Does EV Increase Labor Productivity? Evidence from the States of the USA

By

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Master of Science in Applied Economics

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Declaration

It is hereby declared that

1. The thesis submitted is my original work while completing degree at BRAC University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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Abstract

This study analyzes the causal relationship between electric vehicle (EV) adoption and labor productivity across the U.S. states from 2016-2023. The presented analyses establish a robust positive influence of EV adoption on labor productivity using pooled OLS, fixed effects models, Lewbel GMM, Oster Test and Blinder-Oaxaca decomposition. The outcome of the regional analysis indicates that there is a high level of heterogeneity, i.e. Southern states have productivity deficits that are caused by unobserved institutional factors, and Western states have better resource endowments. On the other hand, the channel analysis on the racial disparities reveals that the states with higher populations of minorities face considerable barriers to EV adoption, especially post-2020. However, these states seem to have comparable productivity due to better resource utilization. Moreover, environmental quality is used as a mediating variable with carbon emission having a negative relationship with productivity. These results provide valuable insights for policymakers who want to foster the adoption of Electric Vehicles and reduce regional and demographic barriers to EV adoption.

Keywords: Electric Vehicle; EV; Labor Productivity.

Dedication

This thesis is dedicated to the memory of my late grandmother. Her unwavering love, support, and prayers have been a constant source of strength and inspiration throughout my life.

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First and foremost, I am deeply grateful to Allah, the Most Merciful, for granting me the strength, patience, and guidance to complete this thesis. Without His boundless blessings, this journey would not have been possible.

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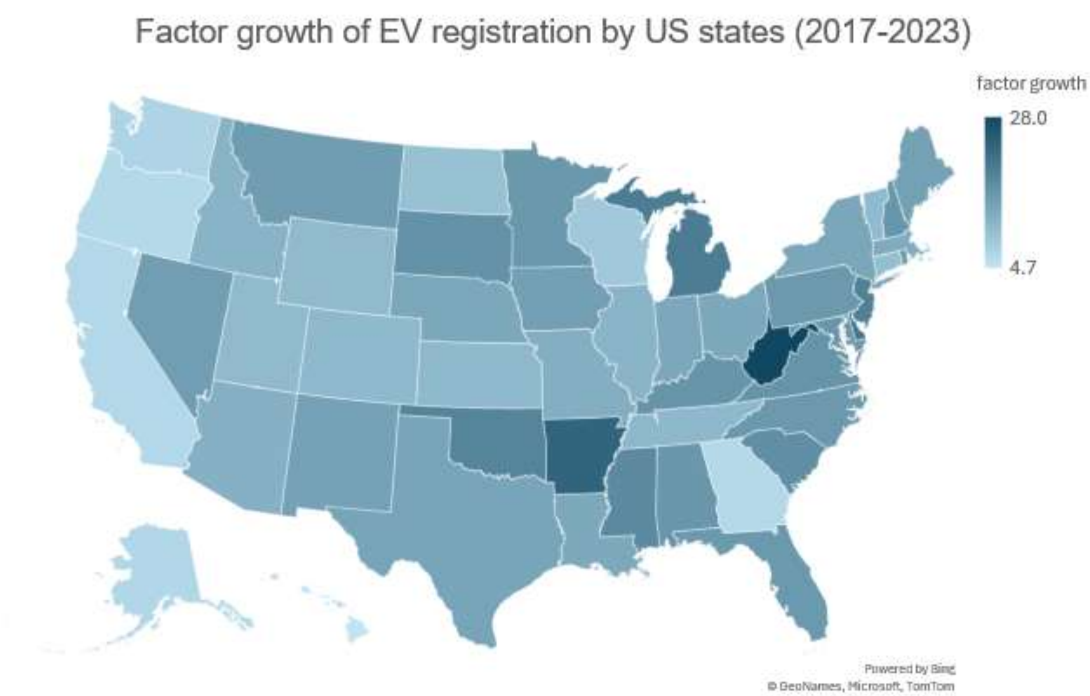
1. Introduction

The transportation sector around the world is seeing a transformation as countries all around the world are struggling to combat the devastating effects of climate change. They are increasingly adopting electric vehicles in order to reduce the harmful effects of greenhouse gas and dependence on fossil fuel, with an aim to make the mediums of transport carbon-free (Qadir, Ahmad et al., 2024). In order to increase EV adoption, countries are providing lucrative incentives to their people. For example, federal income tax credits on the purchase of new electric vehicles (EVs) have been adjusted to between 2,500 and 7,500 dollars based on the battery capacity and gross weight of vehicles (Internal Revenue Service, 2022) to ensure that the US attains a net-zero emission by 2050 (Fam & Fam, 2024). States, too, are offering both financial and non-financial incentives such as tax exemptions, rebates, opportunities to use high-occupancy vehicle (HOV) lanes, reduced toll fees, and free parking in certain states (Xing et al., 2021). According to the Argonne National Laboratory (2024), over 1.4 million plug-in electric vehicles (PEVs) were sold in 2023, and it was more than 50 percent compared to 2022. Figure 1 demonstrates the factor growth of EV registration by US states from 2017 to 2023, with values ranging from 4.7 to 28.

Figure 1: Factor growth of EV registration by US states (2017 – 2023)



While numerous studies have explored the economic impact of subsidies and incentives on EV market growth, the cost-benefit dynamics of environmental externalities, and the implications of EV adoption on energy markets and job creation, there remains a significant gap in the literature regarding the relationship between EV consumption and labor productivity. This study investigates the relationship between EV adoption and productivity of the workers across all 50 US states using panel data from the years 2016 to 2023 to illuminate on the economic impacts of a more sustainable transport system. Figure 2 shows the percentage growth of labor productivity by US states where we can see that some of the states have faced negative productivity growth as low as -2.6% while some have experienced tremendous growth of 25%.

Figure 2: Percentage growth of labor productivity by US states

The findings of the study strongly support the hypothesized relationship as it finds a statistically significant causal relationship between EV Consumption and labor productivity in the USA. The results remain robust across alternative model specifications, econometric methodologies, and controls for potential endogeneity. In order to ensure consistency and reliability of the findings, econometric tools such as pooled OLS, FE and heteroskedasticity-based Lewbel GMM estimations, Blinder Oaxaca decomposition and channel analyses have been employed. The robust outcomes of these methods reinforce that there is a cause-effect relationship between the consumption of EV and employee productivity. And it indicates that the adoption of EVs can enhance labor productivity, environmental sustainability, and economic growth of U.S. states in the long term.

The remainder of the thesis is structured in the following manner: Chapter 2 provides a literature review of electric vehicle and labor productivity as well as formulates testable hypotheses on the relationship between EV adoption and labor productivity. Chapter 3 describes the data sources, variable construction, and methodology of the study. Chapter 4 outlines the statistical model of pooled OLS, fixed effects, instrumental variables, robustness test and decomposition analysis used in this study. Chapter 5 presents an interpretation of regression results, consisting of baseline estimates, robustness tests, geographical decomposition and channel analysis of racial inequalities, infrastructure type and environmental channels. Chapter 6 summarizes the findings, identifies limitations and suggests directions for future research. Finally, Chapter 7 concludes the paper with policy recommendations.

2. Literature Review

EV adoption is gaining significant public interest these days because of its potential to combat climate change and provide sustainability. As a result, the US population are shifting their preference from traditional combustion engine-based vehicles to EV. However, the introduction of this novel technology has raised significant social, economic, and legal concerns. Scholars have influenced the literature debate connecting EV uptake with a number of socio-economic aspects due to concerns regarding long-term socio-economic impacts. The majority of the electric vehicle literature has focused mostly on the effects of EV adoption on the environment and on the market. However, existing research has studied EV adoption and labor productivity separately, and as a result, there remains a clear lack of studies directly exploring the relationship between EV registration and labor productivity.

EVs have significant positive impacts on the environment in comparison to their traditional counterpart, and studies by Javadnejad et al. (2023) and Bibra et al. (2021) demonstrate that EVs are infinitely more efficient, transforming more than 85 percent of energy into motion, unlike the 20-30 percent of ICE-based vehicles. This increased efficiency decreases the reliance on oil-based fuels and significantly reduces greenhouse gas emissions, especially by using energy from low-carbon sources. Moreover, the absence of tail pipe emissions in EVs makes them more environmentally friendly and sustainable as an alternative to the traditional ones. This is also supported by He et al. (2019), who compared the environmental and economic advantages of EV in China, the U.S., and Germany. Their experiment indicates that although the regional data differ in terms of average fuel prices, driving behaviors, and subsidies, EV adopters nonetheless attain significant greenhouse gas savings (32%-63%). The study highlights the need to lower the battery prices (under 100/kWh) and provide diverse types of EVs to facilitate large scale adoptions. Furthermore, Sinton et al. (2024) cite that EVs have a well-to-wheel life-cycle emission that is 10-41% lower than that of ICE vehicles. However, according to Bas et al. (2023), adoption requires governmental policy, infrastructure, and the economics of the market, even though EVs have a direct impact on the reduction of carbon emissions. Zhu et al. (2023) conclude that renewable energy is the best way to maximize the advantages of EV, whereas coal-intense systems and uncontrolled charging constrain these advantages. Therefore, grid decarbonization, battery technologies, and charging systems need to be prioritized in order to leverage the full potential of EVs.

Subsidies, pricing strategies, and broader policy incentives play a significant role in shaping both consumer behavior and market growth. Muehlleger and Rapson (2022) discovered that between 80 and 92 percent of California EV subsidies were transferred to consumers, that raised demand in response to 10 percent price reductions by 31 to 37 percent. Also, a structural model of the EV market in Norway by Springel (2021) compares direct purchase subsidies to the charging infrastructure subsidy in an attempt to demonstrate the multidimensionality of governmental support for EV adoption. Overall, Xing et al. (2021) observed that regular subsidies only help people who would still purchase an EV regardless of these subsidies, which reduces the government's purpose of providing these subsidies. Hence, they suggest income-dependent incentives for low-income households and purchasers of less fuel-productive vehicles to decrease emissions and make these households more equitable and EVs more affordable.

More studies by Li et al. (2023) indicate that there is a complex connexion between consumer anxiety, environmental benefits, and subsidies. Their analytical model demonstrates that EV sales need subsidies, yet the amount depends on financial stimulation and consumer interests concerning

EV behavior and the environment. According to Wee et al. (2018), state-level policy interventions, such as a $1000 rise in model-specific EV subsidies, can boost registrations by 5 percent to 11 percent and they emphasized the necessity of specific financial policies. Yu et al. (2022) also suggest that the collaboration between the government and car manufacturers should be used to subsidize EV charging stations which are, in fact, less expensive to subsidize compared to automaker subsidies. Forsythe et al. (2023) notes that technological progress such as reduced operating costs, acceleration, and efficient charging is the primary driver of EVs demand in the U.S., which makes the market more technology-driven, not market-driven. Lastly, Yu et al. (2024) discovered that the proportion of Zero Emission Vehicles (ZEVs) was 3.8 times higher in non-disadvantaged communities in California compared to the disadvantaged communities, which indicates that the policymakers should also focus on regional disparities to implement EV adoption.

Consumers' decisions on whether to adopt EV or not are affected by financial incentives, charging infrastructure, psychological aspects, and personal preferences. Sierzchula et al. (2014) state that the market share of EVs is affected by financial incentives, local production facilities and charging infrastructure, and the latter is most significant. However, they caution that no amount of money or infrastructure alone can guarantee high EV adoption rates. Hasan (2021) investigates cost, range, recharge option, policies, environmental utility, symbolic importance, and the model availability effects of consumer satisfaction and EV repurchase intentions in a survey-based research on the EV market in Norway. Gong et al. (2020) label the main factors that promote EV adoption as car characteristics, potential governmental support, and market share, highlighting the complexity of consumer decision-making.

Consumers' preferences are also influenced by their regional differences. According to Zhao et al. (2022), younger customers (31-40), people who have high income and education, and urban residents in Shanghai tend to use EVs, whereas larger families avoid it. Other adoption determinants mentioned by Bhat and Verma (2023) included personality, social influence, finances, and infrastructure. Javadnejad et al. (2023) also note that high initial costs, short range, and battery life issues remain the reasons why EVs have not been widely adopted despite incentives and infrastructure enhancements. This highlights the fact that targeted policies and strategies are needed to address such obstacles and enhance the adoption of EVs.

Technology and infrastructure, as well as the market forces, have encouraged the adoption of electric vehicles. Zheng et al. (2024) discovered that the California electric vehicle charging stations (EVCS) raised nearby business expenditure by 1.4 percent in 2019 and 0.8 percent between January 2021 and June 2023. Businesses located within 100 meters of EVCS experience an increase in spending by 2.7% in 2019 and 3.2% in later periods. Corradi et al. (2023) assessed the conversion of electric mobility from a multi-level perspective and focused on infrastructure. They discovered that social status, environmental advantages, and the new business opportunities that electric mobility introduces are causing consumers, industry players, policymakers, and civil society to switch in favor of EVs, who were traditionally resistant to this change.

Technological advancements such as improved battery efficiency and rapid charging capabilities, i.e., the technologies that improve EV performance, also influence Ev adoption. Tzeng et al. (2025) applied the social practice theory to explain the adoption and uptake of EVs in seven large Chinese cities and discovered that power, acceleration, cost, environmental gains, and subsidies influenced the replacement of ICEVs with EVs. Analyzing policies implemented by U.S. states in the years 2012-2020, Mekki et al. (2024) established that renewable energy and CO2 emission policies can boost the adoption of EVs, particularly in environmentally underperforming states. Archsmith et al. (2022) discovered that the U.S. EV demand is driven by intrinsic demand, reduction in battery costs, and subsidies. Their analysis also demonstrates the effects of regional predilection towards sedans and light vehicles and climate change convictions on the adoption of EVs. These works prove the influence of technological improvement and legislative packages on the development of the EV market.

Similar to Electric Vehicle adoption, numerous studies have been conducted over the past decades on labor productivity from multidimensional perspectives. For instance, Akaev and Sadovnichii (2021) have built a mathematical model of the labor productivity of the digital economy in the symbiosis of humans with intelligent machines (IM). They discovered that digital technologies increase production in the case of human labor being dominant in the human IM mix, whereas excessive involvement in programmable IM jobs reduces efficiency. This model predicts that developed economies can continue to grow labor productivity at rates of 3 percent in the mid-2020s to the 2040s. Nasir et al. (2023) examine the influences of technological innovation on labor productivity in 5 ASEAN countries Malaysia, Thailand, the Philippines, Vietnam, and Indonesia, between 2008 and 2018. The study indicates that there is a positive relationship between technology innovation and ASEAN labor productivity. Korkmaz and Korkmaz (2017) discovered that there was a unidirectional relationship between worker productivity and economic growth in seven OECD countries using panel data in the period between 2008 and 2014.

A significant amount of research has focused on electric vehicle adoption and labor productivity respectively, but limited studies have focused on the connection between EV registration and labor productivity. The environmental and market implications of electric vehicles or the factors influencing productivity expansion and efficiency of EV incentive programs have been the subject of literature research to date. It is on this solid yet patchy foundation of knowledge that this study attempts to identify whether an increase in the number of EV registered is correlated with increased labor productivity among U.S. states, holding other economic and environmental factors constant. This hypothesis predicts that the adoption of EV will enhance the sustainability and economic performance of the region.

3. Data and Methodology

The study employed secondary data from the following sources for all U.S. states from 2016 to 2023. Data on labor productivity were sourced from the Bureau of Labor Statistics (BLS). EV registration counts, total EV station counts, and private EV station counts were obtained from the Alternative Fuel Data Center (AFDC). State-level gross domestic product data were collected from Statista.com. Environmental variables such as PM2.5, ozone levels, and CO_2 were obtained from the U.S. Environmental Protection Agency (EPA). Data on political leaning were taken from CNN (2016, 2020). Finally, data on the share of the White population by state for 2016–2019 and 2021–2023 are based on the ACS 1-year estimates (U.S. Census Bureau, 2016, 2017, 2018, 2019, 2021, 2022, 2023). Data for some of the key variables were unavailable prior to 2016 and after 2023, which is why the analysis is limited to the 2016–2023 period.

4. Statistical Framework

4.1. Ordinary Least Squares (OLS)

The baseline econometric specification employs pooled OLS regression to estimate the relationship between EV adoption and labor productivity across U.S. states. The general form of the model is:

$$
\begin{aligned}
\text{Labor productivity} &\\
&= \alpha + \beta_1(\text{Ln EV Registration})_i + \beta_2(\text{EV Station})_i + \beta_3(\text{Ln State GDP})_i \\
&+ \beta_4(\text{Unemployment})_i + \beta_5(\text{Political Leaning})_i + \beta_6(\text{Ozone Level})_i \\
&+\beta_7(\text{PM}_{2.5})_i + \beta_8(\text{COVID Dummy})_i + \varepsilon_i \qquad (1)
\end{aligned}
$$

Labor Productivity is the dependent variable, which is output per hour worked at the state level. Ln EV Registration is the natural logarithm of electric vehicle registrations. The rationale behind using the logarithmic transformation is to tackle the highly skewed distribution of EV registration. EV Station measures the count of publicly accessible EV charging stations, representing the supporting infrastructure for electric mobility. Ln State GDP is the natural logarithm of state gross domestic product, controlling for the overall economic size and prosperity of the state. Unemployment captures labor market slack measured as the unemployment rate. Political Leaning is a binary variable with a 1 representing Democratic-leaning states and 0 representing Republican-leaning states, proxying for policy environments favoring environmental regulation and clean technology adoption. Ozone Level is defined as the concentration of ozone in the atmosphere (in parts per million) on the ground, which is one of the significant parameters of air quality and can have a negative impact on human health and even worker productivity. PM2.5 is a measure of the fine particulate matter (particles size 2.5 micrometers) concentrations in micrograms per cubic meter (mg/m3). COVID Dummy is a binary variable which is equal to one in 2020-2022 and represents the structural change in work organization and productivity caused by the pandemic. Finally, ϵi is the stochastic error term, which is assumed to have a normal distribution with zero mean and constant variance.

The pooled OLS estimator is used to estimate the relationship between EV adoption and productivity and is done by pooling the observations across all the available states and time. The coefficient β1 on Ln EV Registration captures the percentage change in labor productivity in response to 1 percent increase in EV registrations. As a logarithmic transformation has been applied to the key independent variable, it will be interpreted as a semi-elasticity. If both variables were to be logged, it would be interpreted as elasticity. However, pooled OLS estimates may suffer from omitted variable bias unless unobserved state-specific characteristics are controlled, as they can affect both EV adoption and labor productivity. For example, states that have superior institutional quality or higher human capital may exhibit higher EV adoption and greater productivity, which in turn would lead to upward bias in the OLS estimate. On the other hand, if states that face economic challenges adopt EVs as part of revitalization strategies, it might lead to a downward bias. As a result, more complex methods are required to establish unbiased causal relationships.

4.2. Lewbel (2012) Estimation

In order to mitigate potential endogeneity bias, this study has used Lewbel method, which is a heteroskedasticity-based instrumental variables approach developed by Lewbel in 2012. This method is usually used in the context where the external instruments (variables that may affect the endogenous regressor) are not included in the main equation or are difficult to justify.

The Lewbel estimator used two stage regression. In the first stage, it creates internal instruments based on the heteroskedasticity of the error term. The two-stage system is formulated as follows:

First Stage (Equation for the endogenous variable):

$$\text{Ln EV Registration} = Z\alpha + \nu \tag{2}$$

Second Stage (Main equation of interest):

$$\text{Labor Productivity} = Z\beta + \gamma\,(\text{Ln EV Registration}) + \varepsilon \tag{3}$$

In this system, Z is the vector of all exogenous variables, which include EV Station, Ln State GDP, Unemployment, Political Leaning, Ozone Level, PM 2.5, and COVID Dummy. The variable Ln EV Registration is treated as endogenous. Identification is achieved without the need for an explicit exclusion restriction, relying instead on two key assumptions:

$Cov(Z, \varepsilon\nu) = 0$: The exogenous variables are uncorrelated with the product of the structural and first-stage error terms. This is a standard exogeneity condition.

$Cov(Z, \nu^2) \neq 0$: The error term (ν) from the first-stage regression is heteroskedastic. This heteroskedasticity is used to generate instruments, typically of the form $(Z_i - \bar{Z})\,\hat{\nu}$, where $\hat{\nu}$ are the estimated residuals from the first stage.

For this model, the variable EV Station was used as the primary exogenous regressor to help identify Ln EV Registration. This study implements three alternative IV specifications to assess robustness. The Standard IV (2SLS) model uses EV charging station counts as an external instrument for EV registrations, based on the logic that infrastructure availability facilitates adoption but does not directly affect productivity except through enabling EV use. The Generated Instruments (Lewbel) model relies solely on internally constructed instruments from heteroskedasticity patterns among exogenous controls, including state GDP, unemployment, political leaning, air quality variables, and the COVID dummy. The Combined (Generated + External) model integrates both Lewbel-generated internal instruments and the external charging station instrument to potentially improve identification strength and efficiency.

Instrument validity is assessed through multiple diagnostic tests. The Kleibergen-Paap LM statistic tests under identification with the null hypothesis that the model is underidentified (instruments are irrelevant); rejection confirms the instruments are sufficiently correlated with the endogenous regressor. The Kleibergen-Paap Wald F statistic tests weak identification, with values exceeding Stock-Yogo critical values (typically 10 or higher) indicating strong instruments that avoid weak instrument bias. The Hansen J statistic tests overidentifying restrictions when multiple instruments are available, with failure to reject the null supporting the joint exogeneity of instruments.

4.3. Blinder-Oaxaca Decomposition

Blinder-Oaxaca decomposition has been used to assess potential heterogeneity in the relationship between EV adoption and labor productivity across regions and demographic groups. This method answers the question: "Is the productivity gap taking place due to the groups having different levels of characteristics (e.g., fewer EV stations), or because of their getting different returns from those same characteristics?" The method decomposes the mean outcome difference between two groups, Group A and Group B (for example, Southern versus non-Southern states, or states with higher versus lower minority populations), into two parts. Separate regressions have been estimated for each group:

$$Y_A = \alpha_A + X_A\beta_A + u_A \tag{4}$$

$$Y_B = \alpha_B + X_B\beta_B + u_B \tag{5}$$

where XA and XB are the vectors for explanatory variables and βA and βB are the corresponding coefficient vectors. The mean productivity difference can be decomposed as:

$$\bar{Y}_B - \bar{Y}_A = (\hat{\alpha}_B + \bar{X}_B\hat{\beta}_B) - (\hat{\alpha}_A + \bar{X}_A\hat{\beta}_A)$$

$$= \left[(\bar{X}_B - \bar{X}_A)\hat{\beta}^*\right] + \left[\bar{X}_B\left(\hat{\beta}_B - \hat{\beta}^*\right) + \bar{X}_A\left(\hat{\beta}^* - \hat{\beta}_A\right) + (\hat{\alpha}_B - \hat{\alpha}_A)\right] \tag{6}$$

The explained component shows the differences in productivity caused by the variations in observable characteristics, such as having better infrastructure or favorable economic conditions, between the two groups. On the other hand, the unexplained component captures differences in how effectively each group converts these resources into productivity outcomes. The unexplained component is how these resources are transformed into productivity by each of the groups. This component is also known as the coefficient effect, which consists of unobserved factors such as institutional quality, efficiency of management, prejudice and cultural attitudes.

This study has used the Blinder-Oaxaca decomposition test for multiple group comparisons. The first one is regional comparisons contrasting Southern, Western, Midwestern, and Northeastern states against the remainder of the country. And the other one is demographic comparisons, distinguishing states with higher versus lower minority populations. Robust standard errors are used to ensure valid statistical inference for both explained and unexplained components. Detailed decomposition results also report the specific contribution of each explanatory variable (EV adoption, charging infrastructure, GDP, unemployment, etc.) to the explained gap, allowing identification of which resource differences most substantially drive productivity disparities across groups.

4.4. Oster Test

The Oster (2019) method provides a formal framework for assessing how robust the estimated treatment effect is to potential omitted variable bias by calculating the degree of selection on unobservables relative to observables required to eliminate the observed effect.

This method computes a bias-adjusted treatment effect, β^*, under specific assumption about unobservable (δ) and maximum R-squared (Rmax). The analysis looks into the economic effects of EV adoption by adjusting for the possible omitted variable bias with the conservative estimates of $\delta = 1$ (on the assumption that all unobserved confounders are equally influential as observed controls) and Rmax = 1 (on the assumption that the model fits perfectly). The likelihood of unmeasured confounding factors being able to fully account for the observed effect is that the adjusted estimate is positive and consistent with other estimates. This paper used the Oster test to determine the sensitivity of the estimated effect of EV adoption on labor productivity, which also gave strength to the regression analysis.

5. Empirical Results

5.1. Descriptive Statistics

Table 1 summarizes the variables used in this study and shows their key characteristics and trends. The dependent variable is Labor Productivity, which is an indicator of output produced per hour worked at the state level. There are variations among different states and historical periods, and it indicate differences in efficiency and economic success in the sample.

EV Stations and Ln EV Registration gauge the EV uptake. There is a wide range of log-transformed EV registrations per state and year, showing significant differences in adoption across the U.S. EV charging stations are unevenly distributed in the U.S., with some having well-established networks and others having inadequate infrastructure, meaning that access to charging is not evenly distributed throughout the country. Ln State GDP shows moderate diversity in state economies. The unemployment rate was fluctuating in accordance with the time of economic strength and recession, including the COVID 19 pandemic.

The environmental quality variables tend to be uniform across the states. Concentrations of Ozone remain within the regulatory guideline, compared to the PM 2.5 concentrations, which range between high and low concentrations. The Covid Dummy variable represents the effect of the pandemic on labor productivity during the years 2020–2022.

Table 1: Descriptive Statistics

Variables	Observations	Mean	Std. Dev.	Min	Max
Labor Productivity	399	104.394	5.435	92.722	124.929
Ln EV Registration	399	8.573	1.807	4.605	14.044
EV Station	399	715.825	1522.953	3	16,381
Ln State GDP	399	5.499	1.229	3.302	12.658
Unemployment	399	4.355	1.641	1.8	13.5
Political Leaning	399	0.411	0.493	0	1
Ozone Level	399	0.041	0.004	0.0259	0.0511
PM2.5	399	7.528	1.482	2.586	13.858
Covid Dummy	399	0.376	0.485	0	1

5.2. Correlation and Multicollinearity Assessment

5.2.1. Correlation

The correlation matrix in table 2 indicates moderate positive correlations between the worker productivity and the EV registrations and charging stations. This indicates that states with higher EV usage are more productive. The COVID dummy variable is positively associated with productivity, which indicates efficiency gains during the pandemic period. In contrast, the natural logarithm of state GDP displays a weak negative correlation with labor productivity. Other variables, including unemployment, political leaning, and environmental indicators, exhibit weak correlations, which indicate that there are no serious multicollinearity concerns among the explanatory variables.

Table 2: Correlation of all variables

Variables	Labor Productivity	Ln EV Registration	EV Station	Ln State GDP	Unemployment	Political Leaning	Ozone Level	PM 2.5	Covid Dummy
Labor Productivity	1.000								

Variables	Labor Productivity	Ln EV Registration	EV Station	Ln State GDP	Unemployment	Political Leaning	Ozone Level	PM 2.5	Covid Dummy
Ln EV Registration	0.520	1.000							
EV Station	0.367	0.589	1.000						
Ln State GDP	0.195	0.698	0.503	1.000					
Unemployment	0.136	0.074	0.108	0.154	1.000				
Political Leaning	0.227	0.359	0.223	0.182	0.090	1.000			
Ozone Level	0.030	0.078	0.065	0.090	-0.153	-0.046	1.000		
PM 2.5	0.054	0.296	0.221	0.371	0.160	-0.203	0.160	1.000	
Covid Dummy	0.505	0.254	0.093	0.009	0.387	0.014	-0.139	-0.007	1.000

5.2.2. Multicollinearity

Variance Inflation Factors (VIF) have been computed for all independent variables in order toformally evaluate multicollinearity concerns. VIF indicates how much the variance of a regression coefficient is increased due to correlation with other predictors and values below 5 are considered acceptable. The results show no multicollinearity concerns, as all the values are below 3.23, confirming that the model's estimates can be relied upon.

Table 3: Variance Inflation Factor (VIF) Test Results

Variables	VIF
Ln EV Registration	3.22
Ln State GDP	2.36
EV Station	1.59
Covid Dummy	1.49
PM 2.5	1.40
Political Leaning	1.39
Unemployment	1.38
Ozone Level	1.07
Mean VIF	1.74

5.3. Regression Analysis

5.3.1. Ordinary Least Square (OLS)

The pooled OLS regression results presented in Table 4 indicate that Electric Vehicle (EV) adoption has a significant positive impact on labor productivity. The coefficient for the logarithm of EV registrations is positive and statistically significant, and it implies that higher levels of EV adoption are associated with notable improvements in labor productivity, holding all other factors constant. This relationship is semi-elastic as it is the logarithmic transformation of the independent variable, where percentage changes in EV consumption translate into proportional unit changes in productivity. Similarly, EV charging stations also demonstrate a positive and statistically significant influence on labor productivity. However, the magnitude of this effect is very small — an increase of 100 charging stations translates into an increase of 0.1 units in labor productivity. It indicates that even though the expansion of charging infrastructure has positive contributions, its direct quantitative impact remains limited in the short run.

Interestingly, the coefficient for the logarithm of state GDP reveals a negative and statistically significant relationship with labor productivity. This counterintuitive finding can be explained by the concept of a backward-bending labor supply curve, which implies that when the state incomes are high, the workers choose to substitute leisure for work, reflecting an income effect (King, 2010).

The positive and statistically significant COVID dummy variable suggests that labor productivity increased during the pandemic period. This outcome may reflect structural shifts such as the widespread transition to remote work, the high rate of digitalization, and the improvement of operational efficiency that took place during the pandemic (Phillips, S., 2020 and Jaumotte et al., 2023). It could also capture compositional effects which arose from the exit of less productive workers from the labor force, and in turn, it collectively contributed to higher average productivity levels during this period (Bloom et al., 2025). Other variables, including Unemployment, Political Leaning, Ozone Level, and PM2.5, are statistically insignificant, which indicates that their direct effects on productivity are not meaningful. The model has 46 percent labor productivity variability across the states and years, with a R-squared of 0.464, and the variables have moderate explanatory power.

To test whether the explanatory variables collectively have a significant effect on labor productivity or not, three joint significance tests (F-test, Likelihood Ratio test, and Wald test) have been conducted. The results show that the independent variables together have a highly significant impact on labor productivity. It confirms that the model is well-specified, and the included variables meaningfully explain differences in labor productivity across the states and time.

Three specification tests, including the Breusch-Pagan LM test, Hausman test, and Modified Wald test, have been conducted in order to determine the appropriate panel data model. The Breusch-Pagan LM test confirms the presence of significant state-specific effects, which makes the pooled OLS model inappropriate. The Hausman test rejects the null hypothesis, indicating that unobserved state effects are correlated with the regressors. Hence, the Fixed Effects (FE) model is preferred to the Random Effects (RE) model. The Modified Wald test identifies substantial heteroskedasticity across states. Hence, robust standard errors in the FE estimation will be required. Together, these results support the use of the FE model with robust standard errors in order to account for both unobserved heterogeneity and heteroskedasticity, which would ensure consistent and reliable estimates.

5.3.2. Fixed Effect

The FE model controls for unobserved and time-invariant state characteristics, and thus, it provides more reliable causal estimates by exploiting within-state variation over time. The coefficient for Ln EV Registration shows that a 1% rise in EV registrations within a state is associated with a 2.52% increase in labor productivity, significant at the 1% level. This nearly doubles the OLS estimate, which indicates that pooled OLS may have suffered from downward bias because of omitted state-specific factors, for instance, geography, institutional quality, or industrial composition. The coefficient for EV Station remains positive and significant at the 1% level, maintaining a similar magnitude to OLS. It confirms that absolute impact of infrastructure contribution to productivity is very small.

However, Ln State GDP becomes statistically insignificant, and changes sign from negative in OLS to slightly positive in the Fixed Effect model. This dramatic shift suggests that the negative relationship observed in OLS reflected cross-sectional differences between states, while the FE model focused on within-state dynamics over time. After controlling for state- specific factors, within-state relationship between GDP and productivity becomes negligible which implies that state wealth does not systematically predict productivity changes over time.

Similarly, Unemployment reverses signs dramatically, from slightly negative and insignificant in OLS to positive and highly significant in FE. Each percentage point increase in unemployment raises productivity by 0.91 units. This sign reversal reflects a compositional effect in which firms tend to dismiss their less productive workers during downturns and, consequently, the average productivity of the remaining employees increases (Bloom et al., 2025). The magnitude of the COVID dummy variable is smaller than that of OLS, which implies that within-state productivity gains took place due to pandemic-induced organizational changes such as remote work and digitalization (Phillips, S., 2020 and Jaumotte et al., 2023). Similar to OLS model, Political leaning and air quality variables remain statistically insignificant, confirming their limited impact on labor productivity. Overall, the FE model explains approximately 66% of the variation in labor productivity and it is substantially higher than the OLS model's 46% explanatory power. It demonstrates that accounting for state-specific fixed effects improves the model's explanatory power.

Similar to the joint significance tests in the Pooled OLS model, the fixed effects model also shows strong joint significance across all tests. The results consistently reject the null hypothesis of joint insignificance at the 1% level, indicating that the explanatory variables collectively explain labor productivity even after controlling for state-specific, time-invariant factors.

Table 4: Test Results for OLS and Fixed Effect

Variables	**Dependent Variable**	**(Labor Productivity)**
	Pooled OLS	Fixed Effect
Ln EV Registration	1.378*** (0.230)	2.522*** (0.301)
EV Station	0.001*** (0.000)	0.001*** (0.000)
Ln State GDP	-0.921*** (0.259)	0.607 (0.358)
Unemployment	-0.090 (0.146)	0.920*** (0.133)
Political Leaning	0.643 (0.484)	0.557 (0.923)

Variables	Dependent Variable	(Labor Productivity)
Ozone Level	76.931 (55.728)	47.94 (162.5)
PM2.5	-0.108 (0.175)	0.058 (0.256)
Covid Dummy	4.416*** (0.594)	1.657*** (0.463)
Constant	93.356*** (2.501)	74.12*** (7.348)
Observations	399	399
R-squared	0.464	0.657
Joint Significance Test	**Pooled OLS**	**Fixed Effect**
F Test	46.66***	41.39***
LR Test	122.98***	183.29***
Wald Test	42.23***	41.39***
Test	**Test Statistic**	**Null Hypothesis (H_0)**
Hausman Test	36.33***	Random effects model is consistent
Modified Wald Test (FE)	4072.66***	Homoskedasticity
Breusch-Pagan LM Test (RE)	139.19***	No random effects (pooled OLS preferred)

Notes: ***, ** & * indicate statistical significance at the 1, 5 & 10 levels of significance
Robust standard errors are in parentheses.
All joint significance tests reject the null hypothesis that coefficients are jointly equal to zero.
LR test is only valid under homoskedasticity and cannot be computed with robust standard errors. Therefore, the LR test result under FE model is reported for the non-robust specification for comparison purposes only. F-test and Wald test use robust standard errors.

5.3.3. Lewbel (2012) GMM

In order to assess the robustness of the estimated relationship between EV adoption and labor productivity, three alternative instrumental variable (IV) models have been estimated using the Lewbel GMM approach. The first model uses EV station count as an external instrument for EV adoption (Ln EV Registration), the second one relies solely on internally generated instruments, while the third one combines both external and generated instruments.

The Standard IV (2SLS) model performs strongly across all identification tests. The under-identification test rejects the null hypothesis, and the weak instrument diagnostics show that the variable EV stations is both a relevant and valid instrument for EV adoption. As the model is exactly identified, the overidentification test is not applicable here.

In contrast, the Lewbel model, relying only on internally generated instruments, shows weak identification, which implies that the instruments have limited predictive power for EV registrations. Even though the overidentification test fails to reject exogeneity, the weak identification reduces the reliability of its causal estimates.

The combined model, which uses both generated and external instruments, passes all three instrument tests. This makes the combined model the most reliable and credible model, as it adequately addresses endogeneity concerns while maintaining robustness and validity.

Table 5: IV Regression Results Using Lewbel Method and Variants

Variables / Tests	**Standard IV**	**Generated Instruments**	**Generated + External Instruments**
Ln EV Registration	3.354***	1.361***	1.953***
	(0.62)	(0.336)	(0.441)
Ln State GDP	-2.389***	-0.600**	-1.132**
	(0.728)	(0.298)	(0.449)
Unemployment	0.318	-0.106	0.020
	(0.221)	(0.157)	(0.17)
Political Leaning	-1.207	0.947*	0.307
	(0.731)	(0.559)	(0.638)
Ozone Level (O_3)	60.35	82.82	75.15
	(64.8)	(54.9)	(56.5)
PM2.5	-0.436**	-0.052	-0.166
	(0.215)	(0.19)	(0.194)

Variables / Tests	Standard IV	Generated Instruments	Generated + External Instruments
Covid Dummy	2.212**	4.613***	3.9***
	(0.935)	(0.73)	(0.76)
Constant	87.87***	91.35 ***	90.3***
	(3.18)	(2.49)	(2.65)
MODEL FIT			
Observations (N)	399	399	399
R-squared	0.33	0.45	0.44
INSTRUMENT TESTS			
Underidentification test (Kleibergen-Paap rk LM Test)	11.540***	25.111***	48.339***
Weak Identification (Kleibergen-Paap Wald F)	15.036	52.239	16.948
Hansen J (Overidentification)	Exactly identified	15.438***	8.521

Notes: Robust standard errors are in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively
The dependent variable is labor productivity.
The endogenous regressor is ln EV Registration, instrumented using variables specified in each column.
Standard IV uses EV Station as the excluded instrument.
Kleibergen-Paap rk LM statistic tests under-identification of the instrument(s) in the respective Lewbel (2012)estimates. H0: Instrument is not correlated with endogenous regressor(s) and model is under-identified.
The Kleibergen–Paap Wald F statistics test for weak instruments; instruments are considered strong when the Kleibergen–Paap Wald F-statistic exceeds 10, potentially weak when it lies between 5 and 10, and severely weak when it is below 5.
The Hansen J statistic tests overidentifying restrictions; non-significant results ($p > 0.05$) support instrument validity.
All models are estimated with robust standard errors to correct for heteroskedasticity.

5.3.4. Blinder Oaxaca Decomposition

The Blinder-Oaxaca decomposition analysis reveals that the Southern region of the USA faces a productivity disadvantage compared to the rest of the country. As shown in Table 6 and Figures 3–6, the South exhibits notably lower labor productivity, and this gap remains largely unexplained by observable factors such as EV adoption, infrastructure, or state GDP. The decomposition indicates that most of the differences stem from unobserved influences rather than measurable economic characteristics. These hidden factors may include institutional quality, regional policies, or cultural attitudes toward innovation and adoption of new technology. This finding aligns with research done by DiRusso, Kabir et al. in 2025, which documents that Southeastern consumers focus more on economic and practical benefits rather than environmental concerns when considering EV adoption. The authors argue that EV messaging should be more targeted to cultural and political audiences. They need to focus less on environmental benefits and more on practical and functional advantages of electric vehicles, such as long-term financial savings, lifestyle relevance, and shared values (DiRusso, Kabir et al, 2025).

The West, Midwest and Northeast, however, have moderate and context-specific variances. The West demonstrates a mild productivity edge over other regions because of stronger economic fundamentals and higher EV adoption. The Midwest does not have any meaningful overall difference in productivity. However, it utilizes its resources better than anticipated with low endowments. The Northeast, meanwhile, does not have statistically significant coefficients for any of the differences. These regional patterns highlight that the South's productivity challenge is unique in its magnitude and in being driven primarily by unmeasured factors, while other regions show either resource advantages (West), efficiency compensation (Midwest), or general parity (Northeast) with the rest of the country.

This pattern can also be explained by the K-shaped nature of the U.S. economy, where different sectors, industries, or income groups experience divergent growth trajectories: some segments of the economy thrive and expand rapidly (forming the upper arm of the “K”), while others stagnate or even decline (forming the lower arm). In this context, the Blinder–Oaxaca decomposition shows that Southern states face a persistent productivity deficit largely driven by unobserved institutional and structural factors, placing them on the lower arm of the “K”, while Western and other more-dynamic states—benefiting from stronger economic fundamentals and higher EV adoption—occupy the upper arm, reflecting the same kind of bifurcated growth pattern at the regional level.

Table 6: Blinder Oaxaca Decomposition Results

Component	South vs. Others	West vs. Others	Midwest vs. Others	Northeast vs. Others
Group 1	103.463***	104.095***	104.200***	105.080***
(Region = 0)	(0.360)	(0.275)	(0.452)	(0.696)
Group 2	104.833***	105.240***	104.454***	104.242***
(Others = 1)	(0.360)	(0.689)	(0.328)	(0.294)
Difference	-1.370**	1.145	-0.254	0.837
	(0.509)	(0.742)	(0.559)	(0.755)
Explained	-0.639	1.666**	-1.199**	0.306
	(0.423)	(0.533)	(0.455)	(0.506)
Unexplained	-0.730*	-0.520	0.945*	0.532
	(0.422)	(0.609)	(0.414)	(0.638)

Figure 3: Productivity gap by regions (South vs. Others)

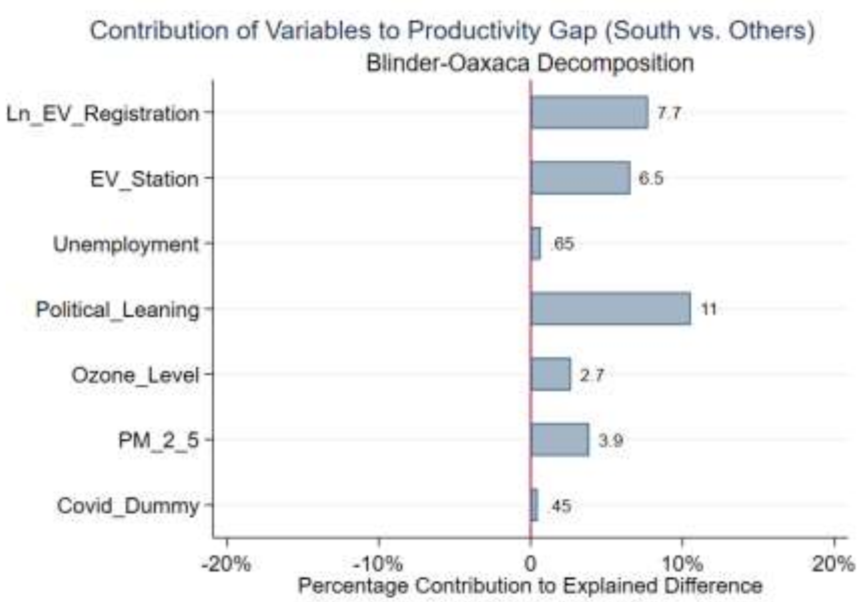


Figure 4: Productivity gap by regions (West vs. Others)

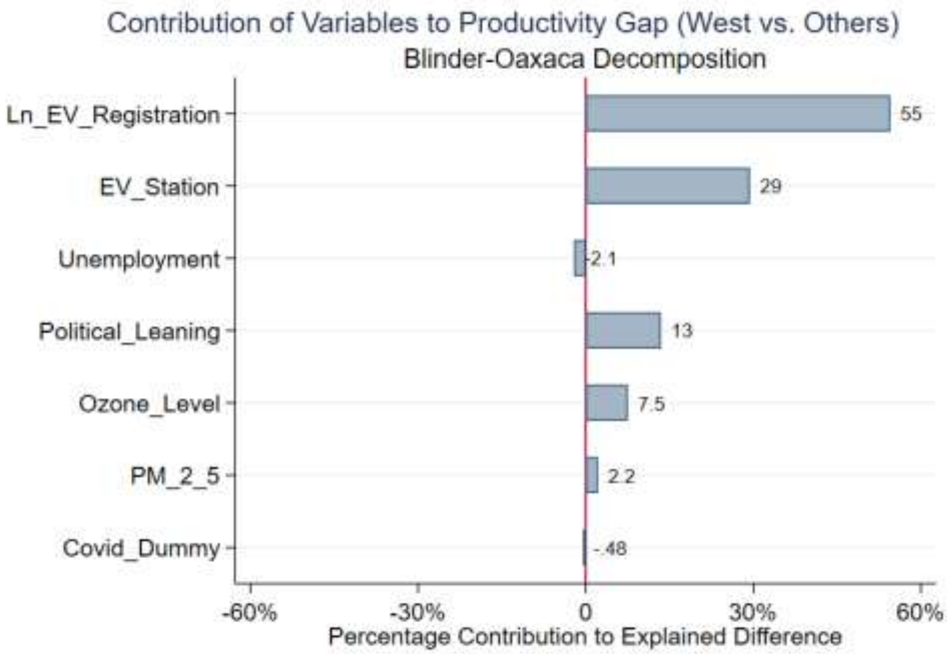


Figure 5: Productivity gap by regions (Midwest vs. Others)

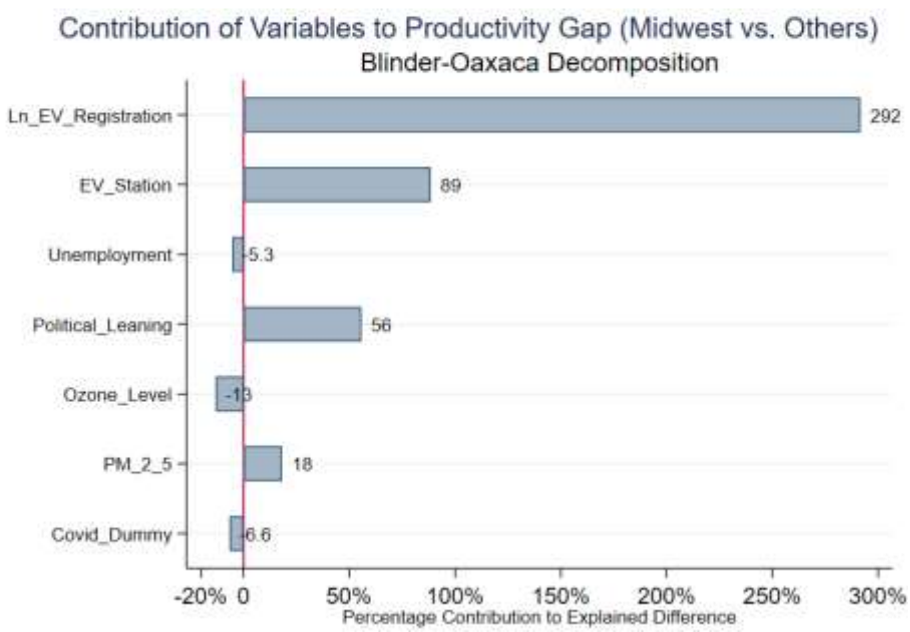
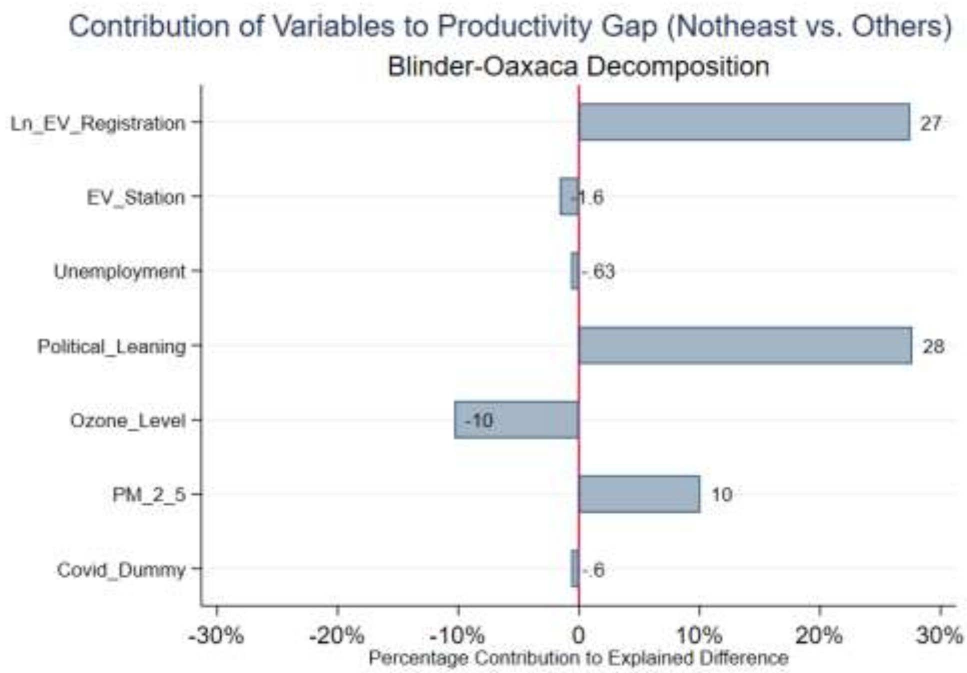


Figure 6: Productivity gap by regions (Northeast vs. Others)



5.3.5. Oster (2019) Test

The Oster (2019) test assesses whether the impact of EV adoption on labor productivity is robust to omitted variable bias or not by examining how the coefficient would change if unobserved factors were included. The test compares the Full Model and Restricted Model with state fixed effects where calculated β* = 1.422 under conservative assumptions (δ = 1, Rmax = 1). Here, δ = 1 means that unobserved factors are as important as observed controls, and Rmax = 1 represents a hypothetical perfect model. The key finding demonstrates that parameters are stable as coefficients move from 2.523 (restricted) to 3.160 (full model) to 1.422 (bias-adjusted), yet remain positive and economically significant throughout, indicating that although the omitted variables may be slightly decreasing the estimated effect, they would not erase the positive EV adoption and Labor productivity Relationship. Here, β*, which is the bias adjusted beta, does not change sign and magnitude is similar to those from other estimates which indicates that unobserved factors are not driving the entire result, confirming that the EV adoption- labor productivity relationship is robust to omitted variable bias and strengthening confidence that EV adoption genuinely enhances labor productivity.

Table 7: Oster Test Results

Model	Dependent Variable	Full Model	Restricted Model	Oster Test Statistics
State Fixed Effects	Ln EV Registration	3.160***	2.523***	$\beta^* = 1.422$
				$\delta = 1$
Model Statistics		$R^2 = 0.458$	$R^2 = 0.657$	Rmax = 1

Notes: A State + Year Fixed Effects model was estimated; however, the results were not statistically significant. A Year Fixed Effects model was also estimated; however, the results were not statistically significant. Additionally, since the dataset already includes a time-related variable (Covid Dummy), it can effectively serve as a proxy for Year Fixed Effects.

The baseline analysis provides strong economic evidence that electric vehicle (EV) and labor productivity have a causal relationship at the state level across the United States. From an economic perspective, this relationship demonstrates how innovative and cleaner transportation technology contributes to improving the efficiency of the labor force. By reducing commuting costs, encouraging technological advancement, and potentially improving environmental quality, higher EV adoption levels can be translated into greater output per hour worked. The auxiliary role of EV charging infrastructure, albeit minor, points to the necessity of investments in the infrastructure to assist this technological shift, which once again proves that the development of infrastructure is a key to the economic benefits of EV adoption maximization.

The interaction of conventional economic variables with labor productivity reveals important labor market and structural dynamics. The initially observed negative relationship between state GDP and labor productivity in the OLS model reflects cross-sectional differences rather than causal effects. The fixed effect model neutralizes this relationship by controlling for unobserved state factors. The positive correlation between unemployment and productivity among states reveals that economic recessions redistribute labor force, eliminating less productive workers and enhancing the productivity of the rest. These results demonstrate that EV adoption directly influences economic performance and labor efficiency, which can justify governmental efforts to promote the adoption of green technology to sustain the environment and ensure economic growth and innovation. Robustness checks using Lewbel methods further validate positive productivity impact of EV adoption.

5.4. Channel Analysis

This section investigates the specific mechanisms through which Electric Vehicle (EV) adoption may influence labor productivity. The three channels that the study employs are: racial disparities, role of private versus public infrastructure, and the environmental pathway via emissions reduction.

5.4.1. Racial Disparity

The Race variable, which is measured by the proportion of the white population in each state, shows significant differences across time periods and model specifications. The impact of racial differences on labor productivity in both pooled OLS and fixed effects models was not significant before 2020 (Table 8), which suggests that the demographic composition was not the predictor of productivity prior to the pandemic. However, the relationship changed noticeably in the post-pandemic period. Estimates of the pooled OLS model indicate that states with higher white populations tend to have higher labor productivity. The coefficient in the Fixed effects model remains insignificant, and it suggests that cross-sectional differences drive this association. In Table 9, instrumental variable estimates show that post-2020, states with higher white populations consistently exhibit higher productivity, whereas before 2020, the effect was minimal or insignificant.

These temporal transitions are brought into light by the Blinder-Oaxaca decomposition in Table 10. Prior to 2020, the differences in productivity between states with a higher number of minorities and those with fewer were minimal, and the amount of both explained and unexplained difference was not substantial. Labor productivity gaps were not much affected by demographic composition. After 2020, the Blinder-Oaxaca decomposition reveals a shift in the relationship between demographic composition and labor productivity. The overall productivity difference between states with larger minority populations and those with fewer minorities remains small and statistically insignificant. However, states with more minority residents face notable disadvantages in observable characteristics, and it reflects that resource constraints or barriers may limit access to EV adoption.

The post-2020 demographic impacts indicate that the pandemic can have deteriorated the resource disparity, especially in EV implementation and infrastructure. This aligns with the findings of Ugwu et al (2025), who document that People of Color (POC) face significantly greater concerns about EV charging than that of the White respondents. They note that POC are 3.2 times more likely to be affected by charging prices, 2.2 times more likely to be concerned about charging station availability, and 2.0 times more likely to be affected by charging times when considering EV ownership. These barriers to EV adoption among minority communities can explain the resource disadvantage (explained component) in states with more minorities after 2020. However, states with more minorities demonstrate superior resource utilization (unexplained components) and it allows them to maintain comparable overall productivity even though they face obstacles in adopting EV technology. The findings suggest that promoting EV adoption among minority communities requires policies that would address their financial barriers and provide access to public charging infrastructure in order to close the resource gap while leveraging their efficient resource utilization ability. This evolving racial-and-resource dynamic after 2020 is consistent with the K-shaped structure of the U.S. economy, where certain groups and regions advance rapidly along the upper arm of the "K" while others—such as minority-concentrated states facing EV-infrastructure and financial barriers—occupy the lower arm, yet manage to maintain comparable aggregate productivity through more efficient resource utilization.

Table 8: Regression Results for Labor Productivity (White Population Percentage Before and After 2020)

Variables	**Before 2020 (White Majority)**		**After 2020 (White Majority)**	
	Pooled OLS	Fixed Effect	Pooled OLS	Fixed Effect
Ln EV Registration	0.454**	1.557**	2.175***	-5.385***
	(0.201)	(0.716)	(0.573)	(1.342)
EV Station	0.000	0.005***	0.001***	0.001*
	(0.000)	(0.001)	(0.000)	(0.001)

Variables	Before 2020 (White Majority)		After 2020 (White Majority)	
Ln State GDP	-0.235	-0.176	-0.363	89.912***
	(0.159)	(0.105)	(0.480)	(12.820)
Unemployment	-0.735***	0.548	0.435	0.866**
	(0.222)	(0.530)	(0.437)	(0.389)
Political Leaning			1.657*	(omitted)
			(0.906)	
Ozone Level (O_3)	23.36	-117.277	37.171	457.489***
	(51.531)	(112.74)	(101.190)	(144.070)
PM2.5	-0.064	-0.167	-0.504	-0.467
	(0.156)	(0.267)	(0.315)	(0.286)
Race (White Majority)	0.002	-0.579	0.174***	-0.492
	(0.016)	(0.901)	(0.034)	(0.609)
Covid Dummy			0.962	0.252
			(0.922)	(0.750)
Constant	100.94***	131.120**	76.200***	-326.866***
	(2.45)	(65.991)	(5.630)	(80.972)
Observations	199	199	150	150
R-squared	0.178	0.442	0.387	0.539

Notes: Robust standard errors are in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.
Political Leaning variable omitted in FE regression after 2020 due to collinearity.
Covid Dummy applicable only for post-2020 period.

Table 9: IV Regression Results Using Lewbel Method and Variants

Variable	Standard IV (Before 2020)	Generated Instruments (Before 2020)	Generated + External Instruments (Before 2020)	Standard IV (After 2020)	Generated Instruments (After 2020)	Generated + External Instruments (After 2020)
Ln EV Registration	0.575	0.973 **	0.330	7.153***	3.567 ***	4.133 ***
	(0.565)	(0.390)	(0.294)	(1.584)	(0.912)	(0.722)

Variable	**Standard IV (Before 2020)**	**Generated Instruments (Before 2020)**	**Generated + External Instruments (Before 2020)**	**Standard IV (After 2020)**	**Generated Instruments (After 2020)**	**Generated + External Instruments (After 2020)**
Ln State GDP	-0.307	-0.617 **	-0.117	-4.348 **	-1.144	-1.650 **
	(0.414)	(0.310)	(0.229)	(1.797)	(0.852)	(0.798)
Unemployment	-0.686*	-0.512*	-0.793***	1.252 **	0.680	0.770 *
	(0.332)	(0.288)	(0.235)	(0.514)	(0.476)	(0.457)
Political Leaning	-	-	-	-1.727	0.802	0.403
				(1.444)	(0.960)	(1.016)
Ozone Level (O_3)	23.32	21.793	24.268	-25.489	26.735	18.487
	(50.455)	(50.792)	(50.530)	(115.526)	(98.233)	(95.518)
PM2.5	-0.074	-0.115	-0.049	-0.572	-0.526 *	-0.534 *
	(0.166)	(0.167)	(0.155)	(0.386)	(0.304)	(0.309)
Covid Dummy	-	-	-	3.110 **	1.487	1.743 *
				(1.338)	(0.934)	(0.949)
Race (White Majority)	0.005	0.020	-0.004	0.270***	0.191 ***	0.204 ***
	(0.024)	(0.020)	(0.016)	(0.055)	(0.039)	(0.035)
Constant	100.079***	97.331***	101.774 ***	44.73 ***	66.287 ***	62.882 ***
	(4.536)	(3.416)	(2.973)	(9.100)	(6.827)	(5.948)
Observations	199	199	199	150	150	150
Underidentification test (Kleibergen-Paap rk LM Test)	9.533**	8.052	33.210***	5.784 **	5.512	18.972 **
Weak Identification (Kleibergen-Paap Wald F)	16.712	55.091	16.691	18.558	6.616	15.432
Hansen J (Overidentification)	0 (exactly identified)	14.295***	17.856***	exactly identified	8.699	16.066 **

Notes: Robust standard errors are in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively
The dependent variable is labor productivity.
The endogenous regressor is ln EV Registration, instrumented using variables specified in each column.
Standard IV uses EV Station as the excluded instrument.

Kleibergen-Paap rk LM statistic tests under-identification of the instrument(s) in the respective Lewbel (2012)estimates. H0: Instrument is not correlated with endogenous regressor(s) and model is under-identified.
The Kleibergen–Paap Wald F statistics test for weak instruments; instruments are considered strong when the Kleibergen–Paap Wald F-statistic exceeds 10, potentially weak when it lies between 5 and 10, and severely weak when it is below 5.
The Hansen J statistic tests overidentifying restrictions; non-significant results (p > 0.05) support instrument validity.
All models are estimated with robust standard errors to correct for heteroskedasticity.

Table 10: Blinder Oaxaca

Comparison	Component	Before 2020	After 2020
Group 1	Minority = 0	100.879*** (0.262)	107.526 *** (0.717)
Group 2	Majority = 1	100.873*** (0.208)	108.096 *** (0.593)
Difference		0.006 (0.335)	-0.570 (0.930)
Explained		-0.027 (0.270)	3.066 *** (0.748)
Unexplained		0.034 (0.336)	-3.636 *** (0.852)

Notes: Robust standard errors are in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.
The dependent variable is labor productivity.

Figure 7: Explained difference of minority vs majority population before 2020

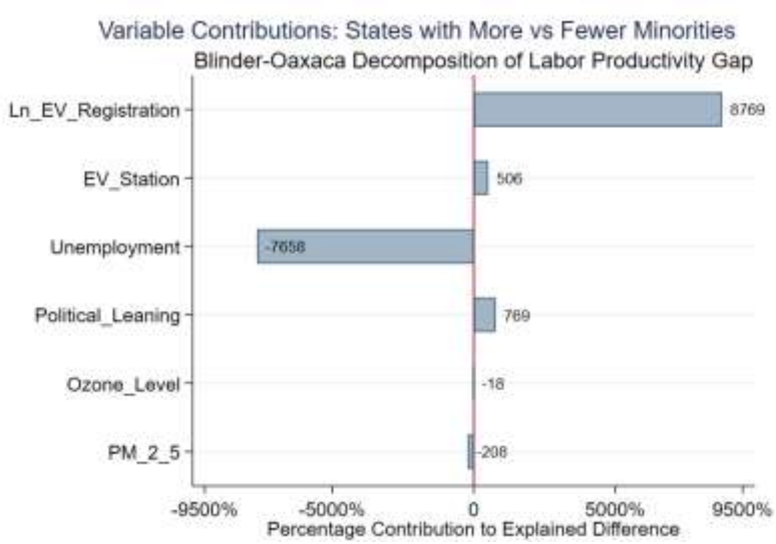
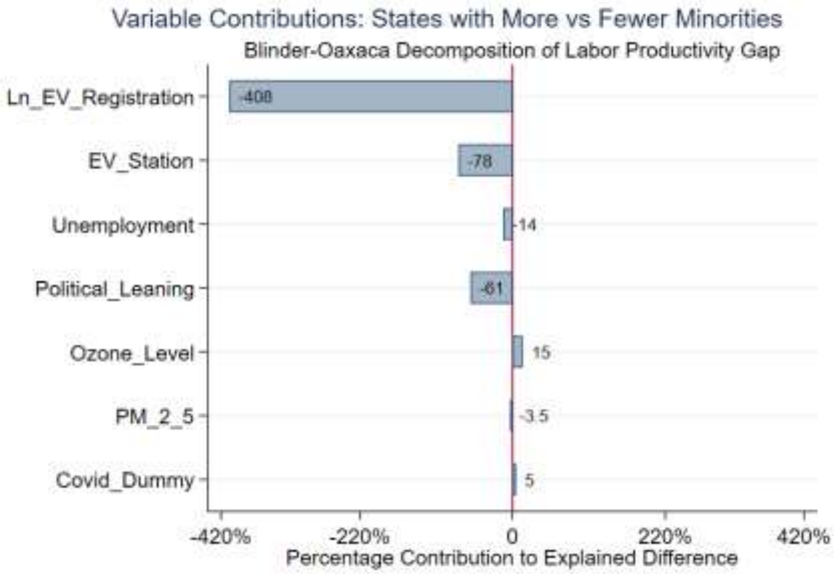


Figure 8: Explained difference of minority vs majority population after 2020



5.4.2. Private EV Station

The findings presented in table 11 reveal that private EV stations do not serve as a significant channel for productivity gains. In the pooled OLS model, the variable private EV stations shows a statistically significant negative relationship with labor productivity, indicating that an unit increase in private EV stations is associated with a small but significant decline in labor productivity. However, this negative effect gets weakened under instrumental variable (IV) estimations. In the standard IV model, where a public EV station is used as the excluded instrument, the negative association remains with only marginal significance. Moreover, in the models using generated instruments and combined (generated + external) instruments, the coefficient of private EV stations turns statistically insignificant. It implies that after accounting for potential endogeneity, the negative effect observed in the pooled OLS model might be biased and not robust. This implies that the instrumented private EV stations did not have any statistically significant effect on productivity and that the previous OLS relationship was probably due to omitted variable bias and not causality. The investigation into the charging infrastructure type clarifies that. The analysis of the charging infrastructure type demonstrates that the private EV stations do not serve as a significant channel for productivity gains.

Table 11: Regression results for Private EV Station

Variables / Tests	Pooled OLS	Standard IV	Generated Instruments	Generated + External Instruments
Ln EV Registration	1.459 ***	12.610 **	1.482 ***	1.727 ***
	(0.223)	(6.364)	(0.419)	(0.323)
EV Station	0.002 ***			
	(0.000)			
Ln State GDP	-0.797***	-8.822*	-0.851 **	-1.027 ***
	(0.235)	(4.550)	(0.346)	(0.327)
Unemployment	0.021	2.389	-0.060	-0.006
	(0.151)	(1.499)	(0.169)	(0.158)
Political Leaning	0.574	-9.806	0.703	0.471
	(0.467)	(6.120)	(0.585)	(0.535)
Ozone Level (O_3)	39.631	-63.492	59.610	56.894
	(62.722)	(197.514)	(61.992)	(62.562)
PM2.5	-0.019	-1.793	-0.072	-0.110
	(0.175)	(1.199)	(0.192)	(0.188)
Covid Dummy	3.956 ***	-8.748	4.387 ***	4.098 ***
	(0.604)	(7.683)	(0.788)	(0.652)
Private EV Station	0.022 ***	-0.046 *	0.003	0.001
	(0.005)	(0.028)	(0.004)	(0.004)
Constant	93.099*** (2.773)	60.770 ***	92.649 ***	91.945 ***
		(21.989)	(2.883)	(2.809)
Observations	394	394	394	394
R squared	0.4832			
Underidentification test (Kleibergen-Paap rk LM Test)	-	3.166 *	30.264***	78.239 ***
Weak Identification (Kleibergen-Paap Wald F)	-	2.638	34.786	32.513

Variables / Tests	Pooled OLS	Standard IV	Generated Instruments	Generated + External Instruments
Hansen J (Overidentification)	-	0 (exactly identified)	19.053 ***	17.147 **

Notes: Robust standard errors are in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively
The dependent variable is labor productivity.
The endogenous regressor is ln EV Registration, instrumented using variables specified in each column.
Standard IV uses EV Station as the excluded instrument.
Kleibergen-Paap rk LM statistic tests under-identification of the instrument(s) in the respective Lewbel (2012)estimates. H0: Instrument is not correlated with endogenous regressor(s) and model is under-identified.
The Kleibergen–Paap Wald F statistics test for weak instruments; instruments are considered strong when the Kleibergen–Paap Wald F-statistic exceeds 10, potentially weak when it lies between 5 and 10, and severely weak when it is below 5.
The Hansen J statistic tests overidentifying restrictions; non-significant results ($p > 0.05$) support instrument validity.
All models are estimated with robust standard errors to correct for heteroskedasticity.

5.4.3. CO2:

The CO_2 variable sheds light on how environmental quality influences labor productivity. Across all model specifications, CO_2 consistently shows a statistically significant negative relationship with labor productivity, and it implies that higher carbon emissions are associated with lower labor efficiency (Chavaillaz et al., 2019). This finding supports the idea that cleaner environments, which can be driven by a high level of electric vehicle (EV) adoption, can enhance workers' performance and overall labor productivity.

The pooled OLS model establishes a negative link between CO_2 emissions and productivity. This relationship becomes stronger and more credible once potential endogeneity is addressed using Instrumental Variable (IV) methods as the negative association remains even after accounting for omitted variable bias between EV adoption and labor productivity.

Model identification tests reveal that the IV specification using generated instruments only provides the most reliable result and it confirms that the instruments are relevant and satisfy exogeneity conditions which ensures that the estimated effect is not biased by endogeneity. The model with generated instruments passes all three diagnostic tests, while the standard IV model shows weaker identification, and the model using both generated and external instruments fails

Hansen J test. Therefore, the IV model with generated instruments is considered the most credible model among the three due to stronger instrument strength and overall model diagnostics. Overall, the findings suggest that reducing CO_2 emissions through increased EV adoption positively contributes to labor productivity, with the best empirical support coming from the model backed by strong and valid instruments under sound identification tests.

Table 12: Pooled OLS and IV Regression Results Using Lewbel Method and Variants

Variables	**Pooled OLS**	**Standard IV**	**Generated Instruments**	**Generated + External Instruments**
Ln EV Registration	0.495 ** (0.213)	3.842 *** (1.116)	0.718** (0.335)	1.163** (0.568)
EV Station	0.001 *** (0.000)	—	—	—
Ln State GDP	0.192 (0.221)	-2.207 ** (1.041)	0.210 (0.281)	-0.135 (0.474)
Unemployment	-0.048 (0.140)	0.464* (0.263)	-0.028 (0.151)	0.042 (0.168)
Political Leaning	0.897 * (0.500)	-2.425* (1.292)	1.102* (0.591)	0.600 (0.740)
Ozon Level (O3)	17.322 (56.706)	31.273 (69.847)	27.788 (55.740)	28.284 (56.532)
PM2.5	-0.004 (0.175)	-0.377 (0.)	0.028 (0.188)	-0.030 (0.191)
COVID Dummy	6.008 *** (0.547)	1.200 (1.796)	6.012*** (0.713)	5.327*** (0.931)
CO2	-0.009 *** (0.003)	-0.014*** (0.004)	-0.007 ** (0.003)	-0.008*** (0.003)
Constant	95.725 *** (2.593)	85.254*** (4.414)	93.167*** (2.717)	92.040*** (3.075)
Observations	349	349	349	349
R-squared	0.558	0.268	0.538	0.532
Underidentification test (Kleibergen-Paap rk LM Test)		15.319 ***	19.345 ***	51.811 ***
Weak Identification (Kleibergen-Paap Wald F)		9.744	24.390	12.580
Hansen J (Overidentification)		0 (exactly identified)	10.758 *	14.308 **

Notes: Robust standard errors are in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively
The dependent variable is labor productivity.
The endogenous regressor is ln EV Registration, instrumented using variables specified in each column.
Standard IV uses EV Station as the excluded instrument.
Kleibergen-Paap rk LM statistic tests under-identification of the instrument(s) in the respective Lewbel (2012)

estimates. H0: Instrument is not correlated with endogenous regressor(s) and model is under-identified.
The Kleibergen–Paap Wald F statistics test for weak instruments; instruments are considered strong when the Kleibergen–Paap Wald F-statistic exceeds 10, potentially weak when it lies between 5 and 10, and severely weak when it is below 5.
The Hansen J statistic tests overidentifying restrictions; non-significant results ($p > 0.05$) support instrument validity.
All models are estimated with robust standard errors to correct for heteroskedasticity.

The channel analysis above presents some of the economic pathways through which electric vehicle (EV) adoption enhances labor productivity. It reveals that racial disparities have become more pronounced in shaping productivity differences in the post-pandemic period as minority communities face uneven access to EV technology and infrastructure. These disparities need to be addressed through targeted policies in order to fully realize the productivity gains from EV adoption. The findings also show that public charging stations are superior to the private ones when it comes to facilitating labor productivity gains, and it highlights the need for investment in public EV charging infrastructure. Finally, the negative relationship between CO_2 emissions and labor productivity reinforces the environmental benefits of EV adoption since cleaner air contributes to healthier and more efficient labor forces. Therefore, it can be said that inclusive access to EV technology, investment in public charging stations and reduction in environmental externalities are required for maximizing the economic returns of the transition to electric mobility.

6. Summary of the Findings

The empirical findings of this study show a highly positive causal relationship between electric vehicle (EV) adoption and labor productivity across U.S. states from 2016 to 2023. Analysis of the various econometric tools such as pooled OLS, fixed effects models, Lewbel GMM instrumental variable approaches, and Oster tests indicate that an increase in EV registration in the USA leads to substantial gains in labor output per hour worked. Despite controlling for economic and environmental variables, accounting for potential endogeneity and omitted variable biases, results remain consistent.

The pattern of these gains, however, reflects the K-shaped structure of the U.S. economy, where different regions and groups experience divergent growth trajectories. Regional heterogeneity is evident, as the Southern region faces productivity challenges driven largely by unobserved institutional and structural factors, placing it closer to the lower arm of the “K”, while the Western region of the USA—characterized by stronger economic fundamentals and higher EV adoption—occupies the upper arm, reaping outsized productivity benefits from the EV transition. At the same time, post-pandemic years have seen increased racial disparities: the channel analysis reveals that minority populations face barriers to EV adoption, which may restrain their productivity gains, consistent with the lower-arm segment of the K-shaped divide. Yet, these minority-concentrated states demonstrate better resource utilization, which helps narrow the overall productivity gap and reflects how efficiency gains in disadvantaged groups can partially offset their structural disadvantages.

Moreover, public EV charging stations, unlike the private ones, play a significant role in enabling productivity gains. Lastly, there is a significant negative relationship between the emissions of CO2 and productivity, implying that more productive work forces are supported by a cleaner environment, which is connected to EVs adoption. Together, these findings indicate the numerous roles of EV adoption that advance economic growth and efficiency in the labor market.

The study's strength lies in its methodical rigor which utilizes an enriched panel dataset of eight years across all fifty US states as well as the application of advanced econometric tools which have addressed potential endogeneity concerns and identified causal effects. Inclusion of Blinder Oaxaca decomposition and Channel analysis has identified heterogeneity across regions and population groups. It has enhanced the pragmatic applicability of the findings and their policy relevance. However, the study is not without its limits.

Within-state and micro-level factors that lead to productivity gain cannot be individualized because of the use of aggregated state-level data. Even with robust controls, institutional quality and cultural attitudes may also bias the findings. Additionally, the study uses COVID dummy to capture time fixed effects, which may not capture temporal shocks. Besides, the U.S. context cannot be generalized to other places. The current study could not address the quality of electricity grids, green R&D spending, and employment patterns in the specific sector, and these are the areas which future research can contribute to. In spite of these shortcomings, this study offers insights into the productivity-enhancing impact of EV adoption and offers evidence-based information to propel equitable and effective green technology policy shifts.

7. Conclusion and Policy Recommendations

This discussion demonstrates that EV adoption significantly boosts the productivity of the workers in the U.S. states between 2016 and 2023. Despite accounting for economic conditions and addressing potential biases, the results of this study consistently show that higher EV registrations lead to greater output per hour worked. Regional differences reveal that while the Southern region faces challenges linked to institutional factors, the Western region benefits from stronger economic fundamentals and higher EV adoption. Some of the critical channels have also been analyzed. Since the year 2020, racial inequities in EV technology access have increased, and the access to public charging stations (rather than private stations) contributes to increasing productivity, and the reduction of carbon emissions by using EVs contributes to making workers healthier and more productive. All in all, the adoption of EV leads to sustainable economic growth through the improvement of environmental quality and the efficiency of the labor market.

These results suggest a number of policy indicators. Firstly, policymakers should design targeted fiscal incentives (such as investment-tax credits or accelerated depreciation for EV-related infrastructure and firm-level EV adoption) rather than blanket subsidies, to reduce fiscal burdens and free-rider effects (Sarker et al.,2020). Secondly, EV-promotion programs should be linked to carbon-pricing or fuel-tax reforms so that the true environmental cost of internal-combustion vehicles is reflected in market prices, thereby reinforcing the efficiency gains from EV-driven labor-productivity improvements (Sarker et al.,2020). Thirdly, to prevent EV-related productivity gains from becoming another dimension of the K-shaped divide, policies should expand publicly funded EV-charging networks in low-income and minority neighborhoods, ensuring proximity to workplaces, transit hubs, and residential areas and offer financial assistance. This will enhance productivity and an inclusive green transition to everyone. Fourthly, EV promotion implementation must be accompanied by carbon-reduction programs to amplify productivity gains by improving the air quality. Lastly, regional differences also call for the need to adapt the policies to local specifications, particularly in the stagnant regions, to enhance institutional capacity and systems of innovation. By combining well-designed fiscal incentives, targeted infrastructure investment, inclusive access programs, and coordinated environmental-quality policies, policymakers can leverage EV adoption as a tool for equitable, efficient, and sustainable economic growth.

Appendix

Data Sources:

1. **EV Registration Count, EV Station Count (Total and Private)**

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