Can Pigou at the Polls Stop Us Melting the Poles?*

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June 4, 2022

Abstract

Economists recommend Pigouvian taxes as the most efficient way to fight climate change. Yet, carbon taxes are difficult to implement politically. To understand why, we study Washington State's two failed carbon tax referendums from 2016 and 2018—the first such votes in the United States. We find that average voters' opposition to the carbon tax can partly be explained by the anticipation of higher energy costs. Meanwhile, ideology—as measured by voting on other initiatives—explains 90% of variation in voting across precincts. These results suggest that ideology plays a crucial role in driving opposition to carbon taxes. We find that revenue recycling interacts with ideology: conservatives preferred the 2016 revenue-neutral policy, while liberals preferred the 2018 green-spending policy. Finally, we forecast that no other state is liberal enough to pass Washington's policies. Thus, opinion surveys showing majority support for the carbon tax can be misleading.

JEL classification numbers: D72, H23, H71, H72, Q52, Q54, Q58

Keywords: Pigouvian taxes, carbon taxes, voting behavior, willingness to pay, state environmental policy

*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, Matthew Incantalupo, and Sheila Olmstead (the editor) and three anonymous referees 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, Brigham Young University, and Stanford University for many helpful comments and suggestions. Ioana Marinescu acknowledges financial support from the Kleinman Center for Energy Policy at the University of Pennsylvania.

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1 Introduction

Estimates for 2020 put the social cost of carbon at \$14-\$152 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 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 can a carbon tax be passed? One view is that forming a bipartisan coalition would be easier if carbon taxes were more acceptable to conservatives who tend to favor limited government. This view supports using carbon tax revenue to lower other taxes, i.e. a revenue-neutral policy. An alternative view sees the bipartisan approach as doomed to failure—presuming that conservatives would reject a carbon tax of any flavor, while progressives would actually prefer to increase government spending. This alternative view supports spending carbon tax revenue on green projects and social programs to maximize liberal support.

How important are energy costs vs. political considerations in explaining voters' willingness to pay (WTP) for carbon taxes? Does revenue recycling matter? Surveys indicate that support is largely driven by political ideology (Egan and Mullin 2017) and can depend on how the revenue is spent (Amdur, Rabe, and Borick 2014; Kotchen, Turk, and Leiserowitz 2017). Do these result hold up in real-world voting? 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—the first carbon tax referendum in the United States—would have lowered the state sales tax from 6.5% to 5.5% and matched the federal Earned Income Tax Credit (EITC) by 25%. Initiative 1632 (I-1631) from 2018 would have devoted 95% of carbon tax revenue to green projects (e.g., renewable energy). I-732 and I-1631 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.

[1] See here: https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.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 dioxide into the atmosphere. Also see here: https://carbonpricingdashboard.worldbank.org/.

[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.

First, we investigate what drives support for the carbon tax among Washington's voters, focusing on ideology and WTP for the carbon tax. To do so, we use observed variation in voter characteristics across precincts, and variation in carbon tax policy parameters between 2016 and 2018. We seek to answer two questions. One: What explains the wide variation in support for the carbon tax across precincts? Overwhelmingly, we find the answer to be ideology. We infer latent ideology from votes on a dozen *other* policies (e.g., clean car subsidies and a higher minimum wage).[3] Ideology alone explains 91% of the variation in vote shares across precincts and predicts votes better than partisanship (as measured by the Republican vote share). In contrast, demographic variables—including key proxies for carbon tax incidence (e.g., car ownership and home size)—predict relatively little of the variation across precincts. Ideology also explains changes in support between 2016 and 2018. 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 that I-1631 performed better in liberal precincts, where it picked up 3.3 percentage points relative to I-732—but worse in conservative precincts, where it lost 0.65 percentage points relative to I-732. Two: Why did the carbon tax fail to gain majority support? Here, we find that part of the answer is opposition to higher energy prices. We calculate the direct tax incidence due to personal energy consumption for each precinct and measure its impact on voting, which allows us to back out the distribution of WTP for the overall policy across precincts. For the average precinct, we find that the tax incidence (about $100 per person per year) is important in driving opposition to the carbon tax. Yet, this tax incidence is similar across precincts, which rationalizes why ideology rather than pocketbook issues explains most of the variation in vote shares across precincts.

Second, we use our regression results to predict how the vote in Washington would have changed, were Washington assigned the same ideology and demographics as other states. This exercise is akin to an out-of-sample forecast for the carbon tax vote shares in other states. Based on this exercise, 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 could have the highest possible chance of passing in Vermont (50.6% 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 (47.1% support). Again, I-732 would do better in both New York and Hawaii (47.2% and 47.8%), but neither state has the popular initiative. The states that show the highest predicted support generally already have some form of carbon pricing, typically through cap-and-trade. In fact, Washington state passed its own cap-and-trade legislation in May 2021. Passing a carbon tax via popular referendum appears to be a more difficult route to achieve carbon pricing.

This paper contributes to the literature in political economy and public economics that uses votes in

[3]Ideology is the latent concept we measure using the observable signals of support for all ballot initiatives during the time of the relevant election. This is a technique used in a variety of studies (Snyder 1996; Gerber and Lewis 2004; Masket and Noel 2012). These studies validate the notion that district ideological opinion is mostly one-dimensional.

referendums to measure policy preferences. We are the first to analyze voting on a carbon tax in the United States, where climate issues remain highly politicized. A carbon tax is arguably *the* most salient policy in environmental economics research: climate change looms as the largest environmental problem we face, carbon taxes are almost always the benchmark by which other policies (e.g., fuel economy standards) are judged, and Pigouvian taxes conceptually underpin the entire sub-field of environmental policy design (e.g., via their symmetry to cap-and-trade programs). The closest papers are Bornstein and Lanz (2008), who study voting on three proposals to tax the energy content (but not the carbon content) of nonrenewable energy in Switzerland in 2000, Kahn and Matsusaka (1997) and Burkhardt and Chan (2017), who estimate demand for environmental policy (but not carbon pricing) using votes on a wide range of initiatives in California, and Holian and Kahn (2015), who study a failed 2010 vote to repeal California's cap-and-trade program (but not a carbon tax).[4]

In addition to our unique focus on a U.S. carbon tax, we make several methodological contributions relative to these papers. First, we measure ideology separately from partisanship using votes on a dozen wide-ranging social, economic, and environmental policy issues. Our approach is related to that of Bornstein and Lanz (2008), who measure ideology using votes on five transportation-related referendums. We show that a more generic measure of left-right ideology is highly predictive of voting on the carbon tax. Second, we go beyond merely explaining vote shares by measuring the overall willingness to pay (WTP) for the policy in dollars. Only one other study does this: Burkhardt and Chan (2017), who estimate median WTP for environmental policy (but not carbon pricing) in California as a whole. We build on this study by estimating WTP for a carbon tax for every precinct in our sample and showing the full distribution across precincts. We find vast heterogeneity in WTP across precincts. In addition, we decompose WTP into four components (vs. two), which allows us to show directly that ideology explains most of the variation in WTP across precincts, while energy tax incidence explains very little. This heterogeneity matters both for understanding distributional impacts and for campaign strategy (e.g., fundraising in the tails and targeting marginal voters). Third, we show based on a bounding exercise that tax incidence also explains relatively little of the variation in WTP across *individuals*. Thus, we are able to say more about individual-level heterogeneity than these other studies, which also rely on aggregate data. Finally, we use out-of-sample forecasts to illustrate the weak prospects for a carbon tax in other states, which is a wholly novel contribution.

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

[4]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.

gap has only widened in recent decades.[5] Our main contribution here is to use *actual voting data* on a carbon tax. Like the survey literature, we find that partisanship is an important driver of support for a carbon tax.[6] 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. Further, our results offer a cautionary tale for the ability of surveys to predict the political viability of carbon taxes: carbon taxes failed at the polls even though they were popular in surveys, with 68% of Americans in a 2018 Yale survey saying they support making fossil-fuel companies pay a carbon tax.[7] Of course, Yale and others can frame their survey questions however they want, and respondents answer hypothetically in a low-information environment, free of political messaging—where it might not be obvious, for example, that a tax on oil companies will lead to higher gasoline prices. But in an actual election, the ballot language is constrained, people are voting for real, and voters are bombarded with all kinds of information, including objective analysis and motivated campaign messaging that emphasizes both positives and negatives.

Finally, we contribute to a literature that studies the political feasibility and durability of carbon regulation, including the role of revenue recycling. See Rabe (2018) for a thorough review. In economics, two papers use post-election surveys to analyze failed Swiss referendums to tax nonrenewable energy. Thalmann (2004) finds that voters in 2000 prefer spending on green projects to cuts in other taxes, but the energy tax rates also differed across these policies (lower for green projects), muddying the comparison of their revenue-recycling schemes.[8] Meanwhile, Carattini, Baranzini, Thalmann, Varone, and Vöhringer (2017) find that voters in 2015 prefer green projects but switch to preferring hypothetical lump-sum rebates when informed in a choice experiment about the progressive distributional effects. In Canada, Mildenberger, Lachapelle, Harrison, and Stadelmann-Steffen (2022) find that survey respondents in 2019 systematically underestimate the size of their federal carbon tax rebates. Conservatives underestimate rebates more than liberals and show no increase in policy support when properly informed, but rather decrease in their belief that they receive more than they pay. In France, Douenne and Fabre (2019) find that survey respondents in 2019 would reject a carbon tax and dividend, in part because they are misinformed about the distributional and environmental 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

[5] 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.

[6] 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, 1980s, and 1990s.

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

[8] Bornstein and Lanz (2008) study the 2000 referendums using actual voting data by municipality but do not focus on the political trade-offs due to differences in revenue recycling.

carbon tax revenue. We compare two different flavors of a carbon tax in back-to-back election cycles in the same state. Thus, we provide the most direct evidence to date on how actual voters perceive and react to different revenue-recycling schemes—with the obvious limitation that we observe only two votes, and that other factors could have been at play. Our WTP 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, if at all. Yet, beyond the average voter, we find that liberal voters prefer green spending, while conservative voters prefer the revenue-neutral policy, implying 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 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. Section 5 tests whether economic incidence has a detectable impact on support for a carbon tax and estimates 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. 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.[9] 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 address distributional concerns), and reduced taxes on manufacturing businesses (to mitigate opposition from energy-intensive industry). Carbon Washington patterned this revenue-neutral "carbon tax swap" after a similar policy adopted by British Columbia in 2008. 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 important and well-resourced 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).[10] The Alliance's strategy was to explicitly

[9] Bauman styles himself as "The world's first and only Stand-Up Economist." See here: http://standupeconomist.com.
[10] See the Alliance's web page for a statement of principals and list of members: https://jobscleanenergywa.com.

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

	I-732	I-1631
Year	2016	2018
Provisions	Revenue-neutral carbon tax swap \$15/tCO2 in July 2017, \$25/tCO2 in July 2018, then increase 3.5% per year to \$100/tCO2 Slower phase-in for farmers and public transportation Reduce state Sales Tax by 1% from 6.5% to 5.5% Reduce state Business & Occupation Tax on manufacturing businesses to 0.001% Offer Working Families Tax rebate (25% match on federal Earned Income Tax Credit)	Carbon emissions fee and spending \$15/tCO2 in January 2020, then increase \$2/tCO2 per year until state's emissions reduction goals met Levied on "large emitters" using and distributing fossil fuels Revenue to three funds: (1) 70% air quality & energy projects, (2) 25% water quality & forest projects, and (3) 5% for communities Establish public oversight board to determine spending from funds Create three panels to make spending recommendations to public oversight board
Results	40.75% Yes, 59.25% No	43.44% Yes, 56.56% No
Spending for	\$3,154,984.98	\$16,398,381.52
Spending against	\$1,418,005.71	\$31,591,364.54
Top spenders for	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 against	Kaiser Aluminum (\$450,000)	BP America (\$13.15 million), Phillips 66 (\$7.2 million), Andeavor (\$6.1 million)

Source: Ballotpedia

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 negotiate 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 who supported and opposed the two initiatives). 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;[11] (2) a belief that 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 similar: a carbon tax starting at \$15/tCO2 and then rising gradually. However, on the revenue-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.[12] 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. Of course, since liberals tend to prioritize immediate action on climate change more than conservatives, these are differences more of degree than of kind.

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 would alienate those progressives and win very few conservatives. Second, the I-1631 ballot language avoids the dreaded word "tax" and instead describes a "fee" on carbon.

In the following sections, we show that the Alliance's forecast was at least partly correct: I-1631 performed substantially better than I-732 in liberal precincts—and somewhat worse in conservative ones. These outcomes are consistent with objective differences in revenue recycling. However, we cannot rule out other contributing factors. For example, forward-looking liberal voters in 2016 might have hoped for a better policy in the near future, which may have dampened their enthusiasm for I-732.[13] The reported frictions between Carbon Washington and the Alliance may have reinforced these feelings. In addition, support for carbon taxes has been trending upward over time, according to the Yale Climate Opinion survey cited in the introduction, and this trend may be stronger among liberals. The surge of enthusiasm among Democratic voters ("blue wave") in 2018 may have further contributed to the divergent outcomes. Finally, total cam-

[11]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. See Ballotpedia here: https://ballotpedia.org/Washington_Carbon_Emission_Tax_and_Sales_Tax_Reduction,_Initiative_732_(2016).

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

[13]This mechanism implies that the difference between the support for 1-732 and I-1631 is larger than what would be predicted by differences in revenue recycling alone. To the extent that voters listen to elite cues instead of *only* paying attention to policy design, it could also be that liberal elites were able to depress support for I-732 and boost support for I-1631.

paign 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). These differences in spending may have influenced both the overall levels and patterns of support for the 2016 and 2018 policies.

3 Voting data

In this section, we describe our data sources and procedures. Our main data come from the State of Washington Secretary of State (WA SOS) and record precinct-level election results from Washington State in the November 2016 and 2018 general elections.[14] 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 two-party share voting Republican in 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. We use Republican vote share to measure partisanship. In addition, the WA SOS data 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 registered voters that recorded a vote either for or against the carbon tax in 2016 and 2018 (carbon tax turnout). The latter measure of turnout is generally lower due to roll-off, which is when voters turn in a ballot without making all possible choices. For comparison, we also calculate similar turnout measures for other initiatives and elections.

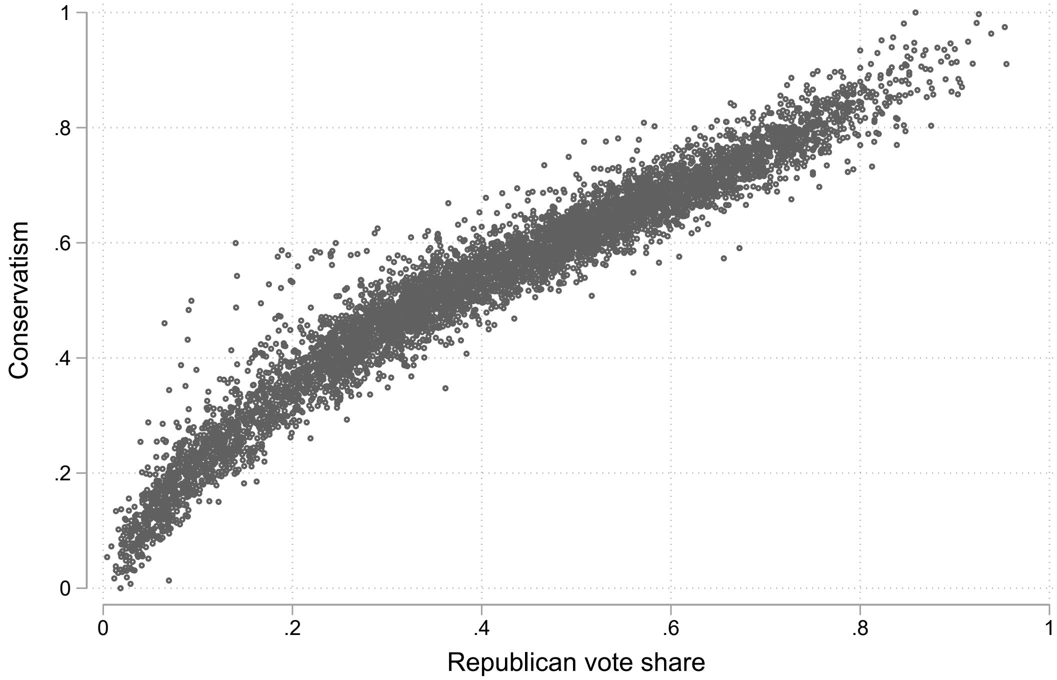
To measure latent ideology, we conduct a principal component decomposition of the precinct-level vote shares on twelve *other* ballot measures from November 2016 and 2018. These measures cover a wide range of social, economic, and procedural issues.[15] We find that the first component in this decomposition explains 80% of the variation in voting on these ballot measures.[16] We interpret this component as an index measure of issues-based latent ideology. We linearly transform this index to range from zero (most liberal) to one (most conservative). In our results, we label our measure of ideology as "conservatism" to facilitate interpretation, since ideology in principle could go from left to right or vice versa. Figure 1 plots our resulting measure of conservative ideology vs. the share voting Republican in each precinct, the latter being a measure of

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

[15] See appendix B for details of each measure and appendix figure 11 for scatter diagrams plotting vote shares on these other state ballot measures versus the presidential vote share. Also see appendix D, which presents summary statistics and figures demonstrating that turnout on these various measures and the carbon tax is uniformly high, is strongly correlated across precincts, and follows the same pattern relative to ideology (i.e., uniformly high for liberal and conservative precincts with a slight dip among moderates). These results are consistent with the same voters (or types of voters) voting on all of the ballot measures, which supports our issues-based approach to measuring a precinct's latent ideology.

[16] The eigenvalue on the first component is 9.60, which implies that this component explains $9.60/12 = 80\%$ of the variation spanned by the twelve ballot measures.

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



Note: This figure plots our constructed index of conservative ideology vs. the Republican party vote share in the 2016 presidential election for 6,219 precincts in Washington State. Our index of conservative ideology is based on votes for ballot measures other than the carbon tax in 2016 and 2018 (see appendix B).
Source: WA SOS.

partisanship. The figure shows that, while these two measures are highly correlated (note the correlation coefficient of 0.97 in table 2 below), they are not perfectly correlated. Indeed, at each level of Republican vote share, there are both relatively conservative and relatively liberal precincts. Thus, we are able to estimate support for the carbon tax conditional on *both* measures below.

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).[17] 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 these population shares to U.S. Census blockgroup aggregate data (e.g., share people age 40-44 or share of households with incomes $50,000-$60,000). 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.[18]

[17]We thank Nicholas Pharris at WA SOS for providing these data.
[18]We calculate for 2016 that 34% of precincts overlap with one block group, 37% overlap with two, 18% overlap with three,

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, or workers 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.[19] 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.[20] Coefficients on these variables (e.g., population share age 40-44) intuitively have the same interpretation as those on a dummy variable (e.g., probability shift for a voter age 40-44). We also control for average household size (i.e., total population divided by number of households).

Given the monocentric city model (von Thünen 1826; Fujita 1989), we expect suburban and rural households to occupy larger single-family homes and to commute longer distances via car, such that they will consume more energy than urban households and be more affected by a carbon tax. We therefore include home size, owner-occupied, number of cars, and car commuting time among our covariates, to capture these important differences between urban, suburban, and rural areas. We also control directly for the share of households in the surrounding county that live in an urbanized area. In some models, we also control for county fixed effects, which absorb this variable and any other observed and unobserved differences across counties, including housing and population density. See table 7 for our full set of covariates.

We make several sample restrictions. First, we limit our analysis to precincts that did not experience boundary changes between 2016 and 2018.[21] Our focus on these precincts allows us to directly measure changes in support for the carbon tax between 2016 and 2018, and to measure a precinct's ideology using ballot initiatives from both years. This restriction omits 9% 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 latent partisanship and ideology.[22] This restriction omits an additional 4% of precincts. Finally, we focus

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.

[19] Our detailed census variables measure population shares by narrow category of: car commute time (for people age 16+); education (for people age 25+); industry (for workers age 16+); number of vehicles (1,2,3,4,5+), annual income, live in urbanized area, owner occupied, home value, and # of rooms (for households); and age, race, and gender (for all people).

[20] 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.

[21] 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.

[22] 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

Table 2: *Summary statistics and correlation coefficients for election-based variables*

	Mean	Std. Dev.
Yes on I-732 (2016)	0.409	0.125
Yes on I-1631 (2018)	0.434	0.172
Yes on carbon tax (pooled)	0.421	0.151
Republican	0.412	0.192
Conservatism	0.530	0.177

	732	1631	Pooled	Rep.	Cons.
732	1.00				
1631	0.94	1.00			
Pooled	0.95	0.96	1.00		
Rep.	-0.94	-0.95	-0.93	1.00	
Cons.	-0.95	-0.98	-0.95	0.97	1.00

Note: The left panel of this table reports means and standard deviations for our estimation sample of 6,219 precincts (12,438 observations in our pooled sample), weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. The first two variables measure share voting "yes" on the carbon taxes in 2016 and 2018. The third variable stacks these outcomes in a pooled sample of precinct-year observations. *Republican* measures the share voting for the Republican (vs. Democrat) in the 2016 presidential election. *Conservatism* measures ideology on a 0-1 index. The right panel reports pairwise correlation coefficients for all five variables, again weighted by total votes cast for the Republican or Democratic candidate for president in 2016.
Source: WA SOS.

on observations with complete census data. This restriction omits just 0.06% of precincts. In the end, we are left with a sample size of 6,219 precincts for 12,438 pooled observations across our two elections (2016 and 2018). Our final sample includes 87% of the 2016 precincts representing 88% of the state's population and 89% of the voter turnout.

Table 2 presents summary statistics and pairwise correlation coefficients for the election-based variables measuring support for the carbon tax in 2016 and 2018, along with Republican share and conservative ideology. We weight by the total presidential vote so that our sample statistics more closely reflect the underlying population of voters, rather than precincts. Note that support for the carbon tax is strongly negatively correlated with both Republican share and conservative ideology (correlation coefficients ranging from -0.93 to -0.98). Meanwhile, table 7 in the appendix reports summary statistics for the full set of census demographic variables, including important correlates of household carbon footprint (e.g., car ownership and home size).

4 Who supports a carbon tax?

In this section, we investigate the correlates of support for the carbon tax using aggregate precinct-level voting data for I-732 and I-1631. We focus on how ideology and partisanship predict votes for the carbon tax at the precinct level, and we document the policy preferences ideology captures. We then compare the 2016 and 2018 carbon tax initiatives in terms of their appeal to different ideological segments of the voting population. Finally, we show that our results are robust to several data issues and modeling choices.

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.

4.1 Explaining overall support using pooled 2016 and 2018 data

Figure 2 shows the share voting "yes" on each of the two carbon taxes by decile of the Republican vote share in the 2016 presidential election.[23] 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 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.[24] In principle, the negative correlation between support for the carbon tax and Republican share in this figure could reflect political ideology—or it might simply reflect the fact that Republicans tend to live in the suburbs, where people own more cars, have longer commutes, and reside in bigger houses, and would therefore see larger increases in energy costs under a carbon tax. Therefore, we also explore the relationship between support for a carbon tax and political ideology in regressions that control for these and other variables.

Table 3 presents OLS regression results for precinct-level carbon tax vote shares conditional on ideology, partisanship, and demographics. We continue to weight by the total presidential vote in each precinct; unweighted results are nearly identical. These regressions pool voting outcomes from 2016 and 2018; each regression includes a 2018 dummy, but the other explanatory variables are purely cross-sectional.[25] Conservative ideology is a highly significant predictor of support for the carbon tax with an R-squared of 91.3% (column 1).[26] On average, support for the carbon tax falls by 81 percentage points 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 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 90.6% (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. These variables both range from 0 to 1 and have nearly identical variance (see figure 1 and table 7), facilitating a direct comparison of their

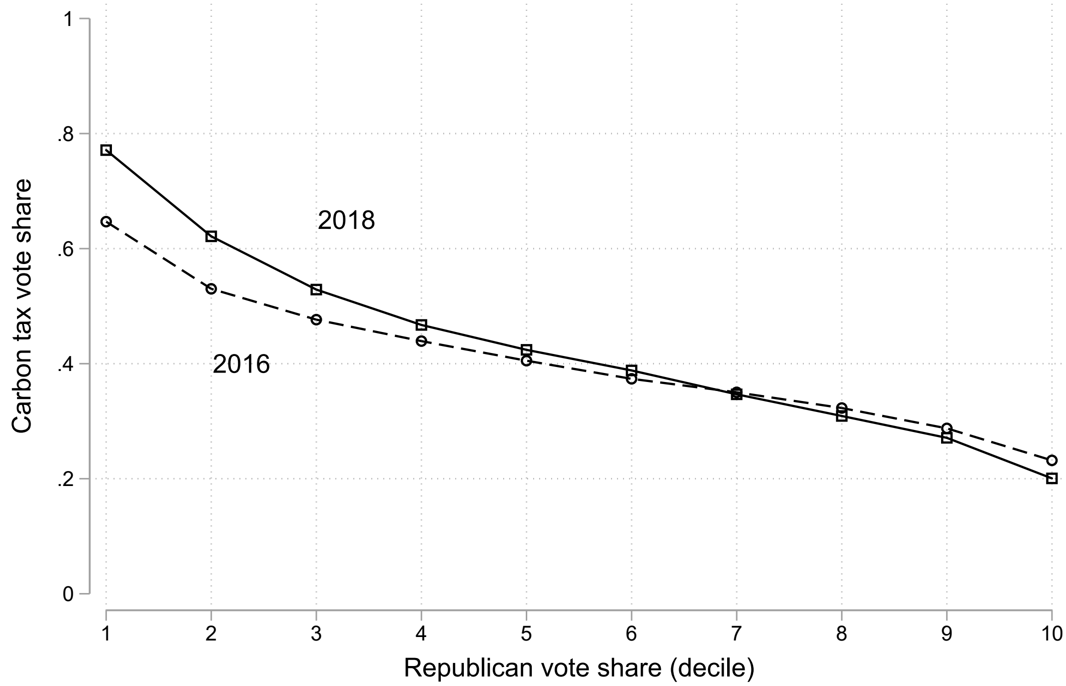
[23] See appendix figure 14 for the underlying precinct-level vote shares.

[24] Figure 15 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 16 for the underlying precinct-level vote shares by conservative ideology.

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

[26] By itself, the 2018 dummy has an R-squared of just 0.7%. Thus, as an approximation, we wholly attribute the R-squared values in this table to the other variables.

Figure 2: *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.

regression coefficients. Thus, if we were to treat this as a causal model (i.e., no correlated omitted variables), the results would imply that ideology is the dominant driver of support for a carbon tax. In principle, there could be some other variable—highly correlated with ideology—that is the true, underlying driver of support for a carbon tax, and controlling for this hypothetical variable would substantially undermine the apparent contribution of ideology. It is difficult to know what such a variable or set of variables might be, given that we already control for partisanship and an exhaustive set of detailed demographic controls. Yet because we cannot rule out this possibility, our results are merely *consistent* with the idea that ideology is the main driver of policy preferences and votes. Either way, the predictive value of partisanship is substantially weakened when we control for ideology, while the reverse is not true.[27] Likewise, demographic variables

[27]This pattern shows that we can separately identify the predictive effect of ideology vs. partisanship, despite the high correlation between the two. If ideology and partisanship were essentially the same, we would expect to see highly imprecisely estimated coefficients when including both.

Table 3: *Predicting the carbon tax vote share at the precinct level (pooled 2016 and 2018)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +County FEs	(6) +Initiatives
Conservatism	-0.814***			-0.669***	-0.665***	
	(0.013)			(0.019)	(0.018)	
Republican		-0.730***	-0.635***	-0.124***	-0.139***	-0.046**
		(0.026)	(0.021)	(0.018)	(0.018)	(0.016)
2018 vote	0.026	0.026	0.026	0.026	0.026	0.026
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	12438	12438	12438	12438	12438	12438
R^2	0.913	0.870	0.906	0.926	0.929	0.932

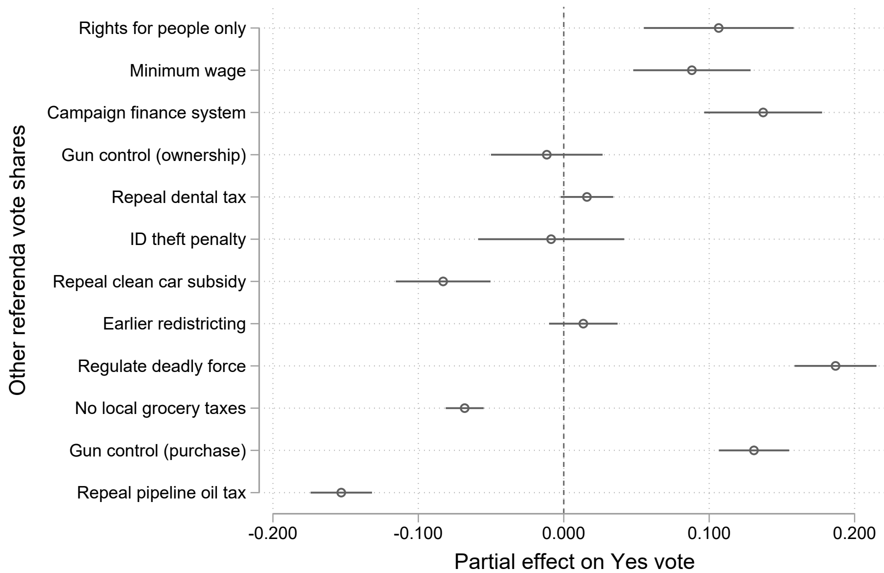
Note: This table presents coefficient estimates from pooled precinct-level OLS regressions modeling the share voting "yes" for the carbon tax in 2016 and 2018 as a function of ideology, demographics, and other factors. *Conservatism* measures ideology on a 0-1 index, computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018 (see appendix figure 11). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. *2018 vote* is an indicator for the 2018 carbon tax (I-1631). Models (3)-(6) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., # vehicles, commute time by car, industry, home value, # rooms, income, gender, age, race, education, household size, urban share, and owner-occupied share). Model (4) then adds ideology. Model (5) then adds county fixed effects. Finally, model (6) replaces ideology with vote shares for the 12 individual ballot initiatives. 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).
$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.
Source: WA SOS & U.S. Census.

(including key proxies for energy tax incidence, such as car ownership) contribute relatively little predictive power to a model that already controls for ideology and partisanship.

As suggested above, one potential concern is that we have omitted important variables that are correlated with partisanship and ideology, undermining our interpretation of these variables as the dominant drivers of support for a carbon tax. We are mainly concerned about omitted correlates of energy use, such as vehicle fuel economy, or local climate conditions. To address this concern, we include county-level fixed effects, which would help control for any such variables that differ across counties. We find that the coefficients on ideology and partisanship do not change (column 5). Overall, these results confirm that the strong correlation we observe in figure 2 between support for a carbon tax and political ideology is *not* primarily driven by differential energy tax incidence for liberals vs. conservatives.

Recall that we measure ideology by exploiting the presence of twelve statewide ballot measures considered by Washington voters in 2016 and 2018 (see appendix B). 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 principal component decomposition. Creating an index allows us to capture the effects of ideology in a single, intuitive measure. This approach is based on the assumption that voting on these other measures is also ideological

Figure 3: *How votes on other ballot measures predict the vote on the carbon tax in 2016 and 2018*



Note: This figure plots coefficients from the regression reported in column (6) of table 3. This is 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). 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 B for more details on each of the measures). Point estimates are represented by dots, while 95% confidence intervals (based on standard errors clustered by county) are represented by horizontal lines. Control variables include the share voting Republican (vs. Democrat) in the 2016 U.S. presidential election, the 2018 vote dummy, detailed census variables (i.e., # vehicles, commute time by car, industry, home value, # rooms, income, gender, age, race, education, household size, urban share, and owner-occupied share), and county fixed effects.
Source: WA SOS & U.S. Census.

in nature and consistent across issues.

To probe deeper, we estimate an additional regression model (6) in table 3. This model is identical to model (5) in the table but replaces the ideological index (Conservatism) with "yes" vote shares for all twelve of the individual ballot measures (i.e., included simultaneously). Figure 3 reports the coefficient estimates on these variables. 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. This result is consistent, however, with the notion of ideology acting as a psychological constraint on beliefs and policy preferences (Converse 1964).

4.2 Comparing two flavors of the carbon tax in 2018 vs. 2016

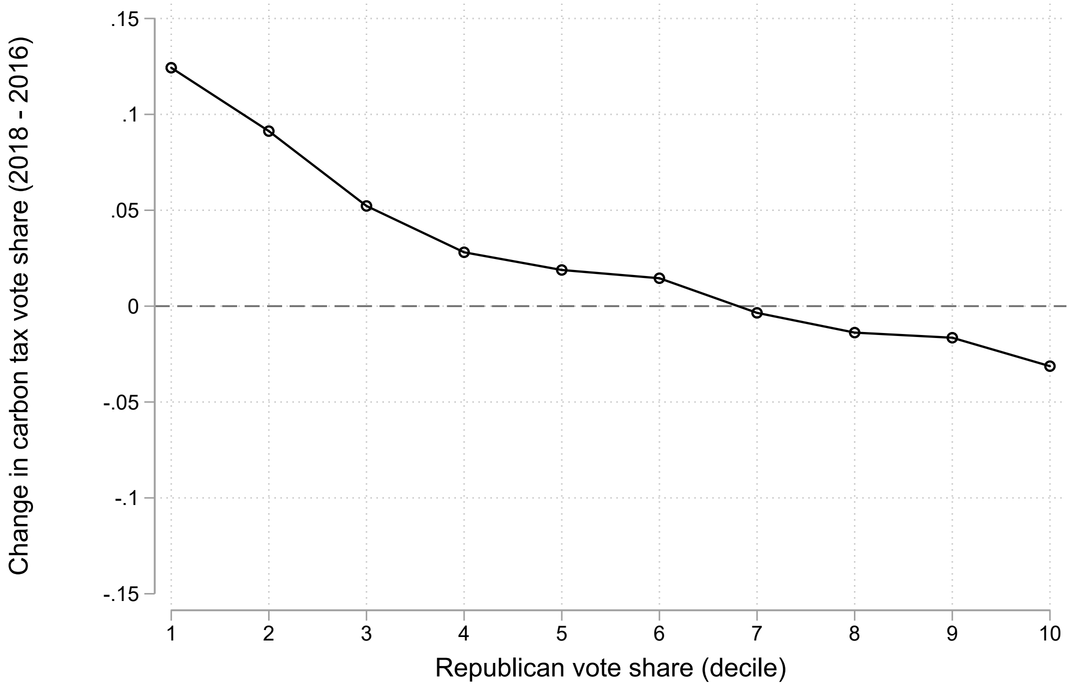
Above, we study the overall *level* of support for carbon taxes. Here, we explore *differences* in support for a green-spending policy (I-1631 in 2018) relative to a revenue-neutral policy (I-732 in 2016). To begin, figure 4 plots the *change* in support for I-1631 relative to I-732 by decile of Republican vote share.[28] The figure shows that 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 3.29 percentage points in cumulative vote share relative to I-732 among more liberal precincts (deciles 1-6) and lost 0.65 percentage points among more conservative precincts (deciles 7-10) for a net gain of 2.64 percentage points.[29] We are hesitant to make any strong causal claims based on a before-after comparison of voting outcomes, since liberal vs. conservative support could have shifted for other reasons. However, the pattern of these gains and losses is consistent with the hypothesis that both the progressive (green-spending) design of I-1631 as well as the moderate- and conservative-appealing design of I-732 worked as intended by their respective promoters—at least to a degree.

Next, we regress *changes* in the precinct-level vote share on ideology, partisanship, demographics, and other variables. Table 4 presents the OLS regression results—with positive coefficients indicating that a 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 27.8 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 44.1% (column 2). On average, the green-spending policy loses 23.7 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). As above, the coefficient on Republican share shrinks dramatically when we control for conservative ideology, while the coefficient on ideology remains high (column 4). Again, these inferences are robust to including county-level fixed effects (column 5). Replacing the ideology variable with support for each of the ballot initiatives does not substantially change the coefficient on Republican (column 6). Our regression results

[28]See appendix figure 14 for the underlying precinct-level changes in vote shares.

[29]Figure 15 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 16 for the underlying precinct-level changes in vote shares by conservative ideology.

Figure 4: *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.

are thus consistent with figure 4, showing that more liberal districts prefer the green-spending version of a carbon tax, while conservatives prefer the revenue-neutral policy. Further, our results are consistent with the idea that ideology (which varies across precincts), interacting with differences in the perceived attributes of the two policies, is the main driver of the shift in support for I-1631 relative to I-732. In principle, there could be some other cross-sectional variable—highly correlated with ideology—that explains why liberals preferred the 2018 policy, such that controlling for this variable would render ideology irrelevant. But this does not seem especially plausible, given our controls for partisanship and demographics. Meanwhile, liberal vs. conservative support for carbon taxes could have been shifting over time for reasons having little to do with the details of these two policies, e.g. changes in the amounts spent on campaigns. Regardless, we can say the predictive value of partisanship is severely undermined when we control for ideology, while demographics contribute relatively little predictive value.

Table 4: *Predicting the change in the carbon tax vote share (2018 minus 2016)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +County FEs	(6) +Initiatives
Conservatism	-0.278***			-0.268***	-0.249***	
	(0.011)			(0.047)	(0.019)	
Republican		-0.237***	-0.224***	-0.020	-0.049*	-0.033
		(0.013)	(0.015)	(0.044)	(0.023)	(0.024)
Observations	6219	6219	6219	6219	6219	6219
R^2	0.514	0.441	0.618	0.634	0.689	0.755

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. Models (3)-(6) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., # vehicles, commute time by car, industry, home value, # rooms, income, gender, age, race, education, household size, urban share, and owner-occupied share). Model (4) then adds ideology. Model (5) then adds county fixed effects. Finally, model (6) replaces ideology with vote shares for the 12 individual ballot initiatives. 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).
$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.
Source: WA SOS & U.S. Census.

4.3 Robustness checks

This subsection discusses the sensitivity of our results to sample selection, shifts in partisanship over time, ecological regression bias, and potential bias caused by differential turnout (e.g., by political party).

Sample selection. Recall from section 3 that our estimation sample omits approximately 9% of precincts due to changing precinct boundaries and an additional 4% of precincts with small vote counts. Regression on this selected sample will yield consistent estimates if the full-sample error terms (u) are uncorrelated with each of the covariates (x_j) in the selected sample: $E(su \cdot sx_j) = 0$, where s is a selection indicator equal to 1 if the observation is included and 0 otherwise (Wooldridge 2020). We test this condition directly by (i) regressing support for the carbon tax in 2016 on Republican share using the full cross-sectional sample of 2016 precincts (analogous to regression 2 in table 3), (ii) generating the residuals, and (iii) regressing these residuals on Republican share in the selected sample. We use Republican vote share for this analysis because Republican share is never missing, while ideology is missing for the 2016 precincts that later experienced boundary changes. The resulting coefficient is 0.0030 (equal to the difference in coefficients between the full and selected samples in 2016) and statistically insignificant with a heteroskedasticity robust standard error of 0.0033. Meanwhile, the model R-squared is just 0.0002, and an F-test for the model's overall significance fails to reject that the model explains nothing (P-value of 0.3082). When we repeat this procedure adding our full set of census demographic controls and county fixed effects, coefficients on Republican share are small and insignificant, model R-squared values remain near zero, and F-tests for overall significance still fail to reject (P-values near 1). Thus, we conclude that the sample selection bias here is minuscule.

Shifts in partisanship. We use a single, cross-sectional measure of partisanship based on the Republican presidential vote share in 2016 to explain support for the carbon tax in both 2016 and 2018. This approach could yield biased estimates if partisanship shifted over time within precincts, perhaps due to differential changes in turnout for Republicans vs. Democrats in a presidential vs. midterm election. To explore this issue, we measure partisanship using 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). We replicate figures 2 and 4 based on this alternative, year-specific measure of partisanship. We find that the results look nearly identical (see appendix figure 17). Likewise, we replicate regression (2) from table 3 using this year-specific measure of *Republican* and obtain a coefficient of -0.853 (see column 4 in appendix table 12). This value is nearly identical to the -0.885 we get when using a cross-sectional measure based on Republican share in 2016 only, to parallel to our current approach (column 2 in the appendix table). Meanwhile, when we include both this new year-specific measure of *Republican* and our old cross-sectional measure of *Conservatism* simultaneously, we continue to find that the coefficient on *Conservatism* is larger (column 5 in the appendix table). This gap only magnifies when we use a cross-sectional measure based on Republican share in 2016 to parallel our current approach (column 3 in the appendix table) or based on a weighted average of Republican share from 2016 and 2018 (column 7 in the appendix table). Thus, our qualitative results are confirmed.

Ecological bias. To interpret the coefficient on Republican share as the effect of being an individual Republican voter on support for the carbon tax, all else equal, we must assume there is no ecological bias. Specifically, we must assume that Republican voters across precincts have the same opinion about the carbon tax (constancy assumption). If Republican voters in more Republican precincts dislike the carbon tax more, then the coefficient on Republican share—while still capturing the effect of partisanship in a generic sense—will overstate the effect of being an individual Republican voter drawn at random from the voting population. Ecological bias is less of a concern for the coefficient on ideology, because our measure of ideology captures aggregate policy preferences more finely, using votes on many other ballot measures. Individual voters differ continuously in their ideology. Thus, support for the carbon tax in a precinct will tend to be higher if there are more liberals in the precinct—or if the liberals in the precinct are *more* liberal. Our aggregate measure of ideology implicitly captures both effects.

Turnout. We measure aggregate support for the carbon tax among people that actually vote, i.e. conditional on turnout. If turnout varies with partisanship, ideology, and demographics, then the regression results in table 3 may not reflect the underlying preferences of voters. For example, suppose we are interested in the preferences of young people. Young people are more likely to support carbon taxes (positive effect on % support) but less likely to vote (negative effect on % support). So will the correlation between %

support and % young accurately reflect the preferences of young vs. old? Or is this correlation biased? Lang and Pearson-Merkowitz (2021) show that the bias is less severe when turnout is high and the level of geographic aggregation is small, and our precinct-level data from Washington compare favorably to similar studies in both dimensions.[30] To further explore this issue, appendix G develops a simple framework to assess whether differential turnout by party, ideology, and demographics is strong enough to severely bias our results. Our results in this appendix suggest that the bias is likely small. But we cannot definitively rule out bias, given the simplifying assumptions of our framework and reliance on aggregate data for calibration. Microdata based on exit polling could potentially speak to these concerns but are no panacea. Exit polling is fraught with challenges. Representative sampling is hard. Non-response is a real problem. If respondents in exit polls are selected on unobservables, the polls will yield neither a representative sample of voters, nor a representative sample of the underlying population, and the correlations based on exit polls could be biased. Meanwhile, our regressions based on aggregate data will at least remain valid as reduced-form correlations between voting outcomes and the underlying population.

5 Tax incidence and willingness to pay for a carbon tax

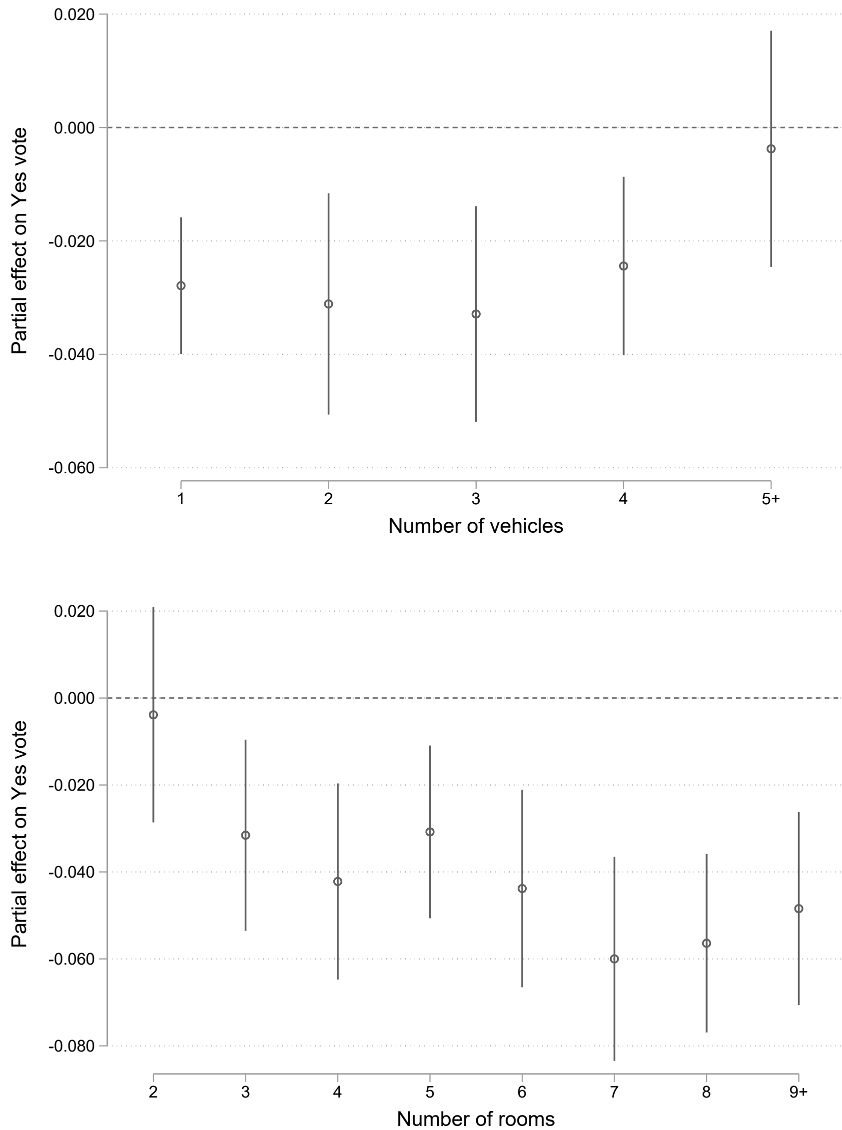
To what extent does personal tax incidence drive opposition to the carbon tax? Voters with the highest personal energy consumption—in particular, those consuming more gasoline to propel their cars, or more electricity and natural gas to power and heat their homes—will tend to incur the largest direct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

To test this proposition, figure 5 reports the coefficient estimates on number of vehicles and home size from model (6) in table 3 above.[31] 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 number of vehicles are all negative (upper panel). Thus, having at least one vehicle is associated with lower support for the carbon tax. Surprisingly, having many vehicles is not associated with especially low support, even though microdata show that gasoline consumption tends to rise linearly with number of vehicles (see appendix figure 19). However, note that fewer than 10% of households have four

[30] Washington turnout in 2016 was 79% among registered voters and 61% among those eligible to vote. These values were 72% and 53% in 2018. See Washington turnout data here: https://www.sos.wa.gov/elections/voter-participation.aspx. Meanwhile, three of the studies we cite use data from California (Kahn and Matsusaka 1997; Holian and Kahn 2015; Burkhardt and Chan 2017). These studies cover the years 1972-2010, during which time turnout averaged 62% among registered voters and 46% among those eligible to vote. These values were 60% and 44% in 2010, the year of California's cap-and-trade referendum, which is the focus of Holian and Kahn (2015). See California turnout data here: https://elections.cdn.sos.ca.gov/sov/2010-general/04-historical-voter-reg-participation.pdf. These California studies use county (Kahn and Matsusaka 1997), zip code (Burkhardt and Chan 2017), and precinct-level (Holian and Kahn 2015) voting data. The other study uses municipality-level data from Switzerland in 2000, reporting voter turnout of just 45% (Bornstein and Lanz 2008).

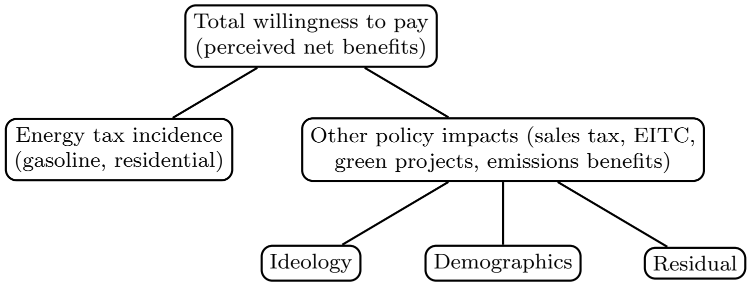
[31] This model controls for the Republican vote share in the presidential election, the votes on the twelve individual ballot measures (i.e., other than the carbon tax), the 2018 dummy, the full suite of census demographic variables—including income, age, gender, and manufacturing industry, which may be necessary to control for the tax reductions and rebates embedded in the I-732 package—and county fixed effects.

Figure 5: *Predicting the carbon tax vote share by precinct in 2016 and 2018: coefficients on number of vehicles and home size*



Note: These figures plot coefficients from the regression reported in column (6) of table 3. This is 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 households with various numbers of vehicles available; the excluded category is households with zero vehicles. The bottom panel plots coefficients on variables measuring the share of households with various numbers of rooms in their home; the excluded category is 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 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, the 2018 vote dummy, detailed census variables (i.e., commute time by car, industry, home value, income, gender, age, race, education, household size, urban share, and owner-occupied share), and county fixed effects.
Source: WA SOS & U.S. Census.

Figure 6: *Decomposition of precinct-level mean willingness to pay for a carbon tax policy*



or more vehicles (see appendix table 7). Meanwhile, the coefficients on the share of households with three or more rooms are all negative (lower panel), while the coefficient on two rooms is almost exactly zero. 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 (see appendix figure 21).[32]

What can this tradeoff between tax incidence and support for the carbon tax tell us about voters' willingness to pay (WTP) for these policies? To answer this question, we push our analysis several steps further by measuring the direct personal energy tax incidence—in dollars—that Washington's proposed carbon taxes would have had on Washington voters. We then estimate a structural discrete-choice random-utility model, relating the probability of voting yes on the carbon tax to dollars of energy tax incidence at the precinct level. Thus, we are able to convert vote shares into precinct-level mean WTP in dollars. This approach yields total WTP for the overall policy package, i.e. the perceived net benefits from the referendum passing (see the top level of figure 6). This package includes the direct energy tax incidence due to higher gasoline and residential energy prices, which enters negatively in the net-benefits ledger, plus other policy impacts (see the middle level of figure 6). These other policy impacts include the lower sales tax and expanded EITC (in 2016), local green-spending projects (in 2018), and environmental benefits accruing to Washington voters and others via reductions in local emissions and global GhGs. Finally, we decompose WTP for these other policy impacts into components that can be explained by political ideology, observed demographics, and a residual (see the bottom level of figure 6).

Our WTP analysis assumes, like all revealed preference studies, that the tax incidence we calculate for Washington voters (i.e., carbon price times carbon footprint) mirrors their actual beliefs about the cost of the 2016 and 2018 policies. We model average support for a carbon tax by precinct. Thus, our assumption is that average beliefs in a precinct align with our calculations for that precinct's average tax incidence. As we discuss

[32] Full results for the census demographic variables, available upon request, show that the coefficients on home size and number of vehicles 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.

below, our calculations are likely to be quite accurate. Further, we think that voters would have been able to form a fairly accurate estimate of their own tax incidence, such that their average beliefs align reasonably well with our calculations, for three reasons. First, Washington has 100% mail-in ballots, which are sent to registered voters at least 18 days prior to election—along with voter guides that provide substantial detail on all statewide ballot initiatives. This gives voters time to learn about the various elections and contemplate their votes while gaining additional information. Second, prior research demonstrates that consumer beliefs and behavior are consistent on average with reasonable forecasts for energy prices (Anderson, Kellogg, and Sallee 2013) and consumption (Anderson and Sallee 2016, see pg. 171–172). Third, as we describe below, web-based carbon tax calculators available at the time would have allowed Washington voters to calculate their personal energy tax incidence under both I-732 and I-1631 prior to voting, and our parameter assumptions are informed by these tax calculators. Of course, voters may not always have availed themselves of these resources, and may have used simple heuristics instead. Thus, we consider several possible sources of divergence between our calculations and voters' beliefs below.

5.1 Empirical approach for estimating willingness to pay

Our analysis proceeds in several steps. First, we calculate tax incidence related to household gasoline consumption and home energy consumption for the average voting-age adult (18+) in each precinct. We assume that voters perceive a $25/tCO2 carbon tax in 2016 and a $15/tCO2 carbon tax in 2018. These values are consistent with web-based tax burden calculators available to households at the time of the 2016 and 2018 votes, as well as with contemporaneous reporting. Meanwhile, using household-level microdata from the 2017 National Household Transportation Survey (NHTS), we regress gasoline consumption on closely related household characteristics: # vehicles, car commute time, # household members, and an indicator for urbanization. Likewise, using microdata from the 2015 Residential Energy Consumption Survey (RECS), we regress home energy emissions on closely related characteristics: # rooms, # household members, and owner-occupied.[33] We then apply the coefficients from these micro regressions to the corresponding precinct-level averages to estimate mean household-level carbon emissions for each precinct. Finally, we divide by the average number of voting-age adults per household in each precinct, and multiply by the perceived carbon taxes in each year, to yield average precinct-level tax incidence per voting-age adult. We detail these procedures in appendix H, in which we argue that our calculations for precinct-level tax incidence are likely to be quite accurate. Of course, an individual household's tax incidence could be higher or lower than the precinct average. But this is not a problem, given that we also model average support for the carbon tax at the precinct level. Intuitively, support for the carbon tax will be lower among households with above-average incidence, and higher among households with below-average incidence. These above- and

[33]For gasoline consumption, we use NHTS data from Washington state. For home energy emissions, we use RECS data from Washington's census division and climate zones.

below-average households will tend to cancel, such that average support will be driven by average incidence within the precinct. Thus, we need only concern ourselves with precinct-level prediction error.

Second, we estimate a logistic model to explain voting on the carbon tax as a function of energy tax incidence, controlling for ideology and census covariates. We show in appendix H how to derive this estimating equation from a standard random-utility discrete-choice model of individual voting behavior. Our precinct-level model takes the form:

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

where $y_i = \ln(s_i/(1 - s_i))$ is mean net utility from the referendum passing and s_i is the share voting "yes" in precinct i, *totaltax* is mean energy tax incidence in the precinct with corresponding coefficient α, *ideology* is a vector of precinct-level ideology variables (i.e., Republican vote share plus vote shares in the twelve other ballot measures) with corresponding coefficient vector β, *demographics* is a vector of all remaining precinct-level control variables (i.e., census demographics and county dummies) with corresponding coefficient vector γ, and ϵ is a precinct-level error. We exclude as controls the census variables we use to calculate tax incidence (e.g., # vehicles and # rooms), since tax incidence is a linear function of these variables. Thus, we assume that these variables only correlate with voting via their relationship to tax incidence, i.e. tax incidence is a sufficient statistic for these variables. Our remaining, fine-grained controls for age, income, industry, and other factors implicitly capture WTP for other policy impacts, including lower sales taxes, EITC rebates, and shifts in production caused by higher energy costs. We estimate this model in a pooled OLS regression in which we stack both years to yield a single coefficient α on tax incidence but allow coefficients to differ by year for all other variables (including the intercept and county dummies). Our identification assumption is the following: tax incidence is uncorrelated with the error term in our model (i.e., no correlated omitted variables). 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 dependent variable as WTP in dollars (see appendix H).

Third and finally, we use the coefficient estimates from our logistic regression to back out mean WTP for the policy in each precinct. Given our model, total WTP in precinct i is given by: $y_i/\hat{\alpha}$, i.e. mean net utility from the referendum passing scaled by the estimated marginal utility of income (see the top level of figure 6). This calculation hinges on a causal interpretation for the estimated coefficient on tax incidence ($\hat{\alpha}$), and immediately yields a decomposition of total WTP into energy tax incidence and other policy impacts (see the middle level of figure 6). To further decompose WTP for these other policy impacts into components (see the bottom level of figure 6), we need a stronger assumption: no omitted variables correlated with tax incidence, the ideology variables taken as a whole ($\hat{\beta}' ideology_i$), or the demographic variables taken as a whole ($\hat{\gamma}' other_i$). Under this stronger assumption, our scaled logistic regression decomposes WTP into energy tax incidence ($totaltax_i$) and three additional components: ideology ($\hat{\beta}' ideology_i/\hat{\alpha}$), demographics ($\hat{\gamma}' demographics_i/\hat{\alpha}$), and a residual ($\hat{\epsilon}/\hat{\alpha}$). To facilitate interpretation, we re-center the ideological variables to equal zero at their sample mean vote shares.[34] Thus, we implicitly measure each additional component of WTP relative to a precinct with average ideology. Below, we report sample means and standard deviations for total WTP and its various components across precincts (weighted by total votes cast for or against a carbon tax) alongside our coefficient estimates.

5.2 Regression results and implied WTP estimates

Table 5 presents the results from this analysis. We begin by testing the restriction that there is a single coefficient on tax incidence, i.e. identical across energy sources and years. Note that *total tax* is the sum of two variables: tax incidence due to gasoline consumption (*vehicle tax*) and tax incidence due to home energy consumption (*room tax*). Column (1) tests that the coefficients on these variables are identical by including *room tax* in addition to *total tax.* The coefficient on *room tax*—equal to the *difference* in coefficients on *vehicle tax* and *room tax* were we to use these two variables instead—is statistically insignificant, implying that we cannot reject identical coefficients on the two underlying sources of tax incidence. Meanwhile, column (2) includes tax incidence interacted with a 2018 dummy (*total tax 2018*), in addition to the variable pooling tax incidence for both years (*total tax*). Again, the coefficient on *total tax 2018* is statistically insignificant, implying that we cannot reject identical coefficients for the two years. Thus, the remaining columns all impose a single coefficient on tax incidence that is identical across years. Columns (3)-(4) present results from a single OLS regression. We report the results in two columns (repeating the coefficient estimate of -0.98) so that we can show estimated WTP separately for 2016 and 2018 at the bottom of the table. The coefficient of -0.98 on *total tax* is negative and statistically significant, suggesting that voters derive negative utility from higher taxes, all else equal. Note that we report coefficients on tax incidence measured in \$1000s (to minimize leading zeros). Thus, the estimated marginal utility of dollars is $\hat{\alpha} = 0.00098$. The coefficient on *total tax* is similar to the coefficient in column (1), which is consistent with most variation in *total tax* coming from *vehicle tax* (see appendix figure 22). Columns (5)-(6) likewise present results from a single regression, but estimated via 2SLS. We return to this 2SLS regression in section 5.3 below.

We now turn to our estimates of precinct-level WTP reported at the bottom of table 5, focusing on the OLS results in columns (3)-(4). We report both mean values and standard deviations (below, in brackets). We first focus on mean values. Total WTP is negative \$409 per voter in 2016 and negative \$293 per voter in 2018. Recall that total WTP in a precinct is given by the log-odds ratio scaled by the marginal utility of dollars ($y_i/\hat{\alpha}$) and note that this value equals zero for a precinct whose voters are indifferent on average

[34] 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.

Table 5: *Logistic model of carbon tax vote shares and implied willingness-to-pay estimates*

	(1) OLS	(2) OLS	(3) OLS-2016	(4) OLS-2018	(5) 2SLS-2016	(6) 2SLS-2018
Total tax	-1.10*	-1.06**	-0.98*	-0.98*	-1.59**	-1.59**
	(0.50)	(0.36)	(0.41)	(0.41)	(0.56)	(0.56)
Room tax	0.97					
	(0.97)					
Total tax 2018		0.31				
		(0.35)				
Total WTP			-409	-293	-252	-181
			[554]	[797]	[342]	[492]
▷ Energy tax incidence			-135	-81	-135	-81
			[22]	[13]	[22]	[13]
▷ Other policy impacts			-274	-212	-117	-100
			[540]	[789]	[328]	[484]
▷ Ideology			-1	4	-1	2
			[492]	[768]	[301]	[473]
▷ Demographics			-273	-216	-117	-102
			[70]	[76]	[43]	[47]
▷ Residual			0	0	0	0
			[126]	[127]	[78]	[79]

Note: The top part of this table presents coefficient estimates from logistic regressions modeling the share voting "yes" for the carbon tax in 2016 and 2018 as a function of energy tax 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. *Total tax* measures total tax incidence (in $1000s) and is the sum of two variables: *vehicle tax* (gasoline tax incidence as predicted by # vehicles, commute time, # household members, and urban status) and *room tax* (home energy tax incidence as predicted by # rooms, # household members, and owner-occupied status). *Total tax 2018* in column (2) interacts *total tax* with a 2018 dummy. Calculations of tax incidence assume a carbon tax of $25/tCO2 in 2016 and $15/tCO2 in 2018. All regressions pool data for 2016 and 2018 and 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: detailed census variables (i.e., industry, home value, income, gender, age, race, and education) and county fixed effects. These pooled regressions also include a dummy variable for the 2018 vote, as well as its interaction with all control variables. For all models, we weight precinct-years by the total votes cast for or against the carbon tax. The regressions in columns (1), (2), and (3)-(4) are estimated via OLS. The regression in columns (5)-(6) is estimated via 2SLS. Instruments include the following variables, plus their interactions with a 2018 dummy, all divided by the # of voting-age adults per household: share of households with 1+ vehicles, commute time, # household members, share urban, # rooms, share owner-occupied, and a constant term. Standard errors are clustered by county (39 clusters).

The bottom part of the table reports precinct-level means for estimated WTP (in $), with the corresponding standard deviations appearing immediately below (in brackets), after weighting by total votes cast for or against the carbon tax. The first row reports total WTP. The next two rows report the decomposition of total WTP into energy tax incidence and other policy impacts. The last three rows report the decomposition of other policy impacts into components explained by ideology, demographics, and a residual. Columns (3)-(4) are based on a single pooled regression, and likewise for columns (5)-(6); we use two columns to report WTP estimates separately by year.

$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.

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

such that exactly 50% of them would vote yes (since $y_i = \ln(s_i/(1-s_i)) = 0$ when $s_i = 0.5$). Thus, this value $(y_i/\hat{\alpha})$ intuitively tells us how far *in dollars* the precinct is from being indifferent to the passage of the referendum. When voters are more sensitive to tax incidence—that is, when α is bigger in magnitude—voters need less monetary compensation to become indifferent, and therefore the mean WTP for the policy is smaller in magnitude. Of course, these results hinge on a causal interpretation for the coefficient on *total tax*.

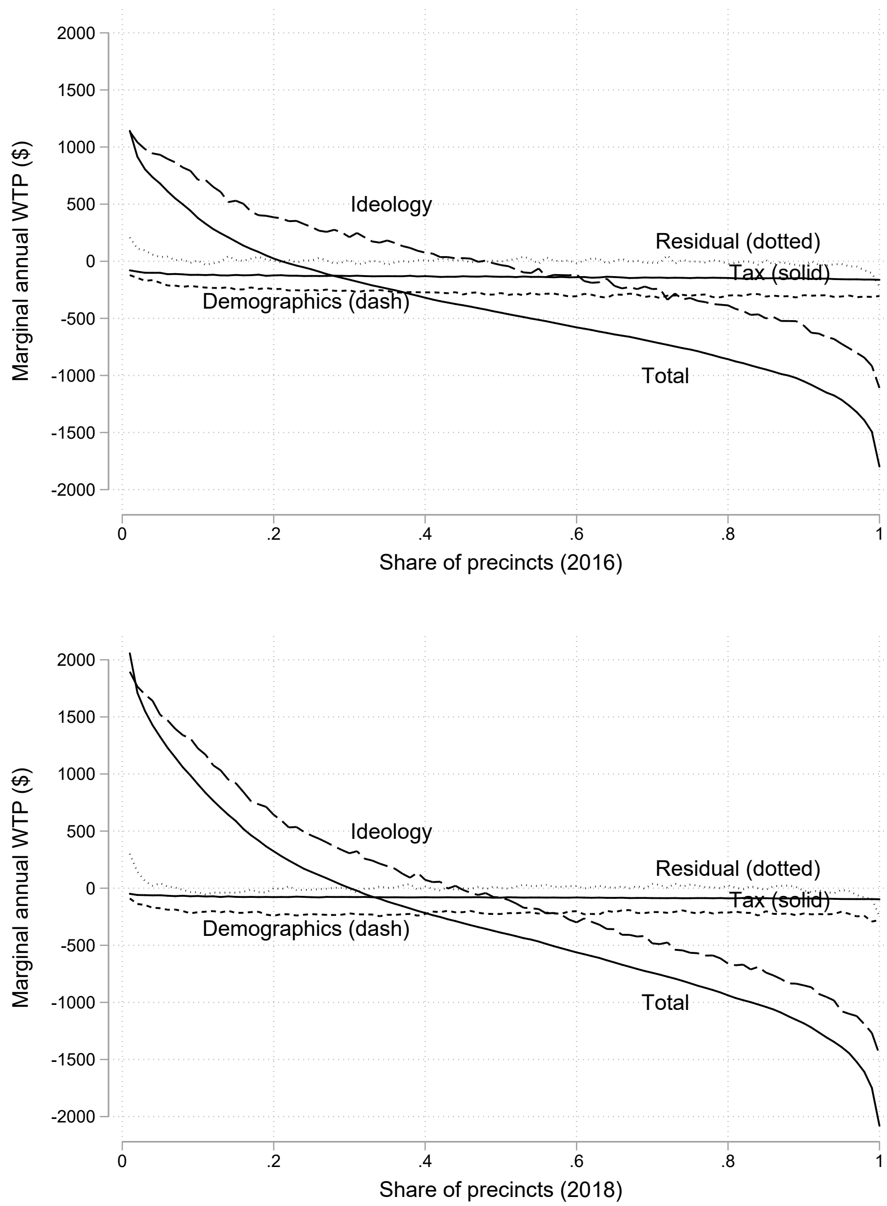
How much of this negative WTP is due to energy tax incidence? Energy tax incidence accounts for negative \$135 in 2016 (column 3) and \$81 in 2018 (column 4). By construction, these values equal the average energy tax incidence across precincts in these years. This leaves other policy impacts (such as sales tax rebates, EITC, green projects, and lower emissions) accounting for negative \$274 in 2016 (column 3) and negative \$212 (column 4). That is, even if the energy tax incidence were zero, voters would have rejected these referendums. Apparently, they do not like these other policy impacts, taken as a whole. Alternatively, they *do* like these other policy impacts, but overestimate the costs of higher energy taxes (Douenne and Fabre 2019).

If we further assume a causal interpretation for our two sets of control variables, then we can decompose WTP for these other policy impacts more fully into components attributable to ideology, demographics, and a residual. In this case, mean WTP attributable to ideology is approximately zero—a direct consequence of our choice to re-center ideology to equal zero on average. Finally, mean WTP attributable to demographics is negative \$273 in 2016 (column 3) and negative \$216 in 2018 (column 4). Note that our decomposition implicitly measures mean WTP attributable to demographics relative to a precinct with average ideology. Of course, the residual component is zero on average—a numerical property of OLS regression.

Overall, we find a negative WTP for the carbon tax policy between \$293 and \$409. Looking at the determinants of WTP, we find that the average voter (precinct, strictly speaking) dislikes the personal cost of higher energy taxes, as expected—but seems barely to credit the potential benefits of a carbon tax. These results contrast with the stated-preference estimates of Kotchen, Turk, and Leiserowitz (2017), who find a positive WTP of \$177 on average for the non-tax benefits of a carbon tax.[35] 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, while proponents of the 2018 initiative hoped to boost support through spending on green projects. However, we estimate a WTP of negative \$212 to \$274 for these other policy impacts, suggesting that this strategy did not work. The results are consistent with voters thinking that the benefits would not reach them. Such 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,

[35]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 7: *Marginal willingness to pay for a carbon tax by precinct*



Note: This figure plots marginal 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, NHTS, and RECS.

Carvalho, and Fankhauser 2018).

To understand what drives variation in WTP across precincts, we now turn to the standard deviations (in brackets). Note that the standard deviations due to energy tax incidence ($13-$22), demographic variables ($70-$76), and residual (26-$127) are all swamped by the standard deviation in WTP due to ideology ($492-$768), which is consistent with our results above that ideology explains most of the variation in voting across precincts. These results underscore the importance of factors other than self-interest in shaping policy preferences (Luttmer 2001).

Figure 7 illustrates these points graphically with estimated marginal WTP curves for the two carbon tax policies, i.e. mean WTP as we move through the distribution of precincts sorted from high to low support. These figures are based on the regression results reported in columns (3) and (4) of table 5 above and group precincts by percentile of WTP. We show both total WTP for the marginal precincts assuming a causal interpretation for the coefficient on tax incidence, as well as a break-down of this WTP into individual components (energy tax incidence, ideology, demographics, and residual) assuming causal interpretations for ideology and other control variables. The WTP attributable to taxes, which averages -$135 in 2016 and -$81 in 2018, is nearly constant throughout the distribution in both years. This finding implies that the characteristics that drive tax incidence (i.e., mainly vehicle ownership and home size) do not differ substantially across precincts with high vs. low support for the carbon tax. The WTP attributable to demographics is also fairly constant across precincts. 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 -$1100 to $1200 in 2016 and about -$1400 to $1900 in 2018. The substantially wider range in 2018 is consistent with our findings above that the 2018 policy was more ideologically slanted, 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) and look closely, we see that WTP due to the tax accounts for about one quarter to one third of overall negative WTP, which is consistent with the summary statistics at the bottom of table 5.

5.3 Robustness of our willingness-to-pay estimates

In this section, we explore the robustness of our WTP estimates. We first consider and rule out the possibility that individual-level variation in energy tax incidence is large enough to overturn our conclusion that ideology trumps tax incidence. Then, we explore the sensitivity of our results to changes in the coefficient on *total tax*, differentiating by the cause of this change: behavioral issues, omitted variables bias, and measurement of energy tax incidence.

Individual-level variation in tax incidence. We estimate the mean and standard deviation in WTP across precincts and report the results in table 5. Based on this analysis, we conclude that variation in precinct-level WTP is mainly driven by ideology, rather than by tax incidence. Of course, this analysis ignores within-precinct variation in WTP. In principle, if within-precinct variation in tax incidence were large relative to within-precinct variation in ideology, then this could overturn our conclusion that ideology trumps incidence (we thank an anonymous referee for clarifying this point). To address this concern, we present a bounding exercise in appendix H.5, which shows that the standard deviation of tax incidence across all individuals ranges \$77–\$100 in 2016 and \$46–\$60 in 2018. These values exceed the standard deviation in tax incidence across precincts: \$22 in 2016 and \$13 in 2018 (see columns 3-4 in table 5). But they are *still* much lower than the standard deviation in WTP across precincts that can be attributed to ideology: \$492 in 2016 and \$768 in 2018 (see columns 3-4 in table 5). Note that these latter values are lower bounds on the variation in WTP across individuals that can be attributed to ideology. Thus, we still conclude that ideology trumps tax incidence, both for precincts on average and for individuals.

Behavioral factors. Figure 5 suggests that votes depend on a binary "car vs. no car" distinction, rather than continuous # vehicles. If voters use a binary heuristic, then our measure of tax incidence will diverge from their beliefs, leading to bias. To account for this divergence, we purge any variation in *total tax* coming from the continuous # vehicles. Mechanically, we do this by estimating our model via 2SLS, instrumenting for *total tax* with % of households with 1+ vehicles (the binary measure), plus the other continuous variables used above to estimate tax incidence.[36] In the first stage, we regress *total tax* on the instruments and controls. In the second stage, we regress support for the carbon tax on *predicted* tax incidence and controls. Thus, our assumption is essentially the same as above: the excluded instruments used to predict tax incidence only correlate with voting via their relationship to tax incidence. Importantly, we are not using 2SLS to overcome any fundamental endogeneity concern present in our OLS approach (e.g., omitted variables). Rather, we are using 2SLS purely for *numerical* reasons: to purge variation in tax incidence coming from the continuous # vehicles (which figure 5 indicates is not salient to voters) while preserving all other sources of variation used to construct this measure.

Columns (5)-(6) of table 5 present the results from this 2SLS regression. As expected, when we focus on variation in *total tax* driven by the binary measure of car ownership, the coefficient on *total tax* increases in magnitude to -1.59. Thus, mean total WTP at the bottom of the table shrinks proportionately to -\$252 in 2016 and -\$181 in 2018 (remember that WTP is $y_i/\hat{\alpha}$, where y_i is the transformed vote share, and to divide the table coefficients by 1000 to get $\hat{\alpha}$), while mean tax incidence remains unchanged in both 2016 and 2018 (by construction). Thus, after accounting for behavioral factors, tax incidence is relatively *more*

[36] Our full set of instruments includes: % of households with 1+ vehicles, commute time, # household members, % urban, # rooms, % owner-occupied, and a constant term, plus interactions of these variables with a 2018 dummy (to capture the lower carbon price in that year), all divided by the # of voting-age adults per household (given our re-scaling of household-level tax incidence per voting-age adult). Note that these instruments would perfectly predict *total tax* were we to use the average # of cars per household instead of the % of households with 1+ vehicles.

important in explaining overall negative WTP for the policies. Meanwhile, mean WTP attributable to ideology remains near-zero (by construction, due to our normalization). Thus, given the overall increase in mean WTP (becoming less negative), the WTP attributable to the "other" category must increase in tandem (becoming less negative in columns 5-6). These results show that our estimate of overall WTP is somewhat sensitive to specification, as is the amount that we attribute to non-tax factors. However, qualitatively, the *variation* in WTP across precincts (standard deviation of \$342-\$492) continues to be dominated by variation that we can attribute to ideology (standard deviation \$301-\$473).

Omitted variables bias. Omitted variables bias in the coefficient on *total tax* has a qualitatively similar effect as that described above. If the true coefficient increases in magnitude, mean WTP shrinks and we attribute a larger share to tax incidence. Meanwhile, if the coefficient decreases in magnitude, these effects are reversed. How sensitive are our qualitative results to the coefficient on *total tax*? Note that total WTP is three times larger than mean tax incidence in column (3), while the ratio is somewhat larger in column (4). Thus, the true coefficient on *total tax* would need to be at least 1.5 times larger for mean tax incidence to account for a majority of the negative WTP overall and 3 times larger for mean tax incidence to exactly equal mean WTP overall. Any larger increase would imply that mean WTP attributable to non-tax factors is strictly positive. Meanwhile, note that the standard deviation of total WTP is 25 times larger than the standard deviation of tax incidence in column (3), and the ratio is even larger in column (4). Thus, the true coefficient on *total tax* would need to be at least twenty-five times larger to overturn our conclusion that variance in total WTP across precincts is dominated by non-tax factors, of which ideology is most important.

Measurement of energy tax incidence. Recall that, in calculating tax incidence, we assume that voters perceived carbon prices of \$25/tCO2 in 2016 and \$15/tCO2 in 2018, since these are the values used by tax calculators available to Washington voters at the time. However, voters may have perceived higher overall prices based on the phased-in tax increases under both policies. See appendix H for an extended discussion. Suppose we doubled the taxes perceived by voters in both years (not unreasonable, based on our reading of the legislation and contemporaneous reporting). This re-scaling would increase precinct-level tax incidence by a factor of two. Meanwhile, the coefficient on *total tax* in table 5 would mechanically shrink by a factor of two, which would inflate all of our other WTP estimates by the same factor. Thus, everything WTP-related in our reported results would get multiplied by two, including the means and standard deviations reported at the bottom of table 5, along with the number labels on the vertical axis in figure 7. Thus, voters perceiving a proportionally higher tax incidence would merely multiply all WTP components by the same factor and thus would not change our conclusions about the relative role of the various components of WTP.

6 Could a carbon tax pass in other states?

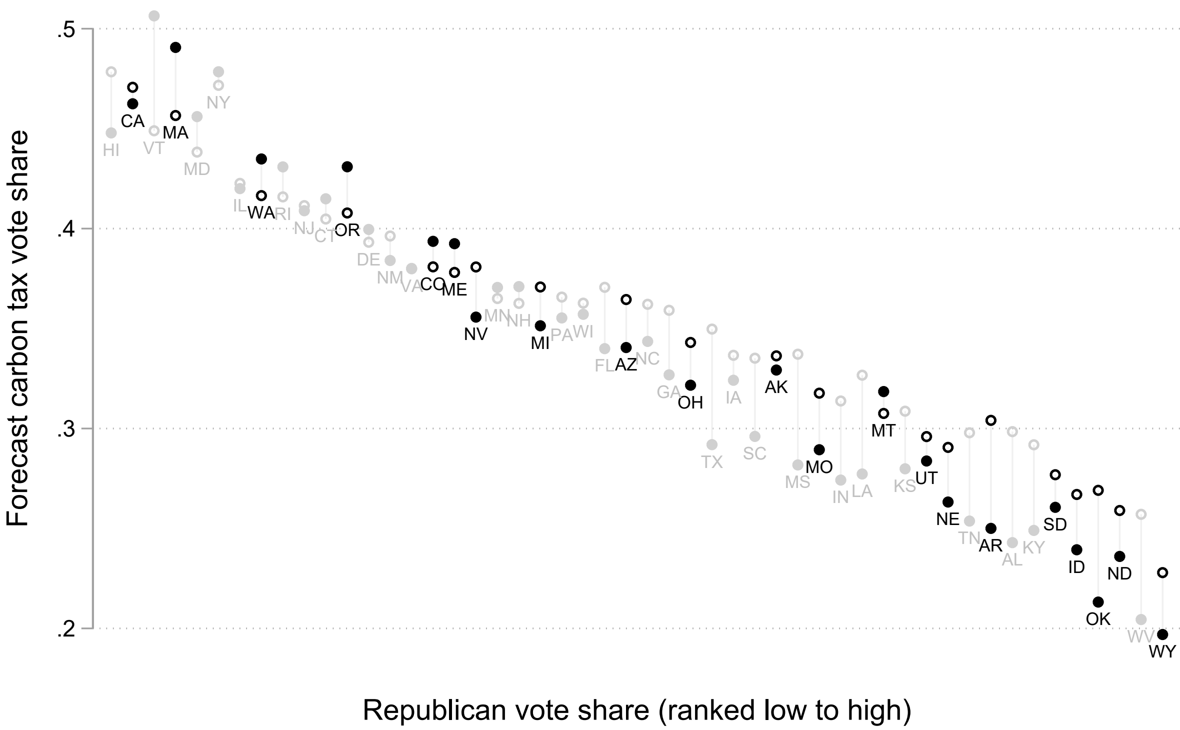
How would policies like I-732 and I-1631 fare in other states? This is a key question for carbon tax policy entrepreneurs hoping to apply lessons from the Washington experience to other states. To address it, we construct a set of 50 out-of-sample forecasts by applying coefficients from a regression of the precinct-level vote in Washington State to the observed state-level demographics and presidential vote shares in all 50 states.[37,38] We base these forecasts on the same specification as model (3) in table 3 above (i.e., Republican share plus census demographics) but estimated separately for 2016 and 2018. See model (3) in appendix tables 10 and 11 for these results. In principle, we could improve these forecasts by controlling for ideology, as in model (4), but we do not observe this measure for other states (since our measure relies on Washington-specific ballot initiatives). In practice, there would be little gain in precision: simple regressions of the predicted values from model (4) on the predicted values from model (3) yield coefficients of 1.000 and R-squared values of 0.97–0.98.

Technically, these 50 out-of-sample forecasts tell us how *Washington* would have voted differently on I-732 and I-1631 if we re-weighted its precincts to have the same demographics and ideology on average as other states. To go further and interpret these forecasts as predictions for how *other* states would have voted, we must assume that the mapping between voting on the carbon tax and ideology/demographics that exists in Washington would hold up elsewhere (i.e., parameter stability across states). Of course, we cannot take this latter assumption too literally. First, and most obviously, many states do not even feature a popular initiative mechanism. Second, measures identical to I-732 and I-1631 would be impossible in many states, e.g. because they lack a state sales tax or have restrictions on how various sources of tax revenue may be used. Third, the incidence of a carbon tax would certainly differ across states, e.g. due to differences in demand for home heating and cooling, energy sources used for electricity generation, and pre-existing regulations such as California's cap-and-trade program. Finally, the information environment that exists in Washington generally (e.g., 100% mail-in ballots and universal distribution of voter guides) and that existed at the time of the 2016 and 2018 votes (e.g., media coverage of internecine political battles) would not transfer exactly to other times and locations. Thus, our forecasts are merely illustrative: they demonstrate the relative challenges facing carbon tax advocates in various states, but we cannot take the specific quantitative results literally.

[37]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.

[38]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 8: *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 10 (for 2016) and regression model (3) in appendix table 11 (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.

Figure 8 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 Republican vote share.

Which states would be most likely to pass a carbon tax? Figure 9 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.[39] 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%.

So then: How liberal would a state need to *be* to pass a carbon tax? Take Washington. Forecast support there is 41.7% in 2016 (8.3% below passing), while the coefficient on Republican share for that year is -0.523 (see table 10). Thus, Republican share would need to be 8.3%/0.523 $\approx$ 16% lower—holding demographics fixed—to pass I-732. Likewise, Washington's forecast support is 43.5% in 2018 (6.5% below passing), while the coefficient on Republican share is -0.747 (see table 11). Thus, Republican share would need to be 6.5%/0.747 $\approx$ 8.7% lower to pass I-1631. Similar calculations can be performed for other states: just multiply the passage gap (50% vote share minus our forecast) by 1/0.523 $\approx$ 1.9 in 2016 and 1/0.747 $\approx$ 1.3 in 2018.

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 is illustrated in figure 8. 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.[40] However, there is still important variation across states explained by other voter characteristics. For example, among the ten most liberal states in figure 9, we forecast that I-1631 would do better than I-732 in Massachusetts and Vermont but marginally worse in California and Hawaii.[41]

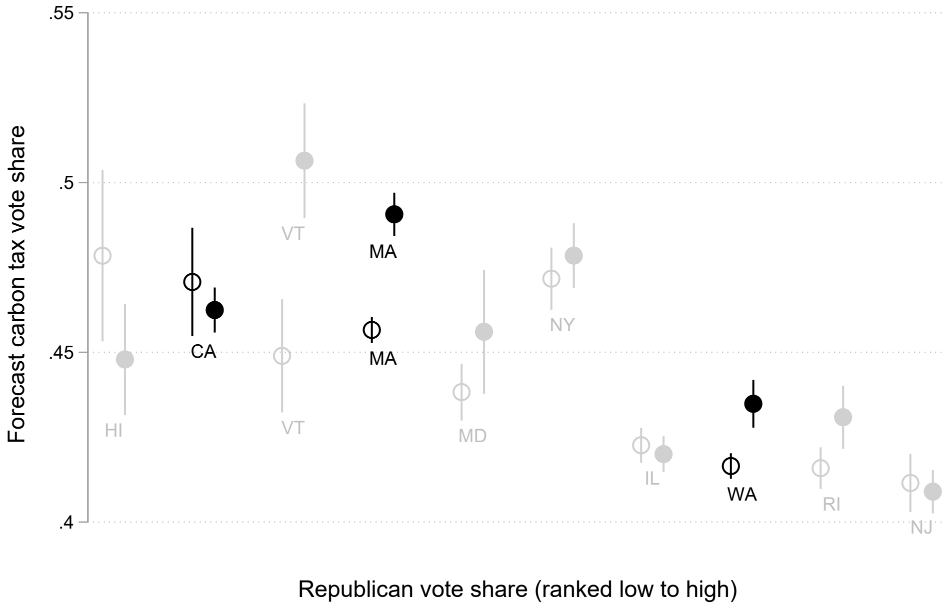
Generally, states for which we forecast a higher vote share in figure 8 already regulate carbon, even if not through a carbon tax. Many of these states have a cap-and-trade mechanism, suggesting that cap-and-trade might be easier to pass politically than a carbon tax. In particular, California has an economy-wide cap-and-trade program, while many Northeastern states participate in 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. Meanwhile, Washington itself recently passed cap-and-trade in April 2021—not via referendum but rather via the legislature (SB 5126). Governor Jay Inslee signed the bill in May and aggressively vetoed provisions that would have made cap-and-trade conditional on enacting some

[39] Moreover, the difficulty in getting on the ballot is highly variable across states. Massachusetts is notoriously difficult to navigate, while Washington and California are easier.

[40] We confirm this pattern in appendix figure 23, which directly forecasts the *difference* in state vote shares based on model (3) in table 4 above.

[41] 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.

Figure 9: *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 10 (for 2016) and regression model (3) in appendix table 11 (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.

other transportation policies; Democrats and Republicans in the legislature have threatened a lawsuit over claimed constitutional overreach by Inslee. As another indicator, many states with high forecast vote shares are members of the U.S. Climate Alliance—a coalition of states that has committed to meeting the Paris Climate Accord's abatement goals. This allicance includes California, six of nine RGGI states, and Hawaii, Washington, Oregon, Colorado, Virginia, Minnesota, and North Carolina.[42]

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.

[42]See here for a list of 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.

We analyze two failed carbon tax initiatives in Washington State using precinct-level aggregate voting data from Washington. 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 is an important factor to explain why voters rejected the two carbon taxes. However, ideology can easily overpower pocketbook concerns. Indeed, we show 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 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 showing that this support is rather shallow and easily overturned with a vigorous (and often negative) political campaign. 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. Furthermore, legislation and unilateral executive action by governors (like Inslee's aggressive line-item veto of conditionality on cap-and-trade) would appear to be more promising avenues to experiment with state carbon taxes.

What political levers might carbon tax advocates pull to boost support and deflect opposition? 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 policies aimed at both ends of the political spectrum were tried in Washington State, and both failed. For a tax-and-spend policy like I-1631 to succeed at the polls, voters must be convinced that the new spending has real value. For a revenue-neutral policy like I-732 to succeed, voters must be informed and convinced that—even though their energy bills will go up—they will benefit from lower taxes elsewhere. A carbon tax-and-dividend policy, whose cash benefits may be more transparent to voters, is a promising avenue for future research.

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

Table 6 summarizes the main supporters and opponents of each measure.

Table 6: *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:

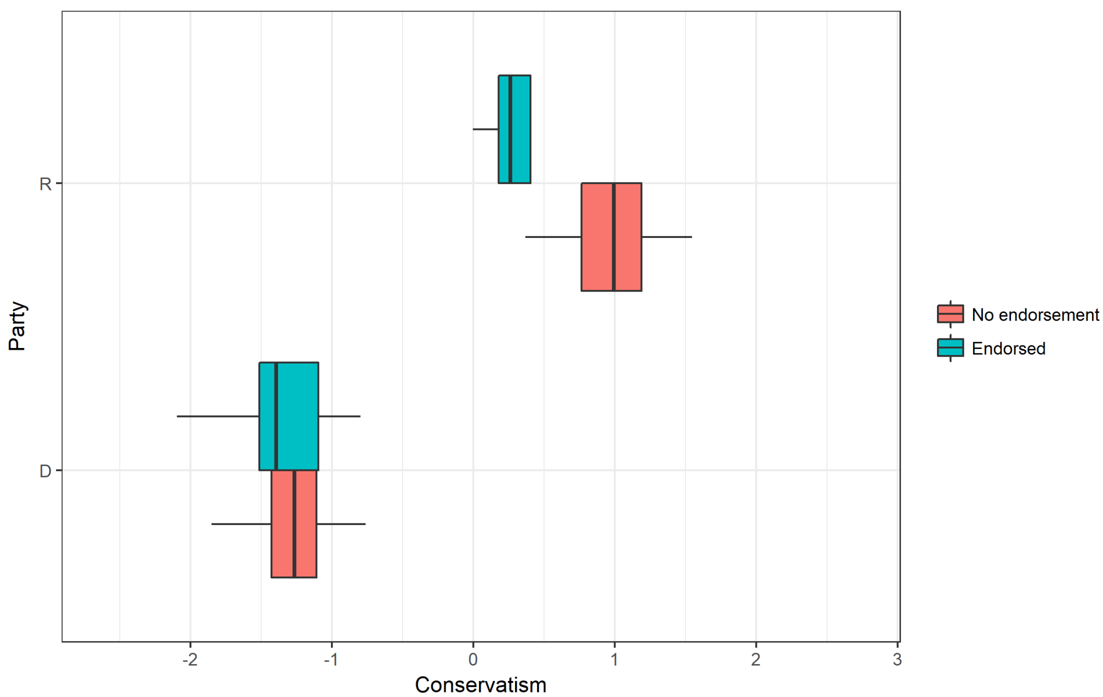
- Communities of color and low-income people are almost always the ones most impacted by pollution and climate change, and as a result they need to be at the front and center of discussions for how to address the problem and mitigate the impacts of both climate change and environmental policy. That wasn't 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 10 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 10: *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 Ballot initiatives and advisory questions in Washington State

B.1 2016 initiatives and advisory questions

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.

B.2 2018 initiatives and advisory questions

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.

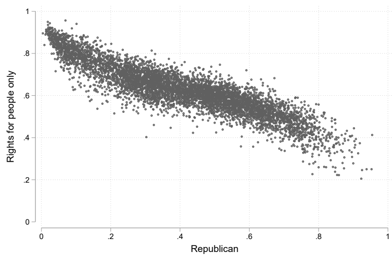
Initiative 1639 implements changes to gun ownership and purchase requirements. It was approved.

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.

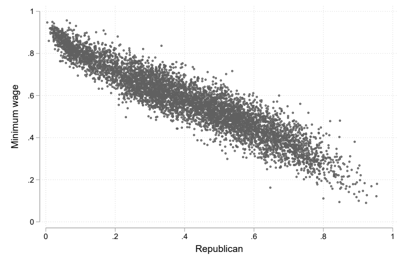
B.3 Voting on ballot initiatives and advisory measures

Figure 11: *Precinct-level vote on all other 2016 and 2018 ballot measures*

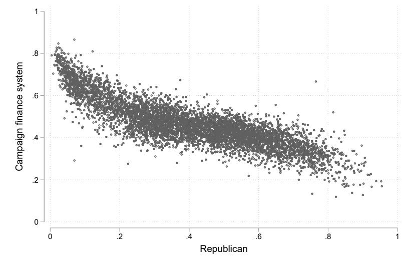
(a) Rights for people only



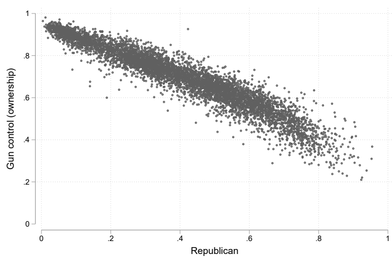
(b) Minimum wage



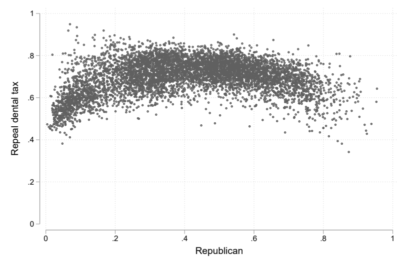
(c) Campaign finance system



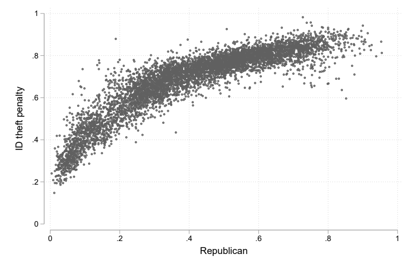
(d) Gun control (ownership)



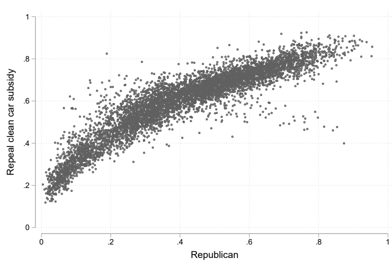
(e) Repeal dental tax



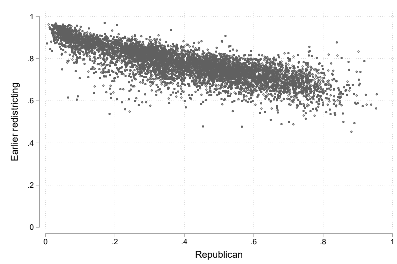
(f) ID theft penalty



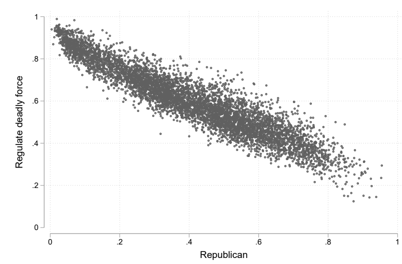
(g) Repeal clean car subsidy



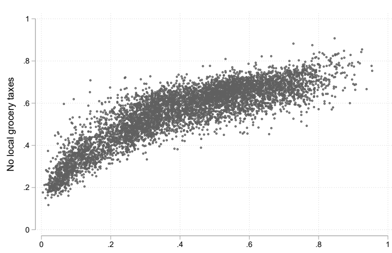
(h) Earlier redistricting



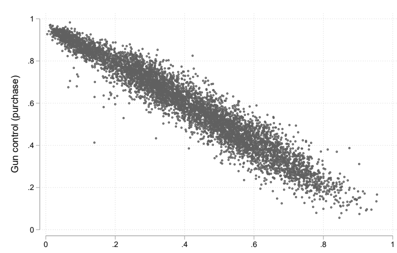
(i) Regulate deadly force



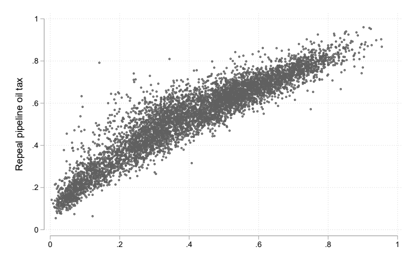
(j) No local grocery taxes



(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 for 6,219 precincts in Washington State. The first eight ballot measures (a-h) are from the 2016 election, while the last four (i-l) are from 2018. See above for details of each measure.

C Full summary statistics

Table 7: *Summary statistics for final estimation sample (Census variables)*

	Mean	Std. Dev.
Vehicles 0	0.056	0.073
Vehicles 1	0.279	0.127
Vehicles 2	0.398	0.105
Vehicles 3	0.179	0.086
Vehicles 4	0.060	0.046
Vehicles 5+	0.029	0.031
Car commute NA	0.517	0.097
Car commute 0-9 minutes	0.054	0.047
Car commute 10-14 minutes	0.065	0.042
Car commute 15-19 minutes	0.078	0.044
Car commute 20-24 minutes	0.074	0.040
Car commute 25-29 minutes	0.034	0.025
Car commute 30-34 minutes	0.066	0.040
Car commute 35-44 minutes	0.036	0.029
Car commute 45-59 minutes	0.039	0.033
Car commute 60+ minutes	0.037	0.032
Ag & mining	0.023	0.054
Construction	0.063	0.044
Manufacturing	0.104	0.060
Transport & utilities	0.051	0.037
Rooms 1	0.020	0.041
Rooms 2	0.029	0.045
Rooms 3	0.075	0.079
Rooms 4	0.138	0.087
Rooms 5	0.170	0.080
Rooms 6	0.171	0.075
Rooms 7	0.137	0.066
Rooms 8	0.106	0.063
Rooms 9+	0.155	0.114
Home value 0-9,999	0.016	0.032
Home value 10,000-14,999	0.006	0.019
Home value 15,000-19,999	0.005	0.017
Home value 20,000-24,999	0.005	0.019
Home value 25,000-29,999	0.004	0.012
Home value 30,000-34,999	0.003	0.013
Home value 35,000-39,999	0.003	0.011
Home value 40,000-49,999	0.005	0.016
Home value 50,000-59,999	0.005	0.015
Home value 60,000-69,999	0.006	0.017
Home value 70,000-79,999	0.008	0.022
Home value 80,000-89,999	0.010	0.026
Home value 90,000-99,999	0.010	0.026
Home value 100,000-124,999	0.038	0.064
Home value 125,000-149,999	0.043	0.064
Home value 150,000-174,999	0.069	0.079
Home value 175,000-199,999	0.063	0.068
Home value 200,000-249,999	0.132	0.104
Home value 250,000-499,999	0.099	0.095
Home value 500,000-749,999	0.114	0.140
Home value 750,000-999,999	0.040	0.075
Home value 1,000,000-1,499,999	0.018	0.047
Home value 1,500,000-1,999,999	0.006	0.021
Home value 2,000,000+	0.006	0.028

	Mean	Std. Dev.
Income < 10,000	0.051	0.049
Income 10,000-14,999	0.034	0.035
Income 15,000-19,999	0.036	0.035
Income 20,000-24,999	0.039	0.034
Income 25,000-29,999	0.038	0.032
Income 30,000-34,999	0.042	0.034
Income 35,000-39,999	0.040	0.032
Income 40,000-49,999	0.038	0.029
Income 50,000-59,999	0.077	0.044
Income 60,000-74,999	0.105	0.050
Income 75,000-99,999	0.139	0.059
Income 100,000-124,999	0.104	0.055
Income 125,000-149,999	0.067	0.048
Income 150,000-199,999	0.074	0.058
Income 200,000+	0.077	0.092
Age 0-4	0.058	0.030
Age 5-9	0.060	0.029
Age 10-14	0.060	0.029
Age 15-19	0.059	0.035
Age 20-24	0.062	0.051
Age 25-29	0.067	0.047
Age 30-34	0.068	0.038
Age 35-39	0.064	0.030
Age 40-44	0.065	0.028
Age 45-49	0.068	0.028
Age 50-54	0.073	0.030
Age 55-59	0.073	0.031
Age 60-64	0.068	0.032
Age 65-69	0.055	0.031
Age 70-74	0.038	0.025
Age 75-79	0.025	0.019
Age 80-84	0.018	0.017
Age 85+	0.019	0.023
Female	0.503	0.042
White	0.751	0.166
Black	0.028	0.049
American Indian	0.010	0.033
Asian	0.072	0.091
Pacific Islander	0.005	0.015
Other race	0.001	0.005
Two or more races	0.042	0.033
Hispanic or Latino	0.090	0.105
High-school diploma	0.181	0.085
GED	0.036	0.029
Some college < 1 year	0.075	0.037
Some college ≥ 1 year	0.166	0.055
Bachelor's degree	0.229	0.112
Master's degree	0.096	0.067
Professional degree	0.025	0.028
Doctorate	0.017	0.023
Household size	2.663	1.925
Urban	0.754	0.301
Owner-occupied	0.687	0.207

Note: This table reports variable means and standard deviations for our estimation sample of 6,219 precincts (12,438 observations in our pooled sample), weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. *Household size* is total population divided by number of households. The remaining variables measure the shares of people, households, or workers belonging to the indicated categories. Categories for vehicles, car commute, rooms, home value, income, age, and race/ethnicity sum to one. Our regressions that include census controls therefore drop the first category listed within each of these groupings of variables.
Source: U.S. Census.

D Turnout tables and figures

Table 8: *Summary statistics for turnout*

	Mean	Std. Dev.
Turnout in 2016 general election	0.796	0.072
President 2016	0.703	0.074
Senate 2016	0.768	0.072
I-732	0.735	0.069
I-735	0.726	0.070
I-1433	0.763	0.071
I-1464	0.725	0.069
I-1491	0.763	0.073
I-1501	0.754	0.070
HB 2768	0.697	0.061
HB 2778	0.693	0.061
SJR 8210	0.688	0.064
Senate 2018	0.732	0.097
I-940	0.729	0.096
I-1631	0.732	0.097
I-1634	0.730	0.096
I-1639	0.735	0.097
SB 6269	0.694	0.090

Note: This table reports means and standard deviations of precinct-level turnout for our estimation sample of 6,219 precincts, weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Turnout in a precinct is measured as total number of ballots cast (general election), total votes cast for the Republican or Democratic candidate (President 2016, Senate 2016, Senate 2018), and total yes/no votes cast for the various ballot initiative and measures, divided by the total number of registered voters in 2016 (same base for all elections). The top 12 rows (before Senate 2018) are from 2016, while the bottom six rows (Senate 2018 and below) are from 2018.
Source: WA SOS.

Table 9: *Correlation matrix for turnout across precincts*

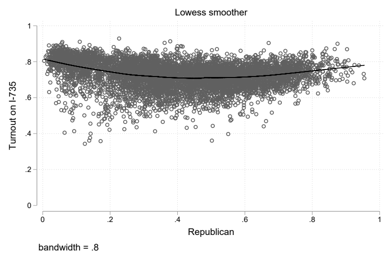
	General	Pres16	Sen16	732	735	1433	1464	1491	1501	2768	2778	8210	Sen18	940	1631	1634	1639	6269
General	1.00																	
Pres16	0.96	1.00																
Sen16	0.99	0.95	1.00															
732	0.97	0.92	0.97	1.00														
735	0.97	0.93	0.97	0.99	1.00													
1433	0.98	0.93	0.98	0.98	0.98	1.00												
1464	0.97	0.91	0.97	0.99	0.98	0.99	1.00											
1491	0.99	0.95	0.99	0.98	0.98	0.99	0.98	1.00										
1501	0.98	0.94	0.98	0.99	0.98	0.99	0.98	0.99	1.00									
2768	0.93	0.88	0.94	0.97	0.95	0.95	0.97	0.95	0.96	1.00								
2778	0.94	0.89	0.94	0.97	0.96	0.95	0.97	0.95	0.96	0.99	1.00							
8210	0.95	0.90	0.95	0.97	0.97	0.96	0.97	0.96	0.97	0.97	0.97	1.00						
Sen18	0.86	0.83	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.83	0.83	0.84	1.00					
940	0.86	0.82	0.85	0.86	0.85	0.86	0.85	0.86	0.86	0.82	0.83	0.83	1.00	1.00				
1631	0.86	0.83	0.86	0.86	0.85	0.86	0.85	0.86	0.86	0.83	0.83	0.84	1.00	1.00	1.00			
1634	0.86	0.82	0.86	0.86	0.85	0.86	0.85	0.86	0.86	0.83	0.83	0.84	1.00	1.00	1.00	1.00		
1639	0.86	0.82	0.86	0.86	0.85	0.86	0.85	0.86	0.86	0.83	0.83	0.84	1.00	1.00	1.00	1.00	1.00	
6269	0.85	0.81	0.84	0.85	0.85	0.85	0.85	0.85	0.85	0.83	0.83	0.83	0.99	0.99	0.99	0.99	0.99	1.00

Note: This table reports a matrix of correlation coefficients for pairs of turnout variables for our estimation sample of 6,219 precincts, weighted by the total votes cast for the Republican or Democratic candidate in the 2016 presidential election. Turnout in a precinct is measured as total number of ballots cast (general), total votes cast for the Republican or Democratic candidate (Pres2016, Sen2016, Sen2018), and total yes/no votes cast for the various ballot initiative and measures, divided by the total number of registered voters in 2016 (same base for all elections). The top 12 rows (before Sen2018) are from 2016, while the bottom six rows (Sen2018 and below) are from 2018. See table 8 for full names of elections.

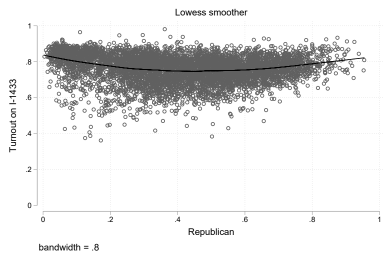
Source: WA SOS.

Figure 12: *Precinct-level turnout on all other 2016 and 2018 ballot measures*

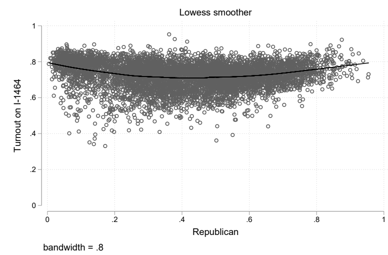
(a) Rights for people only



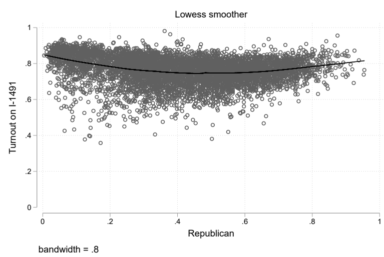
(b) Minimum wage



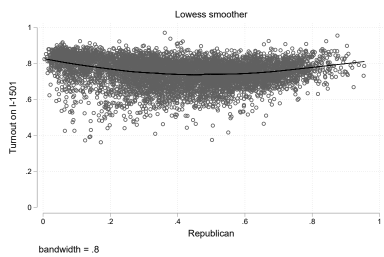
(c) Campaign finance system



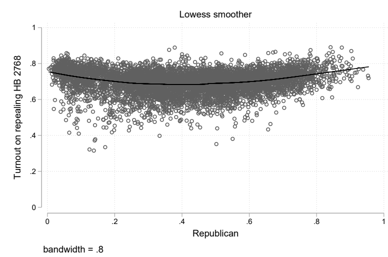
(d) Gun control (ownership)



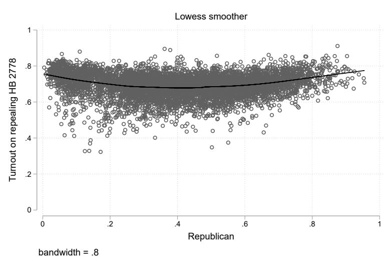
(e) Repeal dental tax



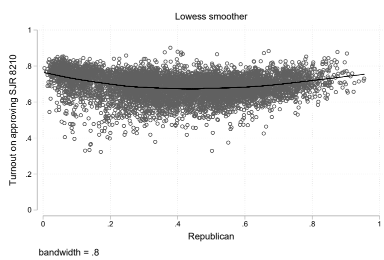
(f) ID theft penalty



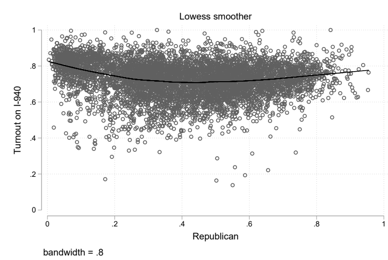
(g) Repeal clean car subsidy



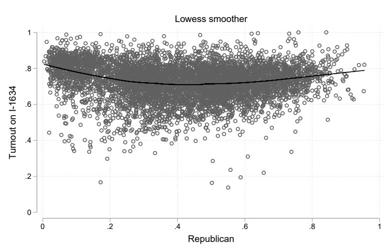
(h) Earlier redistricting



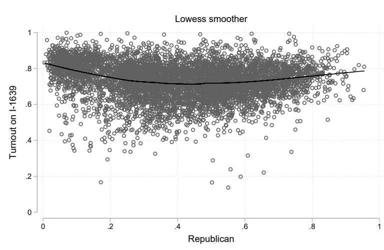
(i) Regulate deadly force



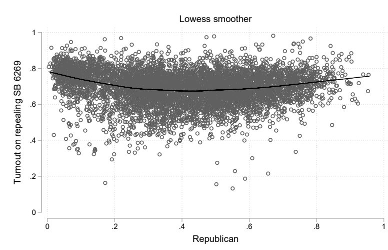
(j) No local grocery taxes



(k) Gun control (purchase)



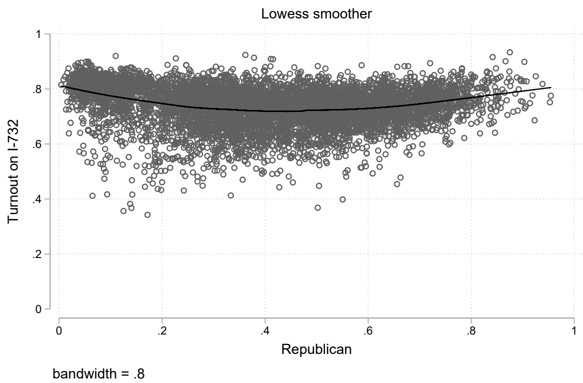
(l) Repeal pipeline oil tax



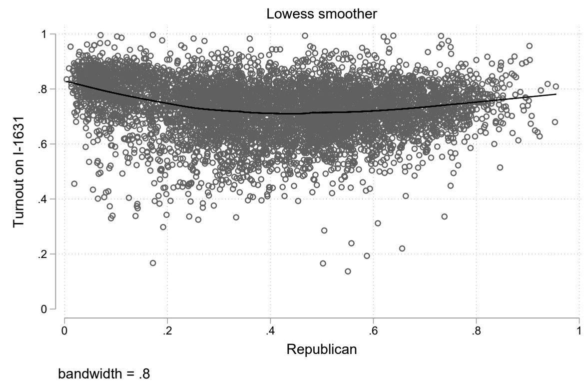
Note: This figure plots turnout on other statewide ballot measures (total votes divided by number of registered voters in 2016) versus the U.S. presidential vote share (Republican Party) in 2016 for 6,219 precincts in Washington State. Black lines are non-parametric (lowess) regression functions. The first eight ballot measures (a-h) are from the 2016 election, while the last four (i-l) are from 2018. See above for details of each measure.

Figure 13: *Precinct-level turnout: carbon taxes, President, and general election*

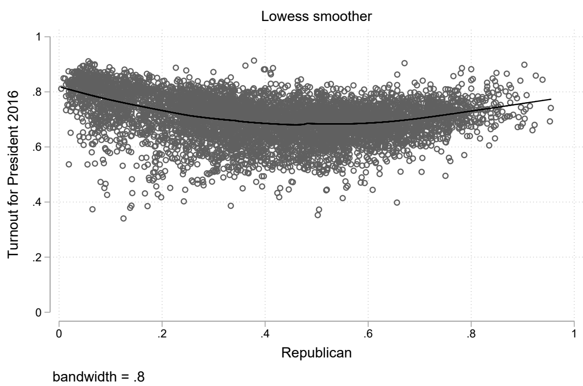
(a) Carbon tax 2016 (I-732)



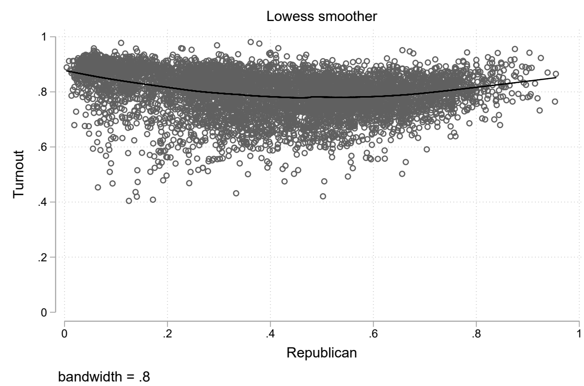
(b) Carbon tax 2018 (I-1631)



(c) President 2016



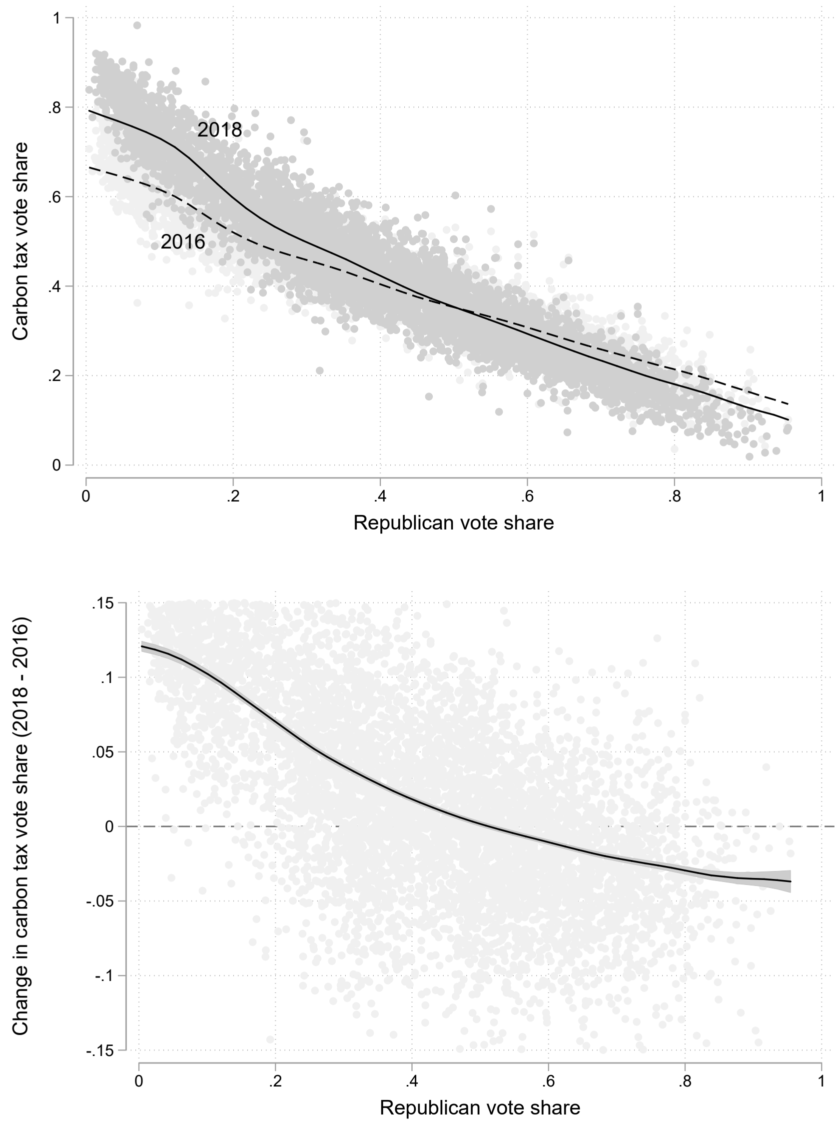
(d) General election 2016



Note: This figure plots turnout for the two carbon taxes (total votes divided by number of registered voters in 2016), the presidential election (total votes for the Democratic and Republican candidates divided by number of registered voters in 2016), and the overall general election (total ballots cast divided by number of registered voters in 2016) versus the U.S. presidential vote share (Republican Party) in 2016 for 6,219 precincts in Washington State. Black lines are non-parametric (lowess) regression functions. See above for details of each measure.

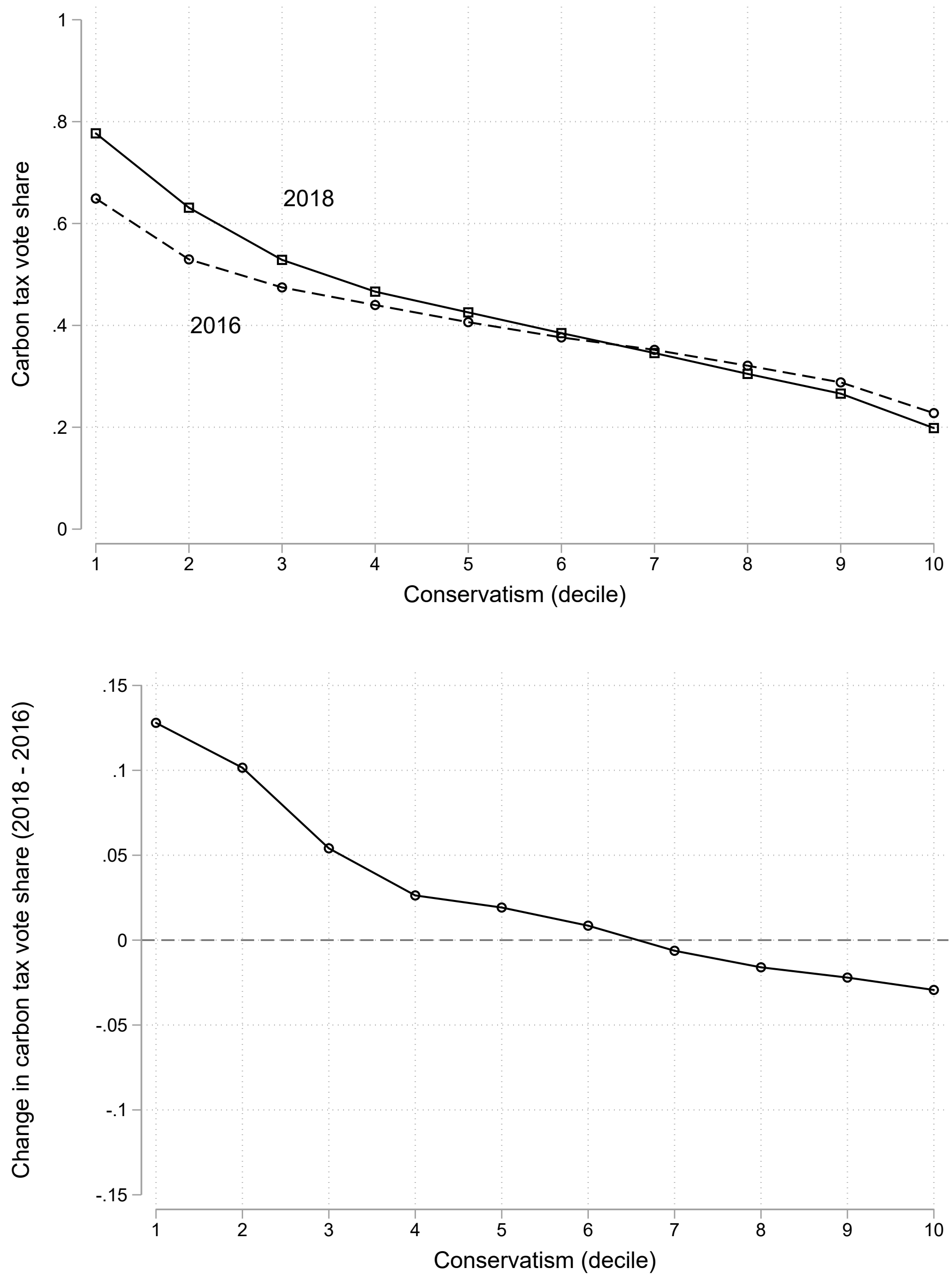
E Additional figures: voting on carbon tax

Figure 14: *Voting on carbon tax vs. Presidential vote (by precinct)*



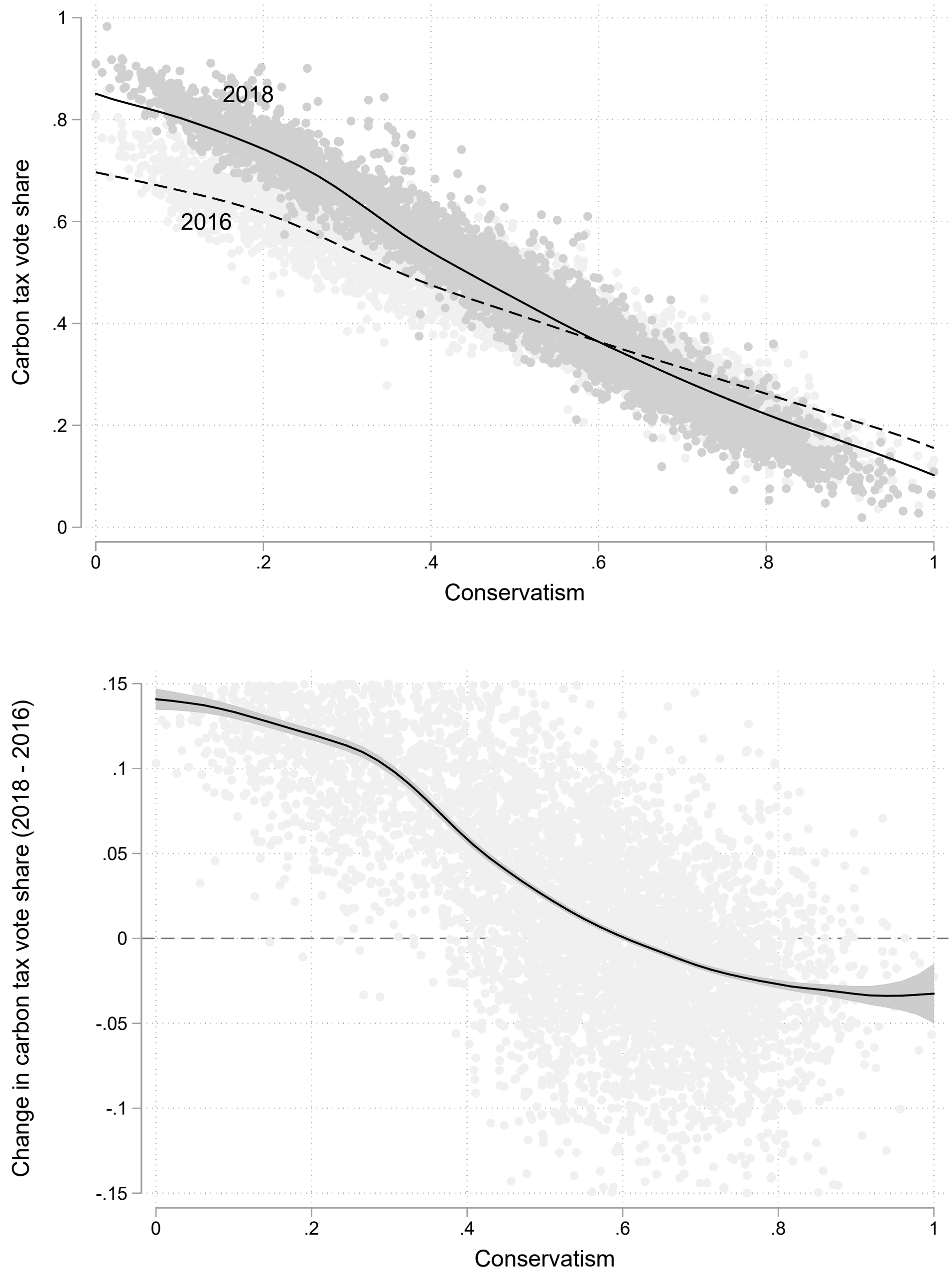
Note: The top panel of this figure plots the “yes” shares on I-1631 in 2018 (gray dots) and I-732 in 2016 (light gray dots) versus the U.S. presidential vote share (Republican Party) in 2016 for 6,219 precincts in Washington State. The solid and dashed lines plot local polynomial fitted values for the 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 15: *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 11).
Source: WA SOS.

Figure 16: *Voting on carbon tax vs. conservative ideology (by precinct)*

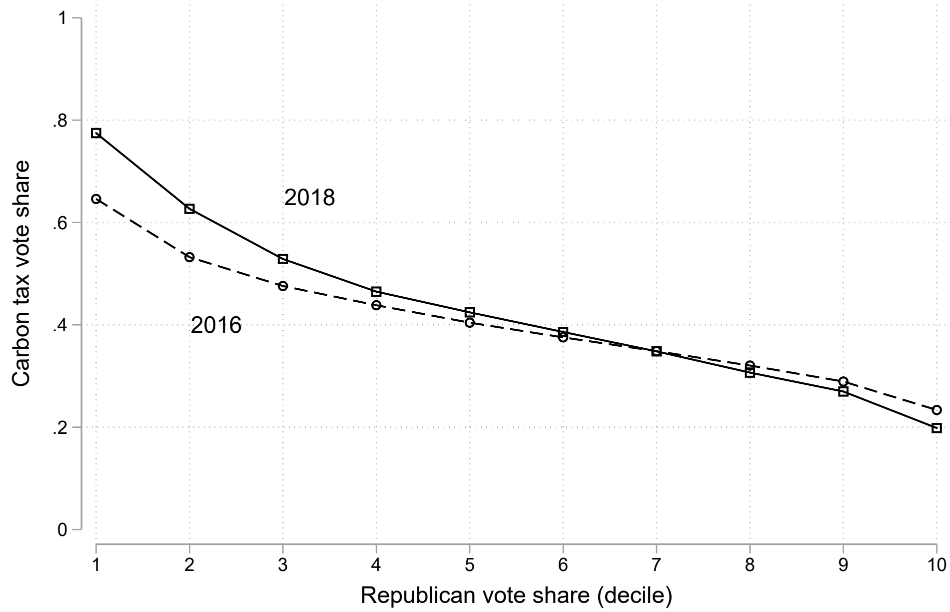


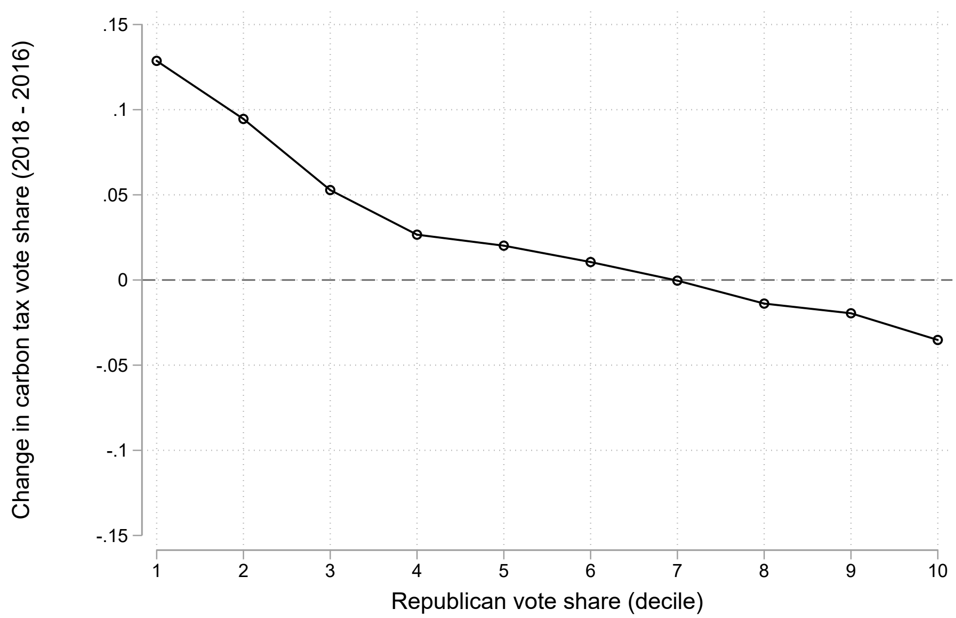
Note: The top panel of this figure plots the "yes" shares on I-1631 in 2018 (gray dots) and I-732 in 2016 (light gray dots) versus the conservatism index for 6,219 precincts in Washington State. The solid and dashed lines plot local polynomial fitted values for the respective years (local linear regression 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 11).

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 17: *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.

F Additional tables: precinct-level regressions

Table 10: *Predicting the carbon tax vote share at the precinct level (2016 only)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +County FEs	(6) +Initiatives
Conservatism	-0.675***			-0.535***	-0.541***	
	(0.010)			(0.023)	(0.024)	
Republican		-0.611***	-0.523***	-0.114***	-0.114***	-0.030
		(0.021)	(0.022)	(0.021)	(0.024)	(0.022)
Observations	6219	6219	6219	6219	6219	6219
R^2	0.905	0.880	0.922	0.941	0.946	0.954

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 11). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. Models (3)-(6) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., # vehicles, commute time by car, industry, home value, # rooms, income, gender, age, race, education, household size, urban share, and owner-occupied share). Model (4) then adds ideology. Model (5) then adds county fixed effects. Finally, model (6) replaces ideology with vote shares for the 12 individual ballot initiatives. 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).

$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.

Source: WA SOS & U.S. Census.

Table 11: *Predicting the carbon tax vote share at the precinct level (2018 only)*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +County FEs	(6) +Initiatives
Conservatism	-0.953***			-0.803***	-0.790***	
	(0.017)			(0.037)	(0.016)	
Republican		-0.848***	-0.747***	-0.134***	-0.164***	-0.063***
		(0.031)	(0.023)	(0.035)	(0.018)	(0.017)
Observations	6219	6219	6219	6219	6219	6219
R^2	0.958	0.898	0.945	0.968	0.974	0.980

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 11). *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. Models (3)-(6) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., # vehicles, commute time by car, industry, home value, # rooms, income, gender, age, race, education, household size, urban share, and owner-occupied share). Model (4) then adds ideology. Model (5) then adds county fixed effects. Finally, model (6) replaces ideology with vote shares for the 12 individual ballot initiatives. 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).

$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.

Source: WA SOS & U.S. Census.

Table 12: *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	-0.814***		-0.669***		-0.495***		-0.626***
	(0.013)		(0.026)		(0.017)		(0.024)
Republican		-0.885***	-0.169***	-0.853***	-0.350***	-0.864***	-0.210***
		(0.026)	(0.028)	(0.025)	(0.017)	(0.025)	(0.025)
2018 vote	0.026	0.026	0.026	0.031**	0.028*	0.026	0.026
	(0.014)	(0.014)	(0.014)	(0.009)	(0.012)	(0.014)	(0.014)
Observations	12438	12438	12438	12438	12438	12438	12438
R^2	0.913	0.862	0.916	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 11). *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).

$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.

Source: WA SOS.

G Do turnout gaps cause substantial bias?

We measure percent support for the carbon tax among people that actively vote yes or no on the carbon tax. This population differs from the full population of voters for which we measure partisanship and ideology, due to roll-off (i.e., abstentions on the carbon tax). This population further differs from the underlying population of residents for which we measure census demographics (e.g., age and income), since not all residents are registered voters, and since not all registered voters actually vote (i.e., turnout is less than 100%). This mismatch leads to potential ambiguity in the interpretation of our estimates. For example, young people are more likely to support carbon taxes (positive effect on % support). Yet young people are less likely to vote (negative effect on % support). So what are we to make of the correlation between % young and support for a carbon tax? Does this correlation reflect the preferences of young voters? Young residents? Both? Neither?

To shed light on these questions, we develop a simple theoretical framework linking an underlying population to the set of voters who actively vote yes or no on the carbon tax. Our framework (which assumes constant turnout and voting preferences by voter type) incidentally bears some similarity to the data-generating process in Lang and Pearson-Merkowitz (2021), which explores related issues via simulation. We show that correlations between support for the carbon tax in the voting population and in the underlying population are approximately the same when (1) the correlation between turnout and underlying ideology/demographics is weak, or (2) the variation in ideology/demographics across precincts ranges widely from one extreme to the other. Intuitively, when turnout is unrelated to ideology/demographics, voters are drawn at random from the underlying population. So correlations with support for the carbon tax are identical. Meanwhile, ambiguity about how voters compare to residents is only salient in diverse precincts. That is, for example, in precincts that are 100% Democrat, the voters are 100% Democrat, regardless of turnout. Meanwhile, in precincts that are 100% Republican, the voters are 100% Republican. Thus, a comparison of ideologically extreme precincts accurately identifies support for a carbon tax among Democrats vs. Republicans, even in the presence of a large turnout gap between Democrats and Republicans. Correlations between % support for the carbon tax among voters and % Republican in a precinct therefore tend to reflect the underlying preferences of Republicans vs. Democrats, assuming that % Republican ranges widely across precincts from one extreme to the other.

Finally, we show empirically that the correlation between turnout and ideology/demographics is generally quite weak across Washington precincts (with the caveat that these correlations are derived from aggregate voting data). Moreover, in the case of partisanship and ideology, where the turnout gap is larger, both partisanship and ideology range widely from one extreme to the other. Thus, for both reasons, correlations derived from the voting population will tend to mirror those of the underlying resident population. We elaborate on these points in the sections below.

G.1 A simple theoretical framework for analyzing turnout bias

For simplicity, assume there are two types of potential voters: A and B. Average support for the carbon tax differs across types, given by s^A and s^B. Likewise, the probability of voting (turnout) differs across types, given by ρ^A and ρ^B. Assume that, conditional on type, support for the carbon tax is independent of turnout. Meanwhile, the distribution of types differs across precincts: let x_i be the fraction of type A in precinct i and $1 - x_i$ be the fraction of type B. Assume that s^A, s^B, ρ^A, and ρ^B are all constant across precincts.

Given these assumptions, voter turnout in precinct i is given by:

$$v_i = x_i \rho^A + (1 - x_i)\rho^B, \tag{2}$$

which is simply the population-weighted average turnout. Meanwhile, the total number of yes votes on the carbon tax is given by:

$$y_i = x_i \rho^A s^A + (1 - x_i)\rho^B s^B, \tag{3}$$

which is simply the population-weighted average of turnout times support. Thus, measured support for the carbon tax among actual voters is given by:

$$s_i = \frac{y_i}{v_i}, \tag{4}$$

where the numerator is total yes votes for the carbon tax and the denominator is turnout.[43] Note that measured support in general is a nonlinear function of the type A population share (x_i).

The parameter of interest is the gap in support for the carbon tax for type A relative to type B: $s^A - s^B$. We are interested in whether this parameter can be inferred from a regression of precinct-level support for a carbon tax (s_i) on the share of the precinct's potential voters that belongs to group A (x_i) in the presence of a possible turnout gap ($\rho^A - \rho^B$). We will consider two limiting cases.

Case 1: Turnout is the same for both groups: $\rho^A = \rho^B = \rho$. In this case, turnout is given simply by $v_i = \rho$, while the total number of yes votes for the carbon tax is given by:

$$y_i = \rho \left\{ x_i(s^A - s^B) + s^B \right\}. \tag{5}$$

Measured support for the carbon tax is therefore given by:

$$s_i = \frac{y_i}{v_i} = x_i(s^A - s^B) + s^B, \tag{6}$$

[43]Here, we abstract away from roll-off, i.e. returning a ballot but abstaining on the carbon tax measure. Our results extend in a straightforward way to this case, as well, where the ρ parameters measure the probability of voting *and* not abstaining on the carbon tax measure.

where note that the ρ's in the numerator and denominator cancel. From here, is clear that the slope of s_i with respect to x_i is constant and exactly equal to $s^A - s^B$, i.e. the support gap. Thus, a regression of s_i on x_i will certainly yield a slope equal to the desired parameter.

Case 2: The population shares for A vs. B are observed to range from one extreme to the other ($x = 0$ and $x = 1$). At the $x = 1$ extreme (100% type A), turnout is given by $v = \rho^A$ and the total number of yes votes is given by $y = \rho^A s^A$, such that measured support for the carbon tax is given by s^A. Meanwhile, at the $x = 0$ extreme (100% type B), turnout is given by ρ^B and the total number of yes votes is given by $y = \rho^B s^B$, such that measured support for the carbon tax is given by s_B. Thus, the support gap $s^A - s^B$ can be inferred by comparing average support at the two extremes.

In-between these two extremes, measured support ($s_i = y_i/v_i$) is a continuously differentiable nonlinear function of the type A share (x_i). Thus, the average (unweighted) slope between the two extremes is exactly equal to the slope of the line connecting the two extremes, i.e. the support gap identified in case 2.[44] A regression of s_i on x_i therefore will tend to yield a coefficient close to the support gap ($s^A - s^B$) when the distribution of x_i ranges widely from one extreme to the other.

G.2 Turnout bias is likely small in practice

We now empirically assess whether differential turnout by ideology and demographics will substantially bias our results. Our results suggest that it will not. But we cannot definitively rule out bias, given the simplifying assumptions of our framework and reliance on aggregate data for calibration.

We begin by regressing carbon tax turnout on ideology, demographics, and other factors. See table 13, which parallels 3 above. We define carbon tax turnout as the total number of yes and no votes on the carbon tax, divided by the total number of registered voters (i.e., the share of registered voters that vote *and* do not abstain on the carbon tax). Column (1) implies that turnout is 11.2 percentage points lower in the most conservative vs. most liberal precincts, while column (2) implies that turnout is 6.1 percentage points lower in exclusively Republican vs. exclusively Democratic precincts. The explanatory power of these regressions is not high (R-squared of 0.056 and 0.020). Controlling for detailed demographics (column 3) kills the partisan correlation and raises the model's explanatory power dramatically (to an R-squared of 0.629). Adding ideology on top of partisanship (column 4) suggests that Republican precincts are more likely to vote conditional on ideology, while conservative precincts are less likely to vote conditional on partisanship, and that these two forces tend to cancel each other out (i.e., since partisanship is strongly correlated ideology with a slope close to 1). These coefficients are robust to the inclusion of county fixed effects (column 5) but the coefficient on Republican share drops substantially when breaking out ideology into its constituent parts (column 6). Overall, these results suggest that turnout in Washington State is driven more by demographics

[44]Proof: Let $s'(x_i)$ be the slope of $s(x_i)$ at x_i. Then the mean slope of $s(x_i)$ on the interval [0,1] is $\int_0^1 s'(x)dx = s(1) - s(0)$.

Table 13: *Explaining turnout on the carbon tax*

	(1) Ideology	(2) Party	(3) +Census	(4) +Ideology	(5) +County FEs	(6) +Initiatives
Conservatism	-0.112***			-0.205**	-0.207**	
	(0.030)			(0.064)	(0.059)	
Republican		-0.061	0.003	0.159**	0.122*	-0.029
		(0.033)	(0.021)	(0.046)	(0.046)	(0.028)
2018 vote	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	12438	12438	12438	12438	12438	12438
R^2	0.056	0.020	0.629	0.635	0.667	0.722

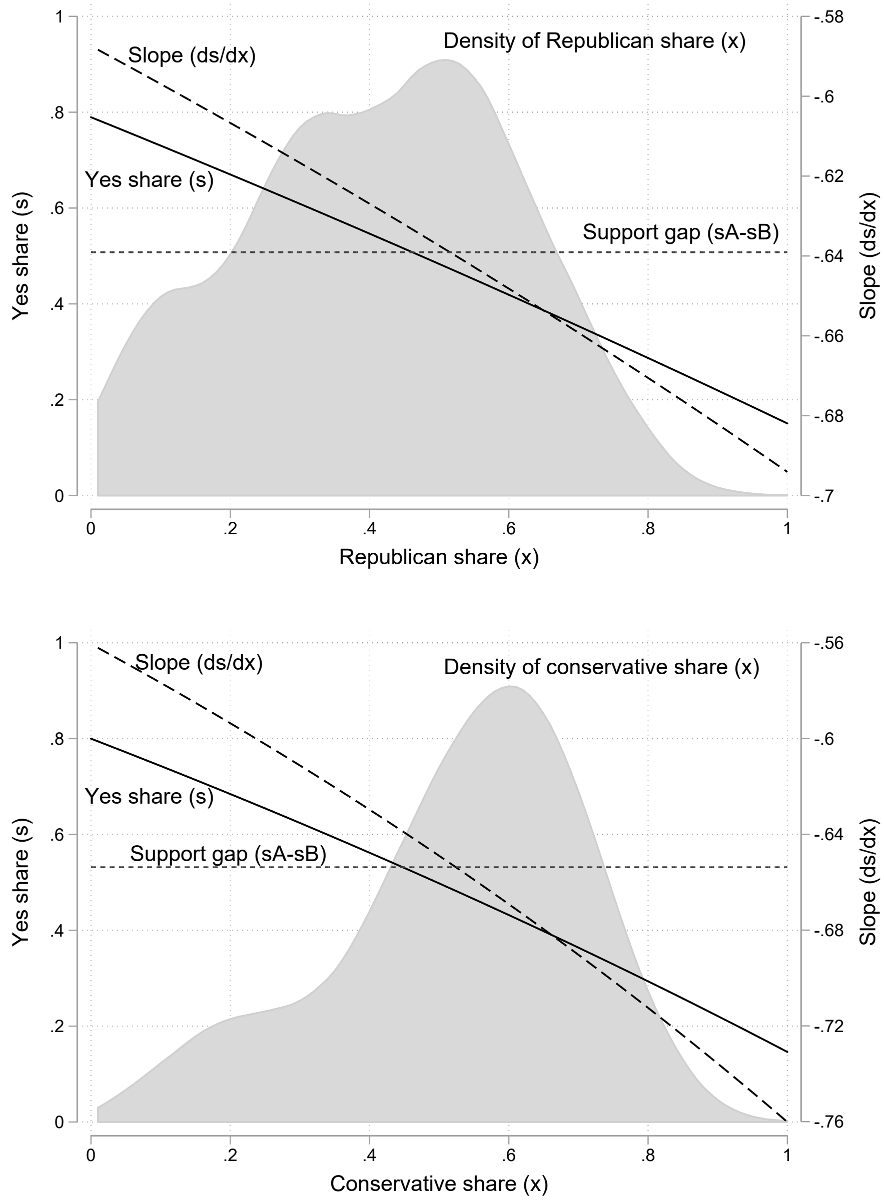
Note: This table presents coefficient estimates from pooled precinct-level OLS regressions modeling carbon tax turnout in 2016 and 2018 as a function of ideology, demographics, and other factors. Turnout in 2016 is the total number of yes and no votes for the carbon tax in 2016 divided by the total number of registered voters in 2016. Turnout in 2018 is the total number of yes and no votes for the carbon tax in 2018 divided by the total number of registered voters in 2016 (i.e., same base year). *Conservatism* measures ideology on a 0-1 index, computed from the precinct's vote shares on 12 ballot measures in 2016 and 2018. *Republican* measures the share voting for the Republican (vs. Democratic) party candidate in the 2016 U.S. presidential election. *2018 vote* is an indicator for the 2018 carbon tax (I-1631). Models (3)-(6) build cumulatively on model (2). Model (3) controls for detailed census variables (i.e., # vehicles, commute time by car, industry, home value, # rooms, income, gender, age, race, education, household size, urban share, and owner-occupied share). Model (4) then adds ideology. Model (5) then adds county fixed effects. Finally, model (6) replaces ideology with vote shares for the 12 individual ballot initiatives. 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).
$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.
Source: WA SOS & U.S. Census

than by political ideology.

To assess whether partisan turnout gaps substantially bias our regression results, we use the simple framework in equations (2)-(4) above to calculate yes share (s) as a function of Republican share (x), with parameters chosen roughly to match our data. Consistent with case 2 above, we parameterize s^A to equal average support for the carbon tax in our data among the top 1% most Republican precincts (based on the 2016 presidential vote) and s^B to equal average support among the top 1% most Democratic precincts. This parameterization implies a support gap of $s^A - s^B = 0.1505 - 0.7896 = -0.6391$. We parameterize ρ^B as the intercept from regression (2) in table 13 (i.e., predicted turnout in an exclusively Democratic precinct) and ρ^A as the intercept plus the coefficient on *Republican* (i.e., predicted turnout in an exclusively Republican precinct). This parameterization implies a turnout gap of $\rho^A - \rho^B = 0.6978 - 0.7585 = -0.0607$. We then calculate yes share (s) as a function of Republican share (x) according to equations (2)-(4). See the solid, downward-sloping line in the top panel of figure 18.

Would a regression of s on x in this case yield a coefficient close to the true (given our parameterization) partisan support gap of -0.6391? Figure 18 illustrates that yes share (solid line) is downward-sloping and

Figure 18: *Assessment of turnout bias*



Note: The top panel plots yes share (solid line) and its slope (dashed line) as a function of Republican share, given assumptions on average support for the carbon tax among Republicans ($s^A = 0.1505$) vs. Democrats ($s^B = 0.7896$), as well as average turnout among Republicans ($\rho^A = 0.6978$) vs. Democrats ($\rho^B = 0.7585$), according to the simple theoretical framework described in the previous section. The support gap (dotted line) and empirical distribution of Republican share (shaded pdf) are both shown for reference. The bottom panel plots yes share (solid line) and its slope (dashed line) as a function of the conservative share, given assumptions on average support for the carbon tax among conservatives ($s^A = 0.1462$) vs. liberals ($s^B = 0.7999$), as well as average turnout among conservatives ($\rho^A = 0.6807$) vs. liberals ($\rho^B = 0.7928$), according to the simple theoretical framework described in the previous section. The support gap (dotted line) and empirical distribution of conservative share (shaded pdf, given by the distribution of our Conservatism index) are both shown for reference.
Source: WA SOS and author calculations.

slightly concave. Thus, its slope (dashed line) varies, ranging from about -0.59 to -0.69. Meanwhile, the support gap, given our parameterization, is -0.6391. Thus, while a regression of yes share (s) on Republican share (x) may yield a coefficient that diverges from the true support gap of -0.6391 (given that the slope is heterogeneous), this divergence could not be very large (since the heterogeneity in the slope is quite modest). Indeed, when we regress s on x using the empirical distribution of Republican share across precincts in our voting data (shaded pdf), we get a value of -0.6278, which is very close to the true support gap.

We repeat this entire exercise to assess how severely the ideological turnout gap biases our estimates of the support gap. As above, we parameterize s^A and s^B based on average support for the carbon tax in the 1% most ideologically extreme precincts, and we parameterize ρ^A and ρ^B based on the slope and intercept from regression (1) in table 13.[45] See the bottom panel of figure 18 for the results. A regression of yes share (s) on conservative share (x) yields a slope coefficient of -0.6457, as compared to a true support gap (given our parameterization) of $s^A - s^B = 0.1462 - 0.7999 = -0.6537$. Again, we conclude that the ideological turnout gap in this case ($\rho^A - \rho^B = 0.6807 - 0.7928 = -0.1121$) is too small to substantially bias our results.

We are also interested in whether turnout gaps potentially bias our estimates for how support for the carbon tax depends on demographics. We are most interested in the coefficients on the number of vehicles and rooms in regression (6) of table 3, since we rely heavily on these variables to calculate tax incidence and thereby estimate WTP for the carbon tax policies. To probe this issue, we re-estimate regression (6) from table 13, replacing the shares of households with 1, 2, 3, 4, or 5+ vehicles with a single variable measuring the share of household with 1+ vehicles (to fit our theoretical framework). The coefficient is 0.0315 with a robust standard error of 0.0162, i.e. turnout is 3.15 percentage points higher in precincts where every household has at least one vehicle vs. precincts where none do, conditional on our many controls. This conditional turnout gap is simply too small to substantially bias our regression results.

To illustrate, we again apply our simple theoretical framework from above. We parameterize the turnout gap to be $\rho^A - \rho^B = 0.0315$, i.e. our estimated turnout gap conditional on controls. We set the levels of $\rho^A = 0.7352$ and $\rho^B = 0.7037$ to match mean turnout in our data (given by $\bar{x}\rho^A + (1 - \bar{x})\rho^B$, where $\bar{x}$ is the mean share of vehicle-owning households). Meanwhile, we provisionally parameterize the support gap to be $s^A - s^B = -0.0301$.[46] We set the levels of $s^A = 0.4197$ and $s^B = 0.4498$ to match mean support for the carbon tax in our data (given by $\bar{x}s^A + (1 - \bar{x})s^B$). Finally, we calculate yes share (s) as a function of the share of households with 1+ vehicles (x) according to the simple theoretical framework in equations (2)-(4)

[45] Given our simple theoretical framework, we implicitly assume that variation in average ideology across precincts is driven entirely by variation in the share of liberals vs. conservatives, rather than by variation in the intensity of ideology across individuals (i.e., we rule out moderates and other intermediate types).

[46] For this exercise, we cannot parameterize the support gap by comparing extreme precincts in which 100% vs. 0% of households own a vehicle, since this simple comparison does not condition on the many control variables that we include in our regressions. Below, we verify that our provisional choice of support gap leads to a hypothetical regression coefficient (s on x) that is consistent with what we obtain in our actual data when we include controls.

above. We find that a regression of yes share (s) on the share of households with 1+ vehicles (x) yields a coefficient of -0.0292 (using the empirical distribution for share with 1+ vehicles). This coefficient exactly equals the coefficient on 1+ vehicles when we re-estimate regression (6) in table 3 using 1+ vehicles in place of the multiple vehicle ownership variables, validating our provisional choice of support gap above. Thus, we conclude the turnout gap causes minimal bias (regression coefficient of -0.0292 versus an actual support gap of -0.0301, given our parameterization).

Finally, we repeat this entire exercise for number of rooms. We again re-estimate regression (6) from table 13, replacing the shares of households with 1, 2, 3, ... 9+ rooms with a single variable measuring the share of households with 6+ rooms (i.e., above the median home size). The coefficient is -0.0248 with a robust standard error of 0.0051, i.e. turnout is 2.48 percentage points lower in precincts where every household has more than the median number of rooms vs. precincts where none do. Thus, applying our theoretical framework, we parameterize the turnout gap to be $\rho^A - \rho^B = 0.7227 - 0.7476 = -0.0248$. Meanwhile, we provisionally set the support gap to be $s^A - s^B = 0.4128 - 0.4328 = -0.0200$. As above, we choose the overall levels of turnout and support to match the means in our data. Finally, we calculate yes share (s) as a function of the share of households with 6+ rooms (x) according to the simple theoretical framework in equations (2)-(4) above. We find that a regression of yes share (s) on the share of households with 6+ rooms (x) yields a coefficient of -0.0200 (using the empirical distribution for share with 6+ rooms). Thus, we conclude the turnout gap causes minimal bias (regression coefficient of -0.0200 versus an actual support gap of -0.0200, given our parameterization).

H Estimating willingness to pay

In this appendix we detail our procedures to estimate willingness to pay (WTP) for the carbon tax policy. We begin by presenting our structural discrete-choice model, describing how we estimate this model via logistic regression of aggregate voting data on precinct-level energy tax incidence and controls, and how we use the results to infer mean WTP by precinct. We then explain how we calculate precinct-level energy tax incidence. This calculation proceeds in several steps. First, using household-level microdata from the 2017 National Household Transportation Survey (NHTS) and the 2015 Residential Energy Consumption Survey (RECS), we regress household gasoline consumption and emissions from home energy consumption on household-level characteristics. Second, we apply the coefficients from these micro regressions to the corresponding precinct-level aggregate census data, to estimate mean household-level carbon emissions for each precinct. Third, we divide the household-level carbon emissions by the average number of voting-age (i.e., over 18) adults per household in each precinct, and multiply by the carbon price ($25/tCO2 in 2016 and $25/tCO2 in 2018), to yield a measure of mean precinct-level energy tax incidence for the average voting-age adult. Our measure of average tax incidence aligns closely with the results of web-based carbon tax calculators that were publicly available at the time of the 2016 and 2018 votes.[47] Finally, we close this appendix by calculating lower and upper bounds on the standard deviation of individual-level energy tax incidence. We argue that this standard deviation is not large enough to overturn our conclusion that variation in WTP is driven mainly by ideology, rather than by tax incidence.

H.1 Structural discrete-choice model estimated using aggregate data

Let the net utility that individual voter n in precinct i perceives from the referendum passing be given by:

$$u_{in} = y_i + \eta_{in}, \tag{7}$$

where y_i is precinct-level mean utility and η_{in} is a mean-zero idiosyncratic error term that varies across individual voters. The precinct-level mean utility is a linear function of underlying components: $y_i = \alpha \cdot totaltax_i + \beta' ideology_i + \gamma' demographics_i + \epsilon_i$. Component $\alpha \cdot totaltax_i$ captures the mean disutility in the precinct from higher energy prices, where $-\alpha$ is the marginal utility of dollars and $totaltax_i$ is the precinct-level mean energy tax incidence (whose calculation we describe in detail below). Components $\beta' ideology_i$ and $\gamma' demographics_i$ capture systematic shifts in mean utility due to observed precinct-level ideology and demographic variables, with corresponding coefficient vectors β and γ. Finally, error ϵ_i captures shifts in mean utility due to a precinct-level unobservable. Thus, the idiosyncratic error (η_{in}) captures deviations from precinct-level mean utility due to heterogeneity in individual-level tax incidence and other factors. We assume η_{in} follows a logistic distribution and normalize its standard deviation to $\pi/\sqrt{3}$.

[47]See, for example, the web-based tax calculator here: http://carbon.cs.washington.edu/.

As is standard, we assume that individuals vote "yes" in the referendum if and only if their perceived net utility from the referendum passing in expression (7) is weakly positive, i.e. as if they are the pivotal voter deciding the outcome of the election. Given this and our other assumptions, the probability that individual voter n in precinct i votes "yes" is given by the following closed-form expression (Train 2009):

$$p_{in} = \frac{e^{y_i}}{1 + e^{y_i}}. \tag{8}$$

Thus, assuming a large number of voters in each precinct, the share that vote "yes" is closely approximated by the same expression:

$$s_i = \frac{e^{y_i}}{1 + e^{y_i}}. \tag{9}$$

Meanwhile, the share that vote "no" is given by:

$$1 - s_i = \frac{1}{1 + e^{y_i}}. \tag{10}$$

Dividing the share voting "yes" by the share voting "no" and taking logs then yields the logistic regression model from the main text:

$$y_i = ln\left(\frac{s_i}{1 - s_i}\right) = \alpha \cdot totaltax_i + \beta' ideology_i + \gamma' demographics_i + \epsilon_i, \tag{11}$$

which can be estimated via linear regression using aggregate vote-shares data.

Note that we can rescale utility in expression (7) by dividing by the marginal utility of dollars (-α) to yield total WTP for the policy, i.e. the perceived net benefits of the referendum passing, in dollars. Thus, the mean total WTP for the policy in precinct i is given by y_i/α (Train 2009). Likewise, this total WTP can be decomposed into components attributable specifically to tax incidence ($totaltax_i$), ideology ($\beta' ideology_i/\alpha$), demographics ($\gamma' demographics_i/\alpha$), and a residual ($\epsilon_i/\alpha$). Further, given our normalization for the standard deviation of the idiosyncratic error η_{in}, this rescaling implies that the standard deviation in individual-level WTP around the precinct-level mean is given by $(1/\alpha) \cdot \pi/\sqrt{3}$.

H.2 Modeling household gasoline consumption using the NHTS

Using the 2017 National Household Travel Survey (NHTS), we first regress household gasoline consumption on household characteristics also found in census data. The NHTS records annual household gasoline consumption across all vehicles, including consumption from light-duty passenger vehicles (cars, SUVs, vans, and pickups), along with other trucks, RVs, motorcycles, and other vehicles. We regress this value on (a) the total number of light-duty passenger vehicles (cars, SUVs, vans, and pickups), (b) average daily one-way car commute time for all household members age 16 and older (including those that do not commute by car, that work from home, or that do not work for pay at all, which all enter as zeros in calculating the average), (c) total number of household members, and (d) a dummy variable indicating that the household lives in an

Table 14: *Explaining household gasoline consumption*

	(1) Gallons	(2) Gallons	(3) Gallons	(4) Gallons
Vehicles	468.95***		411.34***	423.34***
	(48.73)		(47.56)	(50.21)
Average commute			4.93*	9.73
			(1.96)	(5.87)
Total commute		6.85***		-2.63
		(1.54)		(3.45)
Household members			79.53**	87.59**
			(26.27)	(28.82)
Urban			-244.93**	-239.66**
			(84.79)	(84.40)
Constant	23.57	828.75***	72.05	28.78
	(84.97)	(43.66)	(120.84)	(126.19)
Observations	620	620	620	620
R^2	0.342	0.064	0.376	0.377

Note: This table presents coefficient estimates from household-level OLS regressions of annual gasoline consumption (in gallons) as a function of household characteristics. *Vehicles* measures the number of light-duty passenger vehicles (cars, SUVs, vans, and pickups). *Average commute* measures the average, one-way daily car commute time for all household members age 16 and older. *Total commute* measures the cumulative, daily one-way car commute time for all household members age 16 and older. *Household members* is household size. *Urban* is a dummy variable indicating that the household lives in an urbanized area. Sample is limited to households living in Washington State. Observations are weighted by NHTS household sampling weights. Standard errors are robust to heteroskedasticity.
$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.
Source: National Household Transportation Survey (2017).

urbanized area. As an alternative to average car commute time, we also experiment with measuring total car commute time in minutes across all household members age 16 and older, capturing both the number of commuters and their average commute lengths. In our regressions, we limit our sample to Washington households and apply NHTS household sampling weights.

Table 15 presents the coefficient estimates and heteroskedasticity robust standard errors. Column (1) indicates that every household vehicle is associated with 469 additional gallons fuel consumption. Column (2) indicates that every minute of car commute time is associated with 6.85 gallons. Comparing R-squared across columns, we see that vehicles is a much better predictor of gasoline consumption than commute time. Column (3) is our preferred specification and models gasoline consumption as a function of vehicles, average commute time, household size, and the urban dummy. Note that that the coefficients are statistically significant and have the expected signs, but the predictive power of the model increases only slightly relative to the simple regression in column (1). To test the linearity assumptions imposed by this model, we repeat regression (3), using dummy variables in place of the continuous measures for number of vehicles and household size. Figure 19 confirms that gasoline consumption is strongly related to the number of vehicles, and weakly related to household size. Column (4) includes a control for total commute time across all household members, in addition to average commute time, but the coefficient is statistically insignificant.

Having estimated our preferred model in column (3), we then apply the coefficients to the corresponding precinct-level averages from census data, to calculate mean household-level gasoline consumption in each precinct. We calculate precinct-level averages as follows. We calculate the weighted average number of passenger vehicles per household as the share of households with zero vehicles times 0, plus share of households with one vehicle times 1, and so forth.[48] Likewise, we calculate the weighted average car commute time in minutes for people age 16 and over (including those that do not commute by car, that work from home, or that do not work for pay at all, which all enter as zeros in calculating the average). Census reports commute time in discrete increments, so we use the midpoint of each increment when calculating the weighted average.[49] We calculate the mean number of household members as total population divided by total number of households. Finally, we are not able to find urban status for individual block groups or precincts in Washington. Thus, we calculate the share of each county's households located in urbanized areas in 2010, and assign this value to the individual precincts within a county.[50]

Finally, we multiply household gasoline consumption by carbon content of a gallon of gasoline, to yield annual carbon emissions from gasoline in each precinct.

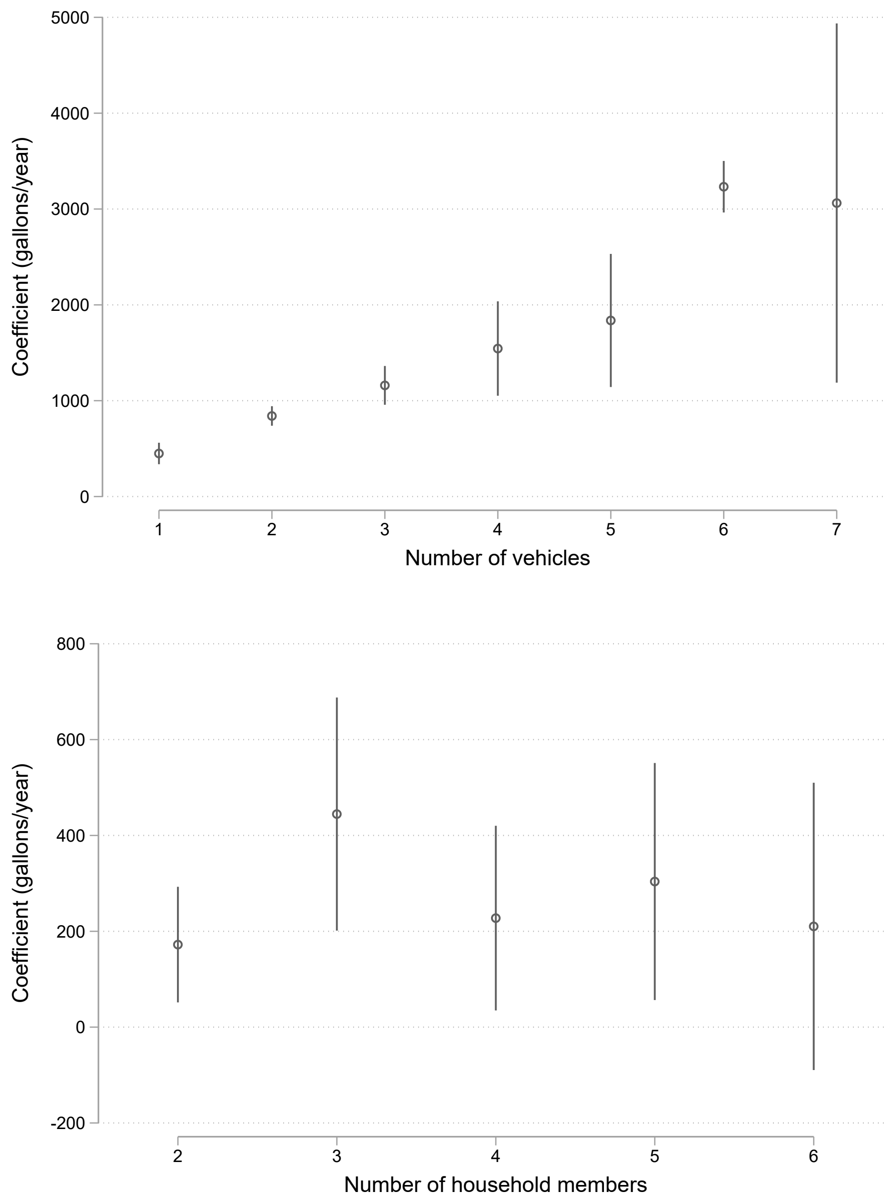
How accurate are our predictions at the precinct level? We cannot answer this question directly, since we generally do not observe gasoline consumption for geographies below the state level. We can, however, explore this issue indirectly. To do so, we replicate our preferred regression (3) in table 14 using the full national sample of NHTS microdata. We then generate a set of simulated pseudo precincts by intersecting a state indicator with an 8-category indicator for the density of housing units in the surrounding census tract (other tract and block-group indicators of density and % owner-occupied available in the NHTS yield similar results). We drop pseudo precincts with fewer than 200 households, leaving 68 such precincts (note that the average precinct size in Washington is 300+ households; cutoffs ranging from 150-250 yield similar results). Finally, we compare average *actual* gasoline consumption to average *predicted* gasoline consumption for each of our pseudo precincts in figure 20. The figure shows a tight correlation between actual and predicted

[48] The ACS groups together households with 5 or more passenger vehicles. We use the 2017 NHTS to calculate the mean number of vehicles per household in Washington, conditional on having 5 more vehicles. We multiply this value by the share of households with 5 or more vehicles in calculating the weighted average.

[49] The ACS groups together commuters with commute lengths of 60 minutes or longer. We use the NHTS to calculate mean car commute time in Washington, conditional on having a commute of 60 minutes or longer, and use this value in calculating the weighted average.

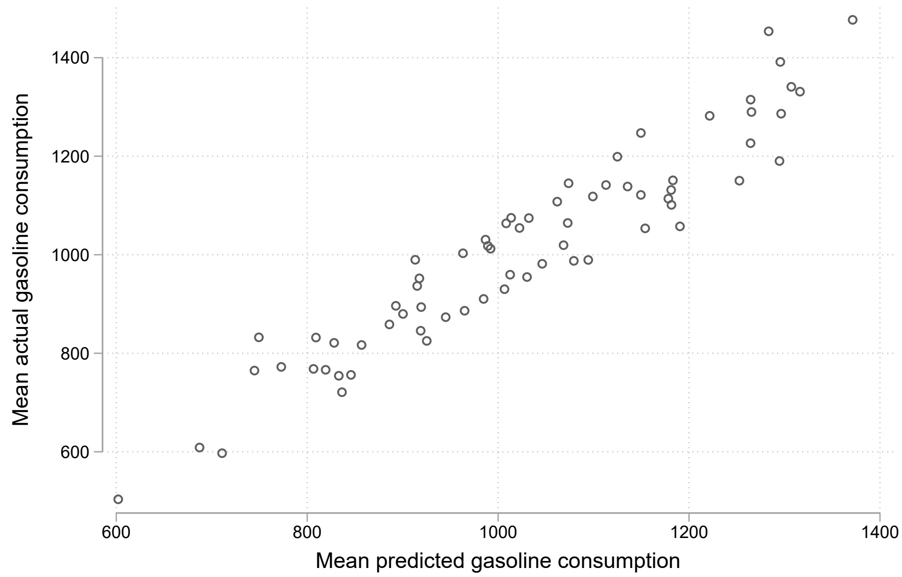
[50] The urban area to county relationship file can be found here: https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.2010.html#par_textimage_470670252.

Figure 19: *Coefficients for number of vehicles and household size*



Note: This figure plots coefficients from a regression of household gasoline consumption on dummies for number of vehicles and household size, controlling for average commute time and an urban area indicator. Sample is limited to 620 households living in Washington State. Observations are weighted by NHTS household sampling weights. Point estimates are represented by dots, while 95% confidence intervals (based on heteroskedasticity robust standard errors) are represented by vertical lines.

Figure 20: *Actual vs. predicted gasoline consumption for pseudo-precincts*



Note: This figure plots actual vs. predicted mean gasoline consumption for 68 pseudo-precincts with at least 200 households in the NHTS. Pseudo-precincts were constructed by intersecting a state indicator with an 8-category indicator for the density of housing units in the surrounding census tract. The vertical axis measures the precinct-level mean of actual household gasoline consumption. The horizontal axis measures the precinct-level mean of predicted household gasoline consumption. Household-level predictions are based on a national-level regression of gasoline consumption on # vehicles, average commute time, # household members, and an urban dummy. A simple regression of actual on predicted yields an R-squared of 0.90.
Source: 2015 NHTS, author calculations

gasoline consumption. Indeed, a simple regression of actual on predicted gasoline consumption yields an R-squared of 0.90. This exercise suggests that our precinct-level predictions based on Washington-specific data are likely to be quite accurate.

H.3 Modeling home energy emissions using the RECS

We estimate carbon emissions from home energy consumption as a function of home size and other variables using the 2015 Residential Energy Consumption Survey (RECS). We then calculate precinct-level carbon emissions by applying our regression coefficients to precinct-level average values for home size and other variables.

Using the 2015 RECS, we first regress home energy emissions on household characteristics also found in census data. The RECS records total annual BTUs of home energy consumption for electricity, natural gas, propane, and fuel oil. We convert the BTU stream for electricity into tons of carbon based on the average carbon content of electricity in Washington in 2016.[51] We convert the BTU streams for natural gas, propane, and fuel oil into tons of carbon based on the known carbon intensity of these fossil fuels.[52] We add carbon emissions from all four streams together to yield total household-level carbon emissions. We then regress household carbon emissions on (a) total number of rooms in the housing unit, (b) total number of household members, and (c) a dummy indicating that the housing unit is owned by one of the household members (which we view as a proxy for a multi-unit vs. single-family housing). We are not able to identify Washington residents, as RECS does not give state of residence. So we focus on a sub-sample of about 500 survey respondents that live in the same census division as Washington (Pacific) and that also live in one of the two RECS climate regions covered by Washington (marine and cold/very cold). The Pacific division (Census) includes Alaska, California, Hawaii, Oregon, and Washington (see here: https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf). For these states, the marine climate region (83% of our RECS sub-sample) extends along the Pacific Coast from Washington and into northern California, while the cold/very cold region (17% of our sub-sample) covers non-coastal areas of Washington, Oregon, and northern California (see here: https://www.eia.gov/consumption/residential/maps.php). In our regressions we apply RECS household sampling weights.

Table 15 presents the coefficient estimates and heteroskedasticity robust standard errors. Column (1) shows a regression of carbon emissions on the number of rooms. On average, every room is associated with 0.25 additional tons of carbon emissions per year. Column (2) is our preferred specification and models home energy emissions as a function of rooms, household size, and the owner-occupied dummy. Note that the coefficients are statistically significant and have the expected signs (owner-occupied correlates with less efficient single-family housing) and that the predictive power increases by about half relative to column (1). To test the linearity assumptions imposed by this model, we repeat regression (2), using dummy variables in place of the continuous measures for number of rooms and household size. Figure 21 confirms that home energy emissions is strongly related to the number of rooms, and weakly related to household size. Column (3) repeats column (2) but limits the sample to data with non-imputed values of all variables. Note that the coefficients do not change substantially.

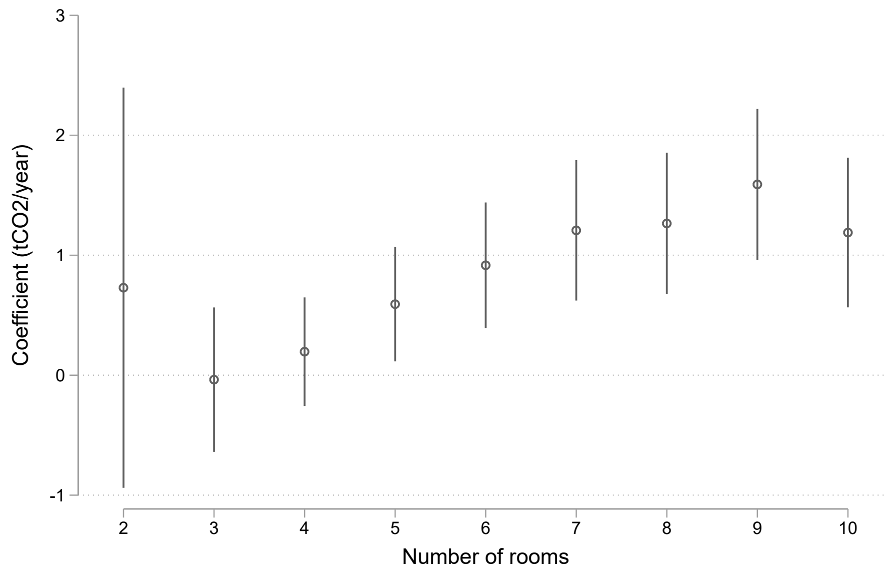
Having estimated our preferred model in column (2), we then apply the coefficients to the corresponding precinct-level averages from census data, to calculate average emissions in each precinct. We calculate precinct-level averages as follows. We calculate the weighted average number of rooms as the share of occupied housing units with one room times 1, plus share with two rooms times 2, and so forth.[53] We calculate the mean number of household members as total population divided by total number of households.

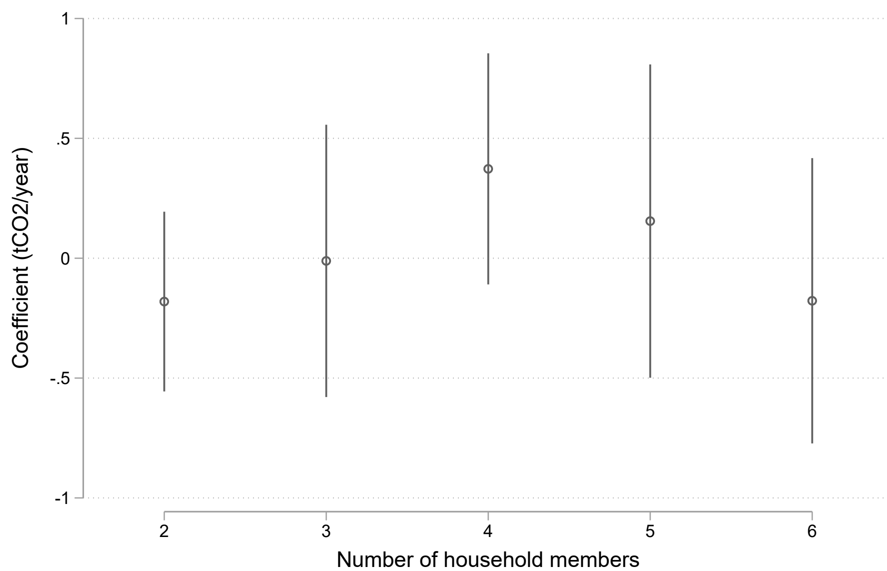
[51]See here: https://www.eia.gov/electricity/state/washington/.

[52]See here for carbon intensity of other fuels: https://www.eia.gov/environment/emissions/co2_vol_mass.php.

[53]The ACS groups together all households with 9 or more rooms. We use the RECS to calculate the mean number of rooms in the relevant regions, conditional on having 9 or more rooms. We multiply this value by the share of households with 9 or more rooms in calculating the weighted average.

Figure 21: *Coefficients for number of rooms and household size*





Note: This figure plots coefficients from a regression of carbon dioxide emissions from home energy consumption on dummies for number of rooms and household size, controlling for an owner-occupied indicator. Sample is limited to 505 households living in both the same census division as Washington state (Pacific) and the same RECS climate regions as Washington State (marine, and cold/very cold). Observations are weighted by RECS household sampling weights. Point estimates are represented by dots, while 95% confidence intervals (based on heteroskedasticity robust standard errors) are represented by vertical lines.

Table 15: *Explaining emissions from home energy consumption*

	(1)	(2)	(3)
	tCO2	tCO2	tCO2
Rooms	0.25***	0.15***	0.16***
	(0.03)	(0.04)	(0.04)
Household members		0.15**	0.15**
		(0.05)	(0.05)
Owner-occupied		0.72***	0.64***
		(0.17)	(0.18)
Constant	0.84***	0.52*	0.51
	(0.21)	(0.25)	(0.27)
Observations	505	505	444
R^2	0.106	0.152	0.146

Note: This table presents coefficient estimates from household-level OLS regressions of annual carbon dioxide emissions from home energy consumption (in tons) as a function of household characteristics. *Rooms* measures the number of rooms in the housing unit. *Household members* is household size. *Owner-occupied* is a dummy variable indicating that a household member owns the housing unit. Sample is limited to households living in both the same census division as Washington state (Pacific) and the same RECS climate regions as Washington State (marine, and cold/very cold). Observations are weighted by RECS household sampling weights. Standard errors are robust to heteroskedasticity.
$*$, $**$, and $***$ indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.
Source: Residential Energy Consumption Survey (2015).

Finally, we calculate the share of households living in owner occupied housing in each precinct.

Unfortunately, we are unable to assess the accuracy of these estimates (as we did for gasoline consumption) for three reasons. First, the full RECS data contain only 1/20 as many observations as the NHTS data. Second, repeating regression (3) from table 15 on various regional sub-samples of the RECS data yields highly variable coefficients. This makes sense: different regions have different climates and rely on different heating fuels, implying different relationships between home size and emissions. Thus, a national-level regression does not make sense. Yet focusing on a single region containing Washington would exacerbate the small-sample limitations. Finally, the RECS data do not provide state indicators or neighborhood-level characteristics that would facilitate the construction of meaningful pseudo-precincts. Fortunately, figure 22 shows that the mean and variance of overall emissions are likely dominated by gasoline consumption, which will tend to mitigate any bias caused by inaccuracy in our predictions for home energy consumption. This hypothesis is borne out in table 5, which shows that the coefficient on *total tax* in column (3) is very similar to the coefficient on *total tax* in column (1); note that column (1) controls for *room tax*, such that the coefficient on *total tax* reflects the independent contribution of gasoline-related tax incidence.

H.4 Precinct-level carbon tax incidence

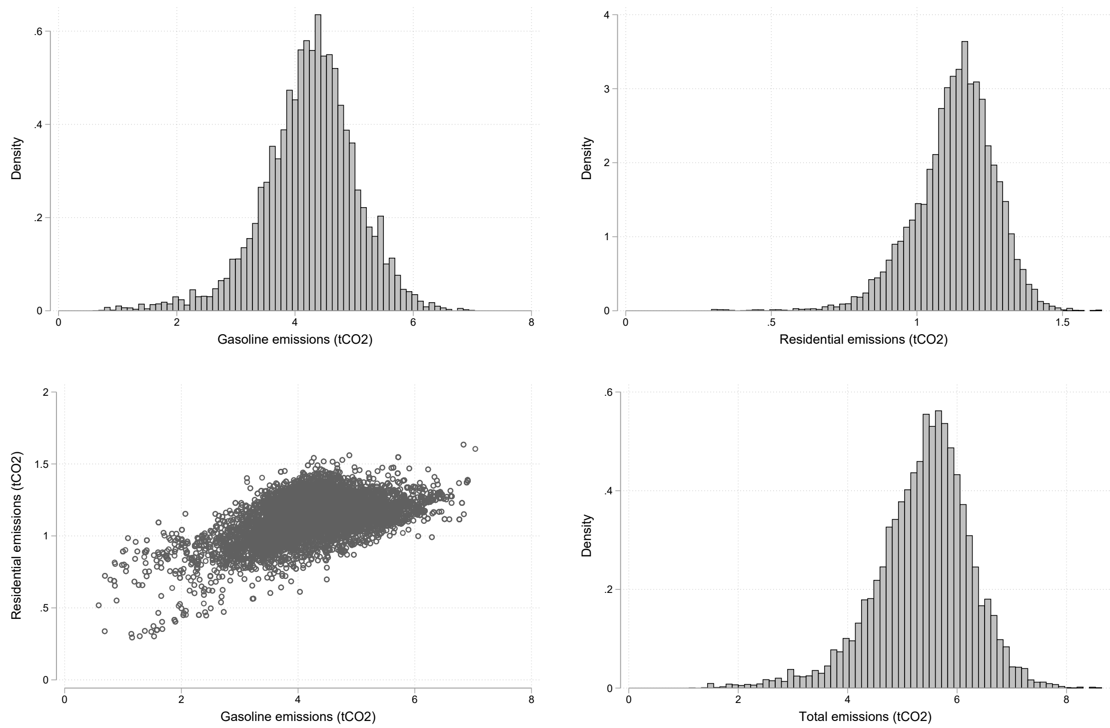
The regressions and predictions described above yield annual average household-level carbon dioxide emissions from gasoline consumption and home energy consumption in each precinct. We divide by the average number of household members age 18 and older in each precinct, to compute average carbon dioxide emissions for the voting-age population (people under 18 do not vote and are assumed not to pay for the cost of the carbon tax). Figure 22 shows the resulting distributions of carbon dioxide emissions. The top left panel shows the distribution of gasoline-related emissions across precincts. The top right panel shows the distribution of home energy related emissions. The bottom left panel shows the joint distribution of these two variables: emissions from gasoline and from home energy consumption are positively correlated. Finally, the bottom right panel shows the distribution of the total carbon dioxide emissions (i.e., gasoline plus home energy consumption) across precincts. The figures show that home energy emissions are much lower and less dispersed than gasoline emissions. Thus, gasoline-related emissions are the main driver of carbon tax burden across precincts in our sample.

By what carbon tax rate should we multiply precinct-level carbon dioxide emissions to yield total tax burden? This is a tricky question to answer, given the gradual increase in the tax rate over time under both I-732 and I-1631 (see table 1). Voters may have formed different beliefs about costs, depending on whether they focused on initial tax burden or average burden over multiple years. In our baseline approach, we use a carbon tax of $25/tCO2 for I-732 in 2016 and $15/tCO2 for I-1631 in 2018, i.e. the baseline tax rates upon which the respective annual increases of 3.5% and $2/tCO2 were applied. This choice is consistent with web-based individual tax burden calculators that were available to Washington residents prior to voting, which assumed $25/tCO2 in 2016 and $15/tCO2 in 2018 (see below for details). This choice is also consistent with contemporaneous reporting that emphasized $25/tCO2 in 2016 and $15/tCO2 in 2018.[54] Finally, the choice of a higher price in 2016 is consistent with contemporaneous reporting that emphasized a higher initial carbon price, higher prices over the first 15-20 years, and a higher maximum price for I-732 relative to I-1631.[55] In fact, our own careful reading of the language of I-732 and I-1631 suggests that carbon prices under the two policies would have followed quite similar trajectories, such that their respective annualized present values would have been $32/tO2 and $33/tCO2 over their first 25 years and $43/tCO2 and $46/tCO2 over their first 50 years (assuming 2% inflation and a 4% real discount rate applied to future price increases).

[54]For example, see here for 2016, which features a graphic prominently displaying $25/tCO2: https://www.vox.com/2016/10/18/13012394/i-732-carbon-tax-washington. See here for 2018, which features sample calculations assuming $15/tCO2: https://www.seattletimes.com/seattle-news/politics/how-much-would-i-1631s-carbon-fee-cost-you-that-depends/.

[55]For example, see here for 2016: https://www.vox.com/2016/10/18/13012394/i-732-carbon-tax-washington. See here for 2018: https://www.vox.com/energy-and-environment/2018/9/28/17899804/washington-1631-results-carbon-fee-green-new-deal.

Figure 22: *Distributions of tax incidence*



Note: The top left panel shows the distribution of gasoline-related carbon dioxide emissions across precincts. The top right panel shows the distribution of home energy related carbon dioxide emissions across precincts. The bottom left panel shows the joint distribution of these two variables across precincts. The bottom right panel shows the distribution of the total combined carbon dioxide emissions across precincts. See text for details.
Source: 2017 NHTS, 2015 RECS, U.S. Census and author calculations.

Revenue forecasts by the Office of Financial Management, which were included in published voter guides for both years, indicate substantially lower revenues for I-1631 than for I-732 over their first five years, perhaps because I-1631 exempted marine fuels, aircraft fuels, and certain coal-fired facilities.[56] Of course, it is doubtful that many voters would have read these obscure details in the 80+ page voter guides, let alone performed their own detailed calculations.

Our empirical methods, and resulting estimates of mean tax incidence, are consistent with web-based energy tax calculators available to Washington residents prior to voting in 2016 and 2018. In particular, independent researchers affiliated with the University of Washington developed a web-based carbon tax swap calculator for I-732 in 2016, so that households and businesses could estimate their overall tax burden under the plan. See here: http://carbon.cs.washington.edu/. This calculator assumes an annual carbon tax of \$25/tCO2 and divides the energy tax burden into gasoline and diesel usage, home energy usage, and air travel. For gasoline and diesel, the calculator prompts respondents to enter total gallons of consumption directly, or helps them calculate this value indirectly based on total spending or total miles driven (consistent with our focus on gallons in NHTS data). For home energy consumption, the calculator prompts respondents to enter their home's annual energy consumption of natural gas, fuel oil, and electricity (consistent with the energy streams we observe in RECS data). If they do not know this information, the calculator prompts them to indicate which energy source they use to heat their home and then to estimate their home's *relative* energy consumption with an explicit reference to home size (consistent with our approach using RECS data). The exact language is as follows:

> As a percentage, how much purchased energy do you think your home uses compared to an average house in Washington (2000 sq ft, 3 bedrooms, etc.)? For example, if your home uses half the energy of an average home, enter 50. If your home uses twice the energy of an average home, enter 200.

In addition, the calculator can be used to estimate sales tax rebates, as well as the EITC to which a household is entitled under the 2016 bill. These calculations are based on family income, number of dependents, and marital filing status. We implicitly capture sales tax reductions and EITC benefits using fine-grained controls for the precinct-level distributions of income, age, and gender.

Likewise, the Washington Policy Center developed a web-based carbon emissions fee calculator for I-1631 in 2018. This calculator also divides the energy tax burden into gasoline, natural gas, and electricity usage. See here: http://www.textmuse.com/carbontax/index.html#. This calculator was later re-purposed to calculate tax burden under a different carbon emissions fee proposed in 2019-2020 (Washington Senate Bill 5971). However, the original purpose "to determine your annual costs in I-1631's first year" is described in contempo-

[56] See here for 2016 voter guide: https://www.sos.wa.gov/_assets/elections/voters%20pamphlet%202016.pdf. See here for 2018 voter guide: https://www.sos.wa.gov/_assets/elections/voters%20pamphlet%202018.pdf.

raneous reporting (see here: https://www.kxly.com/new-calculator-shows-how-much-i-1631-will-cost-you/). Thus, we presume that the tax calculator assumed a carbon emissions fee of \$15/tCO2 at the time it was available to voters in 2018.

H.5 Bounding individual-level variation in energy tax incidence

We estimate the mean and standard deviation in precint-level WTP across precincts and report the results in table 5. Based on this analysis, we conclude that variation in precinct-level WTP is mainly driven by ideology, rather than energy tax incidence. Of course, this analysis ignores within-precinct variation. In principle, if within-precinct variation in tax incidence were large relative to within-precinct variation in ideology, then this could overturn our conclusion that ideology trumps tax incidence. In practice, the overall standard deviation in individual tax incidence (i.e., including both the within-precinct and between-precinct variation) is much smaller than the WTP across precincts that can be attributed to ideology—and this is totally ignoring the within-precinct variation in ideology that we have no way to quantify. Thus, we still conclude that ideology trumps tax incidence among individual voters.

We begin by decomposing the variance in tax incidence into precinct-level and individual-level components. Let tax incidence for individual voter i living in precinct j be given by:

$$\tau_{ij} = \mu_j + \epsilon_{ij}, \tag{12}$$

where μ_j is the precinct-level mean and ϵ_{ij} is an individual-level deviation from this mean, which are uncorrelated by construction. Then the variance in total tax incidence across the full population of voters is given by

$$\sigma_\tau^2 = \sigma_\mu^2 + \sigma_\epsilon^2, \tag{13}$$

where σ_τ^2, σ_μ^2, and σ_ϵ^2 are the population variances of τ, μ, and ϵ. Note that σ_μ^2 is the between-precinct variance in tax incidence (that is, the variance in μ_j across precincts, weighted by the # of individuals in each precinct) and σ_ϵ^2 is the within-precinct variance. Standard deviations for each component are given by σ_τ, σ_μ, and σ_ϵ, i.e. the square roots of the variances.

In our main WTP analysis, we estimate the standard deviation across precincts (σ_μ) for 2016 and 2018 and report the results in table 5. Meanwhile, we can bound the standard deviation in overall tax incidence across all individuals in Washington (σ_τ) based on the household-level NHTS and RECS microdata, as follows.

Let individual-level tax incidence be given by:

$$\tau = v + r, \tag{14}$$

where v is the portion attributable to gasoline consumption (*vehicle tax*) and r is the portion attributable to residential energy consumption (*room tax*), and we have suppressed the i and j subscripts to avoid clutter.

Table 16: *Bounding the individual-level variation in tax incidence*

Year	2016	2018
Carbon tax (\$/tCO2)	25	15
Standard deviation for individuals (\$/tCO2)		
Vehicle tax (σ_v)	86	52
Room tax (σ_r)	25	15
Total tax (σ_τ, lower bound)	77	46
Total tax (σ_τ, upper bound)	100	60

Note: This table reports the standard deviation in individual-level tax incidence due to gasoline consumption (vehicle tax), residential energy consumption (room tax), and their sum (total tax) based on gasoline consumption in the 2017 NHTS and residential energy consumption in the 2015 RECS. Numbers are reported separately assuming a carbon tax of \$25/tCO2 (2016 column) and \$15/tCO2 (2018 column). The lower bound for total tax assumes a correlation coefficient of -1 between vehicle tax and room tax, while the upper bound assumes a correlation coefficient of +1. See text for details. Source: 2017 NHTS, 2015 RECS, and author calculations.

Note that the overall variance is given by

$$\sigma_\tau^2 = \sigma_v^2 + \sigma_r^2 + 2\sigma_{vr}, \tag{15}$$

where σ_v^2 and σ_r^2 are the population variances of the v and r components and σ_{vr} is their covariance. While we can estimate σ_v^2 and σ_r^2 based on the NHTS and RECS samples, we cannot directly estimate σ_{vr} because with the NHTS and RECS we do not observe gasoline consumption and residential energy consumption in the same dataset. We can, however, bound this covariance based on the following identity:

$$\sigma_{vr} = \sigma_v \sigma_r \rho_{vr} \tag{16}$$

where σ_v and σ_r are the standard deviations of v and r and ρ_{vr} is their correlation coefficient, which is bounded between -1 and 1. Thus, the variance of individual-level tax incidence can be bounded according to:

$$\sigma_\tau^2 \in [\sigma_v^2 + \sigma_r^2 - \sigma_v\sigma_r, \sigma_v^2 + \sigma_r^2 + \sigma_v\sigma_r]. \tag{17}$$

Table 16 reports the results of this bounding exercise. We estimate σ_v based on the sample of NHTS households living in Washington, and we estimate σ_r based on the sample of RECS households living in the same Census and climate regions as Washington. We assume carbon taxes of \$25/tCO2 and \$15/tCO2 in 2016 and 2018. We apply these carbon taxes to household-level carbon footprint, divided by the number of household members age 18+. We then report lower and upper bounds on tax incidence by alternatively assuming perfect negative correlation ($\rho_{vr} = -1$) and perfect positive correlation ($\rho_{vr} = 1$) between the two components of individual-level tax incidence. Note that the standard deviation of individual total tax incidence ranges from a lower bound of \$77 to an upper bound of \$100 in 2016 (for a carbon tax of \$26/tCO2), while the standard deviation of individual total tax incidence ranges from a lower bound of \$46 to an upper bound of \$60 in 2018 (for a carbon tax of \$15/tCO2).