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

Abstract

The study examines the socioeconomic impact of California’s cap-and-trade system on household gas use from 2007 to 2019. It uses a Difference-in-Differences (DiD) and PSM to assess the effects on low-income households, with heterogeneous effects depending on gender, education, and household characteristics. The cap-and-trade program in California, designed to cut carbon emissions, has not been thoroughly examined about it has been unfairly burdening vulnerable populations. The findings suggest that the program has a some adverse effect on low-income families, with female-headed households and those with lower educational attainment experiencing higher energy burdens. These groups reduced gasoline consumption primarily due to economic constraints rather than behavioral adaptations, highlighting the regressive nature of the policy. In contrast, higher-income households were better able to adapt by reducing consumption or utilizing alternative transportation options. Hence, the research advocates for targeted compensatory interventions to address these inequities, such as rebates for low-income households, gender-sensitive subsidies, and investments in public transportation infrastructure.

These measures may help mitigate unintended negative consequences and ensure a more equitable distribution of the policy's costs.

Introduction

Climate change is one of our most immediate and important challenges and requires decisive and comprehensive policy responses to contain its damaging impacts on both ecosystems and human populations (Stavins, 2020). Carbon pricing is one of the methods developed to mitigate greenhouse gas emissions, and it has become an essential means of internalizing the external cost of carbon emissions (Stavins, 2020). By giving carbon outputs a price, carbon prices encourage carbon emission reductions and the transition to a low-carbon economy (Metcalf & Weisbach, 2009).

California has become one of the leaders in enacting carbon pricing schemes in the US. Those steps included the adoption of a cap-and-trade program in 2013, which mandates a cap on all greenhouse gas emissions and makes it possible for people to sell their emissions allowances (California Air Resources Board [CARB], 2015). The 2015 expansion of the program to transportation fuels substantially increased its effectiveness as transportation accounts for roughly 41 per cent of California's total greenhouse gas emissions (CARB, 2018). Through forcing fuel distributors to become a part of the cap-and-trade system, the policy drove up the price of gasoline, potentially impacting state household spending.

Although the cap-and-trade regime in California is lauded for its environmental achievements, its socioeconomic costs merit scrutiny. In particular, its effect on household gasoline consumption indicates that the policy has potentially regressive effects on low-income households. These households tend to spend a greater amount of their income on basic goods and services, such as transportation and energy (Drehobl & Ross, 2016). This could result in price hikes for gasoline that unfairly impact vulnerable populations, further fueling existing socioeconomic disparities.

Research Question and Objectives

This study aims to investigate the impact of California's cap-and-trade program on household gasoline expenditures from 2007 to 2019, with a specific focus on low-income households. The research explores differential impacts based on the gender of the household head—distinguishing between female-headed and male-headed households—with additional inspections of incomes and educational levels. The primary research question guiding this study is: *How has the implementation of California's cap-and-trade program affected household gasoline expenditures among low-income households, and what are the differential impacts based on gender and educational levels?* By examining these dynamics, the study seeks to fill critical gaps in the literature and provide insights that can inform more equitable policy designs, ensuring that efforts to combat climate change do not disproportionately burden vulnerable communities.

Background

Understanding the context and mechanisms of carbon pricing is essential for evaluating its impact 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 praised 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).

Finally, 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, Rausch and colleagues (2011) highlight that 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.

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 general 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 are exhaustive in terms of household spending, demographic information, socioeconomic variables, and gasoline prices which are essential for this research. The Consumer Expenditure Survey (CES) of 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 every quarter for a year. It captures crosssectional and longitudinal differences in spending and thus 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 to 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 is chosen to facilitate a balanced comparison between the pre-policy (2007–2014) and post-policy (2015–2019) periods. This period includes sufficient time for observations to identify trends and assess the policy's effectiveness (Meyer, 1995).

Selection of Control Group States

One of the key aspects of this analysis is selecting the 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). Thus, choosing control states that resemble California in many key ways is important to ensure the validity of the causal inference. We selected Florida and Texas as the control states in this study. The selection of these states is rationalized in several ways. Perhaps most significantly, during the study years (2007–2023), neither Florida nor Texas implemented carbon pricing systems, including cap-and-trade schemes or carbon taxes. This prevents any 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 similar to those in California. This similarity in economic size and diversity moderates factors that could affect gasoline prices independently of the policy.

It is also noteworthy that the demographic profiles of Florida and Texas are 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 the policy adoption. Graphical representations and statistical tests confirm that household gasoline spending was roughly equivalent before 2015, as expected from this study's methodology (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 & Variables

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 Models

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:

$$\begin{aligned}\ln\left(\mathrm{Gasoline\_Expenditure}_{it}\right) &= \alpha + \beta_1 \cdot \mathrm{PostTaxPeriod}_t + \beta_2 \cdot \mathrm{California}_i + \beta_3 \left(\mathrm{PostTaxPeriod}_t \cdot \mathrm{California}_i\right) \\ &+ \gamma \cdot X_{it} + \delta_t + \mu_i + \epsilon_{it}\end{aligned}$$

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 inclusion of interaction terms $\text{PostTaxPeriod}_t \cdot \text{California}_i$ (post-tax period and binary variables for treatment states) 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.

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. 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

Because the purpose of the study is to provide policy commentary and analysis, extended approaches to further assess the validity of DiD models would be welcome. One such approach is PSM/DiD (propensity score matching/difference-in-differences). 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, in order 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 describes some highlights of the trends over time of key variables as a whole in the treatment and control groups and how this informs the research design and discussion at the end. Figure 1, which plots household income distributions between the pre- and post-tax periods, shows a slight variation between periods, which suggests that distributions remain stable. The bell-shaped distributions are quite stable from one tax year to the next, indicating that the external economy had minimal effects on household income. This finding supports the inclusion of household income as a control variable in the DiD model. As income was fairly stable, this excludes income as a confounding variable and lends support to the hypothesis that treatment and control populations had similar long-term economic outcomes. This means that any shifts in gasoline spending might more accurately be attributed to the policy intervention rather than to changes in household income. This realization is critical to the research question because it provides a stable economic context within which the effects of carbon pricing on household gasoline consumption can be measured, making it easier to provide a causally clear explanation for policy impacts.

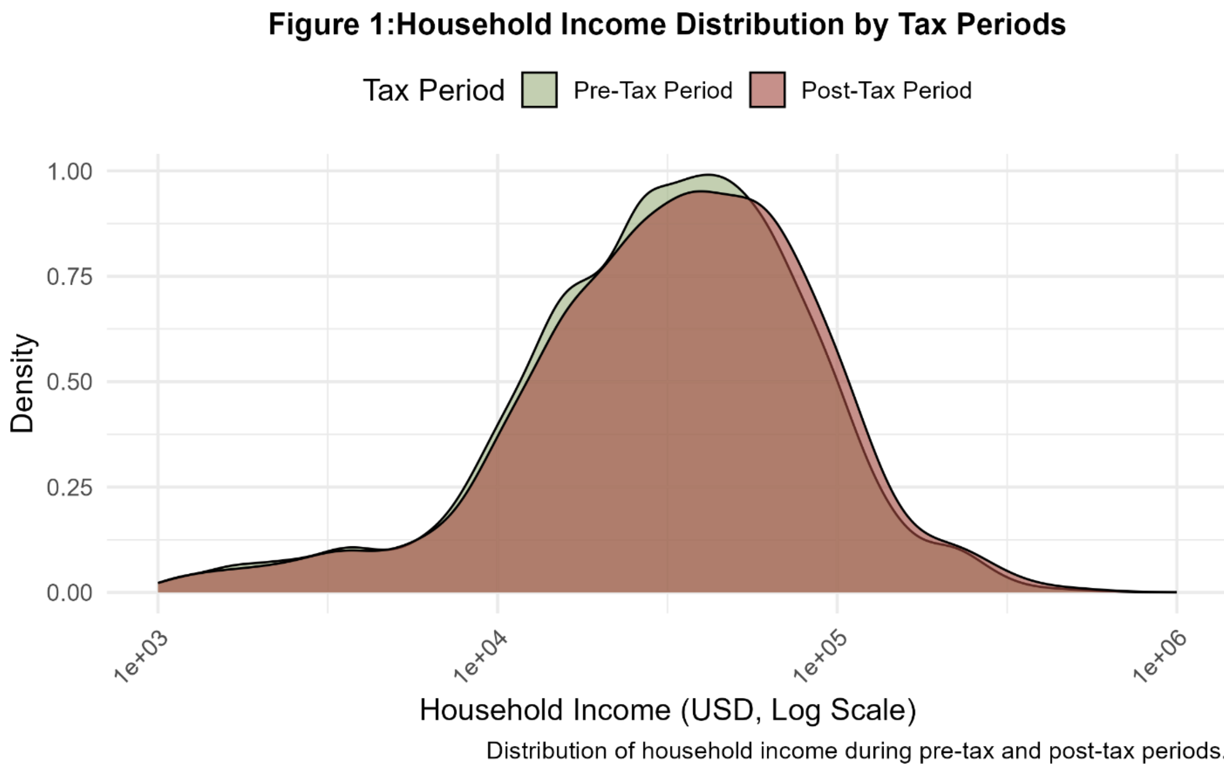


Figure 1: Household Income Distribution by Tax Periods

As for figure 2, it depicts the distribution of household gasoline expenditures for pre-tax and post-tax periods using a violin plot. It shows that median expenditures decreased in the post-tax period, indicating that the carbon pricing policy had a discernible impact on household spending on gasoline. However, the shape of the distributions and the presence of outliers highlight considerable heterogeneity in household responses. This observed variability supports the decision to use interaction terms within the extended DiD model, which allows for a nuanced understanding of differential impacts across households based on characteristics such as gender, income level, and geographical location. Additionally, this graph motivated the use of Propensity Score Matching (PSM) to ensure that households in the treatment and control groups were comparable prior to applying the DiD analysis. By accounting for differences in household characteristics, the study aims to minimize bias and better isolate the impact of the carbon pricing policy. The decrease in median gasoline expenditures suggests that low-income households, likely having more constrained budgets, might have had to reduce their gasoline consumption more significantly, thereby highlighting the policy's potential regressive effects. This observation ties directly into the research question, which seeks to explore the differential impacts of carbon pricing on low-income households, particularly in terms of their vulnerability to price increases.

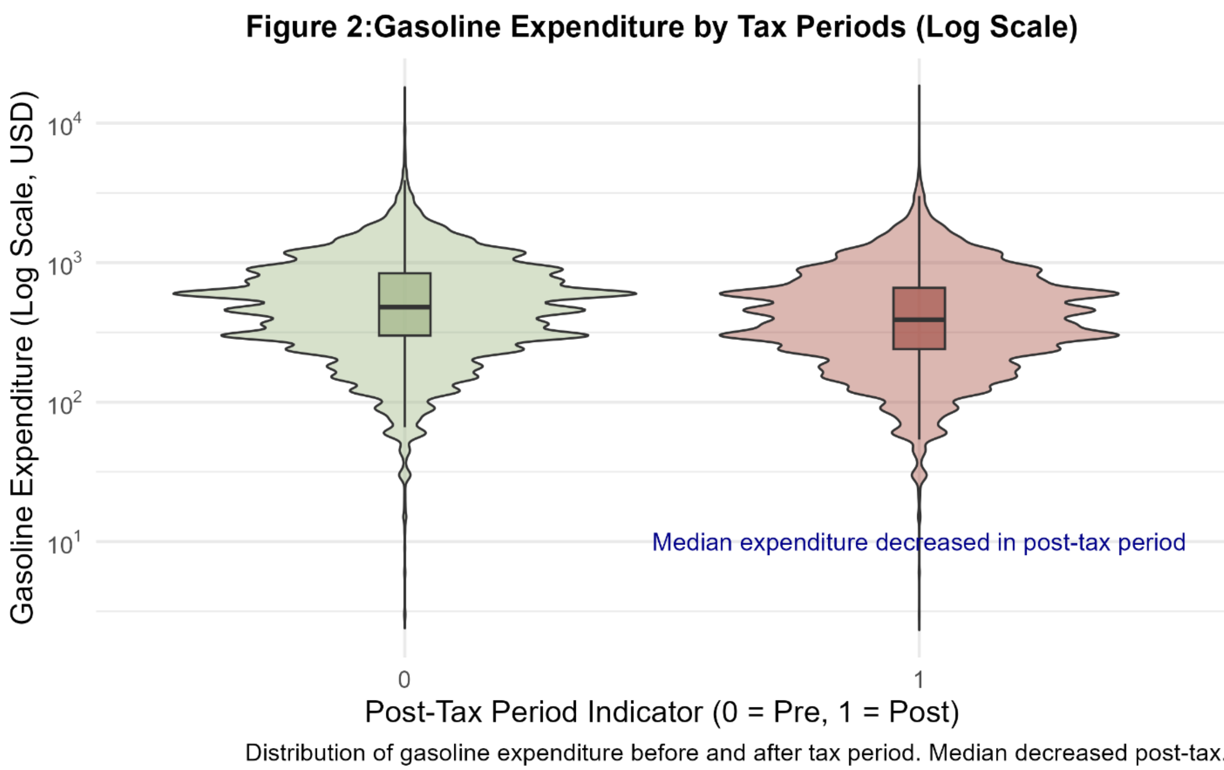
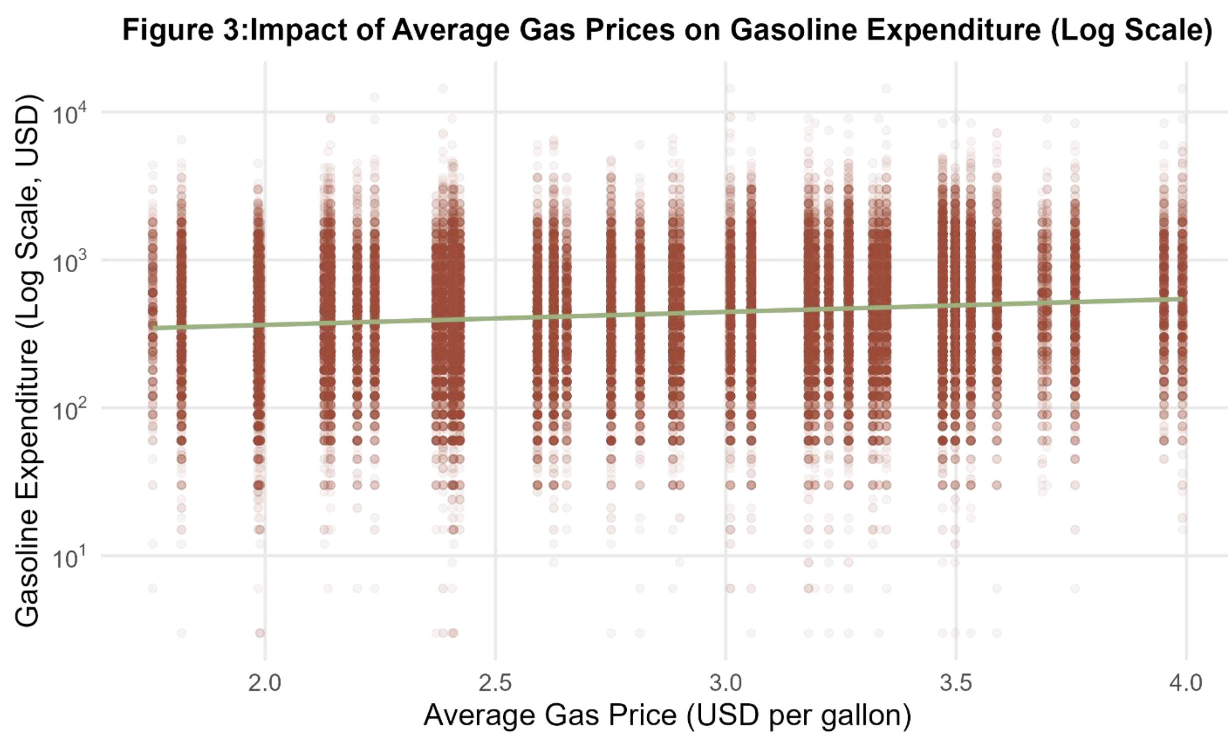


Figure 2: Gasoline Expenditure Distribution by Tax Periods

Figure 3 shows a scatter plot illustrating the relationship between gasoline prices and household gasoline consumption, with the y-axis on a log scale due to the large range in expenditure. The curve indicates a positive correlation (albeit with a low slope), meaning that gasoline price increases are accompanied by only small rises in spending. However, the large number of data points reveals considerable variation in households' reactions to price changes, indicating that consumer behavior is not homogeneous. Such heterogeneity motivated the inclusion of household-level variables—income, education, and family size—as control variables in the extended DiD model. This positive but steady correlation implies that while some households may have weathered the price hikes or decreased gasoline use, others might not have been as able to cope, especially those with rigid transportation requirements. By incorporating interaction terms, the analysis seeks to capture these differential effects to understand the impact of demographic variables on households' ability to respond to high gasoline prices. Theinformation from this graph is useful in identifying which households are most affected by the financial costs borne by carbon pricing and how these costs impact different households.



t illustrating the relationship between average gas prices and gasoline expenditure. The fitted line suggests a trend.

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

Together, these plots influenced the choice of econometric strategies employed in this study. The continuity of income distribution (first graph) justifies the use of income as a control variable, and the heterogeneity of gasoline consumption and price responses (second and third graphs) justifies an extended DiD model with interaction terms and PSM. Such approaches will provide a comprehensive examination of the impact of the cap-and-trade policy, particularly on low-income, women-led, and rural households. Ultimately, the results of this analysis will enhance our understanding of the distributional consequences of the policy and inform future reforms to ensure that environmental policies are both effective and equitable.

Difference-in-Difference Model Results

The Difference-in-Differences (DiD) models presented in Table 1 elucidate several critical variables that significantly enhance our comprehension of California's cap-and-trade policy on household gasoline expenditure. These findings provide essential insights into the primary research question regarding policy's distributional and heterogeneous effects.

Difference-in-Differences Models for Gasoline Expenditure (Quarterly Averages, 2007-2019)

Incomes/Expenditures are Quarterly Averages (2007-2019)

	Baseline Model	Extended Model
(Intercept)	6.705***	6.113***
	(0.075)	(0.073)
Post Tax Period (After Policy = 1, 0 Otherwise)	-0.065***	-0.024
	(0.015)	(0.057)
Treatment Indicator (CA = 1, 0 Otherwise)	0.049***	0.007
	(0.013)	(0.012)
Household Income (Quarterly Average)	0.000***	-0.000***
	(0.000)	(0.000)
Gender (Female = 1, Male = 0)	0.002	-0.031***
	(0.006)	(0.006)
educa2Bachelor’s Degree	-0.116***	-0.048
	(0.034)	(0.039)

	Baseline Model	Extended Model
educa2High School (Grades 9-12), No Diploma	0.155***	0.019
	(0.040)	(0.045)
educa2High School Graduate	0.007	-0.020
	(0.033)	(0.038)
educa2Master’s, Professional, or Doctorate	-0.177***	-0.013
	(0.039)	(0.046)
educa2Nursery, Kindergarten, Elementary (Grades 1-8)	0.142***	0.009
	(0.042)	(0.046)
educa2Other	-0.326***	0.020
	(0.029)	(0.033)
educa2Professional or Doctorate Degree	-0.306***	-0.066
	(0.077)	(0.073)
educa2Some College, No Degree	-0.025	-0.049
	(0.035)	(0.040)
educa2Unknown	0.114	-0.078
	(0.107)	(0.121)
Average Gasoline Price (Quarterly Average)	-0.170***	-0.127***
	(0.029)	(0.027)
factor(year)2008	0.311***	0.268***
	(0.025)	(0.023)
factor(year)2009	-0.177***	-0.177***
	(0.020)	(0.018)
factor(year)2010	0.042**	0.039**
	(0.016)	(0.015)
factor(year)2011	0.271***	0.225***
	(0.028)	(0.026)
factor(year)2012	0.421***	0.361***
	(0.036)	(0.034)
factor(year)2013	0.437***	0.376***
	(0.035)	(0.033)
factor(year)2014	0.355***	0.309***
	(0.031)	(0.029)
factor(year)2015	0.059***	0.035*
	(0.016)	(0.015)
factor(year)2016	-0.154***	-0.144***
	(0.019)	(0.017)
factor(year)2017	-0.043**	-0.050***
	(0.014)	(0.013)
factor(year)2018	0.045**	0.035*
	(0.016)	(0.015)
Post Tax Period x Treatment Indicator	0.057***	0.042**

	Baseline Model	Extended Model
	(0.016)	(0.015)
Family Size (Number of Individuals)		0.239***
		(0.002)
Income Level (Poverty Indicator)		-0.534***
		(0.007)
post_tax_period:gender		0.017
		(0.011)
post_tax_period:educa2Bachelor’s Degree		0.042
		(0.065)
post_tax_period:educa2High School (Grades 9-12), No Diploma		0.042
		(0.078)
post_tax_period:educa2High School Graduate		-0.016
		(0.065)
post_tax_period:educa2Master’s, Professional, or Doctorate		-0.004
		(0.074)
post_tax_period:educa2Nursery, Kindergarten, Elementary (Grades 1-8)		0.073
		(0.086)
post_tax_period:educa2Other		-0.021
		(0.056)
post_tax_period:educa2Some College, No Degree		0.017
		(0.069)
post_tax_period:educa2Unknown		0.353+
		(0.210)
post_tax_period:income_level_poverty		-0.006
		(0.012)
Num.Obs.	93056	93056
R2	0.040	0.185
R2 Adj.	0.040	0.185
AIC	1356346.8	1341137.8
BIC	1356611.2	1341515.4
Log.Lik.	-113658.512	-106041.967
RMSE	0.82	0.76
Household Fixed Effects	Yes	Yes
Number of Observations	93056	93056

- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Standard errors are clustered at the household level. The extended model includes additional interaction terms to capture heterogeneous effects across demographic groups.

Table 1: Difference-in-Difference Model Results (Baseline vs. Extended)

Initially, the Post-Tax Period variable, which captures the temporal impact of California's cap-and-trade policy, demonstrates some significance in the baseline model. This suggests that policy implementation correlates with an overall decline in gasoline expenditure. Specifically, the coefficient of -0.065 ($p < 0.001$) indicates that gasoline spending decreased by a minor degree on average during the post-policy period. However, this effect becomes statistically even more insignificant in the extended model (-0.024) when individual- and household-level controls are incorporated. This shift implies a more nuanced and complex relationship, suggesting that initial reductions may partially result from other concurrent socioeconomic changes rather than from the policy alone.

The baseline model also reveals the Treatment Indicator for California as a significant variable, with a positive coefficient (0.049, $p < 0.001$), indicating higher initial gasoline expenditures in California than in the control states. In the extended model, this coefficient diminishes to 0.007 and loses significance, suggesting that demographic and socioeconomic factors largely explain the initial disparities between California and the other states. The interaction between the post-tax period and the treatment indicator is crucial for addressing the research question. The positive and significant coefficients (0.057, $p < 0.001$ in the baseline model and 0.042, $p < 0.01$ in the extended model) reveal that California households experienced increased gasoline expenditures relative to the control group following tax implementation, contrary to the policy's intended effect of reducing consumption. This outcome potentially indicates a rebound effect in which households may have improved vehicle efficiency or adjusted their behavior, offsetting expected expenditure reductions. These results suggest that policy-induced price increases do not fully translate into lower consumption. Possible explanations include structural constraints, such as limited alternative transportation options, or a deeply rooted automobile-dependent culture in California. These findings imply that the policy's impact on gasoline consumption may have been mitigated by various factors, highlighting the complexity of implementing effective energy consumption reduction measures.

Household Income (quarterly averages) emerges as a critical variable with contrasting signs across the two models. In the baseline model, the positive coefficient (0.000, $p < 0.001$) indicates a direct relationship between income and gasoline expenditures, aligning with the expectation that higher-income households tend to spend more on gasoline, likely due to owning more vehicles or traveling greater distances. Conversely, in the extended model, the coefficient becomes slightly negative (-0.000, $p < 0.001$), suggesting that higher income may enable households to invest in more efficient vehicles or shift to alternative transportation modes. These opposing effects highlight the intricate role of income in shaping household energy consumption behaviors, warranting further investigation into income-based heterogeneity in the policy's impact.

The extended model also sheds light on the Gender of the Household Head, revealing a significant negative effect for female-headed households (-0.031, $p < 0.001$). This indicates that female-headed households are associated with lower gasoline expenditures following the policy's implementation. This might reflect different driving behaviors, such as increased use of public transportation or reduced mileage. Such differential responses are crucial for understanding the distributional impacts of environmental policies and underscore the importance of incorporating gender-based analyses to ensure equitable policy outcomes. Educational attainment variables present several intriguing findings, with significant variations across different education levels. Households headed by individuals with a bachelor's degree or higher generally exhibit lower gasoline expenditures. This negative and significant effect persists across many educational categories in the baseline model but diminishes in the extended model. Introducing interaction terms between education and the post-tax period enriches this analysis. For example, the coefficient for **Post Tax Period × Bachelor's Degree** is positive but not statistically significant, suggesting that the cap-and-trade policy's effect on gasoline expenditures remains relatively consistent across educational groups. However, significant effects for lower education levels, such as Nursery, Kindergarten, and Elementary (Grades 1-8), indicate that these groups may respond differently to gasoline price changes.

Family size is another significant positive factor (0.239, $p < 0.001$), consistent with the notion that larger households typically have greater transportation needs, thereby increasing their gasoline expenditures. This finding emphasizes the role of family structure in determining gasoline-related costs and suggests that larger families may encounter more challenges in reducing gasoline usage, especially when policies lead to price hikes. The Income Level (Poverty Indicator) is a significant variable with a strong negative effect (-0.534, $p < 0.001$), indicating that households below the poverty line spend less on gasoline. This result likely reflects financial constraints that limit gasoline consumption for these households. However, it also highlights the potentially regressive nature of the cap-and-trade policy, where low-income households may disproportionately bear the burden due to their limited capacity to adjust consumption patterns in response to price increases.

Several interaction terms in the extended model are vital for understanding the policy's heterogeneous impacts. For instance, the Post Tax Period × Income Level (Poverty Indicator) term is negative (-0.006) but not statistically significant, suggesting a differential effect for households below the poverty line that is not substantial enough to draw definitive conclusions. Similarly, the Post Tax Period × Gender interaction is not significant, implying that the policy's effect on gasoline expenditures is largely similar between male and female-headed households when controlling for other factors.

The coefficients for Average Gasoline Prices in both models are negative and highly significant, with the extended model showing a coefficient of -0.127 ($p < 0.001$). This indicates that higher gasoline prices are consistently associated with lower expenditures, reflecting the typical price elasticity of demand for gasoline—where increases in prices lead to reduced consumption. This finding is crucial as it validates the core mechanism through which the cap-and-trade policy is expected to influence behavior by raising gasoline prices to incentivize reduced consumption. Overall, the results from Table 1 offer a comprehensive understanding of how California's cap-and-trade policy affects household gasoline expenditures. Key variables such as income, gender, family size, and education significantly influence the observed outcomes. The interaction terms reveal heterogeneous effects across different demographic groups, emphasizing the necessity for targeted policy measures to mitigate unintended regressive impacts. These findings contribute meaningfully to the broader discourse on the equity and efficacy of carbon pricing policies, highlighting both their strengths and limitations in achieving desired environmental and social objectives.

Difference-in-Difference with PSM Matching Model Results

The integration of Propensity Score Matching (PSM) with the Difference-in-Differences (DiD) approach in this study significantly enhances the robustness of estimating the causal effects of California's cap-and-trade policy on household gasoline expenditures. While the DiD method alone accounts for time-invariant differences between treated and control groups, incorporating PSM ensures that these groups are balanced regarding pre-policy characteristics, thereby reducing the potential for selection bias. By creating a matched sample of comparable households, this combined methodology approximates an experimental framework, facilitating a more accurate assessment of the policy's impact.

PSM Difference-in-Differences Models for Gasoline Expenditure (Quarterly Averages, 2007-2019)

Incomes/Expenditures are Quarterly Averages (2007-2019)

	PSM Baseline Model	PSM Extended Model
(Intercept)	5.991***	6.001***
	(0.112)	(0.115)
Post Tax Period (After Policy = 1, 0 Otherwise)	-0.009	-0.072
	(0.024)	(0.068)
Treatment Indicator (CA = 1, 0 Otherwise)	0.011	0.010
	(0.019)	(0.019)
Household Income (Quarterly Average)	-0.000***	-0.000***
	(0.000)	(0.000)
Gender (Female = 1, Male = 0)	-0.027***	-0.035***
	(0.007)	(0.009)
educa2Bachelor's Degree	-0.010	-0.040
	(0.034)	(0.041)
educa2High School (Grades 9-12), No Diploma	0.055	0.029
	(0.040)	(0.048)
educa2High School Graduate	0.001	-0.006
	(0.034)	(0.041)
educa2Master's, Professional, or Doctorate	0.011	-0.001
	(0.040)	(0.049)
educa2Nursery, Kindergarten, Elementary (Grades 1-8)	0.057	0.010
	(0.042)	(0.049)
educa2Other	0.022	0.008
	(0.030)	(0.036)
educa2Professional or Doctorate Degree	-0.075	-0.090
	(0.075)	(0.078)
educa2Some College, No Degree	-0.015	-0.042
	(0.036)	(0.043)
educa2Unknown	0.059	-0.070
	(0.103)	(0.125)
Family Size (Number of Individuals)	0.233***	0.233***
	(0.003)	(0.003)
Income Level (Poverty Indicator)	-0.524***	-0.522***

	PSM Baseline Model	PSM Extended Model
	(0.009)	(0.010)
Average Gasoline Price (Quarterly Average)	-0.083+	-0.079+
	(0.044)	(0.045)
factor(year)2008	0.207***	0.204***
	(0.035)	(0.036)
factor(year)2009	-0.167***	-0.165***
	(0.032)	(0.032)
factor(year)2010	0.036	0.035
	(0.022)	(0.022)
factor(year)2011	0.189***	0.186***
	(0.042)	(0.043)
factor(year)2012	0.316***	0.311***
	(0.055)	(0.056)
factor(year)2013	0.303***	0.299***
	(0.054)	(0.055)
factor(year)2014	0.235***	0.231***
	(0.048)	(0.048)
factor(year)2015	0.011	0.011
	(0.024)	(0.024)
factor(year)2016	-0.140***	-0.140***
	(0.032)	(0.032)
factor(year)2017	-0.072**	-0.071**
	(0.022)	(0.022)
factor(year)2018	-0.004	-0.006
	(0.022)	(0.022)
Post Tax Period x Treatment Indicator (Interaction Term)	0.018	0.016
	(0.022)	(0.022)
Post Tax Period x Gender		0.025
		(0.016)
post_tax_period:educa2Bachelor’s Degree		0.095
		(0.074)
post_tax_period:educa2High School (Grades 9-12), No Diploma		0.088
		(0.089)
post_tax_period:educa2High School Graduate		0.021
		(0.075)
post_tax_period:educa2Master’s, Professional, or Doctorate		0.043
		(0.083)
post_tax_period:educa2Nursery, Kindergarten, Elementary (Grades 1-8)		0.187+
		(0.096)
post_tax_period:educa2Other		0.046

	PSM Baseline Model	PSM Extended Model
		(0.065)
post_tax_period:educa2Some College, No Degree		0.091
		(0.079)
post_tax_period:educa2Unknown		0.403
		(0.221)
Post Tax Period x Income Level (Poverty)		-0.006
		(0.018)
Num.Obs.	46500	46500
R2	0.193	0.193
R2 Adj.	0.192	0.192
AIC	677961.7	677969.0
BIC	678224.1	678318.9
Log.Lik.	-54266.214	-54259.875
RMSE	0.78	0.78
Household Fixed Effects	Yes	Yes
Number of Observations	46500	46500

- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Standard errors are clustered at the household level. The extended model includes additional interaction terms to capture heterogeneous effects across demographic groups.

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

Figures from the PSM Baseline Model and the PSM Extended Model (Table 2) reveal a more comprehensive picture of the policy's impact. The post-tax (after policy = 1) coefficient is negative but remains statistically insignificant in both models (-0.009 for the Baseline Model and -0.072 for the Extended Model). This implies that once households are correctly matched, the underlying reduction in gasoline usage observed after the policy implementation no longer stands out statistically. These results indicate that, if not matched correctly, the original estimates of the policy's impact may have been overestimated, highlighting the significance of PSM in adjusting for pre-existing group differences and providing a more precise assessment of the policy's effect.

Additionally, the Treatment Indicator (CA = 1) is not significant in either model (0.011 and 0.010, respectively). This lack of significance suggests that, once matched, baseline gasoline consumption does not differ significantly between California households and control households. Such an equilibrium reinforces the effectiveness of PSM in making treatment and control groups comparable. Furthermore, the interaction term between the Post-Tax Period and the Treatment Indicator remains statistically insignificant (0.018 in the Baseline Model and 0.016 in the Extended Model). This indicates that California households did not exhibit distinct behavior in gasoline spending under the cap-and-trade policy compared to comparable households outside California.

Moreover, incorporating household-level variables such as household income provides further insights into the determinants of gasoline consumption. The income coefficient is negative and statistically significant in both models (-0.000, $p < 0.001$), indicating that wealthier households spend slightly less on gas. This consistent finding suggests that higher-income families may either source energy from alternative means or invest in more fuel-efficient technologies, thereby reducing their dependence on gasoline. The use of PSM ensures that such variations are not merely artifacts of income differences between groups, providing a more reliable estimate of the income effect.

Regarding the gender parameter, gender-headed households spend less on gas than male-headed households, with both models showing significant coefficients (-0.027 in the Baseline Model and -0.035 in the Extended Model, $p < 0.001$). This is consistent with research suggesting that women might adopt alternative transportation practices—for example, driving more fuel-efficient cars or using public transit more frequently. The persistence of the gender effect after matching suggests that these distinctions are inherent and are not accounted for by other household confounding factors.

Both models exhibit a strong positive correlation between family size and gas spending (0.233, $p < 0.001$), suggesting that larger families require more efficient transportation solutions. This robust conclusion supports the notion that larger households face greater challenges in curbing gasoline use due to their increased transportation needs. Additionally, the Income Level (Poverty Indicator) is highly negative (-0.524 and -0.522, $p < 0.001$) in both models, indicating that individuals living below the poverty level consume less gasoline. This is likely attributable to financial barriers to vehicle ownership and car usage, emphasizing how socioeconomic status affects energy consumption. These findings underscore the varying effects of the policy across different income groups. The Average Gasoline Price coefficient is negative and marginally significant (-0.083 and -0.079, $p = 0.1$), indicating a slight adjustment in gasoline demand. The PSM-DiD data show that although households may alter their gasoline usage in response to increased prices, the elasticity of demand in the matched sample is limited. This result suggests inelasticity in gasoline demand, whereby price increases do not effectively deter usage.

In the Extended Model, additional interaction terms are included to examine the variance of policy impacts across different demographic groups. The positive impact of the Post-Tax Period on gender is statistically negligible (0.025), suggesting no significant gender differences. Similarly, the interactions between education levels (Post-Tax Nursery, Kindergarten, Elementary [Grades 1-8]) have minimal effects. However, the positive coefficient for households with elementary school education (0.187, $p = 0.1$) suggests that such households are less likely to respond effectively to price fluctuations, possibly due to limited resources or skills to adapt their energy use habits. Furthermore, there is no significant interaction between the Post-Tax Period and Income Level (Poverty Indicator) (-0.006), reinforcing the assumption of a homogeneous policy response across income groups once matching is accounted for.

Lastly, this combined PSM-DiD analysis presents a more rigorous test of California's cap-and-trade policy for gasoline spending. The findings reveal that the policy did not significantly affect matched households and suggest that selection bias must be considered when estimating the policy's effect. By employing PSM, the study effectively aligns the treatment and control groups, allowing households to adjust to the policy without substantial changes in their spending habits. These findings contribute to the broader policy debate by indicating that additional interventions may be necessary to achieve significant reductions in gasoline consumption, particularly among households with diverse socioeconomic statuses.

Discussion and Interpretation

Synthesis of Findings

In both the baseline and extended models, the post-tax period variable revealed that the introduction of carbon pricing policies did not produce an immediate, substantial decrease in gasoline consumption. This result supports what Hughes, Knittel, and Sperling (2008) reported as a rather inelastic short-term response to gasoline prices. The fact that there was no dramatic reduction suggests that households might not be able to adapt to rising fuel prices due to a lack of viable alternatives or entrenched driving habits. Furthermore, with the coefficient for household income close to zero, income effects do not appear to play a major role in shifting gasoline consumption. This outcome might indicate the absence of adequate alternatives to gasoline, especially for low-income consumers who lack the financial means to switch to alternative fuels.

Additionally, the interaction terms add more granularity to these results. More precisely, the relationship between the post-tax period and gender shows a small positive coefficient for female-headed households, indicating a slight increase in gasoline purchases due to the policy. This finding could be explained by socio-economic conditions, such as varying commute requirements or child-rearing responsibilities, which constrain the capacity of women-led households to cut back on car use. In keeping with this, Crane (2007) and Loukaitou-Sideris et al. (2009) found that women are increasingly dependent on cars due to multiple-city trips and caregiving roles. This observation provides a crucial addition to the discussion of gendered economics and environmental economics because it highlights the gendered differences in the burden borne by environmental policies.

Furthermore, the use of Propensity Score Matching (PSM) effectively corrects biases caused by variations in household characteristics, thereby making causal estimates more reliable. The extended PSM model explains the effect of education and poverty on gasoline spending. The effect of carbon pricing is moderated by education, with less-educated households being more sensitive to price signals. Specifically, those households without a diploma or those with only elementary schooling reported either no change or increased spending, suggesting limited flexibility or insufficient funds to consider alternative fuels. This finding is consistent with Reames (2016), who points to the low adaptive capacity of less educated or poorer households in dealing with energy costs.

The poverty threshold variable in the extended models consistently showed a strong negative relationship with gasoline consumption, indicating that households at the lower end of the poverty scale spent less on gasoline. However, this drop is probably the result of budgetary constraints rather than a behavioral choice motivated by environmental concerns. This finding echoes Drehobl and Ross (2016), who note how vulnerable low-income households are to energy costs. Such unintended consequences also highlight a potential equity flaw in carbon pricing mechanisms, suggesting that the cost may fall too heavily on the most economically disadvantaged groups. In contrast, family size remained a strong positive predictor of gasoline costs in all models. This result underscores the transport demands of larger families, confirming empirical evidence from transportation economics that larger households tend to take more frequent and longer trips, and therefore consume more gasoline. The fact that the average gasoline price variable continues to matter, even when propensity scores are re-evaluated, further shows that gasoline demand remains relatively rigid. This is typical of essential goods such as fuel, where rising prices do not significantly reduce consumption.

While the Difference-in-Differences (DiD) method provided useful insights into the impact of the carbon tax, robustness validation through PSM ensured that the findings could be justified by making treatment and control groups more comparable. By matching households according to income, educational attainment, and family size, PSM largely eliminated biases caused by inherent differences. This matching is important because the natural demographic and socioeconomic differences among California households could otherwise distort the estimation and obscure the real impact of the policy. The combination of DiD and PSM represents a robust methodological strategy, providing insights not just into aggregate trends but also into the distributional effects across subpopulations. As a result, those with lower incomes or less education seem less likely to be able to handle higher gasoline prices, potentially increasing inequality. Furthermore, the findings indicate that gender and family dynamics have significant economic implications for environmental policies, which suggests that targeted interventions would be needed to achieve an equitable transition to a low-carbon economy.

Policy Implications

The conclusions of this study have substantial implications for how equitable carbon pricing policies are formulated and enforced. One lesson is the need for a differentiated approach that captures household socioeconomic variations. As these results suggest, the regressive nature of gasoline taxes on lower-income families means that other policies should be considered to reduce the burden placed on these groups. For example, providing subsidies or other direct financial transfers to low-income households might help compensate for the higher costs associated with carbon pricing. Such compensatory policies are supported by prior work, such as experiments investigating the welfare impact of Pigouvian taxation in second-best scenarios (Knittel & Sandler, 2018). Developing tailor-made interventions that account for differences in household income and education can help policymakers make carbon pricing more socially acceptable and fair.

Moreover, as the analysis suggests, female-led households face greater spending increases compared to male-led households. This implies that future policy decisions must take gender-specific considerations into account for environmental taxes. One way to intervene would be to create rebates or incentives specifically for female-led households. Investing in transportation systems that are convenient, safe, and women-friendly might be an indirect yet effective way to decrease dependence on gasoline and create greater transportation equity (Crane, 2007). Research conducted by Loukaitou-Sideris and Fink (2009) shows that women tend to face more barriers when accessing public transportation, ranging from safety concerns to inadequate service frequency, which often forces them to rely on private vehicles. This reliance makes them particularly vulnerable to policies that increase fuel prices without compensatory measures. A United Nations report on gender and sustainable development emphasized the need for gender-responsive policies that address women's mobility needs, highlighting how targeted investments in public transit infrastructure can reduce both economic and time burdens faced by female-headed households (UN Women, 2019). Targeted interventions such as offering reduced public transit fares or transportation vouchers for female-led households have also been shown to be effective in easing the financial burden. For instance, a study in New York City by Blumenberg and Pierce (2014) found that subsidizing transportation costs significantly improved access to jobs for low-income women, thereby promoting both economic mobility and energy savings. Additionally, providing community-based carpooling programs or promoting flexible work arrangements for women may help reduce the financial impact of gasoline prices on female-led households. Such initiatives could reduce the need for single-occupancy vehicle trips, effectively decreasing dependence on gasoline and contributing to broader sustainability goals (Blumenberg & Pierce, 2014).

Another potential policy approach could involve instituting a tiered tax structure based on income and gasoline use. An indexed carbon tax would levy higher rates on affluent individuals with greater gasoline consumption while providing exemptions or reduced rates for lower-income groups. Scholars like Metcalf (2009) have supported such an approach, highlighting the potential for equity in well-designed carbon taxes, ensuring that lower-income households are not disproportionately burdened. Microsimulation models, successfully used to evaluate heterogeneous policy impacts (Burtraw & Sekar, 2014), can provide a feasible path for assessing such strategies. Implementing a progressive carbon tax would not only counteract the regressive tendencies observed in the study but also promote fairness by taxing higher consumers more, which aligns with the principle of environmental justice (Grainger & Kolstad, 2010). This approach, coupled with educational outreach to improve energy literacy, could help low-income and less-educated households adapt more effectively to price changes. Hassett et al. (2009) suggested that financial incentives combined with tiered taxation could enhance both emission reductions and economic welfare. By adjusting the tax structure according to income and gasoline use, policymakers can achieve a more balanced carbon pricing policy that mitigates economic burdens on disadvantaged households, fostering equitable progress toward decarbonization.

The heterogeneity in responses to gasoline prices across education levels also highlights the importance of educational campaigns and outreach programs. Training on energy-saving practices, fuel efficiency, and the environmental consequences of burning fossil fuels could help less-educated households respond to price shifts more effectively and reduce their expenditures. A University of Michigan study found that households that are part of outreach programmes tailored to structural inequalities are better equipped to use energy-saving transportation practices such as carpooling (Gromet et al., 2013). When we put knowledge into action, we can adjust economically when gasoline prices rise. Households need to be able to switch away from more expensive sources of energy to cheaper ones. When we understand the reasons behind rising gasoline prices, we can advocate for policies that make energy prices more stable and transfer the burden of energy price volatility onto entities such as producers and sellers rather than onto individuals' incomes (Stern et al., 2016). Increasing household levels of energy literacy, or education about energy, can boost energy-saving behaviors at home. A report by the International Energy Agency (IEA) shows that the more educated a household is, the more likely it is to save energy (IEA, 2019). This confirms that households are economically resilient when they are better able to understand why and how to save energy. More education means more opportunities to avoid financial burdens by applying this knowledge. Collaboration with community groups to spread knowledge and increase energy literacy could be an essential component of this intervention. As found in the literature on the role of education in influencing environmental behavior (McLanahan & Percheski, 2008), specific education initiatives could even generate spillover benefits, encouraging people to adopt broader energy-saving behaviors beyond simply reducing gasoline use.

Expanding on this, a zero-interest loan program for purchasing electric vehicles (EVs) or fuel-efficient cars could provide a viable solution to the barriers lower-income households face in transitioning away from gasoline dependence. Given that income and household size are significant factors in predicting gasoline expenditure, financial incentives can play a transformative role. Governments could collaborate with private finance institutions to subsidize or reduce interest rates on EV loans, making cleaner transportation options more accessible. Such partnerships could be instrumental in alleviating gasoline expenses and accelerating a shift towards a low-carbon economy. A scrappage scheme offering financial incentives for replacing outdated, inefficient vehicles with cleaner alternatives would be another impactful approach. Research by Gallagher and Muehlegger (2011) showed that similar financial incentives have effectively stimulated demand for more environmentally friendly vehicles. This policy would not only reduce emissions but also lessen the financial strain on low-income households, addressing both environmental and economic challenges simultaneously. Moreover, these incentives would promote broader adoption of clean technologies, aligning with policies to mitigate climate change, and supporting marginalized groups to transition equitably into a low-carbon future.

Future research should explore the behavioral responses of households to non-monetary incentives. For instance, investigating how cues, such as incentives for electric vehicles to park in designated areas or the establishment of "green zones" where only electric cars are allowed, can complement traditional economic incentives would be valuable. Additionally, assessing the effects of urban design and accessibility to alternative modes of transportation, including cycling infrastructure and ride-sharing services, could help measure how such interventions influence household choices and gasoline use. Given the far-reaching impacts of California's carbon pricing schemes, additional research on urban planning, public health, and environmental policy would be useful in developing holistic policies for sustainable development.

Conclusion

This paper provides an analysis of California's carbon pricing policy and itseffects on residential gasoline consumption, using Difference-in-Differences (DiD) and Propensity Score Matching (PSM) techniques. The results demonstrate a great deal of heterogeneity in the policy effects on demographic measures, including income, gender, education, and household size. Especially the results indicate that poorer and less educated households find it particularly difficult to change their gas habits, indicating the retrograde nature of the carbon price system. Then there were gender inequalities, and female-headed households carried a greater percentage of the burden. These lessons demand a more nuanced approach to carbon taxes with equity-driven interventions.

There were several policy solutions to better allocate the costs and benefits of carbon pricing. The paper suggests that a complex and complex form of policy (taxation in layers, targeted support, education) might be needed to mitigate negative effects on economically marginalized populations and foster social justice. Moreover, gender-based policies and the adoption of environmentally friendly cars can be equally effective and equitable to carbon pricing policies. Yet this study has drawbacks to consider. For one, the absence of pre-policy information means that the baseline state can't be measured to fully understand the effects of carbon pricing. Second, the data only account for personal gasoline consumption, not wider behavioral change (such as shifting travel patterns, shifting to alternative forms of transport, or long-term adaptation). What's more, though DiD and PSM provide powerful tools for causal inference, unobserved biases from cultural bias or unaccounted policy spillovers might nevertheless have a bearing on outcomes.

Future research could build upon this study by incorporating richer data that includes more detailed pre-policy conditions and broader behavioral metrics beyond gasoline expenditure. Understanding shifts in commuting patterns, vehicle ownership changes, and overall transportation choices would provide a more holistic picture of the effects of carbon pricing. Moreover, a deeper exploration into the intersection between environmental policy and urban planning—such as the influence of public transportation availability and urban design—could yield further insights into how carbon pricing can be integrated effectively with other urban sustainability efforts. Lastly, employing longitudinal surveys to track household responses over time would help capture the evolving impact of policy and the dynamic adaptation of households, ultimately guiding the design of more adaptive and equitable carbon pricing mechanisms. The carbonmbination of these future research avenues and targeted policy measures has the potential to construct a carbon pricing system that is not only environmentally effective but also socially equitable, ensuring that the transition to a low-carbon economy is inclusive of all segments of society.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, *102*(1), 131–166. https://doi.org/10.1257/aer.102.1.131

American Economic Association. (2018). *AEA Code of Professional Conduct*. Retrieved from https://www.aeaweb.org/about-aea/code-of-conduct

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press. Retrieved from https://www.jstor.org/stable/j.ctvcm4j72

Attanasio, O. P., & Weber, G. (2010). Consumption and saving: Models of intertemporal allocation and their implications for public policy. *Journal of Economic Literature, 48*(3), 693–751. https://doi.org/10.1257/jel.48.3.693

Bauer, G. R. (2014). Incorporating intersectionality theory into population health research methodology. *Social Science & Medicine, 110*, 10–17. https://doi.org/10.1016/j.socscimed.2014.03.022

Beauchamp, T. L., & Childress, J. F. (2001). *Principles of biomedical ethics* (5th ed.). Oxford University Press. Retrieved from https://jme.bmj.com/content/28/5/332.2

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics, 119*(1), 249–275. https://doi.org/10.1162/003355304772839588

Blumenberg, E., & Pierce, G. (2014). A driving factor in mobility? Transportation's role in connecting subsidized housing and employment outcomes. *Journal of the American Planning Association*, *80*(1), 52-66. https://doi.org/10.1080/01944363.2014.935267

Blumenberg, E., & Pierce, G. (2014). A driving factor in mobility? Transportation's role in connecting subsidized housing and employment outcomes. *Journal of the American Planning Association*, *80*(1), 52–66. https://doi.org/10.1080/01944363.2014.935267

Blumenberg, E., & Smart, M. (2010). Getting by with a little help from my friends... and family: Immigrants and carpooling. *Transportation*, *37*(3), 429–446. https://doi.org/10.1007/s11116-010-9262-4

Borenstein, S., Davis, L. W., Fowlie, M., & Sallee, J. M. (2019). Do two electricity pricing wrongs make a right? Cost recovery, externalities, and efficiency. *National Bureau of Economic Research*. https://doi.org/10.3386/w25620

Brown, A. E., Blumenberg, E., Taylor, B. D., & Ralph, K. (2017). A taste for transit? Analyzing public transit use trends among youth. *Journal of Public Transportation*, *20*(1), 1–22. https://doi.org/10.5038/2375-0901.20.1.1

Bureau of Economic Analysis. (2021). *Per capita personal income by state*. Retrieved from https://www.bea.gov/data/income-saving/personal-income-by-state

Burtraw, D., & Sekar, S. (2014). Two world views on carbon revenues. *Journal of Environmental Studies and Sciences, 4*(1), 110–120. https://doi.org/10.1007/s13412-013-0164-2

California Air Resources Board. (2015). *Cap-and-trade program*. Retrieved from https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program

California Air Resources Board. (2017). *California's 2017 climate change scoping plan*. Retrieved from https://ww2.arb.ca.gov/sites/default/files/classic//cc/scopingplan/scoping_plan_2017.pdf

California Air Resources Board. (2018). *2018 edition of the California greenhouse gas emission inventory*. Retrieved from https://ww3.arb.ca.gov/cc/inventory/pubs/reports/2000_2016/ghg_inventory_trends_00-16.pdf

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources, 50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317

Crane, R. (2007). Is there a quiet revolution in women's travel? Revisiting the gender gap in commuting. *Journal of the American Planning Association, 73*(3), 298–316. https://doi.org/10.1080/01944360708977979

Crane, R. (2007). "Is there a quiet revolution in women's travel? Revisiting the gender gap in commuting." *Journal of the American Planning Association, 73*(3), 298-316. Available at: https://doi.org/10.1080/01944360708977979

Deaton, A. (1997). *The analysis of household surveys: A microeconometric approach to development policy*. Johns Hopkins University Press. Retrieved from https://documents.worldbank.org/en/publication/documents-reports/documentdetail/593871468777303124/the-analysis-of-household-surveys-a-microeconometric-approach-to-development-policy

Drehobl, A., & Ross, L. (2016). *Lifting the high energy burden in America's largest cities*. American Council for an Energy-Efficient Economy. Retrieved from https://www.aceee.org/research-report/u1602

Energy Information Administration. (n.d.). *Petroleum & other liquids*. Retrieved from https://www.eia.gov/petroleum/

Galiani, S., Gertler, P., & Schargrodsky, E. (2005). Water for life: The impact of the privatization of water services on child mortality. *Journal of Political Economy, 113*(1), 83–120. https://doi.org/10.1086/426041

Garcia, E., & Taylor, B. D. (2018). What does it cost to ride transit? Investigating rider responses to fare changes across Los Angeles. *Transportation Research Record, 2672*(8), 129–138. https://doi.org/10.1177/0361198118758685

Gillingham, K., Jenn, A., & Azevedo, I. M. (2015). Heterogeneity in the response to gasoline prices: Evidence from Pennsylvania and implications for the rebound effect. *Energy Economics, 52*, S41–S52. https://doi.org/10.1016/j.eneco.2015.08.011

Grainger, C. A., & Kolstad, C. D. (2010). Who pays a price on carbon? *Environmental and Resource Economics*, *46*(3), 359–376. https://doi.org/10.1007/s10640-010-9345-x

Grainger, C. A., & Kolstad, C. D. (2010). "Who pays a price on carbon?" *Environmental and Resource Economics, 46*(3), 359–376. https://doi.org/10.1007/s10640-010-9345-x

Hassett, K. A., Mathur, A., & Metcalf, G. E. (2009). The incidence of a U.S. carbon tax: A lifetime and regional analysis. *Energy Journal*, *30*(2), 155–177. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol30-No2-7

Hassett, K. A., Mathur, A., & Metcalf, G. E. (2009). "The incidence of a U.S. carbon tax: A lifetime and regional analysis." *Energy Journal, 30*(2), 155–177. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol30-No2-7

Handy, S., & Mokhtarian, P. (2008). Growing Cooler: The Evidence on Urban Development and Climate Change: Reid Ewing, Keith Bartholomew, Steve Winkelman, Jerry Walters, and Don Chen. Urban Land Institute, Washington, D.C., 2008. 176 pages. $44.95. *Journal of the American Planning Association*, *75*(1), 95–96. https://doi.org/10.1080/01944360802540364

Hausman, D., McPherson, M., & Satz, D. (2016). Economic analysis, moral philosophy, and public policy (3rd ed.). Cambridge University Press. https://www.cambridge.org/highereducation/books/economic-analysis-moral-philosophy-and-public-policy/82579FD39557B4C1235317743280199F#overview

Hsiang, S., & Kopp, R. E. (2018). An economist's guide to climate change science. *Journal of Economic Perspectives, 32*(4), 3–32. https://doi.org/10.1257/jep.32.4.3

Hughes, J. E., Knittel, C. R., & Sperling, D. (2008). Evidence of a shift in the short-run price elasticity of gasoline demand. *The Energy Journal*, *29*(1), 113–134. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol29-No1-7

International Carbon Action Partnership. (2021). *ETS Map*. Retrieved from https://icapcarbonaction.com/en/ets-map

International Energy Agency (IEA) Report. (2019). *Empowering People through Energy Education*. Retrieved from https://www.iea.org/reports/empowering-people-through-energy-education

Jiao, J., & Dillivan, M. (2013). Transit deserts: The gap between demand and supply. *Journal of Public Transportation, 16*(3), 23–39. https://doi.org/10.5038/2375-0901.16.3.2

Jones, C. M., & Kammen, D. M. (2014). Spatial distribution of U.S. household carbon footprints reveals suburbanization undermines greenhouse gas benefits of urban population density. *Environmental Science & Technology, 48*(2), 895–902. https://doi.org/10.1021/es4034364

Knittel, C. R., & Sandler, R. (2018). The welfare impact of second-best uniform-Pigouvian taxation: Evidence from transportation. *American Economic Journal: Economic Policy, 10*(4), 211–242. https://doi.org/10.1257/pol.20160359

Lechner, M. (2011). The estimation of causal effects by difference-in-difference methods. *Foundations and Trends in Econometrics, 4*(3), 165–224. https://doi.org/10.1561/0800000014

Little, R. J. A., & Rubin, D. B. (2019). *Statistical analysis with missing data* (3rd ed.). Wiley. Retrieved from https://onlinelibrary.wiley.com/doi/book/10.1002/9781119482260

Loukaitou-Sideris, A., Bornstein, A., Fink, C., Gerami, S., & Samuels, L. (2009). How to ease women's fear of transportation environments: Case studies and best practices. *Mineta Transportation Institute Report*. Retrieved from https://transweb.sjsu.edu/sites/default/files/2611-women-transportation.pdf

McDaniels, B.W., Harley, D.A., Beach, D.T. (2018). Transportation, Accessibility, and Accommodation in Rural Communities. In: Harley, D., Ysasi, N., Bishop, M., Fleming, A. (eds) Disability and Vocational Rehabilitation in Rural Settings. Springer, Cham. https://doi.org/10.1007/978-3-319-64786-9_3

McGuckin, N., & Nakamoto, Y. (2004). Differences in trip chaining by men and women. *Research on Women's Issues in Transportation, 1*, 49–56. Retrieved from https://onlinepubs.trb.org/onlinepubs/conf/CP35v1.pdf

McLanahan, S., & Percheski, C. (2008). Family structure and the reproduction of inequalities. *Annual Review of Sociology, 34*, 257–276. https://doi.org/10.1146/annurev.soc.34.040507.134549

Metcalf, G. E. (2009). Designing a carbon tax to reduce U.S. greenhouse gas emissions. *Review of Environmental Economics and Policy, 3*(1), 63–83. https://doi.org/10.1093/reep/ren015

Metcalf, G. E., & Weisbach, D. (2009). The design of a carbon tax. *Harvard Environmental Law Review, 33*, 499–556. Retrieved from https://harvardelr.com/wp-content/uploads/sites/12/2019/08/33.2-Metcalf-Weisbach.pdf

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of Business & Economic Statistics*, *13*(2), 151–161. https://doi.org/10.1080/07350015.1995.10524589

Mora, R., & Reggio, I. (2012). Treatment effect identification using alternative parallel assumptions. *Economics Letters, 115*(1), 10–13. https://doi.org/10.1016/j.econlet.2011.11.015

National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research. (1979). *The Belmont Report*. U.S. Department of Health, Education, and Welfare.

Pearce, A., & Stilwell, F. (2008). Green economics: Reform and transformation. *International Journal of Green Economics*, *2*(3), 268–275. https://doi.org/10.1504/IJGE.2008.019481

Poterba, J. M. (1991). Is the gasoline tax regressive? *Tax Policy and the Economy*, *5*, 145–164. https://doi.org/10.1086/tpe.5.20061813

Rausch, S., Metcalf, G. E., & Reilly, J. M. (2011). Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics, 33*(S1), S20–S33. https://doi.org/10.1016/j.eneco.2011.07.023

Reames, T. G. (2016). Targeting energy justice: Exploring spatial, racial/ethnic, and socioeconomic disparities in urban residential heating energy efficiency. *Energy Policy*, *97*, 549–558. https://doi.org/10.1016/j.enpol.2016.07.048

Resnik, D. B., & Shamoo, A. E. (2011). The Singapore statement on research integrity. *Accountability in Research*, *18*(2), 71–75. https://doi.org/10.1080/08989621.2011.557296

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. Wiley. https://onlinelibrary.wiley.com/doi/book/10.1002/9780470316696?__cf_chl_rt_tk=q7H7I0tJfDSjDhMNYJNLtDperLTKQpoSRAVjmVv_s_E-1731285258-1.0.1.1-63f7UabzGspiOb7AF2eFyz7s.sEMm82SayUXRv0z77Q

Singichetti, B., Dodd, A., Conklin, J. L., Hassmiller Lich, K., Sabounchi, N. S., & Naumann, R. B. (2022). Trends and insights from transportation congestion pricing policy research: A bibliometric analysis. *International Journal of Environmental Research and Public Health*, *19*(12), 7189. https://doi.org/10.3390/ijerph19127189

Sivak, M., & Schoettle, B. (2012). Recent changes in the age composition of drivers in 15 countries. *Traffic Injury Prevention*, *13*(2), 126–132. https://doi.org/10.1080/15389588.2011.638016

Small, K. A., & Van Dender, K. (2007). Fuel efficiency and motor vehicle travel: The declining rebound effect. *Energy Journal*, *28*(1), 25–51. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No1-2

Stavins, R. N. (2020). The future of U.S. carbon-pricing policy. *Environmental and Energy Policy and the Economy, 1*(1), 8–64. https://doi.org/10.1086/706792

Sultana, S., & Weber, J. (2007). Journey-to-work patterns in the age of sprawl: Evidence from two midsize southern metropolitan areas. *The Professional Geographer*, *59*(2), 193–208. https://doi.org/10.1111/j.1467-9272.2007.00607.x

U.S. Bureau of Labor Statistics. (n.d.). *Consumer Expenditure Survey (CES)*. Retrieved from https://www.bls.gov/cex/

U.S. Census Bureau. (2020). *QuickFacts: United States*. Retrieved from https://www.census.gov/quickfacts/fact/table/US/PST045219

U.S. Census Bureau. (2024). *Poverty thresholds*. Retrieved from https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

UN Women. (2019). *Gender Equality and Sustainable Urban Mobility*. Retrieved from https://www.unwomen.org/en/digital-library/publications/2019/12/gender-equality-and-sustainable-urban-mobility

Wooldridge, J. M. (2010). *Econometric analysis of cross-section and panel data* (2nd ed.). MIT Press. Retrieved from https://jrvargas.wordpress.com/wp-content/uploads/2011/01/wooldridge_j-_2002_econometric_analysis_of_cross_section_and_panel_data.pdf

Appendix

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

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