Policy Design and Public Support for Carbon Tax: Evidence from a 2018 U.S. National Online Survey Experiment

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Abstract. Public support for policy instruments is influenced by perceptions of how benefits and costs are distributed across various groups. We examine different carbon tax designs outlining different ways to distribute tax revenues. Using a national online sample of 1,606 U.S. respondents, we examine support for a $20/ton carbon tax that is: (1) Revenue Neutral: revenue is returned to citizens via tax cuts; (2) Compensation-focused: revenue is directed to helping actors disproportionately hurt by the tax; (3) Mitigation-focused: revenue funds projects reducing carbon emissions; and (4) Adaptation-focused: revenue is directed to enhancing community resilience to extreme weather events. We find devoting revenue to mitigation raises overall support for carbon tax by +6.3% versus the control (54.9%) where no information on spending is provided. Other frames raise support in specific subgroups only. Revenue neutrality raises support among lower-income households (+6.6%) and political independents (+9.4%), while compensation increases support among lower-income repondents (+6.1%).

Keywords: Policy design, carbon tax, public opinion, climate change

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Introduction

Public support is critical for policy success. Public administrators therefore seek public input to design policies that citizens view as fair and effective (Page and Shapiro, 1983; Howlett, 2009; Lodge, 1994; Majone, 1999; Lodge and Stirton, 2001). Designing such policies becomes challenging when policies are perceived as imposing differential costs and benefits across sectors (Soss and Schram, 2007). And if these costs or benefits are perceived as concentrated on specific sectors (Lowi, 1964; Wilson, 1980), interest groups mobilize to support or oppose the policy. The issue of differential costs and benefits is particularly salient in the context of climate policies because they are perceived as imposing costs on the fossil fuel and manufacturing sector as well as poor households (Drews and van den Bergh, 2016). Less understood is the public support for climate policies that create differential benefits (Amdur, Rabe, and Borick, 2014), or outcome favorability (Esaiasson, Persson, Gilljam, and Lindholm, 2016), an issue we examine here in the context of carbon taxes.

A carbon tax is a fee that the government imposes on anyone who generates carbon dioxide (CO_2), typically by burning fossil fuels. Governments could impose it directly on fuel users (say, tax on gasoline) or on companies (say, on oil refineries) that may or may not fully pass on the increased costs to consumers. By raising the costs of using fossil fuels, carbon taxes are supposed to reduce demand for them, and therefore lower CO_2 emissions. Around 17 countries have enacted national level taxes on CO_2 emissions (World Bank, 2015). Recently, the International Monetary Fund (2019) has called for a carbon tax. Yet, there is also a pushback against carbon taxes in France, Canada, and Australia. In the United States, neither the federal government nor any state government has enacted a carbon tax.

For public administration scholars, carbon taxes provide important insights into budgetary politics, an essential component of governmental dynamics. This is because carbon taxes create a new revenue source to fund governmental projects which encourages pork-barrel politics along with demands from various interest groups regarding the merits of their claims for new governmental spending (Metcalf, 2009; Metcalf and Weisbach, 2009; Kaplowitz and McCright, 2015). Because different policy designs of carbon tax create benefits for different actors, understanding citizen perceptions about different designs becomes important in anticipating their political acceptability. Specifically, we focus on four designs:

1. The revenue-neutral version (sometimes called revenue recycling) returns tax revenue to citizens or businesses via tax cuts or carbon dividends (Parry, 1995;

Hsu, Walters, and Purgas, 2008). This version is typically championed by pro-business actors that want to address climate change but are worried about increasing the size of the government. Both Republicans, such as James Baker and George Schultz, and Democrats, such as Larry Summers and Steven Chu, have advocated a revenue-neutral carbon tax (Climate Leadership Council, 2017).

2. A compensation-focused tax where new revenues are devoted to compensating actors disproportionately hurt by the tax such as fossil fuel workers, or blue-collar industries such as transportation, construction, cement production, or metal finishing (Jenkins, 2014). Similarly, carbon taxes also impose hardships on low income households that devote a high percentage of their family income to energy and transportation. Hence, the tax revenue can be used to reduce the political opposition by compensating such actors (Jagers, Martinsson, and Matti, 2018), as noted in the literatures on "just transition" (Newell and Mulvaney, 2013).

3. A mitigation-focused tax directs new revenues to mitigation projects such as mass transit and renewable energy that create local co-benefits (Nemet, Holloway, and Meier, 2010; West, Smith, Silva, Naik, Zhang, Adelman, Fry, Anenberg, Horowitz, and Lamarque, 2013; Bain, Milfont, Kashima, Bilewicz, Doron, Garðarsdóttir, Gouveia, Guan, Johansson, Pasquali, and Corral-Verdugo, 2016). Such projects seek to provide low emission alternatives to citizens – public transit as opposed to private transport – to fulfill the same need. Thus, such projects reduce CO_2 emissions beyond what is achieved by the carbon tax induced behavioral changes alone. This is probably an important reason why environmentalists support this design of the carbon tax. While climate change policies are often criticized for imposing local costs for creating global public goods (Hardin, 1968), the political appeal of a mitigation-focused carbon tax could be enhanced if citizens view it as creating local co-benefits as well. For example, mass transit projects create co-benefits such as reduced commuting time, improved health, or increases in real estate prices.

4. An adaptation-focused carbon tax directs new revenues to projects that improve community resilience to extreme weather events. Adaptation should be politically popular because no matter how aggressively the world moves to mitigate, climate change is already in motion and communities will need to adapt to it (Moser, 2014). Because adaptation is perceived to create local benefits (as op-

posed to a global public good), citizens should be more willing to pay for adaptation focused tax (Dolšak and Prakash, 2018).

While not central to our argument, we also examine support for a \$50 tax where the use of revenue is not specified. While a low level of tax may not encourage sufficient reductions in CO_2 emissions, a high tax increases the economic burden and encourages carbon leakages (Burniaux and Martins, 2012) by incentivizing businesses to relocate to states with lower taxes (Tosun and Skidmore, 2007; Asplund, Friberg, and Wilander, 2007).

Using a survey experiment administered to a U.S. national online sample of 1,606 respondents, we find that 54.9% support the generic \$20 tax (the control frame) that does not stipulate how the tax revenue will be spent. This level of support is strongly sensitive to how new revenue is used: support across the whole sample rises by 6.3% (95% CI: +1.5% to +11.2%) when carbon tax revenue is devoted to mitigation. No other policy design produces a statistically significant effect on support across the whole sample, though some policies appeal to specific groups. For example, lower income households respond to designs promising revenue neutrality (+6.6% support, 95%CI: +0.0% to +13.0%) and possibly compensation (+6.1% support, *90%*CI: +0.7% to +11.5%), while high income households are repelled by higher carbon taxes (−8.8% support, 95%CI: −1.1% to −16.4%).

Scholars note that climate policy is often embroiled in partisan divisions, especially in North America (McCright and Dunlap, 2011; Konisky, Hughes, and Kaylor, 2015). They note the role of "group centric heuristics" in generating policy support, especially among conservatives (Lawrence, Stoker, and Wolman, 2013). Such partisan divide is revealed in support for different carbon tax designs. Promising revenue neutrality increases support from political independents by 9.4% (95% CI: +0.2% to +18.4%), while Democrats are particularly responsive to mitigation (+7.3% support; 95% CI: +0.2% to +14.3%). Republicans' generally low support for carbon tax makes it especially difficult to discern policy designs that would gain significant support, but the mitigation frame does not appear to reduce their support further.

The lessons for policy designers is that the revenue-neutral carbon tax, which is sometimes portrayed as a bipartisan approach to climate change (Climate Leadership Council, 2017), is not the most broadly politically appealing option. Instead, the mitigation-focused carbon tax that emphasizes local co-benefits seems to have the most public support. The reason is that while directing tax revenues to mitigation projects increases support from Democrats, it does not decrease support among Independents or Republicans.

Public Administration and Policy Design

Public administration scholars recognize the role social construction plays in the issue of policy design, including framing the merits of targeting specific groups for imposition of policy costs and distribution of policy benefits (Stone, 1989; Ingram and Schneider, 1995; Schneider and Sidney, 2009; Lawrence, Stoker, and Wolman, 2013; Pierce, Siddiki, Jones, Schumacher, Pattison, and Peterson, 2014; Bell, 2019). An important lesson is that policies that might be the most economically rational in terms of their aggregate net benefits might not be the most politically feasible ones. For example, as we show below, while the International Monetary Fund and prominent economists make the case for a revenue-neutral carbon tax, our survey experiment results show that this approach is not the most politically attractive. This is also borne out by the 2016 state of Washington carbon tax referendum, as we discuss subsequently.

Why might economically rational policies not be politically attractive? In addition to the issue of asymmetrical distribution of benefits and costs, policies are often complex, making it difficult for citizens to comprehend them. Sometimes policy instruments trigger strong reactions, thereby motivating citizens to focus on their benefits or costs in narrow ways. The phrase "tax" is sometimes identified as such a trigger.

The vast literature on the social construction of policy design emphasizes the construction of target populations that bear benefits and costs. The various designs of carbon tax we examine in this paper implicitly construct the group of beneficiaries. For example, because carbon taxes are perceived as concentrating burdens (or costs) on specific groups (such those working on fossil fuel industries, or underprivileged households who spend a disproportionate share of their incomes on energy bills), a compensation-based tax is designed to appeal to them. Similarly, while climate policy ultimately seeks to provide a global public good, both mitigation-focused and adaptation-focused carbon tax proposals tend to highlight local co-benefits, as we discuss below.

Of course, it is not clear how the social construction of policy will influence individual level perceptions or behavioral responses to the policy. Drews and van den Bergh (2016) identify four ways to conceptualize individual level responses to any public policy including environmental policies: activist behaviors such as participating in protests, non-activist but politically significant behaviors such as accepting or rejecting policies in opinion polls or at the ballot box, household-level environmental action, and workplace-level environmental action. In this paper we focus on a non-active but political significant household-level behavior: response to opinion polls. Moreover, we examine individual response not to different types of policy instruments, but different designs of the same instrument. In doing so, we contribute to important debates in public administration on the issue of rational design of policy instruments, and the importance of understanding how individual perceptions of their benefits and costs vary.

Public administrators also recognize that opinion leaders, including media outlets, play an important role in shaping public perceptions about policies' benefits or costs. For example, for "liberal" policies addressing climate change, conservative outlets might exaggerate costs and minimize benefits. Similarly, for conservative policies addressing "nuclear energy," liberal outlets might exaggerate risks and underemphasize benefits. Thus, from the perspective of public administrators, it is crucial to understand how policies are actually perceived by citizens, as opposed to how they ought to be perceived (Montpetit, 2008; Lavee, Cohen, and Nouman, 2018). Policy dialogues often takes place through stories (Stone, 1989), with individuals telling their experiences with some specific issue. For example, opposition to a gasoline tax by the "Yellow vest" protesters in France is summed up by the comment that President Macron "talks about the end of the world while we are talking about the end of the month" (Rubin, 2018).

The carbon tax is a useful policy instrument to study, especially when it can entail different ways to spend tax revenues. Budgetary appropriation is one of the most important functions of legislative bodies. Legislators seek membership in appropriation committees to direct governmental projects to their districts or constituencies (Owens and Wade, 1984; Healy and Malhotra, 2009). Even expenditures on arguably public goods such as national defense have significant impacts on local economies. Senate and House members with defense industries or military bases in their constituencies are often vocal supporters of high military budgets (Warf, 1997). Given the caricature that governments want to "tax and spend," some suggest that only revenue-neutral carbon tax will be politically feasible because it assures the citizens that climate change is not a pretext for politicians to extract more resources from them. Yet, the state of Washington voted down a revenue-neutral tax in 2016 (I-732) which secured only 40.75% vote (Ballotpedia, 2016). [1] In contrast, the 2018 revenue positive tax (I-1631) where money was to be devoted predominantly to mitigation secured a higher vote share of 43.5% (Ballotpedia, 2018). Both the I-732 and I-1631 experiences reveal the spending issues play an important role in shaping public support for carbon tax.

1 http://www.rff.org/blog/2016/putting-carbon-tax-revenues-work-efficiency-and-distributional-issues

Carbon Tax: Using Surveys to Assess Public Support

In a perfectly functioning market, individual actors bear the full costs and reap the full benefits of their market decisions. However, markets sometimes fail to incorporate all costs and benefits into the market price, thereby creating an externality problem (Bator, 1958). Consequently, an individual's response to price signals is distorted from a social welfare perspective. In an ideal solution, government or some other actor could devise policies that would compel individuals to account for both their private costs (benefits) and the costs (benefits) that are externalized to the society. If such measures are successful, then for individuals, the private costs and benefits of an action would equal its social benefits and costs.

Many actors might enact such measures. In a classic solution, governments can impose a Pigouvian tax to eliminate the externality by aligning private costs with social costs (Hahn and Stavins, 1992). Others believe that the externality problem can be corrected if the property rights over (say) air are clearly defined and allocated. In such situations, the polluter and the receiver of pollution can enter into private bargains regarding the appropriate volume of pollution (Coase, 1960). Others recommend that governments stipulate maximum pollution levels and charge polluters when such levels are exceeded (Baumol and Oates, 1971) or that governments allocate the total level of pollution to polluters in form of tradeable allowances (Montgomery, 1972; Tietenberg, 1973). Yet others believe that groups of resource users can themselves devise rules to address externality problems associated with the over-use of resources (Ostrom, 1990). Finally, some scholars suggest that externality issues can be addressed by reputational incentives, such that firms may join voluntary programs that stipulate stricter emission standards in return for reputational benefits as environmental stewards (Videras and Alberini, 2000).

A carbon tax can be viewed as a Pigouvian solution to the global warming problem. The intuition is that the social cost (Greenstone, Kopits, and Wolverton, 2013) of burning of carbon-based fuels (such as coal, oil, and natural gas) exceeds the private cost to users. A carbon tax is supposed to internalize social costs into the price individual actors pay. Consequently, fossil fuel users will face a higher price and therefore have incentives to alter their behavior in order to reduce their CO_2 emissions.

Carbon taxes can vary on several dimensions, including level of taxation, how the tax monies will be spent, the scope in terms of emissions and sectoral coverage, exemptions, the temporal dimension, approval processes, and public involvement. We focus primarily on how the tax revenue will be used. Table 1 summarizes how six pro-

Table 1. *A Brief Summary of Various Carbon Tax Proposals.*

State/Proposal	Starting level of tax	Return revenue to households & businesses	Low income household assistance	Climate mitigation	Climate adaptation
Massachusetts	$10 per ton	✓			
Oregon	$30 per ton	✓			
Washington (I-732)	$15 per ton	✓	✓		
Vermont	$15 per ton	✓	✓		
Rhode Island	$15 per ton	✓	✓	✓	
New York	$50 per ton		✓	✓	✓

posed carbon taxes in the American states recommend using carbon tax revenues. The table also suggests carbon tax proposers in the US may have some common assumptions regarding the political attractiveness of these policy designs. Sorting the rows and columns of Table 1 carefully ("diagonalizing," as recommended by Bertin, 2010) reveals a pattern: with one exception – New York, which does not return money to households and business – each spending priority is added to a proposal only if the other priorities listed to its left have already been included. Perhaps proposers of carbon taxes see the goals farther to the right of the table (mitigation and adaptation) as either more controversial than the goals listed to the left (revenue neutrality or compensation for low income households), and thus not politically safe to include except in combination with presumedly popular designs. To the extent New York is the most "aggressive" proposal – as evidenced by its higher proposed tax – this proposal's exclusion of the "safe" option of returning revenue fits the pattern as well.

What explains actual public support for carbon tax? Drews and van den Bergh (2016) identify three broad categories of factors: (1) social-psychological factors including partisanship along with knowledge about climate change; (2) the perception of specific policy instruments including policy design, about its policy effectiveness, costs, equity and *the use of potential tax policy revenue*; (3) contextual factors, such as social trust and political and economic institutions. In this paper we focus on how different uses of tax revenue influence policy support. Because we are using an experimental format, we are able to hold other aspects of the policy instrument constant. Further, in our regression analyses, we control for other confounding factors including partisanship that might influence support for a specific version of a carbon tax.

Several polls have examined public support for a carbon tax in the United States.[2] The 2015 Global Warming National Poll commissioned by the New York Times, Stanford University, and RFF (henceforth Stanford) finds that while 61% of respondents support a generic carbon tax, the support increases to 67% for the revenue neutral tax.[3] The 2016 National Survey on Energy and Environment poll conducted by the University of Michigan and Muhlenberg College (henceforth Michigan)[4] reports a 50% support for a generic carbon tax and the support increasing to 62% for a revenue neutral tax, to 66% for a tax that funds research and development but declining to 42% for a tax that is used to reduce federal deficit. The 2016 Climate Change in the American Mind online survey conducted by Yale and George Mason (henceforth Yale)[5] finds that 66% of the public support a revenue neutral tax. In sum, these polls suggest that a majority of respondents support a generic carbon tax and the support is higher for a revenue neutral tax.

As opposed to observational studies, we employed an experimental approach to assess public support for various types of carbon tax. Our approach has several advantages. First, a survey sequentially eliciting information on different dimensions of a topic is susceptible to priming: respondent's exposure to a prior informational input influences her response to a posterior information input (Lenz, 2009). This means that changing the order in which questions are posed can elicit different responses to the same question (van de Walle and van Ryzin, 2011). For example, if the survey first asks respondents about support for a revenue neutral carbon tax and then asks them about their support for a tax that directs funds to say mitigation projects, this will bias their response.[6]

2 In addition to these widely publicized national polls, there are also several studies in this regard. Kotchen, Turk, and Leiserowitz (2017) find that American support a carbon tax when tax revenues are directed to clean energy and infrastructure projects, support displaced coal miners, but less supportive of revenue recycling measures such as reducing income or payroll taxes and returning dividends to households.

3 https://www.nytimes.com/interactive/2015/01/29/us/politics/document-global-warming-poll.html

4 http://closup.umich.edu/national-surveys-on-energy-and-environment/

5 http://climatecommunication.yale.edu/publications/climate-change-american-mind-march-2018/

6 Take the example of the Michigan poll. Q26: What if the carbon fuels tax were "revenue neutral", meaning that every dollar collected by the government would be returned to the public as an income tax rebate. Q27: What if revenues from the tax were used to fund research and development for renewable energy programs?

In contrast, in survey experiments, respondents are randomly assigned to different experimental groups and exposed to information that highlights different dimensions of the issue (Porumbescu, Bellé, Cucciniello, and Nasi, 2017). The basic information on the carbon tax provided to the control group is also included in the text for the experimental groups. In addition, every experimental group is provided with a unique information on how the tax revenue will be used. The $50 group, however, is provided the same information as the control group except for the tax level of $50 as opposed to $20. The text is provided in the appendix. The information unique to each group is underlined. The word count across the frames varied from 285-290 words, and the intervention specific text varied between 24% to 27% of the word count. Because respondents are randomly assigned to different groups, the researchers can make causal inference about how tax design (or the tax level, as in the case of $50 group) impacts public support.

The second criticism of carbon tax surveys is that they do not highlight the concrete costs the tax will impose on the respondents.[7] Consequently, respondents' support for the tax may be based on different understanding of its cost implications and respondents are therefore responding to different (and unknown) informational input. Moreover, absent clear information about costs, respondents may be particularly prone to a social desirability bias (Krumpal, 2013) that inflates their support for the tax. In contrast, our survey experiment provides clear information on how $20 ($50) carbon tax will increase the price of gasoline by 18 cents (44 cents). A focus on gasoline prices mirrors the real-world politics because households, politicians, and the media pay attention to these prices (Fredriksson and Millimet, 2004; Anderson, Kellogg, and Sallee, 2013).[8]

7 The Michigan survey perhaps comes closest in providing clear cost information in terms of percentage increases in "energy" costs. "Q25: What if the carbon fuel tax significantly lowered greenhouse gases but increased your energy costs by 10 percent a month?" While this approach is better, the cost information is still underspecified. First, it is not clear what is included in energy costs. Secondly, even if we limit them to household energy use, these costs often vary across months due to heating/air-conditioning and it is not clear which costs the respondents are taking into account.

8 We note that several studies have employed a willingness to pay measure to assess support for carbon taxes or fuel taxes. Kotchen, Turk, and Leiserowitz (2017)suggest that Americans are willing to pay for a carbon tax that will increase household energy costs by $177 per year, equivalent to 14% increase in energy costs.

Table 2. *Support for Carbon Tax: Experimental Design.*

Frame	Level of tax	Use of tax revenue
1. Control	$20 per ton	–
2. Revenue neutral	$20 per ton	Return to residents via reduction in sales tax
3. Compensation	$20 per ton	Direct to compensating workers and firms
4. Mitigation	$20 per ton	Direct to local mitigation projects
5. Adaptation	$20 per ton	Direct to local adaptation projects
6. Higher carbon tax	$50 per ton	–

Third, while some surveys provide information about how the tax revenue will be deployed, they often do not outline concrete examples.[9] Consequently, it is not clear if respondents are responding to the same informational cues about proposed spending of the tax revenue. Some projects might benefit citizens directly, while others may be in the nature of public goods (reduction of governmental budgetary deficits as in the Michigan survey). In contrast, we outline specific projects towards which the tax money will be funneled.

Experimental Design and Methods

After pre-testing and securing permission from University Human Subjects, we fielded a national online survey on Amazon's Mechanical Turk in April 2018. Respondents were randomly assigned to one of the six frames: a control frame plus five experimental frames (Table 2). The control frame does not indicate how the tax money will be used whereas the four experimental frames do (in the fifth experimental frame, we simply replicate the control frame but with a higher tax level). The experimental frames reflect "ideal" types of carbon taxes that direct revenue to one specific use only. The treatment instruments are provided in an online appendix.

To ensure our treatment instruments resemble real life situations as much as possible, they follow the format of the voter's guide used in the State of Washington's 2018

9 The Stanford poll poses the following question: "Do you think the federal government should or should not require companies to pay a tax to the government for every ton of greenhouse gases the companies put out? All this tax money would be given to all Americans equally by reducing the amount of income taxes they pay."

carbon tax initiative (I-732).[10] This booklet is mailed by the Washington's Secretary of State to every voter and provides information on all initiatives on the ballot. We paid careful attention to the wording of the instrument, the sequence in which the information is provided, and the overall length of the article. Following the literature, we decided to create a (fake) newspaper article that described the various dimensions of the tax. To guard against priming, this was placed at the beginning of the survey before the respondents were asked questions about demographics. After reading the article, the respondents were asked about their willingness to support a carbon tax on a scale of 1-7, where 1 indicated "strong opposition" to the tax and 7 equaled "strong support." Then, we asked questions to evaluate the respondents' comprehension and attentiveness of the survey. Because some respondents incorrectly answered some questions, we dropped 394 of the 2,000 respondents and examined 1,606 respondents only.[11] Even working with this respondent pool, the usable sample size of our survey is considerable larger than other national surveys: Stanford ($n = 1{,}006$), Michigan ($n = 940$), and Yale ($n = 1{,}061$).

To check for balance across groups, to assess the generalizability of our results to the U.S. population, and to investigate potential group-wise variation in treatment effects, we collected a number of additional respondent demographics and attitudes, including: (1) party identification (Democrat, Republican, or Independent), (2) concern for the climate (7-point scale), (3) whether the respondent supports U.S. withdrawal from the Paris Climate Accord, (4) self-assessed experience with extreme weather events, (5) whether the respondent believes "taxes are too high", (6) trust in state legislators, (7) whether the respondent drives more than 15,000 miles per year, (8) household income, (9) sex, (10) age, dummied into ten-year bands, (11) race and ethnicity, (12) level of edu-

10 https://ballotpedia.org/Washington_Carbon_Emission_Tax_and_Sales_Tax_Reduction,_Initiative_732_(2016)

11 After removing participants who missed either the one question regarding the treatment instrument or at least two of three questions on general comprehension, there remain $n = 258$ subjects in control frame, $n = 277$ in the revenue neutral frame, $n = 270$ in the mitigation frame, $n = 286$ in the compensation frame, $n = 265$ in the adaptation frame, and $n = 250$ in the $50 tax frame. Attentive and inattentive subjects seem for the most part to be strongly similar on covariates; see the online appendix for details. The main result of our paper – the effectiveness of the mitigation frame – remains significant even if inattentive respondents are included in the analysis.

cation, (13) experience as a volunteer, (14) religiosity, (15) marital status, and whether the repondent (16) has children or (17) owns a home.[12]

We test covariate balance in two ways. First, to check for significant differences in the distribution of covariates across treatments, we perform a joint orthogonality test by estimating multinomial logistic regressions with assignment to each treatment or control frame as the outcome (McKenzie, 2015). Inclusion of covariates in this model fails to improve fit relative to a null model (deviance test $= 87.48$ on 110 degrees of freedom, $p = 0.94$), suggesting that overall, there is no statistically significant difference between the values of covariates in the treatment arms compared to the control group.

Second, and more important, we follow Imbens and Rubin's (2015) recommendation to test for differences in covariates large enough to affect experimental results, regardless of statistical significance. Comparing each treatment frame to the control group, we find the normalized differences in covariate means for each covariate to be well within safe levels, according to Imbens and Rubin's guidelines. We conclude the various treatment frames are well-balanced with the control group on all observed covariates, which suggests sample-level inference regarding the effects of treatments should be valid.[13]

To improve estimation precision (Dolan, Green, and Lin, 2016) and to allow for subgroup analysis, we intepret the effects of our treatment frames on support for carbon tax by fitting least squares regression models adjusting for all the covariates listed above (our main results, however, do not depend on adjustment). As a check for model dependence, we also investigate models that deal with these covariates through inverse probability weighting using propensity scores and generally find similar results.[14]

In the same spirit, we also present ordered probit models of support for carbon taxes. Like linear regression, ordered probit allows for covariate adjustment, yet it has two

12 The outcome of carbon tax support and the assignment to treatment groups are observed for all 1606 respondents in the final sample; however, there are a small number of missing values for covariates (specifically, 6 cases for age and one case for religion). To ensure that missing data do not cause sample selection bias, we use multiple imputation to create 100 complete datasets with these missings cases filled in (King, Honaker, Joseph, and Scheve, 2001); all analyses in the remainder of the paper combine results across these multiple imputation datasets. However, it turns out that the use of multiple imputation rather than listwise deletion does not affect the substantance or statistical significance of any results herein.

13 Balance tables and normalized differences in means can be found in the online appendix.

14 Detailed results can be found in the online appendix.

further virtues in this application. First, unlike linear regression, ordered probit does not assume the 7-point support scale follows a strict interval measure, instead estimating the difficulty of raising support for each specific rung on this ladder. Second, ordered probit allows us to calculate substantively clearer statements of treatment effects. Specifically, although our estimation procedure takes full advantage of the 7-point support scale, we focus model interpretation on the change in the expected percentage of respondents offering any support (5, 6, *or* 7 on the support scale) as a result of each treatment frame.[15] Because we average the expected change in this percentage for each respondent in the survey, our ordered probit results are sample average treatment effects (SATEs).[16]

Finally, it is reasonable to ask how well the SATE from a Mechanical Turk convenience sample corresponds to the national population average treatment effect (PATE). The respondents' profiles are comparable to a typical Mechanical Turk sample (Berinksy, Huber, and Lenz, 2012): the sample is 50% male, the mean age is 40, 49% have children, 56% are college graduates, and 45% identify as Democrats. Each of these groups is somewhat overrepresented when compared with the national population as measured, for example, by the General Social Survey (NORC, 2019).[17] Ideally, our sample would match the national population. However, recent work by Coppock (2019) using national probability samples to replicate more than a dozen political survey experiments initially administered on Mechanical Turk shows close agreement in estimated treatment effects despite aggregate differences in the subjects sampled. While the differences between our sample and the national population are certainly reason

15 To estimate the probability of support of 5 or above without losing precision in estimation of results (as would occur by collapsing the scale prior to estimating the probit model), we estimate ordered probit using the full scale and only combine the predicted probabilities of each level of support in post-estimation simulations (Hanmer and Kalkan, 2013; King, Tomz, and Wittenberg, 2000). The specific choice of categories to aggregate post-estimation does not affect results materially: we obtain substantively similar findings using higher level of support (6 or 7 only) as the quantity of interest.

16 In our application, one advantage of SATEs relative to ATEs is that SATEs account for the boundedness of the support measure: for example, while least squares ATEs assume that individuals at the maximum level of support could rise "beyond 7.0," the SATEs calculated from ordered probit reflect only feasible movement within the context of the scale. This is particularly important for estimating group-specific treatment effects as some groups are more likely to start out with more extreme levels of support before treatment, relative to other, more moderate groups.

17 The online appendix contains comparisons between our sample and the GSS.

to be cautious, Coppock (2019) suggests Mechanical Turk survey experiments may be useful guides to population average treatment effects even in a case like this, due to the similarity of causal processes at work in Mechanical Turk subjects and the general population.

Results

Our main finding is that the mitigation frame substantially increases support for carbon tax. A linear regression model adjusting for possible confounders finds the average treatment effect (ATE) of the mitigation frame to be a 0.32 point increase in expected support on the 7-point scale (95% CI: +0.09 to +0.54). This result does not depend on the use of a specific parametric model: if we instead use propensity score weighting, we obtain a similar mitigation ATE of +0.37 (95% CI: +0.02 to +0.71).[18]

As noted above, we consider ordered probit a preferable method for estimating treatment effects in this case, as it makes more appropriate assumptions and leads to more interpretable summaries of treatment effects. Figure 1 shows the sample average treatment effect for each treatment frame as estimated from an ordered probit and aggregated across all survey respondents, given their observed covariates. We find a significant effect only for the Mitigation frame, which increases the percentage of repondents strongly supporting carbon taxes by 6.3% (95% CI: +1.5% to +11.2%). No other treatment frame showed significant effects across the whole sample of respondents.[19]

However, we do find significant effects of other treatments in specific populations. We estimated additional ordered probit models allowing for group-specific treatment effects via interaction terms between our treatments and two covariates: household income and party affiliation. In the case of income, this allows us to contrast the effect of each frame on households below and above the median income, respectively (Figure 2). The revenue neutral frame appeals to respondents with lower incomes: 6.6% more of them support the carbon tax given a promise of revenue neutrality, compared to

18 Weighting performed by covariate-balanced propensity scores (Imai and Ratkovic, 2014); other balancing weights produce similar results. Further details of these models, including complete tabular results for each treatment frame, can be found in the online appendix.

19 These findings – that mitigation raises support across the sample, while other treatments have no significant effect sample-wide – are robust across linear regression and propensity score methods, with one exception: in a parametric linear regression with covariates, the $50 tax frame lowers support for carbon tax ($p < 0.1$). Because this result is not robust across estimation methods, we do not emphasize it here.

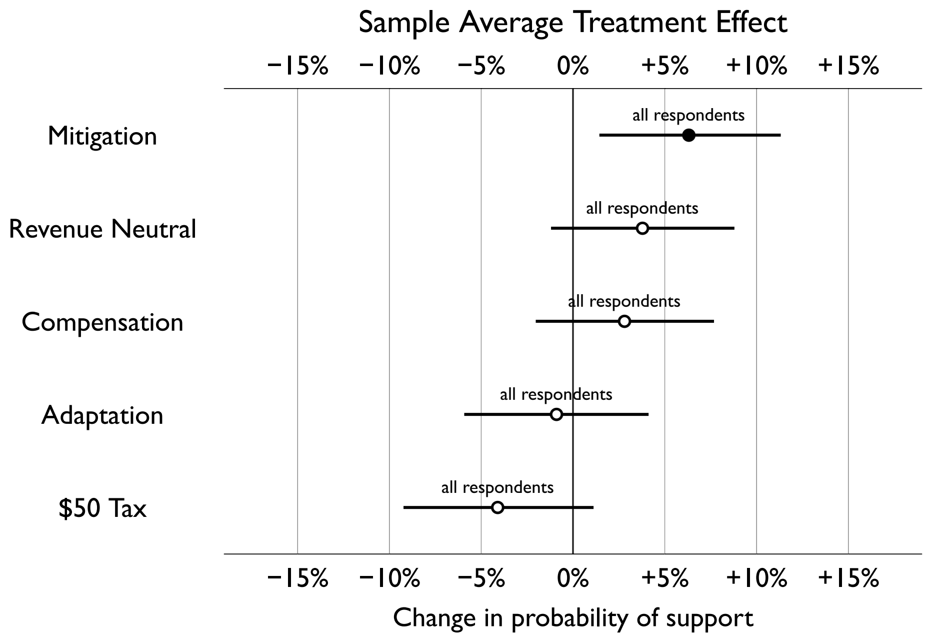

Figure 1. *Sample average treatment effects on support for carbon tax.* Entries represent the estimated average effect of each treatment on the sample of respondents. 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates obtained from an ordered probit adjusting for all covariates, followed by simulation of the change in probability of any support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject, given that subject's observed covariates.

the control group (95% CI: +0.0% to +13.0%). There is some evidence that the compensation frame persuades lower income respondents as well, though this result is only significant at the 0.1 level (+6.1% support, 90% CI: +0.8% to +11.6%). Higher income households are discouraged by higher tax rates: compared to a $20 tax, the $50 tax *lowers* high income support by 8.8% (95% CI: -1.1% to -16.4%). Mitigation, on the other hand, appeals to both high and low incomes similarly (both significantly different from the control group at the 0.1 level).

Finally, in Figure 3 we present party-specific treatment effects. The most noteworthy result is that 9.4% more political independents express strong support for revenue-

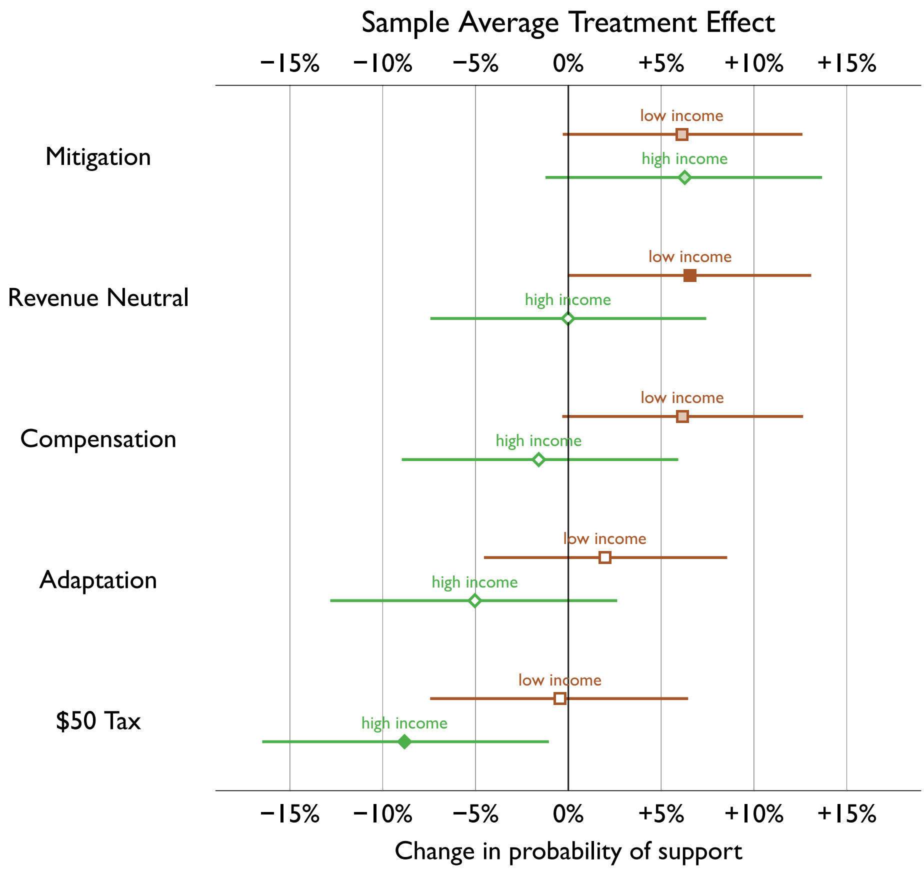

Figure 2. *Income-specific sample average treatment effects on support for carbon tax.* Entries represent the estimated average effect of each treatment on two subsamples of respondents (those above and those below the median household income). 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates obtained from an ordered probit interacting treatment variables with income and adjusting for all covariates, followed by simulation of the change in probability of any support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject in each subsample, given that subject's observed covariates and the specific average treatment effect estimated for that subsample.

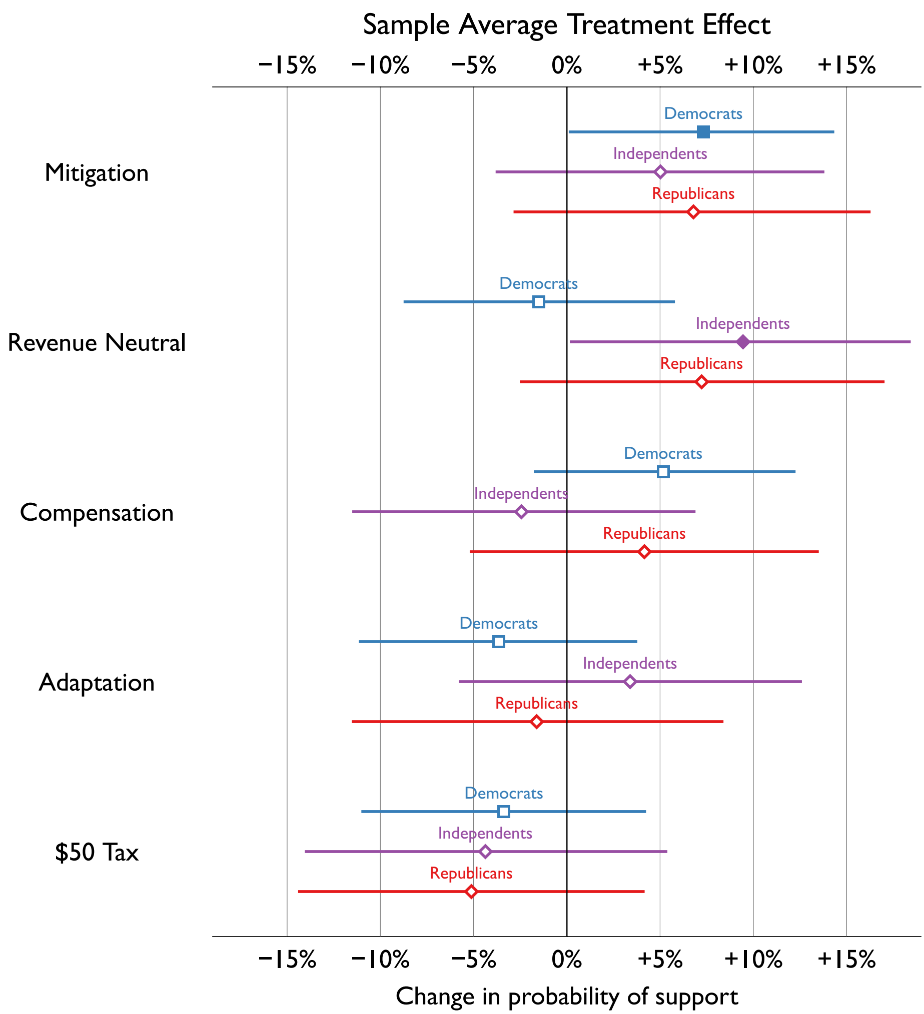

Figure 3. *Party-specific sample average treatment effects on support for carbon tax.* Entries represent the estimated average effect of each treatment on three subsamples of respondents (self-identified Democrats, Independents, and Republicans). 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates obtained from an ordered probit interacting treatment variables with party and adjusting for all covariates, followed by simulation of the change in probability of any support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject in each subsample, given that subject's observed covariates and the specific average treatment effect estimated for that subsample.

neutral carbon taxes compared to the control group (95% CI: +0.2% to +18.4%).[20] Republicans may also be drawn to revenue neutrality (though the effect is far from significant), but Democrats appear unmoved by this treatment versus the control.

Whereas revenue neutrality appeals to Independents, the mitigation frame strongly encourages Democrats to support carbon taxes (+7.3%, 95% CI: +0.1% to 14.2%). Nor does mitigation turn off Independents or Republicans: while their responses to mitigation are not significant, Figure 3 shows they are substantively similar to Democrats. No other frames have significant party-specific effects on the probability of support in the ordered probit model. While it is surprising that Republicans are not repelled by the higher $50 tax, this may be an artifact of Republican's already low support for carbon taxes (28.5% in the control group), which leaves less scope for ordered probit to infer a decline in support. In this case only, linear regression produces a clearly significant reduction in support not present in the ordered probit model (see the online appendix). This mixture of results suggests that although lower tax rates do not increase the share of Republicans positively supporting carbon tax, higher rates may intensify their opposition.

Conclusions and Policy Implications

Scholars recognize that a given policy challenge can be addressed by a variety of policy instruments. Sometimes, groups have strong preferences in favor of or against specific instruments. For example, in the context of environmental policy, it is generally believed that while Democrats favor governmental, command and control policies, Republicans tend to favor market-based solutions. But a given policy instrument can be designed in a variety of ways as well – with each design perceived as conferring benefits and bestowing costs on different constituencies. If so, should we expect variations in public support for a given policy instrument, depending on its policy design? We have examined this question in the context of carbon tax, a policy instrument to combat climate change.

Climate change is among the most visible policy challenges facing the world. The World Economic Forum's (2017) recent Global Risks Reports identifies climate change

20 Political independents are an ideologically diverse group. When we restrict attention to moderate independents – those who score themselves as 3, 4, or 5 on a 7-point left-to-right ideology scale – we find similar significant effects of the revenue neutral frame. Under the revenue neutral frame, +11.7% more moderate independents supported carbon taxes (95% CI: +1.0% to +22.3%). See the online appendix for further details.

among the top risks for the world. Despite elite consensus along with several international treaties starting with the 1992 United Nations Framework Convention on Climate Change, the progress on climate mitigation has been uneven (Victor, 2004). Yet climate policy seems to encountering serious challenges in many parts of the world, including Australia, Brazil, Poland, Canada and the United States.

While climate change mitigation creates a global public good, it imposes local costs. Consequently, even when jurisdictions seek climate action, there is an intense debate about instrument choice in order to minimize the local cost of climate action.

However, in addition to the issue of costs, the debate now focuses on a crucial policy design issue: how should the tax revenue generated by the carbon tax be used? Viewed this way, the carbon tax debate has moved from the normative considerations of protecting the planet from climate change, to political questions about instruments required to achieve this normative goal, and how these instruments ought to be designed. The core insight is that while climate mitigation creates a global public good, revenues created by a carbon tax can create local benefit for specific constituencies. Hence, appropriate policy design can mobilize local interests to serve a global goal.

Our national survey suggests that while the overall support for carbon tax ranges from 47.4% to 61.4% across different frames, the mitigation frame emerges as the winner, due consistent support across low and high income respondents and overwhelming support from Democrats; even support from Independents and Republicans for mitigation is not lower compared to the control frame. This might seem unexpected because of some of the collective action issues referenced above. Yet, when it comes to a carbon tax, the mitigation-focused tax is viewed as financing projects that produce local benefits. The crucial lesson is that climate messaging should be framed in terms of local benefits, and not in terms of costs that communities need to shoulder in order to prevent global catastrophes.

In the full sample, we cannot detect a statistically significant difference in support for the revenue neutral option compared to the control frame. However, in the subsample analysis, Independents and lower income households show higher support for this option. Thus, our study suggests the revenue neutral frame provides an opportunity for environmentalists to build a coalition with the Independents. Of course, environmentalists may not have the political incentives to do so if they believe that the overwhelming support from Democrats for the mitigation frame gives them a win on carbon tax. Yet, a revenue neutral tax can become a first step to broaden the environmental coalition beyond Democrats. Our reading of the construction of existing proposals in the American states suggests this may already a part of carbon tax proposers' strategies.

Our study has several limitations. Surveys capture respondents' attitudes and preferences only; it remains to be seen to what extent does the reported support for a carbon tax on a survey translate to voting behavior (Levitt and List, 2007; Barabas and Jerit, 2010). After all, the revenue positive carbon tax, I-1631, failed in the fairly liberal state of Washington. We think it is important to recognize that survey responses need to be interpreted with caution. In the real world of voting, for example, respondents will be subject to advertising: in I-1631 alone, the YES side spent about $12 million and the NO side spent about $30 million on ads. Further, 2018 was a mid-term election year that did not coincide with the Presidential election cycle, which can change voting dynamics. What surveys such as ours reveal is the relative importance of different frames, all else equal. Indeed, in the 2018 elections, the base of support for the revenue positive I-1631 grew by 6.7% relative to the support received by the revenue neutral I-732 in 2016.

We acknowledge the debate about the usefulness and limitations of online platforms such as Mechanical Turk (Buhrmester, Kwang, and Gosling, 2011; Berinksy, Huber, and Lenz, 2012; Huff and Tingley, 2015). While the comprehension check questions we posed have weeded out the inattentive respondents, or the ones that did not comprehend our questions, we recognize that responses to the same survey in an online platform might differ from say a telephone interview, or a paper format. There are some grounds for optimism, including Coppock's (2019) recent study finding that Mechanical Turk survey experiments on political topics generally identify causal effects consistent with the national population, despite relying on convenience samples. Nevertheless, future research should validate how responses to the same survey might differ across platforms.

Second, it is not clear what level and type of carbon tax will suffice to alter behaviors of firms and households and lead to reduced emissions (Davis and Kilian, 2011; Lin and Li, 2011). Price elasticities of different types of fossil fuel-based activities differ. Further, even when prices of fossil fuels are increased, there might be technological or financial lock-ins that might prevent actors from immediate action. For example, even if gasoline prices rise substantially due to taxes, it is not clear how it will change gasoline consumption in the short run (Hughes, Knittel, and Sperling, 2008).[21] It may

21 Rivers and Schaufele (2015) report that in British Columbia, the introduction of a carbon tax led to a short-term decline in demand for gasoline. Interestingly, they found that this decline was greater than what might have been achieved by an equivalent increase in the price of gasoline

be difficult for consumers to quickly shift to more fuel efficient cars or change their commuting habits.

Third, our paper has not accounted for the secondary benefits and costs of carbon tax (Ekins, 1996). These could range from public health benefits to implications for innovation, research and development (Oates, 1995). Porter and van der Linde's (1995) "double dividend" hypothesis about the dual environmental and economic benefits of appropriately designed environmental regulations falls in this category. Future work could examine how the willingness to support a carbon tax might change if such non-environmental spillover benefits and costs are communicated to citizens.

Fourth, we have tested ideal types of carbon taxes. Although most carbon tax proposals include a mix of spending priorities, in the political discourse, specific taxes get specific labels. For example, Washington's failed I-732 and was labeled as a revenue neutral tax, even though it also provided compensation for low income families and businesses bearing disproportionate tax burden. Future work should test public support for tax proposals that incorporate multiple spending dimensions.

Finally, our experiment does not test how public support for various policy designs might vary at different price points. For example, the support for $50 tax might vary depending on how the revenue is proposed to be spent: it may or may not cohere with the findings for the $20 tax. We have tested one way of designing revenue neutral (revenue recycling) and compensation mechanisms. Arguably, if revenue were to be recycled in a different way (say a reduction in income or corporate tax), the level of support for this frame might differ. Similarly, there are different ways of compensating actors who might be hurt by the carbon tax. We have tested one way this compensation might take place: via tax credits to low-income families, reduced taxes on small businesses, and retraining of workers in fossil fuel industries. Future work can test support for compensation with different sorts of mechanisms.

resulting from regular market fluctuations. Thus, the price elasticity of demand depends not only on the level of price increase but also on the policy instrument through which this increase is achieved.

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ONLINE APPENDIX

To supplement Nives Dolšak, Christopher Adolph, and Aseem Prakash, "Policy Design and Public Support for Carbon Tax: Evidence from a 2018 U.S. National Online Survey Experiment," forthcoming in Public Administration.

This appendix contains five sections presenting (1) balance information regarding the treatment arms of the survey experiment, (2) thoughts and data on the generalizability of the results to the national population, (3) figures displaying robustness checks of the main model and interaction models, (4) tables of regression coefficients for the models used in the main paper, and (5) the text provided to survey participations in each treatment frame.

Balance tests

Table A1 contains the means of each covariate in the control group and each of the five treatment groups. Visual inspection suggests good balance, but more formal tests are possible. One option is to check for statistically significant differences, but with 22×5 comparisons to make, several differences are likely to have $p < 0.05$ purely by chance. To cope with this problem, we implement a joint test of orthogonality across the six groups (McKenzie, 2015). In principle, randomization should preclude systematic relationships between the covariates and the assignment to each treatment arm. That is, if we were to estimate a multinomial logit regression in which the outcome variable is assignment to any of the six groups (the treatment frames or the control), a specification including all the covariates should not fit any better than a null model. We performed this test, and found the difference in the deviance scores of the model with covariates and the null model to be insignificant ($\chi^2 = 87.48$, 110 d.f., $p = 0.94$), suggesting the treatment groups and control group are jointly orthogonal on the covariates.

While this is reassuring, Imbens and Rubin (2015) caution against placing much weight on tests for significant differences in balance tables. Instead, they emphasize the magnitude of differences in covariate means across treatment and control groups, as large differences may indicate poor balance regardless of whether or not the difference is statistically significant. By the same token, small differences are likely to be harmless regardless of statistical significance. Specifically, Imbens and Rubin recommend checking for large normalized differences in covariates across each treatment-group–control-group pairing. For the jth covariate and the kth treatment frame, the

Table A1. *Balance across treatment frames.*

Covariate	Control	Revenue neutral	Compensation	Mitigation	Adaptation	$50 tax
Independent	0.32	0.31	0.31	0.38	0.34	0.32
Republican	0.25	0.22	0.23	0.24	0.18	0.23
Climate concern	4.70	4.88	4.85	4.90	5.01	4.88
Experienced extreme weather	0.28	0.30	0.33	0.28	0.30	0.34
Trust state legislators	3.04	3.32	3.17	3.30	3.19	3.10
Consider taxes too high	0.40	0.50	0.47	0.43	0.46	0.46
Support Paris withdrawl	2.87	2.93	2.85	2.97	2.81	2.79
Drive >15k mi/year	0.09	0.12	0.14	0.13	0.13	0.14
Income above median	0.39	0.47	0.48	0.44	0.43	0.48
Male	0.57	0.48	0.50	0.48	0.48	0.49
Non-Hispanic White	0.78	0.71	0.75	0.79	0.80	0.77
College education or higher	0.55	0.54	0.62	0.52	0.57	0.55
Volunteer	0.49	0.54	0.52	0.55	0.51	0.47
Have children	0.51	0.51	0.50	0.50	0.45	0.50
Married or widowed	0.51	0.48	0.51	0.48	0.43	0.48
Own a home	0.56	0.56	0.56	0.55	0.50	0.60
Religious	0.54	0.62	0.59	0.60	0.55	0.50
Age 31 to 40	0.40	0.36	0.38	0.37	0.37	0.35
Age 41 to 50	0.17	0.19	0.18	0.18	0.18	0.22
Age 51 to 60	0.15	0.13	0.14	0.14	0.12	0.13
Age 61 to 70	0.09	0.07	0.07	0.07	0.11	0.08
Age over 70	0.03	0.01	0.01	0.00	0.02	0.02

Entries are means of each covariate within each treatment frame.

normalized difference between the mean of the covariate in the treatment group and the mean of covariate in the control group is given by

$$\text{Normalized difference}_{jk} = \frac{\bar{\mathbf{x}}_{j,\text{treatment}_k} - \bar{\mathbf{x}}_{j,\text{control}}}{\sqrt{\frac{1}{2}\left(\hat{\sigma}^2_{\mathbf{x}_{j,\text{treatment}_k}} + \hat{\sigma}^2_{\mathbf{x}_{j,\text{control}}}\right)}}, \tag{A-1}$$

where $\bar{\mathbf{x}}$ indicates a sample mean and $\hat{\sigma}^2$ a sample variance. Imbens and Rubin suggest as a guideline that normalized differences greater than 1.00 are problematic, while those less than 0.25 indicate good balance.

Table A2 contains the normalized differences for each covariate for each pairing of a treatment group and the control group. In no case is this normalized difference greater than 0.25, suggesting good balance between the treatments and control.

Table A2. *Normalized differences between treatments and controls, by treatment and covariate.*

Covariate	Revenue neutral	Compensation	Mitigation	Adaptation	$50 tax
Independent	-0.02	-0.02	0.13	0.05	0.01
Republican	-0.06	-0.03	0.00	-0.16	-0.04
Climate concern	0.09	0.08	0.11	0.17	0.09
Experienced extreme weather	0.05	0.11	0.01	0.04	0.13
Trust state legislators	0.18	0.08	0.16	0.10	0.04
Consider taxes too high	0.20	0.14	0.07	0.12	0.12
Support Paris withdrawl	0.03	-0.01	0.05	-0.03	-0.04
Drive >15k mi/year	0.09	0.15	0.13	0.12	0.15
Income above median	0.16	0.18	0.09	0.07	0.17
Male	-0.18	-0.14	-0.19	-0.19	-0.16
Non-Hispanic White	-0.18	-0.07	0.01	0.04	-0.04
College education or higher	-0.03	0.13	-0.06	0.03	-0.01
Volunteer	0.10	0.06	0.12	0.04	-0.03
Have children	0.00	0.00	-0.01	-0.11	-0.02
Married or widowed	-0.06	0.00	-0.08	-0.17	-0.07
Own a home	0.01	0.01	-0.02	-0.11	0.09
Religious	0.16	0.10	0.12	0.04	-0.07
Age 31 to 40	-0.09	-0.04	-0.08	-0.07	-0.11
Age 41 to 50	0.05	0.03	0.03	0.05	0.14
Age 51 to 60	-0.07	-0.03	-0.03	-0.09	-0.07
Age 61 to 70	-0.08	-0.07	-0.07	0.07	-0.05
Age over 70	-0.14	-0.12	-0.21	-0.08	-0.10

Entries are normalized differences (Imbens and Rubin, 2015); larger absolute values indicate more consequential deviations from balance. According to Imbens and Rubin's guidelines, absolute values smaller than 0.25 indicate good balance between the treatment frame and the control group on the given covariate. Absolute values greater than 1.00 indicate poor balance. All values above are smaller than 0.25 in absolute value.

Table A3. *Comparison of MTurk sample with a contemporary national probability survey (GSS).*

	MTurk	GSS	Difference
Has children	49.2	70.7	-21.5
Independent	32.6	41.7	-9.1
Married/Widowed	48.4	55.1	-6.7
Age	40.1	46.2	-6.1
Republican	22.8	22.4	+0.4
Male	50.1	44.8	+5.3
Non-Hispanic White	76.6	64.0	+12.6
Democrat	44.6	31.1	+13.5
College+	56.1	32.5	+23.6

Entries are covariate means in percent (except for *Age*), calculated from the Mechanical Turk sample and the 2018 General Social Survey (GSS).

Generalizability

Our paper uses an Amazon Mechanical Turk convenience sample to make inferences about the US national population. As in any sampling-based study making inferences to a larger population, there is concern about whether there is sample selection bias at work and whether our results are generalizable to the population. Specifically, we would like the sample average treatment effects (SATEs) we estimate to be representative of the population average treatment effects (PATEs). There are two related issues at play. First, does our convenience sample represent the national population as well as a traditional probability weighted randomly sampled national opinion poll. Second, regardless of whether our sample matches traditional polls, does it capture the same causal processes at work in the national population.

Regarding the first question, whether our sample matches other national surveys, we turn to the General Social Survey of 2018 for a point of comparison. We find that in several unsurprising ways, the Mechanical Turk sample differs from the GSS: our sample has more males, more young people, more single respondents, more white respondents, and most notably, more college-educated and more childless respondents. In terms of political differences, our sample has more Democrats, fewer Independents, but a similar share of Republicans when compared to the GSS.

Regarding the second point, a recent, comprehensive review suggests that Mechanical Turk survey experiments may have good generalizability regardless of whether Mechanical Turk samples closely match the population on all covariates (Coppock 2019). Coppock replicates 15 Mechanical Turk convenience-sample survey experiments using national probability samples and finds very similar SATEs in his replication studies when compared to the original MTurk studies. Coppock then investigates whether this similarity is because there is little sample selection bias in MTurk, or because the sample selection bias that occurs – the differences between MTurk samples and national probability samples – does not bias causal estimates of PATEs. His evidence suggests the latter: even though MTurk samples do not exactly match national probability samples, they find very similar causal effects precisely because those causal effects tend to operate in similar ways in Mechanical Turk samples and in nationally representative samples (causal "homogeneity").

Coppock sums up his argument about the use of convenience samples like Mechanical Turk this way:

> "Crucially, simply noting that convenience and probability samples differ in terms of their background characteristics is not sufficient for dismissing the results of experiments conducted on convenience samples. Moreover, in an age of 9 percent response rates (Keeter et al. 2017), even probability samples can only be considered representative of the population under the strong assumption that, after reweighting or post-stratification, no important differences remain between those who respond to the survey and the population." (Coppock 2019, p. 624).

This suggests that even when Mechanical Turk samples do not closely match national probability samples on observables, they may provide reliable estimates of population average treatment effects; moreover, that in the contest between Mechanical Turk and probability samples, there is no *a priori* reason to prefer the latter.

A final concern relating to generalizability relates to our exclusion of inattentive respondents. Respondents were asked three general comprehension questions and one question regading comprehension of the treatment to which they were assigned. Respondents who missed two or three general comprehension questions or who missed the treatment comprehension question were excluded from the study, reducing the inital sample of 2000 to 1606. Table A4 reports the means of each covariate for the 1606 included subjects and the 394 excluded subjects. For the most part, these means seem comparable, though by no means identical. As a further check, we compute normal-

Table A4. *Comparison of cases included or excluded based on comprehension.*

Covariate	Attentive subjects mean	Inattentive subjects mean	Normalized difference
Democrat	0.45	0.48	0.06
Independent	0.33	0.22	-0.23
Republican	0.23	0.30	0.17
Climate concern	4.87	4.86	-0.01
Experienced extreme weather	0.31	0.34	0.07
Trust state legislators	3.19	3.78	0.38
Consider taxes too high	0.45	0.52	0.13
Support Paris withdrawl	2.86	3.20	0.17
Drive >15k mi/year	0.13	0.16	0.08
Income above median	0.45	0.44	-0.02
Male	0.50	0.53	0.05
Non-Hispanic White	0.77	0.69	-0.18
College education or higher	0.56	0.60	0.08
Volunteer	0.52	0.50	-0.03
Have children	0.49	0.46	-0.06
Married or widowed	0.48	0.48	-0.02
Own a home	0.56	0.55	0.00
Religious	0.57	0.67	0.22
Age 31 to 40	0.37	0.44	0.15
Age 41 to 50	0.18	0.16	-0.06
Age 51 to 60	0.14	0.07	-0.20
Age 61 to 70	0.08	0.02	-0.26
Age over 70	0.02	0.01	-0.10
N	1606	394	

Columns 1 and 2 provide covariate means. Column 3 provides normalized differences are defined in Equation A-1.

ized differences using the formula provided in Equation A-1. The vast majority of differences are small (< 0.25); only *Trust in state legislators* and *Age 61 to 70* are greater than 0.25. The values reported even for these cases remain relatively small, suggesting that overall, the differences between the included and excluded cases is not substantial.

Robustness checks

This section reports results for two robustness checks. The first reconsiders the partisan-specific model of Figure 3 using an alternative treatment of political independents. The second considers alternative estimation techniques for all the models in the text (specifically, linear regression with or without covariates, linear regression with propensity score weights, and ordred probit without covariates).

Alternative measures of partisanship

As noted in the text, political independents are ideologically diverse, so one might ask whether the results for independents are driven solely by conservative-leaning independents. It is well-known in American politics that so called "Republican leaners" may be as conservative or more so than self-identified Republicans. On the other hand, it may be truly moderate independents who find revenue neutral proposals persuasive.

To investigate these possibilities, we draw on another question from the survey asking respondents to identify whether they are conservative or liberal on a 7-point scale. We divide independents into three groups based on their responses: conservative independents are those how answered 1 or 2 on the ideology scale, moderate independents answered 3, 4 , or 5, and liberal independents answered 6 or 7. We find that most independents are indeed moderate independents: 381 out of 516 independents total (73.8%). Indeed, there are too few liberal independents or conservative independents for precise analysis of their specific treatment effects.

Instead, we estimate an alternative version of our party-specific interaction model using three groups: all Democrats combined with liberal independents, all Republicans combined with all conservative independents, and all moderate independents. The sample average treatment effects from the ordered probit version of this model are shown in Figure A1. The key results have not changed; in particular, under the revenue neutral frame, +11.7% more moderate independents supported carbon taxes (95% CI: +1.0% to +22.3%). We take this as clear evidence that the response of independents to the revenue neutral frame reported in the main paper is indeed a response of middle-of-the-road independents, rather than an artifact of the presence of "Republicans-in-all-but-name" within the sample of independents.

Alternative estimators

In the main text, we report sample average treatment effects derived from ordered probit models with covariates for three reasons: first, these models are easier to interpret

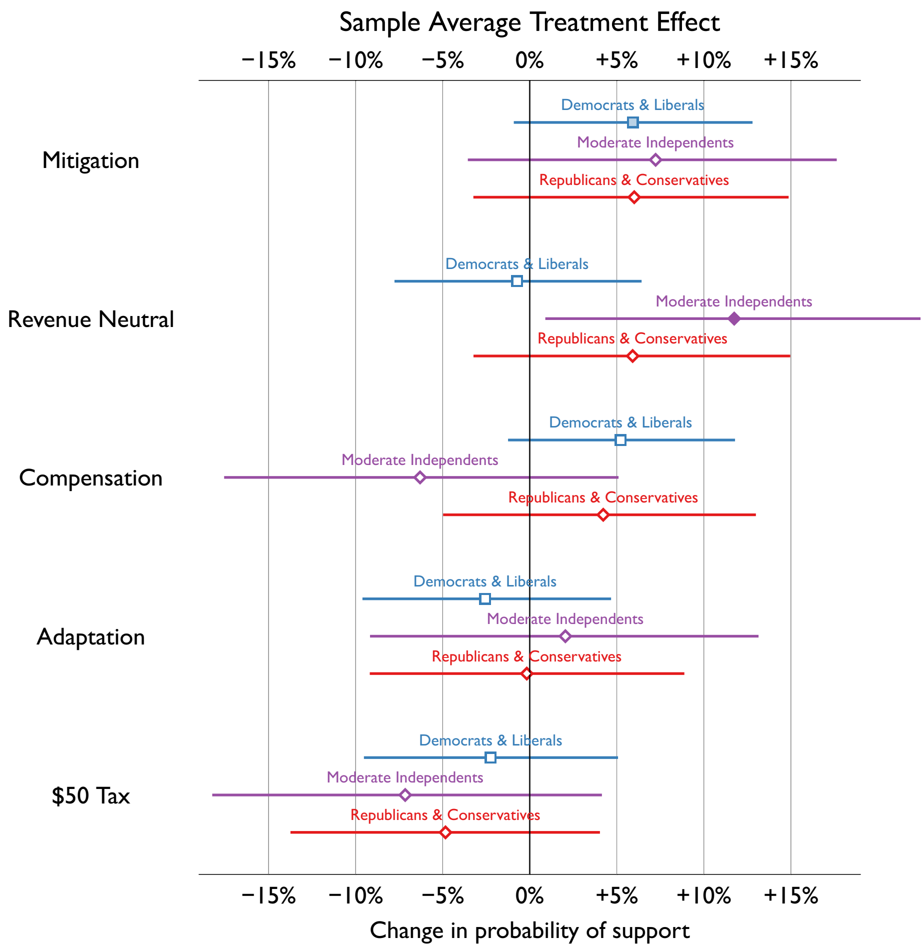

Figure A1. *Party-specific sample average treatment effects on support for carbon tax: alternative treatment of independents.* Entries represent the estimated average effect of each treatment on three subsamples of respondents (those who either self-identify as Democrats or report liberal Ideology, Moderate Independents, and those who either self-identify as Republicans or report conservative Ideology). 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates obtained from an ordered probit interacting treatment variables with income and adjusting for all covariates, followed by simulation of the change in probability of any support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject in each subsample, given that subject's observed covariates and the specific average treatment effect estimated for that subsample.

(they estimate probabilities of support, rather than hard to interpret linear scales); second, these models avoid imposing linearity on the support scale; and third, inclusion of covariates enhances precision of estimates and deals with any confounding left after randomization.

While we prefer the results reported in the text, our findings do not depend on the estimator used. In this section we investigate four alternative approaches: linear regression without covariates (baseline LS), linear regression with covariate adjustment (adjusted LS), linear regression weighted by propensity scores (balanced LS)[1], and ordered probit without covariates (baseline OP). Linear regression models report average treatment affects (linearity ensures the ATE and sample average treatment effect will be the same); we continue to report SATEs for the ordered probit models.

Figure A2 compares results under these four estimators to the "adjusted OP" results, which are reproduced from Figures 1, 2, and 3 in the main text. The Mitigation frame has positive, significant, and substantively similar positive effects on overall support for the carbon tax regardless of estimation technique. For baseline LS, adjusted LS, balanced LS, and the original adjusted OP, this effect is significant at the 0.05 level; for the baseline OP, it is significant at the 0.1 level.

Indeed, the only difference across the estimators is the effect of the $50 tax, which (only) the covariate-adjusted linear regression models find to significantly lower support, and in that case only at the 0.1 level. Given the lack of robustness of this result, we think it should be treated with caution. We suspect the instability of this effect to reflect the combination of two factors: (1) there is tentative evidence that the $50 effect is driven by Republican opposition to higher taxes, and (2) even without higher taxes, Republicans tend to strongly oppose carbon taxes, making it hard to estimate the effect of further discouragement for people already hitting the lower bound of the 7-point support scale.

In addition to estimating the overall effect of the treatment frames, the main text reports group-specific treatment effects based on household income and party affiliation. The models in the main text rely on ordered probit to estimate sample average treatment effects; here we report complementary results using linear regression with covariate adjustment. Slight differences in levels of significance aside, the estimated effects of the treatments on low and high incomes appear substantively the same using linear regression instead of ordered probit (Figure A3).

1 The weights used in the propensity score balanced linear regressions are covariate-balanced propensity scores, but we obtain similar results using a variety of alternative methods for constructing balancing weights.

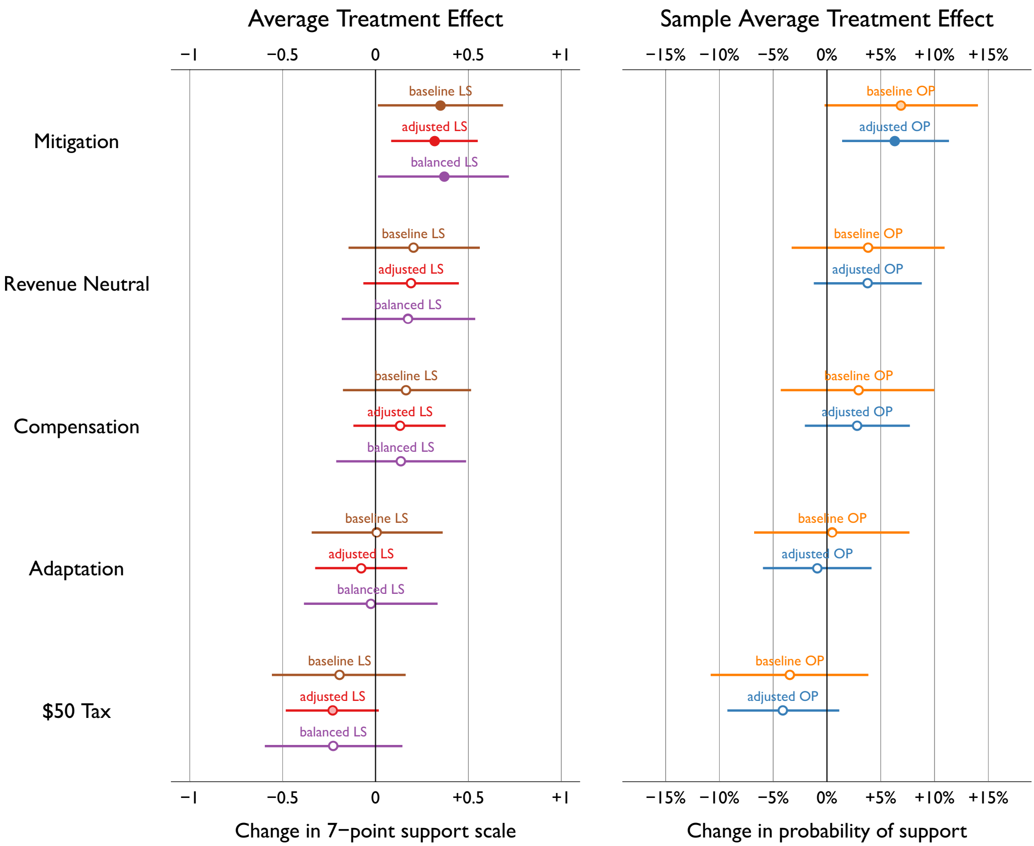

Figure A2. *Robustness of average treatment effects and sample average treatment effects on support for carbon tax.* Entries in the left plot show estimated average treatment effects of each treatment, while entries in the right plot represent the estimated average effect of each treatment on the sample of respondents. "LS" indicates results from linear regression; "OP" denotes results from ordered probit. Results marked "baseline" do not adjust for covariates, those marked "adjusted" do, and those marked "balanced" come from a linear regression with weights derived from propensity scores. 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates on the left are linear regression coefficients; estimates on the right are obtained from an ordered probit, followed by simulation of the change in probability of any support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject, given that subject's observed covariates (where appropriate to the model).

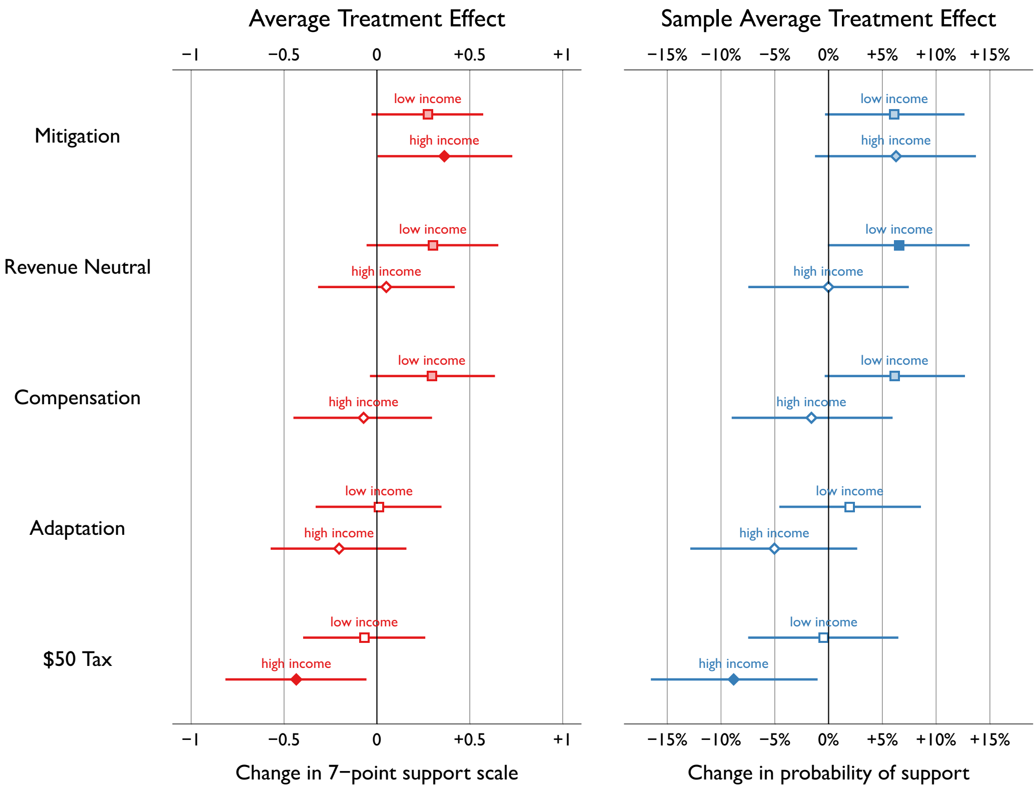

Figure A3. *Robustness of income-specific average treatment effects and sample average treatment effects on support for carbon tax.* Entries in the left plot show estimated average treatment effects of each treatment, while entries in the right plot represent the estimated average effect of each treatment on two subsamples of respondents (those above and those below the median household income). "LS" indicates results from linear regression; "OP" denotes results from ordered probit. Results marked "baseline" do not adjust for covariates, those marked "adjusted" do, and those marked "balanced" come from a linear regression with weights derived from propensity scores. 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates on the left are simulated first differences accounting for the relevant terms of a linear regression with interactions between treatments and income; estimates on the right are obtained from an ordered probit interacting treatment variables with income, followed by simulation of the change in probability of any support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject in each subsample, given that subject's observed covariates (where appropriate to the model) and the specific average treatment effect estimated for that subsample.

Likewise, the preferences of Democrats for mitigation and independents for revenue neutrality also reappear in the linear regression model (Figure A4). The one noteworthy difference between these models is for Republicans. While the ordered probit model reported in the main text finds no effect of the $50 frame in Republicans, as we noted there, the linear regression model does find that the $50 tax significantly lowers Republican support by 0.42 points on the 7-point scale when compared to a $20 tax (90% CI: −0.06 to −0.77; the effect just misses significance at the 0.05 level). The most likely explanation for this discrepancy is that the already very low rate of Republican support for carbon tax means many Republicans are already at the lower bound of the support variable even in the control frame; this makes it hard to discern further reduction on the support scale. Adding the linearity assumption as linear regression could improve precision just enough in this tough case, hence the clearer result than in ordered probit.

Finally, we re-estimate the "alternative party measures" model of Figure A1 using linear regression. The results are shown in Figure A5 and are broadly consistent with those reported for the standard party measures. The one new findings is support by Democrats and liberal Independents for the compensation frame, though it is barely significant at the 0.1 level (+0.29 points; 90% CI: 0.00 to 0.57).

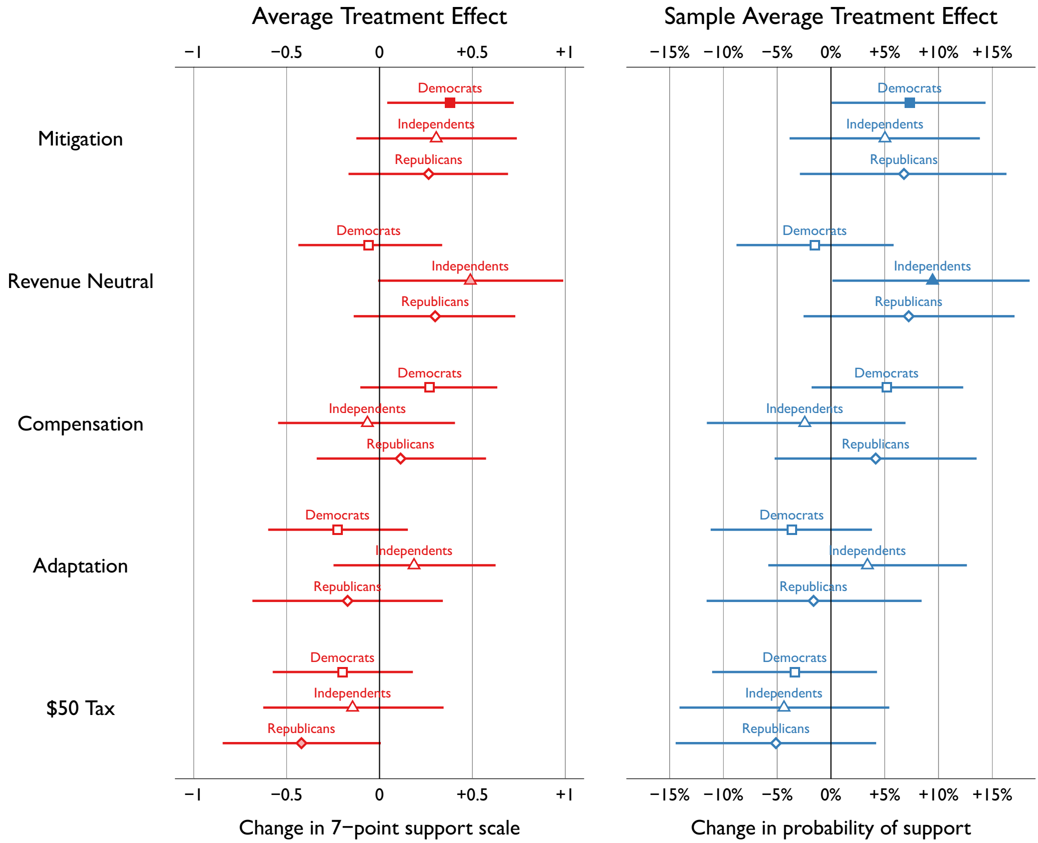

Figure A4. *Robustness of party-specific average treatment effects and sample average treatment effects on support for carbon tax.* Entries in the left plot show estimated average treatment effects of each treatment, while entries in the right plot represent the estimated average effect of each treatment on three subsamples of respondents (self-identified Democrats, Independents, and Republicans). "LS" indicates results from linear regression; "OP" denotes results from ordered probit. Results marked "baseline" do not adjust for covariates, those marked "adjusted" do, and those marked "balanced" come from a linear regression with weights derived from propensity scores. 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates on the left are simulated first differences accounting for the relevant terms of a linear regression with interactions between treatments and party; estimates on the right are obtained from an ordered probit interacting treatment variables with party, followed by simulation of the change in probability of high support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject in each subsample, given that subject's observed covariates (where appropriate to the model) and the specific average treatment effect estimated for that subsample.

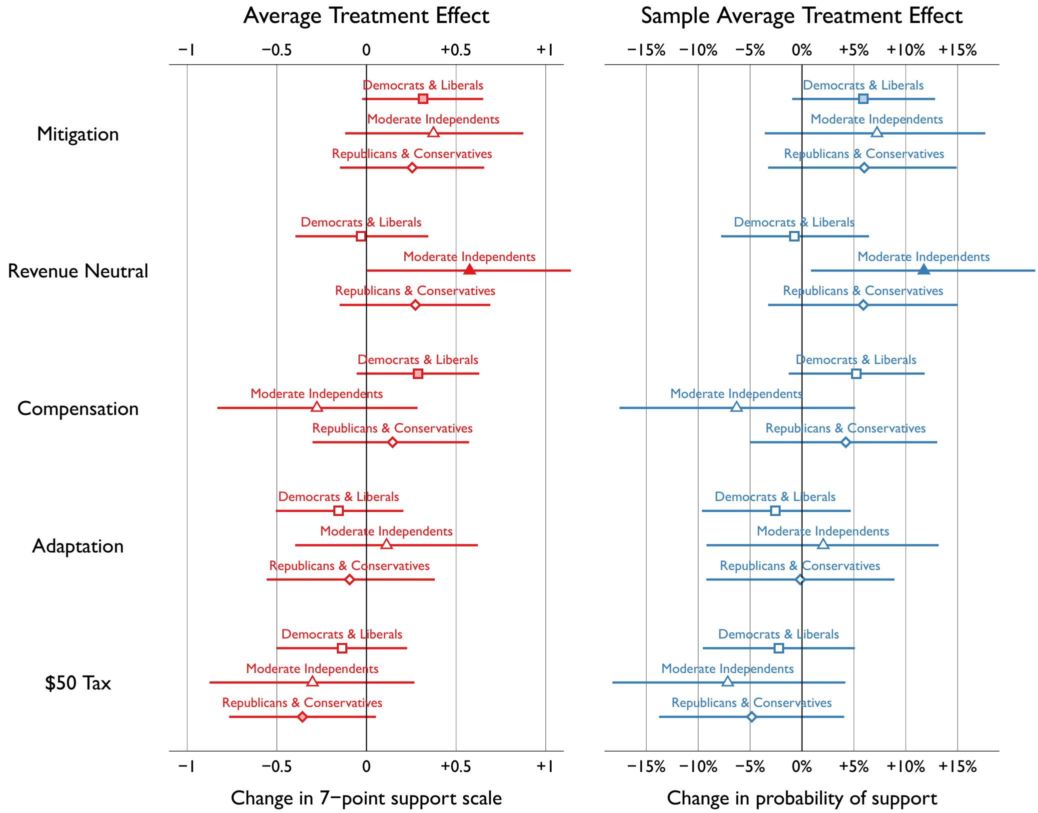

Figure A5. *Robustness of party-specific average treatment effects and sample average treatment effects on support for carbon tax: alternative treatment of independents.* Entries in the left plot show estimated average treatment effects of each treatment, while entries in the right plot represent the estimated average effect of each treatment on three subsamples of respondents (those who either self-identify as Democrats or report liberal Ideology, Moderate Independents, and those who either self-identify as Republicans or report conservative Ideology). "LS" indicates results from linear regression; "OP" denotes results from ordered probit. Results marked "baseline" do not adjust for covariates, those marked "adjusted" do, and those marked "balanced" come from a linear regression with weights derived from propensity scores. 95% confidence intervals shown as horizontal lines. Solid symbols indicate effects significantly different from zero at the 0.05 level. Partially-shaded symbols indicate significance at the 0.1 level. Open symbols indicate non-significant results. Estimates on the left are simulated first differences accounting for the relevant terms of a linear regression with interactions between treatments and party; estimates on the right are obtained from an ordered probit interacting treatment variables with party, followed by simulation of the change in probability of high support for the carbon tax (support = 5, 6, or 7) resulting from applying each treatment to each subject in each subsample, given that subject's observed covariates (where appropriate to the model) and the specific average treatment effect estimated for that subsample.

Regression tables

This section presents in tabular form the estimated regression parameters underlying the average treatment effects presented in Figure 1–3 and Figures A1–A5. To enhance readability, all tables present point estimates and 95% confidence intervals. Ordered probit models also include estimated cutpoints (τ_1 to τ_6). All results have been combined through simulation from separate regressions on 100 multiple imputation datasets (CITE). Confidence intervals for all linear regressions are calculated using heteroskasdicity-consistent standard errors.

Note that in all models, Democrats and Age < 30 are the reference categories for Party and Age, respectively. Age is specified using a series of dummies for 10-year intervals to allow for nonlinearity in the effect of age on support for carbon taxes: in all models, the middle aged are most opposed to carbon taxes, and the young and old most supportive. (The treatment effects reported in the paper do not change if a linear age variable is used instead.)

Table A4 contains the ordered probit results used to produce Figure 1 in the main text, as well as the linear regression results labelled "adjusted LS" in Figure A2 in this appendix.

Table A5 contains the ordered probit results used to produce Figure 2 in the main text as well as the linear regression results labelled "adjusted LS" in Figure A3 in this appendix.

Tables A6 and A7 contains the ordered probit results used to produce Figure 3 in the main text as well as the linear regression results labelled "adjusted LS" in Figure A4 in this appendix.

Tables A8 and A9 contains the ordered probit results used to produce Figures A1, as well as the as well as the linear regression results in Figure A5 in this appendix.

Table A5. *Estimated parameters of baseline models.*

	Linear Regression			Ordered Probit		
		95% CI			95% CI	
Covariate	**est.**	**lower**	**upper**	**est.**	**lower**	**upper**
Revenue neutral	0.195	-0.057	0.447	0.143	-0.047	0.328
Compensation	0.137	-0.110	0.380	0.106	-0.076	0.286
Mitigation	0.320	0.096	0.546	0.242	0.056	0.426
Adaptation	-0.074	-0.318	0.170	-0.032	-0.221	0.151
$50 tax	-0.227	-0.474	0.023	-0.150	-0.339	0.039
Independent	-0.235	-0.417	-0.051	-0.138	-0.265	-0.008
Republican	-0.214	-0.448	0.012	-0.127	-0.297	0.039
Climate concern	0.314	0.255	0.373	0.245	0.207	0.282
Experienced extreme weather	0.230	0.070	0.385	0.171	0.057	0.287
Trust state legislators	0.201	0.154	0.250	0.148	0.112	0.184
Consider taxes too high	-0.883	-1.052	-0.717	-0.607	-0.727	-0.491
Support Paris withdrawl	-0.264	-0.321	-0.206	-0.198	-0.237	-0.159
Drive >15k mi/year	-0.195	-0.405	0.012	-0.154	-0.318	0.007
Income above median	0.046	-0.121	0.210	0.032	-0.090	0.151
Male	0.075	-0.077	0.226	0.043	-0.069	0.153
Non-Hispanic White	-0.038	-0.215	0.139	-0.021	-0.150	0.109
College education or higher	0.044	-0.108	0.197	0.026	-0.086	0.138
Volunteer	0.064	-0.091	0.215	0.029	-0.082	0.136
Have children	-0.025	-0.207	0.159	-0.022	-0.150	0.109
Married or widowed	0.235	0.052	0.416	0.188	0.060	0.318
Own a home	-0.113	-0.266	0.041	-0.085	-0.202	0.031
Religious	-0.105	-0.267	0.057	-0.070	-0.188	0.046
Age 31 to 40	-0.147	-0.350	0.055	-0.102	-0.253	0.048
Age 41 to 50	-0.480	-0.722	-0.236	-0.355	-0.536	-0.176
Age 51 to 60	-0.327	-0.603	-0.050	-0.257	-0.454	-0.058
Age 61 to 70	-0.201	-0.508	0.117	-0.094	-0.330	0.138
Age over 70	-0.105	-0.886	0.684	-0.075	-0.518	0.374
Intercept	3.418	2.876	3.949	—	—	—
τ_1	—	—	—	-0.808	-1.157	-0.463
τ_2	—	—	—	-0.233	-0.577	0.108
τ_3	—	—	—	0.294	-0.052	0.631
τ_4	—	—	—	0.610	0.266	0.949
τ_5	—	—	—	1.487	1.137	1.839
τ_6	—	—	—	2.206	1.849	2.557
N		1606			1606	

Entries are unstandardized linear regression coefficients and ordered probit coefficients, respectively. τ's are ordered probit cutpoints. Confidence intervals for linear regression models are computing using heteroskedasticity-robust standard errors. All results combined from 100 multiply imputed datasets.

Table A6. *Estimated parameters of models interacting treatments and income.*

Covariate	Linear Regression est.	95% CI lower	95% CI upper	Ordered Probit est.	95% CI lower	95% CI upper
Revenue neutral	0.300	-0.049	0.651	0.247	0.003	0.490
Compensation	0.296	-0.035	0.629	0.231	-0.016	0.473
Mitigation	0.275	-0.018	0.568	0.227	-0.015	0.470
Adaptation	0.012	-0.316	0.342	0.073	-0.170	0.311
$50 tax	-0.068	-0.389	0.254	-0.018	-0.273	0.237
Rev. neut. × Income >median	-0.255	-0.762	0.250	-0.249	-0.618	0.122
Compens. × Income > median	-0.368	-0.860	0.124	-0.291	-0.668	0.066
Mitig. × Income > median	0.086	-0.375	0.546	0.021	-0.356	0.400
Adapt. × Income > median	-0.218	-0.707	0.272	-0.260	-0.631	0.115
$50 tax × Income > median	-0.369	-0.867	0.127	-0.308	-0.690	0.073
Independent	-0.223	-0.406	-0.041	-0.134	-0.261	-0.008
Republican	-0.206	-0.438	0.026	-0.124	-0.293	0.041
Climate concern	0.313	0.254	0.372	0.245	0.208	0.282
Experienced extreme weather	0.233	0.076	0.391	0.173	0.058	0.287
Trust state legislators	0.202	0.154	0.250	0.149	0.113	0.185
Consider taxes too high	-0.882	-1.049	-0.716	-0.607	-0.725	-0.488
Support Paris withdrawl	-0.266	-0.324	-0.209	-0.199	-0.239	-0.161
Drive >15k mi/year	-0.195	-0.406	0.018	-0.154	-0.321	0.009
Income above median	0.232	-0.123	0.587	0.212	-0.065	0.491
Male	0.073	-0.078	0.223	0.042	-0.069	0.153
Non-Hispanic White	-0.033	-0.212	0.146	-0.014	-0.144	0.117
College education or higher	0.052	-0.103	0.205	0.028	-0.083	0.139
Volunteer	0.066	-0.086	0.218	0.032	-0.080	0.145
Have children	-0.026	-0.209	0.156	-0.025	-0.157	0.107
Married or widowed	0.246	0.067	0.425	0.198	0.068	0.327
Own a home	-0.117	-0.272	0.039	-0.088	-0.204	0.026
Religious	-0.107	-0.270	0.056	-0.073	-0.189	0.041
Age 31 to 40	-0.154	-0.360	0.053	-0.106	-0.258	0.042
Age 41 to 50	-0.481	-0.728	-0.233	-0.353	-0.536	-0.168
Age 51 to 60	-0.337	-0.612	-0.064	-0.265	-0.465	-0.066
Age 61 to 70	-0.209	-0.530	0.111	-0.095	-0.333	0.145
Age over 70	-0.117	-0.922	0.681	-0.074	-0.525	0.363
Intercept	3.344	2.796	3.892	—	—	—
τ_1	—	—	—	-0.730	-1.096	-0.354
τ_2	—	—	—	-0.155	-0.521	0.215
τ_3	—	—	—	0.372	0.001	0.742
τ_4	—	—	—	0.689	0.322	1.054
τ_5	—	—	—	1.568	1.197	1.938
τ_6	—	—	—	2.289	1.915	2.662
N		1606			1606	

Entries are unstandardized linear regression coefficients and ordered probit coefficients, respectively. τ's are ordered probit cutpoints. Confidence intervals for linear regression models are computing using heteroskedasticity-robust standard errors. All results combined from 100 multiply imputed datasets.

Table A7. *Estimated parameters of models interacting treatments and party identification.*

	Linear Regression			Ordered Probit		
		95% CI			95% CI	
Covariate	est.	lower	upper	est.	lower	upper
Revenue neutral	-0.059	-0.434	0.317	-0.055	-0.321	0.215
Compensation	0.272	-0.088	0.635	0.203	-0.062	0.472
Mitigation	0.382	0.044	0.720	0.296	0.016	0.574
Adaptation	-0.224	-0.600	0.148	-0.130	-0.400	0.137
$50 tax	-0.199	-0.572	0.171	-0.119	-0.392	0.148
Rev. neut. × Independent	0.389	-0.024	0.799	0.552	-0.071	1.180
Compens. × Independent	-0.290	-0.712	0.122	-0.336	-0.930	0.261
Mitig. × Independent	-0.120	-0.532	0.286	-0.073	-0.620	0.472
Adapt. × Independent	0.248	-0.178	0.648	0.412	-0.158	0.983
$50 tax × Independent	-0.034	-0.465	0.394	0.059	-0.548	0.665
Rev. neut. × Republican	0.354	-0.126	0.829	0.358	-0.214	0.921
Compens. × Republican	-0.027	-0.508	0.442	-0.159	-0.733	0.413
Mitig. × Republican	-0.016	-0.495	0.462	-0.119	-0.665	0.422
Adapt. × Republican	0.063	-0.452	0.563	0.052	-0.582	0.692
$50 tax × Republican	-0.104	-0.601	0.387	-0.221	-0.780	0.342
Independent	-0.338	-0.767	0.090	-0.172	-0.471	0.137
Republican	-0.205	-0.602	0.192	-0.180	-0.545	0.187
Climate concern	0.320	0.260	0.379	0.251	0.214	0.289
Experienced extreme weather	0.237	0.078	0.394	0.176	0.062	0.290
Trust state legislators	0.200	0.152	0.248	0.147	0.111	0.184
Consider taxes too high	-0.879	-1.046	-0.712	-0.606	-0.724	-0.486
Support Paris withdrawl	-0.260	-0.318	-0.202	-0.196	-0.235	-0.158
Drive >15k mi/year	-0.187	-0.396	0.024	-0.150	-0.311	0.014
Income above median	0.050	-0.113	0.214	0.035	-0.086	0.155
Male	0.074	-0.078	0.225	0.043	-0.065	0.158
Non-Hispanic White	-0.054	-0.231	0.123	-0.032	-0.163	0.098
College education or higher	0.044	-0.110	0.199	0.023	-0.089	0.134
Volunteer	0.060	-0.093	0.212	0.027	-0.086	0.135
Have children	-0.029	-0.212	0.155	-0.026	-0.157	0.104
Married or widowed	0.232	0.051	0.411	0.187	0.060	0.318
Own a home	-0.105	-0.261	0.053	-0.077	-0.194	0.041
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table A8. *Estimated parameters of models interacting treatments and party identification (continued).*

	Linear Regression			Ordered Probit		
		95% CI			95% CI	
Covariate	est.	lower	upper	est.	lower	upper
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Religious	-0.111	-0.274	0.052	-0.076	-0.194	0.040
Age 31 to 40	-0.141	-0.344	0.063	-0.098	-0.251	0.054
Age 41 to 50	-0.469	-0.711	-0.227	-0.349	-0.528	-0.168
Age 51 to 60	-0.321	-0.596	-0.046	-0.251	-0.454	-0.048
Age 61 to 70	-0.188	-0.511	0.136	-0.088	-0.324	0.152
Age over 70	-0.099	-0.904	0.702	-0.058	-0.507	0.391
Intercept	3.419	2.851	3.990	—	—	—
τ_1	—	—	—	-0.810	-1.180	-0.434
τ_2	—	—	—	-0.232	-0.604	0.138
τ_3	—	—	—	0.298	-0.072	0.663
τ_4	—	—	—	0.616	0.246	0.979
τ_5	—	—	—	1.497	1.126	1.865
τ_6	—	—	—	2.221	1.845	2.600
N		1606			1606	

Entries are unstandardized linear regression coefficients and ordered probit coefficients, respectively. τ's are ordered probit cutpoints. Confidence intervals for linear regression models are computing using heteroskedasticity-robust standard errors. All results combined from 100 multiply imputed datasets.

Table A9. *Estimated parameters of models interacting treatments and party identification, alternative measures.*

	Linear Regression			Ordered Probit		
		95% CI			95% CI	
Covariate	**est.**	**lower**	**upper**	**est.**	**lower**	**upper**
Revenue neutral	-0.029	-0.393	0.326	-0.032	-0.291	0.227
Compensation	0.288	-0.048	0.633	0.200	-0.055	0.452
Mitigation	0.316	-0.015	0.644	0.233	-0.031	0.493
Adaptation	-0.156	-0.504	0.185	-0.100	-0.354	0.150
$50 tax	-0.137	-0.494	0.222	-0.085	-0.342	0.176
Rev. neut. × Independent	0.605	-0.052	1.280	0.434	-0.012	0.880
Compens. × Independent	-0.562	-1.189	0.088	-0.410	-0.855	0.040
Mitig. × Moderate Indep.	0.056	-0.522	0.629	0.015	-0.421	0.466
Adapt. × Moderate Indep.	0.268	-0.334	0.882	0.176	-0.265	0.622
$50 tax × Moderate Indep.	-0.163	-0.810	0.496	-0.152	-0.601	0.310
Rev. neut. × Repub. or Conserv.	0.299	-0.250	0.850	0.281	-0.168	0.730
Compens. × Repub. or Conserv.	-0.145	-0.701	0.398	-0.022	-0.469	0.427
Mitig. × Repub. or Conserv.	-0.060	-0.591	0.479	0.021	-0.438	0.477
Adapt. × Repub. or Conserv.	0.059	-0.517	0.648	0.094	-0.372	0.569
$50 tax × Repub. or Conserv.	-0.223	-0.752	0.310	-0.134	-0.596	0.337
Moderate Independent	-0.276	-0.733	0.176	-0.147	-0.469	0.163
Republican or Conservative	-0.241	-0.640	0.159	-0.208	-0.555	0.134
Climate concern	0.314	0.254	0.373	0.247	0.209	0.284
Experienced extreme weather	0.232	0.072	0.390	0.174	0.058	0.290
Trust state legislators	0.200	0.152	0.248	0.148	0.111	0.184
Consider taxes too high	-0.875	-1.046	-0.708	-0.604	-0.722	-0.485
Support Paris withdrawl	-0.255	-0.312	-0.197	-0.192	-0.232	-0.153
Drive >15k mi/year	-0.191	-0.399	0.019	-0.151	-0.310	0.011
Income above median	0.058	-0.105	0.224	0.039	-0.081	0.159
Male	0.063	-0.089	0.215	0.037	-0.075	0.149
Non-Hispanic White	-0.055	-0.228	0.120	-0.032	-0.162	0.097
College education or higher	0.051	-0.106	0.210	0.029	-0.084	0.142
Volunteer	0.055	-0.100	0.209	0.025	-0.090	0.135
Have children	-0.031	-0.210	0.155	-0.029	-0.161	0.103
Married or widowed	0.244	0.067	0.422	0.196	0.061	0.325
Own a home	-0.105	-0.261	0.054	-0.078	-0.196	0.037
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table A10. *Estimated parameters of models interacting treatments and party identification, alternative measures (continued).*

	Linear Regression			Ordered Probit		
		95% CI			95% CI	
Covariate	est.	lower	upper	est.	lower	upper
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Religious	-0.095	-0.256	0.069	-0.065	-0.182	0.053
Age 31 to 40	-0.151	-0.350	0.055	-0.104	-0.252	0.045
Age 41 to 50	-0.481	-0.726	-0.237	-0.355	-0.539	-0.175
Age 51 to 60	-0.341	-0.620	-0.067	-0.266	-0.468	-0.063
Age 61 to 70	-0.212	-0.532	0.109	-0.100	-0.342	0.140
Age over 70	-0.129	-0.914	0.643	-0.084	-0.533	0.357
Intercept	3.405	2.843	3.982	—	—	—
τ_1	—	—	—	-0.811	-1.188	-0.433
τ_2	—	—	—	-0.230	-0.604	0.139
τ_3	—	—	—	0.300	-0.073	0.668
τ_4	—	—	—	0.619	0.247	0.985
τ_5	—	—	—	1.501	1.127	1.872
τ_6	—	—	—	2.224	1.846	2.605
N		1606			1606	

Entries are unstandardized linear regression coefficients and ordered probit coefficients, respectively. τ's are ordered probit cutpoints. Confidence intervals for linear regression models are computing using heteroskedasticity-robust standard errors. All results combined from 100 multiply imputed datasets.

Control frame

Bipartisan group of legislators calls for a carbon tax to fight climate change
Jake Howard, ETN Newswire April 15, 2018

A group of Republicans and Democrats in the state legislature has proposed a carbon tax to combat global climate change. The plan proposes a tax of $20 per ton of carbon dioxide emitted by businesses or households in the state. This would increase prices of electricity, natural gas, and gasoline. Of course, the total tax a business or a household pays will vary depending on how much energy they use. But in concrete terms, the tax would increase the price of gasoline by about 20 cents per gallon.

We asked Mark Brown, one of the senior legislators in the group, about the rationale for the carbon tax. "Dirty fossil fuels pollute our air and water, harm our kids, threaten our forests, and damage our climate. Carbon tax makes polluters pay. By putting a price on carbon pollution, it reduces emissions and helps us fight global climate change."

The plan's architects said this approach simply follows what others have done. British Columbia enacted a carbon tax in 2008. This reduced their fossil fuel consumption by about 10%, and yet it did not hurt their economic growth.

The carbon tax proposal is likely to meet resistance in the state legislature, among business groups and some labor unions. They argue that a carbon tax would increase the cost of doing business. As a result, some businesses would simply move their operations and jobs across state lines. Further, they point out that increased energy costs would hurt working families who would have to pay higher electricity bills and gasoline prices.

"Nobody wants higher taxes," said Mark Brown, "as voters in our state have spoken many times. However, a carbon tax is the right way to fight global climate change by making polluters pay for their carbon dioxide emissions."

Revenue neutral frame

Bipartisan group of legislators calls for a carbon tax to fight climate change
Jake Howard, ETN Newswire April 15, 2018

A group of Republicans and Democrats in the state legislature has proposed a carbon tax to combat global climate change. The plan proposes a tax of $20 per ton of carbon dioxide emitted by businesses or households in the state. This would increase prices of electricity, natural gas, and gasoline. For example, the price of gasoline would increase by about 20 cents per gallon. Because the proposal calls for a revenue neutral tax, the government would return the carbon tax revenue to all state's residents in the form of a reduced sales tax.

We asked Mark Brown, one of the senior legislators in the group, about the rationale for the carbon tax. "Dirty fossil fuels pollute our air and water, harm our kids, threaten our forests, and damage our climate. Carbon tax makes polluters pay. At the same time, it returns all the new tax money back to residents by lowering their sales tax."

The plan's architects said this approach simply follows what others have done. British Columbia enacted a carbon tax in 2008. This reduced their fossil fuel consumption by about 10%, and yet it did not hurt their economic growth.

The carbon tax proposal is likely to meet resistance in the state legislature, among business groups and some labor unions. They argue that a carbon tax would increase the cost of doing business. As a result, some businesses would simply move their operations and jobs across state lines. Further, they point out that increased energy costs would hurt working families who would have to pay higher electricity bills and gasoline prices.

"Carbon tax will not increase taxes overall because it is designed to be revenue neutral," said Mark Brown. "It will accomplish two things. First, it will reduce carbon dioxide emissions. Second, it will allow us to reduce sales tax for all residents of our state."

Compensation frame

Bipartisan group of legislators calls for a carbon tax to fight climate change

Jake Howard, ETN Newswire April 15, 2018

A group of Republicans and Democrats in the state legislature has proposed a carbon tax to combat global climate change. The plan proposes a tax of $20 per ton of carbon dioxide emitted by businesses or households in the state. This would increase prices of electricity, natural gas, and gasoline. For example, the price of gasoline would increase by about 20 cents per gallon. The generated tax revenue would be used specifically to provide tax credits to low-income families, reduce taxes on small businesses, and retrain workers in fossil fuel industries.

We asked Mark Brown, one of the senior legislators in the group, about the rationale for carbon tax. "Dirty fossil fuels pollute our air and water, harm our kids, threaten our forests, and damage our climate. Carbon tax makes polluters pay and uses the tax money to help low-income families, small businesses, and fossil fuel industry workers, who would be hurt by higher energy prices."

The plan's architects said this approach simply follows what others have done. British Columbia enacted a carbon tax in 2008. This reduced their fossil fuel consumption by about 10%, and yet it did not hurt their economic growth.

The carbon tax proposal is likely to meet resistance in the state legislature, among business groups and some labor unions. They argue that a carbon tax would increase the cost of doing business. As a result, some businesses would simply move their operations and jobs across state lines. Further, they point out that increased energy costs would hurt working families who would have to pay higher electricity bills and gasoline prices.

"Nobody wants higher taxes," said Mark Brown. "But the carbon tax will accomplish two things. First, it will allow us to fight climate change. Second, it will create new resources to provide tax credits to low-income families, lower the tax burden on small businesses, and help retrain workers in fossil fuel industries."

Mitigation frame

Bipartisan group of legislators calls for a carbon tax to fight climate change

Jake Howard, ETN Newswire April 15, 2018

A group of Republicans and Democrats in the state legislature has proposed a carbon tax to combat global climate change. The plan proposes a tax of $20 per ton of carbon dioxide emitted by businesses or households in the state. This would increase prices of electricity, natural gas, and gasoline. For example, the price of gasoline would increase by about 20 cents per gallon. The generated tax revenue would be used by local, county, and state governments specifically to invest in mass transit, bike lanes and electric-car charging stations, and solar and wind energy that will eventually reduce carbon dioxide emissions.

We asked Mark Brown, one of the senior legislators in the group, about the rationale for carbon tax. "Dirty fossil fuels pollute our air and water, harm our kids, threaten our forests, and damage our climate. Carbon tax makes polluters pay. By investing the tax revenue in mass transit, bike lanes and electric-car charging stations, and solar and wind energy, we will reduce emissions, create well-paying local jobs, and strengthen our economy."

The plan's architects said this approach simply follows what others have done. British Columbia enacted a carbon tax in 2008. This reduced their fossil fuel consumption by about 10%, and yet it did not hurt their economic growth.

The carbon tax proposal is likely to meet resistance in the state legislature, among business groups and some labor unions. They argue that a carbon tax would increase the cost of doing business. As a result, some businesses would simply move their operations and jobs across state lines. Further, they point out that increased energy costs would hurt working families who would have to pay higher electricity bills and gasoline prices.

"Nobody wants higher taxes," said Mark Brown. "But the carbon tax will accomplish two things. First, it will allow us to fight climate change. Second, it will create new resources to invest in mass transit, bike lanes and electric-car charging stations, and solar and wind energy that will eventually reduce carbon dioxide emissions."

Adaptation frame

Bipartisan group of legislators calls for a carbon tax to fight climate change

Jake Howard, ETN Newswire April 15, 2018

A group of Republicans and Democrats in the state legislature has proposed a carbon tax to combat global climate change. The plan proposes a tax of $20 per ton of carbon dioxide emitted by businesses or households in the state. This would increase prices of electricity, natural gas, and gasoline. For example, the price of gasoline will increase by about 20 cents per gallon. The increased tax revenue will be used by local, county, and state governments specifically to build infrastructure that increases their capacities to address extreme weather events, such as floods, hurricanes, torrential rainfall, droughts, and wildfires.

We asked Mark Brown, one of the senior legislators in the group, about the rationale for carbon tax. "Dirty fossil fuels pollute our air and water, harm our kids, threaten our forests, and damage our climate. Carbon tax makes polluters pay. By investing the tax revenue in local infrastructure, we will protect our communities and economy from floods, hurricanes, torrential rainfall, droughts and wildfires."

The plan's architects said this approach simply follows what others have done. British Columbia enacted a carbon tax in 2008. This reduced their fossil fuel consumption by about 10%, and yet it did not hurt their economic growth.

The carbon tax proposal is likely to meet resistance in the state legislature, among business groups and some labor unions. They argue that a carbon tax would increase the cost of doing business. As a result, some businesses would simply move their operations and jobs across state lines. Further, they point out that increased energy costs would hurt working families who would have to pay higher electricity bills and gasoline prices.

"Nobody wants higher taxes," said Mark Brown. "But the carbon tax will accomplish two things. First, it will allow us to fight climate change. Second, it will generate new funds to invest in local projects that will protect our communities and economy from floods, hurricanes, torrential rainfall, droughts and wildfires."

$50 tax frame

Bipartisan group of legislators calls for a carbon tax to fight climate change
Jake Howard, ETN Newswire April 15, 2018

A group of Republicans and Democrats in the state legislature has proposed a carbon tax to combat global climate change. The plan proposes a tax of $50 per ton of carbon dioxide emitted by businesses or households in the state. This would increase prices of electricity, natural gas, and gasoline. Of course, the total tax a business or a household pays will vary depending on how much energy they use. But in concrete terms, the tax would increase the price of gasoline by about 45 cents per gallon.

We asked Mark Brown, one of the senior legislators in the group, about the rationale for the carbon tax. "Dirty fossil fuels pollute our air and water, harm our kids, threaten our forests, and damage our climate. Carbon tax makes polluters pay. By putting a price on carbon pollution, it reduces emissions and helps us fight global climate change."

The plan's architects said this approach simply follows what others have done. British Columbia enacted a carbon tax in 2008. This reduced their fossil fuel consumption by about 10%, and yet it did not hurt their economic growth.

The carbon tax proposal is likely to meet resistance in the state legislature, among business groups and some labor unions. They argue that a carbon tax would increase the cost of doing business. As a result, some businesses would simply move their operations and jobs across state lines. Further, they point out that increased energy costs would hurt working families who would have to pay higher electricity bills and gasoline prices.

"Nobody wants higher taxes," said Mark Brown, "as voters in our state have spoken many times. However, a carbon tax is the right way to fight global climate change by making polluters pay for their carbon dioxide emissions."