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18 **1. Data Sources of Variables Used**

19

20 For country-level data on Gross Domestic Product (GDP) per Capita, we used the data from
21 2015 from the World Bank (World Bank 2017c). State-level data on GDP in US-American
22 states were taken from the U.S. Bureau of Economic Analysis (U.S. Bureau of Economic
23 Analysis 2017), state-level data on population and GDP in Canadian provinces were taken from
24 Statcan (Statistics Canada 2017b). Data from China were taken from the National Bureau of
25 Statistics of China (NBS 2017). For all subnational units, GDP per capita from 2015 was used.
26 In order to convert national chained currencies into chained USD, PPP, the PPP conversion
27 rates of the OECD have been applied (OECD 2019).

28 For measuring the level of democracy, we used the PolityIV Score from 2015,
29 published by the Centre for Systemic Peace (Marshall, Gurr, and Jaggers 2017). It consists of

30 several component measures that record key qualities of executive recruitment, constraints on
31 executive authority, and political competition. For subnational jurisdictions, we used the
32 democracy score of the respective nation state.

33 For the coding of the parliamentary system, we used the Parliaments on-Line
34 (PARLINE) open data platform, developed by the Inter-Parliamentary Union (PARLINE
35 2017). Here, we used the data on unicameral parliaments or the respective lower chambers
36 from 2015. We coded the proportional voting system as 1 and all other categories (majority,
37 not applicable, mixed) as 0.

38 For measuring concentration of power, we used the Political Constraint Index Dataset
39 (POLCON), published by the Wharton University of Pennsylvania (Wharton University of
40 Pennsylvania 2017) from 2015. According to the author of the index, Witold J. Henisz, the
41 dataset can be summarized as measuring “the feasibility of a change in policy given the
42 structure of a nation’s political institutions (the number of veto points) and the preferences of
43 the actors that inhabit them (the partisan alignment of various veto points and the heterogeneity
44 or homogeneity of the preferences within each branch)”(Henisz and Zelner 1999).

45 For Good Governance, we used the World Governance Indicators (WGI) from 2015 as
46 conceptualized by Daniel Kauffmann (Kaufmann, Kraay, and Zoido-lobatón 1999) and
47 published by the World Bank (World Bank 2018). They understand governance as the tradition
48 and institutions how authority is exercised in a particular country. This includes (1) processes
49 by which governments are selected, monitored, held accountable, and replaced; (2) the capacity
50 to manage resources efficiently, and formulate, implement, and enforce sound policies and
51 regulations, and (3) the respect of the citizen and the state for the institutions that govern social
52 and economic interactions among them. The WGI summarize their data into six separate
53 indicators, from which we use Regulatory Control as a main indicator and further test also
54 Government Effectiveness and Control of Corruption. Regulatory Quality captures the ability

55 of a government to implement well-designed policies that promote the economic development
56 of a country. Quite similarly, Government Effectiveness captures perceptions about how well
57 political institutions are able to formulate, implement, and enforce policies independent from
58 political pressure and the quality of public services provided that administration. Finally,
59 control of corruption measures the exploitation of public power for private gain, including both
60 petty and grand corruption as well as state capture (Kaufmann, Kraay, and Zoido-lobatón
61 1999).

62 For operationalizing per capita emissions, we used the data on metric tons of CO₂
63 emitted per capita in 2015 provided by the World Bank (World Bank 2017b). For state level
64 data, we used data from the U.S. EIA from 2015 (EIA 2015) for the US states, data from
65 Canada's Official Greenhouse Gas Inventory for the Canadian Provinces and from Deng, Yu,
66 & Liu (2015) for the Chinese provinces. We decided to measure carbon emissions in carbon
67 emissions per capita and not in carbon emissions per GDP because we controlled for level of
68 GDP already separately in our analysis. However, we found that operationalizing carbon
69 emissions as carbon emissions per GDP does not change the results substantially.

70 For measuring the share of oil and coal used in the electricity production of each
71 country, we used the data from 2015 provided by the World Development Indicators (World
72 Bank 2015a, 2015b). For the state-level observation, we used the Electricity Generation by
73 state data provided by the U.S. Energy Information Administration (EIA 2015) for the US
74 states and the data on electricity from fuels, annual generation by electric utility thermal plants
75 by Statcan for Canada (Statistics Canada 2017a). As we were unable to obtain detailed data for
76 the share of electricity production from coal and oil in Chinese provinces, we used the value of
77 federal China for all Chinese provinces.

78 As a proxy for the share of energy-intensive industries, we used data on how much the
79 overall industry sector contributes to national GDP in 2015. We considered a more precise

80 measurement, such as analyzing the percentage of several energy-intensive subsectors (such as
81 chemical industry) on GDP but found that data quality was insufficient. For country-level
82 observations, we used the data provided by the World Bank Development Indicators (World
83 Bank 2017d). Sub-national data on US states and Canadian provinces were obtained by the US
84 Bureau of Economic Administration (U.S. Bureau of Economic Analysis 2017) and CANSim
85 (Statistics Canada 2017a), and for China from the National Bureau of Statistics of China (NBS
86 2017).

87 For measuring the public belief in human-made climate change, we draw on
88 representative public surveys asking survey participants what they perceive the main cause for
89 global warming. For national-level observations we used survey data from Gallup, collected in
90 two survey rounds in 2007-08 and in 2010-2011 (Pelham 2009; Ray and Pugliese 2011). The
91 data was collected by interviewing a representative sample of at least 1000 civilian, non-
92 institutionalized adults, aged 15 and older per telephone or face to face. The number that we
93 used in our analysis refers to the percentage of people believing in anthropogenic climate
94 change as a share of total responses. For estimating public belief in the US states we used the
95 ‘Yale Climate Opinion Maps – U.S. 2014’ which estimates public opinion based on national
96 survey data (n>13,000) gathered between 2008 and 2014 (Howe et al. 2015). For Canadian
97 states we used the data from the Yale Climate ‘Opinion Map Canada’ published in 2016 which
98 estimates public opinion based on a large survey dataset featuring more than 5000 respondents
99 that have been surveyed since 2011 (Mildenberger et al. 2016). As we were unable to obtain
100 detailed data for the share of population believing in anthropogenic climate change in Chinese
101 provinces, we used the value of federal China for all Chinese provinces.

102 Data on air pollution were taken from the World Health Organization’s Ambient Air
103 Pollution Database for cities and localities in 2015 (WHO 2017). The indicator reports the
104 annual mean concentration of particulate matter of less than 2.5 microns of diameter (PM2.5)

105 [ug/m3] in cities and localities. We used the city and localities measures and not the country-
 106 level measure, since data have been more complete in the city and localities database and
 107 because in this way, we could also compute estimates for sub-national entities.

108 Finally, we included two dummy variables for the EU and China to control for the
 109 influence of multilevel governance in jurisdictions that are part of the EU ETS or the Chinese
 110 Pilot ETS.

111 For all predictors, we used data from 2015, in order to minimize the risk of reverse
 112 causality. Where only data from earlier than 2015 have been available, we used the most recent
 113 available data. We coded our dummy variables in 1-100 to increase comparability with the
 114 other variables. Some of our variables are strongly correlated with each other (see table S4).
 115 We therefore computed an VIF Analysis (see Table S5) and excluded predictors that produce
 116 with large VIFs from our central analysis (see table S5).

117

Variable	Operationa- lization	Year	Unit	Scale	Data Source
Weighted Carbon Price	-	2017	US\$ (2017)	1	Original calculation based on World Bank (World Bank 2017a)
		2015	US\$, PPP (constant 2011 int. \$)		NY.GDP.PCAP.PP.KD World Bank (World Bank 2017c); SAGDP10N U.S. Bureau of Economic Analysis (U.S. Bureau of Economic Analysis 2017) Statcan (Statistics Canada 2017b) National Bureau of Statistics of China (NBS 2017)
GDP per Capita	GDP per Capita, PPP			in Thsd.	
Democracy	Polity IV	2015	Index	0-100	Center for Systemic Peace (Marshall, Gurr, and Jaggers 2017)
Regulatory Control	World Governance Indicators	2015	Index	0-100	World Bank (Kaufmann, Kraay, and Zoido-lobatón 1999)
Government Effectiveness	World Governance Indicators	2015	Index	0-100	World Bank (Kaufmann, Kraay, and Zoido-lobatón 1999)
Corruption Control	World Governance Indicators	2015	Index	0-100	World Bank (Kaufmann, Kraay, and Zoido-lobatón 1999)
Public Belief in Human-	Gallup World Poll	2009-2014 ¹	In % of the Population	0-100	National: Gallup Research (Pelham 2009; Ray and Pugliese 2011)

¹ 2009-2011(National Level); 2011-2014 (US and Canadian)

Made Climate Change					US: Yale Climate Opinion Map 2015 (Howe et al. 2015) Canada: Yale Climate Opinion Map (Mildenberger et al. 2016)
Industry on GDP	Industry on GDP	2015	in % of Total GDP	0-100	World Bank(World Bank 2017d); US Bureau of Economic National USA: SAGDP9N Administration (U.S. Bureau of Economic Analysis 2017); CANSim (Statistics Canada 2017a), Bureau of Statistics of China (NBS 2017)
Oil Usage in Electricity Production	% of Electricity produced by oil	2015	in % of electricity produced	0-100	World Bank (World Bank 2015b, 2015a)
Oil Usage in Electricity Production	% of Electricity produced by coal	2015	in % of electricity produced	0-100	U.S. Energy Information Administration (EIA 2015) Statcan Electricity from fuels 25-100019-0 Guangdong civic exchange report (Guangdong Civic Exchange 2013) U.S. EPA (US EPA 2015)
Carbon Emissions	Ton per capita	2014 2015 2015 2015	Metric ton	1	World Bank (World Bank 2017b);; U.S. EIA(EIA 2015) Environment and Climate Change Canada (Canada 2017); Deng, Yu, and Liu (2015)
Air Pollution	annual mean concentration of PM2.5	2009-2015 ²	ug/m3	1	World Health Organization (WHO 2017)
Political Concentration	POLKON	2015	Index	0-100	Witold J. Henisz (Wharton University of Pennsylvania 2017)
Proportional Voting System	Electoral System	2015	Dummy	Dummy	Parline Database (PARLINE 2017)
Part of EU	NA	2015	Dummy	0/100	
Part of China	NA	2015	Dummy	0/100	

118 **Table S1: Operationalization of Variables and Data Sources**

119

120 **2. Summary Statistics of Variables Used**

121

Variable	Scale	Min	Max	Mean	Median	Std. Dev.
Weighted Carbon Price	in US\$	0,00	52,90	1,22	0,00	4,70
GDP per Capita	in Thsd. USD	0,29	169,85	25,56	15,27	24,20
Democracy	Index 0-100	0	100	71,39	90	34,30
Regulatory Control	Index 0-100	3,48	95,21	54,76	51,09	20,75
Government Effectiveness	Index 0-100	6,06	94,73	56,99	58,16	21,20

² Database published May 2016 (Data collected between 2009 and 2015)

Corruption Control	Index 0-100	14,68	95,51	55,74	55,64	21,26
Public Belief in Human-Made Climate Change	In % of the Population	7,00	86,00	38,77	42,50	15,28
Industry on GDP	in % of Total GDP	2,25	95,00	28,59	27,00	12,02
Oil Usage	in % of electricity produced	0,00	100	10,61	0,61	23,13
Coal Usage	in % of electricity produced	0,00	95,77	27,96	0,17	22,15
Carbon Emissions	In metric tons per capita	0,04	108,15	9,76	6,18	12,96
Air Pollution PM2.5	annual mean concentration of PM in ug/m3	3,7	104,62	27,15	17,48	23,81
Political Concentration	Index	0	70,86	34,05	39.,4	17,13
Proportional Voting System	Dummy	0 (196)	100 (57)			
Part of EU	Dummy	0 (234)	100 (28)			
Part of China	Dummy	0 (255)	100 (7)			

122 **Table S2:** Summary statistics of all variables used in our analysis.

123

124 3. Weighted Carbon Prices

125

Jurisdiction	Nominal Price on 1st April 2017	Weighted Price on 1st April 2017	Jurisdiction	Nominal Price on 1st April 2017	Weighted Price on 1st April 2017
<i>California</i>	13,81	11,74	<i>Czech Republic</i>	4,99	2,23
<i>Connecticut</i>	3,45	0,72	<i>Germany</i>	4,99	1,69
<i>Delaware</i>	3,45	0,72	<i>Denmark</i>	15,41	11,71
<i>Maine</i>	3,45	0,72	<i>Spain</i>	4,99	1,84
<i>Maryland</i>	3,45	0,72	<i>Estonia</i>	4,99	2,21
<i>Massachusetts</i>	3,45	0,72	<i>Finland</i>	28,65	25,79
<i>New Hampshire</i>	3,45	0,72	<i>France</i>	17,88	13,41
<i>New York</i>	3,45	0,72	<i>United Kingdom</i>	22,41	5,38
<i>Rhode Island</i>	3,45	0,72	<i>Greece</i>	4,99	2,14
<i>Vermont</i>	3,45	0,72	<i>Croatia</i>	4,99	1,73
<i>Washington</i>	0	0	<i>Hungary</i>	4,99	1,79
<i>British Columbia</i>	22,54	15,78	<i>Ireland</i>	16,47	11,53
<i>Alberta</i>	18,78	16,9	<i>Italy</i>	4,99	1,67
<i>Ontario</i>	13,58	11,14	<i>Japan</i>	2,58	1,75
<i>Quebec</i>	13,81	11,74	<i>Korea, Rep.</i>	18,46	12,55
<i>Beijing</i>	7,57	3,4	<i>Lithuania</i>	4,99	2,48
<i>Tianjin</i>	1,97	1,08	<i>Luxembourg</i>	4,99	0,96
<i>Shanghai</i>	5,67	3,23	<i>Latvia</i>	4,99	2,17

<i>Fujian</i>	5,02	3,01	<i>Mexico</i>	1,54	0,71
<i>Hubei</i>	2,46	0,86	<i>Netherlands</i>	4,99	1,74
<i>Guangdong</i>	2,23	1,34	<i>Norway</i>	16,0	13,95
<i>Chongqing</i>	0,87	0,35	<i>New Zealand</i>	12,02	6,13
<i>Austria</i>	4,99	1,95	<i>Poland</i>	4,99	1,25
<i>Belgium</i>	4,99	2,24	<i>Portugal</i>	6,05	3,87
<i>Bulgaria</i>	4,99	2,59	<i>Romania</i>	4,99	2,81
<i>Switzerland</i>	64,56	28,40	<i>Slovak Republic</i>	4,99	1,2
<i>Chile</i>	5	2,1	<i>Slovenia</i>	11,47	5,74
<i>Colombia</i>	5,21	1,56	<i>Sweden</i>	60,11	52,9
<i>Cyprus</i>	4,99	1,47	<i>Ukraine</i>	0,01	0,01

126 **Table S3:** Nominal and Weighted carbon price.

127

128 4. Cross-Correlation Matrix

129

Variable	Carbon Price	GDP per Capita	Democracy	Reg. Ctrl.	Gov. Effect.	Corr. up. Ctrl.	Public Belief	Industry on GDP	% Oil in Elec.	% Coal in Elec.	Carbon Emissions	Pol. Conc.	Air Pollution
Weightend Carbon Price	X	0,20	0,18	0,31	0,29	0,33	0,27	-0,02	-0,11	-0,01	0,01	0,19	-0,19
GDP per Capita	0,20	X	0,40	0,74	0,75	0,72	0,56	-0,17	-0,11	-0,05	0,51	0,22	-0,49
Democracy	0,18	0,40	X	0,59	0,42	0,54	0,54	-0,06	-0,21	0,20	0,10	0,65	-0,75
Regulatory Control	0,31	0,74	0,59	X	0,94	0,91	0,68	-0,22	0,08	0,12	0,44	0,44	-0,70
Government Effectiveness	0,29	0,75	0,43	0,94	X	0,946	0,68	-0,11	0,20	0,03	0,51	0,35	-0,68
Corruption Control	0,33	0,72	0,54	0,91	0,96	X	0,60	-0,16	0,16	0,01	0,49	0,35	-0,63
Belief in Human-Made Climate Change	0,27	0,56	0,54	0,68	0,68	0,60	X	-0,22	-0,24	-0,06	0,22	0,35	-0,66
Industry on GDP	-0,02	-0,17	-0,06	-0,22	-0,11	-0,16	-0,22	X	-0,09	0,31	0,22	-0,31	0,54
Oil Usage	-0,11	-0,28	-0,19	-0,30	-0,37	-0,32	-0,24	-0,09	X	-0,34	-0,20	0,12	0,15
Coal Usage	-0,11	-0,11	-0,21	0,08	0,20	0,16	-0,06	0,31	-0,34	X	0,33	0,00	0,23
Carbon Emissions	0,01	0,51	0,10	0,44	0,51	0,49	0,22	0,22	-0,20	0,33	X	0,07	-0,19
Political Concentration	0,19	0,22	0,65	0,44	0,35	0,35	0,35	-0,31	-0,12	0,00	0,07	X	-0,50
Air Pollution	-0,19	-0,49	-0,75	-0,70	-0,63	-0,62	-0,66	0,54	0,15	0,23	-0,19	-0,50	X

130 **Table S4:** Cross-correlation matrix for all numerical variables. Person's correlation coefficient
131 was used to estimate the degree of correlation. Correlation coefficients above 0.7 are displayed
132 in bold.

133

134 Furthermore, we also calculated the Variance Inflation Factor (VIF) for all model
135 specifications. The VIF describes the degree of multicollinearity by indicating the percentage
136 degree to which the variance (the squared standard error) of each coefficient is inflated because
137 of linear dependence on other predictors. The threshold above which VIF are cause for concern

138 remains debated and range between 2,5 and 10. High VIF for dummy variables are usually not
 139 a cause for concern. We decided to exclude democracy from our main model, because a VIF
 140 of 9 is perceived by many scholars as concerning.

141

Variable	1 – Central Model	2 – w/ Air Poll.	3 – w/ democracy	4 – w/ pol. variables	5 – alt. carbon	6 – Gov. Effect.	7 – Corrup. Cntrl.
<i>GDP per capita</i>	2,38	2,53	2,35	2,39	1,93	2,36	2,08
<i>Public Belief in %</i>	1,62	1,67	1,66	1,64	3,34	1,67	1,67
<i>Level of Air Pollution</i>		3,61					
<i>Coal in electricity generation in %</i>	1,80	1,81	1,79	1,82		1,72	1,65
<i>Oil in electricity production in %</i>	1,13	1,15	1,13	1,16		1,15	1,14
<i>Carbon Emissions</i>					1,51		
<i>Industry on GDP in %</i>	1,47	1,48	1,57	1,48		1,53	1,52
<i>Democracy</i>			9,05				
<i>Proportional Voting System</i>				1,3			
<i>Concentration of political power</i>				1,61			
<i>Regulatory Control</i>	3,20	3,64	3,26	3,20	3,34		
<i>Government Effectiveness</i>						2,21	
<i>Corruption Control</i>							1,82
<i>EUETS</i>	1,33	1,33	1,35	1,68	1,52	1,32	1,32
<i>CNETS</i>	3,69	4,20	9,85	4,15	2,75	2,74	2,69

142 **Table S5:** Variance Inflation Factors. We excluded Democracy from our central model,
 143 because a VIF of 9 is often perceived as a matter for concern.

144

145 **5. Handling of missing values**

146

147 From all 262 observations covered, around 99 had missing values. In 73 cases, data on local
 148 air pollution was missing. In 42 cases, data on public belief in anthropogenic climate change
 149 has not been available. In 34 jurisdictions, data on electricity generation were missing and in
 150 19 cases data on the sectoral composition of national GDP were incomplete. Moreover,
 151 information on voting system was not available for nine cases and political concentration was
 152 incomplete for twelve cases. Finally, in six jurisdictions data on the level of democracy has not
 153 been not available and in five jurisdictions carbon emissions could not be obtained.

154

155 These missing values are the result of the data collection process: Some databases feature a
 156 smaller number of countries than others. It can be expected that the decision to include
 157 countries in a given dataset follows non-random considerations: smaller and less affluent
 158 nations as well as those in remote locations (in relation to the institute conducting the data
 159 collection) are less likely to be included. These inclusion criteria are directly and indirectly
 160 linked the specific missing value which is expected to be obtained: smaller and poorer countries
 161 outside the Global North are much more likely to have a low score in GDP per capita, in
 162 democracy, lower belief in human-made climate change (due to lower awareness of global
 163 warming), and to have larger agriculture and industry sectors compared to service sectors.
 164 Thereby, the missing observations need to be classified as “Missing Not at Random (MNAR)”
 165 (Kang 2013).

166
 167 Given our sample size is rather small and Missing at Random is not properly satisfied, list wise
 168 deletion as a strategy to deal with missing observations is likely to introduce statistical bias
 169 (Kang 2013). Furthermore, mean substitution is also not a good estimation technique since data
 170 are neither randomly collected nor normally distributed. Instead, multiple imputation or full
 171 maximum likelihood estimation are considered to be most appropriate techniques to deal with
 172 MNAR observations so to reduce bias and preserve standard errors.

173
 174 We therefore used multiple imputation to estimate missing values. Multiple imputation is a
 175 strategy that creates several imputed values, which are each predicted by a slightly different
 176 regression model from the other variables in the dataset and thereby reflect sampling
 177 variability. We implemented the multiple imputation procedure using the R package *mice*
 178 (Azur et al. 2011). This package uses Fully-Conditional-Specification which models the
 179 distribution of each variable separately, also known under chained equations. We estimated
 180 five imputation datasets, which is common practice and the default option of the *mice*
 181 imputation package. We also estimated a model using case-wise deletion instead of multiple
 182 imputation as a robustness check and found no major differences between the two model
 183 estimations (see section 8 and Figure S3).

184

Variable	# missing values
Weighted Carbon Price	0
GDP per Capita	0

Democracy	6
Regulatory Control	0
Government Effectiveness	0
Corruption Control	0
Public Belief in Human-Made Climate Change	42
Industry on GDP	19
% of Oil on Elec. Prod.	34
% of Coal on Elec. Prod.	34
Carbon Emissions	5
Air Pollution PM2.5	73
Political Concentration	12
Proportional Voting System	9
Part of EU	0
Part of China	0

185 **Table S6:** Number of Missing Values.

186

187 6. Coefficients and Marginal Effects

188

189 In our analysis, we concentrated on the Tobit coefficients. For better interpretation, we
 190 exponentiated the coefficient so that it displays the expected percentage change in carbon
 191 prices for every unit increase in the dependent variable. Table S7 summarizes the original Tobit
 192 coefficient and the exponentiated coefficient for each variable in the main model.

193

Variable	Scaling	Min	Max	Std. Dev.	Tobit Coefficient for log-transf. carbon price	Percentage change of carbon price for each unit increase of independent variable
GDP per capita	in 1000 \$US	0,29 (Tibet)	169,8 (District of Columbia)	24,20	-0,014	-1,43%
Public Belief	in % of pop.	7,00 (Liberia)	86,00 (Japan)	15,28	0,052	5,30%
Level of Air Pollution	annual mean concentr. in %	3,7 (New Mexico)	104,6 (Saudi Arabia)	23,77	0,005	5,23%
Coal in electricity generation	in % of electr. prod.	0,00 (Nunavut)	100 (Botswana)	30,51	-0,018	-1,78%
Oil in electricity production	in % of electr. prod.	0,00 (Qatar)	99,59 (Nunavut)	25,47	-0,020	-1,98%
Industry on GDP	in % of GDP	2,25 (District of Columbia)	95,00 (Puerto Rico)	12,02	0.0031	0,31%
Per Capita Emissions	metric tons per capita	0,04 (Burundi)	108,15 (Wyoming)	12,96	-0,044	-4.30%

Democracy	Index, 0-100	0 (Bahrain)	100 (Netherlands)	34,30	0,001	1,00%
Proportional Voting System	Dummy	0	100		0,003	38,34% (0 to 100)
Concentration of political power	Index, 0-100	0 (Bahrain)	70,86 (Congo)	17,13	0,002	0,16%
Regulatory Control	Index, 0-100	3,36 (North Korea)	95,21 (Singapore)	20,25	0,052	5,31%
Government Effectiveness	Index, 0-100	6,06 (Somalia)	94,74 (Singapore)	21,20	0,038	3,89%
Corruption Control	Index, 0-100	14,68 (Equatorial Guinea)	95,51 (New Zealand)	21,26	0,031	3,15%
Part of EU ETS	Dummy	0	100		0,021	724,86% (0 to 100)
Part of Chinese Pilot ETS	Dummy	0	100		0,044	8014,48% (0 to 100)

194 **Table S7:** Summary of Predictors and Coefficients in the main model.

195

196 In addition to the regression coefficient we are also calculated the marginal effect $E_{\text{change}}(y|y>0, x)$ of each predictor on the change of observed carbon prices. However, as the relative
197 magnitude of the marginal effects mirror the relative magnitude of the Tobit coefficients and
198 because of their non-linear and complex interpretation of the marginal effect, we focus on
199 reporting Tobit coefficients for the sake of simplicity.

201

202 The marginal effect describes the non-linear effect of one unit increase on the expected increase in
203 log-transformed carbon prices. For a better interpretation we-also back-transformed the
204 marginal effect so that they display the estimated percentage change on carbon prices at the
205 mean position. It thereby accounts for both, the effect on the likelihood that carbon prices are
206 implemented as well as the expected change in magnitude of the prices (McDonald and Moffitt
207 1980).

208

209 Hence, the marginal effect differs from the Tobit coefficient β by the factor $0 \leq \Phi_i \leq 1$,
210 which represents the likelihood of a unit being uncensored. In our case Φ_i represents the
211 likelihood of a jurisdiction implementing a carbon price. The difference to the Tobit coefficient
212 is small for large values of $x'_i\beta/\sigma$ and large for small values $x'_i\beta/\sigma$. This expectation can be
213 estimated using the inverse Mill ratio λ :

214

215
$$E(y|y>0, x) = \beta x + \sigma \lambda(\beta x | \sigma)$$

Variable	Mean	Marginal Effect on log-transformed Carbon Price at mean position	Back-Transformed marginal effect indicating percentage change of untransformed Carbon Price at mean position
GDP per Capita	24,56	-0,001	-0.12%
Public Belief in Human-Made Climate Change	38,77	0,006	0.62%
Regulatory Control	54,76	0,005	0.51%
Share of Coal in Electricity	27,96	-0,002	-0.20%
Share of Oil in Electricity	10,61	-0,002	-0.20%
Industry on GDP	28,59	0,002	0,17%
Part of EU ETS	0	0,221	24,77%
Part of Chinese Pilot System	0	0,457	57,99%

217 **Table S8:** Marginal Effect of each predictor on the carbon price. The marginal effect is
 218 estimated for the mean value of each predictor.

219

220 The marginal effect depends substantially on the value of the independent variable x_i . For small
 221 values of x_i , most observations do not have a carbon price. Here the marginal effect is very
 222 small, and one unit increase in the independent variable increases only the likelihood of a
 223 carbon price being implemented, without substantially influencing its observed magnitude. As
 224 x_i increases, more observations are being uncensored, and the marginal effect approaches the
 225 Tobit coefficient β once the likelihood of a carbon price being implemented Φ_i approaches 1.

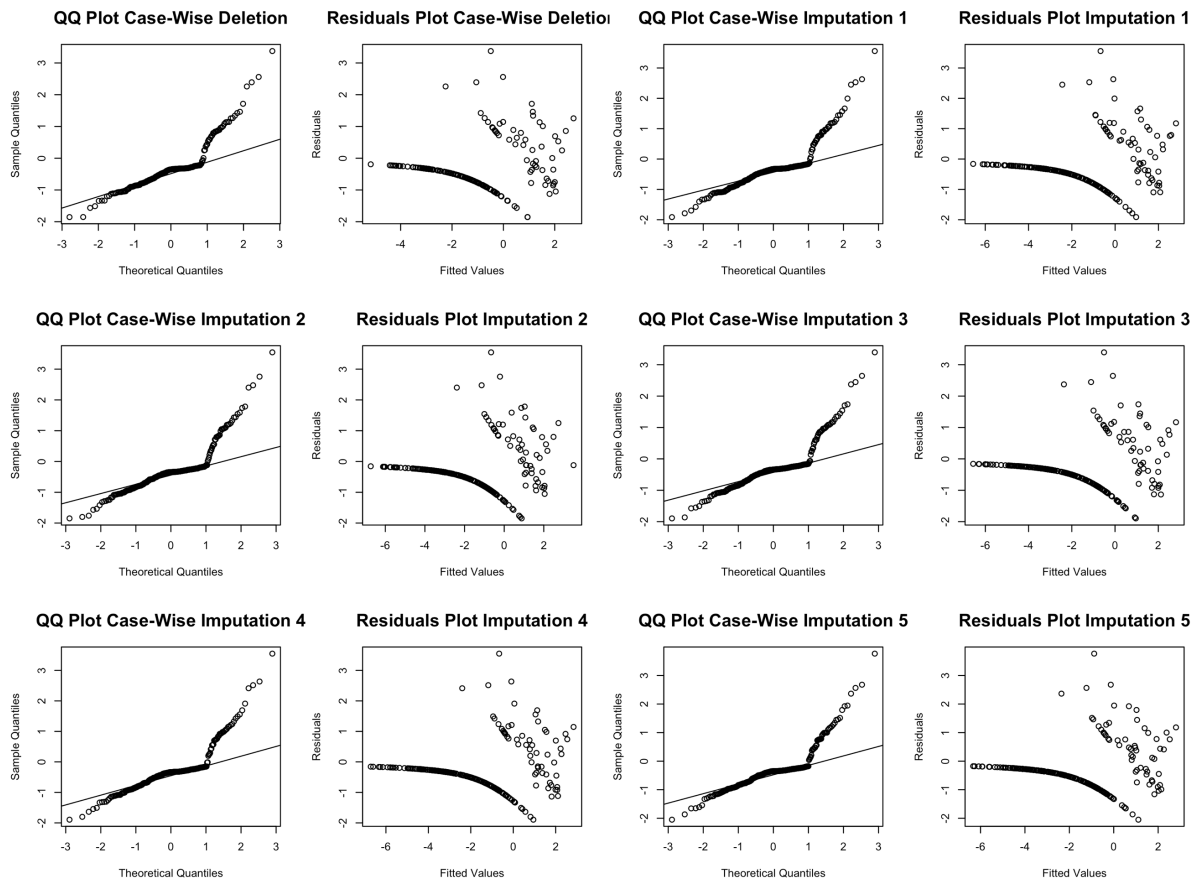
226

227 As it is common practice, we calculated the marginal effects for the mean of the independent
 228 variables. At the mean position of our independent variables, jurisdictions tend to have no
 229 carbon price in place. Therefore, the marginal effect at the mean position is very small
 230 compared to β . At this position, one unit increase in the independent variable increases mostly
 231 the likelihood of a carbon price being implemented, but not substantially its magnitude. Table
 232 S4 displays the marginal effects for each predictor at the mean position as well as the back-
 233 transformed marginal effect so that it displays the percentage change on untransformed carbon
 234 prices at the mean position. We computed the marginal effect for our central model (see Table
 235 S8). Since coefficients and standards errors hardly vary if other distributional assumptions are

236 made, the marginal effects can be expected to be similar for the heteroskedastic Tobit model
237 with gaussian and logistic distribution assumptions.
238

239 7. Model Assumption Test Statistics

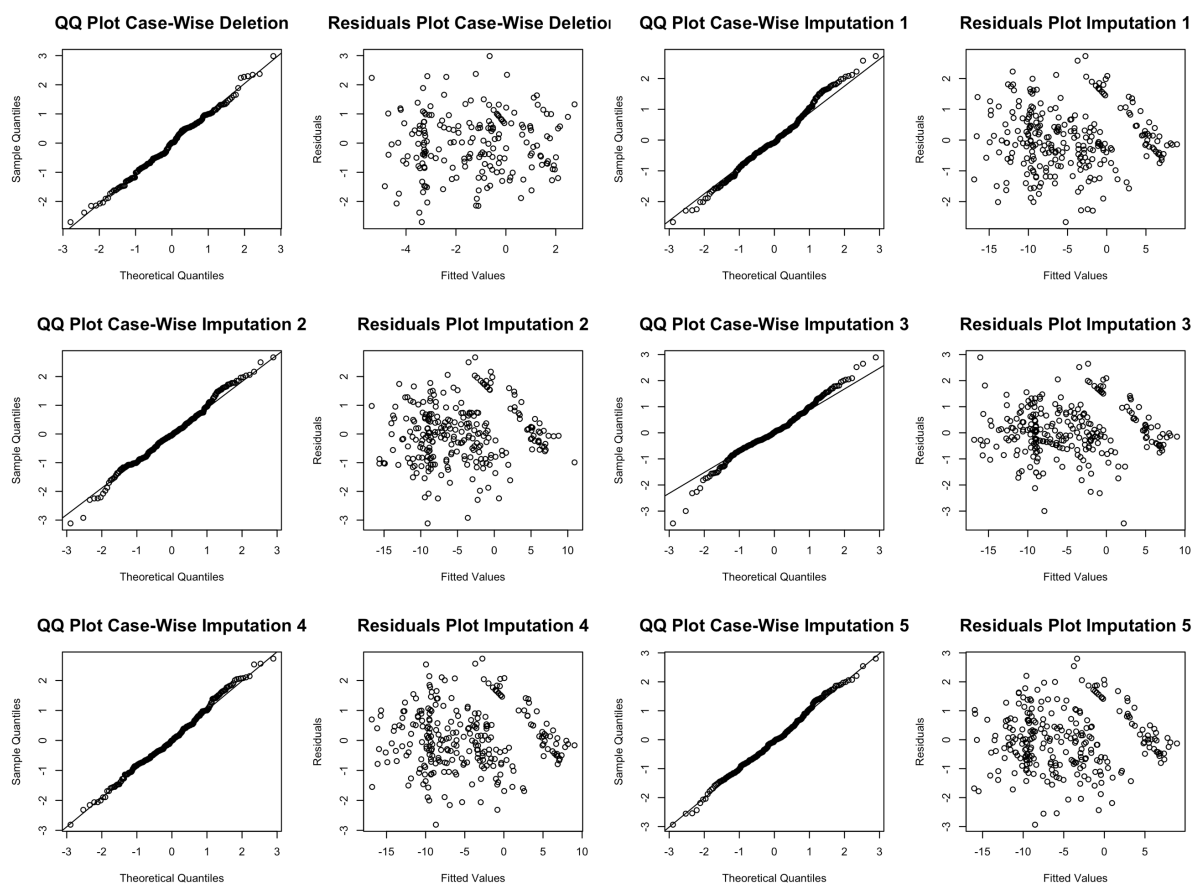
240
241 Standard Tobit models operate under the assumption of normality and homoscedastic of the
242 underlying latent variable model. After computing and examining the generalized residuals we
243 find that these conditions cannot completely be fulfilled with our carbon pricing data (see
244 Figure S1).
245



246
247 **Fig S1:** Diagnostic Plots for the conventional Tobit model using both the case-wise deleted
248 dataset as well as all the imputed data sets. The visual diagnostics indicate that quantile
249 residuals are not distributed reasonably normal and are not homoscedastic. This indicates that
250 the model has not been specified correctly.

251
252 We therefore estimated a model that relaxes these assumptions in which we allow for
253 heteroskedasticity and assume non-normal (logistic) distributions. We tested our model for

254 misspecification error by generating and examining the quantile residuals (Dunn and Smyth
 255 1996). Figure S2 show the Normal Q-Q plots to diagnose normality and the residuals-over-
 256 fitted-values plots to diagnose homoscedasticity. We performed these diagnostic tests for each
 257 of the imputed datasets separately as well as for the dataset, in which missing values were
 258 deleted. For all datasets, visual diagnostics indicate that the quantile residuals are distributed
 259 reasonably normal and homoscedastic. Therefore, we can assume that with the censored
 260 regression model with condition heteroscedasticity, the model can be specified correctly (Dunn
 261 and Smyth 1996).
 262



263
 264 **Fig S2:** Diagnostic Plots for the censored regression model with conditional heteroscedacity
 265 using both the case-wise dataset as well as all imputed data sets. The visual diagnostics indicate
 266 that quantile residuals are distributed reasonably normal and homoscedastic, which indicates
 267 correct model specification.

268

269 8. Robustness Checks

270

271 Table S9 provides an overview of the sensitivity of our results to different sampling techniques,
 272 model specifications and distributional assumptions. Next to our central model (A), we tested
 273 a model in which outlier were removed (B) and a model in which all observations with missing
 274 values have been case-wise deleted instead of using multiple imputation to address missing
 275 values (C). Moreover, we tested a model in which we used a Standard Tobit model (D) and a
 276 heteroscedastic Tobit model with Gaussian distribution assumption (E) instead of the
 277 heteroscedastic Tobit model with a logistic distribution assumption, that we use for our central
 278 model and the alternative specifications discussed in the main manuscript. Finally, we also
 279 specified a model in which we did not log-transformed the carbon prices (F) and a model which
 280 only regards national level observations (G). In model G, we aggregated the carbon price of
 281 the US states, Canadian provinces, and Chinese provinces to the national level, based on the
 282 share of emissions covered by a carbon price. Please see table S10 for the calculation of
 283 aggregated carbon prices for the model with national level observations.
 284

Censored Regression Model on log-transformed weighted carbon price in \$US							
Variable	A Central Model	B w/o Outlier	C Casewise Deletion	D Std. Tobit	E Gaussian Dist.	F Untransf. CO₂ Price	G National Obs.
<i>GDP per capita</i>	-0.014 * (0.008)	-0.013 (0.009)	-0.012 (0.008)	-0.013 * (0.008)	-0.013 * (0.007)	-0.073 (0.049)	-0.025 *** (0.009)
<i>Public Belief in %</i>	0.052 *** (0.012)	0.052 *** (0.012)	0.052 *** (0.012)	0.054 *** (0.013)	0.054 *** (0.012)	0.294 *** (0.076)	0.039 *** (0.01)
<i>Coal in electricity generation in %</i>	-0.018 *** (0.005)	-0.018 *** (0.005)	-0.018 *** (0.005)	-0.018 *** (0.005)	-0.018 *** (0.005)	-0.113 *** (0.035)	-0.011 ** (0.005)
<i>Oil in electricity production in %</i>	-0.02 ** (0.008)	-0.02 ** (0.008)	-0.017 * (0.009)	-0.022 ** (0.01)	-0.022 ** (0.009)	-0.119 ** (0.055)	-0.011 (0.007)
<i>Industry on GDP in %</i>	0.003 (0.013)	0.003 (0.013)	0.006 (0.014)	0.01 (0.013)	0.01 (0.012)	0.042 (0.075)	0.025 * (0.012)
<i>Regulatory Control</i>	0.052 *** (0.014)	0.05 *** (0.015)	0.048 *** (0.014)	0.049 *** (0.013)	0.049 *** (0.013)	0.317 *** (0.088)	0.064 *** (0.015)
<i>EUETS</i>	0.021 *** (0.003)	0.021 *** (0.003)	0.02 *** (0.003)	0.021 *** (0.003)	0.021 *** (0.003)	0.1 *** (0.017)	0.018 *** (0.003)
<i>CNETS</i>	0.044 *** (0.007)	0.044 *** (0.007)	0.042 *** (0.007)	0.042 *** (0.007)	0.042 *** (0.006)	0.238 *** (0.044)	2.413 *** (0.834)
<i>No. of observations</i>	262	262	194	262	262	262	170
<i>Log Likelihood</i>	-112.34	-112.24	-102.92	-113	-113	-216.47	-58.86

*** - $p < 0.01$, ** - $p < 0.05$, * - $p < 0.01$

285 **Table S9:** Robustness Tests. Regulatory Control and Public Belief remain positive and
 286 statistically significant across all alternative model specifications.

287

288 In order to test for outliers, we computed the leverage of each observation and visually
 289 examined the residuals. None of the residuals was particularly high and no observations had a
 290 leverage above 0.5. Therefore, we decided to drop the observation with the highest leverage,
 291 which was the US state of “District of Columbia” with a leverage of 0.3. Excluding the outlier
 292 from the model does not affect our main results (see column B). However, the variable “GDP
 293 per Capita” loses its statistical significance, probably because “District of Columbia” has a
 294 very high GDP per capita and no carbon price.

295 Using case-wise deletion instead of multiple imputation (column C) does not affect our
 296 main results neither. However, the variables “GDP per capita” and “Oil in Electricity
 297 production” loose magnitude and statistical significance. This may be due to the lower number
 298 of observations and due to the fact that many observations that are excluded due to missing
 299 values have been small jurisdictions with no carbon prices and high levels of electricity
 300 generated from oil.

301 Computing a standard Tobit model (which assumes gaussian distribution and
 302 homoscedasticity) produces almost identical results as heteroskedastic model which assumes
 303 gaussian distribution of residuals (columns D and E). Both models moreover produce very
 304 similar results than the heteroskedastic model with logistic distribution assumption, which we
 305 used for our analysis. This shows that our results stay highly robust across different
 306 distributional assumptions.

307 Column F shows that the model quality in terms of log likelihood decreases
 308 substantially if carbon prices are not log transformed. However, most statistical significances
 309 and relative coefficient magnitudes remain robust.

310 Column G shows that the magnitude of public belief and regulatory control and their
 311 statistical significance remain robust if only national level observations are analyzed. The
 312 Share of Oil in Electricity productions loses its statistical significance, but the share of coal in
 313 electricity production remains negative and statistically significantly correlated with the carbon
 314 prices of national jurisdictions.

315

National Level Observation	Subnational Jurisdiction /Scheme	PS - Carbon Price of Jurisdiction(s)	S - Share of national Emissions covered by Scheme	PA - Aggregated Carbon Price
US	California	13.81	0.0719	\$1.05
	RGGI	3.45	0.0179	
Canada	Alberta	18.783	0.2178	\$10.22
	BC	22.54	0.0783	
	Ontario	13.58	0.2548	
	Quebec	13.81	0.1239	

China	Beijing	7.57	0.0082	\$0.43
	Chongqing	0.87	0.0094	
	Fujian	5.02	0.0194	
	Guangdong	2.23	0.0356	
	Hubei	2.46	0.0158	
	Shanghai	5.67	0.0165	
	Shenzhen	5.08	0.0059	
	Tianjin	1.97	0.0115	

316 **Table S10:** Aggregated Carbon Prices for Robustness Model Specification with national-
317 level observations. The Aggregated Carbon Price (PA) has been calculated by building the
318 sum of the nominal Carbon Prices of each Jurisdiction (PS) multiplied by the Share of
319 national emissions that are covered by this respective subnational pricing scheme (S).
320

321 9. Literature

322

323 Azur, Melissa J., Elizabeth A. Stuart, Constantine Frangakis, and Philip J. Leaf. 2011.

324 Multiple Imputation by Chained Equations: What Is It and How Does It Work?

325 *International Journal of Methods in Psychiatric Research* 20 (1): 40–49.

326 <https://doi.org/10.1002/mpr.329>.

327 Canada, Environment and Climate Change. 2017. OVERVIEW OF 2015 REPORTED
328 EMISSIONS.

329 Deng, X., Y. Yu, and Y. Liu. 2015. Temporal and Spatial Variations in Provincial CO₂

330 Emissions in China from 2005 to 2015 and Assessment of a Reduction Plan. *Energies* 8

331 (5). <https://doi.org/10.3390/en8054549>.

332 Deng, Xuankai, Yanhua Yu, and Yanfang Liu. 2015. Temporal and Spatial Variations in

333 Provincial CO₂ Emissions in China from 2005 to 2015 and Assessment of a Reduction

334 Plan. *Energies* 8 (5): 4549–71. <https://doi.org/10.3390/en8054549>.

335 Dunn, Peter K., and Gordon K. Smyth. 1996. Randomized Quantile Residuals. *Journal of*

336 *Computational and Graphical Statistics*.

337 <https://doi.org/10.1080/10618600.1996.10474708>.

338 EIA. 2015. Energy-Related Carbon Dioxide Emissions by State, 2000-2015. 2015.

339 Guangdong Civic Exchange. 2013. Energy Forum 15 Shaping Our Energy Policy:

340 Guangdong and Hong Kong in the Mix.

341 Henisz, Witold J., and Bennet A. Zelner. 1999. Political Risk and Infrastructure Investment.

342 Howe, Peter D., Matto Mildenerger, Jennifer R. Marlon, and Anthony Leiserowitz. 2015.

343 Geographic Variation in Opinions on Climate Change at State and Local Scales in the

344 USA. *Nature Climate Change* 5 (6): 596–603. <https://doi.org/10.1038/nclimate2583>.

345 Kang, Hyun. 2013. The Prevention and Handling of the Missing Data. *Korean Journal of*
346 *Anesthesiology* 64 (5): 402. <https://doi.org/10.4097/kjae.2013.64.5.402>.

347 Kaufmann, Daniel, Aart Kraay, and Pablo Zoido-lobatón. 1999. Governance Matters. *World*
348 *Bank Working Paper*. <https://doi.org/10.2139/ssrn.188568>.

349 Marshall, Monty G., Ted R. Gurr, and Keith Jagers. 2017. POLITYTM IV PROJECT.
350 <http://www.systemicpeace.org/inscr/p4manualv2016.pdf>.

351 Mcdonald, John F, and Robert A Moffitt. 1980. The Uses of Tobit Analysis. *The Review of*
352 *Economics and Statistics* 62 (2): 318–21.

353 Mildenerger, Matto, Peter D Howe, Erick Lachapelle, Leah C Stokes, Jennifer R. Marlon,
354 and Timothy B. Gravelle. 2016. The Distribution of Climate Change Public Opinion in
355 Canada. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2732935>.

356 NBS. 2017. National Bureau of Statistics of China. 2017.

357 OECD. 2019. Purchasing Power Parities (PPP) (Indicator). 2019.
358 <https://doi.org/10.1787/1290ee5a-en>.

359 PARLINE. 2017. PARLINE Database on National Parliaments. 2017.

360 Pelham, Brett W. 2009. Awareness, Opinions About Global Warming Vary Worldwide.
361 Gallup World Poll. 2009. [https://news.gallup.com/poll/117772/awareness-opinions-](https://news.gallup.com/poll/117772/awareness-opinions-global-warming-vary-worldwide.aspx)
362 [global-warming-vary-worldwide.aspx](https://news.gallup.com/poll/117772/awareness-opinions-global-warming-vary-worldwide.aspx).

363 Ray, Julie, and Anita Pugliese. 2011. Worldwide, Blame for Climate Change Falls on
364 Humans. Gallup World Poll. 2011. [https://news.gallup.com/poll/147242/worldwide-](https://news.gallup.com/poll/147242/worldwide-blame-climate-change-falls-humans.aspx)
365 [blame-climate-change-falls-humans.aspx](https://news.gallup.com/poll/147242/worldwide-blame-climate-change-falls-humans.aspx).

366 Statistics Canada. 2017a. Canadian Socioeconomic Database. 2017.
367 ———. 2017b. Statistics Canada. 2017.

368 U.S. Bureau of Economic Analysis. 2017. U.S. Bureau of Economic Analysis. 2017.

369 US EPA. 2015. Energy Markets in China and the Outlook for CMM Project Development in
370 Anhui, Chongqing, Henan, Inner Mongolia, and Guizhou Provinces.

371 Wharton University of Pennsylvania. 2017. The Political Constraint Index (POLCON)
372 Dataset. 2017. <https://mgmt.wharton.upenn.edu>.

373 WHO. 2017. Exposure to Ambient Air Pollution. Public Health, Environmental and Social
374 Determinants of Health (PHE). 2017.
375 http://www.who.int/gho/phe/outdoor_air_pollution/exposure/en/.

376 World Bank. 2015a. Electricity Production from Coal Sources (% of Total).
377 ———. 2015b. Electricity Production from Oil Sources (% of Total).

378 <https://data.worldbank.org/indicator/EG.ELC.PETR.ZS?view=chart>.
379 ———. 2017a. Carbon Pricing Dashboard. 2017.
380 <http://carbonpricingdashboard.worldbank.org>.
381 ———. 2017b. CO2 Emissions (Metric Tons per Capita). 2017.
382 ———. 2017c. GDP per Capita (Current US\$).
383 ———. 2017d. World Development Indicators: Structure of Output.
384 ———. 2018. The Worldwide Governance Indicators (WGI) Project. 2018.
385