NBER WORKING PAPER SERIES

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Working Paper 26146
http://www.nber.org/papers/w26146

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2019

We thank: Aria Kovalovich, Doug Murdoch, Anna Terkelsen, and Yuxian Xiao for valuable research assistance; Nicholas Pharris at the Washington Secretary of State for providing data and GIS expertise; Yoram Bauman, Gail Gatton, Ben Silesky, and Greg Small for helpful background and detailed comments; Matt Kahn, Jim Hines, and Matthew Incantalupo for detailed comments; and seminar participants at UC Davis, Energy Policy Institute at Chicago, UC Berkeley Energy Camp, MSU-UM-WMU EEE Day Workshop, Purdue University, Heartland Environmental & Resource Economics Workshop @ Illinois, Oberlin College, the ASSA Annual Meetings in Philadelphia, Michigan State University, the MPSA meetings in Chicago, the SPPC meeting in College Park, the NBER Summer Institute, Macalester College, and Brigham Young University for many helpful comments and suggestions. Ioana Marinescu acknowledges financial support from the Kleinman Center for Energy Policy at the University of Pennsylvania. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 26146
August 2019
JEL No. D72,H23,H71,H72,Q52,Q54,Q58

ABSTRACT

Surveys show majority U.S. support for a carbon tax. Yet none has been adopted. Why? We study two failed carbon tax initiatives in Washington State in 2016 and 2018. Using a difference-in-differences approach, we show that Washington's real-world campaigns reduced support by 20 percentage points. Resistance to higher energy prices explains opposition to these policies in the average precinct, while ideology explains 90% of the variation in votes across precincts. Conservatives preferred the 2016 revenue-neutral policy, while liberals preferred the 2018 green-spending policy. Yet we forecast both initiatives would fail in other states, demonstrating that surveys are overly optimistic.

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1 Introduction

Estimates for 2015 put the social cost of carbon at \$11-\$105 per metric ton of CO_2.[1] A Pigouvian tax on emissions can internalize the social cost of carbon—as can a system of tradable emissions permits ("cap-and-trade"). Price incentives equalize the marginal cost of reducing emissions across different sources and thereby minimize the total cost of meeting a given emissions target. Meanwhile, revenue from a carbon tax can be used ("recycled") to lower other taxes or to mitigate impacts on low-income households and energy-intensive industries. This logic appeals to economists from across the political spectrum, as well as to many commentators and politicians, as exemplified by the informal Pigou Club and more formal Climate Leadership Council.[2] Yet these economic arguments inevitably must confront a key political hurdle: carbon taxes lead to higher energy prices, which are highly unpopular (see e.g. Knittel 2014, for gas taxes). How then could a carbon tax be passed? One argument is that forming a bipartisan coalition would be easier if carbon taxes were more acceptable to conservatives who tend to favor limited government. Thus, this view supports using carbon tax revenue to lower other taxes, i.e. a revenue-neutral policy. An alternative argument sees the bipartisan approach as doomed to failure since the right would reject a carbon tax of any flavor, while the left would actually prefer to increase government spending. Thus, this alternative view supports spending carbon tax revenue on green projects and social programs to maximize liberal support.

Running parallel to this economic and political debate, recent research in the social science literature uses surveys to measure public support for environmental policies, including a carbon tax. This literature often finds broad, majority support for a carbon tax—depending on how the tax revenue is used (Amdur, Rabe, and Borick 2014; Kotchen, Turk, and Leiserowitz 2017). For example, 50% of Americans in a 2016 survey say they support reducing greenhouse gas emissions by taxing carbon-based fuels.[3] Meanwhile, 68% of Americans in a 2018 survey say they support requiring fossil-fuel companies to pay a carbon tax.[4] This number climbs to 72% in 2019.[5] Yet to date, we have seen no carbon tax adopted in the United States, be it a revenue-neutral policy or a tax-and-spend policy.[6] What explains this disconnect? Are opinion surveys reliable measures of voter preferences for a carbon tax? To what extent are voters actually willing to trade

[1] See here: https://www.epa.gov/sites/production/files/2016-12/documents/social_cost_of_carbon_fact_sheet.pdf. The social cost carbon is the present-discounted value of the stream of present and future economic damages from climate change, caused by releasing one additional ton of carbon into the atmosphere. Also see here: https://openknowledge.worldbank.org/bitstream/handle/10986/24288/CarbonPricingWatch2016.pdf?sequence=4&isAllowed=y.

[2] The "Pigou Club" is a designation credited to founding member and conservative economist, Greg Mankiw, and includes: fellow economists such as Paul Krugman, Ed Glaeser, Kevin Hassett, and William Nordhaus; Democratic politicians such as Al Gore; Republican politicians such as Rex Tillerson and Lindsey Graham; conservative/libertarian pundits such as David Frum and Megan McArdle; liberal/progressive pundits such as Bill Nye and David Leonhardt; and many others from across the political spectrum. The Climate Leadership Council is a bipartisan policy institute founded by Ted Halstead in 2017, which counts former Federal Reserve chairs Ben Bernanke and Janet Yellen among its founding members.

[3] See here: http://closup.umich.edu/files/ieep-nsee-2016-fall-carbon-tax.pdf

[4] See here: https://climatecommunication.yale.edu/visualizations-data/ycom-us-2018/?est=happening&type=value&geo=county

[5] See here: https://climatecommunication.yale.edu/publications/politics-global-warming-april-2019/2/

[6] Several Canadian provinces have implemented a carbon tax—though Alberta recently repealed its carbon tax.

off higher energy prices for reduced emissions and tax rebates? Does the use of revenue matter politically in the real world?

To answer these questions, we study voting patterns in two recent, failed carbon tax initiatives in Washington State from 2016 and 2018. Initiative 732 (I-732) from 2016 would have lowered the state sales tax from 6.5% to 5.5% and matched the federal Earned Income Tax Credit (EITC) by 25%, while Initiative 1632 (I-1631) from 2018 would have devoted 95% of carbon tax revenue to green projects (e.g., renewable energy). These policies were otherwise quite similar, i.e. with tax rates starting at $15/tCO$_2$ and rising gradually thereafter (see table 1). Thus, these initiatives offer an unprecedented opportunity to measure voter preferences for two different flavors of a carbon tax based on actual voting. Our analysis relies on detailed, precinct-level elections data from Washington State for 2016 and 2018. We complement these data with a national survey of 3,000 people fielded on Amazon Mechanical Turk during the November 2018 election (but before the election results were known).

Our findings address five key questions.

First: What drives differences in support for a carbon tax among voters? Overwhelmingly, we find it to be ideology. This message emerges clearly from our analysis of precinct-level voting data and is confirmed in our individual survey data. In both cases, we infer latent ideology from votes and opinions on *other* policies (e.g., stricter gun laws or a higher minimum wage). Ideology alone explains 91% of the variation in actual vote shares across precincts and predicts votes better than partisanship. In contrast, proxies for higher tax incidence (e.g., car commute or home size), which correlate negatively with support for a carbon tax, explain relatively little of the variation across precincts. Likewise, among individual survey respondents, latent ideology explains two times more of the variation in support across respondents than party affiliation, and the results barely budge when including proxies for the incidence of a carbon tax or other demographic controls. The key takeaway is that ideology is the main driver of support for a state carbon tax in a referendum.

Second: Do voters prefer a revenue-neutral tax, or spending on green projects? Again, we find that the answer depends on ideology. I-732 was designed by an economist to be revenue-neutral in an explicit appeal to political moderates, while I-1631 was designed by a progressive coalition with social and environmental justice objectives. Consistent with these different strategies, we find in precinct-level voting data that I-1631 performed better in liberal precincts, where it picked up 3.3 percentage points—but worse in conservative precincts, where it lost 0.7 percentage points relative to I-732. Thus, while the green-spending policy performed slightly better overall (43.4% for I-1631 versus 40.8% for I-732), it also failed to gain majority support. This failure has less to do with opposition from conservatives, whose support fell slightly, than tepid enthusiasm among progressives, whose support only grew modestly.

Third: Do voters value the benefits of a carbon tax? While ideology is the main driver of voting on the carbon tax, we find that tax incidence also matters on the margin, which allows us to back out the distribution of willingness to pay (WTP) for the policy across precincts. We calculate the average incidence of the carbon tax to be $266 per person per year. Meanwhile, we find that voters on average put little value on the other aspects of a carbon tax policy, including the tax rebates built-in to the 2016 initiative. Thus, for the average precinct, tax incidence is pivotal in driving opposition to the carbon tax. When we look beyond the average, we find that WTP for the incidence of a carbon tax is similar across precincts (because the predicted incidence is similar)—but that the WTP for the other aspects of the policy varies greatly. This finding rationalizes why pocketbook issues explain so little of the variation in the vote shares across precincts: voters across all precincts are similarly put-off by higher taxes, while political ideology differs tremendously across precincts, driving large differences in support for a carbon tax.

Fourth: What are the prospects for carbon taxes in other states? To answer this question, we use our regression results from Washington to perform an out-of-sample forecast for vote shares in other states. We find that the best chance for Pigou at the polls would be a carbon tax modeled on I-1631 in Massachusetts (49.1% support). We forecast that this policy would actually pass in Vermont (50.2% support), but the Green Mountain State lacks the popular initiative mechanism. Meanwhile, the best chance for a revenue-neutral policy like I-732 is in California (46.5% support). Again, I-732 would do better in both New York and Hawaii (46.8% and 47.3%), but neither state has the popular initiative. Across all states, we find that our survey over-estimates support for a carbon tax relative to our forecasts based on Washington's actual vote.

Fifth and finally: *Why* do surveys overstate actual votes for a carbon tax? Using our individual survey data, we estimate that support for I-1631 in Washington is 20 percentage points lower than in other states, controlling for ideology and demographics—but find no such gap for eleven *other* environmental policies (e.g., the Kyoto treaty). This comparison can be interpreted as a difference-in-differences estimate in which Washington is the treated state, other states serve as controls, and we measure support for the I-1631 carbon tax relative to other environmental policies. We interpret the Washington penalty emerging from our difference-in-differences estimator as a campaign effect: respondents exposed to Washington's two real-world campaigns and actual vote on a carbon tax exhibit lower support than respondents considering a purely hypothetical initiative. In addition, we find that our survey of Washington respondents over-predicts the actual vote for a carbon tax in Washington, even after carefully re-weighting the data to match the party and demographics of the voting population. In contrast, our re-weighted sample *does* yield accurate predictions for U.S. House votes. We therefore infer that our survey is selected on unobservables that correlate with support for a carbon tax but *not* partisanship. Thus, while the qualitative patterns in our survey data are consistent with the actual vote in Washington—namely, that a carbon tax is more popular among liberal voters—surveys may be unreliable guides to the absolute number of votes in a referendum.

This paper contributes to the literature in public economics that uses votes in referendums to measure preferences for public policy. The closest papers to ours are Kahn and Matsusaka (1997) and Burkhardt and Chan (2017), who estimate demand for environmental policy using votes on a wide range of initiatives in California—and Holian and Kahn (2015), who focus on California's cap-and-trade bill from 2006, drawing on both actual votes and survey data.[7] We are the first paper to analyze voting on a state-level carbon tax. Like us, Burkhardt and Chan (2017) use aggregate voting data to estimate willingness to pay (WTP) for policies separately from their fiscal cost, and conclude that ideology is more important than cost in explaining voting patterns. Our main contribution here is to decompose WTP into a larger number of underlying components, to show the full distribution of this WTP across precincts, and to show that ideology explains most of the variation in WTP across precincts.[8] Meanwhile, Holian and Kahn (2015) emphasize the strong correlation between actual votes and survey data across geography. In contrast, we emphasize the large gap in the average support implied by hypothetical survey questions versus actual votes. Our main contribution here is to show that exposure to a real-world policy significantly dampens the support for a carbon tax. We call this the campaign effect, i.e. all of the information to which people respond when a carbon tax is on the ballot in a given constituency. These results contribute to the literature on the impact of campaigns in direct democracy (Gerber 1999; Bowler and Donovan 2000; Lupia and Matsusaka 2004; De Figueiredo, Ji, and Kousser 2011; Rogers and Middleton 2015; Dyck and Pearson-Merkowitz 2019). Our findings imply that hypothetical votes in a survey likely overstate actual votes for a carbon tax in a real-world election.

We also contribute to a broader social science literature that studies the determinants of public opinion surrounding climate change, including preferences for carbon regulation and carbon taxes in particular. Egan and Mullin (2017) thoroughly review the survey literature, showing that partisan affiliation (i.e., Democrat vs. Republican) is the single-most important driver of support for climate regulation and that the partisan gap has only widened in recent decades.[9] Our main contribution here is to use *actual voting* data on a carbon tax. Like the survey literature, we also find that partisanship is an important driver of support for a carbon tax.[10] However, we show that it is not partisanship per se that mainly drives support but rather political ideology—which is strongly correlated with partisanship but measures something distinct.

Finally, we contribute to a literature that studies the political feasibility and durability of carbon reg-

[7] Burkhardt and Chan (2017) also estimate preferences for non-environmental public goods (e.g., children's hospitals), while Holian and Kahn (2015) study a second low-carbon policy in California: high-speed rail.

[8] In addition, we compute tax incidence based on variation in energy costs rather than marginal income tax rates, measure issues-based ideology separately from partisanship, and include a richer set of demographic controls.

[9] Egan and Mullin (2017) further emphasize (i) the importance of partisanship as a moderating variable for the effects of education and framing, (ii) that beliefs are not particularly susceptible to information (i.e., the "information deficit" model does not hold), and (iii) that belief in climate change does not necessarily lead to support for policy action.

[10] This result is consistent with Holian and Kahn (2015), who find partisanship to be an important driver of actual voting on California's cap-and-trade policy in 2006. In contrast, Kahn and Matsusaka (1997) finds that partisanship is not an important driver of voting on California's other forms of environmental regulation in the 1970s, 80s, and 90s.

ulation. See Rabe (2018) for a thorough review. One vein of this literature focuses on revenue-recycling schemes for carbon taxes or cap-and-trade systems with permit auctions. Carattini, Baranzini, Thalmann, Varone, and Vöhringer (2017) find using a hypothetical choice experiment in Switzerland that people prefer carbon tax revenue to be spent on green projects—but approve of revenue-neutral, lump-sum transfers when informed about the distributional effects. In the United States, survey respondents also prefer green projects to lump-sum transfers or reductions in other taxes (Amdur, Rabe, and Borick 2014; Kotchen, Turk, and Leiserowitz 2017). Our paper is unique in using actual voting data for two policies that differ mainly in how they propose to use carbon tax revenue. Thus, we provide the most direct evidence to date on how actual voters perceive and react to different revenue-recycling schemes. We find that liberal voters prefer green spending, while conservative voters prefer the revenue-neutral policy. Interestingly, our willingness-to-pay framework implies that voters on average are not convinced that a revenue-neutral carbon tax will compensate them for higher energy prices—and do not much value the spending in the green-spending version of the carbon tax. Thus, for the average voter, tax incidence explains most of the opposition to the carbon tax. Yet, beyond the average voter, more ideologically conservative voters tend to favor the revenue-neutral version. It therefore appears that revenue recycling is more of an ideological than a pocketbook issue in the eyes of voters. Thus, a carbon tax initiative with green spending will tend to do better in a liberal state like Washington—but *still* not necessarily well enough to get the initiative passed.

The rest of this paper proceeds as follows. Section 2 details the life of I-732 from its conception to the November 2016 election—and then the life of follow-on initiative I-1631 through its failure in November 2018. Section 3 describes our data sources. Section 4 explores the relationship between ideology and support for carbon taxes using precinct-level voting data and replicates these results using individual-level survey data. Section 5 tests whether economic incidence has a detectable impact on support for a carbon tax and estimates willingness-to-pay (WTP) for the policy's attributes. Section 6 forecasts vote shares for the two carbon taxes in other states based on our precinct-level regressions from within Washington—and explores why surveys tend to overstate these forecasts (as well as the actual vote in Washington). Finally, section 7 concludes with a discussion of lessons-learned and avenues for further research.

2 Washington State's two carbon tax proposals

The I-732 campaign was spearheaded by Carbon Washington—a small grassroots organization led by Yoram Bauman, a professional stand-up comedian and Ph.D. economist by training.[11] Carbon Washington's strategy was to appeal to political moderates and conservatives, as well as liberals, through a revenue-neutral policy and targeted redistribution of carbon tax revenue. Thus, in addition to imposing a carbon tax, their policy would have reduced the state sales tax (to benefit all voters), expanded the EITC (to

[11] Bauman styles himself as "The world's first and only Stand-Up Economist." See here: `http://standupeconomist.com`

Table 1: *Comparing two flavors of a carbon tax: I-732 and I-1631*

	I-732	I-1631
Year	2016	2018
Provisions	Revenue-neutral carbon tax swap	Carbon emissions fee
	Carbon emission tax on fossil fuels, starts \$15/ton, rises to \$25/ton after 6 months, and increases annually by 3.5% to \$100 a ton	\$15/ton of carbon beginning on January 1, 2020
	Phased in more slowly for farmers and public transportation	Increase the fee by \$2 annually until the state's 2035 and 2050 greenhouse gas reduction goals are met
	Reduces State Sales Tax 1% from 6.5% to 5.5%	Levied on "large emitters," including power plants, electricity importers, sellers of fossil fuels, refineries, utilities, gas distributors, log transporters, urban transportation
	Reduces State Business and Occupation Tax on Manufacturing Businesses to .001%	Revenue goes into three funds; (1) 70% to a fund for air quality and energy programs and projects, (2) 25% to a fund for water quality and forest health projects, and (3) 5% to a fund for investments related to communities
	Funds the Working Families Tax rebate program, a 25% match on the federal Earned Income Tax Credit	Establishes a public oversight board responsible for implementing and overseeing these programs
		Creates three panels to provide recommendations to the public oversight board regarding investments from the three funds mentioned above
Voting results	40.75% Yes, 59.25% No	43.44% Yes, 56.56% No
Spending in Support	\$3,154,984.98	\$16,398,381.52
Spending in Opposition	\$1,418,005.71	\$31,591,364.54
Top Spenders in Support	Peter Kelly (\$125,000)	Nature Conservancy (\$3.4 million), League of Conservation Voters (\$1.4 million), Bill Gates and Michael Bloomberg (\$1 million each)
Top Spenders Opposed	Kaiser Aluminum (\$450,000)	BP America (\$13.15 million), Phillips 66 (\$7.2 million), Andeavor (\$6.1 million)

Source: Ballotpedia

address distributional concerns), and reduced taxes on manufacturing businesses (to mitigate opposition from energy-intensive industry). Meanwhile, the state's big player in carbon regulation over many years was the Washington Alliance for Jobs and Clean Energy (henceforth "Alliance"). The Alliance comprised a broad range of environmental, labor, and social justice advocacy groups, i.e. the progressive base. These members included heavy-hitting, national-level environmental groups, such as Sierra Club and National Resources Defense Council, along with various state and local environmental groups. The labor and social justice groups reflected a similar range of national, state, and local advocacy groups—again including many heavy-hitters (e.g., AFL-CIO).[12] The Alliance's strategy was to explicitly tie carbon regulation to a program of spending on green jobs, improved health, and climate adaptation in low-income, historically disadvantaged communities. Thus, from the Alliance's perspective, any tax revenue should be targeted directly to these priorities.

The divergence between Carbon Washington and the Alliance highlights—in microcosm—a strategic fork in the road for would-be crafters of climate policy: appeal to moderates and conservatives through a revenue-neutral, market-based policy, or double-down on the left by spending revenue on the issues and identity groups that liberals care about. Carbon Washington turned right—or rather, aimed for the middle—while the Alliance was veering left.

Carbon Washington unexpectedly gathered the signatures needed to put I-732 on the ballot (over 350,000). The Alliance approached Carbon Washington to discuss a policy compromise that would satisfy both groups and that would, in the Alliance's view, do better at the polls. However, after a complicated discussion and some miscommunication, the two groups were unable to reach a compromise. Carbon Washington proceeded to the polls with I-732, while most members of the Alliance either actively opposed or—like the Sierra Club—declined to support I-732 (see appendix A for more information on the two initiatives' supporters and opponents).

The reasons for this opposition varied across groups but essentially boiled down to four issues: (1) concern that I-732 might lose revenue and put other programs at risk;[13] (2) a belief that carbon tax revenue should be *spent* on issues important to the coalition (e.g., green jobs and climate adaptation); (3) a belief that such spending schemes polled better; and (4) the perception that Bauman and Carbon Washington failed to engage the broader social and environmental justice community in the design of I-732.

After I-732 failed in 2016, the Alliance followed through in crafting and campaigning for I-1631 two years later. Table 1 summarizes the key provisions of I-732 and I-1631. On the tax side, the two policies are quite similar: a state carbon tax starting at \$15/tCO2 and then rising gradually. However, on the revenue-

[12]See the Alliance's web page for a statement of principals and list of members: `https://jobscleanenergywa.com`.

[13]Independent estimates of the revenue impacts varied, highlighting this uncertainty: the Washington Office of Financial Management projected a 0.95% decrease in state revenue; Carbon Washington projected a 1.1% to 1.6% increase; and, the Sightline Institute projected a -0.27% decrease.

recycling side, the two policies differ sharply. I-732 aims to be revenue-neutral, devoting most tax revenue to a reduction in the state sales tax and an expansion of the EITC—to mitigate impacts on low-income households.[14] In contrast, I-1631 allocates 95% of tax revenue to green projects and 5% to local communities. I-1631 tends to be a more ideologically liberal policy, since it spends revenue on green investment, while I-732 tends to be more conservative or moderate, since it is revenue-neutral.

The Alliance hoped that I-1631 would outperform I-732 for at least two reasons. First and most importantly, they thought that progressives would support using revenue for clean energy, while a revenue-neutral measure alienates those progressives and wins very few conservatives. Second, the I-1631 ballot language avoids the dreaded word "tax" and instead describes a "fee" on carbon.

3 Actual and hypothetical voting data

In this section we describe our data sources and procedures. Our main data record actual, precinct-level election results from Washington State in the November 2016 and 2018 general elections. We complement these data with hypothetical, individual-level voting data from a national online survey that we fielded on election eve and election day in November 2018 on Amazon Mechanical Turk.

3.1 Precinct-level election data from Washington in November 2016 and 2018

Our main data come from the State of Washington Secretary of State (WA SOS) and record precinct-level results from the November 2016 and November 2018 general elections.[15] These data record the total number of votes cast for various candidates to elected office, as well as total votes cast for and against various statewide ballot measures. We use these data to calculate—for each precinct—the share voting "yes" (vs. "no") on the two carbon taxes (I-732 in 2016 and I-1631 in 2018), as well as the share voting Republican (vs. Democrat; other small parties are not included in this calculation) in the 2016 U.S. presidential election.[16] These data also record, in a separate file, the total number of registered voters and ballots cast in 2016 (these data are not available for 2018). We use these data to calculate the share of registered voters that cast ballots in 2016 (turnout), as well as the share of ballots cast that recorded a vote either for or against the carbon tax (roll-off).[17]

To measure latent ideology, we conduct a principal component decomposition of the precinct-level vote shares on twelve *other* ballot measures from November 2016 and 2018. These measures cover a wide range of

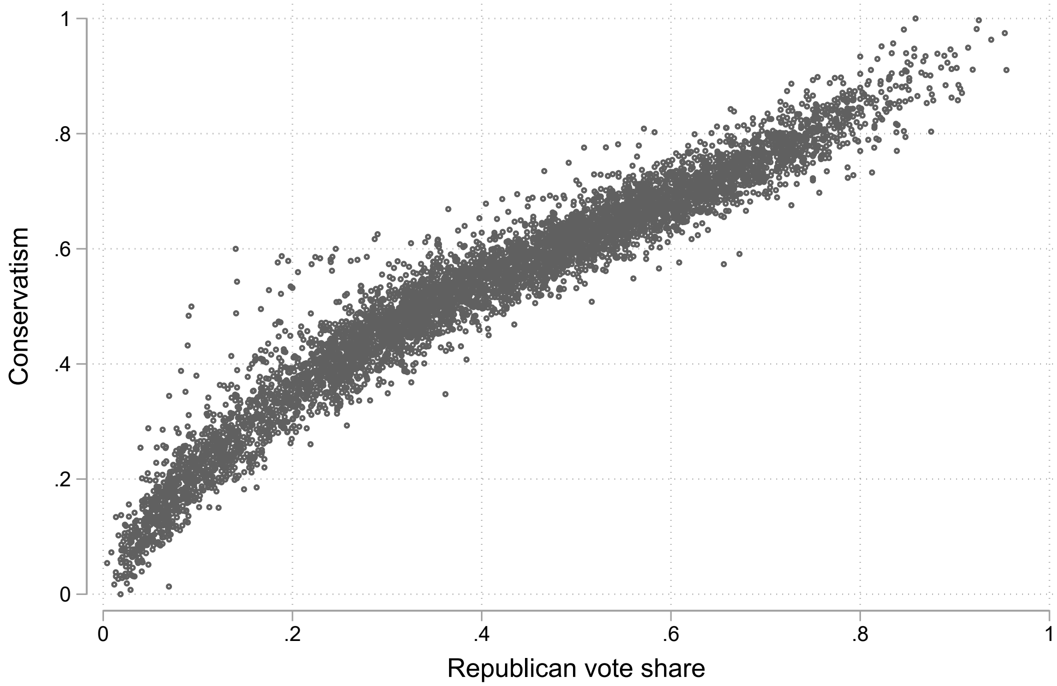
[14] Some may argue that the EITC increase is not a revenue-neutral tax cut but rather an increase in spending.

[15] Available here: `https://www.sos.wa.gov/elections/research/election-results-and-voters-pamphlets.aspx`

[16] Our main results use a measure of Republican share based on the 2016 U.S. presidential election. For robustness checks, we also calculate Republican share separately for 2016 and 2018 based on the two U.S. Senate elections in those years.

[17] In pooled regressions using both 2016 and 2018 data, we calculate roll-off as the the average number of votes cast for or against the carbon tax in 2016 and 2018 divided by the total number of ballots cast in 2016. In regressions that use only 2016 or 2018 data, we calculate roll-off as the total number of votes cast for or against a carbon tax in that year divided by the total number of ballots cast in 2016.

Figure 1: *Precinct-level conservative ideology vs. Republican presidential vote*



Note: This figure plots our constructed index of conservative ideology (based on votes for ballot measures (appendix F) other than the carbon tax from 2016 and 2018) vs. the Republican party vote share in the 2016 presidential election for 6,038 precincts in Washington State.
Source: WA SOS.

social, economic, and procedural issues.[18] We take the first component from this decomposition as an index measure of conservative ideology. We only include the first component, as this variable captures most of the underlying variation in ideology. We linearly transform this index to range from zero (most liberal) to one (most conservative). Figure 1 plots our measure of conservative ideology vs. the share voting Republican in each precinct. The figure illustrates that these two measures are highly correlated. However, they are not perfectly correlated. Indeed, at each level of Republican vote share, there are both relatively conservative and relatively liberal precincts.

We match these voting data to U.S. Census data as follows. First, we obtain data from WA SOS that provides the distribution of each voting precinct's total population in 2010 across Washington's more than 100,000 census blocks (based on block centroids).[19] We use these data to calculate, for each precinct, the share of the population living in each of Washington's roughly 4,800 census blockgroups. Second, we match

[18]See appendix F for details of each measure and appendix figure 18 for scatter diagrams plotting vote shares on these other state ballot measures versus the presidential vote share.
[19]We thank Nicholas Pharris at WA SOS for providing these data.

these population shares to U.S. Census blockgroup aggregate data (e.g., share people age 40 and older or share of households with incomes less than \$50,000). Third, for each precinct, we calculate the population-weighted averages of the blockgroup-level data. Finally, we match these precinct-level weighted averages of the underlying blockgroup-level data to precinct-level election data.[20]

U.S. Census data come from American Community Survey (ACS) 5-year estimates for 2012-2016. In constructing population-weighted averages of blockgroup-level data, we do not rely on blockgroup-level medians. Rather, we rely on blockgroup-level *shares* of people, households, workers, or commuters that fall into narrow categories. For example, we use the share of people age 40-44 or the share of households with incomes of \$50,000-\$59,999 rather than median age and median income.[21] This approach leads to more sensible data aggregation and allows us to more flexibly model the relationship between census covariates and support for a carbon tax.[22] Coefficients on these variables (e.g., population share age 40-44) intuitively have the same interpretation as those on a dummy variable (i.e., probability shift for a voter age 40-44).

We make several sample restrictions. First, we limit our analysis to precincts that did not experience boundary changes between 2016 and 2018.[23] This restriction omits 11% of precincts. Second, we limit our analysis to precincts with at least 50 votes cast in the November 2016 presidential election to more precisely estimate a precinct's latent partisanship and ideology.[24] This restriction omits an additional 4% of precincts. Finally, we focus on observations with complete census data. This restriction omits just 0.05% of precincts. In the end, we are left with a sample size of 6,038 precincts for 12,076 pooled observations across our two elections (2016 and 2018). Our final sample includes 84% of the 2016 precincts representing 85% of the state's population and 85% of the voter turnout.

[20]We calculate for 2016 that 34% of precincts overlap with one block group, 37% overlap with two, 18% overlap with three, 7% overlap with four, 3% overlap with five, and the remaining 1% overlap with six, seven, or eight block groups. In total, 89% of precincts overlap with three or fewer block groups.

[21]Our detailed census variables measure population shares by narrow category of: car commute time (for commuters); industry (for workers); annual income, home value, and # of rooms (for households); and age, race, gender, and education (for all people).

[22]Consider a precinct that overlaps with multiple blockgroups indexed by $j = 1, 2, \ldots, J$. Let μ_j be the share of the precinct's population in blockgroup j with $\sum_{i=1}^{J} \mu_j = 1$. Let θ_j be the share of blockgroup j's population in some demographic category (e.g., age 40-44). Finally, assume that a blockgroup's population is distributed homogeneously through its geographic area (e.g., the age 40-44 population is not concentrated in one part of the blockgroup or another). Then the share of the *precinct* in the given demographic category is $\sum_{i=1}^{J} \mu_j \theta_j$, i.e. the population-weighted average of the blockgroup shares. In contrast, the median value of some demographic variable (e.g., median age) in a precinct is *not* in general the population weighted-average of the blockgroup-level medians, i.e. medians do not aggregate.

[23]Precincts experience boundary changes when they split (creating a new precinct and corresponding precinct code), merge (eliminating an existing code), or shift boundaries to re-balance population (so that old codes correspond to different geographic areas). WA SOS maintains GIS shapefiles that record precinct boundaries for each year. At our request, Nicholas Pharris at WA SOS used these shapefiles to match each of the state's more than 100,000 census blocks to precinct boundaries in 2016 and 2018 (based on block centroids). Thus, we are able to identify precincts that experience boundary changes based on census blocks that match to *different* precinct codes in 2016 and 2018.

[24]Small precincts yield noisy estimates of a precinct's latent partisanship and ideology, leading to multiple cases of 0% and 100% vote shares (e.g., for the Republican party or for a particular ballot measure). These extreme cases skew our regression results. We found that omitting predicts with fewer than 50 presidential votes cast eliminated all such extreme cases. We omit these precincts prior to calculating and re-scaling the latent ideology measures described above.

3.2 Individual-level national survey data from November 2018

We conducted an internet survey using Amazon's Mechanical Turk platform in fall 2018 on Election Eve and Election Day (i.e., November 5-6, 2018), before election results were announced. We only surveyed U.S. residents aged 18 years or older. We surveyed 4,125 respondents, of whom 3,904 had sufficient data to allow us to estimate latent ideology (see below). Our primary question of interest is based directly on the approved text of I-1631 from Washington State. Residents of Washington were asked:

> Washington's ballot initiative I-1631 concerns pollution. This measure would charge pollution fees on sources of greenhouse gas pollutants and use the revenue to reduce pollution, promote clean energy, and address climate impacts, under oversight of a public board. How do you think you will vote?

Residents of the other states were instead asked in the final sentence: "How would you vote if such a measure were put to the ballot in YOUR state?" A total of 3,760 respondents answered the carbon tax question *and* had sufficient other data to estimate latent ideology.

We measured party using a standard two-part question modeled on similar questions in the American National Election Study (ANES)[25] and the Cooperative Congressional Election Study (CCES). First, we asked respondents to identify as Democrat, Republican, or independent. Next, we asked self-described independents if they leaned more to one major party or another. Consistent with other work, we classified respondents as independents only if they declined to identify as Democrat or Republican in both questions. We classified respondents that admitted to leaning Democrat or Republican as partisans, along with those that identified as such in the first question.[26]

3.2.1 Measuring individual-level ideology

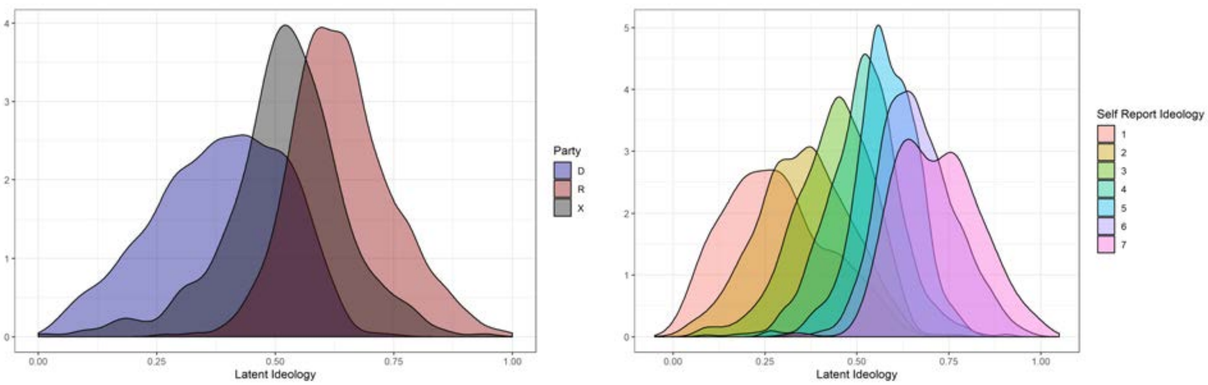
Generating valid measures of ideology for survey respondents is not straightforward. Even in an age of polarized parties, party membership is only partly ideological. Indeed, individuals often hold ideological positions that diverge from their party's platform. An alternative approach is to ask respondents to self-identify their position on a left-right scale, ranging from very liberal to very conservative. While the political science literature has used this approach for decades, it suffers from potentially severe measurement error problems (Ansolabehere, Rodden, and Snyder 2008). Thus, the approach of most modern measurement attempts—and the approach we take here—is to consider ideology as a latent variable to be estimated using a variety of observable issue positions (Jessee 2012; Shor and Rogowski 2018).[27]

[25] See `https://electionstudies.org/`

[26] See, for example, Keith, Magleby, Nelson, Orr, Westlye, and Wolfinger (1992). Also see `https://www.people-press.org/2014/06/12/appendix-b-why-we-include-leaners-with-partisans/`.

[27] Achen (1978) laid the groundwork for this effort. Most scholars rely on public opinion surveys, which yield maximum control over which questions are asked. Examples include Bafumi and Herron (2010), Jessee (2012), Tausanovitch and Warshaw (2013), Shor and Rogowski (2018), and Kousser, Phillips, and Shor (2018). In contrast, Gerber and Lewis (2004) exploit the fact that

Figure 2: *Distributions of latent ideology by self-reported party and by self-reported ideology*



Note: This figure plots the distribution of latent ideology estimated from responses to policy questions in our national-level individual survey data. The left panel shows the distribution of ideological score conditional on self-reported party identification (Democrat, Republican, and Independent). The right panel shows the distribution of ideological score conditional on self-reported ideology on a 1-7 scale (where 1 = ultra-liberal and 7 = ultra-conservative).
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018.

We use the responses to 53 issue questions asked elsewhere in our survey. Of these questions, a total of 11 pertain specifically to energy and environmental issues, while 42 pertain to non-environmental issues. We list all 53 questions in appendix B. We estimate three separate measures of ideology: a combined measure, one that includes only environmental issues, and one that includes only non-environmental issues. We estimate these measures of ideology by fitting a one-dimensional item response theory (IRT) model (Clinton, Jackman, and Rivers 2004) to each of the three sets of issue questions (i.e., combined, environmental, and non-environmental).[28] To ease interpretation, we rescale each of these ideology measures such that, in our sample, they range from 0 (most liberal) to 1 (most conservative).[29] Below, we find that while latent environmental ideology predicts voting on the carbon tax better than other measures in some regressions, the regression coefficients are similar across all three measures.

Figure 2 shows the full distribution of estimated latent ideology. The left panel shows latent ideology conditional on self-reported party identification. Though correlated with party, latent ideology is not fully captured by partisanship. This finding makes sense, since partisanship represents much more than ideology. The right panel shows latent ideology conditional on self-reported ideology. Though the means of the self-reported

states like California hold elections with multiple issue propositions. Analogous to our approach based on precinct-level data above, they use individual-level ballot data from Los Angeles to estimate latent ideology based on actual votes in the 1992 election.

[28]IRT models are standard in political science research. These latent-measurement models take as inputs a series of dichotomous responses and estimate a continuous measure for latent ideology. Any number of dimensions of latent ideology can be estimated, but adding more dimensions typically does not increase explanatory power by much (Jessee 2012). That a single dimension captures most variation in ideology implies that our survey respondents' policy preferences are highly constrained and correlated with each other. We performed the actual estimation using the `pscl` package in `R` (Jackman 2011).

[29]That is, our rescaled measure of ideology for respondent i is $\tilde{x}_i = [x_i - \min(x)]/[\max(x) - \min(x)]$, where x_i is unscaled ideology for respondent i and $\min(x)$ and $\max(x)$ are the sample minimum and maximum values.

categories line up as expected, the distributions of the categories are very wide. Strikingly, a substantial share of self-reported ultra-liberals are *more conservative* than some self-reported ultra-conservatives, as indicated by the overlap in the distributions for self-reported ideology categories 1 and 7. We should be skeptical, then, of using self-reported measures of ideology to predict policy preferences.

3.2.2 Sampling bias and re-weighting

Respondents recruited online through Amazon's MTurk platform obviously are not representative of the general population. MTurkers are typically younger, more educated, and more Democratic and liberal than the general population. Nevertheless, this bias is easily overstated (Berinsky, Huber, and Lenz 2012) and the use of MTurk for survey and experimental work has expanded dramatically in the past decade, including work on the ideological polarization around I-732 (Van Boven, Ehret, and Sherman 2018). This growth in MTurk is partly a response to the high cost of obtaining a representative sample using more traditional survey methods, as well as to rapidly dropping response rates and significant response bias for traditional methods.

To better approximate a nationally representative sample of individuals, we weight our survey data to match self-reported partisanship and demographics from the 2018 exit poll conducted by Edison Research and the National Election Pool.[30] All individual-level models are estimated using these survey weights. Later in the paper, we also aggregate to the state level. To do that, we use a different method of weighting our survey data—multiple regression with poststratification (MRP)—which we describe in greater detail below.

4 Who supports a carbon tax?

In this section, we investigate the correlates of support for the carbon tax—first, using aggregate precinct-level voting data for I-732 and I-1631, and second, using individual-level MTurk survey data for I-1631.

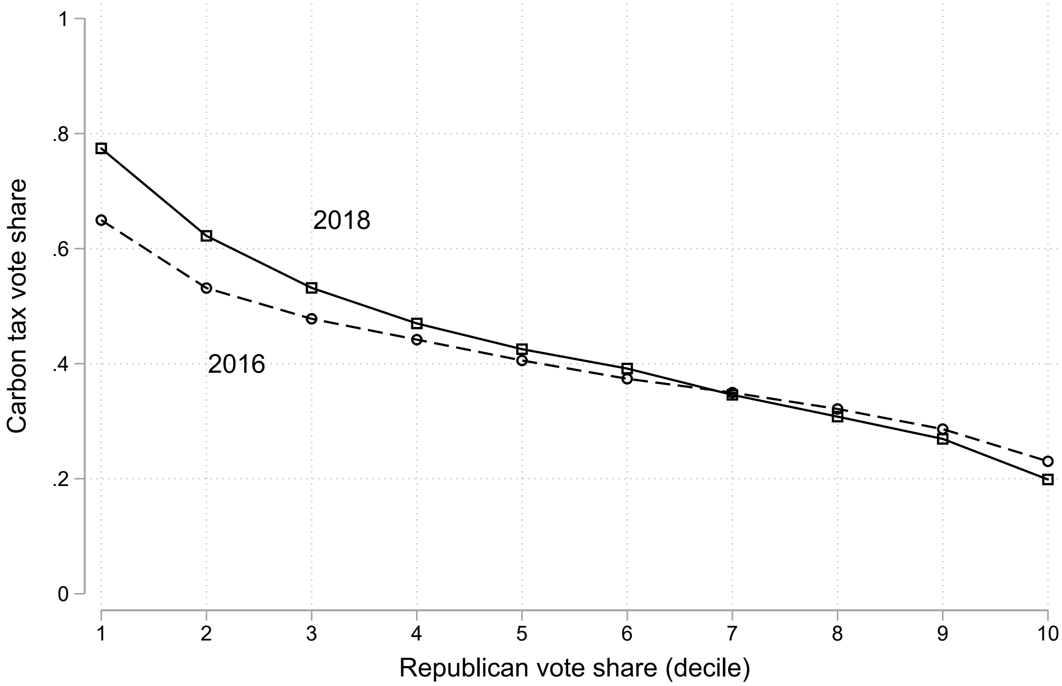
4.1 Evidence from precinct-level voting data

Figure 3 shows the share voting "yes" on each of the two carbon taxes by decile of the Republican vote share in the 2016 presidential election.[31] Deciles for 2018 (solid line) are constructed such that they each capture the same number of votes cast for or against the carbon tax in 2018, rather than the same number of precincts—and similarly for 2016 (dashed line). Thus, the overall share voting "yes" on the carbon tax in a given year can be read visually as the average height of the corresponding line. This figure illustrates clearly

[30] See `https://www.cnn.com/election/2018/exit-polls`. Specifically, we weight on sex, marital status, race, age, education, religious observance, and political party. We use the iterative weighting procedure from DeBell and Krosnick (2009) (implemented in the `anesrake` R package) which is commonly employed by political scientists studying public opinion. The estimated weights ensure that the survey cross-tabs for any two of our chosen demographic variables (e.g., share of sample that is female-married or Republican-college degree) match the population cross-tabs from the 2018 exit poll (for which two-way cross-tabs are publicly available but more detailed data are not).

[31] See appendix figure 19 for the underlying precinct-level vote shares.

Figure 3: *Vote share on carbon taxes in 2016 and 2018 as a function of Republican presidential vote*



Note: This figure plots the "yes" shares on I-1631 in 2018 (solid line) and I-732 in 2016 (dashed line) by decile of the Republican party vote share in the 2016 presidential election. Each decile contains precincts that together add up to one tenth of votes cast in 2016 and 2018 respectively. Deciles for 2018 are constructed from precinct-level data in the following way: sort precincts from the lowest to the highest Republican vote share, and then determine decile cutoffs. Deciles for 2016 (dashed line) are constructed similarly. Thus, the overall vote share can be visualized as the average height of the points.
Source: WA SOS.

that support for the carbon tax falls as the Republican share increases. The relationship is stronger in 2018 (solid line) than in 2016 (dashed line). Indeed, the most liberal precincts (on the left) tend to prefer the 2018 policy, while the most conservative precincts (on the right) tend to prefer the 2016 policy.[32,33]

Table 2 presents OLS regression results for precinct-level carbon tax vote shares conditional on ideology, partisanship, demographics, and turnout. These regressions pool voting outcomes from 2016 and 2018; each regression includes a 2018 dummy, but the other explanatory variables are purely cross-sectional.[34] Conservative ideology is a highly significant predictor of support for the carbon tax with an R-squared of

[32]This figure calculates deciles based on Republican share in 2016. To the extent that Republican share in 2016 is a noisy measure of Republican share in 2018, this approach could understate the negative correlation between support for I-1631 and Republican share in 2018. To explore this issue, we construct deciles using Republican share in the U.S. Senate races in 2016 and 2018, which allows us to match Republican share in 2016 to the carbon tax vote in 2016 (I-732) and Republican share in 2018 to the carbon tax vote in 2018 (I-1631). The resulting figure looks nearly identical. See appendix figure 20.

[33]Figure 21 in the appendix repeats this analysis using conservative ideology in place of the Republican vote share and leads to similar conclusions. Also see appendix figure 22 for the underlying precinct-level vote shares by conservative ideology.

[34]This data structure explains why the coefficients and standard errors on the 2018 dummy are the same in each column.

Table 2: *Predicting the carbon tax vote share at the precinct level (pooled 2016 and 2018)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +Endorse	(6) +County FEs	(7) +Turnout
Conservatism	-0.813***			-0.666***	-0.664***	-0.659***	-0.679***
	(0.013)			(0.022)	(0.022)	(0.019)	(0.013)
Republican		-0.729***	-0.620***	-0.124***	-0.128***	-0.141***	-0.128***
		(0.027)	(0.020)	(0.019)	(0.018)	(0.018)	(0.014)
Endorsement					-0.003*	-0.001	-0.001
					(0.002)	(0.001)	(0.001)
Turnout							-0.109***
							(0.021)
Voted on carbon tax							-0.046**
							(0.017)
2018 vote	0.026	0.026	0.026	0.026	0.026	0.026	0.026
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	12076	12076	12076	12076	12076	12076	12076
R^2	0.914	0.870	0.907	0.926	0.927	0.929	0.930

Note: This table presents coefficient estimates from pooled precinct-level OLS regressions modeling the share voting "yes" for the carbon tax in 2016 and 2018 as a function of ideology, demographics, and other factors. *Conservatism* measures ideology on a 0-1 index, computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 18). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. *Endorsement* indicates that the precinct's state legislator declared his or her support for I-732. *Turnout* is measured as the total number of ballots cast in 2016 divided by the total number of registered voters. *Voted on carbon tax* measures the average number of votes cast for or against the carbon tax in 2016 and 2018 divided by the total number of ballots cast in 2016. *2018 vote* is an indicator for the 2018 carbon tax (I-1631). Models (3)-(7) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., commute time by car, industry, home value, # rooms, income, gender, age, race, and education). Model (4) then adds ideology. Model (5) then adds the endorsement variable. Model (6) then adds county fixed effects. Finally, model (7) adds the two turnout variables. For all models, precincts are weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Standard errors are clustered by county (39 clusters).
Source: WA SOS & U.S. Census.

91.4% (column 1).[35] On average, support for the carbon tax falls by 81 percentage points moving from the most liberal to most conservative precinct. Meanwhile, the share voting Republican in the 2016 presidential election is also a highly significant predictor of support for the carbon tax, but its overall predictive power is slightly lower with an R-squared of 87% (column 2). On average, support falls by 73 percentage points moving from a precinct that votes 100% Democratic to a precinct that votes 100% Republican. Adding a slew of Census demographics to the Republican vote share bumps the R-squared up to 90.7% (column 3), but conservative ideology alone still has slightly higher predictive power (column 1). Adding conservative ideology on top of the Republican vote share and Census demographics further boosts the R-squared to 92.6% (column 4). More interesting, however, is the fact that the coefficient on Republican share shrinks by a factor of five, while the coefficient on conservative ideology remains quite high; ideology is clearly the

[35] By itself, the 2018 dummy has an R-squared of just 0.6%. Thus, as an approximation, we wholly attribute the R-squared values in this table to the other variables.

dominant driver of support for a carbon tax.[36] The endorsement of I-732 by the precinct's state legislator does not explain support for a carbon tax conditional on other variables (column 5), suggesting that local elite support is superfluous in this context.

We then test the robustness of our results to further controls. One potential concern is that we have omitted important spatial demographic variables that are correlated with ideology and partisanship, undermining our interpretation of these variables as the dominant drivers of support for a carbon tax. To address this concern, we control for county-level fixed effects. We find that our coefficients on ideology and partisanship do not change (column 6).[37]

Another potential concern is that the correlations we estimate reflect both differences in underlying preferences and differences in voter turnout for various ideological and demographic groups. For example, young people may strongly support a carbon tax (positive effect on "yes" shares) but may be less likely to vote (negative effect "yes" shares). If so, then the coefficients we estimate—while still valid for predicting aggregate voting outcomes—would reflect neither the underlying preferences of the voting population nor the preferences of the resident population. To address this concern, we control for voter turnout and voting on the carbon tax (roll-off), such that our coefficients implicitly reflect the preferences of the resident population (i.e., holding voter turnout fixed). Again, we find that our coefficients on ideology and partisanship do not change (column 7).[38] Interestingly, the coefficient estimates imply that precincts with higher turnout are *less* likely to support the carbon tax, conditional on ideology and demographics.[39] Thus, more active voters seem to have different preferences on average (since the coefficient on turnout is negative), but this fact does not change our interpretation for which specific groups most support carbon taxes (since the other coefficients barely shift when turnout is included).

4.1.1 Looking under the hood of our ideological index

As previously discussed, we exploit the presence of twelve statewide ballot measures considered by Washington voters in 2016 and 2018 (appendix F). We use vote shares on these measures across precincts to calculate a precinct-level index of political ideology based on the first component from a principle-component decomposition. This approach is based on the assumption that voting on these other measures is also ideo-

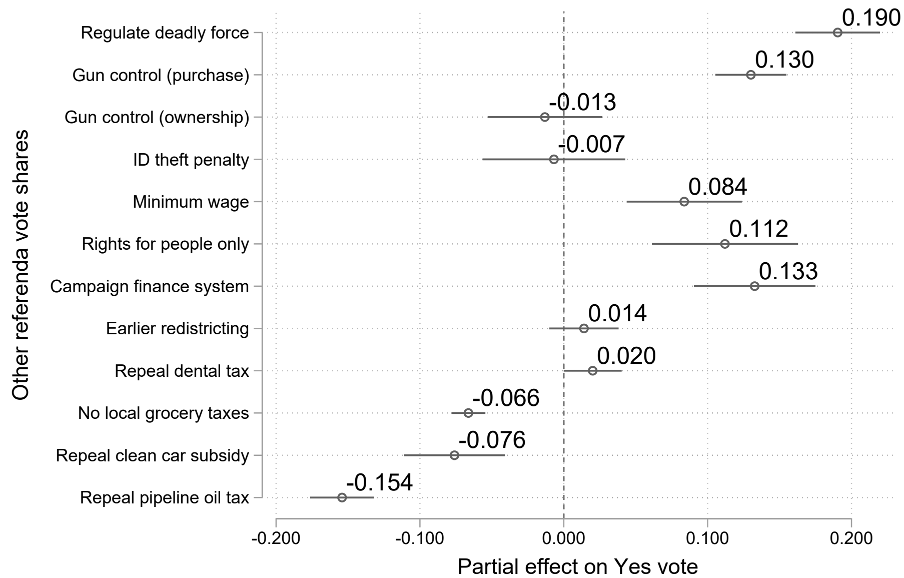
[36] One potential concern is that *Republican* is based on the presidential vote in 2016, while *Conservatism* is based on ballot measures from both 2016 and 2018, which could complicate a direct comparison of these variables. To explore this issue, we replicated models (1) and (2) using two different measures of *Republican* based on U.S. Senate elections in 2016 and 2018: the Republican share in 2016 (similar to our current approach), and a weighted-average with 2/3 weight on the Republican share in 2016 and a 1/3 weight on the Republican share in 2018 (to parallel the ideological index, which includes 8 ballot measures from 2016 and 4 from 2018). The two approaches yield similar results, and both approaches indicate that ideology is the main driver of support for a carbon tax. See appendix table 10.

[37] Full results for the census demographic variables, available upon request, show that coefficients on these variables also barely shift when we include county fixed effects.

[38] Full results for the census demographic variables, available upon request, show that coefficients on these variables also barely shift when we include the two turnout controls.

[39] Appendix tables 8 and 9 show that these results are mainly driven by voting in 2016, for which turnout was strongly negatively correlated with support for I-732.

Figure 4: *How votes on other ballot measures predict the vote on the carbon tax in 2016 and 2018*



Note: This figure plots coefficient estimates from a pooled OLS regression modeling the share voting "yes" for the carbon tax in 2016 and 2018 as a function of the share voting "yes" on other ballot measures (i.e., the basis for ideology index) and the same set of control variables as in column (6) of table 2. The *regulate deadly force* (I-940), *gun control (purchase)* (I-1639), *no local grocery taxes* (I-1634), and *repeal pipeline oil tax* (Advisory vote 19) measures were from 2018. The *Gun control (ownership)* (I-1491), *ID theft penalty* (I-1501), *minimum wage* (I-1433), *rights for people only* (I-735), *campaign finance system* (I-1464), *earlier redistricting* (Senate Joint Resolution No. 8210), *repeal clean car subsidy* (Advisory vote 15), and *repeal dental tax* (Advisory vote 14) measures were from 2016 (see appendix F for more details on each of the measures). Point estimates are represented by dots, while 95% confidence intervals are represented by horizontal lines. Control variables (not shown) include the share voting Republican (vs. Democrat) in the 2016 U.S. presidential election, endorsement by a state legislator, the 2018 vote dummy, detailed census variables (i.e., commute time by car, industry, home value, # rooms, income, gender, age, race, and education), and county fixed effects. 95% confidence intervals are based on clustered standard errors by county (39 clusters).
Source: WA SOS & U.S. Census.

logical in nature and consistent across issues. Creating an index allows us to capture the effects of ideology in a single, intuitive measure.

To explore precinct-level ideology further, we estimate an additional regression model (8) that is not reported in table 2. This model is identical to model (6) in the table but replaces the ideological index (Conservatism) with "yes" vote shares for all twelve of the ballot measures (i.e., included simultaneously). Figure 4 reports the coefficient estimates on these variables. At the bottom of the figure, note that support for repealing a clean car subsidy and repealing an oil pipeline tax both correlate negatively with support for a carbon tax. This is perhaps not surprising, given that these policies also have direct environmental implications. What is noteworthy for our model of ideology, however, is that support for tighter gun control and higher minimum wages—largely or entirely unrelated social and economic policies—also correlate (positively) with support for a carbon tax.

4.1.2 Comparing two flavors of the carbon tax

Above, we study the overall *level* of support for carbon taxes. Here, we explore *differences* in support for a green-spending policy (I-1631 in 2018) relative to a revenue-neutral policy (I-732 in 2016). To begin, figure 5 plots the *change* in support for I-1631 relative to I-732 by decile of Republican vote share.[40] The progressive design of I-1631 worked as intended by its supporters—at least to a degree. Liberal precincts increased their support for I-1631 relative to I-732. At the same time, conservative precincts decreased their support. Specifically, I-1631 gained 3.35 percentage points in cumulative vote share relative to I-732 among more liberal precincts (deciles 1-6) and lost 0.66 percentage points among more conservative precincts (deciles 7-10) for a net gain of 2.7 percentage points.[41,42]

How effectively did I-1631 mobilize liberals? This green-spending policy gained 12.5 percentage points in the most liberal (farthest left) decile. Had all of the left-leaning precincts (deciles 1-6) gained by the same amount, then the overall gain would have been 6.8 percentage points ($0.6 \cdot 12.5 - 0.7$), which would still only bring the overall vote share to 47.6% ($40.8 + 6.8$). In other words, even had all of the left-leaning precincts been as enthusiastic for I-1631 as the most liberal ones, the measure still would not have passed. Thus, the failure of I-1631 had less to do with the fact that it turned off conservatives (though it did), but rather the fact that it failed to galvanize enough liberals. The Alliance—who proposed I-1631 as a better alternative to I-732—was broadly correct in thinking that liberal voters could be moved to vote in favor of a carbon tax. However, the I-1631 package was not powerful enough in moving this constituency—at least not in the throes of a heavily contested campaign with high levels of campaign spending. Indeed, total spending in 2018 was $48 million—more than *ten* times larger than in 2016—and dominated by the "no" campaign, which outspent the "yes" campaign by a factor of two. Meanwhile, total spending in 2016 was just $4.6 million and dominated by the "yes" campaign, which outspent the "no" campaign by a factor of two (see table 1).

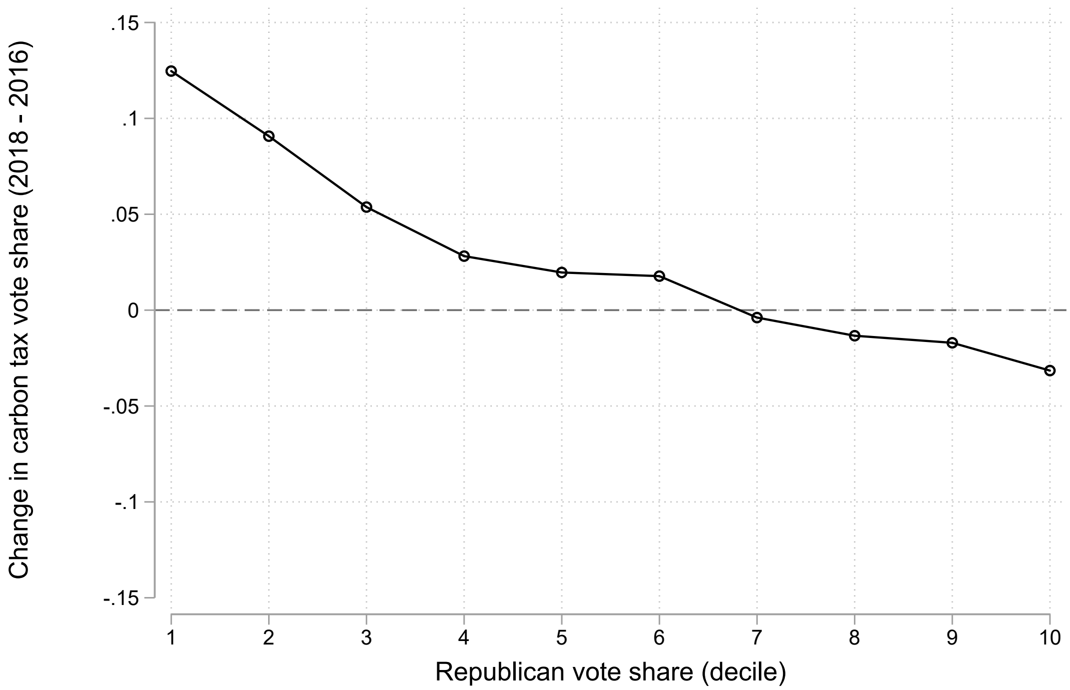
Next, we regress *changes* in the precinct-level vote share on ideology, partisanship, demographics, and other variables. Table 3 presents the OLS regression results—with positive coefficients indicating that a

[40] See appendix figure 19 for the underlying precinct-level changes in vote shares.

[41] Again, this figure—and our conclusions about net gains and losses—are nearly identical when we construct deciles based on Republican voting in the U.S. Senate races, which allows us to match Republican voting in 2016 to I-732 and Republican voting in 2018 to I-1631. See appendix figure 20.

[42] Figure 21 in the appendix repeats this analysis using conservative ideology in place of the Republican vote share and leads to similar conclusions. Also see appendix figure 22 for the underlying precinct-level changes in vote shares by conservative ideology.

Figure 5: *Change in vote share on carbon tax (2018 minus 2016) vs. Presidential vote (by decile)*



Note: This figure plots changes in average "yes" shares (I-1631 in 2018 relative to I-732 in 2016) by decile of the U.S. presidential vote share (Republican) in 2016. Each decile contains precincts that together add up to one tenth of votes cast in 2016 and 2018 respectively. Deciles for 2018 are constructed from precinct-level data in the following way: sort precincts from the lowest to the highest Republican vote share, and then determine decile cutoffs. Deciles for 2016 are constructed similarly. Thus, the overall difference in vote shares between 2018 and 2016 can be visualized as the average height of the points.
Source: WA SOS.

given variable is associated with an increase in vote share for the green-spending package (I-1631 in 2018) relative to the revenue-neutral policy (I-732 in 2016). Conservative ideology is a highly significant predictor of the change in vote share with an R-squared of 51.4% (column 1). On average, the green-spending policy loses 27.7 percentage points in relative support moving from the most liberal to the most conservative precinct. Meanwhile, the share voting Republican in the 2016 presidential election is also a highly significant predictor of the change in vote share, but its overall predictive power is lower with an R-squared of just 43.8% (column 2). On average, the green-spending policy loses 23.5 percentage points in relative support moving from a precinct that votes 100% Democratic to a precinct that votes 100% Republican. Adding Census demographics increases the R-squared but has virtually no effect on the coefficient for Republican share (column 3). Strikingly, upon adding precinct-level ideology, the share voting Republican totally vanishes as a predictor of relative support, while the coefficient on ideology remains as high as ever (column 4). Again, these inferences are robust to including county-level fixed effects and controls for turnout and roll-

Table 3: *Predicting the change in the carbon tax vote share (2018 minus 2016)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +Endorse	(6) +County FEs	(7) +Turnout
Conservatism	-0.277***			-0.287***	-0.284***	-0.253***	-0.222***
	(0.012)			(0.050)	(0.051)	(0.020)	(0.016)
Republican		-0.235***	-0.216***	-0.002	-0.009	-0.042	-0.062**
		(0.013)	(0.017)	(0.043)	(0.044)	(0.023)	(0.020)
Endorsement					-0.005	0.002	0.002
					(0.004)	(0.002)	(0.002)
Turnout							0.136***
							(0.019)
Voted on carbon tax							0.117***
							(0.012)
Observations	6038	6038	6038	6038	6038	6038	6038
R^2	0.514	0.438	0.614	0.632	0.632	0.688	0.697

Note: This table presents coefficient estimates from OLS regressions modeling the *change* in share voting "yes" for the carbon tax in 2018 vs. 2016 as a function of ideology, demographics, and other factors. *Conservatism* measures ideology on a 0-1 index. *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. *Endorsement* indicates that the precinct's state legislator declared his or her support for I-732. *Turnout* is measured as the total number of ballots cast in 2016 divided by the total number of registered voters. *Voted on carbon tax* measures the average number of votes cast for or against the carbon tax in 2016 and 2018 divided by the total number of ballots cast in 2016. Models (3)-(7) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., commute time by car, industry, home value, # rooms, income, gender, age, race, and education). Model (4) then adds ideology. Model (5) then adds the endorsement variable. Model (6) then adds county fixed effects. Finally, model (7) adds the two turnout variables. For all models, precincts are weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Standard errors are clustered by county (39 clusters).
Source: WA SOS & U.S. Census.

off (columns 6 and 7). Our regression results are thus consistent with figure 5, showing that more liberal districts prefer the green-spending version of a carbon tax, while conservatives prefer the revenue-neutral policy. Further, our results establish that ideology is indeed the main driver of support for I-1631 relative to I-732.

4.2 Evidence from individual-level survey data

We now turn to the individual-level survey data. Our raw, unweighted data indicate that 77% of respondents nationally would vote for a state carbon tax modeled on I-1631, while 23% would vote against. Of course, our survey disproportionately samples young, liberal, and Democratic voters. Indeed, when we re-weight our data to match the national demographics and party identification of the 2018 exit poll, we find somewhat lower support: 67% of respondents nationally would vote for I-1631, while 33% would vote against. Even after re-weighting, however, a large majority of voters favor the policy.

4.2.1 Overall results from individual-level survey data

Next, we model individual-level, self-reported support for I-1631 using a linear probability model. Table 4 presents the OLS regression results.[43] All regressions weight observations to make the data representative at the national level using the official 2018 exit poll. In addition, all regressions include a dummy variable for Washington State respondents, as well as a full set of individual-level demographic control variables.[44]

We find that self-reported party identification and demographics together explain 17% of the variation in individual-level support for I-1631 (column 1). Relative to Democrats with similar demographics, support is 34 percentage points lower among Republicans and 22 percentage points lower among Independents. Meanwhile, latent ideology and demographics together explain 30% of the variation in support (column 3), whereas *self-reported* ideology and demographics explain just 20% of the variation (column 2)—barely better than the party-only model (column 1). Note that mean ideology for Republicans is 0.64, while mean ideology for Democrats is 0.38, for a difference of 0.26. Thus, the coefficient of -1.28 on latent ideology (column 3) implies that support for a carbon tax decreases by $0.26 \cdot 128 = 33$ percentage points on average, moving from the ideology of a typical Democrat to that of a typical Republican. Appendix E presents full regression results for the demographic variables, some of which are statistically significant at conventional levels. In particular, women, African-Americans, Asian-Americans, and younger voters are all more likely to support the I-1631 carbon tax. Overall, however, these controls explain very little of the variation in survey responses, conditional on party and especially on ideology. Indeed, appendix E shows that latent conservative ideology by itself explains 28% of the variation in individual-level support, while adding demographic controls barely increases the R-squared to 30% (see column 3 here). When latent ideology and party are included together, the coefficients on Republican and Independent shrink to near-zero, while the coefficient on latent ideology holds steady, and the model R-squared barely budges (column 4). Again, these results all point to ideology as the dominant driver of support for a carbon tax in the individual-level survey data—just as in the precinct-level voting data above.

What about respondents from Washington State, who—in the weeks leading up to our survey—were exposed to real-world campaigns for and against the I-1631 carbon tax, followed by an actual vote? Strikingly, we find across all specifications in table 4 that respondents from Washington State are about 20 percentage points less likely to support I-1631 than respondents from other U.S. states. We explore this finding in greater detail below.

Above, we estimated a one-dimensional measure of ideology based on responses to all 53 dichotomous issue questions. Here, we estimate and explore two separate versions of latent ideology: one measure based

[43] Logit results are available in appendix E and provide equivalent findings.

[44] There are fewer observations in this table than the 3,904 respondents for whom we have valid ideology estimates. This gap is due to a substantial number of missing values for at least one of the demographic control variables. Appendix E shows that we obtain very similar results on the full sample that omits these control variables.

Table 4: *Predicting support for the carbon fee I-1631 across the United States in November 2018: individual linear probability model*

	Party Only	Self Report Only	Latent Only	Latent Plus Party	All
Republican	-0.34 ***			-0.03	-0.04
	(0.02)			(0.02)	(0.03)
Independent	-0.22 ***			-0.06 *	-0.06 *
	(0.03)			(0.03)	(0.03)
Self Reported Ideology		-0.10 ***			0.00
		(0.00)			(0.01)
Latent Ideology			-1.28 ***	-1.22 ***	-1.22 ***
			(0.04)	(0.05)	(0.06)
Washington State	-0.16 **	-0.16 **	-0.20 ***	-0.20 ***	-0.20 ***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
N	2815	2783	2815	2815	2783
R2	0.17	0.20	0.30	0.30	0.31

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Note: This table summarizes the results of five separate linear probability (OLS) models of the survey response to a question about the I-1631 ballot language. All models weight observations using inverse probability weights based on sex, marital status, race, age, education, religious observance, and political party using the 2018 exit poll (using R's svyglm command). All models include demographic controls. Model (2) includes a seven-category self-reported ideology response. Model (3) includes a measure of latent conservative ideology estimated from 53 individual issue questions elsewhere in the survey (appendix B). Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and the 2018 exit poll by Edison Research and the National Election Pool for the weights.

on environmental issues only (11 questions), and a second measure based on non-environmental issues only (42 questions). Table 5 presents OLS regression results using these two different measures of ideology; all regressions control for self-reported party affiliation, the Washington State dummy, and the full set of demographic control variables. We find that conservative environmental ideology performs substantially better than conservative non-environmental ideology in explaining individual-level support for I-1631 (compare the R-squared of 38% in column 2 to the R-squared of 26% in column 1). Meanwhile, adding non-environmental ideology on top of environmental ideology does nothing to improve the model's fit (compare the R-squared values in columns 3 and 2). At the same time, however, none of our qualitative conclusions change when using a measure of latent ideology devoid of energy and environmental issues.

4.2.2 Why is support for I-1631 so much lower in Washington?

What's the matter with Washington? Why is support for I-1631 so much lower there? Could it be that Washington voters are simply more conservative on energy and environmental issues than would be predicted by their ideology and demographics? In short: no. Rather, it appears that exposure to the real-world campaigns of 2016 and 2018 actually depressed the support of Washington voters.

To arrive at this answer, we repeat our regression analysis above, modeling support for I-1631 as a function of latent ideology, demographic control variables, and the Washington State dummy (see model 3 in table

Table 5: *Predicting support for the carbon fee I-1631 across the United States: individual linear probability model (environmental vs. non-environmental ideology)*

	Non-Envir Ideology	Envir Ideology	Combined
Environmental Ideology		-0.93 ***	-0.85 ***
		(0.03)	(0.04)
Non-Environmental Ideology	-0.97 ***		-0.22 ***
	(0.05)		(0.06)
Republican	-0.09 ***	-0.05 **	-0.02
	(0.02)	(0.02)	(0.02)
Independent	-0.08 **	-0.08 ***	-0.06 *
	(0.03)	(0.02)	(0.02)
Washington State	-0.19 ***	-0.20 ***	-0.21 ***
	(0.05)	(0.05)	(0.05)
N	2815	2814	2814
R2	0.26	0.38	0.38

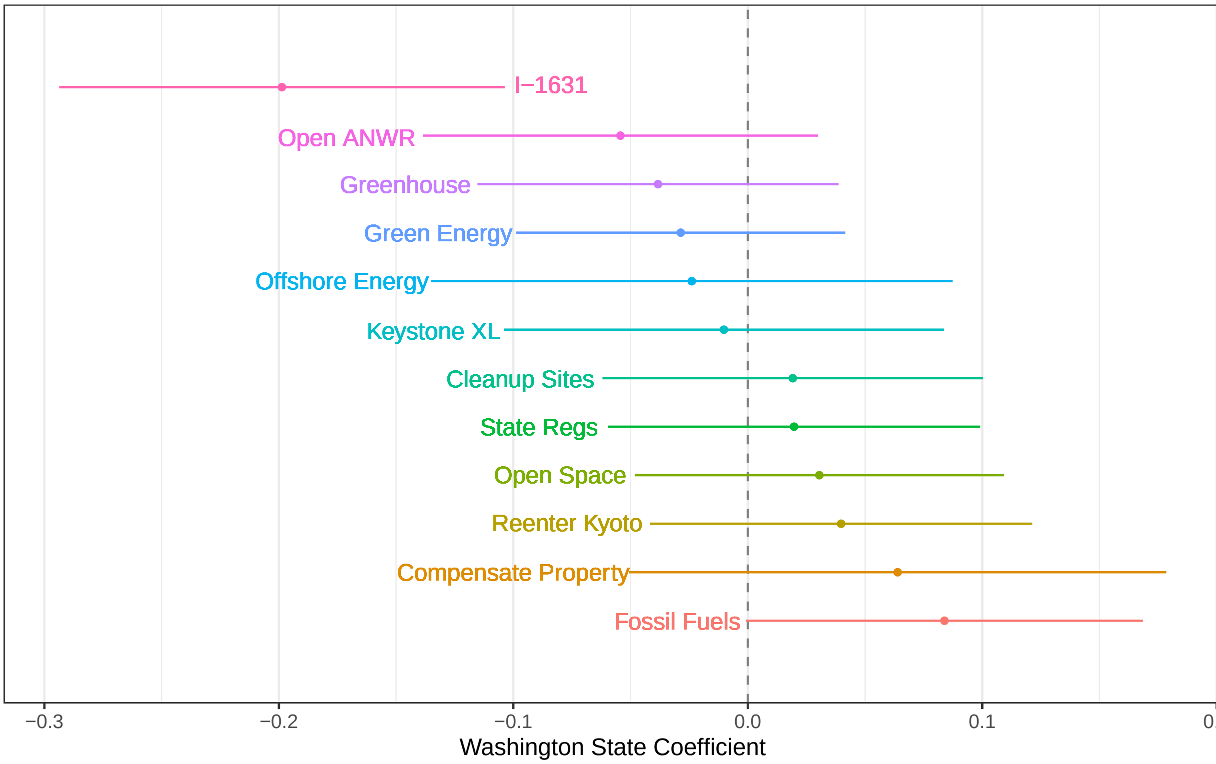
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Note: This table summarizes the results of three separate linear probability (OLS) models of the survey response to a question about the I-1631 ballot language. All models weight observations using inverse probability weights based on sex, marital status, race, age, education, religious observance, and political party using the 2018 exit poll (using R's svyglm command). All models include demographic controls. *Non-Environmental Ideology* estimates latent conservative ideology from 42 issue questions that are not about the environment or energy. *Environmental Ideology* estimates latent conservative ideology from the 11 questions on the environment and energy (appendix B).
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and the 2018 exit poll by Edison Research and the National Election Pool for the weights.

4 above). We then replicate this regression, modeling support for 11 other energy and environmental issues in place of I-1631 (all coded so that 1 is the liberal position and 0 is the conservative position). Figure 6 plots the resulting coefficient estimates on the Washington State dummy. Point estimates are represented by dots, while 95% confidence intervals are represented by horizontal lines. As above, the coefficient for I-1631 is -0.2 and statistically different from zero. However, for the 11 other energy and environmental issues, the coefficient ranges narrowly from about -0.05 (opposition to opening ANWR for oil exploration) to about 0.08 (opposition to the increased production of domestic fossil fuels). Only one such coefficient (opposition to fossil fuels) is statistically different from zero, but it is positive (i.e., consistent with Washington respondents being more liberal). Thus, while support for I-1631 is 20 percentage points lower in Washington, we find no evidence that Washington voters are generically less likely to support the liberal position on other environmental issues (conditional on ideology and demographics).

We take these comparisons one step further by estimating 11 difference-in-differences models, in which Washington is the treated state, other states serve as controls, and we measure support for the carbon tax relative to the 11 other energy and environmental policy issues. Our dependent variable is the *difference* in the individual dichotomous response on I-1631 and the responses on each of the 11 other issues (again, re-coded so that 1 is liberal and 0 is conservative). Thus, for example, a respondent opposing the carbon tax

Figure 6: *Coefficient estimates of Washington State fixed effects*

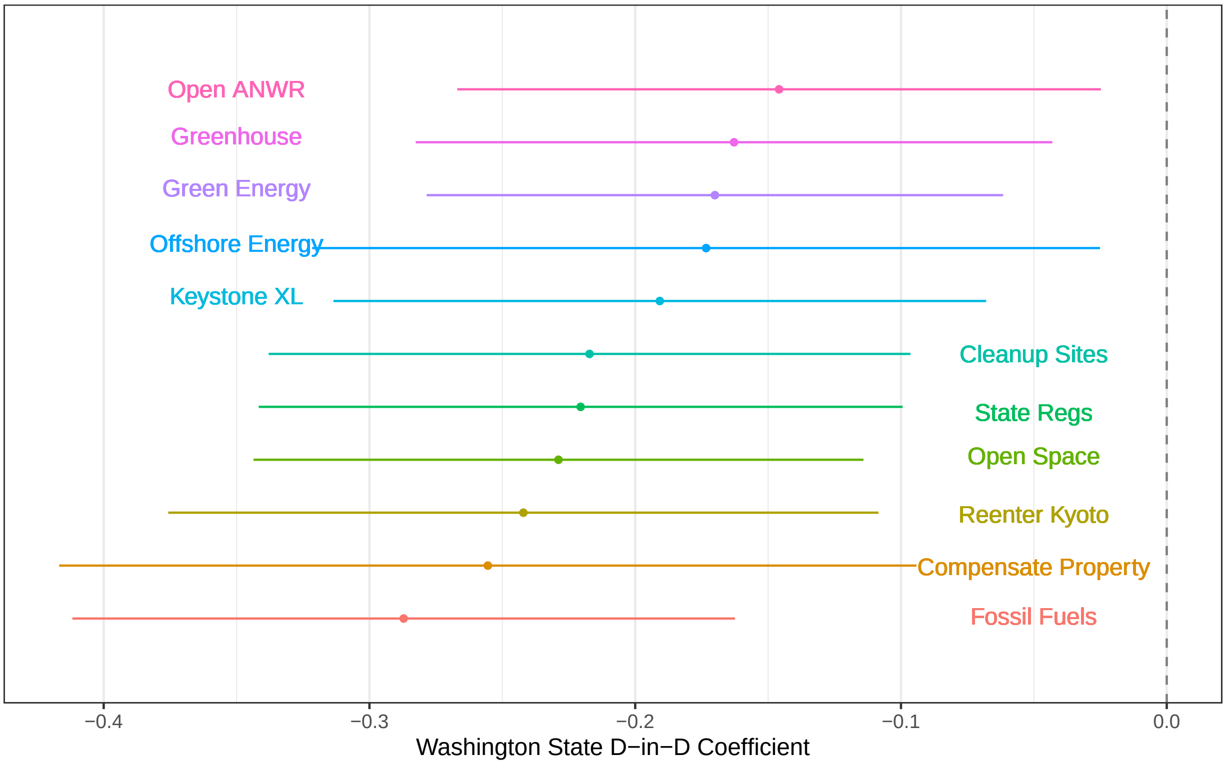


Note: This figure plots the estimated coefficients on the Washington State indicator from 11 separate regression models replicating model 3 from table 4, with model 3 as the topmost estimate. The outcome variable is a 0/1 indicator of support for the I-1631 carbon tax and 11 other environmental issues (all coded so that 1 is the liberal position and 0 is the conservative position). All regressions include an array of ideological, demographic, and geographic control variables. Negative coefficients imply that respondents from Washington State are less likely to support the liberal position (e.g., support a carbon tax) than respondents from other states, conditional on controls. The other environmental issues relate to: (1) oil exploration in the Arctic National Wildlife Refuge, (2) support for federal regulation of greenhouse gas emissions, (3) funding for renewable energy, (4) support for offshore energy production, (5) support for the Keystone XL pipeline, (6) cleanup of polluted sites, (7) support for stricter state environmental standards, (8) support for open space preservation, (9) support for the Kyoto climate change treaty process, (10) compensation for environmental regulations, (11) appropriate production of carbon-based fuels. See appendix B for more detail on each of these issues.
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018.

(0) but supporting re-entry into the Kyoto treaty process (1) would be scored as a -1. We then regress this dependent variable on the Washington State dummy, controlling for latent ideology and demographics.

Figure 7 presents the coefficients on the Washington State dummy for each of these 11 difference-in-differences regressions. Point estimates are represented by dots, while 95% confidence intervals are represented by horizontal lines. Support for I-1631 is about 15-25 percentage points lower in Washington relative to other states, as compared to support for other environmental policies—so about 20 percentage points

Figure 7: *Difference-in-differences estimates of I-1631 campaign effect in Washington State*

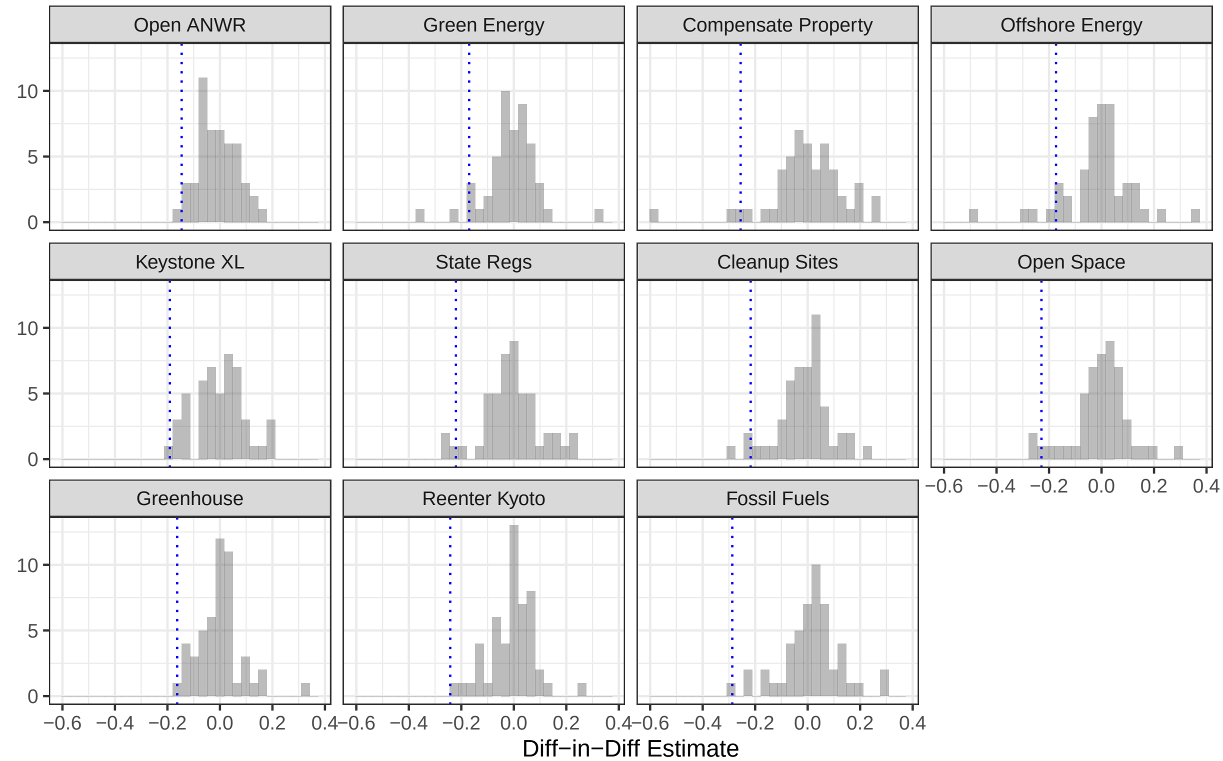


Note: This figure plots the estimated difference-in-differences coefficients on the Washington State indicator from 11 separate regression models based on model 3 from table 4. The outcome variable in each regression is the *difference* between the 0/1 indicator of support for a carbon tax and the 0/1 indicator of support for the 11 other environmental issues (all coded so that 1 is the liberal position and 0 is the conservative position). All regressions include an array of ideological, demographic, and geographic control variables. Negative coefficients imply that respondents from Washington State are less likely to support the carbon tax relative to other environmental issues, as compared to respondents from other states. The other environmental issues relate to: (1) oil exploration in the Arctic National Wildlife Refuge, (2) support for federal regulation of greenhouse gas emissions, (3) funding for renewable energy, (4) support for offshore energy production, (5) support for the Keystone XL pipeline, (6) cleanup of polluted sites, (7) support for stricter state environmental standards, (8) support for open space preservation, (9) support for the Kyoto climate change treaty process, (10) compensation for environmental regulations, (11) appropriate production of carbon-based fuels. See appendix B for more detail on each of these issues.
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018.

lower on average—and statistically different from zero (denoted by the vertical dashed line) in every case. We interpret these coefficients as plausible estimates for the net causal effect on Washington voters' support for I-1631 from being exposed to actual campaigns for and against the carbon tax, along with actual voting in 2016 and 2018.

How anomalous are the results for Washington State? To answer this question, we repeat the above exercise 49 times, estimating 11 difference-in-differences models for each of the other 49 states, i.e. re-defining these

Figure 8: *Difference-in-differences estimates of I-1631 campaign effect in 50 states*



Note: This figure plots the histograms of estimated difference-in-differences coefficients on the state indicator from 11 separate regression models for all 50 states based on model 3 from table 4. The dotted vertical lines indicate the coefficient estimates for Washington State. The outcome variable in each regression is the *difference* between the 0/1 indicator of support for a carbon tax and the 0/1 indicator of support for the 11 other environmental issues (all coded so that 1 is the liberal position and 0 is the conservative position). All regressions include an array of ideological, demographic, and geographic control variables. Negative coefficients imply that respondents from a given state are less likely to support the carbon tax relative to other environmental issues, as compared to respondents from other states. The other environmental issues relate to: (1) oil exploration in the Arctic National Wildlife Refuge, (2) funding for renewable energy, (3) compensation for environmental regulations, (4) support for offshore energy production, (5) support for the Keystone XL pipeline, (6) support for stricter state environmental standards, (7) cleanup of polluted sites, (8) support for open space preservation, (9) support for federal regulation of greenhouse gas emissions, (10) support for the Kyoto climate change treaty process, and (11) appropriate production of carbon-based fuels. See appendix B for more detail on each of these issues.
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018.

other states to be the "treated" group instead of Washington. No matter which of the 11 other environmental policies we choose for comparison, Washington State's difference-in-differences estimate lies at the extreme left end of the distribution (see figure 8). That is, Washington State respondents exhibit substantially lower support for the carbon tax relative to other environmental issues, and this is true in comparison to every other state.

Why did the two real-world campaigns depress support for I-1631 in Washington? There are multiple possibilities. Our identification strategy does not allow us to disentangle their relative importance, since we can only estimate an overall Washington effect. However, we can speculate about a few likely mechanisms, given anecdotal evidence from Washington and prior research in political science.

First, voters in Washington were exposed to extra information, which may have nudged them toward a "no" vote. Consider the information environment at the start of the campaign. The "yes" side had every advantage: strategically chosen ballot language, a carefully crafted message to frame their measure, and—after many months gathering signatures and preparing for the vote—a well-organized team. Meanwhile, the "no" side was not organized at all and was forced to hit the ground running. At the same time, since "rationally ignorant" voters tune in quite late, the opposition had plenty of time to make up ground. One way it did so was by providing information to voters. In particular, while the I-1631 ballot language strategically described a "fee" on carbon emissions rather than a "tax," the opposition was free to inform voters that I-1631 was in fact a tax increase.[45] Moreover, moderate and conservative voters unfamiliar with the carbon tax could be able, with more information, to place the measure as increasing the size and importance of government in energy and environmental matters.[46] Conservative and Republican support in Washington dropped. Meanwhile, in other states, conservatives profess deep support for carbon taxes—likely a very misleading result, since carbon taxes are typically not well-understood and no active campaigns exist to inform these voters. If trusted elites were to transmit messages of opposition, support in these other states would also likely fall (Zaller 1992).

Second, the literature on direct democracy highlights a possible role for status-quo bias (Bowler and Donovan 2000; De Figueiredo, Ji, and Kousser 2011). Because the status quo is known for certain, while changes to the status quo are uncertain, risk-averse voters might rationally default to the status quo when considering a policy change via initiative. While survey votes from respondents outside of Washington were purely hypothetical, respondents in Washington faced an actual vote, which could have triggered feelings of risk-aversion and status-quo bias. This interpretation is consistent with evidence that early support for state initiatives tends to wane as the election draws near (De Figueiredo, Ji, and Kousser 2011).

Third, campaign spending may have played an important role. The "no" campaign on I-1631 outspent the "yes" campaign by a factor of two (see table 1), and prior literature finds significant causal effects of campaign spending on ballot propositions (De Figueiredo, Ji, and Kousser 2011; Rogers and Middleton 2015). Data from California show that, when the opposition spends twice as much, initiatives that begin with 51% support later fail with just 40% support (De Figueiredo, Ji, and Kousser 2011). This result is broadly consistent with the negative campaign effect we estimate for Washington and suggests that the campaign

[45]Indeed, the "no" campaign website prominently says: "I-1631 Imposes a New $2.3 Billion Energy Tax on Washington Consumers". See here: `https://votenoon1631.com/get-the-facts/`.

[46]See, for example, Lupia (1994) on the ability of low-information voters to make reasonable choices when presented with technically complex choices on initiatives.

against I-1631 was very effective. In contrast, spending on I-732 was much lower overall and was dominated by the "yes" campaign (see table 1). Thus, it is plausible that I-1631 was handicapped at the polls relative to I-732 due to lopsided spending by the "no" campaign. While I-1631 outperformed I-732, it also seems to have galvanized the opposition, leading to increased effort and fundraising by its opponents. It is not at all clear, then, that positioning I-1631 to the left had only positive effects.

5 Tax incidence and willingness-to-pay for a carbon tax

To what extent does personal tax incidence drive opposition to the carbon tax? Voters with the highest personal energy consumption—in particular, those consuming more gasoline to propel their cars, or more electricity and natural gas to power and heat their homes—will tend to incur the largest direct costs from a carbon tax. Thus, we might expect lower support from such voters, all else equal.

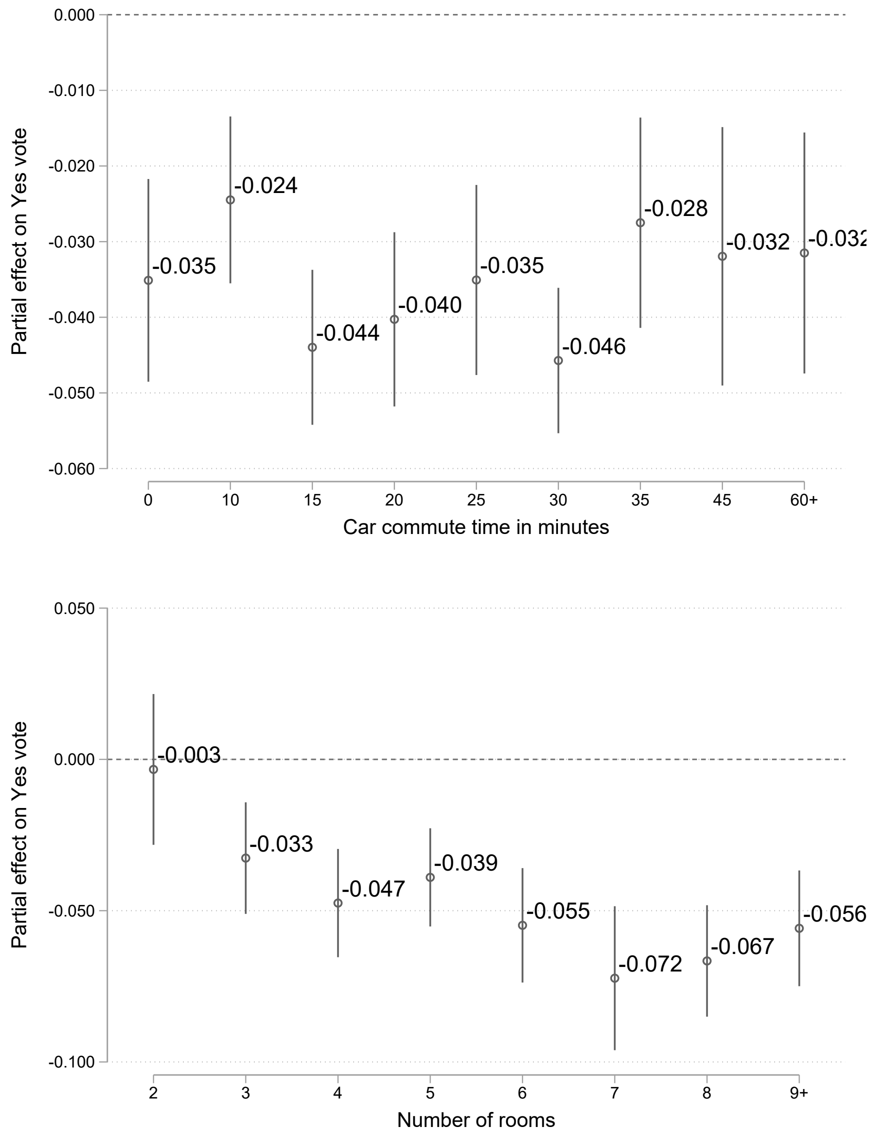
To test this proposition, figure 9 reports the coefficient estimates on car commute time and home size from model (8) described in section 4.1.1 above.[47] These variables proxy for personal energy consumption. Point estimates are represented by dots, while 95% confidence intervals are represented by vertical lines. Overall, our results support the idea that voters facing higher direct costs are less likely to support the carbon tax. The coefficients on the share of commuters with varying car commute times are all negative (upper panel). Thus, relative to commuting by other means, car commutes of any length are associated with lower support for the carbon tax. Especially long commute times are not associated with especially low support—perhaps because total gasoline consumption does not scale proportionately with commute time. Meanwhile, the coefficients on the share of households with three or more rooms are all negative (lower panel). Thus, relative to homes with just one or two rooms, larger homes are associated with lower support for the carbon tax. Moreover, support tends to decline as homes get larger, which is consistent with higher energy consumption for larger homes.[48]

What can this tradeoff between tax incidence and support for the carbon tax tell us about willingness-to-pay (WTP) for the policy? To answer this question, we push our analysis several steps further by measuring the economic incidence—in dollars—that Washington's proposed carbon taxes would have had on car commuters and households residing in large homes. We then model the relationship between "yes" vote shares and precinct-level economic incidence in a logistic regression derived from an individual-level random utility model. Thus, we are able back out the average WTP for the policy in each precinct, which we can

[47]This model controls for the Republican vote share in the presidential election, the votes on the twelve individual ballot measures (i.e., other than the carbon tax), the legislator endorsement variable, the 2018 dummy, the full suite of Census demographic variables—including income and manufacturing industry, which may be necessary to control for the tax rebates embedded in the I-732 package—and county fixed effects. Recall that this model omits the two turnout controls.

[48]Full results for the census demographic variables, available upon request, show that the coefficients on home size are not especially sensitive to the inclusion of county fixed effects nor to the use of 12 individual ballot measures in place of the ideological index. Meanwhile, coefficients on car commute times increase somewhat in magnitude with the inclusion of county fixed effects and individual ballot measures.

Figure 9: *Predicting the carbon tax vote share by precinct in 2016 and 2018: coefficients on car commute and home size*



Note: These figures plot coefficient estimates from a pooled OLS regression modeling the share voting "yes" for the carbon tax in 2016 and 2018. The top panel plots coefficients on variables measuring the share of commuters with car commute times ranging 0-9 minutes (0), 10-14 minutes (10), 15-19 minutes (15), and so forth; the excluded category is implicitly commuters that do not commute by car. The bottom panel plots coefficients on variables measuring the share of households with various numbers of rooms in their home; the excluded category is implicitly homes with just one room. Point estimates are represented by dots, while 95% confidence intervals (based on standard errors clustered by county) are represented by vertical lines. Control variables (not shown) include the share voting "yes" on twelve other ballot measures (i.e., the basis for our index of ideology), the share voting Republican (vs. Democrat) in the 2016 presidential election, endorsement by a state legislator, the 2018 vote dummy, detailed census variables (i.e., industry, home value, income, gender, age, race, and education), and county fixed effects.
Source: WA SOS & U.S. Census.

then use to estimate the full distribution of average WTP across precincts. Consistent with our regression results above, we find that ideology is the main driver of variation in WTP across precincts. However, for the average precinct, tax incidence is pivotal in driving opposition to the carbon tax.

Our analysis proceeds in several steps. First, we calculate average economic incidence for each precinct. Using the carbon tax phase-in schedules described in the legislation for I-732 and I-1631, we calculate the annualized average carbon tax rates implied by both policies to be approximately \$50/tCO2. Meanwhile, using data from the U.S. Environmental Protection Agency (EPA) and the Residential Energy Consumption Survey (RECS), we calculate average annual emissions associated with car ownership and home size (i.e., number of rooms). Thus, we are able to calculate implied economic incidence per car and per room. Finally, we multiply the per-car incidence by the share of a precinct's commuters that commute by car, and we multiply the per-room incidence by the average number of rooms per household in the precinct, to yield precinct-average economic incidence in dollars.

Second, we model voting on the carbon tax as a function of economic incidence and our full set of detailed control variables in an OLS logistic regression. Our regression equation takes the form:

$$y_i = \alpha \cdot totaltax_i + \beta' ideology_i + \gamma' other_i + \epsilon_i, \tag{1}$$

where $y_i = \ln(s_i/(1-s_i))$ and s_i is the share voting "yes" in precinct i, *totaltax* is measurable tax incidence for the precinct (i.e., based on car ownership and home size) with corresponding coefficient α, *ideology* is a vector of precinct-level ideology variables (i.e., the Republican vote share plus vote shares in all twelve other ballot measures) with corresponding coefficient vector β, *other* is a vector of all remaining precinct-level control variables (i.e., census demographics and county dummies) with corresponding coefficient vector β, and ϵ is a mean-zero precinct-level residual. We estimate this equation separately for 2016 and 2018 to yield distinct coefficients for α in each year. We also estimate a pooled regression in which we stack both years to yield a single coefficient α but allow different coefficients by year for all other variables (including the intercept and county dummies). In these regressions, we weight precinct-years by the total number of votes cast for or against a carbon tax. We interpret the coefficient α as the marginal utility of income, which allows us to re-scale and express the fitted values from this regression as WTP in dollars.[49]

Third and finally, we use the coefficient estimates and fitted values from our OLS logistic regression to back out mean WTP for the policy in each precinct. Given our model, mean WTP in precinct i is given by:

[49]Note that this estimating equation for aggregate "yes" shares can be derived from an individual random utility model of the form: $u_{in} = \alpha \cdot totaltax_i + \beta' ideology_i + \gamma' other_i + \epsilon_i + \eta_{in}$, where u_{in} is the net utility that voter n in precinct i derives from voting "yes" versus "no" in the referendum (i.e., assuming the voter is pivotal to the outcome). Coefficient α is the (negative) marginal utility in the precinct from paying a higher average tax bill. Components $\beta' ideology_i$ and $\gamma' other_i$ capture systematic shifts in the precinct's net utility due to ideology and other observed variables (e.g., precinct demographics and county dummies). The ϵ_i is a precinct-level residual. Finally, the η_{in} is an idiosyncratic error term distributed iid extreme value across individual voters with mean zero and standard deviation $\sigma\pi/\sqrt{3}$, where $\sigma = -1/\alpha$. Given a large number of voters within each precinct, aggregate "yes" shares can be modeled using the estimating equation above (i.e., a logistic regression model).

$y_i/\hat{\alpha}$, i.e. net utility scaled by the estimated marginal utility of income. Further, given our linear model, we can decompose WTP into each of its individual constituents: measurable economic incidence ($totaltax_i$), ideology ($\hat{\beta}' ideology_i/\hat{\alpha}$), other non-tax variables ($\hat{\gamma}' other_i/\hat{\alpha}$), and the residual ($\hat{\epsilon}/\hat{\alpha}$). For this exercise, we re-center the ideological variables to equal zero at their sample mean vote shares.[50] Thus, we implicitly measure each component of WTP relative to a precinct with average ideology. Below, we report sample means and standard deviations of these components across precincts (weighted by total votes cast for or against a carbon tax) alongside our OLS coefficient estimates.

Before presenting our results, we caution that our inferences about the mean and variance in WTP hinge on a causal interpretation for the coefficient on total tax, i.e. no omitted variables bias. We have tried to control for all relevant observables at our disposal. However, if the true all-else-equal coefficient on *totaltax* (i.e., the marginal utility of income) were substantially bigger than we estimate, then the mean and variance in WTP due to non-tax factors would both fall accordingly. Likewise, if the true coefficient were smaller, then the mean and variance would rise.[51] That said, we find in models (6) and (7) from table 2 above that coefficients on car commuting and home size are unaffected by the inclusion of county fixed effects and turnout controls, which partially ameliorates such concerns.

Table 6 presents the results from this analysis. We present regression results separately for 2016 (columns 1-2) and 2018 (columns 3-4). We also present regression results when we pool data across years and impose that the coefficients on tax incidence are the same across years—but allow all other coefficients to vary by year (columns 5 and 6-7). Columns (1), (3), and (5) show results when we measure economic incidence on commuters (car tax) separately from economic incidence on home size (room tax), while columns (2), (4), and (6-7) show results when we measure the combined economic incidence for both commuters and home size (total tax). Coefficients on estimated tax incidence are negative and statistically significant in all regressions, suggesting that voters derive negative utility from higher taxes, all else equal. The coefficient on car tax is smaller than the coefficient on room tax in all regressions, but they are of the same order of magnitude.[52] Our preferred results use the combined measure of incidence in columns (2), (4), and (6-7).

[50] That is, we use re-centered variables $\tilde{v}_i = v_i - \bar{v}$, where $\bar{v}$ is the sample mean of ideology variable v. Our ideology variables include the Republican vote share in the 2016 presidential election plus the vote shares on the twelve other ballot measures from 2016 and 2018.

[51] Consider average net utility in precinct i: $y_i = -\alpha tax_i + z_i$, where α is the (positive) marginal utility of dollars, tax_i is the average tax bill, and z_i is the average net utility due to all other factors. The portion of WTP due to the tax is given directly by tax_i. Meanwhile, the portion due to all non-tax factors can be written as $z_i = y_i/\alpha + tax_i$. Then the sample average WTP due to the tax bill across precincts is tax, while the average WTP due to all non-tax factors is $\bar{z} = \bar{y}/\alpha - tax$. Thus, as α rises, the mean WTP due to non-tax factors falls. Meanwhile, the sample variance in WTP due to the tax bill is $var(tax_i)$, while the variance due to non-tax factors is $var(z_i) = var(y_i)/\alpha^2 + 2cov(y_i, tax_i)/\alpha + var(tax_i)$. This variance falls monotonically in α if $cov(y_i, tax_i) > 0$. If $cov(y_i, tax_i) < 0$, then the variance initially falls (i.e., starting from $\alpha = 0$) and eventually rises. We estimate $var(y_i) = 0.4645$ and $cov(y_i, tax_i) = -16.2248$ in our data. Thus, the variance is falling up to about $\alpha = 0.0286$, which is more than 20 times larger than our estimate (divide the estimates in table 6 by 1000 to get the coefficient on total tax measured in dollars).

[52] Coefficients could differ in magnitude for a variety of reasons, including differences in tax salience, scaling issues due to different numbers of commuters vs. households vs. voters in an average precinct, or omitted variables bias.

Table 6: *Logistic model of carbon tax vote shares, and implied willingness-to-pay (WTP) estimates*

	(1) 2016	(2) 2016	(3) 2018	(4) 2018	(5) Pooled	(6) Pooled-2016	(7) Pooled-2018
Car tax	-0.84***		-1.04***		-0.94***		
	(0.08)		(0.08)		(0.06)		
Room tax	-3.13***		-1.37***		-2.25***		
	(0.44)		(0.36)		(0.29)		
Total tax		-1.21***		-1.09***		-1.15***	-1.15***
		(0.10)		(0.09)		(0.07)	(0.07)
Mean_Total_WTP		-331		-260		-347	-247
_SD_Total_WTP		454		721		476	686
Mean_Tax		-266		-266		-266	-266
_SD_Tax		35		35		35	35
Mean_Ideology		-1		3		-1	3
_SD_Ideology		398		690		418	655
Mean_Other		-64		3		-80	16
_SD_Other		53		69		56	66
Mean_Residual		0		0		0	0
_SD_Residual		102		113		107	107

Note: This table presents coefficient estimates from OLS logistic regressions modeling share voting "yes" for the carbon tax in 2016 and 2018 as a function of measurable economic incidence and various controls. The dependent variable is the log-odds ratio: $y_{it} = \ln(s_{it}/(1 - s_{it}))$, where s_{it} is the share voting "yes" in precinct i in year t. *Car tax* is the annual gasoline tax incidence due to car ownership as measured by car commuting (in $1000s). *Room tax* is the annual home energy bill tax incidence due to home size as measured by # rooms (in $1000s). *Total tax* is the sum of these two variables (in $1000s). All models include a full set of controls. Controls for ideology are: the share voting Republican (vs. Democrat) in the in 2016 presidential election, plus the full set of "yes" vote shares on the twelve other ballot measures from 2016 and 2018. Controls for other non-tax variables are: the endorsement dummy; detailed census variables (i.e., industry, home value, income, gender, age, race, and education); and county fixed effects. For all models, we weight precinct-years by the total votes cast for or against the carbon tax. The pooled regressions in columns (5) and (6-7) combine data from both years and impose that the coefficient on tax incidence is the same across years; these regressions additionally include a dummy variable for the 2018 vote, as well as its interaction with all control variables. Standard errors are clustered by county (39 clusters).
Implied WTP calculations at bottom report sample mean and standard deviations for estimated precinct-level WTP (in $) and its underlying components (i.e., tax, ideology, other, and residual) after weighting by total votes cast for or against the carbon tax. Columns (6) and (7) are based on the the same pooled regression; we use two columns to report WTP calculations separately by year.
Source: WA SOS, U.S. Census, U.S. EPA, and RECS.

We now turn to our estimates of precinct-level WTP reported at the bottom of the table. Mean total WTP is negative $331-$347 in 2016 and negative $247-$260 in 2018. Across all models, mean WTP for measurable tax incidence is negative $266, i.e. voters would pay $266 on average to avoid the carbon tax's incidence. By construction, this statistic equals the average tax bill across precincts. Meanwhile, mean WTP based on ideology is approximately zero—a direct consequence of our choice to re-center ideology to equal zero on average.[53] Finally, mean WTP based on other non-tax attributes is negative $64-$80 in 2016 and positive

[53]For taxes, both the absolute level and units have economic content in terms of WTP. For the other variables, however, all that matters is *relative* ideology or *relative* demographics (e.g., age). Thus, the allocation of WTP between ideology and other non-tax variables is inherently arbitrary.

$3-$16 in 2018. Note that our decomposition implicitly measures WTP for these other non-tax variables relative to a precinct with average ideology.

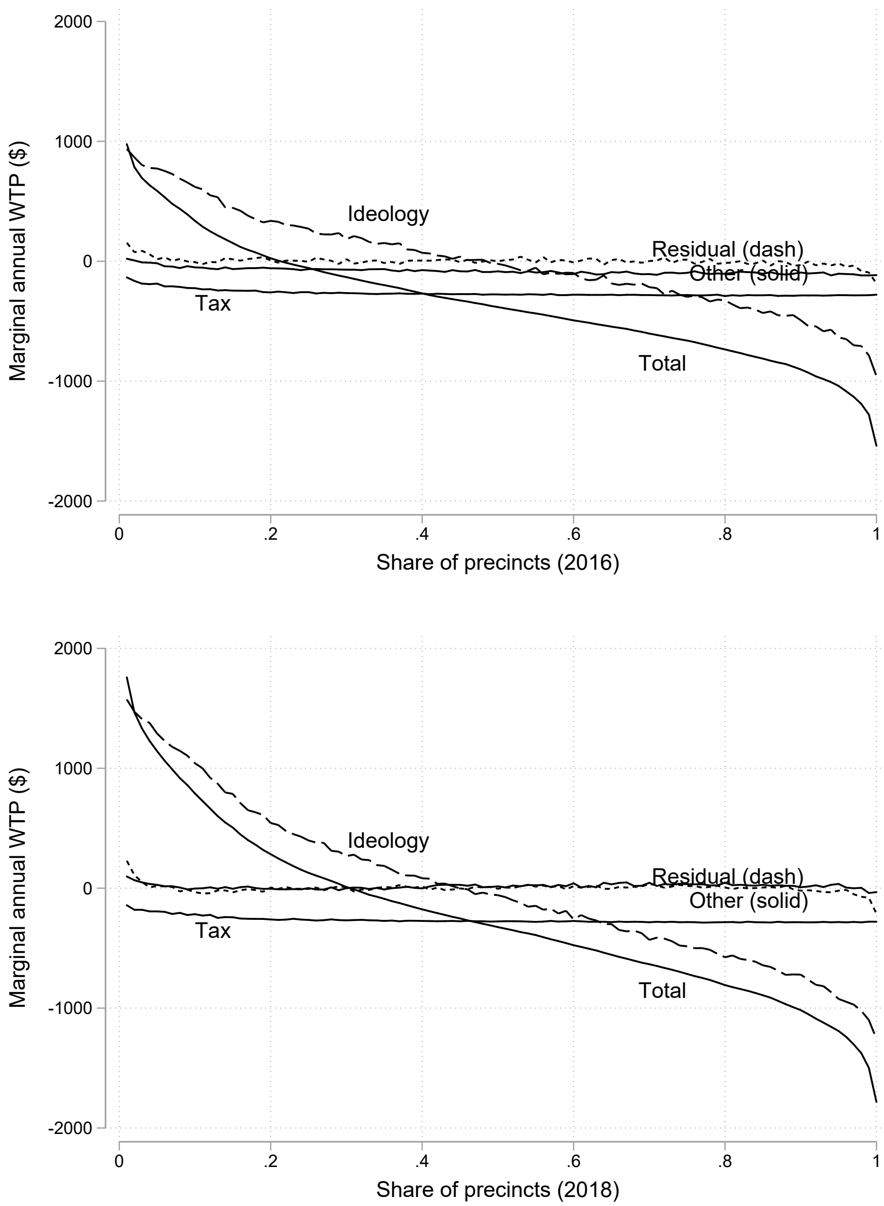
Taken at face value, these results imply that the average precinct's voters dislike the personal cost of higher energy taxes—as expected—but seem barely to credit the potential benefits of a carbon tax. Indeed, the results imply that the average voter actually values the other aspects of the 2016 policy *negatively*—including an expanded EITC and lower state sales tax. These results contrast with the stated-preference estimates of Kotchen, Turk, and Leiserowitz (2017), who find a positive WTP of $177 on average.[54] Proponents of the 2016 initiative hoped that returning carbon tax revenue to residents through a lower state sales tax and expanded EITC would directly counteract voters' dislike for the carbon tax. However, our results imply that this strategy did not work: apparently, voters on average were not convinced that what one hand takes, the other hand gives back. This lack of trust in the management of the revenues by public authorities is one of the issues believed to hinder the adoption of carbon taxes (Carattini, Carvalho, and Fankhauser 2018).

Our results indicate that, for the average voter, pocketbook issues explain the overall negative WTP and are pivotal in driving opposition to the carbon tax. However, the standard deviations in the precinct-level tax bill ($35), other non-tax variables ($53-$69), and residual ($102-$113) are all swamped by the standard deviation in WTP for ideology ($398-$690), which is consistent with our results above that ideology explains most of the variation in voting across precincts.

Figure 10 illustrates these points graphically with estimated marginal WTP curves (i.e., demand curves) for the two carbon tax policies. These estimates are based on the pooled regression results reported in columns (6) and (7) of table 6 above. We show both total mean WTP for the marginal precinct, as well as a break-down of this WTP into its individual components, i.e. tax, ideology, other, and residual. The WTP attributable to taxes, which averages -$266, is nearly constant throughout the distribution in both years. This finding implies that the characteristics that drive tax incidence (i.e., car commuting and home size) do not differ substantially across precincts with high vs. low support for the carbon tax. The WTP attributable to the "other" category is also fairly constant across precincts, averaging -$80 in 2016 and $16 in 2018. The residual component is $0 on average but turns slightly positive in the left tail and slightly negative in the right, i.e. unobservables tend to be relatively more important in explaining extreme voting outcomes than average outcomes. Ideology is clearly the main driver of variation in WTP across precincts, ranging from about -$1000 to $1000 in 2016 and about -$1200 to $1500 in 2018. The wider range in 2018 is consistent with our findings above that the 2018 policy was more ideologically salient, gaining support in liberal precincts and losing support in conservative ones. Finally, note that if we focus on the median precinct (i.e., 0.5 on the horizontal axis), we find that the WTP due to the tax remains near -$266 while

[54] Note that Kotchen, Turk, and Leiserowitz (2017) estimate average preferences nationwide for a national-level carbon tax, whereas we estimate average preferences in Washington for a state-level carbon tax.

Figure 10: *Marginal willingness to pay for a carbon tax by precinct*



Note: This figure plots marginal willingness to pay (WTP) curves for the 2016 (top panel) and 2018 (bottom panel) carbon tax policies. The horizontal axis ranks precincts from highest to lowest total WTP for a carbon tax in each year. The vertical axis measures, for the marginal precinct, total WTP along with a break-down of its individual components (i.e., tax, ideology, other, and residual). To estimate marginal WTP, we sort precincts from lowest to highest WTP, divide them into percentiles, and calculate mean WTP within each percentile. In constructing percentiles, we weight by total carbon tax votes cast; thus, each percentile represents the same number of voters. Likewise, when calculating mean WTP within each percentile, we weight by total votes cast.

Source: WA SOS, U.S. Census, U.S. EPA, and RECS.

the WTP due to all non-tax factors is near-zero. Thus, the figure clearly illustrates that, while ideology is the main driver of *variation* in WTP across precincts, for the median precinct and *average* voter, aversion to taxes dominates all other factors.

6 Could a carbon tax pass in other states?

How would policies like I-732 and I-1631 fare in other states? This is a key question for carbon tax policy entrepreneurs hoping to apply lessons from the Washington State experience to other states. In this section, we use precinct-level voting data from Washington as well as survey data from our MTurk sample to forecast support for I-732 and I-1631 in states other than Washington.

6.1 Forecast based on precinct-level voting in Washington

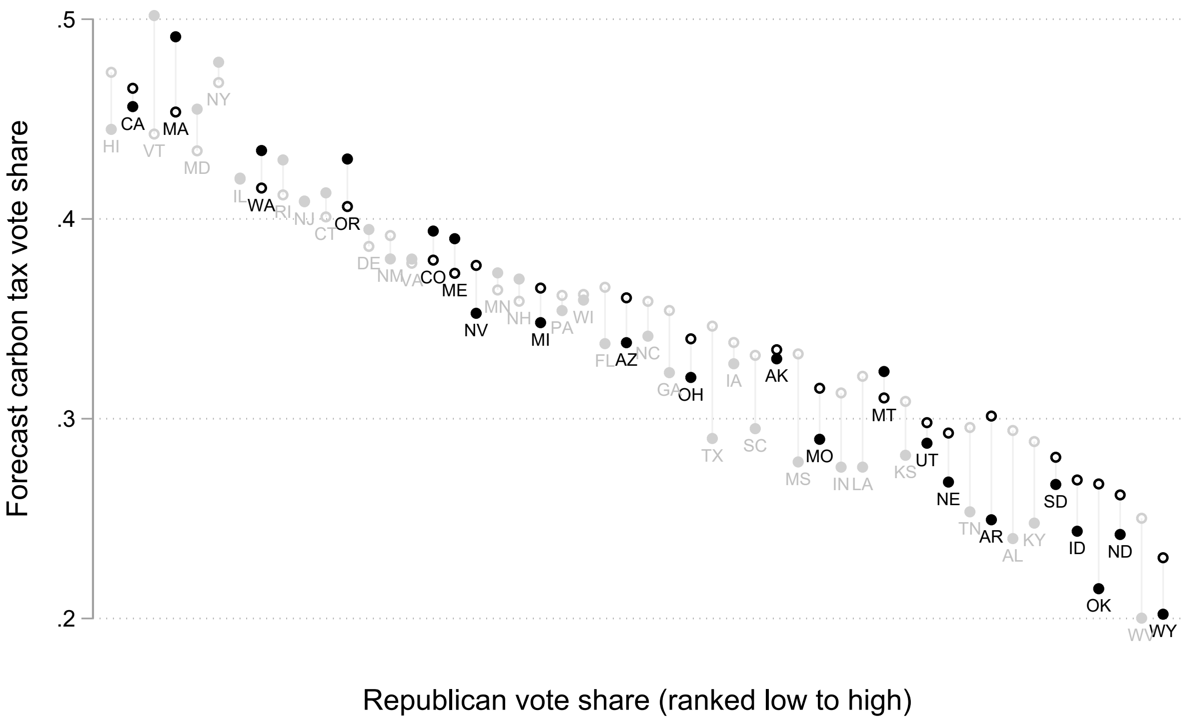
We construct a set of 50 out-of-sample forecasts for the hypothetical statewide vote on I-732 and I-1631 by applying coefficients from a regression of the precinct-level vote in Washington State to the observed state-level demographics and presidential vote shares in all 50 states.[55,56] We base these forecasts on the same specification as model (3) in table 2 above (i.e., Republican share plus census demographics) but estimated separately for 2016 and 2018 (see appendix tables 8 and 9). This forecast implicitly assumes that Washington's precincts are microcosms of U.S. states and that voters in other states are confronted with identical ballot language, voter guides, media exposure, and so forth leading up to the 2016 and 2018 elections. The forecast further assumes that voters with certain characteristics in Washington vote in the same way as voters with the same characteristics elsewhere, such that the coefficients can be applied to these other states. Finally, the forecast abstracts away from the fact that measures identical to I-732 and I-1631 would be *impossible* in many states, e.g. due to the fact that popular initiatives are not allowed, or due to pre-existing taxes or restrictions on how various sources of tax revenue may be used.

Figure 11 plots the resulting state-level forecasts for "yes" on I-732 (hollow dots) and I-1631 (full dots) versus the ranked Republican vote share in the 2016 presidential election. States that feature the popular initiative are shown in black, while states that lack a popular initiative are shown in gray. Overall, states with higher Republican vote shares would be less likely to pass these measures, which is consistent with ideology driving the vote for a carbon tax. The individual state forecasts do not decrease monotonically with Republican vote share due to variation in the composition of the electorate for variables other than the

[55] Our state-level demographics come from the U.S. Census and measure the same variables in the same years as our precinct-level data from Washington but at the state level (e.g., share of people living in California aged 40-44). Our presidential voting data come from the U.S. Federal Elections Commission and record statewide vote shares for various parties in the 2016 U.S. presidential election. See here: `https://transition.fec.gov/pubrec/fe2016/federalelections2016.pdf`. We use these data to calculate the share voting Republican (vs. Democrat) for each state.

[56] Recall that we define our variables based on *shares* of voters, people, households, and so forth living in different Washington precincts. Thus, we can apply our regression coefficients directly to the corresponding state-level aggregate variables from other states, and obtain the same forecast were we to instead apply our coefficients to the corresponding precinct-level variables from other states (which we do not observe) and then aggregate to the state level.

Figure 11: *Forecast carbon tax vote share by state, for the 2016 and 2018 carbon tax versions*



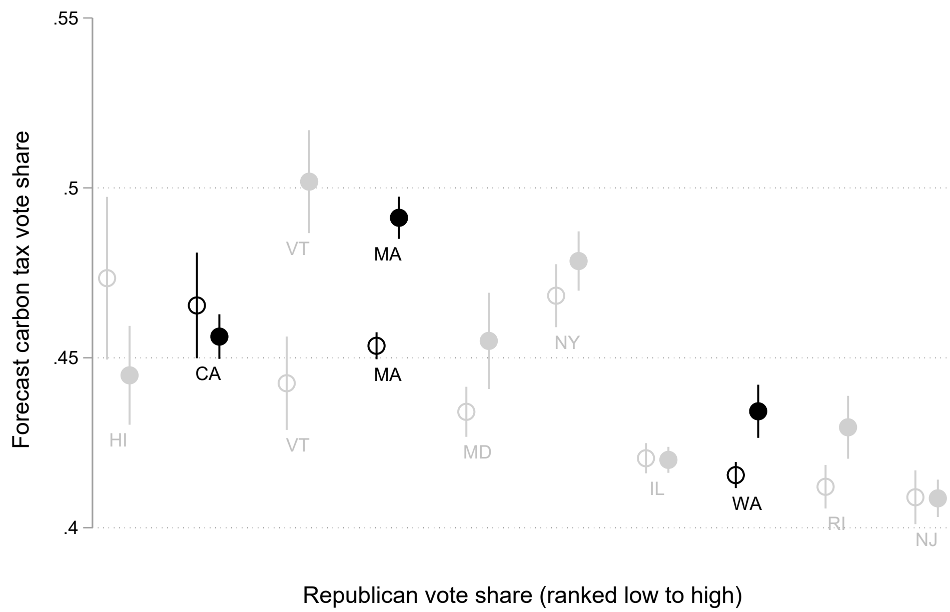
Note: This figure plots out-of-sample forecasts by state for the share voting "yes" on I-732 in 2016 (hollow dots) and I-1631 in 2018 (full dots) versus the ranked Republican vote share in the 2016 presidential election (with connecting lines to facilitate comparison). Forecasts are based on regression model (3) in appendix table 8 (for 2016) and regression model (3) in appendix table 9 (for 2018), both regressions being performed using Washington State precinct-level data. State forecasts are generated by applying coefficients from these Washington State precinct-level regressions to the same variables measured at the state level in all 50 states. States that feature a popular initiative mechanism are shown in black, while states that lack an initiative process are shown in gray.
Source: WA SOS, U.S. Census, and U.S. Federal Election Commission.

Republican vote share.

Which states would be most likely to pass a carbon tax? Figure 12 zooms in on the ten states with the lowest Republican share and provides confidence intervals. Only three of these states—Washington, Massachusetts, and California—feature a popular initiative mechanism.[57] Even ignoring that fact, we forecast that *no other state* would pass I-732, while just one state—Vermont, which lacks a popular initiative—would pass the more progressive I-1631. Of the initiative states, we forecast that Massachusetts comes closest to passing I-1631 with 49.1% of votes in favor and a 95% confidence interval that reaches to 49.7%.

[57]Moreover, the difficulty in getting on the ballot is highly variable across states. Massachusetts is notoriously difficult to

Figure 12: *Top-10 most Democratic states: forecast carbon tax vote share by state for the 2016 and 2018 carbon taxes*



Note: This figure plots out-of-sample forecasts by state for the share voting "yes" on I-732 in 2016 (hollow dots) and I-1631 in 2018 (full dots) versus the ranked Republican vote share in the 2016 presidential election. Forecasts are based on regression model (3) in appendix table 8 (for 2016) and regression model (3) in appendix table 9 (for 2018). State forecasts are generated by applying coefficients from these precinct-level regressions to the same variables measured at the state level in all 50 states. States that feature a popular initiative mechanism are shown in black, while states that lack an initiative process are shown in gray. Point estimates are represented by circles, while 95% confidence intervals are represented by vertical lines.
Source: WA SOS, U.S. Census, and U.S. Federal Election Commission.

Since I-1631 is more progressive than I-732, we should expect it to perform relatively better in liberal states and relatively worse in conservative states. This hypothesis is borne out in figure 11. On the left side of the figure (more liberal), the I-1631 forecast (full dots) tends to exceed the I-732 forecast (hollow dots). Meanwhile, on the right side of the figure (more conservative), the pattern is reversed.[58] However, there is still important variation across states explained by other voter characteristics. For example, among the ten most liberal states in figure 12, we forecast that I-1631 would do better than I-732 in Massachusetts and Vermont but marginally worse in California and Hawaii.[59]

Overall, the forecasts in figure 11 align closely with the status of carbon pricing across states: gener-

navigate, while Washington and California are easier.

[58]We confirm this pattern in appendix figure 23, which directly forecasts the *difference* in state vote shares based on model (3) in table 3 above.

[59]Our forecast that I-1631 performs marginally worse in California and Hawaii is due, in part, to the high shares of Asians and Pacific Islanders in these states—and the fact that, within Washington, I-1631 tends to perform worse than I-732 in precincts with higher shares for these demographic groups. Indeed, when we omit our controls for race and ethnicity altogether, we forecast that I-1631 performs better than I-732 in California and Hawaii.

ally, states for which we forecast a higher vote share are already active in carbon regulation, even if not through a carbon tax. California already has an economy-wide cap-and-trade program. Meanwhile, many Northeastern states are participant to the Regional Greenhouse Gas Initiative (RGGI) and its cap-and-trade program for electricity-sector emissions. These states include Vermont (highest forecasted vote share for I-1631), Massachusetts, New York, Maryland, Rhode Island, Connecticut, Delaware, Maine, and New Hampshire. The U.S. Climate Alliance—a coalition of states that has committed to meeting the Paris Climate Accord's abatement goals in the wake of the U.S. federal government's decision to withdraw—includes California, six of nine RGGI states, and Hawaii, Washington, Oregon, Colorado, Virginia, Minnesota, and North Carolina.[60]

6.2 Forecast based on individual-level survey data

Our survey data allow us to estimate state-level support for the carbon tax more directly: instead of relying on voting data only for Washington, we use our I-1631 survey question that residents from all states answered. While our survey includes thousands of respondents from all 50 states, this sample is not large enough to naively disaggregate the survey by state. Small states such as North Dakota and Alaska have far too few respondents, while large states such as California and Texas may have enough.

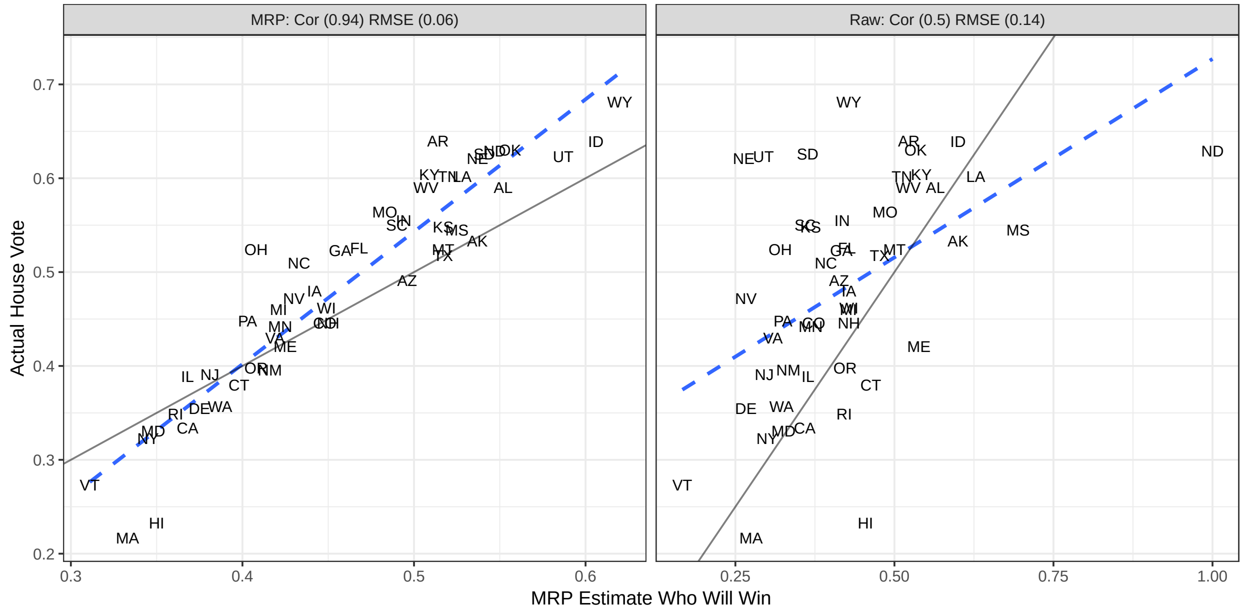
Multiple regression and poststratification (MRP) is a newly popular alternative for generating valid small-area estimates with modest survey samples (Gelman and Little 1997; Park, Gelman, and Bafumi 2004; Lax and Phillips 2009). This estimation procedure also helps to address the unrepresentative sampling in our MTurk data. Indeed, Gelman, Goel, Rivers, and Rothschild (2016) use MRP to address even deeper sampling problems in a survey fielded on the Xbox gaming console. Intuitively, the MRP procedure first estimates a multilevel predictive model using respondents' observed covariates (i.e., demographics and partisanship), along with state-specific effects. Then, the procedure generates state-level predictions based on the covariates—re-weighted to match a given state's observed demographics and partisanship—plus the estimated state-specific effect. Crucially, for this prediction, the procedure puts relatively less weight on individual-level data for states with fewer observations, and more weight on the model. This is called "borrowing strength" in the MRP literature.

We use two alternative strategies for generating post-stratification weights for the state-level aggregate data. Our first approach draws weights from the pooled American Community Survey from the U.S. Census (2012-2017; 17 million observations), which is the most common approach in the MRP literature. However, Census data only contain information on demographics and geography[61]—not partisanship, which may be particularly important in this context. Our second approach addresses this limitation by pooling all

[60] See here for a list of alliance members, a statement of principles, and further background: `https://www.usclimatealliance.org/`. Maryland, Maine, and New Hampshire are the only RGGI states that are not alliance members—and note that Maine and New Hampshire have the lowest forecast vote shares among RGGI states.

[61] Specifically, we poststratify on the interaction of race and sex, age, education, marital status, and state of residence.

Figure 13: *Predicting the state-level House vote using our MTurk survey adjusted with multilevel regression with poststratification (MRP)*



Note: The left panel plots the actual Republican House vote share vs. the predicted share based on multilevel regression with poststratification (MRP). For comparison, the right panel plots the actual vs. predicted Republican House vote share based on the unadjusted MTurk survey data. Solid lines in both panels correspond to a theoretical perfect correspondence between our survey and the actual outcome, while dashed lines correspond to an OLS fit between our survey estimate and the actual outcome.

Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and Cooperate Congressional Election Study 2006-2017.

Cooperate Congressional Election Study (CCES) surveys from 2006-2017, which comprises roughly 400,000 total observations. This smaller sample restricts the complexity of the multilevel regression model that we can run.[62] Thus, we obtain somewhat noisier poststratification weights for our geographic-demographic-partisan cells.[63] Nevertheless, if partisanship (or ideology) is the dominant predictor of individuals' specific issue opinions, trading a smaller sample for the ability to poststratify on ideology or partisanship might be worth it. In practice, both stratification approaches give similar results. The second approach (i.e., that stratifies by partisanship) leads to a slight improvement in fit. Thus, we use this second approach to present our results.

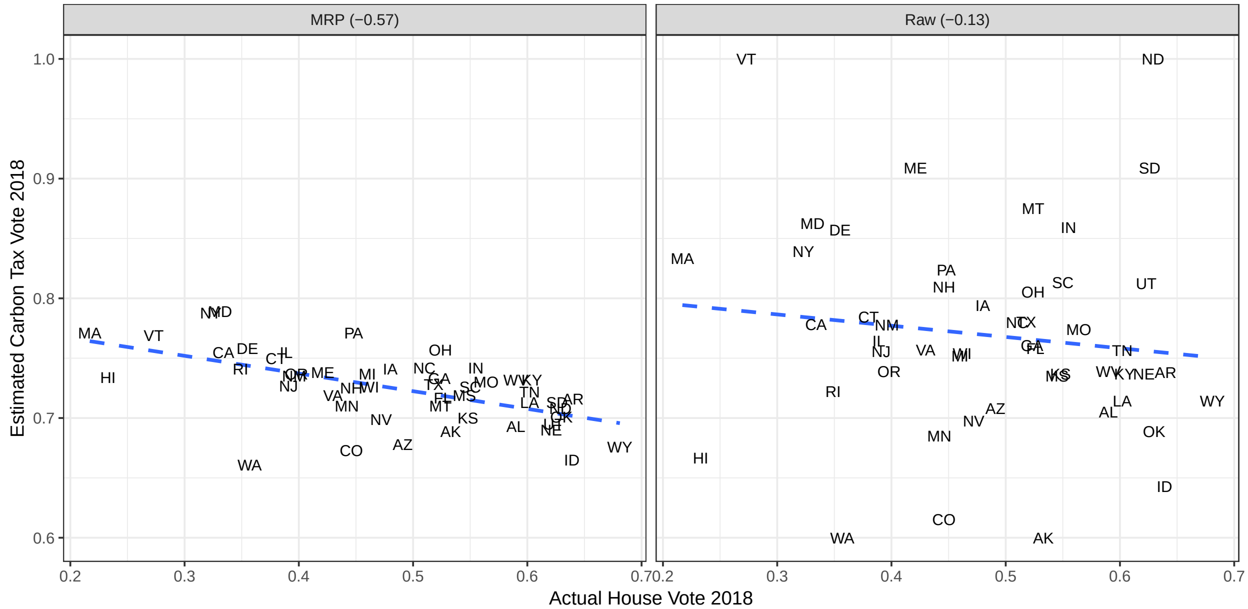
We validate these estimates using a survey question about U.S. House vote expectation,[64] which we then compare to the actual state-level U.S. House popular vote. See figure 13, which plots the actual house vote

[62] Here, we poststratify on three-category party identification (i.e., Democrat, Republican, and non-major party/Independent), race, age, and state of residence.

[63] An alternative approach for generating post-stratification weights that reflect partisanship would be to add extra stages to MRP instead of choosing a different poststratification target (Kastellec, Lax, Malecki, and Phillips 2015).

[64] We obtain similar results using the U.S. House vote *intention*. For a comparison of expectation and intention, see Rothschild and Wolfers (2013).

Figure 14: *Predicting the state-level vote for a I-1631 carbon fee using our MTurk survey adjusted with multilevel regression with poststratification (MRP)*

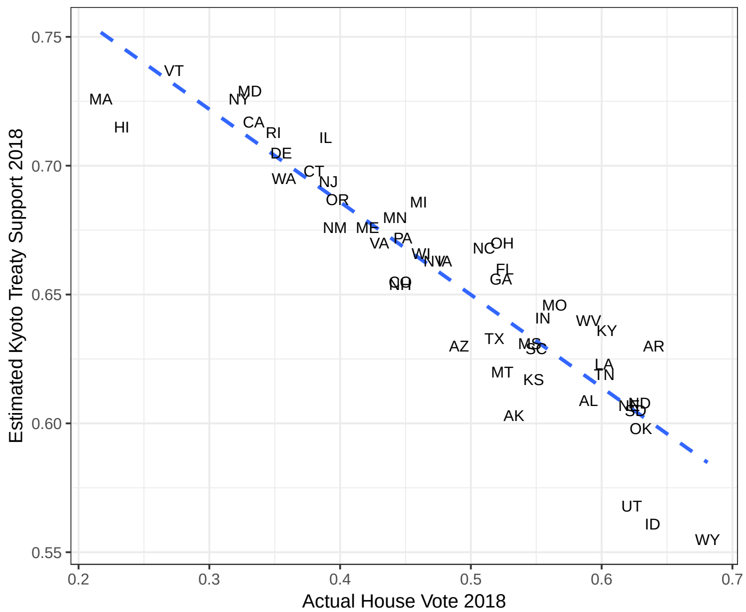


Note: The left panel plots the estimated 'yes" vote share on the I-1631 carbon fee based on multilevel regression with poststratification (MRP) vs. the actual Republican House vote share, by state. For comparison, the right panel instead plots the unadjusted "yes" vote share from the MTurk survey data vs. the actual Republican House vote share. In both panels, dashed lines correspond to OLS fitted values.
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and Cooperate Congressional Election Study 2006-2017.

versus our forecast. The black line represents a perfect fit. The right panel of figure 13 shows the results for naive disaggregation by state. The disaggregated results are correlated with the actual election outcomes (r=0.50), but they are pretty badly off (RMSE=0.14). Meanwhile, the left panel shows the results based on our MRP procedure. Actual and estimated outcomes match closely in terms of both correlation (r=0.94) and correspondence (RMSE=0.06). Thus, MRP has erased much of the bias in our MTurk survey and allows us to predict House votes quite accurately.

Next, we switch to survey opinion on the I-1631 style carbon tax. See figure 14. Again, the left panel shows the MRP estimates, while the right panel shows the naive disaggregated estimates. We focus on the MRP results in the left panel. As expected, more liberal states such as Hawaii and Vermont show greater support for the policy than conservative states such as Idaho and Wyoming. However, we note three striking observations. First, the overall level of support is surprisingly high, exceeding 65% in every state. This is in large part a reflection of the very high levels of national support for the policy in the survey, including from Republicans and conservatives. Second, support in Washington is substantially lower than we would predict based on the U.S. House Republican vote alone (the horizontal axis). This gap could be interpreted as the

Figure 15: *Predicting the state-level support for ratifying the Kyoto treaty using our MTurk survey adjusted with multilevel regression with poststratification (MRP)*



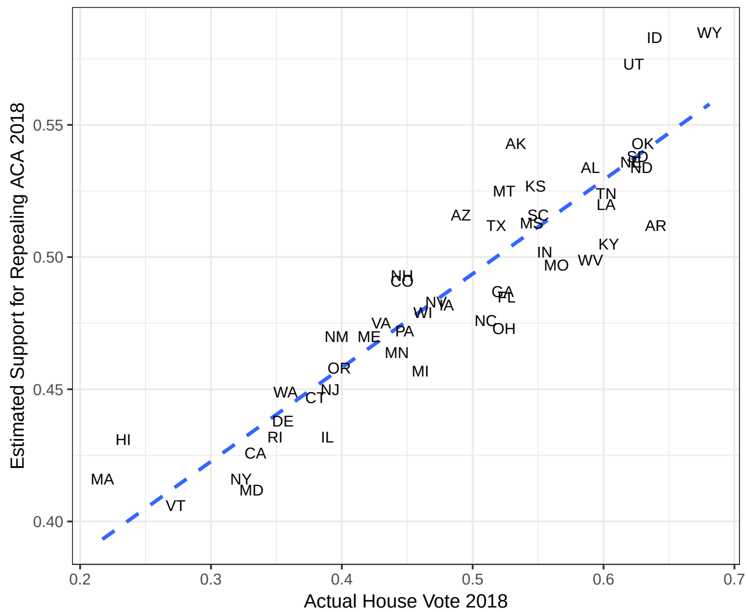
Note: This figure plots the share that supports ratifying the Kyoto treaty based on multilevel regression with poststratification (MRP) vs. the actual Republican House vote share, by state. The dashed lines corresponds to OLS fitted values.
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and Cooperate Congressional Election Study 2006-2017.

impact of exposure to the actual electoral campaign of I-1631 (and I-732), in which opponents spent twice as much as supporters. This result suggests that estimates of high support may be biased upward by the hypothetical character of the carbon tax in states other than Washington. Third, the MRP estimate for I-1631 in Washington is considerably higher than the actual outcome. Interestingly, the only published opinion poll we could find on I-1631—the Elway Poll, conducted one month before the election—also overestimated support for the initiative.[65]

Why is support for I-1631 so low in Washington? Compare the gap in support for the carbon tax in Washington relative to other states (figure 14, left panel) to the gap in support for the Kyoto treaty (figure 15).[66] A traditional environmentally progressive position would be to sign the treaty. Figure 15 shows that more conservative states are more likely to oppose ratifying Kyoto, as expected. At the same time, Washington State is no outlier, as it was for the carbon tax question. The difference between the two questions is obvious: Washington was exposed to a real-world campaign featuring strong arguments from the opposition against the carbon tax, but not so for the Kyoto treaty. This comparison parallels the

[65] Polling was conducted during October 4-9, 2018 and yielded a sample of 400 registered voters. The poll indicates 50% voting for, 36% against, and 14% undecided.
[66] The Kyoto treaty is an international climate-change protocol that the U.S. signed but has never ratified (the only major signatory not to do so).

Figure 16: *Predicting the state-level support for repealing the 2009 Affordable Care Act using our MTurk survey adjusted with multilevel regression with poststratification (MRP)*



Note: This figure plots the share that supports repealing the 2009 Affordable Care Act based on multilevel regression with poststratification (MRP) vs. the actual Republican House vote share, by state. The dashed lines corresponds to OLS fitted values.
Source: Our Amazon Mechanical Turk survey on November 5-6 2018, and Cooperate Congressional Election Study 2006-2017.

analysis in section 4.2.2 above, where we estimate a campaign effect of negative 20 percentage points using a difference-in-differences approach.

Why is the MRP approach over-predicting support for I-1631 in Washington compared to the actual vote there in 2018? Could it be that the MRP process is somehow failing to fully adjust for the liberal MTurk sample? To answer this question, we use MRP to model state-level support for repealing the Affordable Care Act (ACA), President Obama's big health care reform package from 2009—an issue question we posed to respondents in our MTurk survey. Figure 16 plots our state-level MRP estimates versus the actual U.S. House vote in 2018. Support for repealing the ACA rises with the Republican share, just as we would expect. Note that the average level of support across the states is about 50%. This result is consistent with high-frequency, national-level polling data on the ACA by organizations such as the Kaiser Family Foundation, which show that the country is split roughly equally between support and opposition.[67] Thus, our MRP estimates using MTurk data are not systematically biased, but are consistent with nationally representative surveys—at least when focusing on well-known federal policy issues such as the Affordable Care Act.

Overall, our MRP-adjusted national survey data predicts that, across states, support for a carbon tax falls

[67] For more, see `https://www.kff.org/interactive/kff-health-tracking-poll-the-publics-views-on-the-aca`.

as the House Republican vote share increases. The states most likely to pass a carbon tax are Maryland, New York, Massachusetts, Vermont, and Pennsylvania (see figure 14). These states are—with the exception of Pennsylvania—all among the top ten most likely to pass a carbon tax according to our forecasts using actual voting data (see figure 12). Overall, forecasts using national survey data and actual voting data from Washington lead to similar rankings (compare figure 11 and figure 14). However, the forecast based on the actual vote in Washington implies much lower *levels* of support, since it reflects Washington's actual voting experience, including the negative campaign effect. The forecasts using voting data are likely to be more realistic: they caution that passing a state carbon tax is going to be difficult but perhaps feasible in a handful of liberal states such as Massachusetts.

7 Conclusion

Climate policy is one of the most politically polarized topics in the United States, making the adoption of federal legislation to limit greenhouse emissions especially difficult. States represent a potentially valuable laboratory for learning about the politics of climate policy—including the politics of Pigouvian taxes on carbon emissions, which are the subject of substantial research by economists.

We analyze two failed carbon tax initiatives in Washington State using both precinct-level aggregate voting data from Washington and carefully weighted MTurk survey data for the entire United States. Comparing the carbon tax with other environmental policies across states, we show that the campaigns in Washington State caused support for the carbon tax to fall by 20 percentage points. This difference-in-differences finding is consistent with the "no" campaign spending twice as much as the "yes" campaign in 2018. We estimate that the direct economic incidence of the carbon tax is similar across Washington's precincts on average. Thus, for the median precinct, resistance to higher energy prices—combined with a near total disregard for tax rebates and green spending—can explain why voters rejected the two carbon taxes. However, ideology can easily overpower pocketbook concerns. Indeed, we show that that ideology is by far the best and most important predictor of variation in support for the carbon tax *across* precincts, explaining more than 90% of the variation in vote shares.

What do our results imply about the prospects for carbon taxes at the state level? After all, nationwide surveys—including ours—show strong majorities in favor and support that extends even to the most conservative states in the country. However, we present evidence based on actual voting and survey data showing that this support is shallow and can be significantly weakened through campaign spending. Overall, our results suggest that a carbon tax modeled on recent policies from Washington State would—without deeper efforts to inform and persuade voters—be unlikely to pass in the near term. The best prospects for a carbon tax continue to be in liberal states, especially in Massachusetts, where voters are likely to prefer policies that spend tax revenue on liberal objectives. However, even in a liberal state, positioning carbon taxes too far left by eschewing revenue-neutrality may galvanize conservative and industry opposition, as seems to have been the case for I-1631 in Washington.

What political levers might carbon tax advocates pull to boost support and deflect opposition? Future attempts to pass a carbon tax at the state level can learn from our estimates for the combined effects of ideological positioning and campaigns. Washington's experience shows that a revenue-neutral policy can appeal to moderates and conservatives—or at least limit their opposition—while a tax-and-spend policy can appeal to liberals. But careful policy design does not seem to be enough, for both ends of the political continuum were tried in Washington State, and both failed. For a revenue-neutral policy like I-732 to win at the polls, voters must be informed and convinced that—though they will pay higher energy prices—they will benefit from lower taxes elsewhere. Likewise, for a tax-and-spend policy like I-1631 to win, voters must be convinced that the new spending has real value. Persuading voters could, in the end, prove too costly in the short term. Alternatively, a traditional legislative strategy to adopt carbon taxes may prove promising. If not, successful attempts may have to await further changes in public opinion (perhaps pushed by generational change), or elite position change (more conservative elites changing their mind on climate).

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A Supporters and opponents of I-732 and I-1631

Table 7 summarizes the main supporters and opponents of each measure.

Table 7: *Supporters and opponents*

	I-732	I-1631
Year	2016	2018
Primary Sponsor	Carbon Washington	Alliance for Jobs and Clean Economy
Recommended "support"	The Audubon Society, the Sightline Institute, the Citizens Climate Lobby, Leonardo de Caprio, Dr. James Hansen, (former Director of the NASA Goddard Institute for Space Studies), George P. Schultz (former U.S. Secretary of State, Secretary of the Treasury, and Secretary of Labor), Steven Chu (Former sec. of energy), local Democratic party chapters, renewable energy industry, miscellaneous environmental groups	Jay Inslee, Pramila Jayapal, Bernie Sanders, Bill and Melinda Gates, 350.org, Audubon WA, Carbon Washington, Climate Solutions, Defenders of Wildlife, EarthJustice, Green Party of Washington State, Front and Centered, the Climate Reality Project, The Nature Conservancy, Union of Concerned Scientists, Washington Environmental Council, labor organizations, social justice groups, small environmental groups, health advocacy groups, Native American tribes, renewable energy industry, faith groups
Recommended "not support"	Sierra Club, 350.org, Climate Solutions, Washington Environment Council	
Recommended "oppose"	Alliance for Jobs and Clean Energy, Washington State Democratic Party, Front and Centered, State Labor Council, Association of Washington Businesses, Chambers of Commerce, American Exploration and Mining Associations, Kaiser Aluminum, American Fuel & Petrochemical Manufacturers, Koch Industries, local chambers of commerce, utilities, agricultural and food processing, and trucking, labor groups, social justice groups, environmental groups	Western States Petroleum Association, Association of Washington Business (AWB)

Source: Ballotpedia

As can be seen, some environmental groups did not support I-732. Sierra Club's (Washington Chapter) official position statement on I-732 contains a particularly cogent and explicit expression of this reasoning. We reproduce this statement in its entirety here:

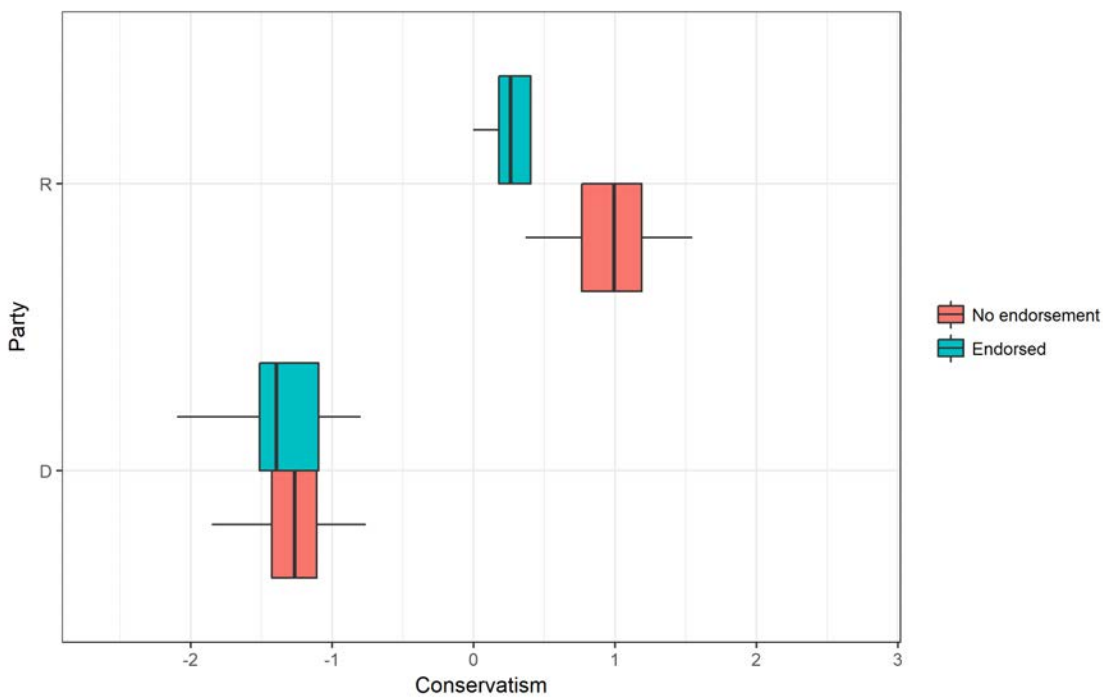
> September 2016
>
> Sierra Club has adopted a Do Not Support position concerning Initiative 732, rather than Support, Neutral, or Oppose. Given the urgency of the climate crisis, this was not a decision reached

> lightly. Members of the Club expressed deep concerns that the initiative does not include all that is needed for an equitable climate policy and just transition to a clean energy economy, while at same time, other members of the Club worked tirelessly in support of the initiative. Sierra Club is taking a Do Not Support position because:
>
> - Communities of color and low-income people are almost always the ones most impacted by pollution and climate change, and as a result they need to be at the front and center of discussions for how to address the problem and mitigate the impacts of both climate change and environmental policy. That wasn't the approach taken by I-732. As a result, the initiative fails to affirmatively address any of the stated needs of those communities: more investment in green jobs, energy efficiency, transit, housing, and renewable energy infrastructure.
> - There remains justifiable concern about I-732's revenue projections. While I-732 was intended to be revenue neutral, the State Department of Revenue predicts I-732 will result in about $200 million of lost revenue per year in its first four years. A subsequent analysis by Sightline Institute, a respected environmental think tank, found flaws in the state forecast but still estimated a nearly $80 million annual revenue loss over the same time period. At a time when our state needs additional revenue to fund education, parks, environmental programs, and social services, we are concerned about any projected revenue cuts.
>
> Whether I-732 passes or not, the Sierra Club is committed to working together as a movement after the election with our allies in the labor, social justice, immigrant, and Tribal communities to support efforts to stop climate change and preserve a clean, healthy environment for future generations.

What about elected officials? 24 of 147 elected state legislators made public endorsement decisions on I-732. All were in favor of the initiative, so we compare endorsers with non-endorsers. Figure 17 shows this comparison, divided by party. Democrats who endorsed I-732 hardly differed from their colleagues who made no such pronouncements. On the other hand, Republicans who endorsed I-732 were decidedly more liberal than those who refused to endorse. This suggests that these endorsements are cheap talk for Democrats but a costly signal for Republicans.

The only sitting legislator who had a position on I-1631 was Senator Reuven Carlyle, who is actually in the most conservative quarter of his party. It is unclear why I-1631 attracted so much less attention from state legislators than I-732.

Figure 17: *Ideology of state legislators that supported I-732*



Note: This figures shows the distribution of ideological scores for current and former (recent) state legislators in Washington that expressed support for I-732. The horizontal axis is a conservative ideological score as estimated by Shor and McCarty (2011, 2018).

B Issue questions used in estimating latent ideology

B.1 Environmental Questions

1. Do you support the federal regulation of greenhouse gas emissions?
2. Do you support reducing restrictions on offshore energy production?
3. Should states enact environmental regulations even if they are stricter than federal law?
4. Do you support the U.S. re-entering the Kyoto treaty process to limit global warming?
5. Do you support opening a select portion of the Arctic National Wildlife Refuge for oil exploration?
6. Use state funds to clean up former industrial and commercial sites that are contaminated, unused or abandoned.
7. Do you support building the Keystone XL pipeline (from Canada to Texas)?
8. Do you support state funding for the development of renewable energy (e.g. solar, wind, thermal)?
9. Do you support increased production of traditional domestic energy sources (eg, coal, natural gas, and oil)?
10. Do you support funding for open space preservation?
11. Should states fully compensate citizens when environmental regulations limit uses on privately owned land?

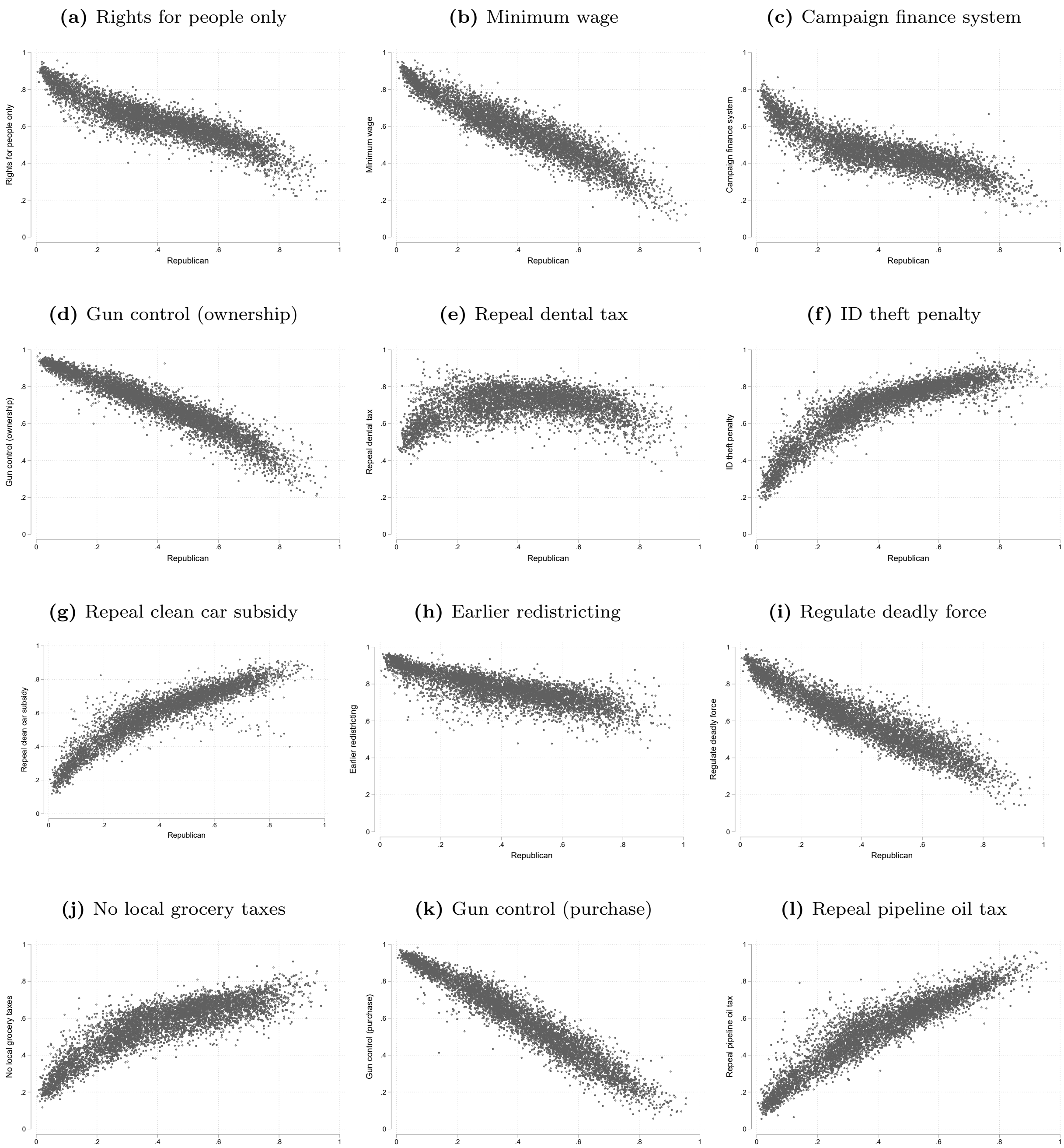
B.2 Non-Environmental Questions

1. Do you support federal spending as a means of promoting economic growth?
2. Do you support reducing government regulations on the private sector in order to encourage investment and economic expansion?
3. Should we increase the minimum wage?
4. In order to balance the budget, do you support an income tax increase on any tax bracket?
5. Do you support an increase in state funds to provide child care for children in low-income working families?
6. Do you support limiting benefits given to recipients if they have additional children while on welfare?
7. Do you support requiring welfare applicants to pass a drug test in order to receive benefits?
8. Should we increase funding for state job-training programs that re-train displaced workers or teach skills needed in today's job market?
9. Do you support same-sex marriage?
10. Do you support abstinence-only sexual education programs?
11. Do you support legalizing physician assisted suicide in your state?
12. Do you support the inclusion of sexual orientation in your state's anti-discrimination laws?
13. Do you agree that providing health care to all citizens is a responsibility of the state government?
14. Do you support having a national health plan – or a single-payer plan- in which all Americans would get their insurance from a single government plan?
15. Do you support repealing the 2010 Affordable Care Act ("Obamacare")?
16. Do you support Medicaid expansion through your state's health care programs?
17. Should the U.S. use military force in order to prevent governments hostile to the U.S. from possessing a nuclear weapon?
18. Do you support increased American intervention in Middle Eastern conflicts beyond air support?
19. Should the US withdraw from the Iran Nuclear Accord and reimpose sanctions on Iran?
20. Should citizens be allowed to carry concealed guns?
21. Do you support the use of the death penalty in your state?
22. Do you support affirmative action in public college admissions?
23. Do you believe that minors accused of a violent crime should be prosecuted as adults?

24. Do you support the legalization of marijuana for recreational purposes?
25. Should parents be provided state-funded vouchers to send their children to any public, private or religious school?
26. Should states provide funding to increase teacher salaries?
27. Do you support using a merit pay system for teachers?
28. Do you support national standards and testing of public school students?
29. Do you support requiring immigrants who are unlawfully present to return to their country of origin before they are eligible for citizenship?
30. Do you support decreasing the number of legal immigrants allowed into the country?
31. Do you support amnesty for illegal immigrants already working in the United States?
32. Do you support the enforcement of federal immigration laws by state and local police?
33. Do you support the construction of a wall along the Mexican border?
34. Do you support prohibiting public funding of abortions and organizations that advocate or perform abortions?
35. Do you support prohibiting the late-term abortion procedure known as partial-birth abortion?
36. Should abortion be legal when the pregnancy resulted from incest or rape?
37. Should abortion be allowed before the 20th week of pregnancy?
38. Do you generally support pro-choice or pro-life legislation?
39. Do you support requiring a government-issued photo identification in order to vote at the polls?
40. Do you support the regulation of indirect campaign contributions from corporations and unions?
41. Do you support limits on the contributions to political candidates by individuals?

C Additional figures

Figure 18: *Precinct-level vote on all other 2016 and 2018 ballot measures*



(a) Rights for people only **(b)** Minimum wage **(c)** Campaign finance system

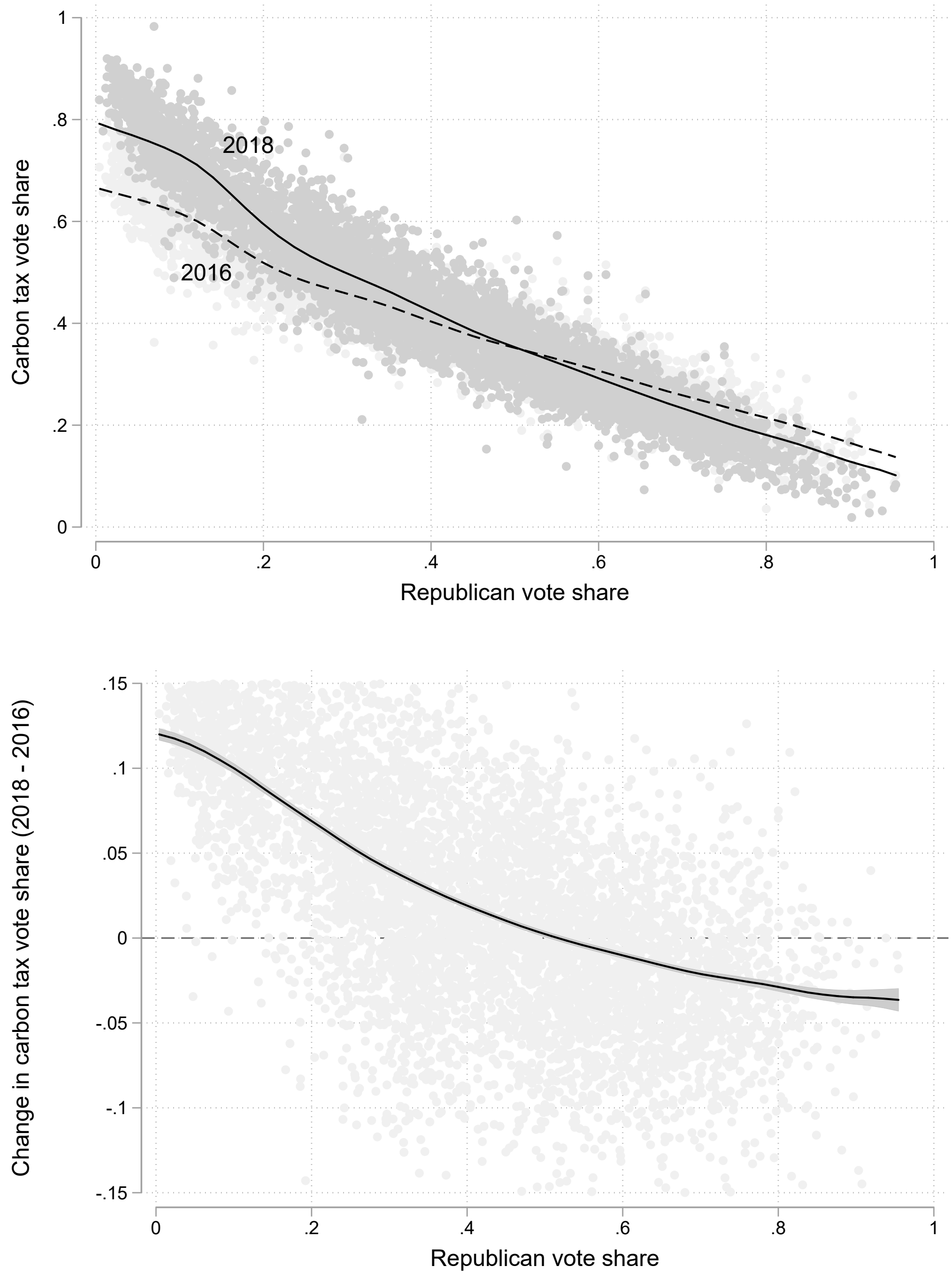
(d) Gun control (ownership) **(e)** Repeal dental tax **(f)** ID theft penalty

(g) Repeal clean car subsidy **(h)** Earlier redistricting **(i)** Regulate deadly force

(j) No local grocery taxes **(k)** Gun control (purchase) **(l)** Repeal pipeline oil tax

Note: This figure plots "yes" vote shares on other statewide ballot measures versus the U.S. presidential vote share (Republican Party) in 2016. The first eight ballot measures (a-h) are from the 2016 election, while the last four (i-l) are from 2018. See appendix F for details of each measure.

Figure 19: *Voting on carbon tax vs. Presidential vote (by precinct)*

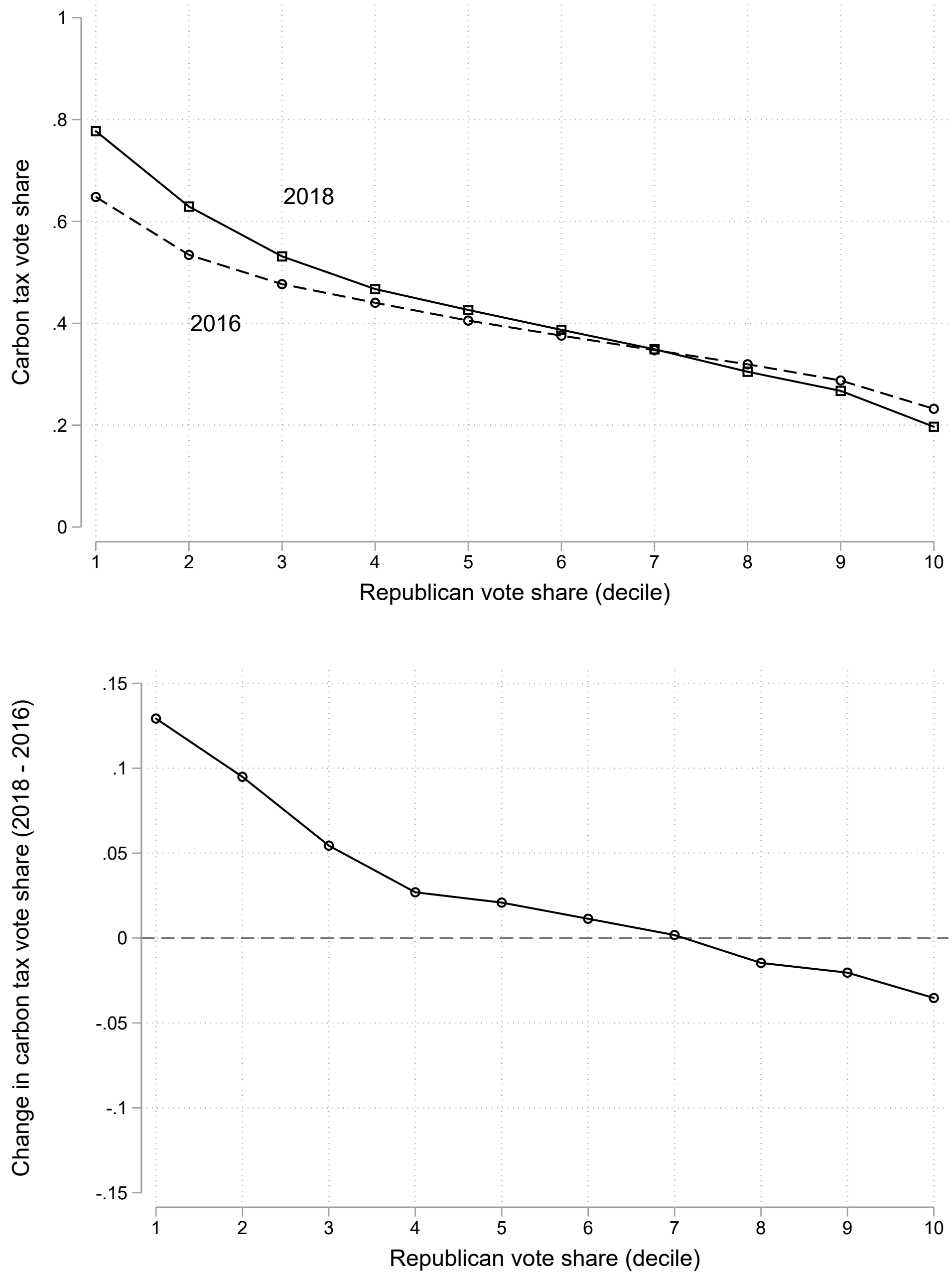


Note: The top panel of this figure plots the "yes" shares on I-1631 in 2018 (gray dots) and I-732 in 2016 (light gray dots) versus the U.S. presidential vote share (Republican Party) in 2016 for 6,038 precincts in Washington State. The solid and dashed lines plot local polynomial fitted values for the respective years (local linear regression weighted by total votes cast for or against the carbon tax in the respective year).

The bottom panel of this figure plots the difference between the "yes" shares on I-1631 in 2018 and the "yes" shares on I-732 in 2016 versus the U.S. presidential vote share (Republican Party) in 2016. The solid line plots local polynomial fitted values for the difference (local linear regression weighted by total votes cast for or against the carbon tax in both years).

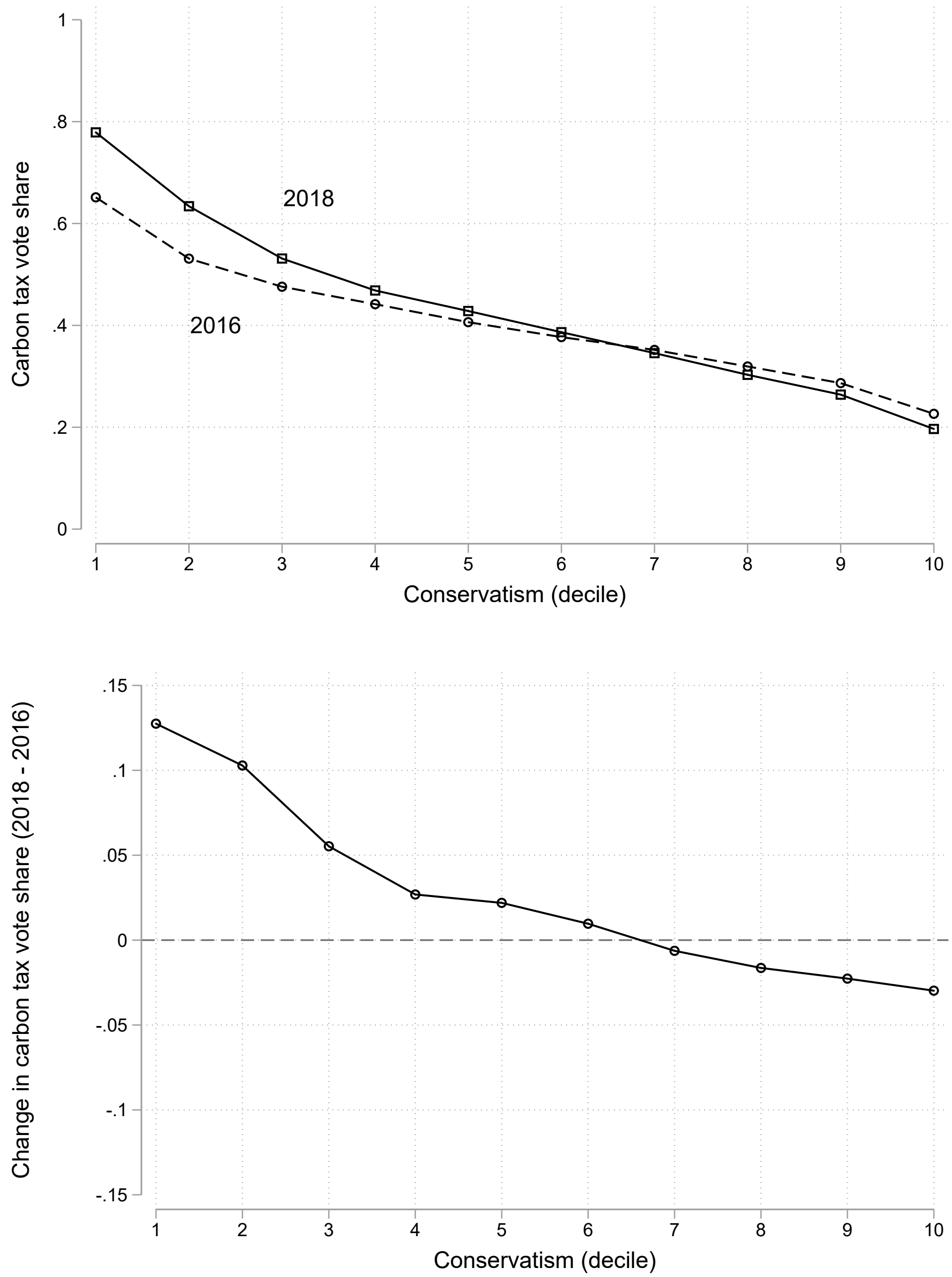
Source: WA SOS.

Figure 20: *Voting on carbon tax vs. Senate vote*



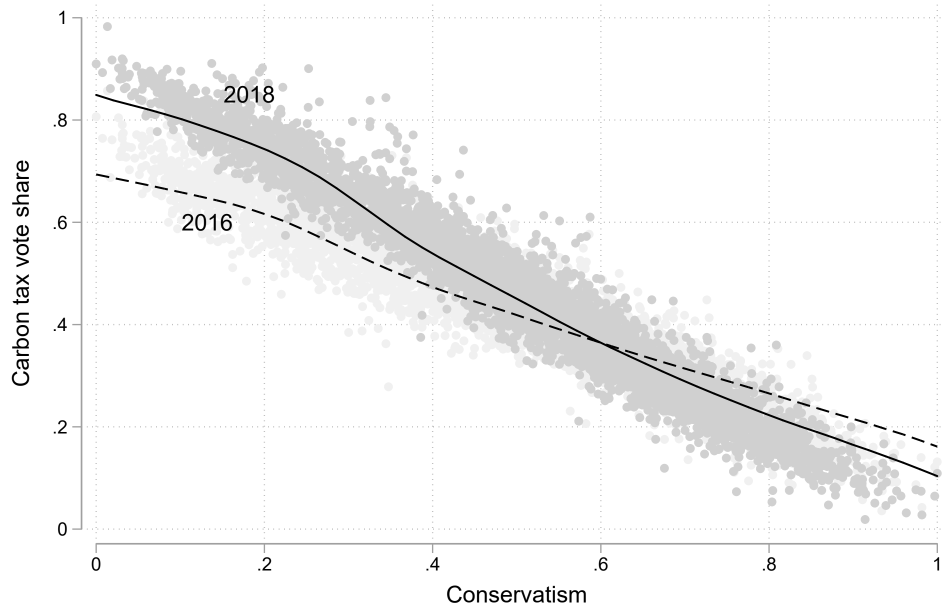
Note: The top panel of this figure plots the "yes" shares on I-1631 in 2018 (solid line) and I-732 in 2016 (dashed line) by decile of the Republican party vote share in the U.S. Senate election in the corresponding year. Each decile contains precincts that together add up to one tenth of votes cast in 2016 and 2018 respectively. Deciles for 2018 are constructed from precinct-level data in the following way: sort precincts from the lowest to the highest Republican vote share in 2018, and then determine decile cutoffs. Deciles for 2016 (dashed line) are constructed similarly. Thus, the overall vote share can be visualized as the average height of the points.
The bottom panel plots the *difference* by decile. Deciles are constructed for 2018 and 2016 as in the top panel. Thus, the overall difference in vote shares between 2018 and 2016 can be visualized as the average height of the points.
Source: WA SOS.

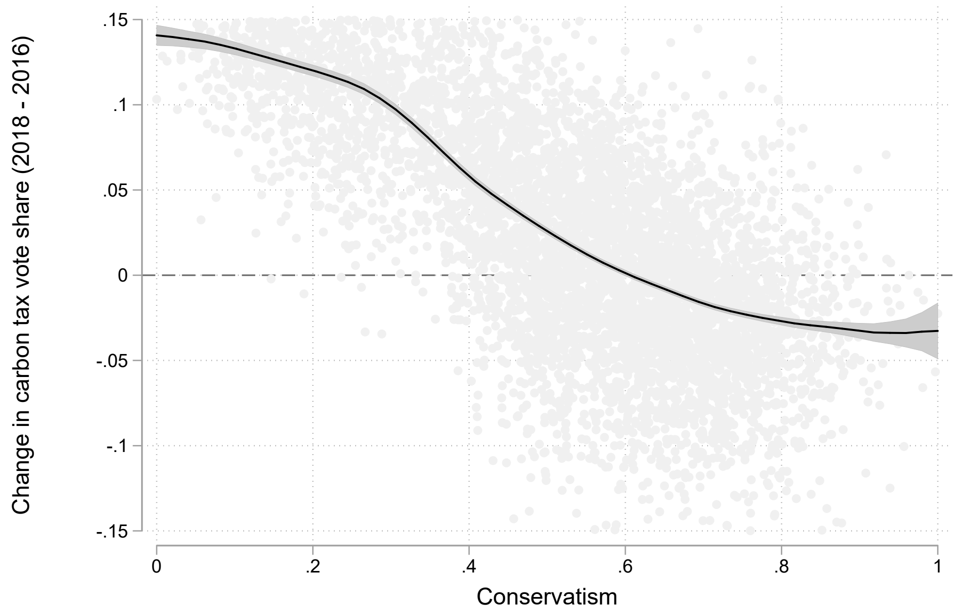
Figure 21: *Voting on carbon tax vs. conservative ideology (by decile)*



Note: This figure plots the "yes" shares on I-1631 in 2018 (solid line) and I-732 in 2016 (dashed line) by decile of conservative ideology. Each decile contains precincts that together add up to one tenth of votes cast in 2016 and 2018 respectively. Deciles for 2018 (solid line) are constructed from precinct-level data in the following way: sort precincts from the lowest to the highest conservative ideology, and then determine decile cutoffs. Deciles for 2016 (dashed line) are constructed similarly. Conservative ideology is a 0-1 index computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 18).
Source: WA SOS.

Figure 22: *Voting on carbon tax vs. conservative ideology (by precinct)*



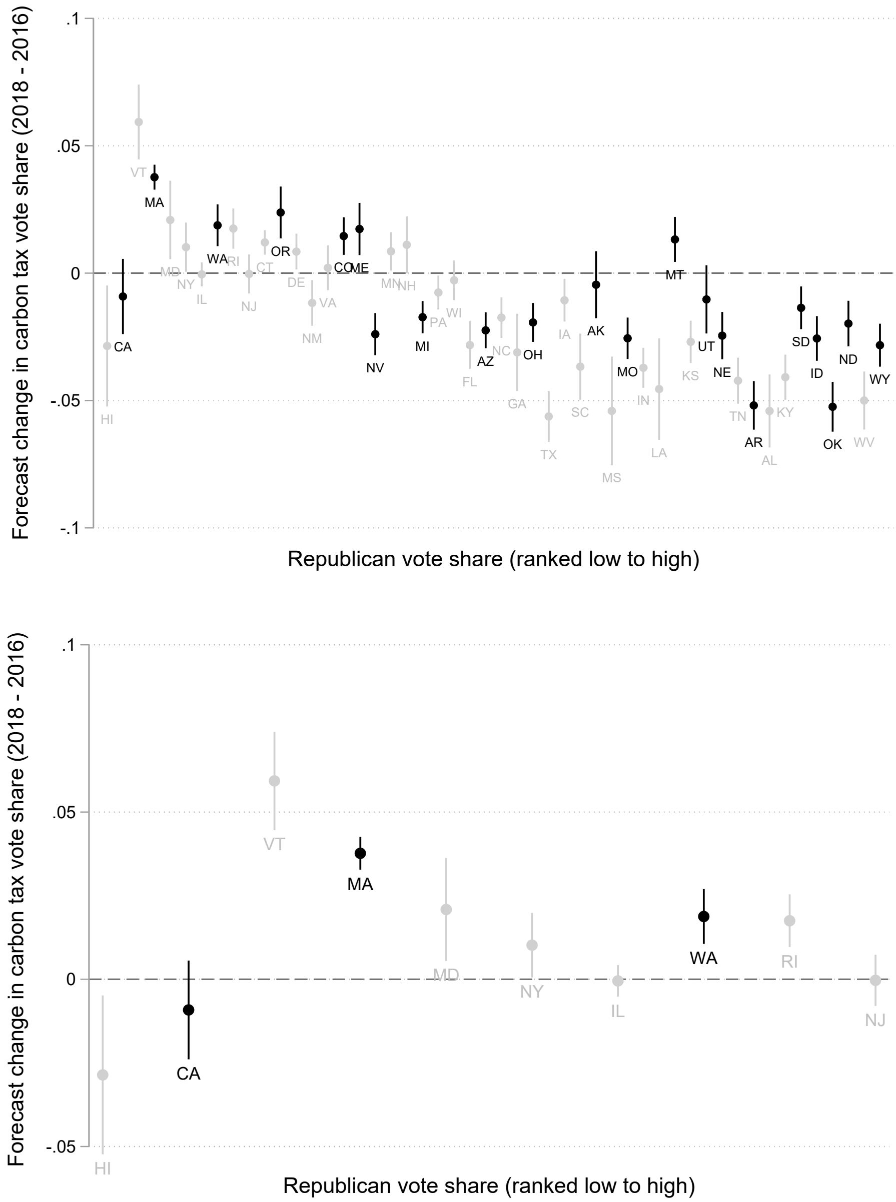


Note: The top panel of this figure plots the "yes" shares on I-1631 in 2018 (gray dots) and I-732 in 2016 (light gray dots) versus the conservatism index for 6,038 precincts in Washington State. The solid and dashed lines plot local polynomial fitted values for the respective years (local linear regression weighted by total votes cast for or against the carbon tax in the respective year). Conservative ideology is a 0-1 index computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 18).

The bottom panel of this figure plots the difference between the "yes" shares on I-1631 in 2018 and the "yes" shares on I-732 in 2016 versus the conservatism index. The solid line plots local polynomial fitted values for the difference (local linear regression weighted by total votes cast for or against the carbon tax in both years).

Source: WA SOS.

Figure 23: *Forecast change in carbon tax vote share (2018 minus 2016) by state*



Note: This figure plots out-of-sample forecasts by state for the *change* in share voting "yes" on a carbon tax (2018 vs. 2016) versus the ranked Republican vote share in the 2016 presidential election. Forecasts are based on regression model (3) in table 3. State forecasts are generated by applying coefficients from this precinct-level regression to the same variables measured at the state level in all 50 states. States that feature a popular initiative mechanism are shown in black, while states that lack an initiative process are shown in gray. The top panel shows all states, while the bottom panel shows the ten states with the lowest Republican vote share. Point estimates are represented by circles, while 95% confidence intervals are represented by vertical lines.
Source: WA SOS, U.S. Census, U.S. Federal Election Commission.

D Additional tables: precinct-level regressions from Washington

Table 8: *Predicting the carbon tax vote share at the precinct level (2016 only)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +Endorse	(6) +County FEs	(7) +Turnout
Conservatism	-0.674***			-0.522***	-0.522***	-0.532***	-0.566***
	(0.010)			(0.024)	(0.024)	(0.025)	(0.016)
Republican		-0.611***	-0.512***	-0.123***	-0.123***	-0.120***	-0.095***
		(0.022)	(0.019)	(0.020)	(0.021)	(0.024)	(0.018)
Endorsement					-0.001	-0.001	-0.001
					(0.003)	(0.002)	(0.001)
Turnout							-0.184***
							(0.015)
Voted on I-732							-0.126***
							(0.024)
Observations	6038	6038	6038	6038	6038	6038	6038
R^2	0.906	0.881	0.924	0.942	0.942	0.946	0.949

Note: Note: This table presents coefficient estimates from precinct-level OLS regressions modeling the share voting "yes" for the carbon tax in 2016 as a function of ideology, demographics, and other factors. *Conservatism* measures ideology on a 0-1 index, computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 18). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. *Endorsement* indicates that the precinct's state legislator declared his or her support for I-732. *Turnout* is measured as the total number of ballots cast in 2016 divided by the total number of registered voters. *Voted on carbon tax* measures the total number of votes cast for or against the carbon tax in 2016 divided by the total number of ballots cast in 2016. Models (3)-(7) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., commute time by car, industry, home value, # rooms, income, gender, age, race, and education). Model (4) then adds ideology. Model (5) then adds the endorsement variable. Model (6) then adds county fixed effects. Finally, model (7) adds the two turnout variables. For all models, precincts are weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Standard errors are clustered by county (39 clusters).
Source: WA SOS & U.S. Census.

Table 9: *Predicting the carbon tax vote share at the precinct level (2018 only)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +Endorse	(6) +County FEs	(7) +Turnout
Conservatism	-0.951***			-0.809***	-0.806***	-0.786***	-0.789***
	(0.017)			(0.041)	(0.041)	(0.016)	(0.015)
Republican		-0.847***	-0.728***	-0.125**	-0.132***	-0.162***	-0.159***
		(0.033)	(0.023)	(0.036)	(0.035)	(0.018)	(0.017)
Endorsement					-0.006**	0.000	0.000
					(0.002)	(0.001)	(0.001)
Turnout							-0.042
							(0.028)
Voted on I-1631							0.014
							(0.009)
Observations	6038	6038	6038	6038	6038	6038	6038
R^2	0.958	0.897	0.945	0.967	0.968	0.974	0.974

Note: This table presents coefficient estimates from precinct-level OLS regressions modeling the share voting "yes" for the carbon tax in 2018 as a function of ideology, demographics, and other factors. *Conservatism* measures ideology on a 0-1 index, computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 18). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. *Endorsement* indicates that the precinct's state legislator declared his or her support for I-732. *Turnout* is measured as the total number of ballots cast in 2016 divided by the total number of registered voters. *Voted on carbon tax* measures the total number of votes cast for or against the carbon tax in 2018 divided by the total number of ballots cast in 2016. Models (3)-(7) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., commute time by car, industry, home value, # rooms, income, gender, age, race, and education). Model (4) then adds ideology. Model (5) then adds the endorsement variable. Model (6) then adds county fixed effects. Finally, model (7) adds the two turnout variables. For all models, precincts are weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Standard errors are clustered by county (39 clusters).
Source: WA SOS & U.S. Census.

Table 10: *Predicting the carbon tax vote share at the precinct level using the U.S. Senate vote*

	(1) Ideology	(2) Rep2016	(3) Rep2016	(4) RepSameYr	(5) RepSameYr	(6) RepAvgYr	(7) RepAvgYr
Conservatism	-0.813***		-0.668***		-0.495***		-0.625***
	(0.013)		(0.027)		(0.017)		(0.024)
Republican		-0.884***	-0.170***	-0.852***	-0.350***	-0.863***	-0.210***
		(0.028)	(0.028)	(0.026)	(0.017)	(0.027)	(0.025)
2018 vote	0.026	0.026	0.026	0.032**	0.028*	0.026	0.026
	(0.014)	(0.014)	(0.014)	(0.009)	(0.012)	(0.014)	(0.014)
Observations	12076	12076	12076	12076	12076	12076	12076
R^2	0.914	0.863	0.917	0.899	0.925	0.879	0.917

Note: This table presents coefficient estimates from pooled precinct-level OLS regressions modeling the share voting "yes" for the carbon tax in 2016 and 2018 as a function of ideology, demographics, and other factors. *Conservatism* measures ideology on a 0-1 index, computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 18). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in one or more U.S. Senate elections. *2018 vote* is an indicator for the 2018 carbon tax (I-1631). Model (1) omits Republican share. Models (2) and (3) relate voting on the carbon tax to the Republican share in the 2016 U.S. Senate election. Models (4) and (5) relate voting on the carbon tax in a given year to the Republican share in the U.S. Senate election from the same year (i.e., voting on I-732 is matched to the Republican share in the 2016 election and voting on I-1631 is matched to the Republican share in the 2018 election). Models (6) and (7) relate voting on the carbon tax to a weighted average of the Republican share in the U.S. Senate elections from 2016 (2/3 weight) and 2018 (1/3 weight). For all models, precincts are weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Standard errors are clustered by county (39 clusters).
Source: WA SOS.

E Additional tables: individual-level regressions

Table 11: *Predicting support for the carbon fee I-1631 across the United States: individual linear probability model, displaying coefficients for controls*

	Party Only	Party Plus	Ideology Only	Ideology Plus	Combined
Latent Ideology			-1.28 ***	-1.28 ***	-1.22 ***
			(0.03)	(0.04)	(0.05)
Republican	-0.36 ***	-0.34 ***			-0.03
	(0.02)	(0.02)			(0.02)
Independent	-0.26 ***	-0.22 ***			-0.06 *
	(0.02)	(0.03)			(0.03)
Washington State	-0.20 ***	-0.16 **	-0.23 ***	-0.20 ***	-0.20 ***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Female		0.08 ***		0.06 ***	0.06 ***
		(0.01)		(0.01)	(0.01)
Bachelors Degree		0.02		-0.02	-0.02
		(0.02)		(0.01)	(0.01)
Income > 60k		0.00		0.02	0.02
		(0.02)		(0.01)	(0.01)
Car Commute		0.01		0.03 *	0.03
		(0.02)		(0.02)	(0.02)
House 3+ BR		-0.00		-0.01	-0.01
		(0.02)		(0.02)	(0.02)
Age		-0.05 ***		-0.04 ***	-0.04 ***
		(0.01)		(0.01)	(0.01)
Black		-0.02		0.08 **	0.07 **
		(0.03)		(0.03)	(0.03)
Hispanic		-0.01		0.03	0.02
		(0.04)		(0.03)	(0.03)
Asian		0.05		0.13 ***	0.12 **
		(0.04)		(0.04)	(0.04)
Multiracial		-0.00		-0.02	-0.02
		(0.03)		(0.03)	(0.03)
Constant	0.92 ***	0.89 ***	1.39 ***	1.36 ***	1.35 ***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)
N	3760	2815	3760	2815	2815
R2	0.17	0.17	0.28	0.30	0.30

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Note: This table summarizes the results of five separate linear probability (OLS) models of the survey response to a question about the I-1631 ballot language. All models weight observations using inverse probability weights based on sex, marital status, race, age, education, religious observance, and political party using the 2018 exit poll (using R's svyglm command). Models (3)-(5) include a measure of latent ideology estimated from 53 individual issue questions elsewhere in the survey (appendix B). Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and the 2018 exit poll by Edison Research and the National Election Pool for the weights.

Table 12: *Predicting support for the carbon fee I-1631 across the United States: individual linear probability model, distinguishing between environmental and non-environmental ideology and displaying coefficients for controls*

	Non-Envir Ideology	Envir Ideology	Combined
Environmental Ideology		-0.93 ***	-0.85 ***
		(0.03)	(0.04)
Non-Environmental Ideology	-0.97 ***		-0.22 ***
	(0.05)		(0.06)
Republican	-0.09 ***	-0.05 **	-0.02
	(0.02)	(0.02)	(0.02)
Independent	-0.08 **	-0.08 ***	-0.06 *
	(0.03)	(0.02)	(0.02)
Washington State	-0.19 ***	-0.20 ***	-0.21 ***
	(0.05)	(0.05)	(0.05)
Female	0.07 ***	0.04 ***	0.04 ***
	(0.01)	(0.01)	(0.01)
Bachelors Degree	-0.01	-0.02	-0.02
	(0.01)	(0.01)	(0.01)
Income > 60k	0.02	0.00	0.00
	(0.01)	(0.01)	(0.01)
Car Commute	0.03	0.03 *	0.03 *
	(0.02)	(0.01)	(0.01)
House 3+ BR	-0.01	-0.00	-0.01
	(0.02)	(0.02)	(0.02)
Age	-0.04 ***	-0.04 ***	-0.04 ***
	(0.01)	(0.01)	(0.01)
Black	0.04	0.08 ***	0.09 ***
	(0.03)	(0.02)	(0.02)
Hispanic	0.01	0.04	0.04
	(0.03)	(0.03)	(0.03)
Asian	0.11 **	0.13 ***	0.14 ***
	(0.04)	(0.04)	(0.04)
Multiracial	-0.02	-0.02	-0.03
	(0.03)	(0.03)	(0.03)
Constant	1.23 ***	1.11 ***	1.17 ***
	(0.03)	(0.02)	(0.02)
N	2815	2814	2814
R2	0.26	0.38	0.38

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Note: This table summarizes the results of three separate linear probability (OLS) models of the survey response to a question about the I-1631 ballot language. All models weight observations using inverse probability weights based on sex, marital status, race, age, education, religious observance, and political party using the 2018 exit poll (using R's svyglm command). *Non-Environmental Ideology* estimates latent ideology from 42 issue questions that are not about the environment or energy. *Environmental Ideology* estimates latent ideology from the 11 questions on the environment and energy (appendix B).
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and the 2018 exit poll by Edison Research and the National Election Pool for the weights.

Table 13: *Predicting support for the carbon fee I-1631 across the United States: individual logistic model, displaying coefficients for controls*

	Party Only	Self Report Only	Latent Ideology Only	Latent plus Party	Combined
	(1)	(2)	(3)	(4)	(5)
Republican	−2.07***			0.33**	0.25
	(0.11)			(0.15)	(0.18)
Independent	−1.53***			−0.39**	−0.46**
	(0.15)			(0.18)	(0.19)
Self Reported Ideology		−0.65***			0.03
		(0.03)			(0.06)
Latent Ideology			−12.81***	−13.76***	−13.90***
			(0.64)	(0.78)	(0.84)
Washington State	−1.02***	−1.06***	−1.70***	−1.72***	−1.73***
	(0.30)	(0.32)	(0.39)	(0.39)	(0.39)
Female	0.52***	0.55***	0.43***	0.40***	0.39***
	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)
Bachelors Degree	0.13	0.14	−0.004	−0.02	−0.003
	(0.10)	(0.11)	(0.12)	(0.12)	(0.12)
Income ¿ 60k	0.01	0.02	0.12	0.11	0.11
	(0.10)	(0.11)	(0.12)	(0.12)	(0.12)
Car Commute	0.09	0.14	0.21	0.14	0.14
	(0.12)	(0.13)	(0.14)	(0.14)	(0.14)
House 3+ BR	−0.04	−0.03	0.001	−0.02	−0.04
	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
Age	−0.31***	−0.31***	−0.20**	−0.19**	−0.19**
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Black	−0.17		0.02	0.09	0.06
	(0.22)		(0.22)	(0.22)	(0.22)
Hispanic	−0.08	−0.01	0.01	0.03	0.03
	(0.26)	(0.25)	(0.26)	(0.26)	(0.27)
Asian	0.38	0.55*	0.94**	0.89**	0.87**
	(0.33)	(0.33)	(0.37)	(0.38)	(0.38)
Multiracial	0.003	−0.09	−0.46	−0.42	−0.42
	(0.23)	(0.23)	(0.29)	(0.29)	(0.29)
Constant	2.23***	3.75***	8.08***	8.58***	8.59***
	(0.17)	(0.22)	(0.41)	(0.46)	(0.47)
Observations	2,815	2,783	2,815	2,815	2,783
Log Likelihood	−1,273.21	−1,207.33	−982.05	−974.02	−958.03
Akaike Inf. Crit.	2,574.42	2,438.65	1,990.11	1,978.04	1,948.06
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: This table summarizes the results of five separate logistic models of the survey response to a question about the I-1631 ballot language. All models weight observations using inverse probability weights based on sex, marital status, race, age, education, religious observance, and political party using the 2018 exit poll (using svyglm from the `survey` package in `R`). Models (3)-(5) include a measure of latent ideology estimated from 53 individual issue questions elsewhere in the survey (appendix B). Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018.

Table 14: *Predicting support for the carbon fee I-1631 across the United States: individual logistic model, distinguishing between environmental and non-environmental ideology and displaying coefficients for controls*

	Environmental Ideology	Non-Environmental Ideology	Combined
	(1)	(2)	(3)
Environmental Ideology	-7.91^{***}		-6.92^{***}
	(0.39)		(0.44)
Non-Environmental Ideology		-9.13^{***}	-3.79^{***}
		(0.60)	(0.69)
Republican	-0.38^{***}	-0.22	0.11
	(0.15)	(0.15)	(0.16)
Independent	-0.75^{***}	-0.61^{***}	-0.50^{**}
	(0.20)	(0.17)	(0.20)
Washington State	-1.93^{***}	-1.42^{***}	-2.02^{***}
	(0.44)	(0.34)	(0.45)
Female	0.35^{***}	0.49^{***}	0.36^{***}
	(0.12)	(0.11)	(0.12)
Bachelors Degree	-0.01	0.02	-0.02
	(0.12)	(0.11)	(0.12)
Income ¿ 60k	-0.02	0.12	0.01
	(0.12)	(0.11)	(0.13)
Car Commute	0.24	0.09	0.23
	(0.15)	(0.14)	(0.15)
House 3+ BR	-0.05	-0.02	-0.04
	(0.14)	(0.13)	(0.14)
Age	-0.27^{***}	-0.22^{***}	-0.24^{***}
	(0.08)	(0.08)	(0.09)
Black	0.30		0.26
	(0.24)		(0.23)
Hispanic	0.26	-0.07	0.22
	(0.29)	(0.25)	(0.28)
Asian	0.92^{**}	0.71^{**}	1.00^{***}
	(0.37)	(0.36)	(0.38)
Multiracial	-0.27	-0.27	-0.38
	(0.27)	(0.27)	(0.29)
Constant	5.01^{***}	6.05^{***}	6.28^{***}
	(0.27)	(0.35)	(0.38)
Observations	2,814	2,815	2,814
Log Likelihood	-912.05	$-1{,}089.65$	-893.91
Akaike Inf. Crit.	1,854.11	2,207.31	1,819.81
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table summarizes the results of three separate logistic models of the survey response to a question about the I-1631 ballot language. All models weight observations using inverse probability weights based on sex, marital status, race, age, education, religious observance, and political party using the 2018 exit poll (using R's svyglm command). *Non-Environmental Ideology* estimates latent ideology from 42 issue questions that are not about the environment or energy. *Environmental Ideology* estimates latent ideology from the 11 questions on the environment and energy (appendix B).
Source: Our Amazon Mechanical Turk survey on November 5-6 in 2018, and the 2018 exit poll by Edison Research and the National Election Pool for the weights.

F Ballot initiatives and advisory questions in Washington State in 2016 and 2018

F.1 2016 initiatives and advisory questions in Washington State

See `https://ballotpedia.org/Washington_2016_ballot_measures` for more details.

Initiative 732 would have imposed a carbon emission tax on certain fossil fuels and fossil-fuel-generated electricity. The measure was defeated.

Initiative 735 urged a federal constitutional amendment that limits constitutional rights to people, not corporations. The measure was approved.

Initiative 1433 was designed to increase the state minimum wage to $13.50 by 2020. It was approved.

Initiative 1464 would have created a campaign-finance system allowing residents to direct state funds to qualifying candidates, repealed the non-resident sales-tax exemption, restricted employment of former public employees and lobbying, and revised campaign-finance laws. The measure was defeated.

Initiative 1491 authorized courts to issue extreme risk protection orders to remove an individual from access to firearms. The measure was approved.

Initiative 1501 increased criminal identity-theft penalties and expand civil liability for consumer fraud targeting seniors and vulnerable individuals. It exempted certain information regarding vulnerable individuals and in-home caregivers from public disclosure. The measure was approved.

Advisory Vote 14 asked voters whether to repeal or maintain a tax on certain dental plans whose premiums are $25 to $50 per member per month. The repeal option won.

Advisory Vote 15 asked voters whether to repeal or maintain a sales tax exemption on the first $32,000 of the purchase price of qualifying new alternative fuel vehicles. The repeal option won.

The Washington Advancement of Date for Completion of Redistricting Plan Amendment, also known as Senate Joint Resolution No. 8210, was on the November 8, 2016, ballot in Washington as a legislatively referred constitutional amendment. It was approved.

F.2 2018 initiatives and advisory questions in Washington State

See `https://ballotpedia.org/Washington_2018_ballot_measures` for more details.

Initiative 940 requires specific training for law enforcement and changes the standards for use of deadly force. It was approved.

Initiative 1631 establishes a carbon fee and funds environmental programs. It was defeated.

Initiative 1634 prohibits local governments from enacting taxes on groceries. It was approved.

Initiative 1639 implements changes to gun ownership and purchase requirements. It was approved.

Advisory Vote 19 advises legislature to either repeal or maintain Senate Bill 6269 which expanded the oil spill response tax to apply to pipelines. The repeal option won.