temperatures rise throughout a period, they will fall again at a later point. Therefore, the standard deviation lies far above the mean or median. We refrain from using logarithms due to low skewness.

3.5 Petrol prices

We scrape monthly petrol price data for all states between May 2017 to February 2023 from PetrolDieselPrice (2023), and adjust it to Q2 2017 to Q1 2023, equating to 720 observations. Retrieved data includes both petrol and diesel prices, which are generally highly correlated. Due to potential multicollinearity in our models and a relatively low share of diesel powered vehicles, we drop the diesel data to test our Alternative Prediction 3.

Adjustments to the raw data include the aggregation to a quarterly level for which we compute the mean price over the respective quarter.

The descriptive statistics in Table 2 indicate a petrol price mean of 82.98 Indian Rupees and a median of 78.41 Indian Rupees indicating a relatively symmetric distribution. Based on this, we refrain from using logarithms. We observe a standard deviation of 13.47 Indian Rupees.

3.6 Night-time light data

NASA (2023) publishes different products for night-time light data emissions in the form of the Black Marble product suite. The Day/Night Band sensor of the Visible Infrared Imaging Radiometer Suite, carried by the Suomi-National Polar-orbiting Partnership and Joint Polar Satellite System satellite creates records of visible and near-infrared light. To improve the quality of the raw records, several corrections are made to the data. Firstly, radiation occurring due to the moon is filtered out to ensure that only upward surface radiation from artificial light is captured. Further corrections are made for other biases from extraneous sources of radiation and seasonal changes in vegetation. The world map data is published for different composites gridded into 36 horizontal and 18 vertical non-overlapping land times. Each tile provides data on 2400 times 2400 pixels. As the different products mostly differ in timewise resolution, we choose the monthly composite which is named VNP46A3 (Román et al., 2021). To resemble the whole surface of India's territory 14 tiles in total are needed per month. A total of 1,007 files is downloaded for the period between Q1 2017 and Q4 2022.

To bring the data into a format that is usable for our analysis, comprehensive adjustments and modifications are necessary. Among others, the following steps are required:

1. For each month, all land tiles and the respective pixels need to be placed in the right place according to their latitude and longitude.

2. All Indian states need to be mapped to the pixels.

3. Computation of the desired measure and storage in a table.

As our Alternative Prediction 4 examines the impact of variability in night-time light data, we use "AllAngle_Composite_Snow_Free_Std" data points to compute the standard deviation of night-time light in a given state. This is oriented at the approach of Alam (2013) to approximate grid outages in India. While the author of the paper considers the share of stable light pixels in total normalized average visible light, the required composites are not available for the needed time period. However, similar to our approach his concept relies on the variability of nighttime light radiation. As a downside to his approach, the author mentions that the data used in his analysis is not adjusted for the overall level of emissions, i.e. in areas with higher emissions from night-time lights, the variation in radiation is likely also higher. To account for this, we standardize the standard deviation of a state by dividing by the mean of the "AllAngle_Composite_Snow_Free" composite's actual values representing actual night-time light radiation.

The final sample consists of 816 observations. Based on a mean of 0.89 and a median of 0.53, it is again right skewed. Thus, we consider logarithms of the original values for our analysis. Lastly, we observe a standard deviation of 1.09. More details can be found in Table 2.

4 Findings

With our research we aim to investigate the role of liquid deposits in the recent development of the share of EVs in India. As depicted above, the latter saw a sharp increase after Q4 2020. Thus, we will analyze if the estimated relationship holds over time and see if other financial, environmental or technical concerns had an additional impact.

4.1 Main hypothesis

Full sample

To test Main Hypothesis, we examine how the amount of deposits in a specific Indian state impacts the share of newly registered EVs in this state or year. To test for causality, we include different control variables and conduct the analysis with different sub-samples which will be discussed in the following subsections. We estimate the following regression model including state and quarter fixed effects as well as heteroskedasticity consistent standard errors:

$$Log(ShareofEVs)_{i,t} = \beta_1 Log(Deposits)_{i,t} + \beta_{c,1} Controls_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t}$$

As discussed above, our dependent variable, $Log(Share\ of\ EVs)_{i,t}$, depicts the mean share of electric vehicles in all new vehicle registrations in Indian state i and quarter t and is denoted as a percentage. Consequently, it can take values from one to one hundred. The second main variable, $Log(Deposits)_{i,t}$, sheds light on the total number of liquid deposits in Indian state i and quarter t and is denoted in thousand crores, i.e. it can take values from zero to infinity. Our $Controls_{i,t}$ include: the number of banking centers in Indian state i and quarter t, the temperature changes in Indian state i and quarter t, petrol prices in Indian state i and quarter t and lastly the adjusted night-time light radiation in in Indian state i and quarter t. We analyze the relationship over different time periods.

The main focus lies on the regressor *Log(Deposits)*$_{i,t}$. Under our assumptions, the estimator for *Log(Deposits)*$_{i,t}$ would in an ideal outcome provide a measure for the causal effect of the number of deposits on the share of EVs. This will discussed later in this paper and be tested by adding various controls to the model which proxy for other variables that might influence *Log(Share of EVs)*$_{i,t}$. To avoid omitted variable bias, state and quarter fixed effects were included. While state fixed effects control for factors that do not vary over time for a given state, quarter fixed effects control for changes across all states in a given quarter.

Table 3 presents the estimates for all regressors for a regression considering the full sample. Generally, the columns of all tables illustrate estimates including an increasing number of controls. Thereby, the robustness of coefficient estimates across models should be ensured.

Looking at the results depicted in Table 3, one recognizes that the coefficient estimates for *Log(Deposits)*$_{i,t}$ lie between 4.65 and 8.29 and are all significant at a one percent level. From this, we see that a one percent change in the amount of deposits is predicted to lead to a increase in *Log(Share of EVs)*$_{i,t}$ of between 4.65 percent and 8.29 percent. Furthermore, we see that *Log(Deposits)*$_{i,t}$ adds great explanatory power to our model represented by an adjusted R^2 of 0.623 from a univariate regression. The variability in coefficient estimates for *Log(Deposits)*$_{i,t}$ shows a lack of robustness towards other variables. Especially, when including petrol prices and night-time light radiation, we observe that these have a significant impact on *Log(Share of EVs)*$_{i,t}$. These variables, however, have very limited explanatory and we observe that *Log(Deposits)*$_{i,t}$ is the main driver of *Log(Share of EVs)*$_{i,t}$. Nevertheless, this also shows that our models suffer from omitted variable problems. Other variables that we expect to influence *Log(Share of EVs)*$_{i,t}$ are discussed later on and were not included in our model due to data availability.

Concluding, the data predicts that the amount of liquid deposits is the major driver of the share of EVs in India considering the whole sample period which is in line with our Main Hypothesis. Even though, the overall petrol powered ICE sales grew by approximately 8.2% year-on-year between 2021 and 2022, the EV sales more than tripled over the same time period (Ministry of Road Transport & Highways, n.d.). We argue that more deposits foster the implementation of EVs by providing sufficient financial means to cover the acquisition cost of the vehicle which is in line with academia (Moeletsi, 2021; Tongwane and Moeletsi, 2021; Collett et al., 2021; Dioha et al., 2022a). In the following subsections, we will give a more differentiated view on different sub-samples.

Sub-sample analysis: Pre Q4 2020 vs. Post Q4 2020

Figure 2 shows that the share of EVs has been relatively flat over years and started to increase steeply from Q4 2020 onwards. To ensure that the estimates from our first model hold over time, we also include a sub-sample analysis. Thereby, we estimate the same regression model as depicted above for t including all values from Q1 2017 to Q4 2020, and also for t spanning from Q4 2020 to Q2 2022.

Considering the period from Q1 2017 to Q4 2020, the coefficient estimates depicted in Table 4 show that *Log(Deposits)*$_{i,t}$ also had a significant impact on the share of EVs throughout the first sub-sample period. Represented by estimates between 2.71 and 5.68, one can make two different observations. Firstly, we see again that a one percent increase in *Log(Deposits)*$_{i,t}$ yields *Log(Share of EVs)*$_{i,t}$ to increase by 2.71 percent to 5.68 percent. Secondly, we see once more that our coefficient estimates lack robustness against other variables. We observe that from Q1 2017 to Q4 2020, all control variables had a significant impact on *Log(Share of EVs)*$_{i,t}$. However, when considering the adjusted R^2 of the different models, we see that the control variables yield only limited explanatory power and *Log(Deposits)*$_{i,t}$ remains the major driver of *Log(Share of EVs)*$_{i,t}$ yielding an adjusted R^2 of 0.38 from a univariate regression.

For the time period from Q4 2020 to Q2 2022, Table 5 presents the results of our analysis. We observe coefficient estimates for *Log(Deposits)*$_{i,t}$ that lie in a range between 9.66 and 14.63 and are all significant, i.e. a one percent change in *Log(Deposits)*$_{i,t}$ is predicted to increase *Log(Share of EVs)*$_{i,t}$ by 9.66 percent to 14.63 percent. Again, *Log(Deposits)*$_{i,t}$ adds great explanatory power depicted by an adjusted R^2 of 0.486 from a univariate regression and appears to be the major driver of *Log(Share of EVs)*$_{i,t}$. Again, there is variability in the coefficient estimates as petrol prices seem to be the second force behind the development of *Log(Share of EVs)*$_{i,t}$.

Taken together, Table 4 and Table 5 show that the share of EVs in India has constantly and to the major extend be driven by the amount of liquid deposits. We see that the data is consistent with our Main Hypothesis. However, we also see our models predict a greatly increased influence of *Log(Deposits)*$_{i,t}$ on *Log(Share of EVs)*$_{i,t}$ during the 2$^{\text{nd}}$ time period, e.g. after adding all control variables the coefficient estimate increased from 2.94 to 9.79 relative to the first sub-sample. At the same time, petrol prices are the only other variable with partly significant coefficient estimates. While we argue that financial constraints for Indian household affect the purchasing behavior of the latter, i.e. if Indian households do not posess sufficient liquidity, they will not be able to afford an EV, we could not find evidence for the increase of the coefficient estimates for *Log(Deposits)*$_{i,t}$ on *Log(Share of EVs)*$_{i,t}$ between the time periods. Also when looking at Figure 4, we see that there were no changes in the trend in the mean amount of liquid deposits while the share of EVs increased steeply after Q4 2020. Therefore, one might argue that the investigated relationship is rather technical and based on correlation instead of causality. This will be addressed in the following subsection.

Sub-sample analysis: Wealth groups

To test wether there is a causal relationship between the amount of liquid deposits and the share of EVs, we build further sub-samples. These are based on the estimated liquid deposits per household in a given state and quarter. These numbers are computed by dividing the amount of liquid deposits that we use for our regression models by the number of households. We then build three sub-samples including the lower 33%, the middle 33% and the top 33% of observations based on the estimated liquid deposits per household. We refrain from using the household-level data in other parts of our analysis as there are a few caveats to it. Firstly, it is based on estimates and secondly, it was only available on a yearly basis. We estimate the following regression model for each sub-sample for the time period between Q1 2017 and Q2 2022:

$$Log(ShareofEVs)_{i,t} = \beta_1 Log(Deposits)_{i,t} + \beta_{c,1} Controls_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t}$$

Generally, the variables and data used remain the same as before. Table 6 depicts the results from the model for the lower 33rd percentile sub-sample. We observe that the coefficient estimates for *Log(Deposits)*$_{i,t}$ are between 5.97 and 7.20 before adding petrol prices. After the latter are included in the model the estimates drop to around one and become insignificant. This means that a one percent increase in *Log(Deposits)*$_{i,t}$ is predicted to yield a approximately one percent in crease in *Log(Share of EVs)*$_{i,t}$. Compared to the estimates from previous regressions, this estimate is greatly lower. Table 7 represents the results for the middle 33rd percentile sub-sample. While the coefficient estimates for *Log(Deposits)*$_{i,t}$ drop again after adding petrol prices, their estimated influence on *Log(Share of EVs)*$_{i,t}$ is higher than for the first sub-sample and the estimates remain significant throughout all specifications. The estimates lie between 5.05 and 9.09 meaning that a once percent increase in *Log(Deposits)*$_{i,t}$ is predicted to yield an increase of at least 5.05%. The results from the top 33rd percentile sub-sample show the highest coefficient estimates for *Log(Deposits)*$_{i,t}$ and are presented in Table 8. We observe estimates between 5.68 and 9.90, translating to an increase in *Log(Share of EVs)*$_{i,t}$ of at least 5.68% if *Log(Deposits)*$_{i,t}$ increases by one percent. Summarizing, we observe that the estimated influence of liquid deposits on the share of EVs is higher for observations where liquid deposits per household are high. However, we also observe that coefficient estimates are volatile and decrease especially after adding petrol prices as a control variable indicating a lack of robustness.

We attribute the low coefficient estimates for the lower sub-sample to the inability of these households to cover the acquistion cost of an EV. Similarly, we argue that households possessing more liquid deposits are able to cover the acquisition cost of EVs and therefore show higher coefficient estimates.

While we see these results as a confirmation that there is a relationship between liquid deposits and the share of EVs, i.e. financial constaints affect the purchasing behaviour of households in India, we want to be careful with claiming causality. While we argue that our results might reflect a causal relationship between liquid deposits and the share of EVs, we also argue that our analysis suffers from omitted variable bias, i.e. the recent EV success story in India was driven by other factors as well, and therefore its background is likely multicausal. Especially our results for petrol prices indicate that their recently soaring levels have also helped to make EVs economically more attractive. Besides that, we expect that support for households under India's National Electric Mobility Mission Plan has been a rationale behind the recent increase in EVs on India's streets. Our findings are in line with the findings of academic scholars. Similar to Ramakrishnan et al. (2020); Dash et al. (2013) and Gupta (2013), we observe that higher financial means lead to the acquisition of more expensive (electric) cars. This intuitively makes sense as these means enable the household to cover the acquisition cost of the vehicles. Consequently, the data is in line with our Main Hypothesis.

4.2 Alternative views

Alternative Prediction 1

To test our Alternative Prediction 1, we examine how the number of banks affects the share of EVs in India. More specifically, we estimate the following regression model:

$$Log(ShareofEVs)_{i,t} = \beta_1 Banks_{i,t} + \beta_{c,1} Controls_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t}$$

All variables remain the same as for our Main Hypothesis. Furthermore, we again include state and quarter fixed effects and report heteroskedasticity consistent standard errors. The results from our analysis are presented in Table 9. While the coefficient estimate for $Banks_{i,t}$ is significant for a univariate regression, it becomes insignificant after adding control variables. Furthermore, the estimate drops from 0.003 to 0.00002 after adding all control variables. This means that per additional bank, $Log(Share\ of\ EVs)_{i,t}$ will increase by 0.002%. Thus, the marginal impact from an additional banking center is close to zero.

Concluding, the data contradicts our Alternative Prediction 1 which we consequently reject. This might have two reasons. The first possibility is that a great share of Indian citizens does not receive any loans and thus must rely on liquid deposits. Looking at the findings of Aditya et al. (2019), we see that only half of the households have access to credit in rural areas in Eastern India. However, what contradicts this is that most of the 5,254 charging stations in India are located in urban areas where more banking centers are available (Ministry of Power, 2023), i.e. the access to credit should also be improved where the majority of EVs are present. On the other hand, the NITI Aayog and Rocky Mountain Institute (2021) states that while banks dominate the market for Electric Four-Wheelers (E4Ws), Non-Banking Financial Companies (NBFCs) such as microfinance institutions and car manufacturers are most active in the two-wheeler market. Considering that we use the absolute number of newly registered vehicles, it seems reasonable that our findings predict that loans from banks have only very little influence on the share of EVs as the vast majority of EVs in India are represented by E2Ws. Consequently, when considering total investment amount, loans from banks might have a larger influence due to the relatively higher prices of E4Ws.

Alternative Prediction 2

Our Alternative Analysis 2 examines the relationship between temperature changes and the share of EVs for observations where temperature changes lie above the country's median temperature change. To empirically test this hypothesis, we estimate the following model:

$$Log(ShareofEVs)_{i,t} = \beta_1 Temperature_{i,t} + \beta_{c,1} Controls_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t}$$

The regression model once more features state and quarter fixed effects. Furthermore, all variables remain compared to the prior two models while $Temperature_{i,t}$ represents the changes in temperature in state i in quarter t. The sub-sample used for this analysis is limited to observations where the temperature change lies above the long-term country median. Table 10 depicts the respective coefficient estimates. We observe a similar picture as when examining the effects of banking centers. The estimates for *Temperature*$_{i,t}$ are close to -0.003 and insignificant for the univariate regression as well as after adding control variables. This theoretically translates to *Log(Share of EVs)*$_{i,t}$ decreasing by 0.3% if *Temperature*$_{i,t}$ increases by one percentage point. While the cyclical behavior of temperature makes the practical implications of this finding generally questionable, the negative implications on *Log(Share of EVs)*$_{i,t}$ are also contrary to our expectations. As described before, we expected that higher temperature changes would increase the awareness for climate change and therefore increase the share of EVs.

The data contradicts with our Alternative Prediction 2 which we reject following our analysis. As Choi et al. (2020) found, abnormally high temperatures lead to broader awareness of climate change in the society. Consequently, in states with relatively high temperature changes, the environmental benefits of EVs might yield motivation to buy an EV. When looking at our findings, one observes that this is not the case. Rather, we observe that higher temperature changes are associated with a lower share of EVs in newly registered vehicles. Studies show that higher temperatures yield lower economic output in India (Somanathan et al., 2021). Even though, it appears that the relationship between economic output and wages has not been assessed for India, Blecker (2016) finds that demand is more likely to be profit-led in the short-run in the U.S. Taken together, we see that higher temperatures will cause less demand for relatively expensive EVs. This is clearly not in line with the findings of Ouadghiri et al. (2019) which show that sustainable financial solutions outperform during abnormally high temperatures.

Alternative Prediction 3

Next, we want to study our Alternative Prediction 3 which states that petrol prices in an Indian state have an impact on the share of EVs in newly registered vehicles in this state. To quantitatively assess this question, we estimate the following regression model including state and quarter fixed effects:

$$Log(Share of EVs)_{i,t} = \beta_1 Petrol_{i,t} + \beta_{c,1} Controls_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t}$$

Again, the variables used remain constant. Petrol prices are denoted in Indian Rupees which leads to a higher magnitude of prices.

The results presented in Table 11 show that *Petrol*$_{i,t}$ is predicted to have a positive influence on *Log(Share of EVs)*$_{i,t}$. This is in line with our expectation that EVs are preferrably chosen as a subsitute for petrol powered cars in case of high running costs in terms of petrol prices. With significant estimates between 0.0005 and 0.001 which continously drop after adding additional control variables, we see that if petrol prices increase by one rupee, the share of EVs will increase by around 0.05%. From this variability in estimates, we also recognize a lack of robustness when adding other control variables. Nevertheless, it seems that the relationship between petrol prices and the share of EVs held over time.

Consequently, we do not reject our Alternative Prediction 3 as the data is in line with our prediction. We see that the running cost of an ICE must be higher to make the usage of an EV economically feasible. This is in line with the current observations of The Economic Times (2022) which report that especially electric cabs have received tailwind because of up to 75% lower operational cost compared to ICEs due to the recently soaring energy prices.

Alternative Prediction 4

Lastly, we want to examine wether and if so, how radiation from night-time lights in an Indian state is related to the share of EVs in newly registered vehicles in this state. For this purpose, we estimate the following model:

$$Log(ShareofEVs)_{i,t} = \beta_1 Log(NTL)_{i,t} + \beta_{c,1} Controls_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t}$$

As in the previous models, we include state and quarter fixed effects and do not change the variables. $NTL_{i,t}$ depicts the standardized standard deviation of night-time light radiation in state i and quarter t. To standardize the standard deviation, we adjusted the standard deviation of night-time light radiation for the respective mean value to account for absolute radiation levels. Table 12 depicts the results from our model. While the coefficient estimate for $Log(NTL)_{i,t}$ from a univariate regression is not significant, the latter becomes significant after adding control variables. The estimates lie between -0.48 and -0.85, i.e. if standardized standard deviation of night-time lights increases by one unit, the share of EVs will decrease by roughly half a percent. As shown by Table 4 and Table 5, this relationship is only significant for the period between Q1 2017 to Q4 2020.

Concluding, the data shows that more grid outages lead to a lower share of EVs and is in line with our Alternative Prediction 4 for the first sub-sample period. This complies with the findings of other scholars (Shetty et al., 2020; Rakesh Kumar and Padmanaban, 2019). Unfortunately, data on charging stations has not been available at state and quarter level. We use grid outages as an alternative as the latter cause that charging of EVs is not possible, i.e. they have the same effect as a lack of charging stations. We use variation in night-time lights as a proxy for grid outages. From our findings, we see that more grid outages significantly harm the share of EVs, and conclude that the opportunity of a reliable charging infrastructure is another important factor when deciding for an EV. This is in line with the findings of the aforementioned studies.

4.3 External validation

To test wether our claims with regards to liquid deposits and petrol prices made above also hold in other EMs, we gathered a reduced data set for Brazil. The latter was our country of choice as it also belongs to the so called BRIC states, consisting of Brazil, Russia, India and China. Therefore, we expected that Brazil would offer comparatively similar prospects for EVs. A detailed description of the process, the variables gathered and their descriptive statistics can be found in Appendix B. For the purpose of external validation, we estimated the following model:

$$ShareofEVs_t = \beta_1 Deposits_t + \beta_2 Petrol_t + \beta_3 NTL_t + \gamma_t + \epsilon_t$$

As all variables are on country level, we only include month fixed effects. *Share of* EVs_t depicts the share of EVs in newly registered vehicles in Brazil in month t including all months between January 2014 and December 2022. Similarly, $Deposits_t$, $Petrol_t$ and NTL_t represent liquid deposits, petrol prices and the standardized standard deviation of night-time lights in Brazil in month t. Table 13 shows that the coefficient estimates for $Deposits_t$ are highly significant from a univariate regression and after adding petrol prices and night-time light data. The estimates are 0.0004 in all cases, meaning that an increase of one billion Brazilian Real of liquid deposits yields a 0.0004% higher share of EVs in newly registered vehicles. The coefficient estimates for $Petrol_t$ are 0.074 and 0.075 which is also in line with our previous findings, however, are not significant at a 10% significance level. If petrol prices increase by one Brazilian Real, the share of EVs is predicted to increase 0.074% to 0.075%. The same applies for the coefficient estimate for NTL_t which is -0.079. This means that if night-time lights deviate by one unit more, i.e. more grid outages, *Share of* EVs_t will be 0.079% lower.

Compared to our previous results, we observe lower adjusted R^2 of 0.094 and 0.103 representing decreased explanatory power. While the statistically significant relationship between the amount of liquid deposits and the share of EVs is clearly confirmed, it seems that other variables also had greater effect on the latter compared to our findings for India.

5 Conclusion

In this study, we investigated different drivers behind the recent EV success story in India. Looking at our variables, we sort them in three clusters.

Firstly, we see that financial concerns have been the main rationale behind the steep increase in the share of EVs. Reflecting our Main Hypothesis, we find that the amount of liquid deposits has been the major single driver behind the increase of EVs in Indian vehicle registrations. Furthermore, higher opportunity cost in terms of higher petrol prices also yield motivation to purchase an EV.

On the contrary, we find that our second cluster, environmental concerns, has not been a rationale for the higher share of EVs.

Lastly, technical concerns in the form of charging infrastructure also influence the share of EVs on Indian streets. A larger amount of grid outages and thus lower reliability of EVs leads to a lower share of EVs.

Based on this, we see that governmental policies should be focused on improving household liquidity at first place.

Our findings are based on a balanced unique panel data set. However, we identify data availability to be the major barrier to this study due to two reasons. Firstly, the latter has generally led to a relatively low number of observations. Secondly, we had to rely on proxies to a large extend because data on the actual variables that we intended to test was not available. For future studies, we deem two other variables particularly important which we could not retrieve data on a state and quarter level for. On the one hand, it would be important to examine the effect of charging stations on the share of EVs. Secondly, we expect that subsidies incentivizing the purchase of an EV have also had a significant impact on the share of EVs. This opens many doors for future research in order to ensure a bright future for EVs in India and other EMs on the global path towards net-zero.

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Acronyms

2W Two-Wheeler

CC Climate Change

E2W Electric Two-Wheeler

E4W Electric Four-Wheeler

EM Emerging Market

EV Electric Vehicle

GHG Greenhouse Gas

HIC High Income Country

ICE Internal Combustion Engine

IPCC Intergovernmental Panel on Climate Change

NBFC Non-Banking Financial Company

A Appendix

Table 1: Price range of EVs and ICEs from most purchased brands

The table depicts the ten manufacturers with most vehicles sold in 2022 according to India's Ministry of Road Transport & Highways (n.d.), their numbers of vehicles sold as an actual number, the vehicle type and its respective offered price range denoted in Indian Rupees.

Brand	Number of vehicles	Vehicle Type	Lowest price	Highest Price	Source
		Electric Vehicles			
Ola Electric Technologies Pvt Ltd	109,383	E2W	109,999	139,999	Ola Electric (n.d.)
Okinawa Autotech Pvt Ltd	101,688	E2W	99,645	186,006	Okinawa AutoTech (n.d.)
Hero Electric Vehicles Pvt. Ltd	97,829	E2W	72,000	86,391	Hero Electric (n.d.)
Ampere Vehicles Private Limited	79,862	E2W	104,900	149,000	Ampere Vehicles (n.d.)
Ather Energy Pvt Ltd	51,803	E2W	169,149	169,149	Ather Energy (n.d.)
Tvs Motor Company Ltd	47,160	E2W	106,384	106,384	TVS Motor (n.d.a)
Tata Motors Passenger Vehicles Ltd	30,378	E4W	869,000	1,203,999	Tata Motors (n.d.a)
Yc Electric Vehicle	27,881	E2W	140,000	179,000	Rickshaws360 (n.d.)
Bajaj Auto Ltd	25,186	E3W	306,550	306,550	Bajaj Auto (n.d.a)
Saera Electric Auto Pvt Ltd	19,559	E2W	125,000	125,000	E-Vehicleinfo (n.d.)
		Internal Combustion Engine Vehicles			
Hero Motocorp Ltd	5,029,519	2W	69,816	79,252	Hero Motorcorp (n.d.)
Honda Motorcycle And Scooter India (P) Ltd	3,735,145	2W	74,207	85,083	Honda India (n.d.)
Tvs Motor Company Ltd	2,338,181	2W	65,514	73,036	TVS Motor (n.d.b)
Bajaj Auto Ltd	1,652,425	2W	59,104	70,400	Bajaj Auto (n.d.b)
Maruti Suzuki India Ltd	993,980	4W	426,500	551,500	Maruti Suzuki (n.d.)
Royal-Enfield (Unit Of Eicher Ltd)	644,284	2W	166,901	221,297	Royal Enfield (n.d.)
Suzuki Motorcycle India Pvt Ltd	631,236	2W	81,832	90,223	Suzuki Motorcycle (n.d.)
India Yamaha Motor Pvt Ltd	544,348	2W	78,600	91,230	Bikedekho (n.d.)
Hyundai Motor India Ltd	319,654	4W	573,400	1,087,000	Hyundai Motors India (n.d.)
Tata Motors Passenger Vehicles Ltd	278,422	4W	559,900	1,055,990	Tata Motors (n.d.b)

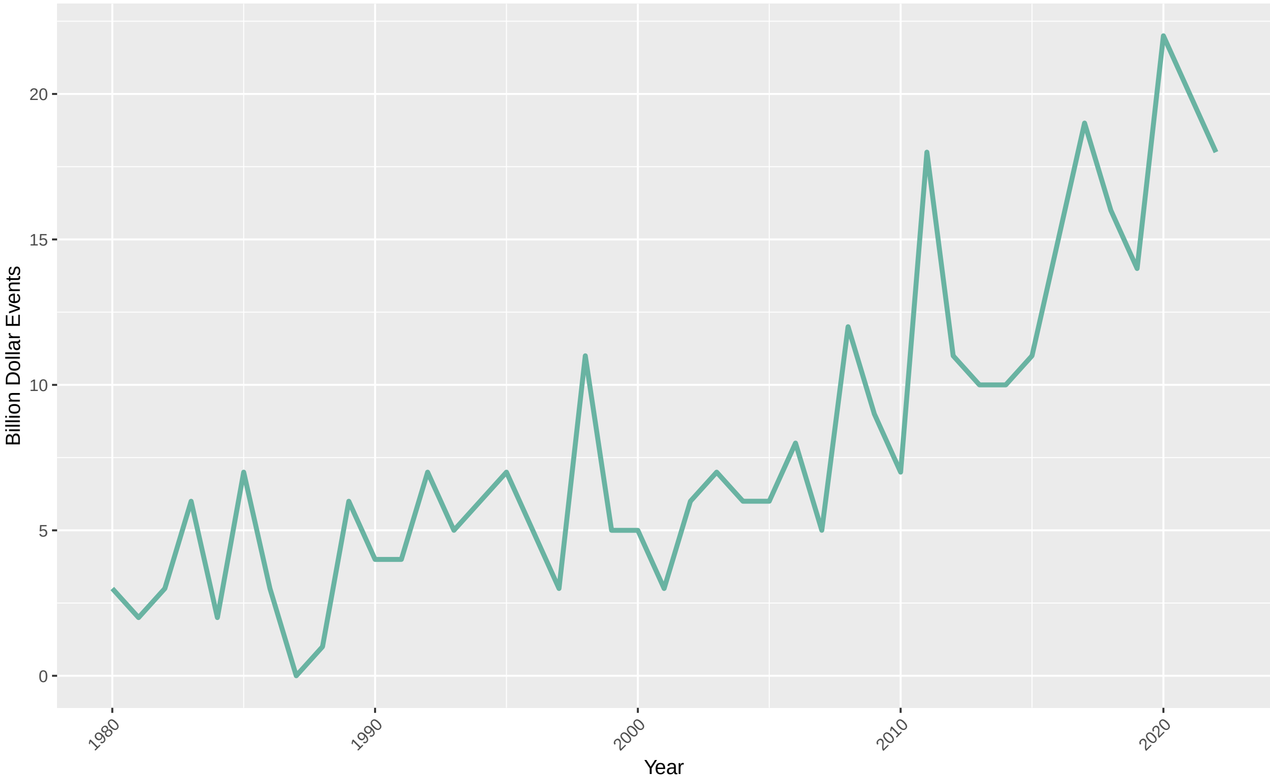

Figure 1: Time-Series of Billion Dollar Events between 1980 and 2022

This figure illustrates the number of billion-dollar weather and climate events in the U.S. We observe that the number of such events has continously increased over the period from 1980 to 2022. During 2022, eighteen separate billion-dollar disaster events were observable. These included among others: eleven storm events and three tropiclal cyclones (National Oceanic and Athmospheric Administration, 2023).

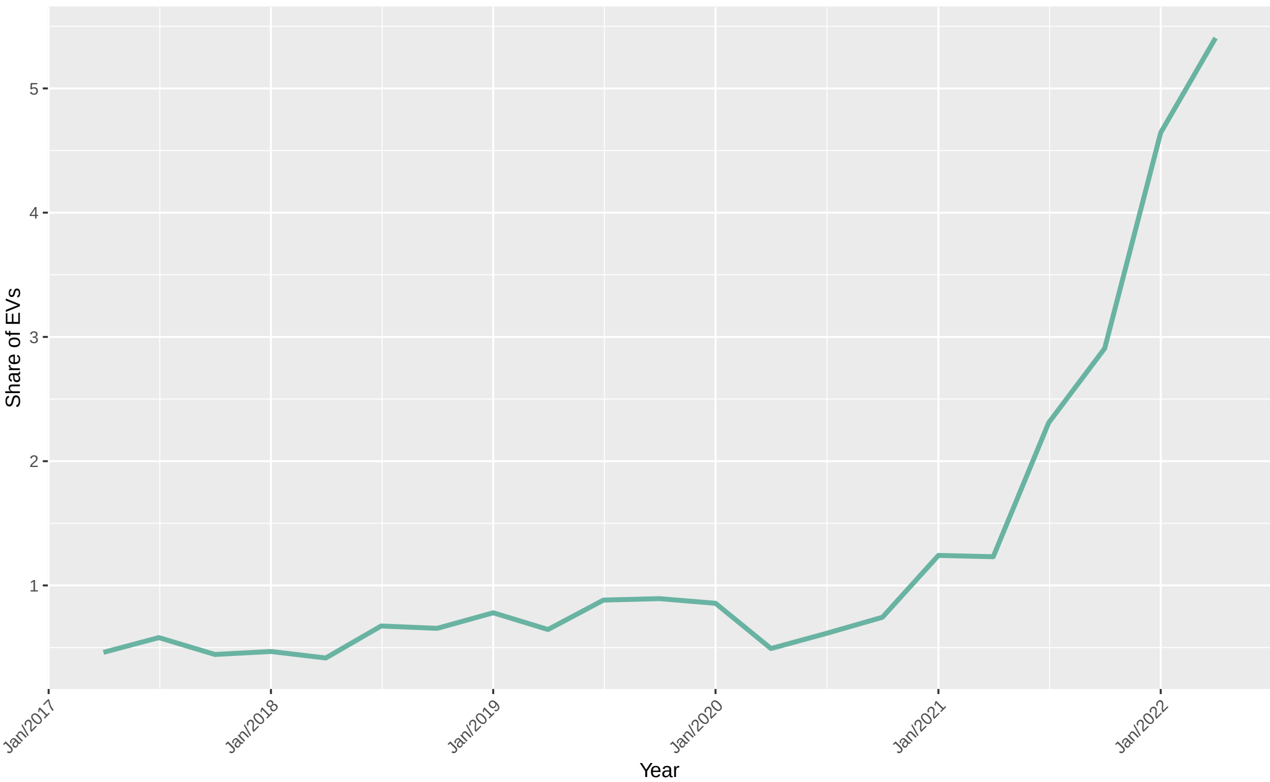

Figure 2: Time-Series of the share of EVs in India Between 2017 and 2022

The figure illustrates the mean share of EVs in newly registered vehicles across all Indian states. We observe that from Q4 2020 onwards, the share has increased continously and steeply. During the course of 2022, the share of EVs crossed the five percent threshold (Ministry of Road Transport & Highways, n.d.).

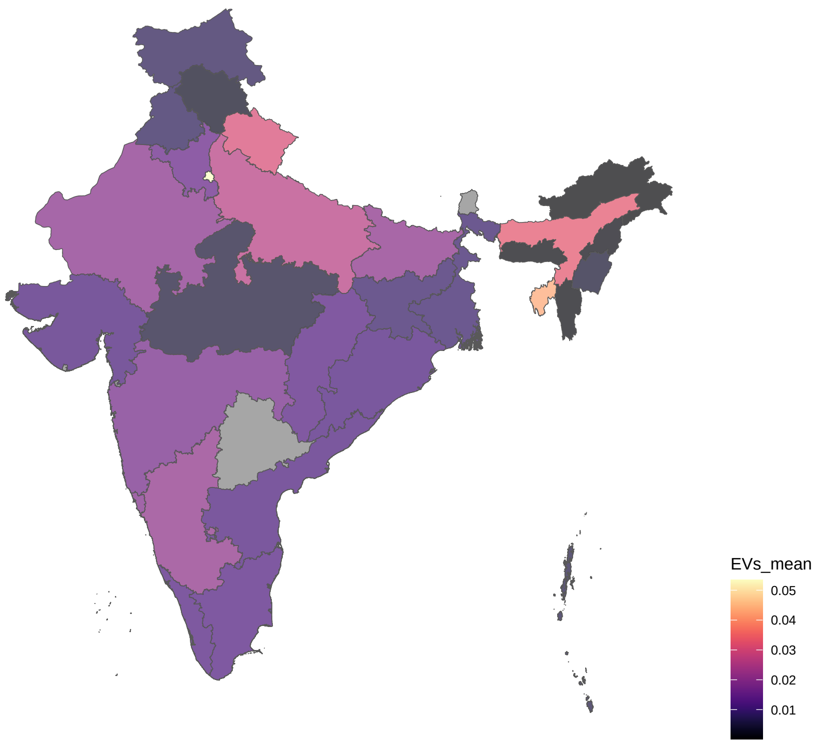

Figure 3: Geographic distribution of the mean share of EVs

The heatmap shows the mean share of EVs across all Indian states and years. It appears that this measure tends to be higher in states that are located in the north of the country while there are no clear outliers observable (Ministry of Road Transport & Highways, n.d.).

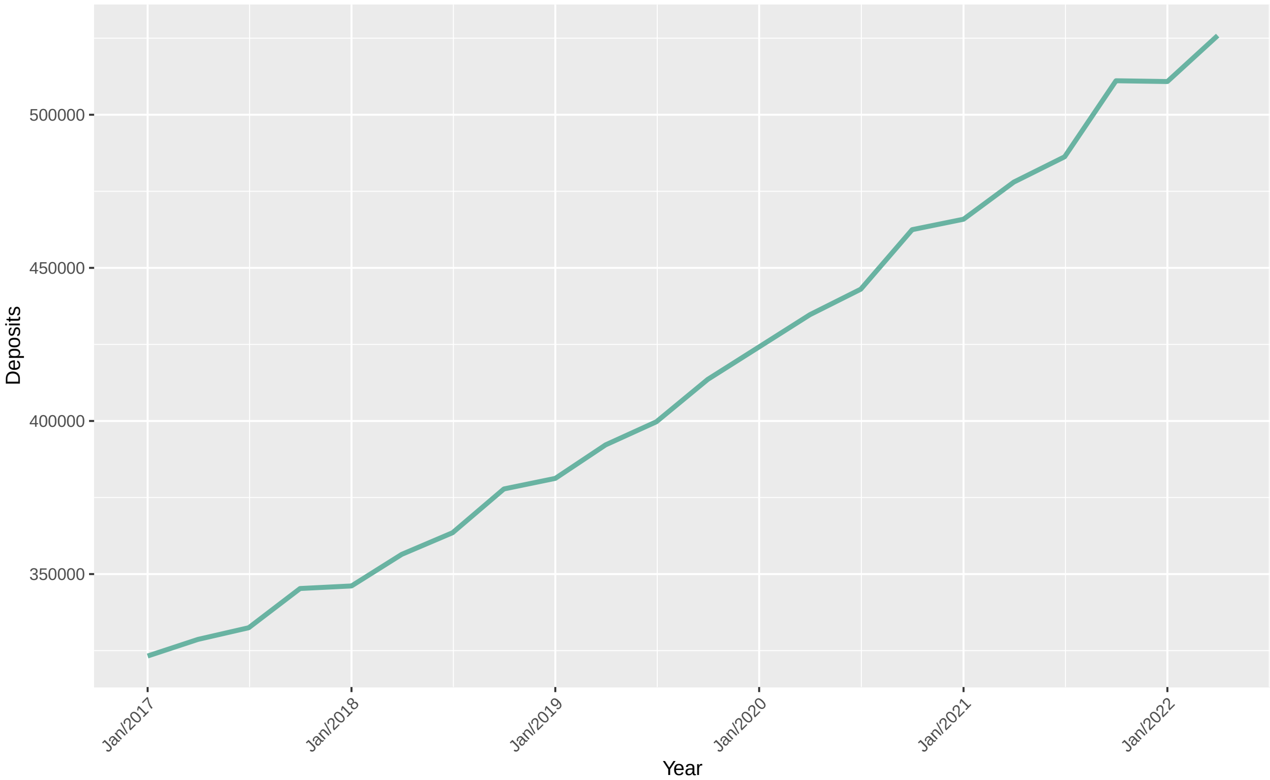

Figure 4: Time-Series of the mean number of deposits between 2017 and 2022

The figure illustrates the mean amount of liquid deposits across all Indian states. We observe that the amount grew steadily throughout the whole period. We consider nominal deposits (Reserve Bank of India, 2023a).

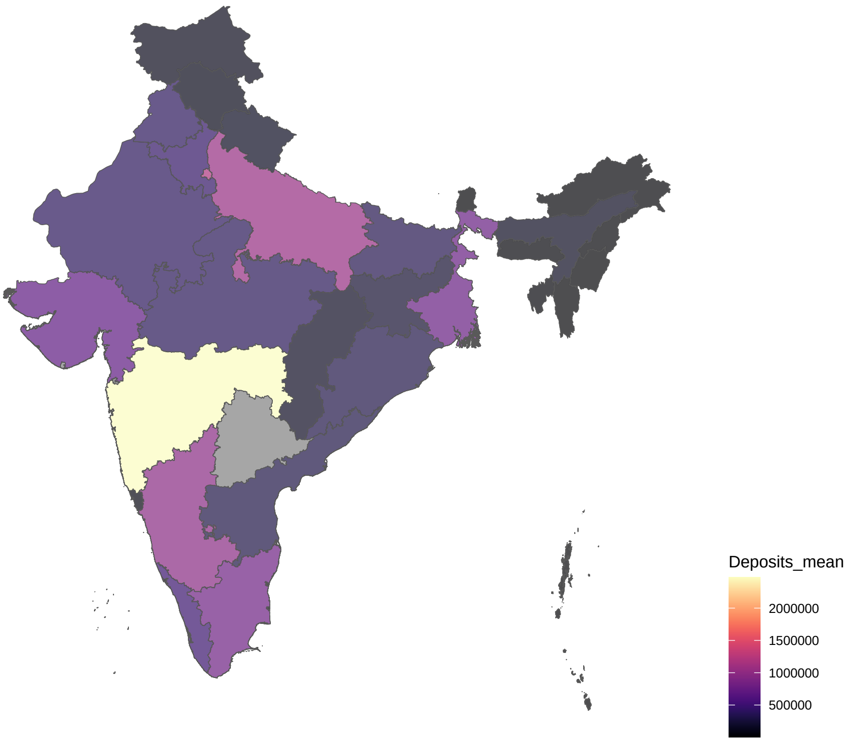

Figure 5: Geographic distribution of the mean amount of liquid deposits

The heatmap presents the mean amount of deposits in each Indian state and years. Especially the state Maharashtra stands out due to a relatively high amount of deposits. We assign this to the fact that the capital of the state, Mumbai, is the largest financial hub in India. Besides that there are no clear geographic trends observable when it comes to the geographic distribution of liquid deposits (Reserve Bank of India, 2023a).

Table 2: Descriptive Statistics

The table presents the sample descriptive statistics for all variables in our data. For each variable, the number of observations, mean, standard deviation, median as well as the P25/P75 percentile are presented. In the models used to determine coefficient estimates, we use a lower number of observations because not all variables were reported for the same states. Thus, observations were lost when merging all data. We also use logarithms for *Share EVs*, *Deposits* and *NTL* for our regression models. This is based on non-normality in the data, i.e. the data is right skewed in all cases. However, in this table the actual values are presented. All variables are defined in Table A14.

	N	Mean	SD	Median	P25	P75
EVs	708	2,590.26	5,776.94	416.50	27.00	2,085.75
Petrols	708	143,216.61	161,665.79	104,374.50	9,301.50	227,137.50
Share EVs	708	1.51	2.34	0.42	0.07	1.92
Deposits	704	413.76	563.40	195.35	24.76	526,64
Banks	928	4,309.92	4,291.75	2,924.50	381.50	7,025.25
Temperature	506	3.22	33.64	-3.24	-0.11	0.06
Petrol	720	82.98	13.47	78.41	72.1	96.01
NTL	816	0.89	1.09	0.53	0.43	0.78
Households	216	8,647.50	10,940.61	3,783.07	448.05	12,818.80

Table 3: Effects of liquid deposits on the share of EVs - full sample

This table depicts OLS regression coefficient estimates showing the effects of the amounts of liquid deposits on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the logarithm of the amount of deposits denoted in thousand crores Indian Rupees. The sample period is Q1 2017 to Q2 2022. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(Deposits)	7.802***	8.287***	8.293***	4.646***	5.191***
	(0.316)	(0.476)	(0.476)	(0.917)	(0.956)
Banks		−0.0003	−0.0003	−0.00001	0.00002
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Temperature			−0.002	−0.002	−0.002
			(0.002)	(0.002)	(0.002)
Petrol				0.0005***	0.0004***
				(0.0001)	(0.0001)
Log(NTL)					−0.482+
					(0.251)
Observations	359	359	359	359	359
Adjusted R^2	0.623	0.624	0.625	0.646	0.649

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 4: Effects of liquid deposits on the share of EVs - Q1 2017 to Q4 2020

This table depicts OLS regression coefficient estimates showing the effects of the amounts of liquid deposits on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the logarithm of the amount of deposits denoted in thousand crores Indian Rupees. The sample period is Q1 2017 to Q4 2020. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(Deposits)	5.682^{***}	4.180^{***}	4.182^{***}	2.714^{**}	2.939^{**}
	(0.446)	(0.696)	(0.683)	(0.936)	(0.940)
Banks		0.001^{**}	0.001^{**}	0.001^{**}	0.001^{***}
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Temperature			-0.005^{**}	-0.004^{**}	-0.004^{**}
			(0.002)	(0.002)	(0.002)
Petrol				0.0003^{*}	0.0003^{*}
				(0.0001)	(0.0001)
Log(NTL)					-0.400^{+}
					(0.234)
Observations	234	234	234	234	234
Adjusted R^2	0.380	0.399	0.422	0.433	0.438

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 5: Effects of liquid deposits on the share of EVs - Q4 2020 to Q2 2022

This table depicts OLS regression coefficient estimates showing the effects of the amounts of liquid deposits on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the amount of deposits denoted in thousand crores Indian Rupees. The sample period is Q4 2020 to Q2 2022. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(Deposits)	14.637***	14.440***	14.476***	9.664**	9.785**
	(1.258)	(1.634)	(1.659)	(3.276)	(3.284)
Banks		0.0002	0.0003	0.0002	0.0002
		(0.001)	(0.001)	(0.001)	(0.001)
Temperature			−0.0003	−0.00004	−0.001
			(0.002)	(0.002)	(0.002)
Petrol				0.0004+	0.0003
				(0.0002)	(0.0002)
Log(NTL)					−0.351
					(0.419)
Observations	125	125	125	125	125
Adjusted R^2	0.486	0.481	0.477	0.486	0.484

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 6: Effects of liquid deposits on the share of EVs - lower 33rd percentile of liquid deposits per household

This table depicts OLS regression coefficient estimates showing the effects of the amounts of liquid deposits on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the amount of deposits denoted in thousand crores Indian Rupees. The sample period is Q1 2017 to Q2 2022. The sub-sample is restricted to the observations included in the lower 33rd percentile of liquid deposits per household, i.e. total liquid deposits in a given state and quarter divided by the number of household in the respective state and quarter. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(Deposits)	5.966***	7.234***	7.196***	0.825	1.335
	(0.457)	(1.317)	(1.322)	(1.661)	(1.837)
Banks		−0.001	−0.001	0.0002	0.0002
		(0.001)	(0.001)	(0.001)	(0.001)
Temperature			−0.002	−0.002	−0.003
			(0.003)	(0.002)	(0.003)
Petrol				0.001***	0.001***
				(0.0001)	(0.0002)
Log(NTL)					−0.324
					(0.493)
Observations	120	120	120	120	120
Adjusted R^2	0.575	0.576	0.573	0.662	0.661

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 7: Effects of liquid deposits on the share of EVs - middle 33rd percentile of liquid deposits per household

This table depicts OLS regression coefficient estimates showing the effects of the amounts of liquid deposits on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the amount of deposits denoted in thousand crores Indian Rupees. The sample period is Q1 2017 to Q2 2022. The sub-sample is restricted to the observations included in middle 33rd percentile of liquid deposits per household, i.e. total liquid deposits in a given state and quarter divided by the number of household in the respective state and quarter. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(Deposits)	9.091***	7.885***	7.885***	5.048*	5.067*
	(0.679)	(0.924)	(0.930)	(2.015)	(2.045)
Banks		0.001+	0.001+	0.001*	0.001*
		(0.0004)	(0.0004)	(0.0005)	(0.0005)
Temperature			0.00002	0.0002	0.0001
			(0.003)	(0.003)	(0.003)
Petrol				0.0004	0.0004
				(0.0002)	(0.0002)
Log(NTL)					−0.032
					(0.502)
Observations	119	119	119	119	119
Adjusted R^2	0.590	0.599	0.595	0.601	0.597

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 8: Effects of liquid deposits on the share of EVs - top 33rd percentile of liquid deposits per household

This table depicts OLS regression coefficient estimates showing the effects of the amounts of liquid deposits on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the amount of deposits denoted in thousand crores Indian Rupees. The sample period is Q1 2017 to Q2 2022. The sub-sample is restricted to the observations included in the higher 33rd percentile of liquid deposits per household, i.e. total liquid deposits in a given state and quarter divided by the number of household in the respective state and quarter. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(Deposits)	9.210^{***}	9.860^{***}	9.899^{***}	5.676^{***}	6.941^{***}
	(0.477)	(0.611)	(0.610)	(1.549)	(1.554)
Banks		-0.001^{+}	-0.001^{+}	-0.00001	-0.0001
		(0.0004)	(0.0004)	(0.0005)	(0.0004)
Temperature			-0.003	-0.002	-0.003
			(0.002)	(0.002)	(0.002)
Petrol				0.0005^{**}	0.0003^{*}
				(0.0002)	(0.0002)
Log(NTL)					-0.856^{**}
					(0.288)
Observations	120	120	120	120	120
Adjusted R^2	0.753	0.757	0.759	0.775	0.790

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 9: Effects of the number of banking centers on the share of EVs

This table depicts OLS regression coefficient estimates showing the effects of the number of banking centers on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the number of banking centers denoted as an actual number. The sample period is Q1 2017 to Q2 2022. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Banks	0.003***	−0.0003	−0.0003	−0.00001	0.00002
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(Deposits)		8.287***	8.293***	4.646***	5.191***
		(0.476)	(0.476)	(0.917)	(0.956)
Temperature			−0.002	−0.002	−0.002
			(0.002)	(0.002)	(0.002)
Petrol				0.0005***	0.0004***
				(0.0001)	(0.0001)
Log(NTL)					−0.482+
					(0.251)
Observations	359	359	359	359	359
Adjusted R^2	0.289	0.624	0.625	0.646	0.649

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 10: Effects of temperature changes on the share of EVs

This table depicts OLS regression coefficient estimates showing the effects of changes in temperature on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable are temperature changes denoted as a percentage. The sample period is Q1 2017 to Q2 2022, however, the sample is restricted to observations that lie above the country median. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Temperature	-0.002	-0.004	-0.004	-0.003	-0.003
	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)
Log(Deposits)		8.276^{***}	8.942^{***}	5.356^{***}	5.414^{***}
		(0.464)	(0.694)	(1.346)	(1.495)
Banks			-0.0005	-0.0002	-0.0002
			(0.0004)	(0.0004)	(0.0004)
Petrol				0.0005^{**}	0.0004^{*}
				(0.0001)	(0.0002)
Log(NTL)					-0.044
					(0.486)
Observations	187	187	187	187	187
Adjusted R^2	-0.113	0.617	0.618	0.637	0.635

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 11: Effects of petrol prices on the share of EVs

This table depicts OLS regression coefficient estimates showing the effects of petrol prices on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable are petrol prices denoted in Indian Rupees. The sample period is Q1 2017 to Q2 2022. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Petrol	0.001***	0.0005***	0.0005***	0.0005***	0.0004***
	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Deposits)		4.598***	4.627***	4.646***	5.191***
		(0.728)	(0.728)	(0.917)	(0.956)
Temperature			−0.002	−0.002	−0.002
			(0.002)	(0.002)	(0.002)
Banks				−0.00001	0.00002
				(0.0003)	(0.0003)
Log(NTL)					−0.482+
					(0.251)
Observations	359	359	359	359	359
Adjusted R^2	0.606	0.647	0.647	0.646	0.649

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 12: Effects of variability in night-time lights on the share of EVs

This table depicts OLS regression coefficient estimates showing the effects of variability in night-time lights on the share of EVs in newly registered vehicles. The dependent variable is the logarithm of the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the logarithm of the standardized standard deviation of night-time light radiation. The sample period is Q1 2017 to Q2 2022. Heteroskedasticity consistent standard errors are reported in parentheses. All variables are defined in Table A14.

	Dependent variable:				
	Log(Share EVs)				
	(1)	(2)	(3)	(4)	(5)
Log(NTL)	-0.554	-0.790^{***}	-0.854^{***}	-0.480^{+}	-0.482^{+}
	(0.389)	(0.230)	(0.232)	(0.250)	(0.251)
Log(Deposits)		7.845^{***}	7.864^{***}	5.230^{***}	5.191^{***}
		(0.311)	(0.310)	(0.790)	(0.956)
Temperature			-0.003^{+}	-0.002	-0.002
			(0.002)	(0.002)	(0.002)
Petrol				0.0004^{***}	0.0004^{***}
				(0.0001)	(0.0001)
Banks					0.00002
					(0.0003)
Observations	359	359	359	359	359
Adjusted R^2	-0.050	0.635	0.637	0.650	0.649

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 13: Effects of liquid deposits on the share of EVs *in Brazil*

This table depicts OLS regression coefficient estimates showing the effects of liquid deposits and control variables, including petrol prices and the standardized standard deviation of night-time lights as an approximation for grid outages on the share of EVs in newly registered vehicles in Brazil. The dependent variable is the share of EVs in newly registered vehicles denoted as a percentage. The key independent variable is the amount of liquid deposits in Brazil. The sample period is Q1 2014 to Q4 2022. Heteroskedasticity consistent standard errors are reported in parentheses. More details are provided in Appendix B.

	Dependent variable:		
	Share EVs		
	(1)	(2)	(3)
Deposits	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)
Petrol		0.074	0.075
		(0.055)	(0.055)
NTL			−0.079
			(0.504)
Observations	108	108	108
Adjusted R^2	0.095	0.103	0.094

Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table A14: Variable Definitions

Variable	Description
EVs	EVs depicts the number of newly registered electric vehicles in India. These include all vehicles from E2Ws to E4Ws. Data was retrieved on a state level and in monthly resolution and is presented as an actual number.
Petrols	Petrols depicts the number of newly registered petrol powered vehicles in India. Data was retrieved on a state level and in monthly resolution and is presented as an actual number.
Share EVs	Share EVs represents the share of electric vehicles in newly registered vehicles. Diesel powered cars have been excluded due to high correlation between diesel and petrol prices. Data was computed on a state level and in monthly resolution and is denoted in percent.
Deposits	Deposits are all current and savings deposits to represent household liquidity. Term deposits have been excluded as they do not represent liquid deposits. Data was obtained on a state level and in quarterly resolution in India and is denoted in ten billion Indian Rupees.
Banks	Banks represents the total number of banking centers in India. Data was obtained on a state level and in quarterly resolution and is presented as an actual number.
Temperature	Temperature depicts changes in temperature in India. Data was obtained on a state level and in monthly resolution and is denoted in percent.
Petrol	Petrol represents petrol prices in India. Data was obtained on a state level and in monthly resolution and is denoted in Indian Rupees.
NTL	NTL depicts the standardized standard deviation of night-time light radiance in India. Data was obtained on a pixel level and in monthly resolution.
Households	Households is the total number of households in India and was computed by dividing the total population by the average number of persons in an Indian household. Data was obtained on a state and year level and is presented as an actual number.

B External Validation

In this section, we will provide more details on the data that was used for external validation. For this purpose, we chose Brazil as it also belongs to the so-called BRIC states which include Brazil, Russia, India and China and we expect that these countries offer comparatively similar prospects for the implementation of EVs. Furthermore, the share of EVs in newly registered vehicles has evolved relatively similar compared to India. We include explanatory variables that we have found to have an impact on the share of EVs in India, meaning deposits, petrol prices and night-time light radiation. Data was generally obtained on a country level.

To ensure comparability, we gathered data for EVs and petrol powered ICEs in Brazil to compute the share of EVs in newly registered vehicles. The Associação Brasileira do Veículo Elétrico (2023) published monthly data on the newly registered EVs in Brazil since the beginning of 2012 until May 2023. Data for petrol powered vehicles was obtained from Brazilian Association of Automotive Vehicle Manufacturers (n.d.) which publishes the number of newly registered vehicles from January 1957 to May 2023 including different vehicle types. For the purpose of our analysis, we considered the sum of all vehicle classes as no differentiation was made for EVs either. When computing the share of EVs in newly registered vehicles, we observe a similar pattern as in India. The share is relatively flat and below one percent, but starts increasing greatly in 2020. Looking at Table A15, we see that the mean share of EVs is 0.75% with a standard deviation of 0.97. Even though the data is right skewed, we refrained from using logarithms as the skewness coefficient is low.

The data for liquid deposits in Brazil was obtained from International Monetary Fund (n.d.) which publishes monthly data for different economic indicators for Brazil. We obtained data from January 2014 to March 2023. For the purpose of our analysis, we chose *Broad Money* as an indicator. Even though the latter does not perfectly resemble household liquidity, it includes among others deposits with short-term maturities in an economy (OECD, n.d.) and is therefore used as a proxy for liquid deposits by us. We convert the data to billion Brazilian Real for our analysis and consider nominal amounts as prices for EVs must be paid at nominal levels. From Table A15, we learn that the mean amount of deposits is 6,830.53 billion Brazilian Real with a standard deviation 1,829.64 billion Brazilian Real. Similar to the amount of liquid deposits in India, the level of deposits also rose continously over the years in Brazil. As the data is only minimally skewed, we refrain from using logarithms.

Agência Nacional do Petróleo e Gás Natural e Biocombustíveis (2023) published prices for different fuels from January 2013 to May 2023. We consider solely petrol prices to be consistent with the computation of the share of EVs. These are denoted in Brazilian Real per litre. While the global soaring of fuel prices was also observable in Brazil, current prices declined to 2018 levels again. Table A15 depicts a mean price for petrol of 4.35 Brazilian Real with a standard deviation of 1.08 Brazilian Real. The prices are again only minimally skewed which is the rationale why we deem refraining from using logarithms appropriate.

As for India, NASA (2023) also published data on night-time lights for Brazil. We follow the same procedure as described above to compute the standardized standard deviation of night-time lights to approximate grid outages, however, compute the values on a country level. Due to the longer time horizon, i.e. January 2014 to December 2022, and Brazil's size, data in the amount of roughly 25 gigabyte is obtained. As shown in Table A15, we see that the standardized standard deviation of night-time lights have a mean of 0.73 and a standard deviation of 0.05. The data is only minimally skewed.

The following table presents the descriptive statistics of the aforementioned data used for external validation.

Table A15: Descriptive Statistics (External Validation)

The table presents the sample descriptive statistics for all variables used for external validation. For each variable, the number of observations, mean, standard deviation, median as well as the P25/P75 percentile are presented. The number of observations is similar as data was only obtained for the time period between January 2014 and December 2022. While the values for *Share EVs* is denoted in percent, *Deposits* are denoted in billion Brazilian Real and *Petrol* in Brazilian Real. A detailed description of the variables can be found in Appendix B.

	N	Mean	SD	Median	P25	P75
Share EVs	112	0.75	0.97	0.16	0.04	0.99
Deposits	112	6,830.53	1,829.64	6,357.15	5,414.20	8,162.26
Petrol	112	4.35	1.08	4.21	3.63	4.60
NTL	112	0.73	0.05	0.73	0.70	0.77