

# Machine Learning and the Politics of Climate Change

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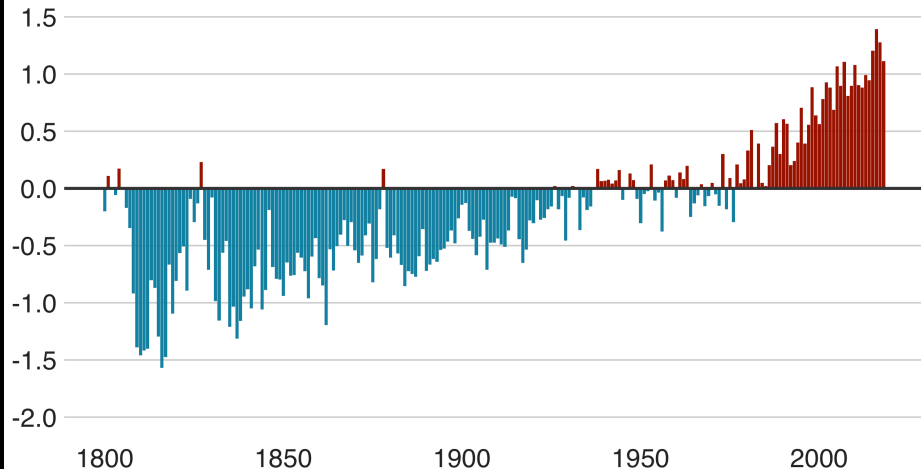
Liam F. Beiser-McGrath

[www.liambeisermcgrath.com](http://www.liambeisermcgrath.com)

Universität Konstanz & ETH Zürich

# The world has been getting warmer

Annual mean land temperature above or below average (°C)

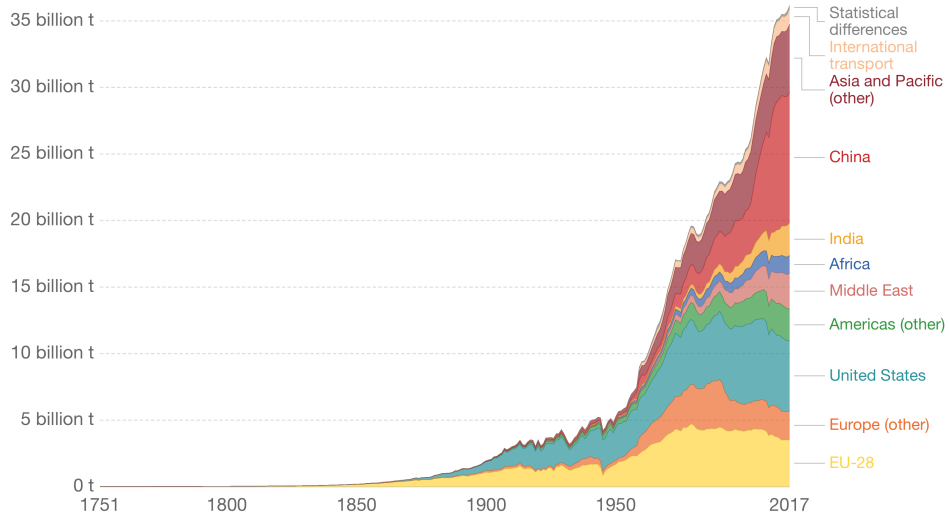


Note: Average is calculated from 1951-1980 land surface temperature data

Source: University of California Berkeley

# Annual total CO<sub>2</sub> emissions, by world region

Our World  
in Data



Source: Carbon Dioxide Information Analysis Center (CDIAC); Global Carbon Project (GCP)

Note: "Statistical differences" notes the discrepancy between estimated global emissions and the sum of all national and international transport emissions.

[OurWorldInData.org/co2-and-other-greenhouse-gas-emissions](https://OurWorldInData.org/co2-and-other-greenhouse-gas-emissions) • CC BY

# THE WALL STREET JOURNAL.

THURSDAY, JANUARY 17, 2019

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Original Co-Signatories Include (full list on reverse):

- 4** Former Chairs of the Federal Reserve (All)
  - 27** Nobel Laureate Economists
  - 15** Former Chairs of the Council of Economic Advisers
  - 2** Former Secretaries of the U.S. Department of Treasury
- 

## Economists' Statement on Carbon Dividends



# Machine Learning to Understand Climate Change Politics

**Complexity:** Multiple design choices and solutions

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⇒ Inference in high-dimensional settings



# This Talk:

Value added of machine learning:

# This Talk:

Value added of machine learning:

1. Regional variation

# This Talk:

Value added of machine learning:

1. Regional variation
2. Individual heterogeneity

# Policy Design and Support for Carbon Taxation

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SCIENCE ADVANCES | RESEARCH ARTICLE

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SCIENCE POLICY

# Could revenue recycling make effective carbon taxation politically feasible?

Liam F. Beiser-McGrath<sup>\*†</sup> and Thomas Bernauer<sup>\*</sup>

A



B



# Effect of Carbon Tax Design Features Upon Political Feasibility

1. Price of Tax
2. Revenue Usage
3. Inclusion of Other Countries
4. Border Adjustments
5. Domestic Exemptions

1. Cost of carbon tax	<ol style="list-style-type: none"> <li>1. \$10 per metric ton (\$144 per year for average consumer)</li> <li>2. \$20 per metric ton (\$288 per year for average consumer)</li> <li>3. \$30 per metric ton (\$432 per year for average consumer)</li> <li>4. \$40 per metric ton (\$576 per year for average consumer)</li> <li>5. \$50 per metric ton (\$720 per year for average consumer)</li> <li>6. \$60 per metric ton (\$864 per year for average consumer)</li> <li>7. \$70 per metric ton (\$1008 per year for average consumer)</li> </ol>	4. Similar carbon tax introduced by	<ol style="list-style-type: none"> <li>1. No other countries</li> <li>2. European countries (European Union)</li> <li>3. China</li> <li>4. United States</li> <li>5. India</li> <li>6. Canada</li> <li>7. Japan</li> <li>8. All industrialized countries</li> <li>9. All developing countries</li> </ol>
2. Energy-intensive products imported from other countries	<ol style="list-style-type: none"> <li>1. Fully exempted (pay no carbon tax)</li> <li>2. Taxed at half rate (pay only half of the carbon tax)</li> <li>3. Taxed equally (pay full carbon tax)</li> </ol>	<p><b>[Randomly assigned to be seen by half of the respondents]</b></p> <p>5. Additional public revenue, i.e., carbon dividends, used for</p>	<ol style="list-style-type: none"> <li>1. Tax rebate paid to everyone</li> <li>2. Reduce federal government deficit</li> <li>3. Fund renewable energy sources (e.g., solar, wind, and geothermal power)</li> <li>4. Fund infrastructure (e.g., railways, roads, and public transportation)</li> <li>5. Fund programs for low-income families</li> <li>6. Reduce income tax</li> <li>7. Reduce corporate tax</li> <li>8. Fund retraining programs for workers in fossil fuel sector</li> </ol>
3. Domestic companies exporting energy-intensive products to other countries	<ol style="list-style-type: none"> <li>1. Fully exempted (pay no carbon tax)</li> <li>2. Taxed at half rate (pay only half of the carbon tax)</li> <li>3. Taxed equally (pay full carbon tax)</li> </ol>		



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31 Features = A-Beyond Z testing

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= 366 features

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## 1. Regional Heterogeneity



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- 50 US States  $\times$  366 Features = 18300

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## 366 Features

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### 2. Individual Heterogeneity

- {age, sex, income, PID}  $\times$  366 Features  $\approx$  4026

# Effect of Carbon Tax Design Features Upon Political Feasibility

366 Features

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## 2. Individual Heterogeneity

- {age, sex, income, PID}  $\times$  366 Features  $\approx$  4026

$\Rightarrow$  Need for Machine Learning

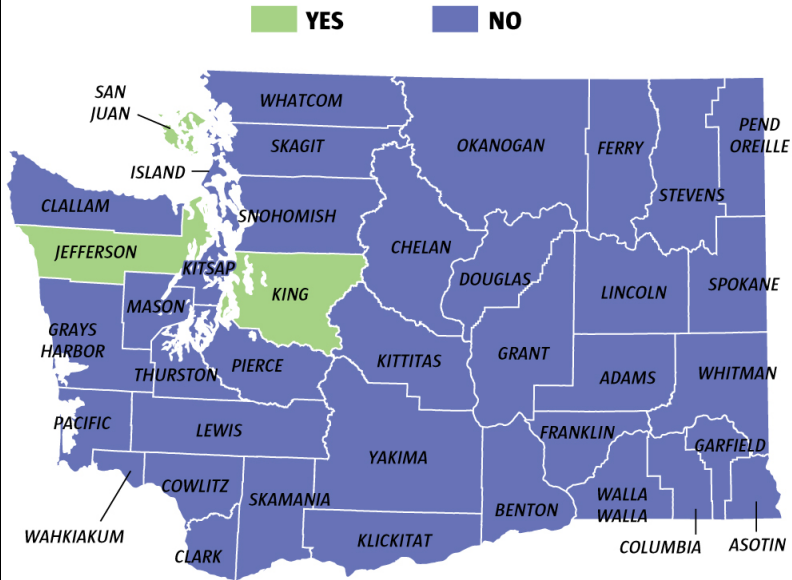
# Geographic Heterogeneity

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**YES ON**  
**1631**

County-by-county results, in Tuesday's vote count.



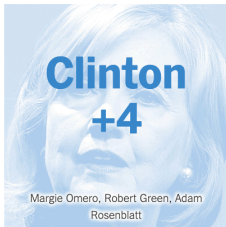
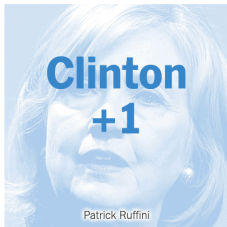
Source: Washington Secretary of State

MARK NOWLIN / THE SEATTLE TIMES

# We Gave Four Good Pollsters the Same Raw Data. They Had Four Different Results.

By **NATE COHN** SEPT. 20, 2016

How four pollsters, and The Upshot, interpreted 867 poll responses:





## Letter

# **BARP: Improving Mister P Using Bayesian Additive Regression Trees**

JAMES BISBEE *New York University*

# BARP: Bayesian Additive Regression Trees with Post-Stratification

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1. Bayesian Additive Regression Trees to predict individual support

# BARP: Bayesian Additive Regression Trees with Post-Stratification

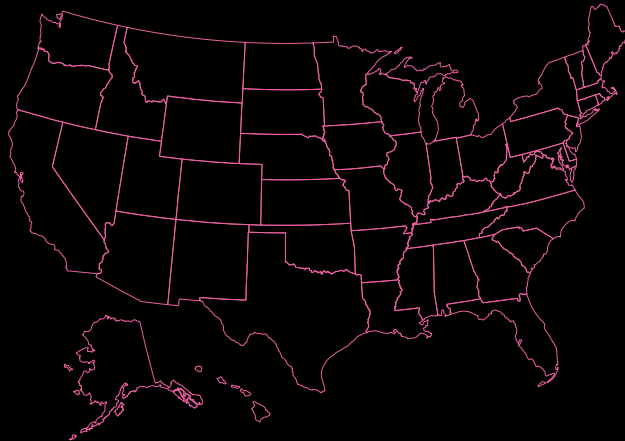
1. Bayesian Additive Regression Trees to predict individual support
2. Combine with state demographic data

# BARP: Bayesian Additive Regression Trees with Post-Stratification

1. Bayesian Additive Regression Trees to predict individual support
2. Combine with state demographic data

⇒ robust regional predictions from individual data

## \$50 Carbon Tax: Support by State



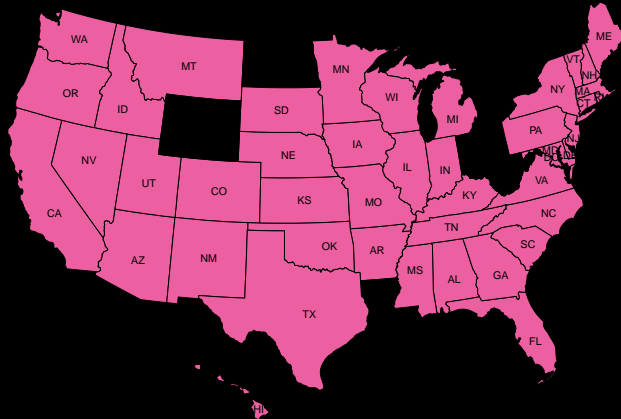
# \$50 Carbon Tax: No Revenue Use & No Other Countries

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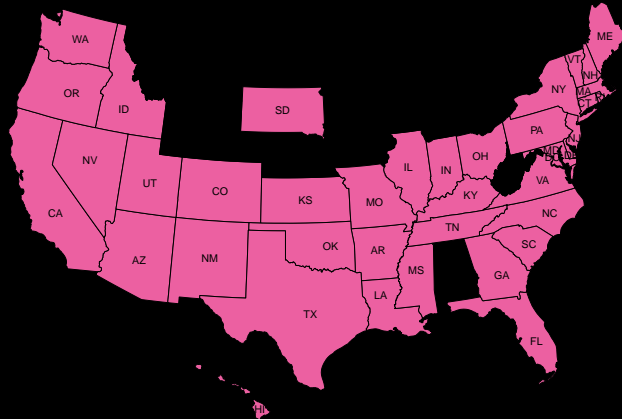




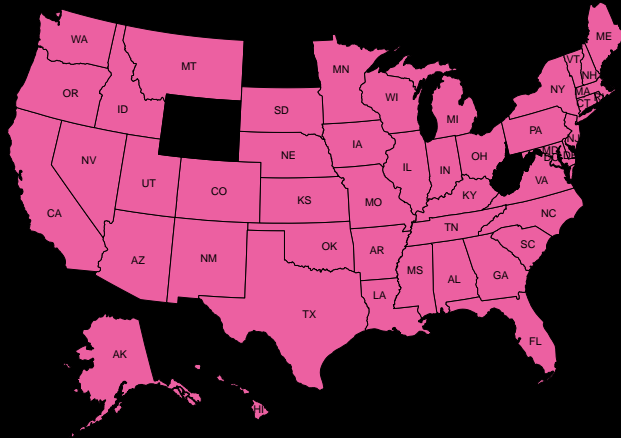
# \$50 Carbon Tax: Tax Rebate & No Other Countries



# \$50 Carbon Tax: No Revenue Use & Industrialised Countries



# \$50 Carbon Tax: Tax Rebate & Industrialised Countries



# Individual Heterogeneity

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# Optimising Individual Treatment Assignment

- **Standard Goal:** Maximise ability to predict outcome

# Optimising Individual Treatment Assignment

- **Standard Goal:** Maximise ability to predict outcome
- **Alternative Goal:** Maximise based on subgroup effect in subgroups (*“lift”*)

*The Annals of Statistics*

2019, Vol. 47, No. 2, 1148–1178

<https://doi.org/10.1214/18-AOS1709>

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# GENERALIZED RANDOM FORESTS

BY SUSAN ATHEY<sup>\*</sup>, JULIE TIBSHIRANI<sup>†</sup> AND STEFAN WAGER<sup>\*</sup>

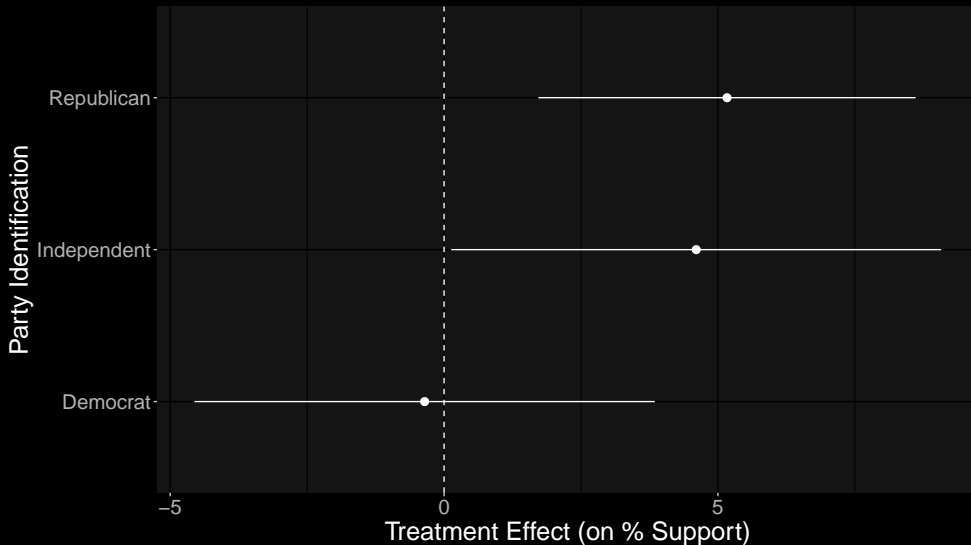
*Stanford University<sup>\*</sup> and Elasticsearch BV<sup>†</sup>*

# Individual Characteristics

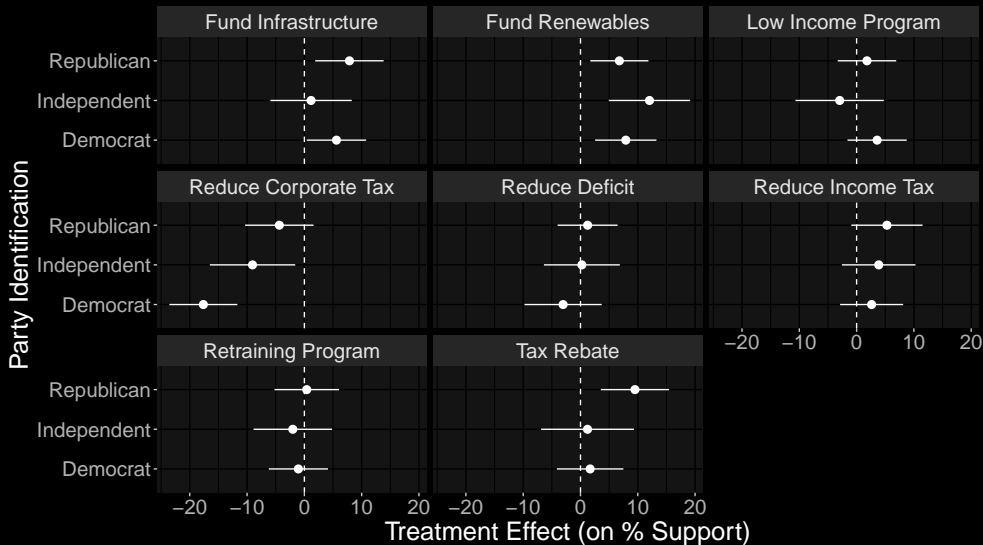
- Age
- Climate Scepticism
- Education
- Income
- Party Identification
- Sex



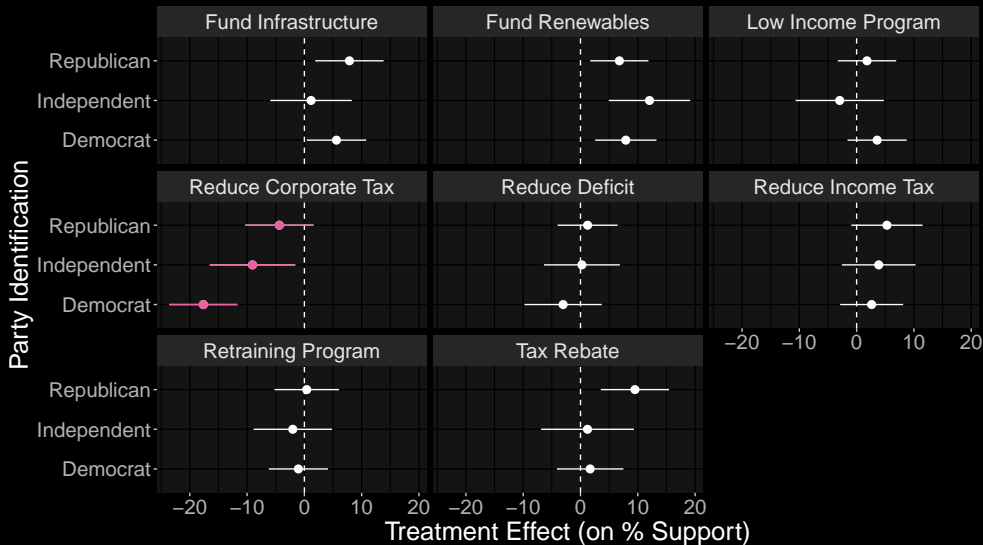
# Effect of Revenue Information by Party Identification



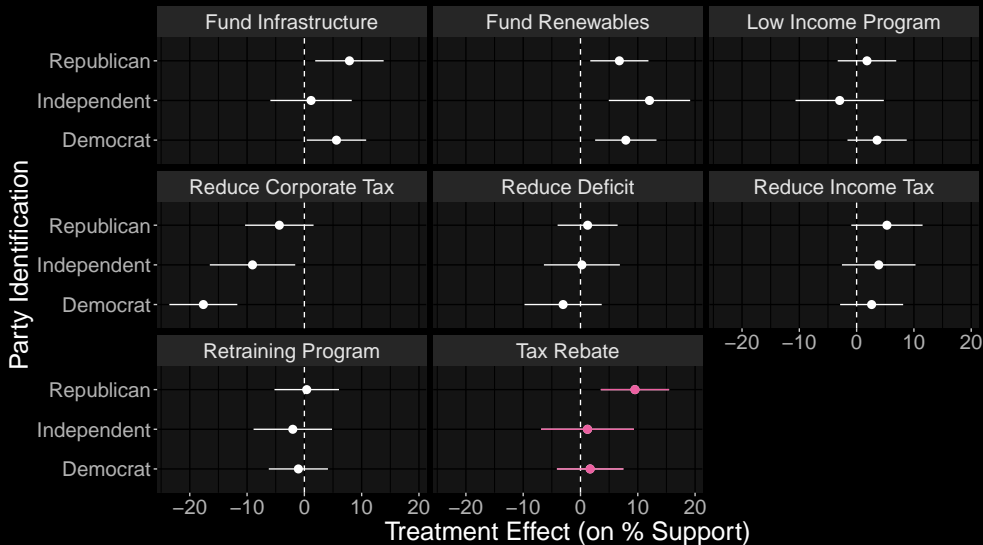
# Effect of Revenue Usage by Party Identification



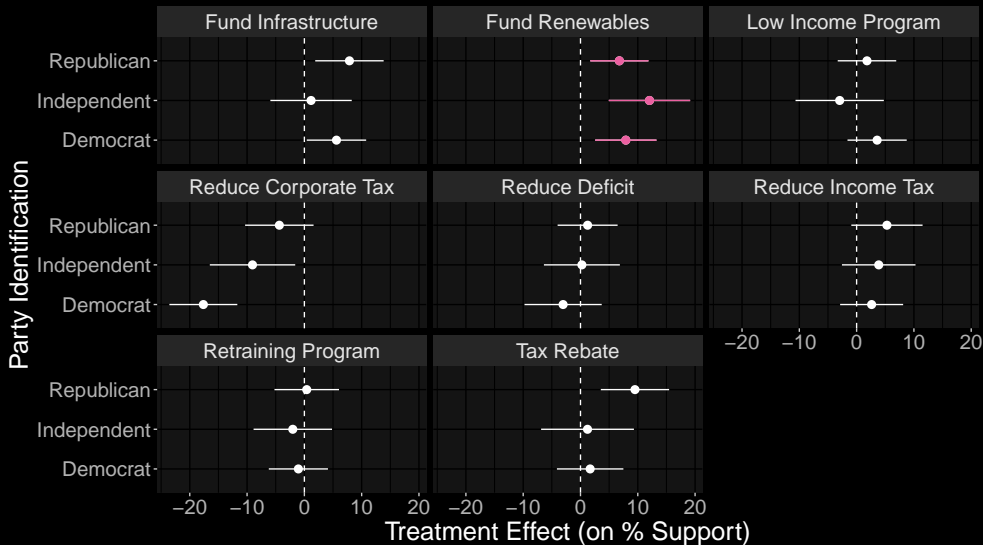
# Effect of Revenue Usage by Party Identification



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# Effect of Revenue Usage by Party Identification



## Conclusion

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Politics integral to Climate Change

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Complexity



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Machine Learning provides additional answers

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- Robust estimates of individual and regional heterogeneity
- Allowing for conditional effects

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Thank you!

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