INTERNATIONAL MONETARY FUND

The International Diffusion Of Policies for Climate Change Mitigation

Manuel Linsenmeier, Adil Mohommad, Gregor Schwerhoff

2022
JUN

WORKING PAPER

WP/22/115

IMF Working Paper
Research Department

The International Diffusion of Policies for Climate Change Mitigation
Prepared by Manuel Linsenmeier, Adil Mohommad, Gregor Schwerhoff*

ABSTRACT: In this paper, we study the international diffusion of carbon pricing policies. In the first part, we empirically examine to what extent the adoption of carbon pricing in a given country can explain the subsequent adoption of the same policy in other countries. In the second part, we quantify the global benefits of policy diffusion in terms of greenhouse gas emission reductions elsewhere. To do so, we combine a large international dataset on carbon pricing with several other datasets. For causal identification, we estimate semi-parametric Cox proportional hazard models. We find robust and statistically significant evidence for policy diffusion.

---

* "The author(s) would like to thank" footnote, as applicable.

The international diffusion of policies
for climate change mitigation

Manuel Linsenmeier*   Adil Mohommad†   Gregor Schwerhoff‡

May 20th, 2022

Abstract

In this paper, we study the international diffusion of carbon pricing policies. In the first part, we empirically examine to what extent the adoption of carbon pricing in a given country can explain the subsequent adoption of the same policy in other countries. In the second part, we quantify the global benefits of policy diffusion in terms of greenhouse gas emission reductions elsewhere. To do so, we combine a large international dataset on carbon pricing with several other datasets. For causal identification, we estimate semi-parametric Cox proportional hazard models. We find robust and statistically significant evidence for policy diffusion. The magnitude of the estimated effects is substantial. 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. Motivated by this result, we use Monte Carlo simulations based on our empirical estimates to quantify both direct domestic and indirect foreign emission reductions of policy adoption and subsequent diffusion. The results based on our central empirical estimates suggest that for most countries indirect emission reductions of carbon pricing can exceed direct emission reductions. Overall, our results provide additional support for the adoption of stringent climate policies, especially in countries where climate change mitigation policies might so far have been considered as being of relatively little importance because of a relatively small domestic economy.

Disclaimer: The views expressed herein are those of the author and should not be attributed to the IMF, its Executive Board, or its management

*London School of Economics and Political Science, Department of Geography and Environment, and Grantham Research Institute on Climate Change and the Environment. Contact: m.linsenmeier@lse.ac.uk

†International Monetary Fund.

‡International Monetary Fund.

1 Introduction

Despite the need for more stringent climate policies to achieve the Paris climate target (IPCC 2021), many countries appear reluctant to ratchet up their mitigation efforts. Possible reasons include concerns about political backlashes, about international competitiveness, and about the limited effectiveness of domestic policies in reducing global greenhouse gas (GHG) emissions. Indeed, in 2021 the top 10% largest emitters contributed about 80% percent of global greenhouse gas emissions, suggesting that policies in relatively small countries will have small effects on future climate change. However, this perspective neglects that countries' domestic climate policies can also influence GHG emissions elsewhere. For example, domestic policy adoption can demonstrate political feasibility and lower concerns about international competitiveness, thereby increasing the likelihood that the same or a similar policy is adopted in other countries. Existing empirical evidence on climate policy diffusion is however mixed (Baldwin et al., 2019; Dolphin and Pollitt, 2021; Fankhauser et al., 2016; Sauquet, 2014; Thisted and Thisted, 2020) and its effectivenesss in terms of GHG emission reductions has not yet been quantified.

In this paper we empirically examine the international diffusion of climate policies from 1988 to 2020 and quantify indirect emission reductions that can plausibly be attributed to policy diffusion. We focus 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, countries' characteristics, and geographic and trade linkages between countries. We then estimate Cox proportional hazard models that include spatial lags of policy adoption. The spatial lags are contructed 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 a back-of-the-envelope methodology and 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 find robust statistical evidence for an international diffusion of carbon pricing policies. Countries are more likely to adopt carbon pricing if other countries that are relatively close to them in terms of geography or trade links adopted the policy previously. We find the best model fit for a proximity metric in the spirit of a gravity model that combines the GDP of countries with the geographic distances between them. The magnitude of the diffusion effect is substantial. For example, according to our main estimates adoption of carbon pricing in Canada increases the probability of subsequent adoption in the USA by about 11 percent.

We use several robustness checks to corroborate our main findings. Possible violations of the proportional hazard assumption are addressed with covariates and stratification of the Cox proportional hazard model and systematically assessed with statistical tests. In the main specification, we use carbon pricing policies at the national and subnational level, but the results are robust to using only national pricing schemes. Furthermore, in the main specification we use both carbon taxes and ETS. If we restrict the sample to only either of the two types of carbon pricing, we find coefficients with similar magnitude but no significance. We also conduct placebo tests and do not find any evidence that would suggest spurious diffusion (Braun and Gilardi, 2006).

Our main contribution to the literature is the quantification of indirect emission reductions that can be attributed to policy diffusion, which we derive with a back-of-the-envelope calculation and Monte Carlo simulations. The indirect emission reductions quantify the emission reductions elsewhere that can be attributed to the adoption of carbon pricing in a given country. To isolate the effect of diffusion, we simulate and compare scenarios with and without policy adoption in the given country. Overall, our results suggest that the global benefits of policy diffusion are substantial. In a first set of simulations, we assume for every country that it was the first to adopt carbon pricing in 1988. We find that the indirect emission reductions due to diffusion are larger than domestic emission reductions in about 85 % of countries (1988-2019). We next examine scenarios in which a country is the next to adopt carbon pricing in 2020, given the actual distribution of pricing policies by the end of 2020, and find that indirect emission reductions exceed direct emission reductions in 76 % of the remaining countries (2020-2050).

In the last part of the analysis, we use Monte Carlo simulations to quantify to what extent policy diffusion as observed in the past can help to increase the geographical coverage of carbon pricing policies in the future. Based on the distribution of policies by the end of 2020 and the dynamic of policy adoption and diffusion over the period 1988-2020, we simulate policy adoption for future scenarios with and without diffusion (2020-2050). We find that by 2050, about 11 percentage points more countries will adopt carbon pricing in the scenario with diffusion than in the scenario without diffusion. While for individual countries the global benefits from policy diffusion are therefore substantial, the possible contribution of policy diffusion to the achievement of a high geographical coverage of carbon pricing policies over the next decades appears limited.

We also contribute new empirical evidence on international policy diffusion, specifically diffusion of climate policies (Sauquet, 2014; Fankhauser et al., 2016; Kammerer and Namhata, 2018; Skovgaard et al., 2019; Baldwin et al., 2019; Abel, 2021; Steinebach et al., 2021; Torney, 2015; Thisted and Thisted, 2020). In agreement with the quantitative analysis of

Steinebach et al. (2021) and the qualitative analysis of Thisted and Thisted (2020) we find evidence for an international diffusion of carbon pricing policies. In this respect, our results differ from the results obtained by Dolphin and Pollitt (2021) who report no evidence for diffusion of either carbon taxes or ETS, which they consider as two distinct policies. Our results therefore reconcile this seemingly contradictory prior evidence by accommodating for different implementations of the same policy. This choice is supported by the fact that in the EU (Harrison, 2010) and possibly in other cases, the decision to adopt carbon pricing was made before the instrument design was chosen. Furthermore, Skovgaard et al. (2019) find no systematic differences between countries that adopted either a tax or an ETS and observe that both designs were used in all waves of carbon pricing adoption.

Our findings also contribute new evidence using quantitative methods to prior more qualitative work that has often focused on few selected countries. This literature suggests that international coordination has been part of climate policy from its beginning, most prominently represented by the Kyoto protocol and the Paris climate agreement. This coordination in turn provides a supportive context for policy diffusion. For example, Harrison (2010) points out strong mutual influences among the world's first adopters of carbon pricing policies in Scandinavia after climate change attracted global attention for the first time in the 1980s. According to Thisted and Thisted (2020), the subsequent adoption of carbon pricing by other countries can at least partially be explained with emulation of existing 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) (Biedenkopf et al., 2017). Strong evidence for international diffusion has been reported for example for California (Bang et al., 2017), Kazakhstan (Gulbrandsen et al., 2017), and China (Heggelund et al., 2019), and the influence of multilateral initiatives has been acknowledged for carbon pricing policies in Latin America (Ryan and Micozzi, 2021). We consider these mechanisms and channels of international climate policy diffusion reported in prior literature as possible explanations of our results.

The remainder of the paper is structured as follows. In Section 2, we introduce the econometric model and estimation techniques before describing and illustrating our data. In Section 3, we present first our empirical results on past international diffusion of carbon pricing including several robustness tests and then the results from our back-of-the-envelope calculations and Monte Carlo simulations. We discuss and conclude in Section 4.

2 Methods

2.1 Empirical analysis of policy diffusion

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 grouped and referred to as learning, competition, emulation, and coercion (Braun and Gilardi, 2006; Simmons et al., 2006; Shipan and Volden, 2008; Volden et al., 2008; Shipan and Volden, 2012; Jordan and Huitema, 2014). Prior literature on climate policies has especially focused on emulation and learning (Biedenkopf et al., 2017; Thisted and Thisted, 2020), which has also been identified as important mechanisms for similar diffusion processes, for example for the diffusion of cash transfer programs in Latin America (Sugiyama, 2011). Depending on the mechanism, adoption in one jurisdiction is more relevant for some jurisdictions than for others. For example, diffusion through competition suggests that policy adoption has a larger influence on jurisdictions with similar specialisation, while diffusion through coercion suggests that this influence is restricted to those jurisdiction over which a jurisdiction has a power advantage.

To identify diffusion we estimate an econometric 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 (Sauquet, 2014; Kammerer and Namhata, 2018; Abel, 2021; Dolphin and Pollitt, 2021). 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 and trade which we consider as potentially representing some of the alternative diffusion mechanisms mentioned above.

The choice of our model is informed by some characteristics of our data. The first characteristic is that policy adoption is only observed up until 2021, the most recent year in our sample. This means that our dependent variable is generally right-censored. 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 (Sugiyama, 2011; Sauquet, 2014; Abel, 2021; Dolphin and Pollitt, 2021). 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 (Lee and Wang, 2003). Formally, we estimate models of the general form

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

The hazard function $h(.)$ of a unit i in year t represents the probability that the policy is adopted by that unit 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 matrixes $X_{i,t-1}$ 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. The matrix $X_{i,t-1}$ accounts for possible domestic influences in country i in year $t - 1$. Informed by prior literature on domestic influence on the adoption of carbon pricing (Dolphin et al., 2019; Best et al., 2020), we include GDP per capita, the growth rate of GDP per capita, emissions of CO2 per GDP, the service share of GDP and the export share of GDP. All explanatory variables are lagged by one year to address concerns about reverse causality. As a robustness test, we obtain similar results with models with longer lag times (Appendix Table 4).

The matrix $W_{i,t-1}$ is a weighted average of policies adopted in other countries $j = 1, ..., N_c, i \neq j$ at time $t - 1$, sometimes also referred to as a spatial lag. We explain the construction of this matrix further below.

For both the left-hand side and the right-hand side of Equation 1 we model adoption 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. In this panel setting with time-varying covariates, observations of the same unit in subsequent years are implemented as independent of each other. To account for their dependency, we cluster the standard errors of our estimates at the level of individual units.

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 units is constant over time. We address possible violations of this assumption with our set of control variables and with stratification. The control variables include GDP per capita, the growth rate of GDP per capita, emissions of CO2 per GDP, the service share of GDP and the export share of GDP. The stratified version of our model

$$h(t, X_{i,t-1}, W_{i,t-1}) = h_{0,k}(t) \exp\left(X_{i,t-1}\beta_X\right) \exp\left(W_{i,t-1}\beta_W\right) \tag{2}$$

5

allows for different baseline hazards $h_{0,k}(t)$ for different strata with index k in our sample. For the stratified version of the model, the hazards are assumed to be proportional within strata but not necessarily across them. We use a division of the world into six continents North-America, Latin-America, Europe, Africa, Asia, and Oceania for stratification. We consider countries on the same continent as likely exposed to the same shocks that are unrelated to climate policy making. For every model, we use a statistical test based on Schoenfeld residuals to identify possible violations of the proportional hazard assumption (Grambsch and Therneau, 1994).

The matrix W is constructed from several data sources, depending on which channel is investigated. 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 $m_{i,j,t}$ (percentage of exports from country i into destination j in year t out of all exports from country i in year t, analogously for imports) for every pair of countries in the data (i,j) and every year t. We then calculate a weighted average:

$$W_{i,t} = \frac{\sum_{j=1, j\neq i}^{N_c} w_{i,j,t} Y_{j,t}}{\sum_{j=1, j\neq i}^{N_c} w_{i,j,t}} \tag{3}$$

with $w_{i,j,t} = x_{i,j,t}$ and $w_{i,j,t} = m_{i,j,t}$ for exports and imports respectively. Note that unlike the weights described below, the weights based on trade are generally not symmetric for a pair of countries, i.e. $w_{i,j,t} \neq w_{j,i,t}$.

For geographical proximity we construct similar measures using two alternative definitions of proximity. For the first measure we use a binary variable indicating whether two countries (i,j) share a land border. The second measure is calculated from the distance between centroids of countries $d_{i,j}$ as:

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

Furthermore, we construct an additional metric that is based on geographic proximity but also take 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

$$w_{i,j,t} = \frac{\text{GDP}_{j,t}}{d_{i,j}} \tag{5}$$

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 generally related to gravity models of international trade that make similar assumptions (Baier and Standaert, 2020).

The number of carbon pricing policies has continuously increased over the last thirty years. To address concerns about spurious diffusion (Braun and Gilardi, 2006), we conduct a placebo test. For this purpose we construct an additional matrix $W_{i,t}$ for which we assign a random value for proximity to every country pair $w_{i,j}$ by drawing from a Weibull distribution that we fit to the empirical distribution of the distances between countries.

2.2 Modelling the effect of policy diffusion on GHG emissions

2.2.1 Back-of-the-envelope calculations

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. We do so in two ways, first with a back-of-the-envelope calculation and then with Monte Carlo simulations. Both methods are briefly described here and in more detail in Appendix A.1.

For the back-of-the-envelope calculation, we compare a scenario in which country i adopts carbon pricing in year t with a scenario 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 can then be considered the additional hazard of policy adoption in country j that can be attributed to policy diffusion from country i.

To map the hazard rates onto greenhouse gas emissions, we we assume that carbon pricing reduces emissions in all countries by the same percentage r. This assumption has been made in the literature prior to our study (Eskander and Fankhauser, 2020; Best et al., 2020). Its major limitation is that it does not take into account that countries that adopt more stringent carbon pricing policies in terms of the price and sectoral coverage of the policy are likely to achieve proportionally larger emission reductions. In our idealised simulations we cannot directly use information on the stringency of policies, as for many countries no carbon pricing policy has been adopted yet. Nevertheless, we can use past carbon pricing policies to examine whether in the past earlier adopters tended to implement more or less stringent pricing policies than later adopters. If this was the case and if it was more generally representative for the international diffusion of this policy, our simulated indirect emission reductions would be biased.

We hence examine trends in the economy-wide average price in the year of the first implementation of carbon pricing policies, which we consider the best proxy for the stringency of the policy. The results are shown in the Appendix in Figure 8. Reassuringly for our

assumption, we do not find any clear trend in the data. While some of the first adopters implemented relatively stringent policies, the trend in more recent years appears slightly positive, especially if members of the EU ETS are considered as only one observation.

2.2.2 Monte-Carlo simulations

The back-of-the-envelope calculations neglect differences between countries in terms of their socioeconomic characteristics and associated baseline hazard and also neglects that policies can diffuse iteratively from one country to the next. To address these limitations, we do a more comprehensive quantification of indirect emission reductions. 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. As for the back-of-the-envelope calculations we construct counterfactual scenarios that allow us to quantify the emission reductions that can be attributed to diffusion. More details can be found in Appendix A.2.

For every scenario, we simulate policy adoption and diffusion over the time period 1988 and 2021, which is the time period for which we obtain our empirical estimates of diffusion. We again assume that adoption of the policy reduces greenhouse gas emissions by one percent per year and compute the cumulative emission reductions up to the year 2021.

2.3 Data

We use data on carbon pricing including carbon taxes and ETS from the Carbon Pricing Dashboard of the World Bank. The dataset includes pricing policies at the national and subnational level. We assign subnational pricing schemes to the corresponding countries and then drop for every country all but the first national or subnational pricing policy from the sample. For EU member countries, we set the year of adoption to 2003 regardless their year of ascension to avoid that the staggered EU ascension might be interpreted as diffusion in our data. The adoption of carbon pricing over time in our sample is illustrated in Figure 1.

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 explanatory variables we use additional data from the World Development Indicators of the World Bank, which we complement with replication data from a comprehensive study on carbon pricing effectiveness across countries (Best et al., 2020). Descriptive statistics of all covariates are shown in Table 1.
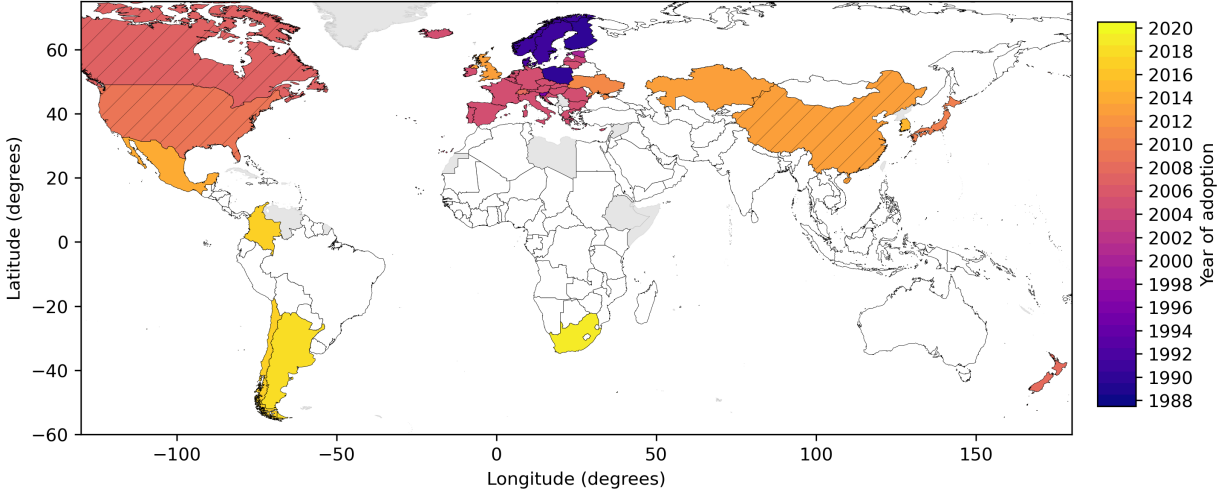
Figure 1. **Time of adoption of the first carbon pricing policy by country**. Hashes indicate countries in which the first policy was adopted at the subnational level.

Table 1. Descriptive statistics. The sample contains 179 countries and covers the years 1988 to 2021. A map of countries is shown in Figure 11 in the SI.

Variable	Unit	Mean	Std.	Min.	Max.	No. obs.
log GDP per capita PPP	2010 USD	8.42	1.50	5.23	11.63	6086
GDP per capita PPP growth rate	-	0.02	0.05	-1.05	0.88	6086
Exports share of GDP	percent	39.82	27.92	0.01	228.99	6086
Imports share of GDP	percent	46.85	28.96	0.00	424.82	6086
Services share of GDP	percent	21.31	13.63	0.15	55.47	6086
Emissions CO2eq per GDP	t per k 2010 USD	0.62	0.95	0.00	18.39	6086

3 Results

3.1 Descriptive evidence

The diffusion of policies can be thought of as a web of leader-follower relationships, whereby policy adoption in the leading country increases the likelihood of adoption in the following country. To better understand patterns of policy diffusion in our data, we illustrate some of those bilateral leader-follower relationships. In the empirical model that we estimate below, adoption by a follower is influenced by all leaders, but for ease of visualisation here we only plot diffusion from the leader that is closest to each follower. Proximity is based on the gravity model, which emerges as our preferred metric from the econometric analysis in the next Section.

We focus on Europe, the American continent, and Asia and Oceania, which encompasses all carbon pricing schemes in our data except the one in South Africa (Figure 2). We ignore
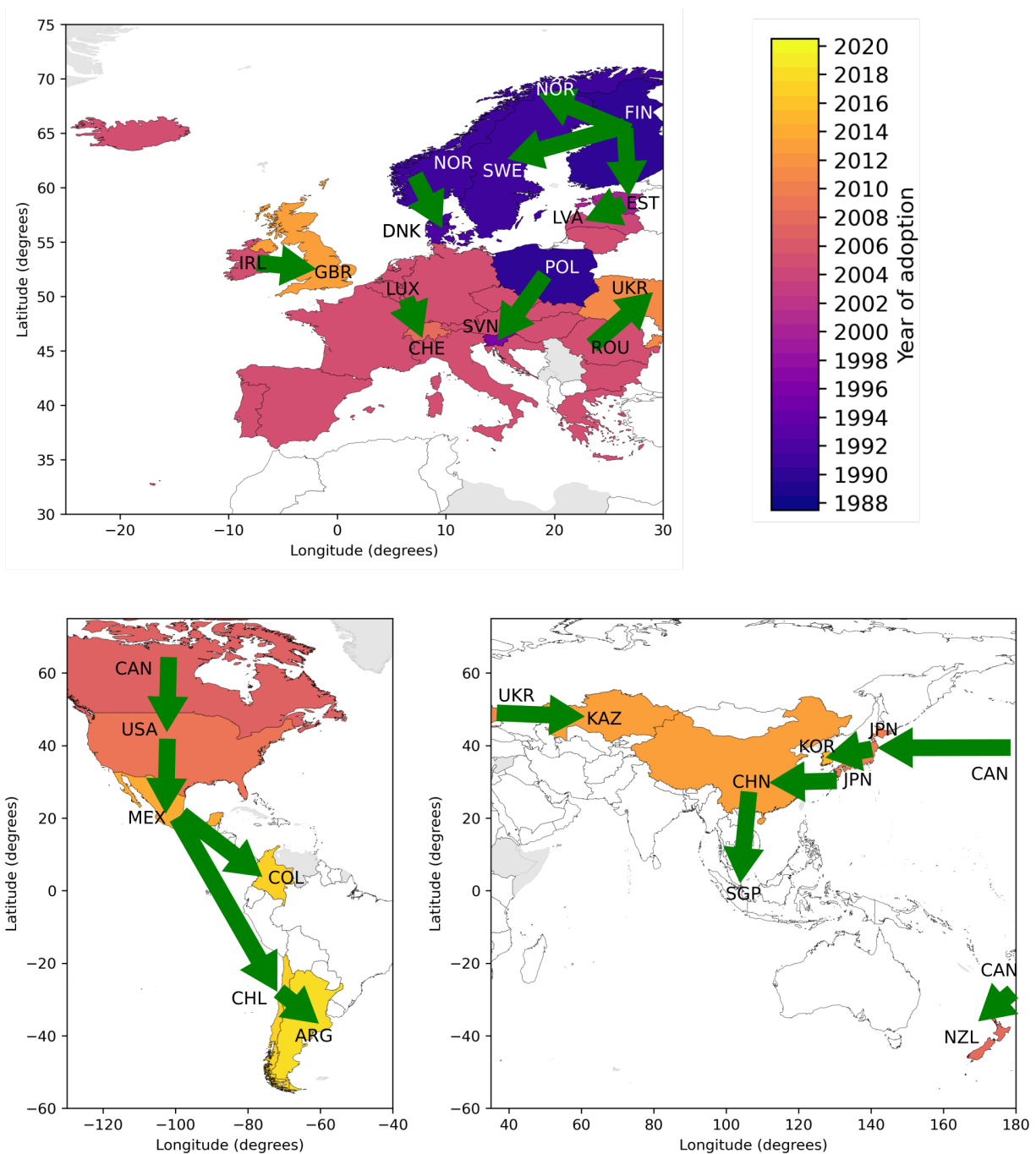
9

Figure 2. **Descriptive evidence on possible leader-follower relationships among adopters of carbon pricing**. Arrows point from earlier adopters to later adopters, but arrows are only shown from the leader that is closest to each of the followers according to the gravity metric. To make the figure readable, policy diffusion to members of the EU-ETS is not shown.

diffusion to member countries of the EU-ETS to make the figure more readable. In Europe, policies appear to have diffused initially from Finland to other Scandinavian countries and in the Baltics. This is supported by Harrison (2010), who highlights the importance of the pioneering adoption in Finland, which was soon "emulated by its Nordic neigbors" (p. 515). In addition, carbon pricing in Poland appears to have had a relatively large influence on carbon pricing in Slovenia. Furthermore, the EU-ETS appears to have influenced the adoption of carbon pricing in the UK, Switzerland, and Ukraine, most strongly through the respective neighbouring countries Ireland, Luxemburg, and Romania.

On the American continent, pricing policies appear to have diffused from North to South, starting with subnational policies in Canada and the USA. Furthermore, Mexico appears to have played a central role in the subsequent adoption of pricing policies in South-America, specifically Colombia, Chile, and Argentina. In Asia, countries appear to have initially emulated pricing policies in Europe and North-America. Moreover, carbon pricing in Japan appears to have had a relatively large influence on its subsequent adoption in Korea, China, and Singapore.

This analysis of policy diffusion based on Figure 2 is of course simplistic. In the next Section, we better account for the possible complexity of the drivers of policy adoption by estimating Cox proportional hazard models, which simultaneously model the influence of a year-specific baseline hazard, several country characteristics, and prior policy adoption in all other countries.

3.2   Model estimates

We first examine whether there is evidence for international policy diffusion and if so, which metric of the connectedness of countries describes the diffusion of carbon pricing best. To do so, we estimate the Cox proportional hazard model as in Equation 1 with our six explanatory variables and the spatial lag of carbon pricing constructed from six alternative metrics of the proximity between countries: the inverse geographic distance, the presence of a shared land border, import shares, export shares, the average proximity based on these four metrics, and as gravity metric the product of the inverse distance and the GDP of a country. Similar to a gravity model, this latter metric reflects the idea that a country is more influential for domestic policy adoption the closer it is in space and the larger its economy is. The results are presented in Columns 1-6 in Table 2.

For all metrics we find a statistically significant and positive coefficient of the spatial lag of policy adoption. We interpret this as evidence in favour of an international diffusion of carbon pricing policies. To identify which metric describes this diffusion best, we examine the model fits using the AIC statistic. We find the best model fit for the gravity metric,

11

Table 2. Results of estimation of Cox proportional hazard models with different metrics used for the construction of the spatial lag.

Policy:	Carbon price					
Proximity metric:	Proximity	Border	Exports	Imports	Average	Gravity
Column:	1	2	3	4	5	6
Spatial lag of carbon pricing	6.8155***	1.9726***	2.4389**	2.8316**	4.8575***	6.7053***
	(1.3603)	(0.4822)	(1.0013)	(1.2728)	(1.1399)	(1.3469)
GDP per capita PPP	11.5349***	10.4090***	9.9847***	10.1008***	10.6275***	11.5662***
	(3.6650)	(3.5146)	(3.6180)	(3.6419)	(3.6460)	(3.6787)
GDP per capita PPP sq.	-0.5512***	-0.4926***	-0.4666**	-0.4751**	-0.5032***	-0.5529***
	(0.1887)	(0.1820)	(0.1871)	(0.1891)	(0.1880)	(0.1895)
GDP per capita PPP growth	2.0603	2.2431	2.0444	2.1894	2.0292	2.0597
	(3.1070)	(3.1997)	(3.1228)	(3.0227)	(3.1429)	(3.1010)
Export share	-0.0056	-0.0085*	-0.0078*	-0.0068	-0.0071	-0.0054
	(0.0045)	(0.0049)	(0.0047)	(0.0047)	(0.0047)	(0.0045)
Services share of GDP	0.0273**	0.0309**	0.0276**	0.0288**	0.0297**	0.0271**
	(0.0136)	(0.0135)	(0.0127)	(0.0128)	(0.0139)	(0.0136)
Emissions CO2 per GDP	-0.0127	-0.0064	-0.0443	-0.0076	0.0021	-0.0121
	(0.1140)	(0.1078)	(0.1005)	(0.1063)	(0.1070)	(0.1140)
Time at risk	5277	5277	5277	5277	5277	5277
log-likelihood	-177.6	-181.3	-183.5	-183.7	-179.5	-177.5
AIC	369.2	376.5	381.0	381.5	372.9	369.1
N	5239	5207	5075	5078	5082	5252

Notes: Standard errors clustered by country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

followed by the inverse geographical distance between countries and the average metric. In the remainder of the paper, we therefore use the gravity metric as our preferred metric and consider the corresponding estimates in Column 6 in Table 2 as our baseline estimates.

We next quantify the magnitude of the estimated coefficients of the spatial lag of carbon pricing. To this aim, we select a few pairs of countries and calculate how much the adoption of carbon pricing in one country changes the hazard of policy adoption in the other country, given that no other country has previously adopted the policy. To do so, we multiply the estimated coefficient of the spatial lag of carbon pricing in Column 6 in Table 2 by the corresponding weight of the other country and exponentiate the result. We find that in the USA prior adoption of carbon pricing by Canada increases the hazard by about 16%, or by a factor of 1.16 (95% CI of 1.10 to 1.22). In Germany, prior adoption by France increases the hazard by 17% (10% to 24%), while in China prior adoption by Japan increases it by 10% (6% to 14%). For comparison, in the USA prior adoption by China increases the hazard by 3% and in Germany prior adoption by Japan by slightly more than 1%.

Furthermore, the estimated coefficients suggest that GDP per capita has a negative quadratic association with the hazard of carbon pricing adoption (Column 6 in Table 2).

To illustrate the magnitude of the estimated coefficients and the declining marginal effect of higher income, the results suggest that an increase of average income from 20,000 USD to 30,000 USD is associated with an increase of the hazard by about 17 % and an increase from 30,000 USD to 40,000 USD by about 0.2 %. Furthermore, we find statistically significant coefficients for the service share of GDP, which tends to increase the hazard of carbon pricing adoption.

Variation in the hazard over time that cannot be explained by these covariates is in the model represented by the baseline hazard. We find that the baseline hazard is relatively flat except a peak in the year 2003 (Figure 7 in the Appendix). This year coincides with the adoption of the EU ETS, which cannot sufficiently well be explained by the covariates in the model.

To test for violation of the proportional hazard assumption, we conduct a statistical test based on Schoenfeld residuals (Grambsch and Therneau, 1994). We first estimate a model that only includes the spatial lag of carbon pricing, for which we can reject proportional hazards with high confidence ($p = 0.01$). This results therefore supports our decision to include covariates in our model. For the models with six covariates whose results are shown in Table 2, we cannot reject the null hypothesis of proportional hazards for any of the metrics.

As a first robustness test of our main estimates, we exclude all subnational carbon pricing schemes (Column 1 in Table 3). We find that the estimated coefficients are very similar to the model including subnational pricing policies (Column 2 in Table 2). Carbon pricing has first been implemented as a tax in 22 countries and as an ETS in 38 countries in our sample. We next estimate one model based on the adoption of carbon taxes alone (Column 2 in Table 3) and one based on the adoption of ETS (Column 3). We find positive but insignificant coefficients of the spatial lag for both models, suggesting that it is important to allow for alternative implementations of carbon pricing when examining its international diffusion.

As additional robustness tests, we next estimate a stratified model as in Equation 2. We stratify the sample with a division of the world into the six continents North-America, Latin-America, Europe, Africa, Asia, and Oceania. We choose continents because we assume that countries on the same continent are likely to be affected similarly by possibly confounding annual shocks that are not absorbed well by the flexible baseline hazard of an unstratified model. This stratified model allows for possibly different baseline hazards on different continents after adjusting for the covariates included in the model. We find that stratification barely changes the results (Column 4 in Table 3). Next, we allow for even more heterogeneity in the hazard rate by including an additional dummy variable that indicates whether a country is listed on Annex I of the Kyoto protocol and therefore has specific obligations under this framework. Our hypothesis is that countries with such obligations had a

13

Table 3. Results of estimation of Cox proportional hazard models with different policies, with stratification and an additional control variable, and with a placebo spatial lag.

Policy:	Carbon price	Tax	ETS	Carbon price		
Proximity metric:	Gravity			Gravity		Placebo
Administrative level:	National	All		All		
Stratification:	None			Continents		None
Column:	1	2	3	4	5	6
Spatial lag of carbon pricing	5.3678***	3.9343	1.6888	6.4526***	5.5863**	4.4097
	(1.3377)	(3.9888)	(2.1695)	(2.4602)	(2.1772)	(7.9662)
GDP per capita PPP	13.5128***	6.1164*	13.0358***	10.7602***	10.2111***	10.6679***
	(4.0646)	(3.5528)	(3.9409)	(2.4706)	(2.4188)	(3.3850)
GDP per capita PPP sq.	-0.6514***	-0.2705	-0.6155***	-0.5171***	-0.5065***	-0.4994***
	(0.2087)	(0.1886)	(0.2013)	(0.1246)	(0.1194)	(0.1755)
GDP per capita PPP growth	1.4117	-3.3774	7.6394**	2.0850	0.8861	2.1416
	(2.4841)	(2.1766)	(3.4996)	(4.4817)	(4.6117)	(2.3829)
Export share	0.0009	-0.0090	-0.0042	0.0003	0.0061	-0.0044
	(0.0032)	(0.0084)	(0.0048)	(0.0044)	(0.0042)	(0.0032)
Services share of GDP	0.0545***	0.0509	0.0511***	0.0419*	0.0446**	0.0453***
	(0.0173)	(0.0313)	(0.0179)	(0.0221)	(0.0216)	(0.0166)
Emissions CO2 per GDP	0.3475	0.3735	0.4084	0.6553***	0.5766**	0.6332*
	(0.5183)	(0.5549)	(0.4692)	(0.1935)	(0.2679)	(0.3245)
Kyoto Annex I					40.5713*	
					(20.6120)	
Time at risk	5277	5600	5395	5277	5277	5277
log-likelihood	-177.5	-98.2	-157.6	-129.3	-78.9	-186.1
AIC	369.1	210.4	329.3	272.6	173.9	386.3
N	5252	5575	5332	5252	5252	5074

Notes: Standard errors clustered by country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

systematically higher baseline hazard of adopting carbon pricing than countries without such obligations. We find that the results are also robust to this additional variable (Column 5). Furthermore, we increase the lag time of the spatial lag and find similar results for periods between 1 and 5 years, with possibly the best model fit according to the AIC statistics for a lag time of 3 years (Table 4 in the Appendix).

As a last robustness check, we conduct a placebo test. For this test, we construct the spatial lag of policy adoption by assigning random numbers to the proximities between countries. If our previous results are due to spurious diffusion, for example because of certain trends in the data, we would expect that we also find a statistically significant coefficient of prior policy adoption in this excercise. Reassuringly, we find no significance for this placebo spatial lag (Column 6 in Table 3).

3.3 Emission reductions

The results from the empirical analysis above suggest that between 1988 and 2020, carbon pricing policies diffused internationally, possibly due to the learning and emulation mechanisms that we discuss. We next examine how this diffusion can contribute to reductions of greenhouse gase emissions globally. To this aim, we 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. We first do some back-of-the-envelope calculations and then use Monte-Carlo simulations.

For the back-of-the-envelope calculations, we use the estimated coefficient of the diffusion of carbon pricing from the model with proximity calculated from an average metric i.e. $\beta_W = 6.7053$ (Column 6 in Table 2). Moreover we assume a baseline hazard of $h_0^\star = 0.01$. In an additional robustness check, we set the baseline hazard to 0.05. Furthermore, we assume that adopting carbon pricing reduces total annual emissions of GHG by $r = 1$ percent per year, irrespective the total emissions of a country. This assumption is in more detail discussed in Section 2.2.1. We emphasise that this value does not influence the comparison of direct and indirect emission reductions, as both values scale with this number. We assume that the policy was implemented at the end of the year $t = 2018$ and base our calculations on actual domestic emissions E in the year $t + 1 = 2019$.

With these assumptions, we calculate direct and indirect emission reductions (Equations 11 and 10, respectively, in Appendix A.1). Because we calculate indirect emissions from diffusion for every country separately, indirect emission reductions for different countries are not additive. We find that indirect emission reductions can be substantial and similar in size to direct emission reductions. For a baseline hazard of $h_0^\star = 0.01$, indirect emission reductions exceed direct emission reductions for about 38 percent of countries (Figure 3 left). For a baseline hazard of 0.05, the share of countries increases to 73 percent (Figure 3 right).

For this quantification we assumed an equal and constant baseline hazard. Furthermore, we examined only the emission reductions over the year immediately following the introduction of the policy. For this reason, the results do not account for different probabilities of adoption due to different socioeconomic contexts of countries (covariates in the empirical analysis) and ignore the possibly cascading effects of policy diffusion over several years. To address these limitations, we next conduct Monte Carlo simulations of policy diffusion.

We first assume that carbon pricing is for the first time introduced in a given country in 1988 and then diffuses from there. For the coefficient of the spatial lag and the baseline hazard, we estimate the model shown in Column 6 in Table 2. For simplicity, we assume a constant baseline hazard (exponential survival function), which means that in these for-
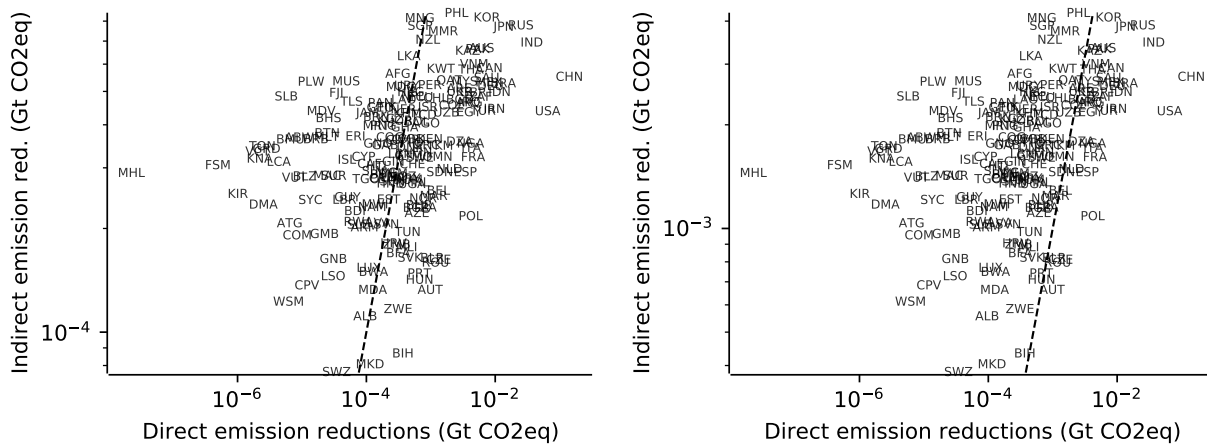
Figure 3. **Direct and indirect emission reductions from a back-of-the-envelope calculation**. Emission reductions calculated over one year for a policy with effectiveness of $r = 0.01$ and a baseline hazard of $h_0^\star = 0.01$ (left) and 0.05 (right). For countries to the left of the straight lines indirect emission reductions exceed direct emission reductions.

ward simulations differences in the hazard of policy adoption stem from the spatial lag and the covariates only. The indirect emission reductions for different countries are again not additive.

The Monte Carlo simulations result in probabilities of policy adoption which we translate into expected direct and indirect emission reductions (Equations 12 and 13, respectively, in Appendix A.2). The results are shown in Figure 4. We find that indirect emission reductions are as large as or even larger than direct emission reductions in the majority of countries. Overall, 89 % of countries have larger indirect than direct emission reductions (Figure 4 left). For most of these countries, indirect emission reductions exceed direct emission reductions by a factor of 1-100, but we also find few small economies with even larger factors (Figure 5 left).

Countries with large indirect emission reductions tend to be be relatively centrally located and close to countries with relatively large emissions. For example, the two countries with the largest indirect emission reductions are Belgium and Czech Republic. Most of the world's largest emitters are members of the G20. Those countries show a wide range of indirect emission reductions (Figure 4 left). Owing to their large economies, most of these countries have larger direct than indirect emission reductions, but for many of them the two tend to be of a similar order of magnitude.

This first exercise simulates policy diffusion for fictitious scenarios in which a given country is the first and only country to adopt carbon pricing in 1988. We next conduct a similar exercise which starts in 2020 from the actually observed adoption of carbon pricing by the end
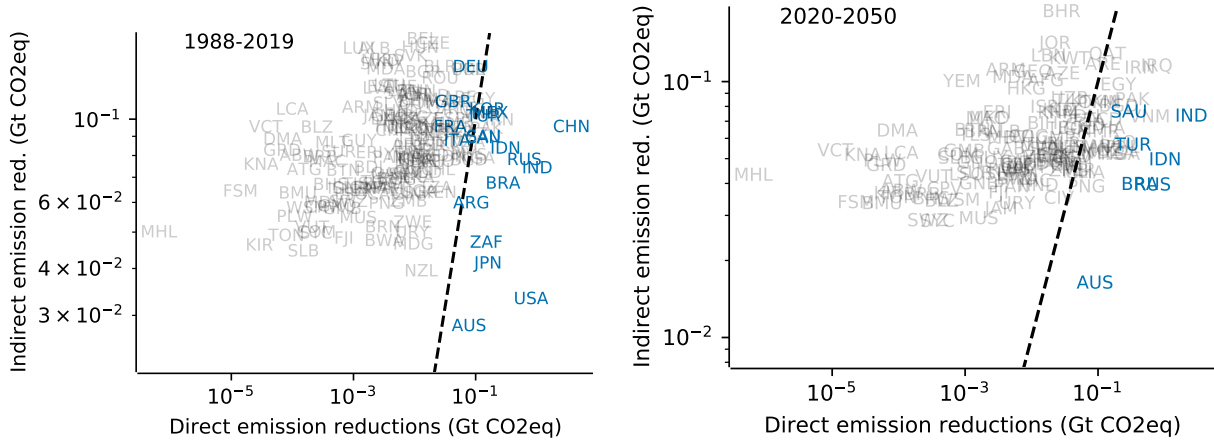
16

Figure 4. **Direct and indirect emission reductions from Monte Carlo simulations**. Left: Emission reductions calculated over period 1988-2019 assuming no policies prior to 1988. Right: Emission reductions calculated over period 2020-2050 starting from implemented policies by the end of 2020. Parameter $r = 0.01$. G20 economies are shown in blue.

of 2020. We again examine two counterfactual scenarios for every country without a carbon price in 2020. In the first scenario, the country adopts carbon pricing in 2020, whereas in the second scenario it does not. The main differences to the previous simulations are therefore that policies diffuse from countries that already adopted carbon pricing by 2020 but policies cannot diffuse to them, which reduces the indirect emission reductions from diffusion for all countries but more so for some than for others. We again assume a constant baseline hazard and keep the values of all covariates at their value in 2019 (see also Appendix Figure 12). The results are qualitatively similar to the previous results (Figure 4 right). Indirect emission reductions are larger than direct emission reductions in 76 % of countries in the sample (Figure 5 left).

Furthermore, we find that indirect emission reductions are far more equally distributed across countries than direct emission reductions (Figure 5 right). This is the case for the exercise starting in 1988 and the exercise starting in 2020. This distribution of emission reductions suggests that total emission reductions from policy adoption are more equally distributed across countries if one takes into account the emission reductions from international diffusion.

In the last part of the analysis, we examine how diffusion affects the future geographical coverage of carbon pricing policies. To this aim, we again conduct Monte Carlo simulations starting in 2020 and compare two counterfactual scenarios, one in which we use our empirical estimate of the diffusion parameter ($\beta_W = 6.7053$) and one in which we set this parameter to
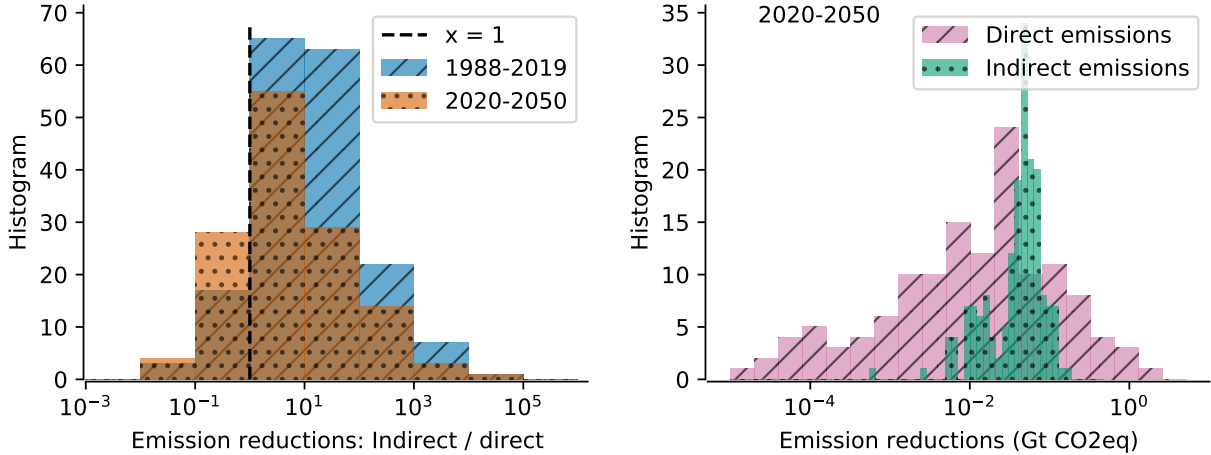
17

Figure 5. **Frequency distribution of emission reductions from Monte Carlo simulations.** Left: Histogram of ratio of indirect to direct emission reductions. Right: Histogram of direct and indirect emission reductions for the sample of 179 countries. Based on emission reductions shown in Figure 4.

zero ($\beta_W = 0$). Both simulations start from carbon pricing policies that were implemented by the end of 2020. In contrast to the previous exercise, we do not need to run these simulations separately for every country because we are not interested in the effect of diffusion if a specific country adopts carbon pricing next, but instead in the effect of simultaneous diffusion from all countries with existing carbon pricing policies. All other parameter values are chosen as in the previous exercise, including the baseline hazard of policy adoption.

It appears plausible that the probability of carbon pricing adoption is generally larger in 2020-2050 than it was in 1988-2020. In a sensitivity analysis, we therefore double the baseline hazard. Importantly, in the sensitivity analysis we double the baseline hazard in the scenario with diffusion and in the scenario without diffusion to be able to again isolate the effect of diffusion.

We find that policy diffusion substantially increases the geographical coverage of carbon pricing over the time period 2020-2050 (Figure 6). By 2030, carbon pricing policies cover about 3.5 percentage points more countries and a 3 percentage points larger share of global greenhouse gas emissions in the scenario with diffusion than in the scenario without diffusion. By 2050, the effect of diffusion increases to 11 and 9 percentage points, respectively. Furthermore, with diffusion a similar share of countries has adopted carbon pricing by 2030 as without diffusion by 2050.

These estimates are obtained with the baseline hazard over the period 1988-2020 and the values of covariates in 2019. In the sensitivity analysis with twice the baseline hazard, the
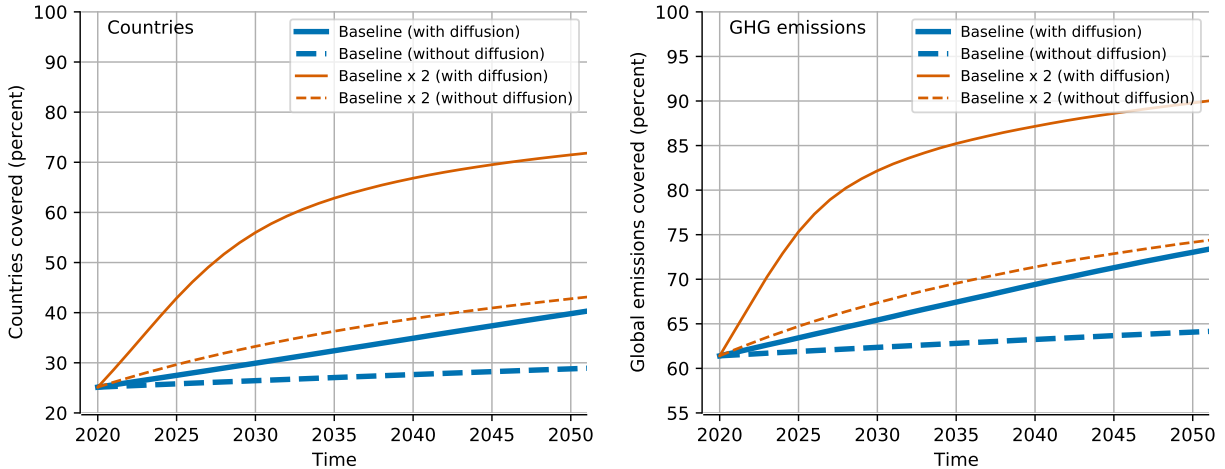
Figure 6. **Geographical coverage of carbon pricing policies from Monte Carlo simulations for 2020-2050 with and without diffusion.** The diagram shows the share of countries (left) and the share of global emissions (right) covered by carbon pricing policies for scenarios with diffusion and without diffusion. All scenarios start from carbon pricing policies implemented by the end of 2020. Based on sample of 179 countries and baseline hazard as estimated for period 1988-2020. Sensitivity analysis uses twice that baseline hazard.

benefits of diffusion become several times larger, especially in 2030. For example, the share of countries with carbon pricing in 2030 is about 23 percentage points larger in the scenario with diffusion than in the scenario without diffusion.

These results add another nuance to the importance of international policy diffusion. While our results suggest that policy diffusion can substantially increase the geographical coverage of carbon pricing policies, this coverage increases only by about 11 percentage points of countries by 2050 relative to a scenario without diffusion (29 percentage points in the sensitivity analysis).

4   Discussion and Conclusions

A possible reason for the slow progress in mitigating global climate change are concerns about limited effectiveness of emission abatements in relatively small economies. Countering that concern, researchers have identified additional global benefits of a country's leadership in climate change mitigation beyond domestic emission reductions (Schwerhoff, 2016; Höhne et al., 2018). For example, stringent climate policies can support international diffusion of technological innovations that reduce mitigation costs in other countries (Dechezleprêtre et al., 2011; Barrett, 2021), demonstrate political feasibility, and create incentives related to trade (Steinebach et al., 2021) and diplomacy (Kammerer and Namhata, 2018) that nudge

other countries to adopt the same or similar policies. Overall, adoption of a climate policy at home is likely to also reduce some emissions abroad, possibly also because of the international diffusion of that policy.

In this paper, we empirically examine the diffusion of carbon pricing policies over the last 30 years and quantify the indirect emission reductions that can be attributed to policy diffusion. As compared to previous work on domestic influences on climate policy adoption (Dolphin et al., 2019; Best and Zhang, 2020; Eskander and Fankhauser, 2020), we focus on international influences. Our results are however in line with this earlier work and provide support for the importance of domestic factors, suggesting for example a positive influence of the level of GDP per capita on the adoption of carbon pricing with a declining marginal effect at higher values.

The empirical part of our paper builds on prior work on the diffusion of climate policies. Some of this prior work has also used proportional hazard models (Sauquet, 2014; Dolphin and Pollitt, 2021). Three studies have examined the diffusion of carbon pricing using qualitative (Thisted and Thisted, 2020) and similar quantitative methods (Dolphin and Pollitt, 2021; Steinebach et al., 2021). With the exception of Dolphin and Pollitt (2021), who find mixed evidence, all prior work reports evidence in support of an international diffusion of climate policies. We find robust statistical evidence for an international diffusion of carbon pricing policies. The magnitude of this diffusion is substantial: according to our estimates prior adoption of the policy by a neighbouring country increases the probability of adoption in a given year by on average about 10 %.

In contrast to the most similar prior work on the international diffusion of carbon pricing (Dolphin and Pollitt, 2021), 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 (Skovgaard et al., 2019). Furthermore, we consider it likely that in many cases the decision to adopt carbon pricing is likely made before the choice of instrument design, as in the case of the EU ETS (Harrison, 2010).

To some extent, the plausibility of this assumption also depends on the mechanism of diffusion. Our work does not propose a specific mechanism, but previous work suggests that learning and emulation are important for the diffusion of carbon pricing (Biedenkopf et al., 2017; Thisted and Thisted, 2020). On the one hand, if the observed diffusion is mostly due to learning from earlier experiences, as it might have been the case for the ETS in Kazakhstan that was modelled after the EU ETS (Gulbrandsen et al., 2017) and the ETS in California that intentionally differed from the EU ETS in some design parameters (Bang et al., 2017), instrument design might play a relatively more important role in diffusion. On the other hand, to the extent that diffusion is explained by emulation, for example due to an

emerging international norm of carbon pricing (Thisted and Thisted, 2020), specific design parameters might be relatively less important for diffusion. Given the relatively short time periods between the adoption of carbon pricing policies in neighbouring countries in our sample, which leave little time for learning, we consider emulation as the more important process.

International coordination of climate policy is likely to be an important factor underlying this observed diffusion. Especially the Kyoto protocol and Paris climate agreement created incentives for countries to ratchet up their mitigation efforts. Ratcheting up alone can however not explain our main results, because trends over time are absorbed by the (stratified) Cox baseline term in our empirical model and our results also pass a related Placebo test. Instead, we consider it likely that the diffusion of carbon pricing can partially be explained by the efforts of early adopters to promote carbon pricing in other countries (Biedenkopf et al., 2017) and by multilateral initiatives that supported exchange of knowledge such as the International Carbon Action Partnership.

In additional analysis, we use our emprically estimated coefficients to quantify emission reductions that can plausibly be attributed to diffusion, which we refer to as indirect emission reductions. By comparing the results of a treatment and a counterfactual scenario we are able to isolate the effect of international diffusion. However, the resulting values should not be considered at face value as estimates of actual emission reductions. Above all, our results for the time period 1988-2019 are based on hypothetical scenarios in which a country adopted carbon pricing as the first and only country in 1988. To address this limitation, we also conduct simlations for the time period 2020-2050 that start from the actual adoption of carbon pricing policies in 2020. This analysis is limited in turn by the use of empirical estimates obtained from the earlier period which are extrapolated into the future. For simplicity, we also assume that carbon pricing in all countries reduces GHG emissions proportionally with a uniform annual rate. We address this limitation by comparing direct and indirect emission reductions which both scale with this parameter. Lastly, due to the construction of the scenarios indirect emission reductions attributed to policy diffusion for a specific pioneering country are not additive with those indirect emission reductions attributed to other pioneering countries.

Given these limitations, our main objective here is to derive an order of magnitude of indirect emission reductions that is based on our empirical estimates and on assumptions that we consider plausible, and that takes the heterogeneous socioeconomic environments, linkages between countries, and the cascading nature of policy diffusion into account. Our results suggest that these indirect emission reductions can be substantial: using Monte Carlo simulations we find that for the majority of countries (89 % for 1988-2019 and 76 % for 2020-

2050) indirect emission reductions are larger than the direct domestic reductions.

Moreover, our results suggest that indirect emission reductions due to policy diffusion are much more equally distributed across countries than domestic GHG emissions. This means that policy diffusion tends to matter relatively more in relatively small economies. Furthermore, it means that if one accounts for policy diffusion, the overall effectiveness of domestic policy adoption becomes more equal across countries. These results take into account our empirical findings that suggest that larger economies tend to have a larger effect on international diffusion. The benefits of a larger economy appear however small in our empirical results, somewhat consistent with the observation of Skovgaard et al. (2019) and the insights obtained from our descriptive analysis that many of the early adopters of carbon pricing were relatively small countries.

This insight that the emission reductions from international diffusion are relatively more important for small countries does not suggest that emission reductions in large economies are not important. Indeed, these results for small countries embody an intentional adoption of carbon pricing by large economies that is influenced by prior adoption in smaller countries. Furthermore, this insight does not conflict with possible barriers to the adoption of stringent climate policies in small countries which might be particularly exposed to competition on international markets, but highlights the possible benefits of overcoming those barriers.

In the last part of the analysis, we examine to what extent international policy diffusion as observed in the past can increase the geographical coverage of carbon pricing policies in the future. To isolate the effect of diffusion, we simulate scenarios with diffusion and without diffusion over the period 2020-2050. Our results suggest that diffusion can incrase the share of countries with carbon pricing by about 11 percentage points by 2050 relative to the scenario without diffusion. As a sensitivity test, we repeat the same exercise for scenarios in which the future baseline hazard is twice as large as the historical baseline hazard, in which case the effect of diffusion increases to 29 percentage points. The results similary show that with diffusion a similar number of countries adopts carbon pricing by 2030 as without diffusion by 2050. We emphasise again that these estimates should not be considered at face value, but indicate an order of magnitude of the effects. Overall, our results suggest that while for individual countries the global benefits from policy diffusion are therefore substantial, the possible contribution of policy diffusion to the achievement of a high geographical coverage of carbon pricing policies over the next decades appears limited.

Our study is subject to certain limitations and our results point to some avenues for future research. The empirical analysis necessarily focuses on the time period 1988 to 2020, over which the diffusion of carbon pricing might have benefitted from a generally cooperative international political environment. To what extent a possibly more fragmented international

political environment will affect similar diffusion processes in the future remains an open question. More generally, any extrapolation from past policy diffusion to future diffusion should of course be made and interpreted with caution.

We focus on the adoption decision of carbon pricing policies and do not account for differences in the stringency of carbon pricing policies. For example, for the calculation of direct and indirect emission reductions, we assume the same effectiveness of carbon pricing policies for domestic emission reductions as for emission reductions in other countries. This assumption is motivated by the fact that there is no information about stringency for many countries for which we simulate policy adoption as those countries, by the end of 2021, have not yet adopted such policy. Reassuringly, we examine data on all carbon pricing policies implemented by the end of 2020 and do not find any clear trend in the initial carbon price over time, which justifies our assumption that followers implement policies with similar stringency as their leaders. Future research might examine how the stringency of pricing policies affects their diffusion and possibly the stringency of later policies.

Our analysis focuses on carbon pricing policies and subsequent work might extend this work to other climate policies. Earlier work has focused, for example, on the ratification decisions of the Kyoto protocol (Sauquet, 2014), feed-in-tariffs and renewable energy quotas (Baldwin et al., 2019; Dolphin and Pollitt, 2021), and local funding schemes for solar photovoltaic (Abel, 2021). We consider it plausible that the international political environment of climate policy will be similarly supportive to the diffusion of other types of policies and that emulation and learning will play an important role in the adoption of those policies too. More generally, we consider it plausible that those processes also matter for ratcheting up the stringency of existing climate policy, for example increases in carbon prices.

Similarly, future research might study the diffusion of carbon pricing policies at the sectoral level. International competition and the possibility of linking national ETS suggests some coordination on the inclusion of specific sectors. For example, Bullock (2012) point out how New Zealand synchronised the inclusion of agriculture in their ETS with its inclusion in the ETS considered by Australia at that time. At the same time, sectoral coverage is an important part of the stringency of a pricing scheme and might therefore influence the perceived ambitiousness of a pricing policy relative to prior policies adopted elsewhere. For example, according to Crowley (2013), the sectoral coverage relative to the EU ETS was an important consideration of the proposed ETS in Australia. Future research might therefore want to study sectoral coverage in the context of international diffusion also as a determinant of the stringency of policies.

This study focuses on international influences on climate policy adoption. Several previous studies have examined domestic influences (Fankhauser et al. (2015); Klenert et al.

(2018); Dolphin et al. (2019); Levi et al. (2020), among others). Furthermore, over the last 20 years countries tended to adopt carbon pricing at the end of climate policy sequences, in most cases after the adoption of a variety of other instrument types including regulatory instruments, subsidies, research and development, and procurement and investment (Linsen-meier et al., 2022). Future research might attempt to study those international and domestic influences in one empirical framework. Furthermore, we focus on geographic proximity and trade relationships and future work might consider additional channels through which countries learn and imitate each other. For example, Kammerer and Namhata (2018) examine to what extent international climate diplomacy plays a role in diffusion.

Our results provide evidence for large positive spillovers of domestic climate policy adoption. They can be interpreted as 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.

References

Abel, D. (2021). The diffusion of climate policies among German municipalities. *Journal of Public Policy*, 41(1):111–136.

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

Baldwin, E., Carley, S., and Nicholson-Crotty, S. (2019). Why do countries emulate each others' policies? A global study of renewable energy policy diffusion. *World Development*, 120:29–45.

Bang, G., Victor, D. G., and Andresen, S. (2017). California's Cap-and-Trade System: Diffusion and Lessons. *Global Environmental Politics*, 17(3):12–30.

Barrett, P. (2021). Can International Technological Diffusion Substitute for Coordinated Global Policies to Mitigate Climate Change? *IMF Working Papers*, 2021(173).

Best, R., Burke, P. J., and Jotzo, F. (2020). Carbon Pricing Efficacy: Cross-Country Evidence. *Environmental and Resource Economics*, 77(1):69–94.

Best, R. and Zhang, Q. Y. (2020). What explains carbon-pricing variation between countries? *Energy Policy*, 143:111541.

Biedenkopf, K., Müller, P., Slominski, P., and Wettestad, J. (2017). A Global Turn to Greenhouse Gas Emissions Trading? Experiments, Actors, and Diffusion. *Global Environmental Politics*, 17(3):1–11.

Braun, D. and Gilardi, F. (2006). Taking 'Galton's Problem' Seriously: Towards a Theory of Policy Diffusion. *Journal of Theoretical Politics*, 18(3):298–322.

Bullock, D. (2012). Emissions trading in New Zealand: Development, challenges and design. *Environmental Politics*, 21(4):657–675.

Crowley, K. (2013). Irresistible Force? Achieving Carbon Pricing in Australia. *Australian Journal of Politics & History*, 59(3):368–381.

Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N., and Ménière, Y. (2011). Invention and Transfer of Climate Change–Mitigation Technologies: A Global Analysis. *Review of Environmental Economics and Policy*, 5(1):109–130.

Dolphin, G., Pollitt, M. G., and Newbery, D. M. (2019). The political economy of carbon pricing: A panel analysis. *Oxford Economic Papers*, page gpz042.

Dolphin, G. G. and Pollitt, M. G. (2021). The international diffusion of climate policy: Theory and evidence. page 60.

Eskander, S. M. S. U. and Fankhauser, S. (2020). Reduction in greenhouse gas emissions from national climate legislation. *Nature Climate Change*, 10(8):750–756.

Fankhauser, S., Gennaioli, C., and Collins, M. (2015). The political economy of passing climate change legislation: Evidence from a survey. *Global Environmental Change*, 35:52–61.

Fankhauser, S., Gennaioli, C., and Collins, M. (2016). Do international factors influence the passage of climate change legislation? *Climate Policy*, 16(3):318–331.

Grambsch, P. M. and Therneau, T. M. (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, 81(3):515–526.

Gulbrandsen, L. H., Sammut, F., and Wettestad, J. (2017). Emissions Trading and Policy Diffusion: Complex EU ETS Emulation in Kazakhstan. *Global Environmental Politics*, 17(3):115–133.

Harrison, K. (2010). The Comparative Politics of Carbon Taxation. *Annual Review of Law and Social Science*, 6(1):507–529.

Heggelund, G., Stensdal, I., Duan, M., and Wettestad, J. (2019). China's Development of ETS as a GHG Mitigating Policy Tool: A Case of Policy Diffusion or Domestic Drivers? *Review of Policy Research*, 36(2):168–194.

Höhne, N., Fekete, H., den Elzen, M. G., Hof, A. F., and Kuramochi, T. (2018). Assessing the ambition of post-2020 climate targets: A comprehensive framework. *Climate Policy*, 18(4):425–441.

Jordan, A. and Huitema, D. (2014). Innovations in climate policy: The politics of invention, diffusion, and evaluation. *Environmental Politics*, 23(5):715–734.

Kammerer, M. and Namhata, C. (2018). What drives the adoption of climate change mitigation policy? A dynamic network approach to policy diffusion. *Policy Sciences*, 51(4):477–513.

Klenert, D., Mattauch, L., Combet, E., Edenhofer, O., Hepburn, C., Rafaty, R., and Stern, N. (2018). Making carbon pricing work for citizens. *Nature Climate Change*, 8(8):669–677.

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

Levi, S., Flachsland, C., and Jakob, M. (2020). Political Economy Determinants of Carbon Pricing. *Global Environmental Politics*, 20(2):128–156.

Linsenmeier, M., Mohommad, A., and Schwerhoff, G. (2022). Policy sequencing towards carbon pricing - empirical evidence from G20 economies and other major emitters. *IMF Working Paper No. 2022/066*.

Ryan, D. and Micozzi, M. (2021). The politics of climate policy innovation: The case of the Argentine carbon tax. *Environmental Politics*, 30(7):1155–1173.

Sauquet, A. (2014). Exploring the nature of inter-country interactions in the process of ratifying international environmental agreements: The case of the Kyoto Protocol. *Public Choice*, 159(1-2):141–158.

Schwerhoff, G. (2016). The economics of leadership in climate change mitigation. *Climate Policy*, 16(2):196–214.

Shipan, C. R. and Volden, C. (2008). The Mechanisms of Policy Diffusion. *American Journal of Political Science*, 52(4):840–857.

Shipan, C. R. and Volden, C. (2012). Policy Diffusion: Seven Lessons for Scholars and Practitioners. *Public Administration Review*, 72(6):788–796.

Simmons, B. A., Dobbin, F., and Garrett, G. (2006). Introduction: The International Diffusion of Liberalism. *International Organization*, 60(04).

Skovgaard, J., Ferrari, S. S., and Knaggård, Å. (2019). Mapping and clustering the adoption of carbon pricing policies: What polities price carbon and why? *Climate Policy*, 19(9):1173–1185.

Steinebach, Y., Fernández-i-Marín, X., and Aschenbrenner, C. (2021). Who puts a price on carbon, why and how? A global empirical analysis of carbon pricing policies. *Climate Policy*, 21(3):277–289.

Sugiyama, N. B. (2011). The diffusion of Conditional Cash Transfer programs in the Americas. *Global Social Policy*, 11(2-3):250–278.

Thisted, E. V. and Thisted, R. V. (2020). The diffusion of carbon taxes and emission trading schemes: The emerging norm of carbon pricing. *Environmental Politics*, 29(5):804–824.

Torney, D. (2015). Bilateral Climate Cooperation: The EU's Relations with China and India. *Global Environmental Politics*, 15(1):105–122.

Volden, C., Ting, M. M., and Carpenter, D. P. (2008). A Formal Model of Learning and Policy Diffusion. *American Political Science Review*, 102(3):319–332.

A Quantification of the global benefits of diffusion

A.1 Back-of-the-envelope calculations

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. We do so in two ways, first with a back-of-the-envelope calculation and then with Monte Carlo simulations.

For the back-of-the-envelope calculation, we compare two counterfactual scenarios: scenario A in which country i adopts carbon pricing in year t and scenario B in which it does not do so. For both scenarios, we calculate the hazard of policy adoption at time $t+1$ for all countries $j \neq i$. The additional hazard that is due to policy diffusion from country i to country j can then be calculated as the difference between the hazards of the two scenarios.

Formally, for all countries $j \neq i$ we compare the two hazards (Equation 1)

$$h^A(t+1, X_{j,t}, W_{j,t}^A) = h_0(t+1) \exp\left(X_{j,t}\beta_X\right) \exp\left(W_{j,t}^A \beta_W\right) \tag{6}$$

and

$$h^B(t+1, X_{j,t}, W_{j,t}^B) = h_0(t+1) \exp\left(X_{j,t}\beta_X\right) \exp\left(W_{j,t}^B \beta_W\right) \tag{7}$$

For simplicity, we assume that in scenario B, no country has adopted the policy at time t, i.e. $Y_{j,t} = 0 \; \forall j$, which implies that the spatial lag is zero for all countries, i.e. $W_{j,t}^A = 0 \; \forall j$ (Equation 3). Furthermore, we assume that after adjusting for covariates all countries j have the same baseline hazard, i.e. $h_0(t+1) \exp\left(X_{j,t}\beta_X\right) = h_0^*(t+1) \; \forall j$.

With these assumption, we can calculate the additional hazard in country j from policy adoption in country i as

$$\begin{aligned} \Delta h_{j,t+1} &= h^B(t+1, X_{j,t}, W_{j,t}^B) - h^A(t+1, X_{j,t}, W_{j,t}^A) \\ &= h_0^*(t+1) \left[\exp\left(W_{j,t}^B \beta_W\right) - 1\right] \end{aligned} \tag{8}$$

Because in scenario B only country i adopts the policy, i.e. $Y_{j,t} = 0 \; \forall j \neq i$, we can calculate the spatial lag as (Equation 3)

$$W_{j,t}^B = \frac{w_{i,j,t}}{\sum_{i=1, i \neq j}^{N_c} w_{i,j,t}} \forall j \tag{9}$$

The total indirect emission reductions due to diffusion can then be calculated as

$$R_{i,t+1}^{\text{indirect}} = r \sum_{j \neq i} \Delta h_{j,t+1} E_{j,t+1} \tag{10}$$

where $E_{j,t}$ are the total CO2 emissions of country j in year t and r is the rate at which emissions are reduced per year. We compare these indirect emission reductions with the direct emission reductions obtained with similar assumptions

$$R_{i,t+1}^{\text{direct}} = r E_{i,t+1} \tag{11}$$

For these calculations, we use actual CO2 emissions in the year 2019, which is the last year prior to the pandemic with Sars-CoV-2.

For the back-of-the-envelope calculations we only quantify emission reductions in year $t + 1$. Subsequent emissions reductions, including those from further diffusion of the policy, are quantified with Monte Carlo simulation as described in the following.

A.2 Monte-Carlo simulations

The Monte Carlo simulations are based on Equations 6 and 7. We start the simulations in the year $t = 1988$ and assume that no country has adopted the policy prior to that. For every country i, we then conduct simulations for the same two scenarios A and B as above: in scenario A, no country adopts the policy in the year $t = 1988$. In scenario B, only country i adopts the policy at $t = 1988$.

For both scenarios, we then simulate adoption and diffusion of climate policies from the year 1989 onwards. To do so, at every timestep $1989 \leq t \leq 2021$ 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 timestep.

We conduct 5,000 simulations for every country for scenario B and 10,000 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, $P_{i,j,t}^B$ with $\sum_{t=1988}^{2021} P_{i,j,t}^B = 1 \ \forall i, j$. The simulations of scenario A result in another matrix $P_{j,t}^A$ that again satisfies $\sum_{t=1988}^{2021} P_{j,t}^A = 1 \ \forall j$. Because there is no difference in the counterfactuals, this matrix $P_{j,t}^A$ 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. The indirect emission reductions again refer to emisson reductions that can be

attributed to the diffusion of the policy from country i to other countries and onwards. For both direct and indirect emission reductions, we use actual emission growth rates and subtract the effect of the carbon pricing policy from them. Formally, for every country i we calculate the direct emission reductions from 1988 - 2019 of implementing the policy in year 1988 as

$$\hat{R}_{i,2019}^{\text{direct}} = \sum_{t=1988}^{2019} \left[E_{i,t} - E_{i,1988} \prod_{l=1988}^{t} (1 + g_{i,l} - r) \right] \tag{12}$$

where $g_{j,t}$ is the actually observed 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 the indirect emission reductions that can be attributed to policy diffusion from country i to other countries, we use the probabilities of policy adoption $P_{j,t}^{A}$ and $P_{i,j,t}^{B}$ of the scenarios A and B respectively. In mathematical terms, we take the difference between the expected emission reductions between the two scenarios:

$$\hat{R}_{i,2019}^{\text{indirect}} = \sum_{j \neq i} \left[\sum_{\xi=1988}^{2019} \left[\left(P_{i,j,\xi}^{B} - P_{j,\xi}^{A} \right) \left[\sum_{t=1988}^{\xi} E_{j,t} + E_{j,\xi} \prod_{l=\xi}^{2019} (1 + g_{j,l} - r) \right] \right] \right] \tag{13}$$
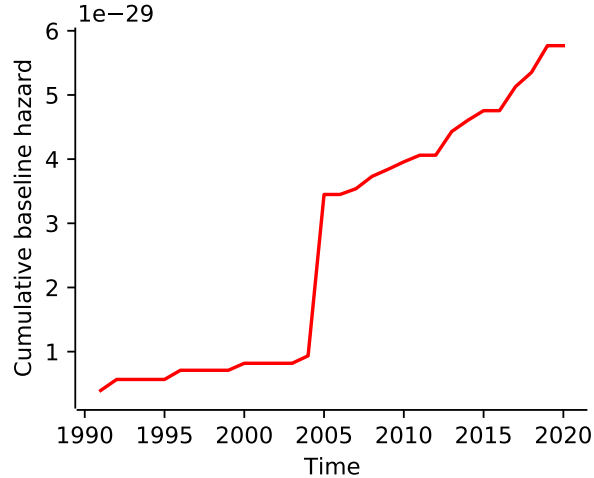
B   Additional results

Figure 7. Cumulative baseline hazard of the Cox proportional hazard model in Equation 1 with six covariates. Estimated coefficients of this model are shown in Column 2 in Table 2.
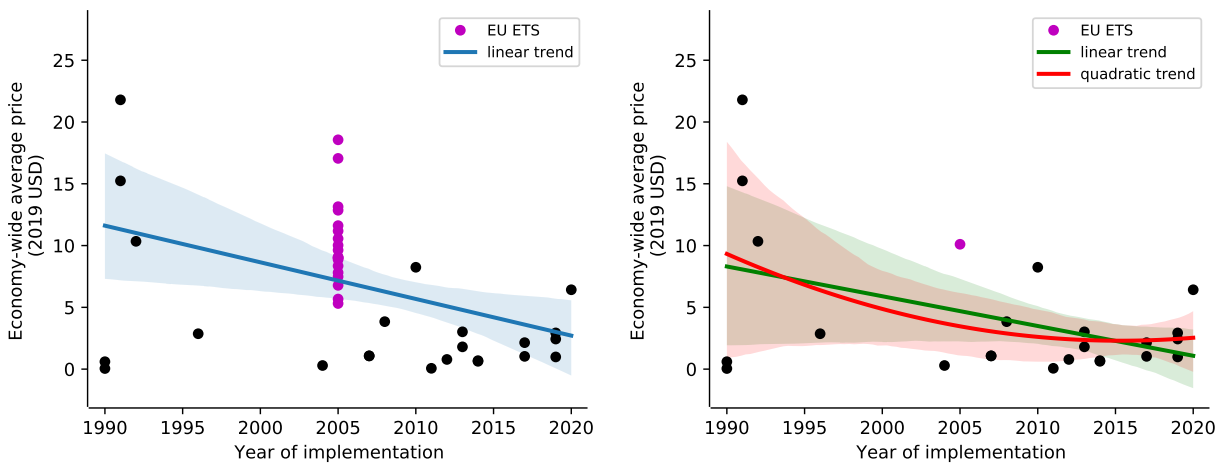
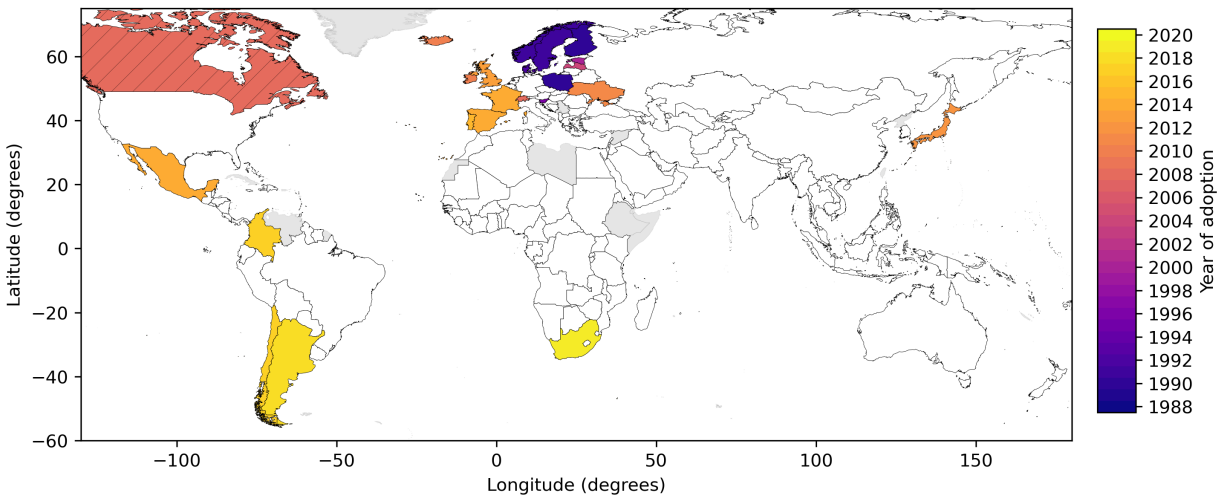Figure 8. Scatter plot of economy-wide emission-weighted average carbon prices over time.

Figure 9. Time of adoption of the first carbon tax policy by country. Hashes indicate countries in which the first policy was adopted at the subnational level.
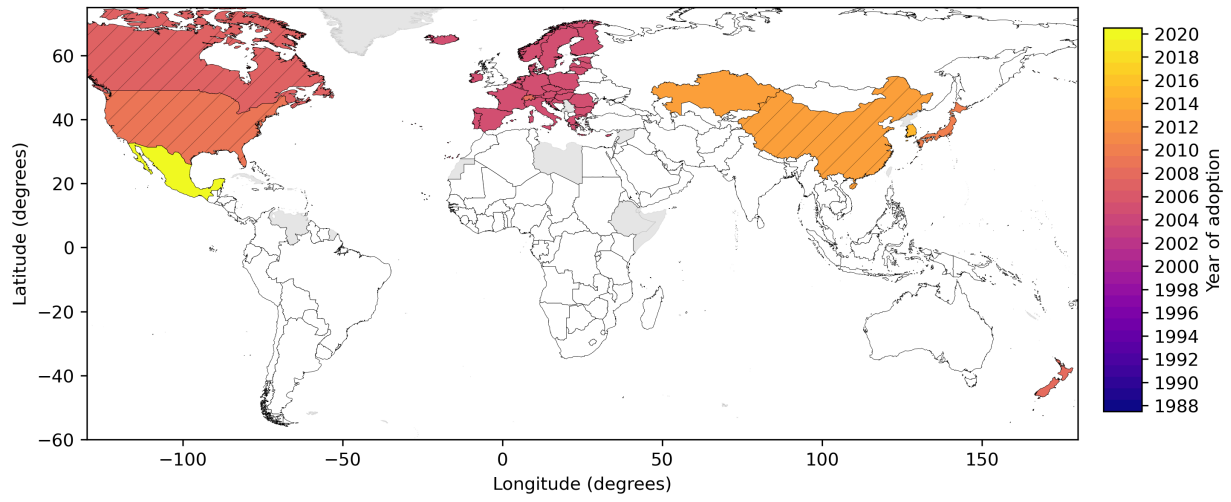
Figure 10. Time of adoption of the first ETS policy by country. Hashes indicate countries in which the first policy was adopted at the subnational level.
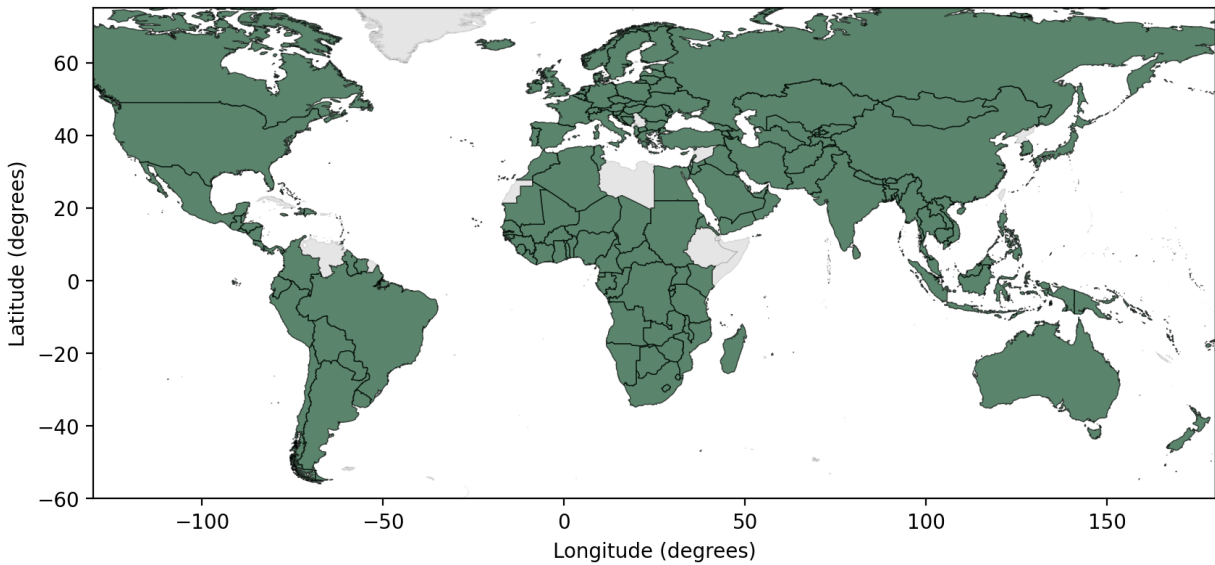

Figure 11. Map of the sample of 179 countries used in this study.

33

Table 4. Results of estimation with different lag times.

Policy:	Carbon price				
Proximity metric:	Gravity				
Lag time:	1	2	3	4	5
Column:	1	2	3	4	5
Spatial lag of carbon pricing	6.7053***	6.3749***	6.5309***	6.5649***	6.9365***
	(1.3469)	(1.3561)	(1.4128)	(1.4821)	(1.5248)
GDP per capita PPP	11.5662***	11.0535***	11.2919***	10.1004***	9.7194***
	(3.6787)	(3.5089)	(3.3388)	(3.0844)	(2.9444)
GDP per capita PPP sq.	-0.5529***	-0.5279***	-0.5368***	-0.4788***	-0.4623***
	(0.1895)	(0.1806)	(0.1730)	(0.1610)	(0.1535)
GDP per capita PPP growth	2.0597	2.0058	8.1873***	5.6635***	3.9481
	(3.1010)	(4.2026)	(1.6269)	(2.1262)	(3.8003)
Export share	-0.0054	-0.0054	-0.0069	-0.0057	-0.0042
	(0.0045)	(0.0043)	(0.0044)	(0.0045)	(0.0041)
Services share of GDP	0.0271**	0.0251*	0.0230*	0.0219*	0.0206*
	(0.0136)	(0.0135)	(0.0124)	(0.0123)	(0.0115)
Emissions CO2 per GDP	-0.0121	-0.0083	-0.0049	-0.0197	-0.0008
	(0.1140)	(0.1107)	(0.1203)	(0.1013)	(0.0976)
Time at risk	5277	5277	5277	5277	5277
log-likelihood	-177.5	-179.5	-177.3	-180.3	-182.1
AIC	369.1	373.0	368.6	374.6	378.1
N	5252	5230	5203	5174	5142

Notes: Standard errors clustered by country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
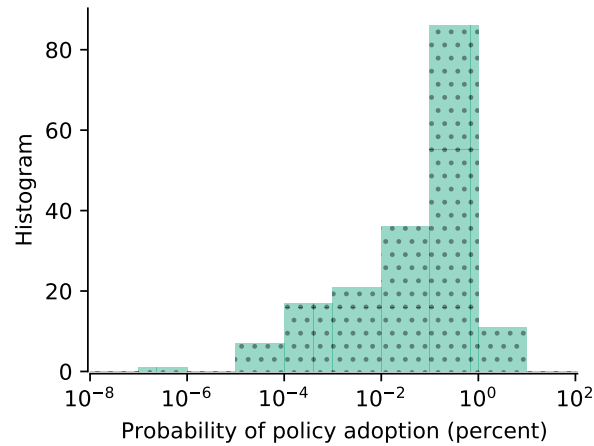

Figure 12. Histogram of estimated baseline hazard adjusted for covariates in 2020 for the sample of 179 countries. Median and mean values are 0.14 and 0.32 percent, respectively. Probabilities of 0.32, 1, and 5 percent imply a cumulative probability of policy adoption by the end of a period of 30 years of 9, 26, and 79 percent, respectively.

PUBLICATIONS