Global benefits of the international diffusion of carbon pricing policies

Manuel Linsenmeier[1,2,*], **Adil Mohommad**[3], **and Gregor Schwerhoff**[3]

[1]Climate School, Columbia University, 2910 Broadway, New York, 10025, USA
[2]Department of Geography and Environment, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, United Kingdom
[3]Research Department, International Monetary Fund, 19th Street N.W., Washington, D.C., 20431, USA
[*]Corresponding author: mpl2157@columbia.edu

ABSTRACT

We study the international diffusion of carbon pricing policies and quantify its global benefits. We first empirically examine to what extent the adoption of carbon pricing in one country can explain the subsequent adoption of carbon pricing in other countries. We find robust and statistically significant evidence for policy diffusion. For two neighbouring countries, policy adoption in one country increases the probability of subsequent adoption in the other country on average by several percentage points. We then use Monte Carlo simulations to translate our empirical estimates into global emission reductions from diffusion. The results suggest that for many countries, emission reductions from policy diffusion can be larger than domestic emission reductions. Overall, our results provide additional support for the adoption of stringent climate policies, especially in countries where climate change mitigation might have been considered as being of relatively little importance because of relatively small domestic emissions.

Despite the need for more stringent climate policies to achieve the Paris climate targets (IPCC 2021), many countries appear reluctant to ratchet up their mitigation efforts. This may partly be because the costs of mitigation are incurred domestically and immediately while most of its benefits will be reaped globally and in the future, but more ambitious climate action is also hindered by possible concerns about the limited effectiveness of domestic abatement efforts if other countries do not similarly reduce their greenhouse gas (GHG) emissions. This consideration is especially pertinent in relatively small countries. Indeed, in 2021 the smallest 90% of emitters contributed only about 20% of global GHG emissions. This narrow perspective neglects, however, that international leadership in climate change mitigation can yield substantial benefits beyond domestic emission reductions[1,2]. For example, stringent climate policies at home can support international diffusion of technological innovations that reduce mitigation costs in other countries[3,4]. Furthermore, domestic climate policies can demonstrate political feasibility and certain benefits of carbon pricing[5], and they can create incentives related to trade[6] and diplomacy[7] that can nudge other countries to adopt the same or similar policies. This latter process whereby adoption of a policy in one country increases the probability of adoption in other countries is usually referred to as policy diffusion[8].

Results from qualitative studies provide ample evidence for climate policy diffusion. For example, evidence has been described for strong mutual influences among the world's first adopters of carbon pricing policies in Scandinavia in the 1980s[9]. According to[10], the subsequent adoption of carbon pricing by other countries can at least partially be explained with emulation of earlier policies and learning from prior experiences. International diffusion has also been actively promoted by early adopters themselves and through multilateral initiatives such as the World Bank's Partnership for Market Readiness (PMR)[11]. Furthermore, several case studies of carbon pricing policies report empirical evidence for international diffusion for example for California[12], Kazakhstan[13], and China[14], and the influence of multilateral initiatives has been acknowledged for carbon pricing policies in Latin America[15]. Earlier work also examined the diffusion of support for carbon pricing at the subnational level and between firms/organisations[16,17]. Also several quantitative studies report evidence in support of an international diffusion of climate policies[6,18–22].

In this study we empirically examine the international diffusion of climate policies from 1988 to 2021 and for the first time quantify its global benefits. The analysis focuses on carbon pricing policies, which can be considered the most salient and possibly most stringent policies for climate change mitigation. We first construct a global dataset on carbon pricing policies, countries' characteristics, and linkages between countries related to geography, trade, and international organisations. We then estimate Cox proportional hazard models that include spatial lags of policy adoption (Methods). The spatial lags are constructed using alternative metrics of the proximity of countries. Possible concerns about causality are addressed with a series of robustness tests and a placebo test. In the last part, we use our empirical estimates to calculate the expected emission reductions due to policy diffusion using Monte Carlo simulations. We consider these indirect emission reductions as a proxy for the international leverage of a country's domestic climate policy and examine its variation across countries. We use these simulations also to quantify the global coverage of carbon pricing policies that can be expected because of policy diffusion.

Results

We first examine our dataset on carbon pricing policies from 1988 to 2021 to identify possible patterns of policy diffusion. Visual inspection of the relative timing of policy adoption shows that carbon pricing was often introduced successively by geographically close countries (Figure 1a). In Europe, for example, the earliest carbon pricing policy in Finland was followed by similar policies in Scandinavian countries, the Baltics, and other parts of Europe. Qualitative work on the role of diffusion in this context highlighted the importance of the pioneering adoption in Finland, which was soon "emulated by its Nordic neigbors" (p. 515)[9]. Similarly, in the Americas, relatively early carbon pricing policies in Canada and Mexico were followed by other pricing policies in the same region. For Latin America, the role of international organisations has been emphasised[15]. In Asia, early carbon pricing policies in Japan were followed by pricing policies in China and South Korea.

Motivated by these findings, we next conduct an econometric analysis to more systematically identify whether the adoption of carbon pricing in one country affected the probability of its subsequent adoption elsewhere. To do so, we estimate a Cox proportional hazard model (Methods, Equation 1) with several country characteristics as explanatory variables. We use Lasso regressions and a detailed examination of multicollinearity for the selection of variables (Methods; SI Tables S5-S7). Based on a statistical test using Schoenfeld residuals[23] we cannot reject the null hypothesis of proportional hazards for models with the preferred five or more control variables. To model international diffusion, we also include a spatial lag of prior carbon pricing adoption in other countries. For this variable, we use several alternative metrics of the proximity of countries (Methods). We find the best model fits for a metric that combines the GDP of countries with the geographic distances between them in the spirit of gravity models of international trade, and for a metric based on joint membership in international organisations (SI Table S8). We then multiply these two metrics to create a new hybrid metric for the empirical analysis and simulations. Furthermore, in our main specification we focus on the first policy in every country and we consider all members of the EU ETS without a prior carbon tax together as one country that adopted its first carbon pricing policy in 2005 (Methods; SI Figure S2).

Our empirical analysis yields robust statistical evidence for an international diffusion of carbon pricing policies (Table 1 Column 1). The magnitude of the estimated coefficient of policy diffusion is substantial. For example, according to our main estimates (Table 1, Column 1), prior adoption of carbon pricing by Canada increases the probability of adoption in the USA by a factor of about 1.78, or by 78% (95% CI of 35% to 134%). In Germany, prior adoption by France increases the probability by 20% (10% to 31%), while in China prior adoption by Japan increases it by 25% (12% to 39%). For comparison, in the USA prior adoption by China increases the probability of adoption by 8.5% and in Germany prior adoption by Japan by about 1.9%.

In our main specification we consider carbon taxes and ETS as two alternative designs of the same policy. This is informed by earlier findings that there are no systematic differences between countries that chose either of the two designs[24]. Furthermore, we consider it likely that in many cases the decision to adopt carbon pricing was made before the choice of instrument design, as in the case of the EU ETS[9]. Consistent with this idea, we find stronger evidence for policy diffusion if we consider ETS and taxes as the same policy then if we distinguish between them (Table 1). In additional analysis, we find suggestive evidence that carbon pricing policies with higher stringency (higher economy-wide average carbon prices, taking into account sectoral prices and emissions) exert stronger influence on subsequent adoption elsewhere (SI Table S9 Column 5).

We conduct several robustness checks (Methods). This includes three ways of treating members of the EU ETS (SI Figure S2, SI Table S9 Columns 1-3), dropping subnational policies (SI Table S9 Column 4), adding control variables (SI Table S10 Columns 1-2), changing the imputation method (SI Table S10 Columns 3), and stratifying the model (SI Table S10 Column 4). We find that our results are overall very robust. An additional placebo test does not show evidence of spurious diffusion[25]. Furthermore, we find the best model fit for a lag time of 1-2 years (SI Table S12). Additional evidence suggests that the marginal effect of a new policy decreased with the total number of existing policies (SI Table S11, SI Figure S5a). We use this insight on "saturation" as motivation to estimate a non-linear model that we then use for all simulations (SI Figure S5b).

Overall, the results of the empirical analysis suggest that between 1988 and 2021, carbon pricing policies diffused internationally. We next examine how much this diffusion can contribute to reductions of greenhouse gas emissions globally. Specifically, we use our estimated model to quantify the emission reductions that can be attributed to the adoption of carbon pricing in a given country distinguishing between direct (domestic) emissions reduction and indirect (foreign) emission reductions due to diffusion. All results are based on the empirical estimates from the econometric analysis but we assume a constant baseline hazard, which means that all differences in the probability of policy adoption between countries can be attributed to the spatial lag and country characteristics. Given the probabilistic nature of our model, we conduct Monte Carlo simulations. All simulations start in 2022 from the carbon pricing policies adopted by the end of 2021. For every country without a carbon price, we conduct 30,000 simulations in which this country adopts carbon pricing in 2022. We then compare

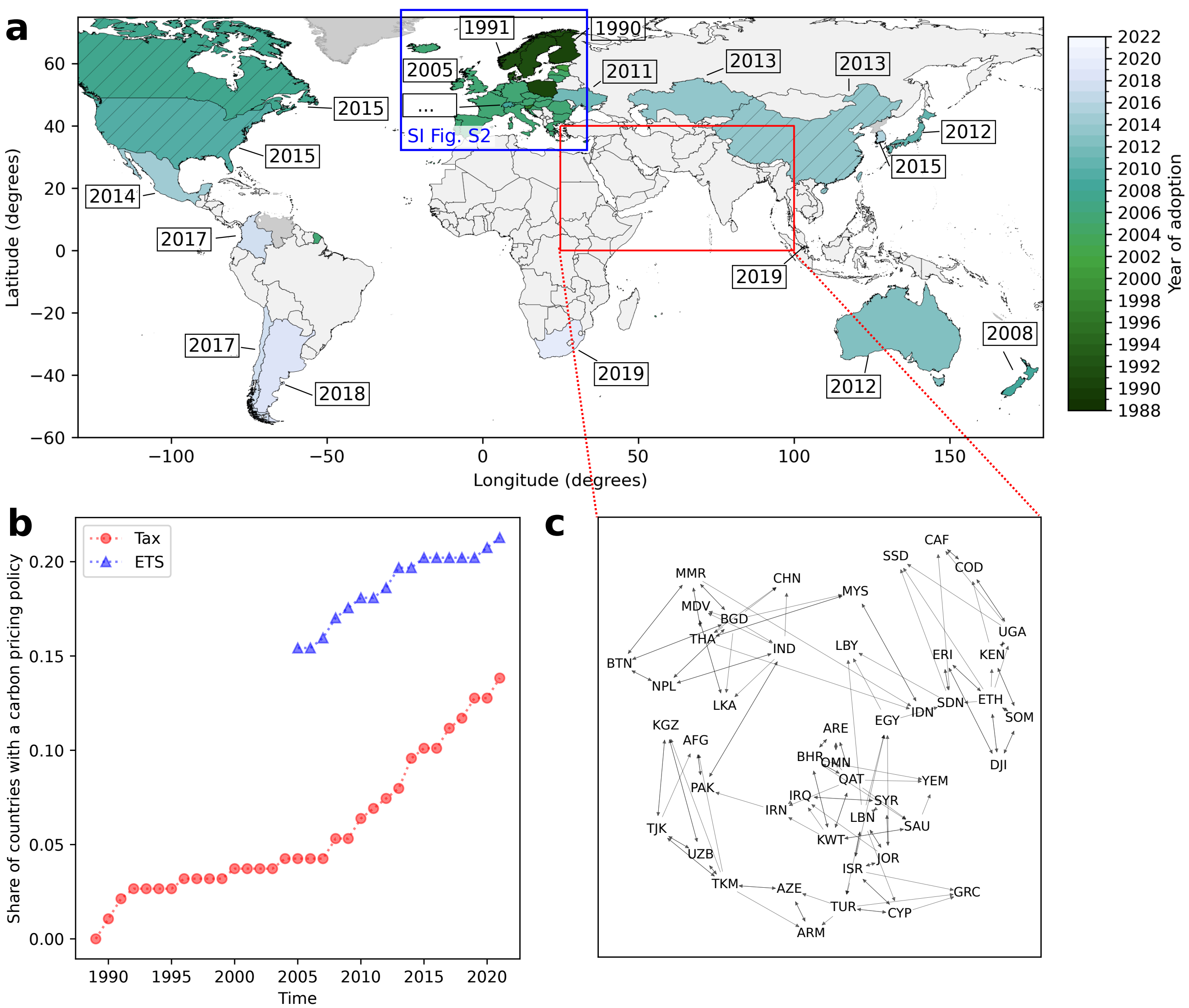

Figure 1. Adoption of carbon pricing policies over time and around the world. **a.** Map shows the adoption of the first carbon pricing policy for every country. Hashes indicate countries where the first policy was a subnational policy. See SI Figure S2 for a more detailed map of Europe. **b.** Adoption of carbon taxes and emission trading systems (ETS) over time. **c.** Proximity of countries based on physical distance, GDP, and joint membership in international organisations. Arrows indicate three strongest influences on every country; position in chart approximates average distances. See SI Figure S3 for the complete version of c.

Table 1. Results of empirical analysis of policy adoption 1988-2021 with Cox proportional hazard models. Column 1 shows main specification. Columns 2 and 3 show results for only carbon taxes and only emission trading systems (ETS), respectively. Results are based on the gravity-IO proximity metric. Results for other metrics are shown in SI Table S8. Results excluding subnational policies and for different ways of dealing with Europe are shown in SI Table S9. See also additional robustness tests in SI Tables S10 and S11. Standard errors clustered by country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Policy:	Carbon price	Tax	ETS
Column:	1	2	3
Spatial lag of carbon pricing	0.9152***	0.3423	0.8619***
	(0.2251)	(0.2885)	(0.1816)
Log real GDP per capita PPP	0.4782	0.5221	-0.4602
	(0.4226)	(0.3880)	(1.0017)
Government effectiveness	-0.2327	-0.0758	0.5461
	(0.4439)	(0.3869)	(1.1770)
Regulatory quality	1.4777***	0.6952*	1.7684**
	(0.4559)	(0.3969)	(0.8692)
Reserves of oil	0.0093	0.0192	-0.0492
	(0.1408)	(0.1917)	(0.3266)
Government expenditure	0.3199	0.0399	0.0140
	(0.2221)	(0.4410)	(0.5959)
Gov. expendit. welfare	0.1914	0.4893	0.9689**
	(0.2184)	(0.3730)	(0.4885)
Democracy index	0.6016	0.7486	-0.3912
	(0.5236)	(0.6450)	(0.8534)
Emission intensity	0.3478**	0.3392***	0.1653
	(0.1393)	(0.1189)	(0.2152)
Growth rate of debt to GDP ratio	0.2975*	0.4281***	0.3717*
	(0.1785)	(0.1558)	(0.2175)
AIC	173.4	219.3	81.8
log-likelihood	-76.7	-99.7	-30.9
N	5322	6061	5295
Time at risk	5322	6061	5295
Countries	167	188	159
Policies	25	26	11

the results with results from counterfactual simulations in which this country does not adopt carbon pricing in 2022. This comparison allows us to attribute policy adoption in other countries to the diffusion of one specific policy.

We find that indirect emission reductions are as large as or even larger than direct emission reductions in the majority of countries. Specifically, from 2022-2050 about 70 % of countries (97 of 138) have larger indirect than direct cumulative emission reductions (Figure 2a). Furthermore, we find that indirect emission reductions are far more equally distributed across countries than direct emission reductions (Figure 2b). This result also suggests that the total emission reductions from policy adoption and diffusion are more equally distributed than only direct domestic emission reductions.

For simplicity, we assume that carbon pricing policies reduce greenhouse gas emissions by the same rate $r = 1\%$ per year in all countries relative to a situation without a carbon pricing policy. This rate is conservative compared to known emission reductions in existing ETS and estimated reductions for carbon taxes (Methods). In a sensitivity analysis, we vary the value of this parameter between 0.1% and 10% and find that this changes the number of countries with larger indirect than direct emission reductions only by few percentage points (SI Figure S7). We do not find evidence that later adopters tended to adopt systematically more or less stringent polices than earlier adopters (SI Figure S6). Furthermore, we find similar results for alternative proximity metrics (SI Figure S8).

We find that indirect emission reductions are largest throughout the Middle East and in South Asia and South-East Asia (Figure 2a,c). The proximity metrics suggest that countries with large indirect emission reductions tend to be relatively centrally located, members in similar international organisations as large emitters, and also physically close to countries with relatively large emissions and no carbon pricing policies as of the end of 2021. To further explore these determinants of indirect emission reductions, we calculate for every country its "network centrality" based on the proximities and GHG emissions of all countries

(Methods Equations 9-11). We find that network centrality can explain about 13 percent percent of the variation in indirect emission reductions across countries, which increases to 43 percent if we take into account the emissions of other countries, and to 58 percent if we better account for the "cascading nature" of policy diffusion (Methods Equation 11).

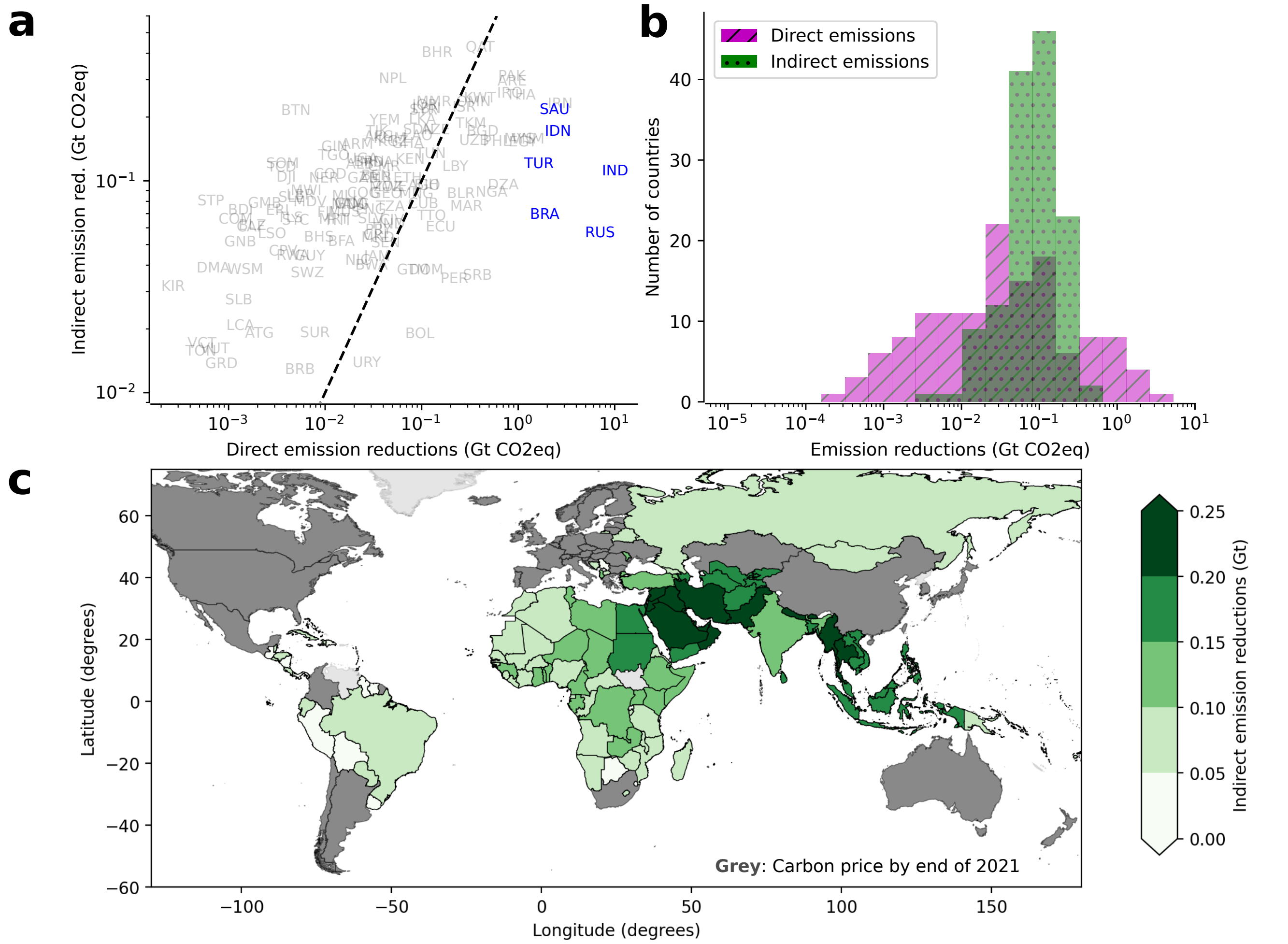

Figure 2. Direct and indirect emission reductions from carbon pricing policies based on Monte Carlo simulations of future policy adoption. All figures show cumulative emission reductions from simulated policy adoption 2022-2050. **a.** Scatter plot of direct and indirect emission reductions. Dashed black line indicates where indirect emission reductions are larger than direct emission reductions. G20 economies are shown in blue. Countries with a carbon price by the end of 2021 are omitted. **b.** Histogram of direct and indirect emission reductions **c.** Map of indirect emission reductions; countries with a carbon pricing policy by end of 2021 are shown in dark grey.

In the last part of the analysis, we examine how diffusion affects the future geographical coverage of carbon pricing policies. To this aim, we conduct similar Monte Carlo simulations starting in 2022 until 2100. Both scenarios start from existing policies. In the first scenario we use our empirically estimated relationship between the spatial lag of carbon pricing and the probability of policy adoption. In the second scenario, we set international policy diffusion to zero. All other parameter values are chosen as in the previous exercise.

We find that policy diffusion substantially increases the geographical coverage of carbon pricing over the time period 2022-2050 (Figure 3). In our simulations, by 2050 carbon pricing policies will be in place in about 50 percent of countries, 21 percentage points more than without diffusion. By 2100, the difference increases to more than 30 percentage points (Figure 3a). In a sensitivity analysis we multiply the baseline hazard and the diffusion term in the model with factors between 0.5 and 2. Both parameters have a positive effect on the number of countries with a carbon price (Figure 3b). Similarly, the effect of diffusion increases with either of the two parameters. For example, as the factor of the baseline hazard is increased from 1 to 2, the additional global coverage of carbon pricing due to diffusion by 2050 increases from 21 to 32 percentage points.

These results add an important detail to the global benefits of international policy diffusion. From an individual country's perspective, policy diffusion can add substantial global emission reductions to domestic emission reductions. From a global perspective, however, a high baseline probability of policy adoption and/or a strength of mutual influences (both in historical perspective) are required to reach, for example, 80 percent coverage by 2050. Because most of the countries that adopt carbon pricing late in our simulations have relatively small domestic emissions, the projected global coverage of pricing policies is generally higher in terms of global greenhouse gas emissions than in terms of countries, and the results are less sensitive to the two parameters (SI Figure S11).

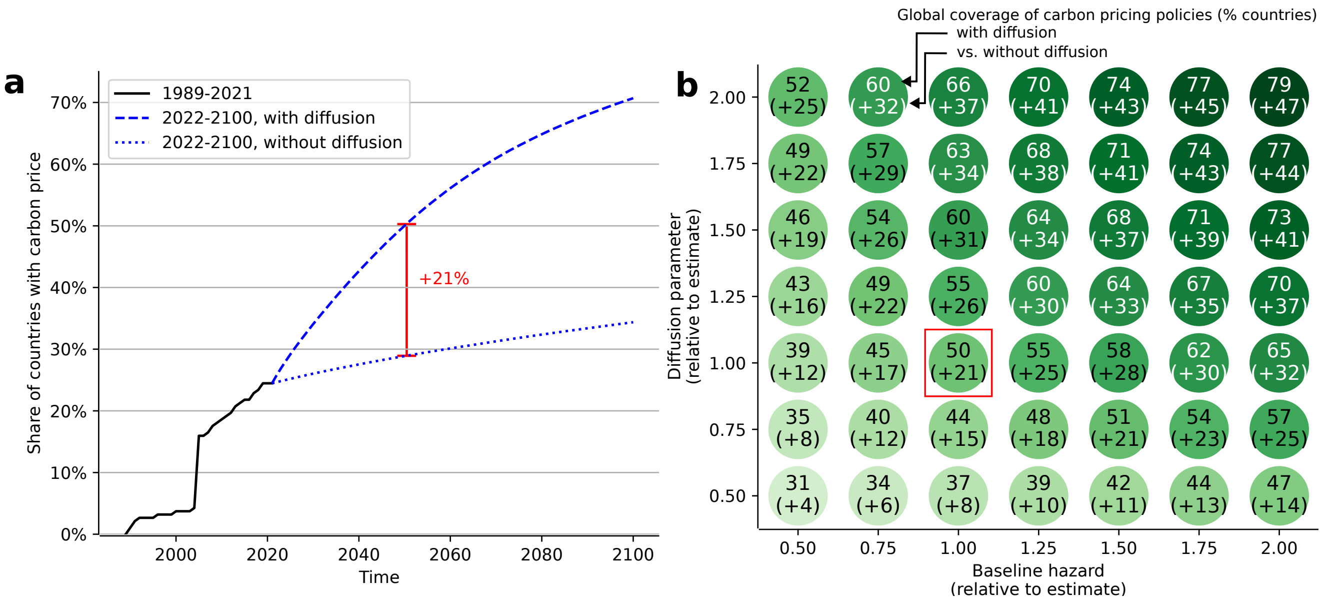

Figure 3. Future global coverage of carbon pricing policies based on Monte Carlo simulations of future policy adoption. All figures show future number of countries with carbon pricing policies as share of all countries for simulations starting in 2022 from existing policies by end of 2021. **a.** Timeseries of future policy adoption for parameter values set to empirical estimates, for simulations with and without diffusion. **b.** Share of countries with carbon pricing policies by 2050 for different parameter values of the baseline hazard and the diffusion coefficient. Red square indicates empirical estimates. See SI Figure S11 for results in global GHG emissions.

Discussion

The main contribution of this paper is the quantification of greenhouse gas emission reductions that can be attributed to the international diffusion of carbon pricing policies. These indirect emission reductions can be interpreted as a quantitative measure of the international leverage of a country in terms of global greenhouse gas emission reductions due to future diffusion of its policy. Overall, our results suggest that the magnitude of indirect emission reductions can be substantial. With our empirically estimated parameters, future indirect emission reductions will be larger than domestic emission reductions in 63% of countries that did not have a carbon pricing policy in place by the end of 2021. This evidence for large positive spillovers of domestic climate policy adoption provides additional support for the adoption of stringent climate policies, especially in countries where climate policies might so far have been considered as being of relatively little importance because of a relatively small domestic economy.

Our results speak to a long-standing debate about free-riding in global environmental policy[26]. According to this theory, unilateral climate policy weakens the incentives of other countries to implement climate policy themselves. In this paper, we show that free-riding is not the only possible reaction of countries to unilateral climate policy in the case of carbon pricing policies. Instead, we find that these policies diffuse internationally. We consider this as evidence consistent with the idea that leadership in climate policy can send a credible signal about the willingness to cooperate to other countries, supporting the formation of global climate coalitions that have been proposed[27,28]. Similarly, ex-ante modeling studies have repeatedly predicted carbon leakage[29] as a consequence of leadership. Empirical studies, however, find that leakage is a very minor or no concern[30–32]. Similar to other studies that examine the evidence for free-riding in climate policy[33], our results provide a possible (partial) explanation for this lack of leakage.

We find large indirect emission reductions especially for countries in close proximity to large emitters without a carbon pricing policy. This includes several countries on the Arabian peninsula and in South and South-East Asia. Our analysis of network centrality as determinant of countries' international leverage suggests that the "cascading" nature of policy diffusion is important to explain some of these results. Importantly, we find that countries have become more similar over the last 30 years in terms of their international leverage, suggesting that the benefits from policy diffusion have also become globally more equally distributed (SI Figure S8).

The results on emission reductions from the simulations for a specific country should however not be considered as precise estimates because of some necessarily neglected heterogeneity. Specifically, some of the empirically estimated parameters are likely to differ between countries with large uncertainty, including the effectiveness of future carbon pricing policies. To assess the robustness of our results, we conduct a sensitivity analysis in which we change this and other parameters. Furthermore, due to the construction of the scenarios indirect emission reductions simulated for a specific pioneering country are not additive with those simulated for another pioneering country. This means that our estimates for individual countries can in some sense be considered as upper bounds.

Theories of policy diffusion propose several mechanisms through which the adoption of a policy in one jurisdiction can influence the adoption of the same or a similar policy elsewhere. These mechanisms are often referred to as learning, competition, emulation, and coercion[25,34–39]. Prior literature on climate policies has especially focused on emulation and learning[10,11]. Somewhat consistent with this, we do not find evidence that shared export markets have been important for international diffusion, suggesting a limited role for international competition. Furthermore, our results suggest that international organisations contributed to policy diffusion, possibly due to international coordination and exchanges of information consistent with an important role of emulation and learning, and possibly compliance with international norms[10]. We consider this to be an encouraging finding for present and future attempts to increase the geographical coverage of carbon pricing policies through international relations.

Prior qualitative research suggests that also certain design attributes of carbon pricing policies have diffused due to emulation[13,40]. Future research might examine the overall relevance of the diffusion of policy design using similar quantitative methods. For example, we consider it plausible that international diffusion also matters for ratcheting up the stringency of existing climate policies, for example increases in carbon prices.

Methods (online only)

Empirical analysis of policy diffusion

We use econometric models to identify policy diffusion in the data on past policy adoption. To do so, we estimate a model that relates adoption of a policy in a country i at time t to the adoption of the same policy in other countries $j = 1, ..., N_c, j \neq i$ prior to time t (with N_c being the number of countries in the sample). This is a common empirical strategy to identify policy diffusion and has been used in the literature on climate policy[7,20,21,41]. Technically, the model accounts for the mutual influences between countries with spatial lags, which are calculated as a weighted average of prior policy adoption in all other countries. We use alternative weighting schemes based on geographic proximity, trade, and international institutional linkages, which we consider as representing some of the alternative diffusion mechanisms cited in the main text.

The choice of our model is informed by two characteristics of our dependent variable. The first characteristic is that any possible future policy adoption is unobserved, which means that our dependent variable is right-censored. Specifically, at the time of analysis policy adoption is only recorded in the World Bank Carbon Pricing Dashboard up until April 2022, which means that 2021 is the most recent year in our sample. The second characteristic is that our dependent variable is binary taking on only values 0 or 1. Both these characteristics are common in survival analysis, which is also referred to as event history analysis, and can be addressed with proportional hazard models.

We thus follow previous work on policy diffusion and model policy diffusion with semi-parametric Cox proportional hazard models[20,21,38,41]. As compared to parametric proportional hazard models, the Cox model does not require an assumption about a specific functional form of the survival function and the results can therefore be considered more robust to model missspecification[42]. Formally, we estimate models of the general form

$$\begin{aligned} h(t, X_{i,t}, W_{i,t}) &= h_0(t) \exp\left(X_{i,t-1}\beta_X\right) \exp\left(W_{i,t-1}\beta_W\right) \\ &= h_0(t) \exp\left(X_{i,t-1}\beta_X + W_{i,t-1}\beta_W\right) \end{aligned} \tag{1}$$

The hazard function $h(.)$ of a country i in year t represents the probability that the policy is adopted by that country in that year conditional on it not yet being implemented at time $t-1$. This hazard rate is composed of a baseline hazard rate $h_0(t)$ and a second partial hazard term that includes the time-dependent matrices $X_{i,t-1}$ and $W_{i,t-1}$. In the Cox model, the functional form of the baseline hazard is not prescribed a-priori and not necessarily smooth, but estimated based on the patterns of policy adoption in the data. For robustness, we also estimate a stratified version of the model with different baseline hazards $h_{0,k}(t)$ whereby the six continents are indexed by k.

For both the left-hand side and the right-hand side of Equation 1 we model policy adoption $Y_{i,t}$ as a binary variable that takes on the value 1 for all years $t, t+1, ..., T$ if a policy has been adopted prior to or in year t. To account for autocorrelation, we cluster standard errors at the level of individual countries.

The model is estimated from panel data on countries' adoption of climate policies by maximising a likelihood function. Unbiasedness of the estimated coefficients relies on the proportional hazard assumption. This assumption is satisfied if conditional on all explanatory variables the hazard ratio of two countries is constant over time. We address possible violations of this assumption with our set of control variables and with stratification and conduct statistical tests of Schoenfeld residuals[23]. The control variables are discussed further below.

The matrix $X_{i,t-1}$ accounts for possible domestic influences in country i in year $t-1$. All explanatory variables are lagged by one year to address concerns about reverse causality.

The matrix $W_{i,t-1}$ is a weighted average of policies $Y_{j,t-1} \in \{0,1\}$ adopted in other countries $j = 1,...,N_c, i \neq j$ at time $t-1$, also referred to as a spatial lag. Other countries are weighted based on a certain metric of proximity between countries. In mathematical terms, we calculate

$$W_{i,t} = \frac{\sum_{j=1,j\neq i}^{N_c} w_{i,j,t} Y_{j,t}}{\sum_{j=1,j\neq i}^{N_c} w_{i,j,t}} \tag{2}$$

where the weight $w_{i,j,t}$ quantifies how much country j influences country i in year t based on a specific metric.

These weights $w_{i,j,t}$ are constructed from several alternative data sources. For trade, we use data on annual bilateral trade flows from the IMF and calculate the export share $x_{i,j,t}$ and import share $m_{i,j,t}$ for every pair of countries in the data (i,j) and every year t. We then use these shares as weights, i.e. $w_{i,j,t} = x_{i,j,t}$ and $w_{i,j,t} = m_{i,j,t}$ for exports and imports respectively. Note that the weights are generally not symmetric for a pair of countries, i.e. $w_{i,j,t} \neq w_{j,i,t}$.

For indirect trade links, we compare the vectors of export shares of every pair of countries (i,j) for every time step t, $x_{i,k,t}$ and $x_{j,k,t}$, and calculate the L1 norm of the difference between the two vectors:

$$w_{i,j,t} = \frac{\sum_{k\notin\{i,j\}} |x_{i,k,t} - x_{j,k,t}|}{N_c - 2} \tag{3}$$

For geographical proximity we calculate the distance between centroids of countries and use the inverse distance $d_{i,j}$ as weight:

$$w_{i,j} = \frac{1}{d_{i,j}}. \tag{4}$$

Furthermore, we construct an additional metric that is based on geographic proximity but also takes the size of countries into account. This is motivated by the hypothesis that policies in larger economies have a stronger effect on policy adoption elsewhere. The size of countries is expressed by the GDP of a country. In mathematical terms, we define another set of weights

$$w_{i,j,t} = \frac{\log \mathrm{GDP_{j,t}}}{d_{i,j}} \tag{5}$$

where $d_{i,j}$ is again the distance between countries. A country is therefore considered more influential for domestic policy adoption the closer it is in space and the larger its economy is. This metric is closely related to gravity models of international trade that make similar assumptions about the factors that determine trade between countries[43].

We also consider shared membership in international organisations as important for policy diffusion. For this metric, we use data on membership of individual countries in international organisations from the Correlates of War database. For the sample of countries and years of our data, the dataset includes 431 international organisations with at least one member. For the weights w we calculate for every pair of countries how many memberships in international organisations are shared. That is, we divide the number of international organisations in which both countries are members by the number of organisations in which any of the two or both countries are members:

$$w_{i,j,t} = \frac{\sum_k \{i \in O_{k,t} \wedge j \in O_{k,t}\}}{\sum_k \{i \in O_{k,t} \vee j \in O_{k,t}\}} \tag{6}$$

with the sets of member countries of the international organisation k in year t denoted as $O_{k,t}$.

The datasets on trade and memberships in international organisations do not cover all years for all countries. Specifically, the dataset on trade tends to cover only the more recent years, whereas the dataset on international organisations covers only the years up to 2014. To keep a consistent sample throughout the empirical analysis without making assumptions about time trends or relationships between variables, we fill missing values by keeping values constant at the beginning and at the end of our sample period. The datasets overlap for 188 countries, which is our main sample of countries in the analysis. The largest countries not included in the sample are Venezuela and North Korea. A map of countries can be found in SI Figure S1.

For domestic control variables we consider a large number of possible variables. Informed by the prior literature (e.g.[6,21,22,44–49]), they include GDP per capita, the growth rate of GDP per capita, government debt as a share of GDP, emissions of CO2 per GDP, the service and the industry shares of GDP, the import and export shares of GDP, reserves of fossil fuels, a variety of governance indicators from the World Bank such as government effectiveness, control of corruption, and regulatory quality, air quality, government expenditure for welfare as share of GDP, public belief in climate change, and indices of democracy. In total, we collect data from 9 different sources (SI Table S1) for 21 variables (SI Table S3).

Many of these variables have missing values, for earlier years and for certain countries (SI Table S2). This results in a dilemma. On the one hand, we want to consider as many domestic influces as possible to avoid omitted variable biases. On the other hand, for the analysis of diffusion it is important to have a relatively complete set of countries due to the geographic dimension of the phenomenon. As a way out of this dilemma, we use iterative multiple imputation to fill the missing values. To limit the extent of extrapolation across countries, we first use multiple imputation to fill missing values for countries for which at least one observation of that variable exists. We also include the year as possible predictor to model country-specific time trends. In the second step, we fill missing values of all other variables and countries. Our only criterion to consider a country for our analysis is thus the availability of at least one observation of real GDP provided from the World Bank, which is the case for 211 countries including all 188 countries for which we also have data for our spatial lags (SI Figure S1). As a robustness test, we also construct a dataset in which we only keep values constant for every country and variable, without any other imputation. We find that with this method we can construct a set of 145 countries for which data on 17 variables is available. Reassuringly, we find that our main results are robust to this alternative method (SI Table S10 Column 3).

The choice of which of the domestic control variables to include in our model represents a trade-off. We do not want to exclude important variables to avoid omitted variable biases, but including too many variables, many of which are highly correlated, leads to multicollinearity. To find a good trade-off, we use a two-step procedure. In the first set, we use Lasso regression in combination with 10-fold crossvalidation, the latter of which addresses concerns of over-fitting, to identify a set of important predictors. This yields a set of six most important variables (SI Table S5). In addition, to gain additional insights into the relative importance of these variables, we also estimate Lasso model with higher penalty parameters α.

In the second step, we examine multicollinearity for these six variables using the Variance Inflation Factor (VIF). We find that for a model with all six variables the typical upper limit for VIF of 10 is exceeded by one variable (SI Table S6). We hence stepwise drop variables from the model until the upper limit is satisfied. At every step, we focus on the variable with the highest VIF and examine its correlation with all other variables. We then drop the variable itself or the most strongly correlated variable depending on which of the two variables is considered as more important by the additional Lasso regressions in SI Table S5. We thus step-wise drop the industry share of GDP.

This yields our preferred model specification with nine control variables for domestic influences on climate policy: GDP per capita, government effectiveness, regulatory quality, reserves of oil, government expenditure, government expenditure for welfare (health, education, and social protection), a democracy index, emission intensity of the economy, and the growth rate of the debt to GDP ratio. The influence of all the remaining variables is examined in robustness tests. The results of these robustness tests are reassuring, as our main estimates for the spatial lag of carbon pricing are barely affected by any of the domestic influences (SI Table S10).

Modelling the effect of policy diffusion on GHG emissions

In the second step of the analysis, we use our empirical estimates to calculate the expected CO2 emission reductions that can be causally attributed to policy diffusion. For this purpose, we use the estimated coefficients of all control variables and the spatial lag and feed them into Monte Carlo simulations of policy adoption and policy diffusion using the model in Equation 1.

We construct counterfactual scenarios that allow us to quantify the emission reductions that can be attributed to diffusion. For every country i, we compare a scenario A in which country i adopts carbon pricing in year t with a scenario B in which country i does not do so. For each of the two scenarios, we calculate the hazard rate of policy adoption at time $t+1$ for all other countries $j \neq i$ based on Equation 1. The difference between the hazard rates of the two scenarios A and B can then be considered the additional hazard of policy adoption in country j that can be attributed to policy diffusion from country i.

The Monte Carlo simulations are based on Equation 1. We assume the actually implemented carbon pricing policies for the year $t = 2021$ and let the simulations run from 2022 onward. That is, we simulate adoption and diffusion of climate policies from 2022 to 2050. To do so, at every time step $2022 \leq t \leq 2050$ we update the spatial lag $W_{j,t}$ of every country, calculate its hazard of policy adoption, and use this hazard to draw from a probability distribution to determine whether the country adopts or does not adopt the policy at this time step.

We conduct 30,000 simulations for every country for scenario B and 100,000 simulations for scenario A, which is the counterfactual of scenario B for all countries. The simulations of scenario B result for every country i in one matrix of probabilities of policy adoption of country j in year t, $P^B_{i,j,t}$ with $\sum_{t=2022}^{2050} P^B_{i,j,t} = 1 \; \forall i, j$. The simulations of scenario A result in another matrix $P^A_{j,t}$ that again satisfies $\sum_{t=2022}^{2050} P^A_{j,t} = 1 \; \forall j$. Because there is no difference between the counterfactuals, this matrix $P^A_{j,t}$ is the same for all countries i.

Based on these probabilities, for every country i we subsequently calculate the expected direct emission reductions and the expected indirect emission reductions due to policy diffusion. To map the probabilities of policy adoption onto greenhouse gas emissions, we assume that a carbon pricing policy reduces emissions by the same percentage $r = 1\%$ per year in all countries. A similar assumption, namely that climate policies and carbon pricing policies are similarly effective across countries, has been made in the literature prior to our study[50, 51]. The assumed value of 1 percent per year is slightly conservative relative to estimated emission reductions from carbon pricing policies 2003-2016 of about 3 percent per year[51]. Existing ETS with gradually tighter caps on emission permits also allow for a comparison of this number. For example, in the EU ETS, between 2013 and 2020 the number of permits was reduced by 1.74 % per year. In California, over the same period the cap was decreased by between 2 and 3.3 percent per year.

Because we use the same value for the parameter r for direct and indirect emission reductions from policy adoption, our results on their relative sizes are relatively robust to changes in the parameter. We confirm this with a sensitivity analysis in which we vary the rate between 0.5 and 10 percent per year, showing that this rate does not substantially affect our comparison of indirect and direct emission reductions (SI Figure S7). Reassuringly, we do not find clear time trends in the data on economy-wide average carbon price among past policies, which suggests that there has not been a systematic difference in stringency between followers and leaders (SI Figure S6).

Formally, for every country i we calculate the direct emission reductions from 2022 - 2050 of implementing the policy in year 2022 as

$$\hat{R}^{\text{direct}}_{i,2050} = \sum_{t=2022}^{2050} \left[E_{i,t} - E_{i,2022} \prod_{l=2022}^{t} (1 + g_{i,l} - r) \right] \tag{7}$$

where we assume for simplicity $g_{j,t}$ is the expected growth rate of CO2 emissions of country j in year t and r is the effectiveness of carbon pricing as in the Section above. For simplicity, we assume $g_{j,t} = 0$. For indirect emission reductions that can be attributed to policy diffusion from country i to other countries, we use the probabilities of policy adoption $P^A_{j,t}$ and $P^B_{i,j,t}$ of the scenarios A and B respectively. In mathematical terms, we take the difference between the expected emission reductions between the two scenarios:

$$\begin{aligned}\hat{R}^{\text{indirect}}_{i,2050} = \sum_{j \neq i} \Bigg[\sum_{\xi=2022}^{2050} \Bigg[\left(P^B_{i,j,\xi} - P^A_{j,\xi} \right) \\ \left[\sum_{t=2022}^{\xi} E_{j,t} + E_{j,\xi} \prod_{l=\xi}^{2050} (1 + g_{j,l} - r) \right] \Bigg] \Bigg]\end{aligned} \tag{8}$$

The indirect emission reductions are influenced by a country's proximity to other countries and the emissions and existing carbon pricing policies of those other countries. To understand the importance of these different influences, we use common metrics to quantify the centrality of a node in a network and adjust them for our purposes. Our first measure of centrality is the closeness centrality for directed graphs:

$$\text{Centrality A}_i = \sum_{j=1, j \neq i}^{N_c} w_{j,i} \tag{9}$$

Our second measure additionally takes the emissions of other countries into account:

$$\text{Centrality B}_i = \sum_{j=1, j \neq i}^{N_c} w_{j,i} e_j \tag{10}$$

Our third measure takes the emissions of other countries into account on which a country has an indirect influence (through a third country). For this third metric we calculate

$$\text{Centrality C}_i = \sum_{j=1, j \neq i}^{N_c} w_{j,i} \left(\sum_{k=1, k \notin \{i,j\}}^{N_c} w_{k,j} e_k \right) \tag{11}$$

Data

We use data on carbon pricing from the Carbon Pricing Dashboard of the World Bank. The dataset includes pricing policies at the national and subnational level (SI Table 2). We assign subnational pricing schemes to the corresponding countries and focus on the first carbon pricing policy in every country. For a robustness test, we ignore subnational pricing policies. Furthermore, for another two robustness tests we keep only either carbon tax or ETS policies in the sample. For the analysis of price levels, we combine this dataset with the World Carbon Pricing Database[52]. For the explanatory variables we use 9 different sources (SI Table S2) for 21 raw variables (SI Table S3). We use iterative multiple imputation to fill missing values (see Methods). Descriptive statistics of all covariates are shown in the SI Table S4. Our main sample covers 188 countries from 1988-2021 (SI Figure S1).

References

1. Schwerhoff, G. The economics of leadership in climate change mitigation. *Clim. Policy* **16**, 196–214, DOI: 10.1080/14693062.2014.992297 (2016).
2. Höhne, N., Fekete, H., den Elzen, M. G., Hof, A. F. & Kuramochi, T. Assessing the ambition of post-2020 climate targets: A comprehensive framework. *Clim. Policy* **18**, 425–441, DOI: 10.1080/14693062.2017.1294046 (2018).
3. Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N. & Ménière, Y. Invention and Transfer of Climate Change–Mitigation Technologies: A Global Analysis. *Rev. Environ. Econ. Policy* **5**, 109–130, DOI: 10.1093/reep/req023 (2011).
4. Barrett, P. Can International Technological Diffusion Substitute for Coordinated Global Policies to Mitigate Climate Change? *IMF Work. Pap.* **2021**, DOI: 10.5089/9781513585765.001 (2021).
5. Goulder, L. H. Climate change policy's interactions with the tax system. *Energy Econ.* **40**, S3–S11, DOI: 10.1016/j.eneco.2013.09.017 (2013).

6. Steinebach, Y., Fernández-i-Marín, X. & Aschenbrenner, C. Who puts a price on carbon, why and how? A global empirical analysis of carbon pricing policies. *Clim. Policy* **21**, 277–289, DOI: 10.1080/14693062.2020.1824890 (2021).
7. Kammerer, M. & Namhata, C. What drives the adoption of climate change mitigation policy? A dynamic network approach to policy diffusion. *Policy Sci.* **51**, 477–513, DOI: 10.1007/s11077-018-9332-6 (2018).
8. Walker, J. L. The Diffusion of Innovations among the American States. *Am. Polit. Sci. Rev.* **63**, 880–899, DOI: 10.2307/1954434 (1969).
9. Harrison, K. The Comparative Politics of Carbon Taxation. *Annu. Rev. Law Soc. Sci.* **6**, 507–529, DOI: 10.1146/annurev.lawsocsci.093008.131545 (2010).
10. Thisted, E. V. & Thisted, R. V. The diffusion of carbon taxes and emission trading schemes: The emerging norm of carbon pricing. *Environ. Polit.* **29**, 804–824, DOI: 10.1080/09644016.2019.1661155 (2020).
11. Biedenkopf, K., Müller, P., Slominski, P. & Wettestad, J. A Global Turn to Greenhouse Gas Emissions Trading? Experiments, Actors, and Diffusion. *Glob. Environ. Polit.* **17**, 1–11, DOI: 10.1162/GLEP_e_00412 (2017).
12. Bang, G., Victor, D. G. & Andresen, S. California's Cap-and-Trade System: Diffusion and Lessons. *Glob. Environ. Polit.* **17**, 12–30, DOI: 10.1162/GLEP_a_00413 (2017).
13. Gulbrandsen, L. H., Sammut, F. & Wettestad, J. Emissions Trading and Policy Diffusion: Complex EU ETS Emulation in Kazakhstan. *Glob. Environ. Polit.* **17**, 115–133, DOI: 10.1162/GLEP_a_00418 (2017).
14. Heggelund, G., Stensdal, I., Duan, M. & Wettestad, J. China's Development of ETS as a GHG Mitigating Policy Tool: A Case of Policy Diffusion or Domestic Drivers? *Rev. Policy Res.* **36**, 168–194, DOI: 10.1111/ropr.12328 (2019).
15. Ryan, D. & Micozzi, M. The politics of climate policy innovation: The case of the Argentine carbon tax. *Environ. Polit.* **30**, 1155–1173, DOI: 10.1080/09644016.2021.1899648 (2021).
16. Meckling, J. *Carbon Coalitions: Business, Climate Politics, and the Rise of Emissions Trading* (The MIT Press, 2011).
17. Paterson, M., Hoffmann, M., Betsill, M. & Bernstein, S. The Micro Foundations of Policy Diffusion Toward Complex Global Governance: An Analysis of the Transnational Carbon Emission Trading Network. *Comp. Polit. Stud.* **47**, 420–449, DOI: 10.1177/0010414013509575 (2014).
18. Baldwin, E., Carley, S. & Nicholson-Crotty, S. Why do countries emulate each others' policies? A global study of renewable energy policy diffusion. *World Dev.* **120**, 29–45, DOI: 10.1016/j.worlddev.2019.03.012 (2019).
19. Fankhauser, S., Gennaioli, C. & Collins, M. Do international factors influence the passage of climate change legislation? *Clim. Policy* **16**, 318–331, DOI: 10.1080/14693062.2014.1000814 (2016).
20. Sauquet, A. Exploring the nature of inter-country interactions in the process of ratifying international environmental agreements: The case of the Kyoto Protocol. *Public Choice* **159**, 141–158, DOI: 10.1007/s11127-012-0033-y (2014).
21. Dolphin, G. G. & Pollitt, M. G. The international diffusion of climate policy: Theory and evidence. *RFF Work. Pap.* (2021).
22. Raghoo, P. & Shah, K. U. A global empirical analysis on the diffusion & innovation of carbon pricing policies. *J. Clean. Prod.* **362**, 132329, DOI: 10.1016/j.jclepro.2022.132329 (2022).
23. Grambsch, P. M. & Therneau, T. M. Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika* **81**, 515–526, DOI: 10.1093/biomet/81.3.515 (1994).
24. Skovgaard, J., Ferrari, S. S. & Knaggård, Å. Mapping and clustering the adoption of carbon pricing policies: What polities price carbon and why? *Clim. Policy* **19**, 1173–1185, DOI: 10.1080/14693062.2019.1641460 (2019).
25. Braun, D. & Gilardi, F. Taking 'Galton's Problem' Seriously: Towards a Theory of Policy Diffusion. *J. Theor. Polit.* **18**, 298–322, DOI: 10.1177/0951629806064351 (2006).
26. Hoel, M. Global environmental problems: The effects of unilateral actions taken by one country. *J. Environ. Econ. Manag.* **20**, 55–70, DOI: 10.1016/0095-0696(91)90023-C (1991).
27. Nordhaus, W. & Chen, X. A sharper image? Estimates of the precision of nighttime lights as a proxy for economic statistics. *J. Econ. Geogr.* **15**, 217–246, DOI: 10.1093/jeg/lbu010 (2015).
28. Parry, I. W. H., Black, S. & Roaf, J. Proposal for an International Carbon Price Floor Among Large Emitters. *IMF Staff. Clim. Note No 2021/001* (2021).
29. Böhringer, C., Fischer, C., Rosendahl, K. E. & Rutherford, T. F. Potential impacts and challenges of border carbon adjustments. *Nat. Clim. Chang.* **12**, 22–29, DOI: 10.1038/s41558-021-01250-z (2022).
30. Naegele, H. & Zaklan, A. Does the EU ETS cause carbon leakage in European manufacturing? *J. Environ. Econ. Manag.* **93**, 125–147, DOI: 10.1016/j.jeem.2018.11.004 (2019).
31. Dechezleprêtre, A., Gennaioli, C., Martin, R., Muûls, M. & Stoerk, T. Searching for carbon leaks in multinational companies. *J. Environ. Econ. Manag.* **112**, 102601, DOI: 10.1016/j.jeem.2021.102601 (2022).
32. Eskander, S. M. S. U. & Fankhauser, S. The Impact of Climate Legislation on Trade-Related Carbon Emissions 1996–2018. *Environ. Resour. Econ.* DOI: 10.1007/s10640-023-00762-w (2023).

33. Schmidt, R. C., Drupp, M., Nesje, F. & Hoegen, H. Testing the free-rider hypothesis in climate policy. *arxiv* DOI: 10.48550/ARXIV.2211.06209 (2022).

34. Simmons, B. A., Dobbin, F. & Garrett, G. Introduction: The International Diffusion of Liberalism. *Int. Organ.* **60**, DOI: 10.1017/S0020818306060267 (2006).

35. Shipan, C. R. & Volden, C. The Mechanisms of Policy Diffusion. *Am. J. Polit. Sci.* **52**, 840–857, DOI: 10.1111/j.1540-5907.2008.00346.x (2008).

36. Volden, C., Ting, M. M. & Carpenter, D. P. A Formal Model of Learning and Policy Diffusion. *Am. Polit. Sci. Rev.* **102**, 319–332, DOI: 10.1017/S0003055408080271 (2008).

37. Shipan, C. R. & Volden, C. Policy Diffusion: Seven Lessons for Scholars and Practitioners. *Public Adm. Rev.* **72**, 788–796, DOI: 10.1111/j.1540-6210.2012.02610.x (2012).

38. Sugiyama, N. B. The diffusion of Conditional Cash Transfer programs in the Americas. *Glob. Soc. Policy* **11**, 250–278, DOI: 10.1177/1468018111421295 (2011).

39. Jordan, A. & Huitema, D. Innovations in climate policy: The politics of invention, diffusion, and evaluation. *Environ. Polit.* **23**, 715–734, DOI: 10.1080/09644016.2014.923614 (2014).

40. Wettestad, J. & Gulbrandsen, L. H. (eds.) *The Evolution of Carbon Markets: Design and Diffusion*. Transforming Environmental Politics and Policy (Routledge, Taylor & Francis Group, London New York, 2019), first issued in paperback edn.

41. Abel, D. The diffusion of climate policies among German municipalities. *J. Public Policy* **41**, 111–136, DOI: 10.1017/S0143814X19000199 (2021).

42. Lee, E. T. & Wang, J. W. *Statistical Methods for Survival Data Analysis*. Wiley Series in Probability and Statistics (Wiley, 2003), 3rd edn.

43. Baier, S. & Standaert, S. *Gravity Models and Empirical Trade* (Oxford University Press, 2020).

44. Stadelmann, M. & Castro, P. Climate policy innovation in the South – Domestic and international determinants of renewable energy policies in developing and emerging countries. *Glob. Environ. Chang.* **29**, 413–423, DOI: 10.1016/j.gloenvcha.2014.04.011 (2014).

45. Dolphin, G., Pollitt, M. G. & Newbery, D. M. The political economy of carbon pricing: A panel analysis. *Oxf. Econ. Pap.* DOI: 10.1093/oep/gpz042 (2019).

46. Best, R. & Zhang, Q. Y. What explains carbon-pricing variation between countries? *Energy Policy* **143**, DOI: 10.1016/j.enpol.2020.111541 (2020).

47. Levi, S., Flachsland, C. & Jakob, M. Political Economy Determinants of Carbon Pricing. *Glob. Environ. Polit.* **20**, 128–156, DOI: 10.1162/glep_a_00549 (2020).

48. Linsenmeier, M., Mohommad, A. & Schwerhoff, G. Policy sequencing towards carbon pricing among the world's largest emitters. *Nat. Clim. Chang.* **12**, 1107–1110, DOI: 10.1038/s41558-022-01538-8 (2022).

49. Zhou, S., Matisoff, D. C., Kingsley, G. A. & Brown, M. A. Understanding renewable energy policy adoption and evolution in Europe: The impact of coercion, normative emulation, competition, and learning. *Energy Res. & Soc. Sci.* **51**, 1–11, DOI: 10.1016/j.erss.2018.12.011 (2019).

50. Eskander, S. M. S. U. & Fankhauser, S. Reduction in greenhouse gas emissions from national climate legislation. *Nat. Clim. Chang.* **10**, 750–756, DOI: 10.1038/s41558-020-0831-z (2020).

51. Best, R., Burke, P. J. & Jotzo, F. Carbon Pricing Efficacy: Cross-Country Evidence. *Environ. Resour. Econ.* **77**, 69–94, DOI: 10.1007/s10640-020-00436-x (2020).

52. Dolphin, G. & Xiahou, Q. World carbon pricing database: Sources and methods. *Sci. Data* **9**, 573, DOI: 10.1038/s41597-022-01659-x (2022).

53. Minx, J. C. *et al.* A comprehensive and synthetic dataset for global, regional, and national greenhouse gas emissions by sector 1970–2018 with an extension to 2019. *Earth Syst. Sci. Data* **13**, 5213–5252, DOI: 10.5194/essd-13-5213-2021 (2021).

Acknowledgements

We are grateful to Shekhar Shankar Aiyar (IMF, unless otherwise noted), Max Aufhammer (UC Berkeley), Mook Bangalore (LSE), Helge Berger, Simon Black, Wenjie Chen, Sam Fankhauser (Oxford University), Florence Jaumotte, Tatsiana Kliatskova (World Bank), Vladimir Kluyev, Vimal Thakoor, as well as participants of internal seminars at IMF and LSE, the summer conference of the Association of Environmental and Resource Economists, and the annual conference of the European Association of Environmental and Resource Economists for valuable comments and suggestions. ML gratefully acknowledges financial support by the UK's Economic and Social Research Council (ESRC). All remaining errors are our own.

Author contributions statement

ML, AM, and GS designed the research. ML collected the data and conducted the analysis. ML, AM, and GS wrote and reviewed the manuscript.

Additional information

Competing interests statement: The authors declare no competing interests.
Code availability statement: A replication package will be made available prior to publication.

Data availability statement: All data is publicly available at no cost.

- Data on carbon pricing policies:
  - Carbon Pricing Dashboard of the World Bank https://carbonpricingdashboard.worldbank.org/
  - World Carbon Pricing Database: https://github.com/g-dolphin/WorldCarbonPricingDatabase
- Data on country characteristics:
  - World Development Indicators of the World Bank (WDI): https://databank.worldbank.org/source/world-development-indicators
  - World Governance Indicators (WGI): https://info.worldbank.org/governance/wgi/
  - Greenhouse gas emissions (Minx et al. 2021[53]): https://doi.org/10.5281/zenodo.5566761
  - Reserves of fossil fuels from the Energy Intelligence Agency (EIA): https://www.eia.gov/
  - Global Debt Database (GDD): https://www.imf.org/external/datamapper/datasets/GDD
  - Government Finance Statistics (GFS): https://data.imf.org/?sk=a0867067-d23c-4ebc-ad23-d3b015045405
  - Expenditure by Function of Government (COFOG): https://data.imf.org/?sk=5804c5e1-0502-4672-bdcd-671bcdc565a9
  - Democracy Index (Polity 5): https://www.systemicpeace.org/polityproject.html
  - Public belief in climate change (Gallup): https://news.gallup.com/poll/117772/awareness-opinions-global-warming-vary-worldwide.aspx