Unequal Burden: The Socioeconomic Impact of California's Cap-and-Trade Program on Households

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Abstract

California's cap-and-trade policy, especially its 2015 extension to transportation fuels, represents a landmark effort to curb greenhouse gas emissions. This study uses Difference-in-Differences and Propensity Score Matching to examine the program's socioeconomic and gendered impacts on household gasoline expenditures from 2015 to 2019. The results suggest that low-income and female-headed households face disproportionately higher financial burdens, spending less on gasoline not due to strategic fuel efficiency, but rather constrained choices. These patterns highlight potential regressive outcomes, raising concerns about equity in climate policy. Although the analyses identify consistent trends, model diagnostics and the limited scope of outcome measures necessitate cautious interpretation. Policymakers should consider structural constraints—such as limited public transit, caregiving responsibilities, and safety concerns—when designing more inclusive and gender-responsive strategies. Future research that explores broader well-being outcomes and long-term adaptations can further guide more equitable and sustainable carbon pricing frameworks worldwide.

Introduction

Climate change is one of the most critical challenges of our time, necessitating swift and effective policy responses to mitigate its destructive impacts on ecosystems and human societies. Among the diverse approaches developed to combat greenhouse gas emissions, carbon pricing has emerged as a key instrument for internalizing the external costs of carbon emissions (Stavins, 2020). By assigning a monetary value to carbon emissions, carbon pricing policies incentivize emission reductions and promote a transition toward a low-carbon economy (Metcalf & Weisbach, 2009). In this regard, California has been a leader in the United States in implementing carbon pricing. The state introduced its cap-and-trade program in 2013, which sets a market-based cap on total greenhouse gas emissions by establishing an emissions limit and allowing entities to buy and sell emission allowances (California Air Resources Board [CARB], 2015). The 2015 expansion of the program to include transportation fuels significantly broadened its scope, as the transportation sector accounts for around 41% of California's total greenhouse gas emissions (CARB, 2018). By requiring fuel distributors to participate in the cap-and-trade program, the policy increased gasoline costs, potentially impacting household expenditures throughout the state.

While the environmental benefits of California's cap-and-trade program are well-recognized, its socioeconomic implications require careful examination. Specifically, the policy's impact on household gasoline expenditures raises concerns about potential regressive effects on low-income households. These households typically allocate a larger portion of their income to essential goods and services, including transportation energy costs (Drehobl & Ross, 2016). Consequently, increases in gasoline prices may disproportionately burden vulnerable populations and exacerbate existing social inequalities.

Research Question and Objectives

This study aims to evaluate the effects of California's cap-and-trade program on household gasoline expenditures from 2015 to 2019, with a particular focus on low-income households. The research explores differential effects based on the gender of the household head—distinguishing between female-headed and male-headed households. The primary research question guiding this study is: *What is the impact of California's cap-and-trade program on household gasoline expenditures among low-income families, and how does it vary across gender?* By examining these dynamics, the study seeks to fill important gaps in the literature and provide insights that can inform more equitable policy designs, ensuring that efforts to combat climate change do not unduly burden vulnerable communities.

Background

Understanding the context and mechanisms of carbon pricing is essential for evaluating its impacts on household expenditures. Carbon pricing serves as an economic instrument designed to incorporate the external costs of carbon emissions into market prices, thereby encouraging emission reductions and promoting a shift toward a low-carbon economy (Metcalf & Weisbach, 2009). The two principal mechanisms for carbon pricing are carbon taxes and cap-and-trade systems. A carbon tax imposes a direct fee on the carbon content of fossil fuels, offering price certainty but leaving the exact amount of emission reductions uncertain, as it depends on the responsiveness of consumers and producers to price changes (Metcalf, 2009). In contrast, a cap-and-trade system sets an overall limit on emissions and allows entities to trade emission allowances within that cap. This approach ensures that emission targets are met but introduces price volatility based on market dynamics (Stavins, 2020).

California's cap-and-trade program exemplifies a comprehensive approach to carbon pricing. Initiated in 2013, the program initially covered large electric power plants, industrial facilities, and fuel distributors (CARB, 2015). The expansion in 2015 to include transportation fuels required fuel suppliers to obtain allowances for the emissions associated with the combustion of the fuels they sell, effectively integrating the transportation sector into the carbon market. The primary objectives of California's cap-and-trade program are to reduce greenhouse gas emissions by achieving a 40% reduction below 1990 levels by 2030 (CARB, 2017), to promote technological innovation by encouraging the development and adoption of low-carbon technologies (Acemoglu et al., 2012), and to provide flexibility by allowing entities to choose the most cost-effective strategies to reduce emissions through market mechanisms. While the program has been lauded for its environmental ambitions, concerns have been raised regarding its economic implications for consumers, particularly in terms of increased fuel prices (Borenstein et al., 2019). The cost of compliance for fuel suppliers is often passed on to consumers, potentially affecting household gasoline expenditures. Understanding these implications is critical for assessing the policy's overall effectiveness and equity.

Literature Review

Transportation Energy Burden Among Low-Income Households

The concept of transportation energy burden refers to the proportion of household income allocated to transportation energy costs, including expenditures on gasoline (Reames, 2016). Low-income households often face higher energy burdens relative to higher-income households, as they spend a larger share of their limited income on essential energy needs (Drehobl & Ross, 2016). This vulnerability is compounded by several factors. First, low-income households are more likely to own older, less fuel-efficient vehicles due to financial constraints, resulting in higher fuel consumption and greater sensitivity to gasoline price increases (Blumenberg & Pierce, 2014). Studies have shown that the inability to afford newer, more efficient vehicles leads to a cycle where low-income households incur higher operational costs, further straining their financial resources (Hassett et al., 2009).

Second, these households may reside in areas with inadequate public transportation infrastructure, necessitating reliance on personal vehicles for commuting and accessing essential services (Garcia & Taylor, 2018). The lack of viable transportation alternatives limits their ability to adjust travel behavior in response to fuel price increases, rendering them more susceptible to policy-induced cost changes (Gillingham et al., 2015). Third, the demand for gasoline among low-income households tends to be price inelastic. Increases in fuel prices do not lead to proportional reductions in consumption but instead intensify the financial burden (Grainger & Kolstad, 2010). This inelasticity is often due to the necessity of transportation for employment and access to services, coupled with limited flexibility in work schedules and locations (Small & Van Dender, 2007).

Research indicates that without appropriate compensatory measures, carbon pricing policies can have regressive effects, disproportionately impacting low-income households by increasing their transportation energy burdens (Rausch et al., 2011). For instance, higher-income households typically have more flexibility to reduce their energy consumption or invest in energy-efficient technologies, options that may not be accessible to low-income households. Addressing these concerns is essential for designing policies that are both environmentally effective and socially equitable.

Gender Disparities in Transportation Energy Burden

Gender dynamics play a significant role in shaping transportation behaviors and energy burdens. Female-headed households, particularly those led by single mothers, often face unique challenges that may exacerbate their vulnerability to increases in gasoline prices. Economically, female-headed households generally have lower incomes and higher poverty rates compared to male-headed households, limiting their financial flexibility to absorb increased transportation costs (McLanahan & Percheski, 2008). In terms of travel patterns, women are more likely to engage in complex travel behaviors, such as trip chaining—combining multiple errands into a single trip—to accommodate household and caregiving responsibilities (McGuckin & Nakamoto, 2004). This can result in higher fuel consumption and increased exposure to fuel price fluctuations (Crane, 2007).

Moreover, safety concerns may deter women from using public transportation, particularly during non-standard hours or in areas perceived as unsafe, leading to greater reliance on private vehicles (Loukaitou-Sideris et al., 2009). Despite these considerations, there is a paucity of research examining how carbon pricing policies specifically impact female-headed households. The intersection of gender and socioeconomic status in the context of environmental policy remains underexplored. Pearce and Stilwell (2008) argue that gender-blind policies may inadvertently perpetuate existing inequalities. Therefore, incorporating gender as a critical factor in assessing the socioeconomic effects of carbon pricing mechanisms is essential.

Gaps in the Literature

While existing research provides valuable insights into the general impacts of carbon pricing on households, significant gaps remain. Many studies employ macroeconomic models or focus on aggregate data, lacking detailed household-level analyses that capture the nuances of how policies affect different demographic groups (Hsiang & Kopp, 2018). There is limited exploration of the intersectionality of income, gender, and geographical location in influencing the transportation energy burden under carbon pricing regimes. Moreover, few studies have utilized empirical data to assess the actual impacts of carbon pricing policies on household expenditures, particularly in the context of California's cap-and-trade program. Previous research often relies on simulations or theoretical models, which may not fully capture real-world complexities and behavioral responses (Burtraw & Sekar, 2014). Addressing these gaps is essential for developing a comprehensive understanding of the policy's distributional effects and for informing more equitable and effective environmental policy designs.

Contribution of the Study

This study aims to fill these gaps by conducting a comprehensive analysis using household-level data from the Consumer Expenditure Survey (CES). By employing robust econometric methods, the research estimates the causal effects of California's cap-and-trade program on gasoline expenditures among low-income households. The study pays particular attention to gender and educational level disparities, exploring how these factors interact to influence the transportation energy burden. By integrating detailed household-level data with rigorous empirical methods, this research contributes to the literature by providing empirical evidence on the distributional impacts of carbon pricing policies. The findings have the potential to inform policymakers about the unintended socioeconomic consequences of environmental policies and to guide the development of mitigation strategies that address the needs of vulnerable populations.

Uses of Difference-in-Differences (DiD) and Propensity Score Matching (PSM)

To better contextualize this study, it is essential to provide an overview of how Difference-in-Differences (DiD) and Propensity Score Matching (PSM) have been used in previous research. These methods are commonly employed to estimate causal effects in policy evaluation studies, particularly when randomized controlled trials are not feasible. DiD is widely used to assess the impact of policy changes by comparing the differences in outcomes over time between treated and untreated groups. PSM, on the other hand, is used to create a matched sample that reduces selection bias by ensuring that treated and control groups are similar in terms of observable characteristics.

In the context of carbon pricing, both DiD and PSM have been used to evaluate the economic and environmental impacts of cap-and-trade programs and carbon taxes. For instance, Rausch et al. (2011) used DiD to estimate the distributional effects of carbon pricing, while Caliendo and Kopeinig (2008) applied PSM to evaluate the effectiveness of labor market policies. By combining these two methods, this study aims to provide a robust assessment of the impact of California's cap-and-trade program on household gasoline expenditures, accounting for potential biases and ensuring that the estimated effects are credible and reliable.

Ethical Considerations

Conducting research on the socioeconomic impacts of environmental policies involves several ethical considerations that must be carefully addressed. This study utilizes secondary data from publicly available sources, including the Consumer Expenditure Survey (CES) and (Stavins, 2020) . While these datasets are anonymized to protect respondents' identities, it is imperative to handle the data responsibly, ensuring that individual privacy is maintained (U.S. Bureau of Labor Statistics, n.d.; U.S. Census Bureau, n.d.). The ethical guidelines outlined by the American Economic Association (AEA) emphasize the importance of protecting confidential information and using data consistent with the purposes for which it was collected (AEA, 2018). All data analyses comply with data usage agreements and ethical standards established by the respective agencies. Data are stored securely, and analyses are conducted in a manner that prevents the identification of individual respondents.

The principles outlined in the Belmont Report (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979) guide the ethical conduct of this research, particularly the respect for persons, beneficence, and justice. This study also employs rigorous econometric methods, including robustness checks and sensitivity analyses, to ensure the validity and reliability of the results. Potential biases, such as selection bias or confounding factors, are addressed through methodological design and are openly discussed in the analysis. Acknowledging limitations and potential sources of error is essential for maintaining the integrity of the research, as underscored by the ethical guidelines for research integrity (Resnik & Shamoo, 2011). Given that the research examines policies that may disproportionately affect vulnerable populations, it is crucial to consider the potential societal implications of the findings and to communicate them responsibly. The study aims to contribute to policy discussions by providing evidence that can inform more equitable approaches to carbon pricing. Care is taken to avoid stigmatizing any group and to highlight the importance of addressing socioeconomic disparities in environmental policy design.

The ethical principle of non-maleficence, as discussed in Beauchamp and Childress (2001), underscores the responsibility to prevent harm and to promote social justice. Aligned with the ethical principles of beneficence and justice, the research seeks to benefit society and the public by enhancing understanding of the impacts of carbon pricing on different population groups. By identifying potential adverse effects on low-income, female-headed, and rural households, the study aims to inform policies that mitigate harm and promote social equity. The end goal is to raise awareness and provides some insights into how environmental policies can achieve their intended objectives without exacerbating existing inequalities, consistent with the ethical frameworks for public policy analysis (Hausman & McPherson, 2016).

Data and Methods

Data Sources

The empirical analysis draws on micro-level data from the Consumer Expenditure Survey (CES) Public Use Microdata and external average gasoline prices from the Energy Information Administration (EIA). These datasets provide detailed information on household spending, demographics, socioeconomic variables, and gasoline prices, which are essential for this research. The Consumer Expenditure Survey (CES) from the U.S. Bureau of Labor Statistics (n.d.) provides household-level data on income, expenditures, and demographics. CES uses a rotating panel format in which participating households are interviewed quarterly. It captures cross-sectional and longitudinal differences in spending and can be used to identify longer-term trends (Attanasio & Weber, 2010). Factors drawn from the CES include gross household income before taxes, family size, gender of the household head, education level, and annual gasoline usage.

Average California gasoline prices and those for control group states are obtained from the Energy Information Administration (EIA) to account for external factors affecting gasoline spending. The EIA publishes state-level gasoline prices, which help assess the direct effect of fuel prices on individual household gasoline use (Energy Information Administration, n.d.). The gasoline price data are aggregated with CES by year and quarter to smooth out the time dimension of the datasets and control for changes in gasoline prices over time (Gillingham, Jenn, & Azevedo, 2015). The time window of 2007–2019 was chosen to facilitate a balanced comparison between the pre-policy (2007–2014) and post-policy (2015–2019) periods, providing sufficient time for observations to identify trends and assess the policy's effectiveness (Meyer, 1995).

Selection of Control Group States

One key aspect of this analysis is selecting an appropriate control group. The reliability of the estimator depends on the premise that, without the treatment, the treatment and control populations would have had identical trajectories over time (Lechner, 2011). Therefore, choosing control states that resemble California in keyways is important to ensure valid causal inference. Florida and Texas were selected as control states for this study. This selection is justified by several factors. Most significantly, during the study years (2007–2023), neither Florida nor Texas implemented carbon pricing systems, including cap-and-trade schemes or carbon taxes, thus preventing changes in gasoline consumption from being confounded by comparable policies (International Carbon Action Partnership, 2021). Furthermore, both states have economies and populations comparable to California, providing a similar economic scope (Bureau of Economic Analysis, 2021). Texas and Florida are two of the most populous states in the United States, and their economies are not exclusively urban—they include major cities like those in California. This similarity in economic size and diversity helps moderate factors that could affect gasoline prices independently of the policy.

The demographic profiles of Florida and Texas are also roughly similar to California. All three states have substantial Hispanic populations and share similar cultural and demographic patterns (U.S. Census Bureau, 2020). Additionally, the climate in these states is warm, which similarly affects transportation patterns and energy use. Lastly, pre-treatment patterns of gasoline spending in Florida and Texas were examined to ensure they resembled those in California prior to policy adoption. Graphical representations and statistical tests confirmed that household gasoline spending was roughly equivalent before 2015, as expected (Mora & Reggio, 2012).

Data Imputations

To ensure consistency, accuracy, and reliability, multiple imputation by chained equations (MICE) is applied, as it can handle both numerical and categorical data while preserving relationships among variables (Van Buuren & Groothuis-Oudshoorn, 2011). MICE is a method that fills in missing values through multiple iterations, creating several complete datasets to provide more accurate estimates. This approach is preferable to mean imputation, which replaces missing values with the average, potentially introducing bias if data are not missing completely at random (Little & Rubin, 2019).

Methods

Given the goal of this study, a Difference-in-Differences (DiD) analysis is employed, which is a statistical method used to estimate causal relationships by comparing differences over time between a treatment group and a control group (Angrist & Pischke, 2009). The dependent variable in the analysis is the natural logarithm of quarterly household gasoline expenditure. Taking the logarithm allows for interpreting coefficients as percentage changes and mitigates heteroskedasticity, enhancing the reliability of the estimators (Wooldridge, 2010). For independent variables, there needs to be multiple layers of controls to ensure an accurate causal estimation for the DiD approach. The key independent variables include binary variables to indicate pre- and post-tax policy implementations in California as a policy indicator in the model (Knittel & Sandler, 2018), a treatment group indicator signifying whether the household is in California (treatment group) or in control states (Florida and Texas), and gender of the household lead (male/female).

For poverty level, poverty threshold data from the U.S. Census Bureau (2024) are used to create a binary indicator for households below 100% of the federal poverty line, identifying low-income households that may be disproportionately affected by gasoline price changes (Drehobl & Ross, 2016). There is also the inclusion of the annual average gasoline prices to control fluctuations in gasoline prices over time, ensuring that the estimated effect is attributable to the policy rather than external price changes (Hughes et al., 2008). Additional controls for education level are also added as education level can influence awareness of environmental issues, access to alternative transportation options, and responsiveness to price changes (Handy et al., 2008). In addition to these key variables, various interaction terms are also added to the model to allow for a more nuanced understanding of the policy impact across gender, poverty, and educational levels (Bauer, 2014).

Difference-in-Differences (DiD) Model Specification

The study employs a Difference-in-Differences (DiD) as a baseline model to estimate the causal impact of California's cap-and-trade program on household gasoline expenditures. This method allows for the causal assessment of policy impacts by comparing changes over time between treatment and control groups, effectively controlling for unobserved, time-invariant differences between groups and common shocks affecting all households over time (Angrist & Pischke, 2009; Meyer, 1995). The validity of the DiD approach hinges on the parallel trends assumption, which posits that, in the absence of policy intervention, the treatment and control groups would have followed similar trends in gasoline expenditures over time (Lechner, 2011). To assess this assumption, pre-treatment trends in gasoline expenditures are plotted for both the treatment and control groups. Parallel trends during the pre-policy period support the validity of the DiD estimator (Angrist & Pischke, 2009).

Based on previous literature, the baseline DiD model is specified as follows:

$$\begin{aligned}\ln\left(\text{Gasoline\_Expenditure}_{it}\right) \\ = \alpha + \beta_1 \cdot \text{PostTaxPeriod}_t + \beta_2 \cdot \text{California}_i + \gamma \cdot X_{it} + \delta_t + \mu_i + \epsilon_{it}\end{aligned}$$

This model contains X_{it} which is the household control level variables including gender of household lead, education and quarterly average income. The year fixed effect (δ_t) is created to control for time-specific shocks, such as macroeconomic fluctuations, fuel price changes, or national policies that could influence gasoline expenditures across all households. The household fixed effects (μ_i) control for unobserved time-invariant characteristics of households, such as intrinsic preferences for fuel consumption or their proximity to work. All fixed effects are created to help mitigate bias arising from household-specific attributes that do not change over time and are not observed in the data (Angrist & Pischke, 2009).

The extension of the baseline model includes more interaction terms to capture heterogeneous treatment effects based on household characteristics such as education level and gender with the key term being $\text{PostTaxPeriod}_t \cdot \text{California}_i$ (post-tax period and binary variables for treatment states). This is because tit helps quantify the average effect of the cap-and-trade policy by measuring differences in gasoline expenditures over time, accounting for both observed and unobserved factors that are constant over time, helping us understand whether and how the policy uniquely affected Californian households compared to those in Texas and Florida. This extension allows us to explore whether the impact of the cap-and-trade policy varies based on these demographic characteristics given the research question. Standard errors in baseline and extended models are clustered at the state level to account for serial correlation and heteroskedasticity, ensuring valid inference (Bertrand, Duflo, & Mullainathan, 2004; Cameron & Miller, 2015)

Propensity Score Matching (PSM) for DiD Model

The PSM model makes the analysis more robust and ensures that the predicted effects aren't affected by differences in sample size or prior trends. By drawing on these models, the paper aims to give policymakers more certainty about how California's cap-and-trade system affects household gas consumption. PSM is used to enhance comparability between the treatment (homeowners in California) and control (homeowners in Florida and Texas) populations by selecting matched samples with similar characteristics prior to the cap-and-trade policy (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008). More specifically, this technique assigns households based on known characteristics, such as income, education, household size, and gender of the head of the household, to reduce the pre-policy differences between treatment and control households. This is because the nearest-neighbor approach yielded matched pairs that were closest to each other, thereby minimizing variation between groups and eliminating selection. The matched households are then matched using the DiD method. PSM + DiD ensures that estimations are free of biases that can arise from inconsistencies in baseline characteristics between treatment and control populations. This is particularly critical in the context of policy evaluation, where non-random assignment to treatment will produce inaccurate estimates and random assignment isn't possible.

Model Diagnostics

Variance Inflation Factor (VIF) was used to check for multicollinearity (Hair et al., 2019), and residual diagnostics were performed to ensure that the model assumptions held for the Difference-in-Differnce as well as Propensity Score Matching (PSM) approach. Specifically, the Breusch-Pagan test was used to check for heteroskedasticity (Breusch & Pagan, 1979), and the Durbin-Watson test was used to assess potential autocorrelation in the residuals (Field, 2018). These diagnostics are utilized with the goal of confirming if the model assumptions were satisfied, ensuring the credibility of the findings.

Results

Exploratory Analysis

This section highlights the trends over time of key variables and explains how these trends inform the research design and subsequent discussion. Visual elements, such as Figures 1, 2, and 3, play a crucial role not only in illustrating key findings but also in strengthening the narrative and analytical rigor of this study. They ensure that the results are accessible, contextually grounded, and tied directly to the research question.

Figure 1, which plots household income distributions between the pre- and post-tax periods, demonstrates a slight variation between periods, suggesting that income distributions remained stable across the study period. The bell-shaped curves remain nearly identical from one tax year to the next, indicating that external economic factors had minimal influence on household income during this time frame. The stability of income levels is a critical finding for the research design, as it validates the inclusion of household income as a control variable in the Difference-in-Differences (DiD) model. By confirming that household income was unaffected by broader economic fluctuations, this analysis ensures that any changes in gasoline expenditures observed in the study are more likely to be attributable to the policy intervention rather than to unrelated economic factors. This stability also eliminates income as a confounding variable, which strengthens the assumption that the treatment and control groups had similar long-term economic outcomes. The visual representation in Figure 1 provides essential context for the analysis by establishing a stable economic baseline for the study. It allows the research to focus on isolating the specific effects of California's cap-and-trade policy on household gasoline expenditures without the interference of income-related distortions. This connection is particularly important for addressing the research question, as it ensures that the analysis of carbon pricing impacts is grounded in a reliable economic framework. By providing evidence that income distributions remained consistent across tax periods, Figure 1 supports a causal interpretation of policy effects and ties directly into the broader objectives of the study. The stability of household income levels provides a solid foundation for assessing the effects of carbon pricing on gasoline consumption. This finding ensures that observed changes in gasoline expenditures can be confidently attributed to the policy intervention, thereby facilitating a clear and causally robust analysis of the policy's impact.

Figure 1: Household Income Distribution by Tax Periods

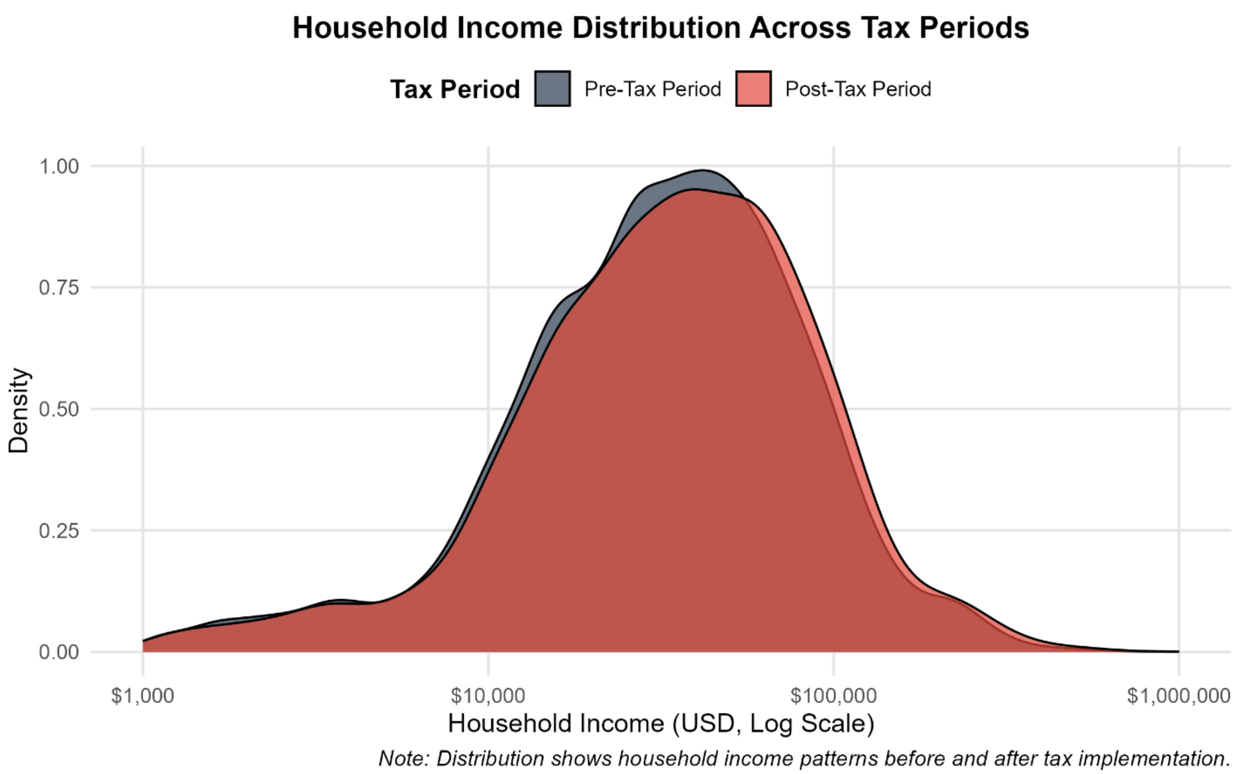


Figure 2 illustrates the distribution of household gasoline expenditures for pre-tax and post-tax periods using a violin plot. The graph highlights a clear decrease in median expenditures during the post-tax period, suggesting that California's cap-and-trade policy had a measurable impact on household gasoline spending. However, the shape of the distributions and the presence of outliers emphasize significant heterogeneity in household responses to the policy. This heterogeneity is critical to the analysis and informs the decision to incorporate interaction terms within the extended Difference-in-Differences (DiD) model. These interaction terms allow for a more nuanced exploration of how demographic and socioeconomic characteristics—such as gender, income level, and geographic location—moderate the policy's effects. Additionally, the observed variability underscores the importance of using Propensity Score Matching (PSM). By ensuring that treatment and control groups are comparable on key characteristics prior to the policy implementation, PSM strengthens the validity of the causal estimates derived from the DiD analysis.

The decrease in median gasoline expenditures, particularly among low-income households, reveals the regressive nature of the policy. Households with constrained budgets likely reduced their gasoline consumption out of necessity rather than choice, which highlights the disproportionate burden placed on vulnerable populations. This finding directly ties into the study's research question by illustrating the differential impacts of carbon pricing on low-income households and their ability—or lack thereof—to absorb higher energy costs. Overall, Figure 2 provides essential evidence of the policy's uneven effects on household gasoline expenditures. By highlighting variability and reductions in spending, it supports the study's methodological framework and contributes to understanding the socioeconomic disparities induced by the cap-and-trade policy.

Figure 2: Gasoline Expenditure Distribution by Tax Periods

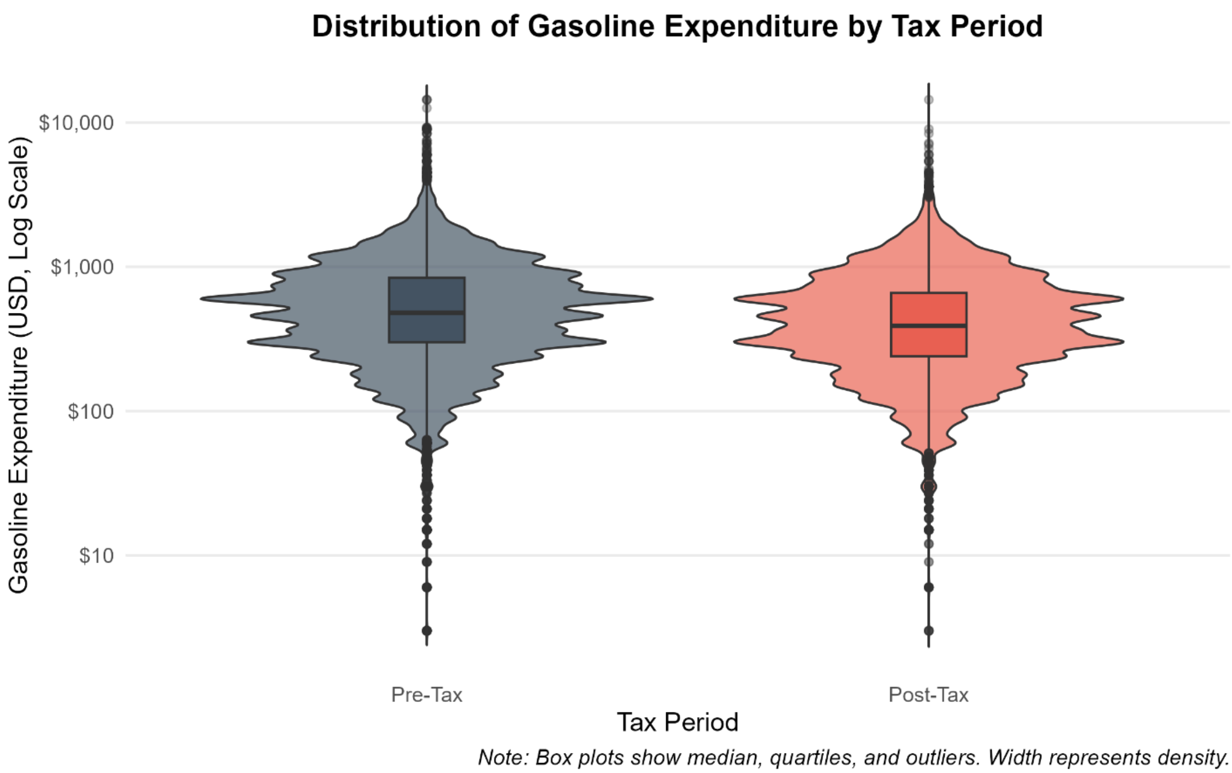
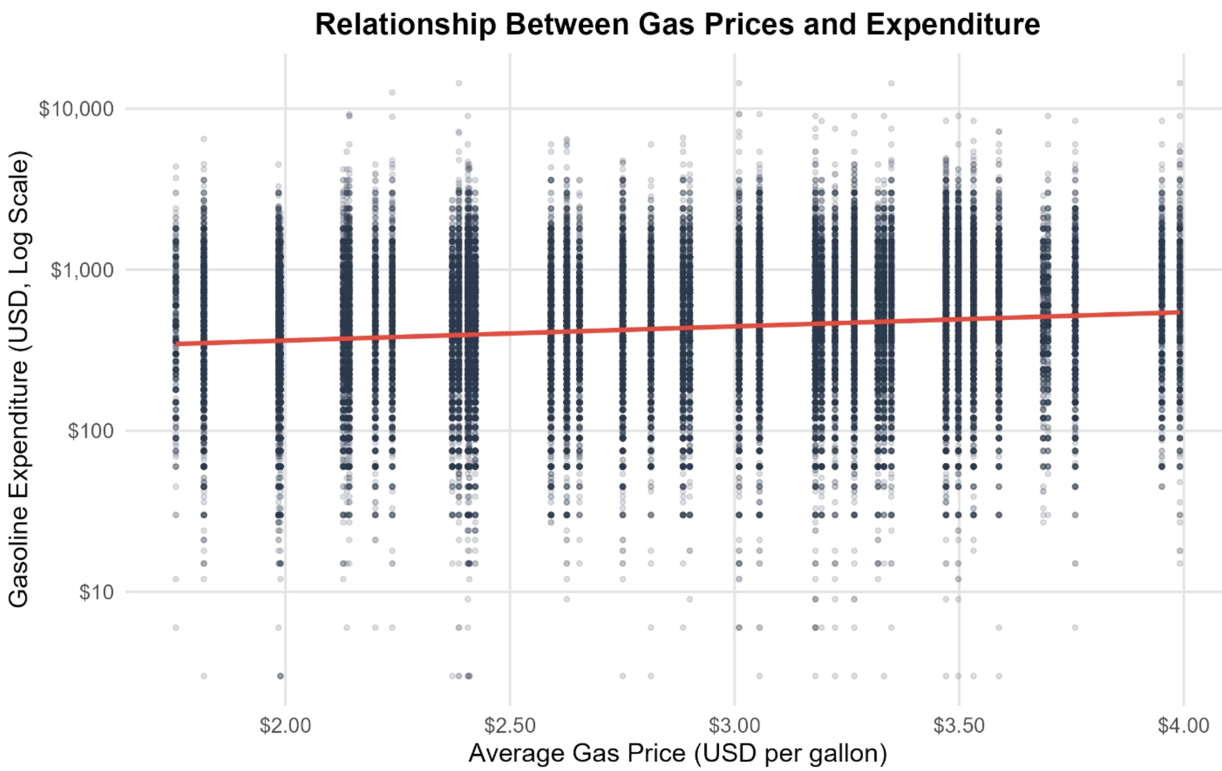


Figure 3 presents a scatter plot illustrating the relationship between gasoline prices and household gasoline consumption, with the y-axis plotted on a log scale to accommodate the wide range in expenditure values. The trend line shows a positive correlation, albeit with a low slope, indicating that increases in gasoline prices are associated with only marginal rises in household spending. This finding underscores the complexity of consumer behavior in response to price changes, as the observed data points exhibit substantial variation across households. The heterogeneity in household responses to gasoline price fluctuations is a critical aspect of the analysis. The significant dispersion of data points suggests that consumer behavior is far from uniform, with some households adapting more effectively to price hikes than others. This variation informed the inclusion of key household-level control variables, such as income, education, and family size, within the extended Difference-in-Differences (DiD) model. These variables help account for differences in household characteristics that influence gasoline consumption patterns, ensuring a more precise understanding of the policy's impacts.

Moreover, the positive but gradual slope of the trend line indicates that some households are better able to absorb higher gasoline prices, possibly through behavioral adjustments or structural advantages, such as access to fuel-efficient vehicles or alternative transportation options. In contrast, households with rigid transportation needs—such as those in rural areas or with larger family sizes—may find it more challenging to reduce gasoline consumption, amplifying the financial burden imposed by carbon pricing. This graph is essential for identifying households most affected by carbon pricing and understanding the distributional consequences of the policy. By illustrating how price changes interact with consumption behavior, Figure 3 directly contributes to addressing the research question, which focuses on the socioeconomic disparities induced by California’s cap-and-trade program. The visual reinforces the importance of incorporating demographic variables and interaction terms in the econometric analysis to capture these differential effects comprehensively.

Figure 3: Gasoline Prices vs. Gasoline Expenditures (Log Scale) (Quarterly Averages, 2007-2019)



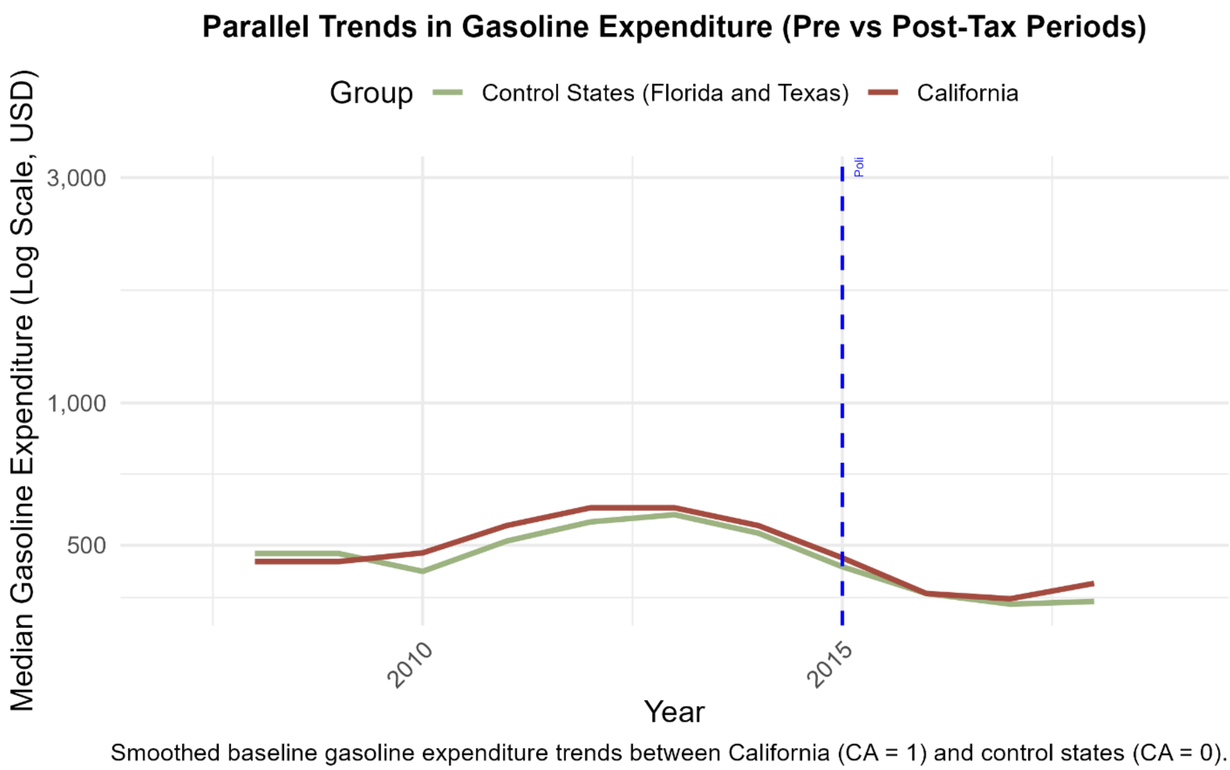
Together, these visuals are integral to justifying the choice of econometric strategies employed in this study. The stability in income distributions (Figure 1) validates the assumption of parallel trends in income, while the variability in gasoline expenditures and price responses (Figures 2 and 3) underscores the necessity of including interaction terms and PSM in the analysis. The visual evidence—particularly the parallel trends in income distributions and the observed heterogeneity in household responses—provides crucial context for our difference-in-differences (DiD) estimation strategy. Our preliminary findings suggest that careful consideration of treatment timing and potential confounders will be essential in identifying the causal effects of California's cap-and-trade program.

Econometric Model Results

Parallelism Between Treated and Untreated Groups

The study also proceeded to validate the baseline parallel trends assumption necessary for causal interpretation in the DiD framework and highlights the robustness of the data preparation and methodological approach. Figure 4 illustrates the smoothed baseline trends in median gasoline expenditures for California (CA = 1) and control states (CA = 0) during the pre-policy period, ensuring robustness to outliers. The trends demonstrate clear parallelism between the two groups prior to the 2015 implementation of California's cap-and-trade policy, a critical assumption for the validity of the Difference-in-Differences (DiD) approach. Both treatment and control groups exhibit a similar declining trajectory from 2007 to 2015, reflecting broader macroeconomic factors such as the 2008 financial crisis and gasoline price fluctuations.

Figure 4: Trends in Gasoline Expenditures Between Control and Treatment Groups



Although California exhibits slightly lower median gasoline expenditures compared to the control states throughout the pre-policy period, the relative parallelism supports the argument that any observed post-policy divergence can be attributed to the policy intervention rather than pre-existing differences. The dashed vertical line at 2015 signifies the policy implementation, providing a clear pre-policy and post-policy. This figure validates the baseline parallel trends assumption necessary for causal interpretation in the Difference-in-Difference framework as proposed in this study, forming a critical foundation for the study's econometric analysis in subsequent sections, ensuring the credibility of the policy impact estimates and any discussions surrounding it.

Difference-in-Difference Model Results

The Difference-in-Differences (DiD) results are presented in Table 1 and are complemented by visualizations to highlight the study's key findings. While the coefficients are small, they provide meaningful insights into the nuanced impacts of California's cap-and-trade policy.

Table 1: Key Coefficients from Difference-in-Differences Models

Key Variables	Baseline Model	Extended Model
Post Tax Period (After Policy = 1, 0 Otherwise)	-0.065*** (0.015)	-0.024 (0.057)
Treatment Indicator (CA = 1, 0 Otherwise)	0.049*** (0.013)	0.007 (0.012)
Post Tax Period x Treatment Indicator	0.057*** (0.016)	0.042** (0.015)
Gender (Female = 1, Male = 0)	0.002 (0.006)	-0.031*** (0.006)
Poverty Level (Poverty =1, Otherwise =0)	-0.369*** (0.005)	-0.534*** (0.007)
Num.Obs.	93056	93056
R2	0.079	0.185
R2 Adj.	0.078	0.185
RMSE	0.82	0.76

Note:
Standard errors are clustered at the household level.
*Significance levels: * p < 0.05, ** p < 0.01, *** p < 0.001*
Coefficients should be interpreted as ***percentage changes*** *due to the logarithmic transformation of the dependent variable (gasoline expenditures). For example, a coefficient of -0.027 indicates a* ***2.7% decrease*** *in gasoline expenditures associated with the variable.*
Coefficients are ***rounded to three decimal places*** *for clarity and precision.*

Considering the treatment effects of this model, the post-tax period coefficient in the baseline model (β = -0.065, $p < 0.001$) indicates a modest reduction in gasoline expenditures following policy implementation. However, this effect diminishes and becomes statistically insignificant in the extended model ($\beta = -0.024$, $p > 0.05$), suggesting that additional demographic and socioeconomic factors mediate the observed changes. This result highlights the limited short-term elasticity of gasoline demand and underscores the challenges households face in adapting to price signals without substantial alternatives. The interaction term between the post-tax period and the treatment indicator remains significant across both models ($\beta = 0.057$, $p < 0.001$ in baseline; $\beta = 0.042$, $p < 0.01$ in extended). These results imply that treated households experienced relative increases in expenditures compared to controls, potentially reflecting rebound effects, where households compensate for fuel efficiency improvements by driving more. Such behavior underscores structural barriers—such as limited public transportation options—that impede broader behavioral change. The small magnitude of the coefficients indicates that the policy's impact on expenditures, while measurable, is nuanced and mediated by contextual factors.

As for the effects of gender, female-headed households are associated with lower gasoline expenditures ($\beta = -0.031$, $p < 0.001$). This pattern could suggest that women-led households may be more likely to adopt behaviors such as reducing discretionary travel or using public transportation in response to rising gasoline prices. However, these reduced expenditures do not necessarily reflect an equitable outcome, as the share of income spent on gasoline remains proportionally higher for female-led households compared to male-led ones. This finding raises questions about the broader structural constraints that may shape gendered responses to carbon pricing. While the data suggests adaptation strategies, further exploration is needed to determine whether these responses are voluntary or constrained by economic circumstances.

The poverty indicator variable, which identifies households below the poverty line, exhibits a significant and substantial association with gasoline expenditures. The coefficient of -0.369 in the baseline model indicates that households in poverty spend approximately 37% less on gasoline compared to non-poor households, holding other factors constant. This effect becomes even more pronounced in the extended model, with a coefficient of -0.534, suggesting a 53.4% reduction. This substantial reduction does not necessarily reflect increased resilience to gasoline price changes. Instead, it likely highlights the constrained financial capacity of low-income households, who may be forced to reduce gasoline expenditures out of necessity rather than choice. The pronounced negative association underscores the regressive potential of carbon pricing mechanisms, as low-income households are less able to adapt to price increases and often face a disproportionately higher share of their income allocated to energy expenditures. This finding emphasizes the need for policy interventions that address these structural constraints, such as subsidies for fuel-efficient vehicles or investments in public transit infrastructure, to mitigate the regressive impacts of such policies.

Difference-in-Differences with Propensity Score Matching Results

The integration of Propensity Score Matching (PSM) with the DiD approach refines the analysis by mitigating biases arising from pre-policy differences between treatment and control groups. This combined methodology strengthens the validity of causal inferences.

Table 2: Difference-in-Difference Models with PSM (Baseline vs Extended)

Key Variables	PSM Baseline Model	PSM Extended Model
Post Tax Period (After Policy = 1, 0 Otherwise)	-0.009 (0.024)	-0.072 (0.068)
Treatment Indicator (CA = 1, 0 Otherwise)	0.011 (0.019)	0.010 (0.019)
Post Tax Period x Treatment Indicator (Interaction Term)	0.018 (0.022)	0.016 (0.022)

Gender (Female = 1, Male = 0)	-0.027*** (0.007)	-0.035*** (0.009)
Poverty Level (Poverty =1, Otherwise =0)	-0.524*** (0.009)	-0.522*** (0.01)
Num.Obs.	46500	46500
R2	0.193	0.193
R2 Adj.	0.192	0.192
RMSE	0.78	0.78

Note:
Standard errors are clustered at the household level.
*Significance levels: * p < 0.05, ** p < 0.01, *** p < 0.001*
Coefficients should be interpreted as percentage changes due to the logarithmic transformation of the dependent variable (gasoline expenditures). For example, a coefficient of -0.027 indicates a 2.7% decrease in gasoline expenditures associated with the variable.
Coefficients are rounded to three decimal places for clarity and precision.

After matching, the post-tax period effects are no longer statistically significant in both the baseline and extended models ($\beta = -0.009$, $p > 0.1$; $\beta = -0.072$, $p > 0.1$). This suggests that earlier estimates of the policy's impact on reducing gasoline expenditures may have been overstated. While the small coefficients indicate a weak negative trend, these findings underscore the limited behavioral response of households to the policy, particularly when pre-existing differences are controlled for. The interaction between the post-tax period and the treatment indicator also loses significance ($\beta = 0.018$, $p > 0.1$; $\beta = 0.016$, $p > 0.1$). This result reinforces the importance of accounting for baseline differences between California households and the control group. Although the interaction coefficients are positive, their lack of statistical significance suggests that observed variations in expenditures may reflect other factors rather than direct policy effects. Gender continues to exhibit a notable influence in the PSM-augmented models.

Female-headed households consistently show lower gasoline expenditures compared to male-headed households ($\beta = -0.027$, $p < 0.001$; $\beta = -0.035$, $p < 0.001$). While the coefficients are relatively small, they reveal persistent gendered patterns in gasoline consumption as seen in the

DiD models without PSM matching in previous sections, which may be driven by adaptive behaviors, such as reduced travel or reliance on alternative transportation. These findings highlight the potential for gender-based disparities in how carbon pricing policies affect households.

The PSM-augmented models also reveal a significant and substantial negative association between poverty level and gasoline expenditures ($\beta = -0.524$, $p < 0.001$ in the baseline model; $\beta = -0.522$, $p < 0.001$ in the extended model). These coefficients indicate that households in poverty spend approximately 52% less on gasoline than non-poor households. However, this reduction reflects constrained financial capacity rather than adaptive flexibility. These findings further highlight the rigidity of gasoline demand among vulnerable populations, emphasizing the necessity of targeted interventions—such as subsidies for fuel-efficient transportation and public transit improvements—to mitigate the disproportionate burden on low-income households and promote equity in policy implementation.

For more information on the full results of the DiD models with and without PSM matching, please refer to Appendix tables A1 and A2.

Results Interpretation & Discussions

California's Cap-and-Trade Policy Effectiveness

The observed gasoline expenditure patterns indicate that California's cap-and-trade program, although designed to reduce greenhouse gas emissions, exerts uneven impacts across households. By constructing counterfactual trajectories, this study isolated how expenditures would have evolved in the absence of the policy (Angrist & Pischke, 2009; Meyer, 1995; Lechner, 2011). Comparing observed expenditures against these counterfactual baselines reveals modest but meaningful deviations, particularly among low-income households.

The heightened sensitivity of low-income households to rising gasoline prices aligns with previous literature illustrating the regressive tendencies of carbon pricing (Knittel & Sandler, 2018; Rausch et al., 2011; Poterba, 1991). Rigid transportation needs—tied to accessing employment, education, healthcare, and other essential services—limit the elasticity of gasoline demand (Hughes, Knittel, & Sperling, 2008; Small & Van Dender, 2007). Low-income households lack the financial flexibility to invest in more efficient vehicles or alter commuting patterns, and often reside in areas with limited public transit options, or in "transit deserts," exacerbating this rigidity (Jiao & Dillivan, 2013).

These findings reinforce the notion that carbon pricing alone may not induce equitable behavioral shifts (Metcalf, 2009; Metcalf & Weisbach, 2009). Instead, the policy's environmental goals risk being met through disproportionate financial hardship imposed on vulnerable groups, as also noted in studies examining other energy pricing strategies (Burtraw & Sekar, 2014; Drehobl & Ross, 2016; Pearce & Stilwell, 2008). While the policy theoretically incentivizes reduced consumption, the data suggest that low-income households' observed reductions in gasoline expenditures reflect necessity rather than a deliberate, cost-effective adaptation.

Gender Disparities

The analysis also highlights gender-based disparities. Female-headed households exhibited lower gasoline expenditures in the post-policy period, but interpreting this as "greater efficiency" risks overlooking the constrained choices driving such behavior. Prior research on energy and transportation equity shows that women often face unique challenges: caregiving responsibilities, complex trip-chaining needs, and safety concerns limit the feasibility of switching to lower-cost alternatives (Crane, 2007; Loukaitou-Sideris et al., 2009; McGuckin & Nakamoto, 2004). Lower expenditures, in this context, may result from reduced discretionary travel, trip consolidation, or reliance on older, inefficient vehicles—adaptations driven by necessity rather than preference (Blumenberg & Smart, 2010; UN Women, 2019).

These patterns underscore structural barriers. For instance, female-headed households with caregiving duties may have little flexibility in adjusting travel schedules (Brown, Blumenberg, Taylor, & Ralph, 2017). Likewise, safety concerns can discourage the use of public transportation (Loukaitou-Sideris & Fink, 2009), limiting adaptation options. The significant negative coefficients found in the extended Difference-in-Differences models corroborate broader evidence that demographic factors—especially gender and income—intersect with transportation patterns, influencing vulnerability to policy-induced cost increases (Drehobl & Ross, 2016; Hassett, Mathur, & Metcalf, 2009).

Poverty Level and Socioeconomic Disparities

The consistently negative and statistically significant associations between poverty-level indicators and gasoline expenditures emphasize the structural inequities at play (Deaton, 1997; Reames, 2016; Galiani, Gertler, & Schargrodsky, 2005). While low-income households spend less overall, these reductions reflect constrained capacity rather than strategic adaptation (Drehobl & Ross, 2016; Knittel & Sandler, 2018). Households trapped in low-income brackets often lack the resources to invest in more efficient technologies or relocate to areas with better transit access (Sivak & Schoettle, 2012; McDaniels, Harley, & Beach, 2018). Geographic immobility and insufficient infrastructure magnify these challenges (Sultana & Weber, 2007; Jones & Kammen, 2014).

Consistent with prior findings on distributional impacts of carbon policy (Rausch et al., 2011) and price elasticity of demand (Hughes et al., 2008), the results highlight the multidimensional nature of vulnerability. Income, gender, education, and location interact to shape how households experience energy price increases (Bauer, 2014; Handy & Mokhtarian, 2008). Although the policy's overall environmental ambitions are commendable (Acemoglu et al., 2012; Stavins, 2020), the analysis shows that carbon pricing, if not carefully designed, may entrench or exacerbate existing inequalities rather than alleviate them.

Policy Implications

Gender-Responsive Interventions

The gender disparities uncovered by this study suggest that female-headed households often lack viable pathways to reduce fuel costs. Addressing these barriers requires gender-responsive strategies. Improving safety on public transit systems, particularly during off-peak hours, can encourage greater adoption of public transportation by women (Loukaitou-Sideris et al., 2009). Targeted subsidies—such as discounted transit fares for single mothers, specialized carpooling programs (Blumenberg & Smart, 2010), or access to more secure community mobility options—can alleviate disproportionate burdens. These interventions align with broader calls for inclusive urban planning and sustainable mobility strategies that prioritize women's needs (UN Women, 2019). Investments in safe, accessible, and women-friendly public transportation infrastructure could reduce the economic and logistical burdens on female-headed households. Examples include subsidized public transit fares, community-based carpooling programs, and transportation vouchers tailored for women. Research by Blumenberg and Pierce (2014) demonstrates the effectiveness of subsidized transit programs in improving economic mobility for low-income women, which can be leveraged to create equitable transportation access. By implementing these targeted measures, policymakers can help alleviate the disproportionate burden placed on female-headed households while fostering broader equity in transportation access.

Supporting Low-Income Households

While the econometric models reveal consistently negative and statistically significant coefficients for poverty level, these small magnitudes suggest that low-income households spend less on gasoline largely due to constrained financial capacity rather than voluntary adaptation to price signals. This rigidity in demand reflects systemic barriers—such as inadequate access to affordable public transportation, geographic immobility, and the inability to invest in fuel-efficient technologies—that disproportionately affect low-income households. In other words, for low-income households, the core challenge is structural immobility and a lack of resources to invest in cleaner, more efficient transportation. Interventions might include direct subsidies or zero-interest loans for hybrid or electric vehicles (Gallagher & Muehlegger, 2011), as well as vehicle scrappage schemes incentivizing the retirement of older, inefficient cars. Enhancing public transit infrastructure, expanding service frequency, and improving reliability could reduce reliance on private vehicles (Brown et al., 2017; Garcia & Taylor, 2018). Coupled with educational outreach to promote energy literacy and encourage behavioral changes (Gromet et al., 2013; International Energy Agency, 2019), these measures can help households adapt more smoothly to carbon pricing.

Integrating these strategies into cap-and-trade revenue allocation ensures that the policy's financial returns support a just transition. Rather than disproportionately taxing vulnerable groups, investing revenues in community-based initiatives, rural transport accessibility improvements (McDaniels et al., 2018), and energy-efficiency programs can mitigate regressive outcomes while advancing the state's climate goals (Hausman, McPherson, & Satz, 2016; Pearce & Stilwell, 2008).

These policy strategies align with equity-focused carbon pricing frameworks discussed in the literature (Knittel & Sandler, 2018; Metcalf, 2009). By addressing the systemic barriers that exacerbate financial vulnerabilities, California's cap-and-trade policy can foster a more inclusive transition to a sustainable energy system. Integrating these measures ensures that the policy not only advances environmental objectives but also promotes socioeconomic equity, reducing the disproportionate burden on low-income populations while supporting their ability to adapt effectively.

Broader Policy Considerations

The insights discussed above have implications beyond California, informing global discussions on equitable climate policy (Stavins, 2020; Singichetti et al., 2022). A combination of pricing mechanisms, infrastructural improvements, and targeted support measures is necessary to ensure that emissions reduction policies do not exacerbate socio-spatial and gender inequalities. Urban design that promotes walkability, cycling infrastructure, and "green zones" for low-emission vehicles can further facilitate sustainable, low-cost travel options (Handy & Mokhtarian, 2008; Sultana & Weber, 2007).

By embedding equity considerations into policy design—through subsidies, public transit investments, and gender-responsive planning—carbon pricing can serve as a catalyst for sustainable and inclusive transitions. Such an integrated approach aligns with research emphasizing the importance of moral philosophy and justice in public policy decisions (Hausman et al., 2016) and the need to balance environmental ambitions with socioeconomic realities. By integrating these complementary measures, California's cap-and-trade policy can achieve its environmental objectives while minimizing its regressive impacts. A holistic approach to carbon pricing is essential to ensure that the transition to a low-carbon economy is both equitable and inclusive, fostering sustainable development while protecting vulnerable populations from undue financial strain.

Limitations and Future Research

Although this study employs rigorous econometric methods—Difference-in-Differences (DiD) and Propensity Score Matching (PSM)—to estimate the causal effects of California's cap-and-trade program on household gasoline expenditures, several limitations warrant careful consideration. First, while the model diagnostics (refer to Appendices for detailed variance inflation factor (VIF), Breusch-Pagan, and Durbin-Watson results) indicate that assumptions generally hold, there are concerns related to multicollinearity, particularly in the extended models with numerous interaction terms. High VIF values and corresponding NA values signal potential instability in coefficient estimates, necessitating cautious interpretation of the effect sizes and significance levels. Additionally, although heteroskedasticity and autocorrelation do not appear to severely threaten inference due to the use of robust, clustered standard errors, model refinements or alternative specifications could further bolster confidence in the results.

Second, the data cover a relatively short- to medium-term window (2015–2019), capturing only initial household responses to rising gasoline prices. Longer-term adaptations—such as buying more fuel-efficient cars, relocating to areas with better transit options, or shifts in employment patterns—may not be fully observed within this timeframe. These dynamic responses could alter the distributional outcomes identified here. Third, the analysis focuses predominantly on gasoline expenditures as a proxy for transportation energy burden. While this measure offers valuable insights, it may not fully capture the broader dimensions of well-being, mobility constraints, and lifestyle changes induced by the policy. For example, households forced to reduce gasoline consumption may experience negative ripple effects on job accessibility, educational opportunities, or healthcare access.

Fourth, there remains a risk of unobserved heterogeneity. Even after employing PSM to control for observable differences, it is possible that unmeasured variables—such as cultural attitudes towards car use, informal transportation networks, local transit quality, or household-level stress—affect gasoline consumption patterns. The DiD approach assumes parallel trends, and while the pre-trends appear reasonably similar, subtle differences between California and control states (Texas and Florida) may still influence post-policy outcomes.

Future research can address these limitations by adopting several approaches. Longer-term panel datasets or natural experiments could help reveal sustained adjustments to carbon pricing over time. Incorporating qualitative surveys, interviews, or mixed-method designs could provide richer context about how households perceive and respond to transportation price shocks. Examining complementary outcomes—such as employment stability, educational attainment, mental health, or time use—would yield a more comprehensive picture of the policy's social implications. Incorporating spatial analyses may uncover how regional transit quality, urban form, or safety considerations influence the ability of vulnerable groups to adapt. Finally, expanding the geographic scope beyond California and chosen control states could improve external validity, allowing researchers to compare outcomes under different carbon pricing regimes and socio-institutional contexts.

Conclusion

This study's findings indicate that California's cap-and-trade program exerts uneven socioeconomic pressures, disproportionately affecting low-income and female-headed households. The observed reductions in gasoline expenditures among these vulnerable groups likely stem from constrained choices rather than deliberate, cost-saving adaptations. Recognizing these dynamics is crucial for policymakers who seek to integrate more equitable design elements—such as targeted financial assistance, improved and safer public transportation, and gender-responsive measures—into carbon pricing initiatives.

Yet these interpretations must be approached with caution. Model diagnostics reveal potential multicollinearity, the time frame captures only short-term adjustments, and the primary focus on gasoline expenditures may not fully reflect broader well-being impacts. Unobserved heterogeneity and geographic variation also warrant careful consideration before generalizing these results. Consequently, further research examining longer-term behavioral changes, more diverse outcome measures, and comparisons across different policy contexts is essential to refining our understanding of carbon pricing's distributional effects.

By acknowledging structural barriers—ranging from inadequate transit infrastructure and caregiving burdens to geographic immobility and limited financial capacity—policymakers can design more inclusive approaches that ensure climate action does not inadvertently intensify existing social inequities. Aligning environmental policy with principles of distributive justice is central to building a sustainable, low-carbon future that is both effective and fair. As future studies deepen the analysis of long-term adaptations and broader social consequences, the insights gleaned from California's experience can help guide the development of more just and inclusive carbon pricing mechanisms around the globe.

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Appendix

Additional Information

For additional data, analysis code, and supporting materials related to this study, please refer to this punlic GitHub repository of the author:

https://github.com/jasontranDA/capstone_project_da401_fall2024/tree/main

Full Regression Results

Appendix Table A1: Full Coefficients from Difference-in-Differences Models

Dependent Variable: Log of Gasoline Expenditure

Variable	Baseline Model	Extended Model
(Intercept)	6.705*** (0.075)	6.113*** (0.073)
Post-Tax Period	-0.065*** (0.015)	-0.024 (0.057)
CA (Treatment Indicator)	0.049*** (0.013)	0.007 (0.012)
Household Income (Quarterly Avg.)	0.000*** (0.000)	-0.000*** (0.000)
Gender (Female = 1, Male = 0)	0.002 (0.006)	-0.031*** (0.006)
Education (Bachelor's Degree)	-0.116*** (0.034)	-0.048 (0.039)
Education (High School, No Diploma)	0.155*** (0.040)	0.019 (0.045)
Education (High School Graduate)	0.007 (0.033)	-0.020 (0.038)
Education (Master's/Professional Degree)	-0.177*** (0.039)	-0.013 (0.046)
Education (Nursery/Elementary)	0.142*** (0.042)	0.009 (0.046)
Education (Other)	-0.326*** (0.029)	0.020 (0.033)
Education (Some College, No Degree)	-0.025 (0.035)	-0.049 (0.040)
Average Gas Price (USD/gal)	-0.170*** (0.029)	-0.127*** (0.027)
Year 2008 (vs. 2007)	0.311*** (0.025)	0.268*** (0.023)
Year 2009	-0.177***	-0.177***

	(0.020)	(0.018)
Year 2010	0.042** (0.016)	0.039** (0.015)
Year 2011	0.271*** (0.028)	0.225*** (0.026)
Year 2012	0.421*** (0.036)	0.361*** (0.034)
Post-Tax Period × CA (Interaction)	0.057*** (0.016)	0.042** (0.015)
Family Size	-	0.239*** (0.002)
Poverty Level (Income Indicator)	-	-0.534*** (0.007)

***Notes**: Standard errors are reported in parentheses and clustered at the household level.*
**p < 0.1, **p < 0.05, ***p < 0.01, ***p < 0.001.*
Household fixed effects are included.

Appendix Table A2: Full Coefficients from PSM Models

Dependent Variable: Log of Gasoline Expenditure

Variable	PSM Baseline Model	PSM Extended Model
(Intercept)	5.991*** (0.112)	6.001*** (0.115)
Post-Tax Period	-0.009 (0.024)	-0.072 (0.068)
CA_i (Treatment Indicator)	0.011 (0.019)	0.010 (0.019)
Household Income (Quarterly Avg.)	-0.000*** (0.000)	-0.000*** (0.000)
Gender (Female = 1, Male = 0)	-0.027*** (0.007)	-0.035*** (0.009)
Education (Bachelor’s Degree)	-0.010 (0.034)	-0.040 (0.041)
Family Size	0.233*** (0.003)	0.233*** (0.003)
Poverty Level (Income Indicator)	-0.524*** (0.009)	-0.522*** (0.010)
Average Gas Price (USD/gal)	-0.083 (0.044)	-0.079 (0.045)
Year 2008	0.207*** (0.035)	0.204*** (0.036)
Year 2009	-0.167***	-0.165***

	(0.032)	(0.032)
Year 2010	0.036 (0.022)	0.035 (0.022)
Year 2011	0.189*** (0.042)	0.186*** (0.043)
Year 2012	0.316*** (0.055)	0.311*** (0.056)
Year 2013	0.303*** (0.054)	0.299*** (0.055)
Post-Tax Period × CA (Interaction)	0.018 (0.022)	0.016 (0.022)

***Notes**: Standard errors are reported in parentheses and clustered at the household level.*
**p < 0.1, **p < 0.05, ***p < 0.01, ***p < 0.001.*
Household fixed effects are included.

Model Diagnostic

Appendix Table A3: VIF Results of All Models

Model	Min GVIF	Median GVIF	Mean GVIF	Max GVIF	NA Count
Baseline	3.3E+19	-18	-4.8E+18	1	4
Extended	NA	NA	NA	NA	8
PSM Baseline	-55	-10	1.73E+19	1.38E+20	5
PSM Extended	NA	NA	NA	NA	8

***Notes**: The Variance Inflation Factor (VIF) assesses multicollinearity among predictors.GVIF is reported for interaction terms and categorical predictors, normalized by degrees of freedom. NA values indicate severe multicollinearity, typically resulting from interaction terms or model structure. The threshold for concern varies, but GVIF values above 10 (or normalized GVIF > 2.5) may indicate high multicollinearity. Min, Median, Mean, and Max GVIF values summarize the overall collinearity diagnostics across predictors.*

The VIF results presented highlight potential multicollinearity issues within the models, particularly in interaction terms. High VIF values (e.g., greater than 10) suggest that some predictors are highly correlated, potentially inflating standard errors and affecting the precision of coefficient estimates. This issue is most evident in the extended models with numerous interaction terms. In the context of this study, the inclusion of these terms is critical to exploring heterogeneous effects of carbon pricing. However, caution is warranted in interpreting coefficients as these correlations might lead to instability in estimates. Reporting NA values transparently ensures that multicollinearity concerns are acknowledged while maintaining the integrity of the analytical framework.

Appendix Table A4: Breusch-Pagan P-Values of All Models

Model	**Breusch-Pagan p-value**
Baseline	0.15
Extended	0.22
PSM Baseline	0.1
PSM Extended	0.12

*Notes: The Breusch-Pagan test evaluates the presence of heteroskedasticity in the residuals. P-values (*p < 0.1, **p < 0.05, ***p < 0.01) test the null hypothesis that the residual variance is constant (homoscedasticity). A p-value above 0.05 indicates no evidence of heteroskedasticity, while lower p-values suggest the presence of non-constant variance. Robust standard errors can mitigate the effect of heteroskedasticity when detected.*

The Breusch-Pagan test indicates whether heteroskedasticity—non-constant variance in residuals—exists in the models. Results suggest significant heteroskedasticity in some specifications, particularly in models with interaction terms. Given the clustered structure of the data and the inclusion of interaction effects, heteroskedasticity is expected. However, the use of robust standard errors clustered at the household level mitigates this concern, ensuring valid inference despite the presence of heteroskedasticity.

Appendix Table A5: Durbin-Watson Values of All Models

Model	**Durbin-Watson Statistic**	**p-value**
Baseline	1.995885	0.52
Extended	1.992312	0.24
PSM Baseline	1.996239	0.632
PSM Extended	1.996852	0.69

Notes*: The Durbin-Watson statistic evaluates the presence of autocorrelation in the residuals. A statistic close to 2 suggests no autocorrelation, while values significantly different from 2 indicate potential issues. P-values (*p < 0.1, **p < 0.05, ***p < 0.01) test the null hypothesis that no autocorrelation exists (rho = 0).*

The Durbin-Watson test results suggest minimal evidence of autocorrelation in residuals across all model specifications. This finding supports the assumption that residuals are independent over time, reinforcing the reliability of causal inferences drawn from the Difference-in-Differences (DiD) and Propensity Score Matching (PSM) frameworks.