Climate Change Policy:
Dynamics, Strategy, and the Kyoto Protocol[1]

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Abstract

International environmental agreements are difficult to forge owing to a "tragedy of the commons" problem and free riding. In this paper, we use machine learning and structural econometric modeling to develop and estimate a structural econometric model of the dynamic game among countries making decisions regarding whether to adopt a national greenhouse gas emissions target under the Kyoto Protocol, what target level to adopt, and how much CO_2 to emit. We use the estimated parameters to simulate the effects of counterfactual scenarios on climate change policy, emissions, economic outcomes, and welfare. Results are consistent with the presence of a free-rider problem, and also suggest that the Kyoto Protocol may have had some unintended or even perverse effects. Nevertheless, our counterfactual simulations provide evidence that having the US and the EU as members of the Conference of the Parties (COP) is important for reducing aggregate CO_2 emissions and for reducing mean temperatures in EU countries, but at a cost to GDP. Our results have important implications for climate policy decision-making and the design of international environmental agreements.

Keywords: climate change policy, structural econometric model, dynamic game, international environmental agreements, Kyoto Protocol
***JEL* codes:** Q58, Q54, Q48
This draft: September 2020

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1. Introduction

Climate change is one of the major international environmental challenges facing nations (Nordhaus, 2018), and has the potential to cause catastrophic damages worldwide (Ramanathan et al., 2016). Scientific and economic consensus points to the need for a credible and cost-effective approach to address the threat of global climate change (Barrett and Stavins, 2003). At least since Nordhaus (1977)'s presentation at the 1976 American Economic Association annual meeting, the analysis and management of climate change has been recognized as an important economic problem that requires social science as much as it requires natural science (Hsiang and Kopp, 2018).

Addressing climate change is difficult owing to a "tragedy of the commons" problem. Greenhouse gas emissions from any one country contribute to the total stock of global greenhouse gases in the earth's atmosphere, which affects all countries. Efforts by any one country to reduce its own greenhouse gas emissions are costly and require substantial changes to that country's energy, transportation, and industrial sectors. In the absence of a supranational institution that is endowed with the appropriate jurisdiction to enforce a global environmental target, each country sets its own climate policy based on its own interests, priorities, benefits, and costs, but generally does not internalize the benefits and costs of its climate policy on other countries.[2] As a result, each country has an incentive to free ride on the climate policy of other countries.

The fates of transboundary environmental problems such as global climate change therefore depend on how nation states interact with one another. Shared environments will be safeguarded if international cooperation succeeds, but degraded or even destroyed if it fails (Barrett, 2016). Despite great progress in scientific and economic understanding of climate change, however, it has proven difficult to forge international agreements because of free riding (Nordhaus, 2015). One primary international environmental agreement is the Kyoto Protocol, which establishes legally binding obligations for countries to reduce their greenhouse gas emissions below 1990 levels.

In this paper, we use machine learning and structural econometric modeling to develop and estimate a structural econometric model of the dynamic game among countries making dynamic and strategic decisions regarding whether to adopt a national greenhouse gas emissions target

[2] Even if climate policy could be delegated to a supranational environmental authority, such an authority would face a dynamic inconsistency problem that leads to welfare losses (Pichler and Sorger, 2018).

under the Kyoto Protocol, what target level to adopt, and how much CO_2 to emit. These climate policy decisions are dynamic because they are forms of investments under uncertainty (Dixit and Pindyck, 1994), and because they entail incurring costs in the present to avoid potentially greater damages in the future. These climate policy decisions are strategic because the payoffs to a country from its climate policy decisions depend on the climate policy decisions of other countries in the world. Understanding how climate policy in one country is influenced by climate policies in other countries is important for the analysis of, and progress on, action on climate change (Stern and Rydge, 2012). We use the parameters estimated from our structural econometric model of the dynamic game among countries to simulate the effects of counterfactual scenarios on climate change policy, emissions, economic outcomes, and welfare.

Applying a dynamic structural modeling framework to analyze climate policy decisions has several advantages. First, unlike reduced-form models, a structural econometric model of a dynamic game explicitly models the dynamic and strategic dimensions of countries' climate policy decisions. Second, a structural model enables us to estimate the impact of each state variable on the expected payoffs from climate policy decisions; we therefore estimate parameters that have direct economic interpretations. Third, we can use the estimated parameters to simulate the effects of counterfactual scenarios on climate change policy, emissions, economic outcomes, and welfare.

Our results are consistent with the presence of a free-rider problem, and also suggest that the Kyoto Protocol may have had some unintended or even perverse effects. Nevertheless, results of our counterfactual simulations, which enable us to assess the combined effects of all the different channels, mechanisms, feedback effects, and feed-forward effects on the trajectories for the state and actions variables, provide evidence that having the US and the EU as members of the Conference of the Parties (COP) is important for reducing aggregate CO_2 emissions and for reducing mean temperatures in EU countries, but at a cost to GDP. CO_2 emissions will increase if either US or the EU exits COP. Mean temperatures for EU countries and for countries that adopt a Kyoto target will increase if either the US or the EU exits COP. Non-EU countries will benefit in terms of higher GDP if the EU exits COP; countries that do not adopt a Kyoto target will benefit in terms of higher GDP if the US exits COP. Our results have important implications for climate policy decision-making and the design of international environmental agreements.

The balance of our paper proceeds as follows. In Section 2 we provide background information about the Kyoto Protocol. We review the previous literature in Section 3. We describe our model of the dynamic climate policy game in Section 4, our data in Section 5, and our econometric estimation in Section 3. We present our results in Section 7. In Section 8, we use our estimated structural econometric model to analyze counterfactual scenarios. Section 9 concludes.

2. The Kyoto Protocol

The United Nations Framework Convention on Climate Change (UNFCCC) is an international environmental treaty that was produced at the United Nations Conference on Environment and Development (UNCED), informally known as the Earth Summit, which was held in Rio de Janeiro in June 1992. The objective of the treaty is to stabilize greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system (Minerva, 2016). The parties to the convention have met annually from 1995 in Conference of the Parties (COP) meetings to assess progress in dealing with climate change (Minerva, 2016).

The treaty itself sets no mandatory limits on greenhouse gas emissions for individual countries and contains no enforcement mechanisms. In that sense, the treaty is considered legally non-binding. Instead, the treaty provides for updates (called "protocols") that would set mandatory emission limits (Minerva, 2016).

The principal update is the Kyoto Protocol, which has become much better known than the UNFCCC itself. Adopted during COP 3 in Kyoto, Japan in December 1997, the Kyoto Protocol established legally binding obligations for Annex I countries to reduce their greenhouse gas emissions below 1990 levels over a first commitment period, which started in 2008 and ended in 2012 (Kyoto Protocol, 1997; Minerva, 2016). Annex I countries are classified as industrialized (developed) countries and economies in transition.

During COP 18, which took place in Doha, Qatar in November 2012, the Doha Amendment was made to the Kyoto Protocol for Annex I countries to reduce their greenhouse gas emissions below 1990 levels over a second commitment period, which extends from 2012 until 2020. Unfortunately, owing to a lack of commitments from United States, Canada, Japan, Russia, and New Zealand; as well as from developing countries such as China (the world's largest emitter), India, and Brazil, who are not subject to emissions reductions under the Kyoto Protocol, the Doha Amendment to the Kyoto Protocol is limited in scope to 15% of global carbon dioxide emissions

(Doha Climate Gateway, 2012). Moreover, the Doha Amendment to the Kyoto Protocol has not yet entered into force; as of February 18, 2020, 137 Parties have deposited their instrument of acceptance, which still falls short of the 144 instruments of acceptance (representing three fourths of the Parties to the Kyoto Protocol) required (UNFCCC, 2020).

Countries in the European Union Emissions Trading System (EU ETS), a cap and trade market which started in 2005. can fulfill their 1997 and 2012 Kyoto targets for greenhouse gas emissions by either reducing their emissions or buying emissions credit from other countries. This market is also used to fulfill European Union (EU) emissions reduction targets which are not included in global agreements (European Commission, 2020a).

Table B1 in Appendix B presents the Kyoto targets adopted during COP 3 and COP 18.

Many in the global community had hoped that the Kyoto Protocol would eventually grow into a universal commitment to reduce emissions by some percent below 1990 levels, and that this would translate into a uniform price on carbon; instead, there have been repeated negotiation failures (Cramton, Ockenfels and Stoft, 2015b). Many now agree that the Kyoto Protocol has been largely ineffective (Auffhammer et al., 2016).

Some argue that the Kyoto approach of attempting to negotiate commitments to national emission quantities will likely doom any negotiation process because it fails to inhibit free riding (Cramton, Ockenfels and Stoft, 2015b). Stiglitz (2015) argues that the Kyoto approach, based on dividing up emission rights, has an inherent problem in that such rights could easily reach a monetary value of over a trillion dollars a year, and are therefore difficult to allocate fairly. Another issue with international climate agreements is that they do not cover all countries of the world, and therefore lead to carbon leakage (van der Ploeg and Withagen, 2017).

Barrett and Stavins (2003) assess the Kyoto Protocol as well as alternative policy architectures for international climate change agreements, and find that those approaches that offer cost-effective mitigation are unlikely to induce significant participation and compliance, while those approaches that are likely to enjoy a reasonably high level of implementation by sovereign states are sorely lacking in terms of their anticipated cost effectiveness. Aldy and Stavins (2007) examine the merits of six alternative international architectures for climate policy. Aldy and Stavins (2010) examine a uniquely wide range of core issues that must be addressed if the world is to reach an effective agreement on a successor regime to the Kyoto Protocol.

During COP 21, which was held in 2015 in Paris, the Paris climate agreement was negotiated. While it achieved a broad base of participation among the countries of the world, the Paris climate agreement still failed to achieve adequate collective ambition of the individual nationally determined contributions (Mehling, Metcalf and Stavins, 2017). In addition, United States President Donald Trump subsequently announced on June 1, 2017 that he would withdraw the United States from the Paris climate agreement.[3] Stavins (2017) analyzes the economics and politics of President Trump's announcement, and finds that it would be damaging both to the United States and the world for the United States to withdraw from the Paris climate agreement, a sentiment echoed by others (Bordoff, 2017; Zhang, Chao, Zheng, and Huang, 2017; Zhang, Dai, Lai, and Wang, 2017).

3. Literature Review

3.1. International environmental agreements

Our paper builds on several strand of previous literature. One strand of literature upon which we build is the literature on international environmental agreements (Karp and Zhao, 2009; Kolstad and Ulph, 2011; Harstad, 2012; Hong and Karp, 2012; Karp, 2012; Tirole, 2012; Barrett, 2013; Cramton, Ockenfels and Stoft, 2015a; Eichner and Pethig, 2015; Nordhaus, 2015; Barrett, 2016; Chander, 2017; Eichner and Pethig, 2017; Goeschl and Perino, 2017; Kersting et al., 2017; Mason, Polasky and Tarui, 2017; Takashima, 2017; Ansink, Weikard and Withagen, 2018; Diamantoudi and Sartzetakis, 2018; Eichner and Pethig, 2018; Finus and Al Khourdajie, 2018; Kersting, 2018; Masoudi and Zaccour, 2018; Nyborg, 2018). Studies of international environmental agreements generally involve developing cooperative or non-cooperative game-theoretic models of international cooperation on climate change and using them to analyze the conditions for and properties of a self-enforcing international climate agreement in which all countries find it in their self-interest to abide by the agreement, as well as the stability of global climate cooperation. For example, Barrett (2016) presents simple game-theoretic models showing whether and how international treaties and related institutions can change incentives, aligning states' self-interests with their collective interests.

[3] According to the terms of the agreement, the earliest the United States would be able to formally extricate itself is in 2020 (Jaffe and Scheitrum, 2019).

It has been argued that carbon leakage problems that arise when international climate agreements do not cover all countries of the world (van der Ploeg and Withagen, 2017; Böhringer, Rosendahl and Schneider, 2018) can be overcome to an extent by border tax adjustments or so-called "climate clubs" that punish third non-participating countries with a stiff trade tariff of around 5% (Nordhaus, 2015). For example, in response to US President Donald Trump's announcement to pull the US out of the Paris Agreement, key remaining parties to the Agreement such as Europe and China might call for carbon tariffs on US imports as a sanctioning instrument to coerce US compliance (Böhringer and Rutherford, 2017). Given the possibility of retaliatory tariffs across all imported goods, carbon tariffs might not constitute a credible threat for the US, however: a tariff war with its main trading partners China and Europe might make the US worse off than compliance with the Paris Agreement but China, in particular, should prefer US defection to a tariff war (Böhringer and Rutherford, 2017).

Chan et al. (2018) review and synthesize the literature on international climate change cooperation and identify key policy implications, as well as those findings most relevant for the research community. Zakerinia and Lin Lawell (2020) review models of cooperative and non-cooperative behavior that have been developed to analyze climate change policy and international environmental agreements.

3.2. Dynamic games between countries

A second strand of literature upon which we build is that on the dynamic pollution game between countries. Mason (2017) investigates the dynamic game between a country that imports a commodity whose production contributes to a stock pollution, such as electricity, with a country that produces that commodity. Frutos and Martin-Herrain (2019) analyze a transboundary pollution differential game where pollution control is spatially distributed among a number of agents with predetermined spatial relationships. Grafton, Kompas and Long (2017) analyze a differential game of climate change mitigation in the presence of both agents motivated by Kantian ethics and conventional Nashian agents. Kyle, Ridley and Zhang (2017) address the question of how governments respond to other governments when providing a global public good.

Unilateral climate policies involve the risk of carbon leakage, driven by price changes in the oil market and other international markets (Böhringer, Rosendahl and Schneider, 2018). Böhringer, Rosendahl and Schneider (2014) show that OPEC may have an incentive to increase the oil price as a response to EU climate policy, thereby retaining resource rents and turning carbon leakage through the oil market negative. Böhringer, Rosendahl and Schneider (2018) show that the coalition or cartel size critically affects the scope for rent seeking and leakage reduction.

Hambel and Kraft (2018) develop a dynamic game-theoretical model with multiple countries that allows for international trade between the countries. List and Mason (2001) use a dynamic model with asymmetric players to explore the whether environmental regulations for transboundary pollutants be carried out locally or centrally. Kakeu and Gaudet (2011) model a game among countries who behave in such a way as to improve, via their economic strength, the probability that they will attain the hegemonic position on the world stage; and analyze the effect of the distribution between poorly endowed and richly endowed countries on global pollution. Kakeu and Johnson (2018) analyze information exchange in a model of transnational pollution control in which countries use private information in independently determining their domestic environmental policies. Geisendorf (2018) update the multi-agent "battle of perspectives" climate-economic model. Harrison and Lagunoff (2017) model dynamic mechanisms for global commons whereby countries value both consumption and conservation of an open access resource and the optimal quota maximizes world welfare subject to being implementable by perfect Bayesian equilibria. To achieve Pareto optimality despite disparate cheap-riding incentives in providing for climate change mitigation, Chen and Zeckhauser (2018) propose a Cheap-Riding Efficient equilibrium. Brock and Xepapadeas (2019) develop and analyze a non-cooperative framework with polar amplification, where regions decide emissions by maximizing own welfare.

3.3. Climate change economics

A third strand of literature upon which we build is that on the economics of climate change. The economically efficient way to reduce greenhouse gas emissions is to reduce emissions to the point that the marginal benefits of the reduction equal its marginal costs. This can be implemented by a Pigouvian tax, for example a carbon tax where the tax rate is the marginal benefit of the emissions reduction or, equivalently, the monetized damages from emitting an additional ton of CO_2. The carbon externality will then be internalized and the market will find cost-effective ways to reduce emissions up to the amount of the carbon tax (Gillingham and Stock, 2018).

Many economists would argue that a global carbon tax is the best policy for managing greenhouse gas emissions, since emissions tax systems are relatively straightforward, cost effective and can generate revenues used to offset other distortionary taxes (McEvoy and McGinty, 2018). Gollier and Tirole (2015) argue that, because the free riding generated by the lack of collective action is aggravated by concerns about leakages and by the desire to receive compensation in future negotiations, the climate change global commons problem will be solved only through coherent carbon pricing. Stiglitz (2015) shows that a low-carbon economy could be achieved through the imposition of a moderate carbon price, which would raise substantial revenue and allow a reduction in other taxes, thereby keeping the deadweight loss small. Allowing for an ethical discount rate and a higher market discount rate and for a wide range of sensitivity exercises including damage uncertainty, van der Ploeg and Rezai (2019b) show that pricing carbon is the robust response under rising climate scepticism. van der Ploeg and Rezai (2019a) present a simple integrated assessment framework that gives rules for the optimal carbon price, transition to the carbon-free era, and stranded carbon assets.

Weitzman (2015) finds that while it is difficult to resolve the global warming free-rider externality problem by negotiating many different quantity targets, negotiating a single internationally-binding minimum carbon price counters self-interest by incentivizing agents to internalize the externality: each agent's extra cost from a higher emissions price is counter-balanced by that agent's extra benefit from inducing all other agents to simultaneously lower their emissions in response to the higher price. Weitzman (2014) demonstrates that under some conditions the globally efficient tax rate can be implemented through a majority voting rule. McEvoy and McGinty (2018) examine a uniform emissions tax system in the framework of an international environmental agreement in which only countries that voluntarily participate are subject to the tax; and find that by ignoring the participation decision and assuming commitment by all parties, the efficiency gains from a uniform emissions tax system are overstated.

Wagner and Weitzman (2015) explore the likely repercussions of a hotter planet, and explain climate change as a risk management problem on a global scale. Heal (2017) reviews the economic characteristics of the climate problem, including the choice of discount rates, risk and uncertainty/ambiguity, and the role of integrated assessment models in analyzing policy choices. Nordhaus and Moffat (2017) review studies that estimate the global economic impacts of climate change, including Tol (2009, 2014). Kolstad and Moore (2020) review methods that have been used to statistically measure the effect of climate on economic value, using historic data on weather, climate, economic activity and other variables. Auffhammer et al. (2016) discuss the economics of climate change, and cost-effective and efficient climate policies. Burke et al. (2016) discuss opportunities for advances in climate change economics. Auffhammer (2018) discusses how economists think about parameterizing damage functions and quantifying the economic damages of climate change. Gillingham and Stock (2018) review the costs of various technologies and actions aimed at reducing greenhouse gas emissions. Using the updated DICE model, Nordhaus (2018) finds that it is unlikely that nations can achieve the 2°C target of international agreements, even if ambitious policies are introduced in the near term. Cai and Lontzek (2019) show that the social cost of carbon is substantially affected by both economic and climate risks, and is a stochastic process with significant variation.

Datta and Somanathan (2016) examine climate policy and innovation when the government cannot commit to the level of a policy instrument before R&D occurs. Lemoine and Rudik (2017) decompose the channels through which uncertainty affects climate change policy. Moreno-Cruz, Wagner and Keith (2018) develop an optimal control model to analyze four different climate policies: mitigation, adaptation, carbon geoengineering, and solar geoengineering. Aldy, Chen and Pizer (2019) draw from the economics and machine learning literatures to develop country-specific emission forecasts to enable an assessment and comparison of expected mitigation effort by nearly every country participating in the Paris Agreement.

3.4. Dynamic structural econometric models

A fourth strand of literature upon which we build is that on dynamic structural econometric modeling. Rust's (1987, 1988) seminal papers develop a dynamic structural econometric model using nested fixed point maximum likelihood estimation. This model has been adapted for many applications, including bus engine replacement (Rust, 1987), nuclear power plant shutdown (Rothwell and Rust, 1997), water management (Timmins, 2002), insecticide treated nets (Mahajan, Michel and Tarozzi, 2011), agriculture (Scott, 2013), air conditioner purchases (Rapson, 2014), wind turbine shutdowns and upgrades (Cook and Lin Lawell, 2020), copper mining decisions (Aguirregabiria and Luengo, 2016), crop disease control (Carroll et al., 2020b), vehicle scrappage programs (Li and Wei, 2013), the adoption of rooftop solar photovoltaics (Feger et al., 2017; Langer and Lemoine, 2018), supply chain externalities (Carroll et al., 2020a), organ transplant decisions (Agarwal et al., forthcoming), vehicle ownership and usage (Gillingham et al., 2019), pesticide spraying decisions (Yeh, Gómez and Lin Lawell, 2020; Sambucci, Lin Lawell and

Lybbert, 2020), environmental regulations (Blundell, Gowrisankaran and Langer, 2020), hunting permits (Reeling, Verdier and Lupi, 2020), agroforestry trees (Oliva et al., 2020), the electricity industry (Cullen, 2015; Cullen et al., 2017; Weber, 2019), consumer stockpiling (Ching and Osborne, 2020), urban travel demand (Donna, 2019), and agricultural productivity (Carroll et al., 2019). We also build on the literature on dynamic structural econometric models.

Structural econometric models of dynamic games include a model developed by Pakes, Ostrovsky and Berry (2007), which has been applied to the multi-stage investment timing game in offshore petroleum production (Lin, 2013), to ethanol investment decisions (Thome and Lin Lawell, 2020), and to the decision to wear and use glasses (Ma, Lin Lawell and Rozelle, 2020); a model by Aguirregabiria and Mira (2007), which has been applied to entry, exit, and growth in oligopoly retail markets Aguirregabiria et al. (2007); a model developed by Bajari et al. (2015) and applied to ethanol investment (Yi and Lin Lawell, 2020a; Yi and Lin Lawell, 2020b); and models by Pesendorfer and Schmidt-Dengler (2008), Aguirregabiria and Mira (2010), Srisuma and Linton (2012), and Dearing and Blevins (2019).

Structural econometric models of dynamic games have also been applied to fisheries (Huang and Smith, 2014), dynamic natural monopoly regulation (Lim and Yurukoglu, 2018), Chinese shipbuilding (Kalouptsidi, 2018), industrial policy (Barwick, Kalouptsidi and Zahur, 2020), and coal procurement (Jha, 2020), and preemption (Fang and Yang, 2020).

We also build on the emerging literature combining machine learning with structural econometric models. Chernozhukov et al. (2018) develop double or debiased machine learning (DML) methods for treatment and structural parameters. Semenova (2018) proposes a novel two-stage estimator for the set-identified structural parameter that incorporates a high-dimensional state space into the dynamic model of imperfect competition.

The structural econometric model of a dynamic game we use builds on a model developed by Bajari, Benkard and Levin (2007), which has been applied to the cement industry (Ryan, 2012; Fowlie, Reguant and Ryan, 2016), to the production decisions of ethanol producers (Yi, Lin Lawell and Thome, 2020), to migration decisions (Rojas Valdés, Lin Lawell and Taylor, 2018; Rojas Valdés, Lin Lawell and Taylor, 2020), to the world petroleum market (Kheiravar, Lin Lawell and Jaffe, 2020), to the global market for solar panels (Gerarden, 2019), to calorie consumption (Uetake and Yang, 2018), to the digitization of consumer goods (Leyden, 2019), and to open access groundwater extraction (Sears, Lin Lawell and Walter, 2020).

4. Dynamic Climate Policy Game

We model the dynamic game among countries making dynamic and strategic decisions regarding whether to adopt a national greenhouse gas emissions target under the Kyoto Protocol, what target level to adopt, and how much CO_2 to emit. The actions a_i of each country *i*, which represent country *i*'s decisions regarding Kyoto target adoption the level of the Kyoto target, are assumed to be functions of a set of state variables and private information:

$$a_i = \sigma_i(s, \varepsilon_i), \tag{1}$$

where *s* is a vector of publicly observable state variables and ε_i is a vector of private information shocks to country *i* which are not observed by either other countries or the econometrician.

As explained below, we choose our state variables *s* based on the machine learning results and also on data availability considerations. The state variables *s* include the following country-level state variables: GDP; population; whether the country is below poverty, CO_2 emissions; CO_2 emissions from electricity and heat production; energy intensity level of primary energy; mean temperature; whether the country is a member of the European Union; and whether the country is a member of the EU Emissions Trading System (EU ETS). The state variables *s* also include the following global state variables: world oil price and global CO_2 concentration.

We assume that the per-period payoff function $u_i(\cdot)$ for each country *i* is given by:

$$u_i(a_i, a_{-i}, s_i, \varepsilon_i) = \Phi(a_i, a_{-i}, s_i)'\theta + \varepsilon_i, \tag{2}$$

where $\phi(a, s_i)$ is a vector of terms in the per-period payoff function of the same length as the parameter vector θ .

Let $\sigma(s)$ represent the strategies of all the countries in the world, conditional only on the publicly observable state variables *s*, after integrating over the private information shocks ε_i .

The value function for each country *i* can be represented by:

$$V_i(s; \sigma(s), \theta, \varepsilon_i) = \max_{a_i} u_i(a_i, \sigma_{-i}(s), s_i, \varepsilon_i) + \beta V_i^c\left(s, a_i, \sigma_{-i}(s)\right), \tag{3}$$

where the continuation value $V_i^c\left(s, a_i, \sigma_{-i}(s)\right)$ is the expected value of the value function next period conditional on the state variables and strategies in the current period:

$$V_i^c\left(s,a_i,\sigma_{-i}(s)\right)=\int E_{\varepsilon_i'}V_i(s';\sigma(s'),\theta,\varepsilon_i')dp\left(s';s,a_i,\sigma_{-i}(s)\right) \tag{4}$$

where s' is the vector of next period's state variables, and where $p\left(s';s,a_i,\sigma_{-i}(s)\right)$ is the conditional probability of state variable s' given the current state s, country i's action a_i, and the strategies $\sigma_{-i}(s)$ of all other countries.

We assume that each country optimizes its behavior conditional on the current state variables, other countries' strategies, and its own private shocks, which results in a Markov perfect equilibrium (MPE). The optimal strategy $\sigma_i^*(s)$ for each country i should therefore satisfy the following condition for all state variables s and alternative strategies $\tilde{\sigma}_i(s)$:

$$V_i(s;\sigma_i^*(s),\sigma_{-i},\theta,\varepsilon_i)\geq V_i(s;\tilde{\sigma}_i(s),\sigma_{-i},\theta,\varepsilon_i)\,. \tag{5}$$

Let $V_i(s;\sigma(s),\theta)$ denote the expected value of the value function:

$$V_i(s;\sigma(s),\theta)\equiv E[V_i(s;\sigma(s),\theta,\varepsilon_i)]\,. \tag{6}$$

Since the value function is linear in the unknown parameters θ , the expected value of the value function can be written as:

$$V_i(s;\sigma(s),\theta)=E\left[\sum_{t=0}^{\infty}\beta^t\Phi_i(\sigma(s_t,\varepsilon_t),s_t,\varepsilon_{it})\right]'\theta=W_i(s;\sigma)'\theta\,, \tag{7}$$

where $\Phi_i(a,s,\varepsilon_i)$ is an M-dimensional vector of "basis functions" $\Phi_i^1(a,s,\varepsilon_i)$, $\Phi_i^2(a,s,\varepsilon_i)$, ..., $\Phi_i^M(a,s,\varepsilon_i)$ and where $W_i=[W_i^1\cdots W_i^M]'$ does not depend on the unknown parameters θ .

Applying equation (7) to the condition (5) for a Markov perfect equilibrium, the optimal strategy $\sigma_i^*(s)$ for each player i should satisfy the following condition for all state variables s and alternative strategies $\tilde{\sigma}_i(s)$:

$$W_i(s;\sigma_i^*(s),\sigma_{-i})'\theta\geq W_i(s;\tilde{\sigma}_i(s),\sigma_{-i})'\theta\,. \tag{8}$$

5. Data

We collect and construct an annual country-level panel data set of an extensive set of variables relating to economic factors, energy, the environment, climate, and country-level economic, demographic, political, and social characteristics that includes all the observations we could find and collect of all these variables for all the countries in the world. Appendix A presents and describes our entire annual country-level panel data set of all the variables we collected and analyzed.

As described below, we use several machine learning techniques to help us determine which variables from our large set of variables we want to focus on using. These machine learning techniques include least angle regression, LASSO, K-fold cross-validation and h-step ahead rolling cross-validation for LASSO, square-root LASSO, adaptive LASSO, ridge regression, elastic net, stepwise regression, and backward elimination.

Based on the machine learning results and also on data availability considerations, we choose to focus on the following 8 state variables s for our structural model: country-level GDP, PPP (trillion 2011\$); country-level population; whether the country is below poverty; country-level CO_2 emissions from electricity and heat production (% of total fuel combustion); country-level energy intensity level of primary energy (MJ/\$2011 PPP GDP); country-level mean temperature (Celsius); world oil price (2011\$/barrel); and global CO_2 concentration (ppm).

While our entire annual country-level panel data set of all the variables we collected and analyzed includes all the observations we could find and collect of all the variables for all the countries in the world, the countries and years in the balanced annual country-level panel data set we used for our structural model were selected so that all countries had data on all the state variables for all years in our panel data set.

For the structural econometric model, we use an annual country-level panel data set over the years 1996 to 2014 for 92 countries. The countries and years in our panel data set were selected so that all countries have data on all the action and state variables for at least the years 1996 (first year of data set), 1997 (Kyoto Protocol), and 2012 (Doha Amendment). All countries have data on all the state variables except country-level mean temperature for all years in our panel data set. We do not use data prior to 1995 since the first COP meeting was in 1995.

There are 40 Annex I countries in our data set, of which 15 countries are members of the European Union (15) countries throughout the entire 1996-2014 period, and 13 additional countries become members of the European Union during the 1996-2014 period, but after COP 3 takes place in Kyoto in 1997. Our data set includes all countries that are members of the EU at some point during the 1996-2014 period except Monaco and Liechtenstein, which are city-state countries with less than 40,000 populations each for which we only have data on their population, not any other state variables.

The 92 countries in the annual country-level panel data set that we use for our structural model are: Algeria, Armenia, Australia, Austria, Bahrain, Bangladesh, Belarus, Belgium, Benin, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Ecuador, Egypt, Estonia, Finland, France, Germany, Greece, Honduras, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Kuwait, Kyrgyzstan, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mauritius, Mongolia, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Nicaragua, Nigeria, Norway, Oman, Pakistan, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Senegal, Serbia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tanzania, Thailand, Togo, Tunisia, Turkey, Turkmenistan, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, and Zimbabwe.

We obtain country-level GDP, PPP (trillion 2011$) and country-level population from the World Bank World Development Indicators.

We designate a country as being below poverty in a particular year if the nominal GDP per capita in that country (in current US$) is below the nominal US federal poverty line for a one-person household for that year. The US federal line for a one-person household in each year is from the U.S. Department of Health & Human Services (2020). The nominal GDP per capita in each country in each year is from the World Bank World Development Indicators.

Our data for country-level CO_2 emissions (Mt); country-level CO_2 emissions from electricity and heat production (% of total fuel combustion); and country-level energy intensity level of primary energy (MJ/$2011 PPP GDP) come from the International Energy Agency (IEA). Negative values of CO_2 emissions from other sectors excluding residential buildings and commercial and public services may arise because there are some sinks (the IPCC Sink Categories) for negative emissions.

We extract country-level mean temperature (Celsius) from the National Oceanic and Atmospheric Administration (NOAA) Global Historical Climatology Network (GHCN) database.

For membership in the EU Emissions Trading System (EU ETS), the participants in the first phase of EU-ETS (2005-2007) were EU 27 countries, which are all of the countries in our data set that were members of the EU at one point during 1997-2013. Croatia is not part of EU 27 since it joined EU in 2014. In phase 2 (2008-2012), Norway, Iceland and Liechtenstein joined the EU ETS (on top of EU 27). Finally, for the third phase (2013-2020) Croatia also joined EU-ETS (European Commission, 2020b; Glowacki, 2020).

For the global CO_2 concentration (ppm), we use the NOAA Earth System Research Laboratory (ESRL) data base. For world oil price, we use annual average crude oil price (InflationData.com, 2020).

Summary statistics for our Kyoto target adoption, Kyoto target, and CO_2 emissions action variables in the data set we use in our structural model are presented in Table B2a, B2b, and B2c, respectively, in Appendix B. Table B2d in Appendix B presents the summary statistics of the sate variables in the data set we use in our structural model.

6. Econometric estimation

Finding a single equilibrium is computationally costly even for problems with a simple structure. In more complex problems – as in the case of our dynamic game among countries making dynamic and strategic decisions regarding whether to adopt a national greenhouse gas emissions target under the Kyoto Protocol, and what target level to adopt, where many agents and decisions are involved – the computational burden is even more important, particularly if there may be multiple equilibria. Bajari, Benkard and Levin (2007) propose a method for recovering the dynamic parameters of the payoff function without having to compute any single equilibrium. The crucial mathematical assumption to be able to estimate the parameters in the payoff function is that, even when multiple equilibria are possible, the same equilibrium is always played.

Building on the econometric model developed by Bajari, Benkard and Levin (2007), we estimate the structural econometric model in two steps. In the first step, we use econometrics and machine learning techniques to characterize the equilibrium policy functions for the countries' Kyoto target adoption and Kyoto target level decisions as well as the transition densities, and apply these techniques to our entire annual country-level panel data set of an extensive set of variables relating to economic factors, energy, the environment, climate, and country economic, demographic, political, and social characteristics that includes all the observations we could find and collect of all these variables for all the countries in the world.

We use several machine learning techniques to help us determine which variables from our large set of variables we want to focus on using. These machine learning techniques include least angle regression, LASSO, K-fold cross-validation and h-step ahead rolling cross-validation for LASSO, square-root LASSO, adaptive LASSO, ridge regression, elastic net, stepwise regression, and backward elimination.

Based on the machine learning results and also on data availability considerations, we choose to focus on the following 8 state variables s for our structural model: country-level GDP, PPP (trillion 2011$); country-level population; whether the country is below poverty; country-level CO_2 emissions from electricity and heat production (% of total fuel combustion); country-level energy intensity level of primary energy (MJ/$2011 PPP GDP); country-level mean temperature (Celsius); world oil price (2011$/barrel); and global CO_2 concentration (ppm).

In the second step, we apply a simulated minimum distance estimator to estimate the structural parameters θ using the optimality condition (8) for a Markov perfect equilibrium in order to estimate parameters that minimize profitable deviations from the optimal strategy $\sigma_i^*(s)$ estimated in the first step. Following methods in Hotz et al. (1994) and Bajari, Benkard and Levin (2007), we calculate the terms $W_i(s;\sigma(s))$ in the expected value $V_i(s;\sigma(s),\theta)$ of the value function via forward simulation.

We estimate the parameters θ by finding the parameters θ such that profitable deviations from the optimal strategy $\sigma_i^*(s)$ are minimized. The optimal strategy $\sigma_i^*(s)$ is given by the equilibrium policy functions estimated in the first step. The set of alternative strategies $\tilde{\sigma}_i(s)$ we consider are perturbations to the optimal strategy $\sigma_i^*(s)$ that shift the estimated policy function for the probability of adopting the Kyoto target upwards or downwards by up to 0.80; that shift the estimated policy function for the Kyoto target (in units of % change in emissions relative to 1990 level) upwards or downwards by up to 6; and that shift the estimated policy function for the % change in CO_2 emissions relative to 1990 level upwards or downwards by up to 0.06.

The structural parameters θ we estimate are the coefficients on each of the terms in the country-level per-period payoff function.

Since the per-period payoff is unit-less, and since the magnitudes of the coefficients and per-period payoff are not identified, we normalize the coefficient on "GDP PPP (trillion 2011$)" to be equal to 100. This enables us to pin down the magnitudes of the other parameters, since we can identify the relative magnitudes of all other coefficients with respect to the coefficient on GDP. This also enables us to interpret the per-period payoff in the same units as GDP PPP x 100 (i.e., in units of "10 billion 2011$"), and also interpret the coefficients in the per-period off as measuring trade-offs between GDP and other terms (such as CO_2 emissions).

We are unable to identify the coefficients on any terms that are exogenous and evolve exogenously, since their values would be the same regardless of action choice. If we have any terms in the per-period payoff that are state variables that are exogenous and evolve exogenously, then profitable deviations will be minimized (and 0) if the coefficients on all other terms are 0, since the values of the remaining exogenous terms in the per-period payoff would be the same regardless of action choice. In this case, all deviations yield the same PDV of the entire stream of per-period payoff as the optimal actions, so no deviations are profitable.

We are therefore unable to identify the coefficients on any state variables that are exogenous and evolve exogenously, since their values would be the same regardless of action choice. State variables that are exogenous and evolve exogenously include any characteristic of countries that are fixed over time and/or exogenous (such as the EU dummy, ETS dummy, Annex I dummy); any global variable that is exogenous and evolves exogenously (time trend, oil price (since we assume rational expectations), period in which COP3 Kyoto targets are in place (2008-2012), dummy for any country having adopted before, and constant).

If we want to include state variables that are exogenous and evolve exogenously in the per-period payoff, they need to be interacted with variables that are endogenous.

7. Results

7.1. Policy functions

We estimate equilibrium policy functions for the countries' climate policy decisions regarding whether to adopt a national greenhouse gas emissions target under the Kyoto Protocol, what target level to adopt, and how much CO_2 to emit. We estimate separate policy functions for EU and non-EU countries. The policy functions correlate actions to states and are not meant to have any causal interpretation.

We use several machine learning techniques to help us select the best-fit policy functions, including least angle regression, LASSO, K-fold cross-validation and h-step ahead rolling cross-validation for LASSO, square-root LASSO, adaptive LASSO, ridge regression, elastic net, stepwise regression, and backward elimination. We use coefficients that are significant at a 5% level in our structural model.

7.1.1. Adopt Kyoto target policy function

For our adopt Kyoto target policy function, we estimate a policy function for a country's decision of whether to adopt a national greenhouse gas emissions target under the Kyoto Protocol. For adopt Kyoto target policy function, we use data for only the two years when it would be possible to adopt a Kyoto target: 1997 (COP3) and 2012 (COP18). We use observations from Annex I countries only, since only Annex I countries may potentially adopt a Kyoto target. Moreover, since all countries that were members of the EU at the time of COP3 (1997) adopted a Kyoto target in 1997 and all countries that were members of the EU at the time of COP18 (2012) adopted a Kyoto target in 2012, we use focus on modeling the adopt Kyoto target policy function for non-EU Annex I countries only.

We use ordinary least squares (OLS) and probit regressions correlating actions to state to estimate the adopt Kyoto target policy function for non-EU Annex I countries. We use only observations from 1997 and 2012, the two years when it would be possible to adopt a Kyoto target, for the non-EU Annex I countries for which we have data in 1996, 1997 and 2012 for all of state variables considered.

There are 40 Annex I countries in our data set, of which 25 are non-EU countries in 1997, and of which 13 are non-EU countries in 2012. Thus, there are 38 observations for non-EU countries. There are 37 countries (35 in our data set) that adopt a COP target in 1997, and 35 (33 in our data set) countries that adopt a COP target in 2012.

There are 15 EU countries in our data set in 1997, and 27 EU countries in our data set in 2012. Thus, there are 42 observations for EU countries, and all of them adopt a COP target. There are 2 EU countries that adopt in both 1997 and 2012 that are not in our data set.

There are 20 non-EU countries that adopt in 1997, and there are 6 non-EU countries that adopt in 2012.

According to the results of our adopt Kyoto target policy function for non-EU countries in Table B3 in Appendix B, we find that, as expected a non-EU country is more likely to adopt a Kyoto target if it adopted one previously and if it is a member of the EU ETS. A non-EU country's

GDP squared also has a significant positive correlation with the likelihood of adopting a Kyoto target. The higher a non-EU country's CO_2 emissions, the less likely the country will adopt.

Our result that non-EU countries with higher CO_2 emissions are less likely to adopt is consistent with a free-rider, tragedy of the commons problem: non-EU countries with more CO_2 emissions and therefore who might contribute more to climate change are less likely to adopt a Kyoto target.

7.1.2. Kyoto target policy function

For our Kyoto target policy function, we estimate a policy function for a country's decision of what national greenhouse gas emissions target (in terms of % change in emissions relative to 1990 level) to adopt under the Kyoto Protocol, conditional on adopting. The Kyoto target policy function is the policy function for the level of Kyoto target adopted, conditional on the country adopting a Kyoto target that year. We use the targets during the years they were chosen (i.e., 1997 and 2012), not the years they were in place. The lower the Kyoto target, the more stringent it is. We use ordinary least squares (OLS) regressions correlating actions to state to estimate separate Kyoto target policy functions for EU and non-EU countries. We use only observations from 1997 and 2012, the two years when it would be possible to adopt a Kyoto target, for the countries that adopted.

There are 35 countries in our data set that adopt a COP target in 1997, and 33 countries in our data set that adopt a COP target in 2012. There are 15 EU countries in our data set in 1997, all of whom adopt a COP target in 1997. There are 27 EU countries in our data set in 2012, all of whom adopt a COP target in 2012. There are 20 non-EU countries that adopt in 1997, and there are 6 non-EU countries that adopt in 2012.

According to our results for the Kyoto target policy function for EU countries in Specification (1) of Table B4a in Appendix B, we find that, conditional on adopting a Kyoto target, the higher an EU country's mean temperature, the higher (and less stringent) the Kyoto target it will adopt. In contrast, conditional on adopting a Kyoto target, the higher an EU country's CO_2 emissions, the lower (and more stringent) the Kyoto target it will adopt. We use Specification (1) for our structural model.

For robustness, we also try estimating a Kyoto target policy function for EU countries in which the dependent variable is the difference in that EU country's Kyoto target from the norm (or mode) Kyoto target for EU countries that year (Specification (2) of Table B4a in Appendix B). For COP3 (1997), the EU norm was a Kyoto target of an -8% change in emissions relative to 1990 level. For COP18 (2012), the EU norm was a Kyoto target of an -20% change in emissions relative to 1990 level.

According to our results for the different-from-EU-norm Kyoto target policy function for EU countries in Table B4a in Appendix B, we once again find that conditional on adopting a Kyoto target, the higher an EU country's mean temperature, the higher (and less stringent) the Kyoto target it will adopt relative to the EU norm. We also find once again that, conditional on adopting a Kyoto target, the higher an EU country's CO_2 emissions, the lower (and more stringent) the Kyoto target it will adopt relative to the EU norm.

We find a different set of results for non-EU countries. According to our results for the Kyoto target policy function for non-EU countries in Table B4b in Appendix B, we find that conditional on adopting a Kyoto target, the higher a non-EU country's GDP, the lower (and more stringent) the Kyoto target it will adopt. In contrast, conditional on adopting a Kyoto target, the higher a non-EU country's mean temperature, the higher a non-EU country's CO_2 emissions, and the higher a non-EU country's percent change in CO_2 emissions from its 1990 levels, the higher (and less stringent) the Kyoto target it will adopt.

We highlight the following results from our Kyoto target policy functions for EU and non-EU countries. First, both EU and non-EU countries with higher mean temperature tend to adopt less stringent Kyoto targets.

A second main result is that EU countries with higher CO_2 emissions tend to adopt more stringent Kyoto targets, while non-EU countries with higher CO_2 emissions tend to adopt less stringent Kyoto targets. This consistent with possible free riding by non-EU countries: non-EU countries with more CO_2 emissions, and therefore who might contribute more to climate change, are not only less likely to adopt a Kyoto target, but also tend to adopt less stringent Kyoto targets.

7.1.3. CO_2 emissions policy function

For our CO_2 emissions policy function, we estimate a policy function for a country's decision regarding how much CO_2 (Mt) to emit. We use observations for all 92 countries (including countries that are not in Annex I) for all years from 1996-2014. We use OLS regressions correlating actions to state to estimate separate CO_2 emissions policy functions for EU and non-EU countries. Since Kyoto targets are expressed as % change from 1990, we also try estimating separate CO_2 emissions policy functions for EU and non-EU countries in which the dependent variable is the % change in CO_2 emissions from the country's CO_2 emissions in 1990. The results of our CO_2 emissions policy functions for EU and non-EU countries are in Tables B5a and B5b, respectively, in Appendix B. We use the specifications in which the dependent variable is the % change in CO_2 emissions from the country's CO_2 emissions in 1990 for our structural model.

For both EU and non-EU countries, results show that the % change in CO_2 emissions from the country's 1990 levels is lower if the country has adopted a Kyoto target. This result suggests that countries which adopt a Kyoto target do try to reduce the % change in CO_2 emissions from their 1990 levels.

For EU countries, we find that the more stringent their Kyoto target, the lower their % change in CO_2 emissions from their 1990 levels. In contrast, for non-EU countries, the level of Kyoto target has no significant effect on the % change in CO_2 emissions from their 1990 levels. This result suggests that the non-EU countries may not view their Kyoto target levels as binding, perhaps because their CO_2 emissions reductions would have occurred anyway, or they do not view the Kyoto targets as enforceable.

7.2. Transition densities

We estimate the transition densities for the distribution of future values of our state variables as a function of the current state variables and of the countries' policies. We assume the changes of state variables through countries actions take one period to occur, which is a standard assumption in discrete time models.

We estimate transition densities for the following state variables: country-level GDP, country-level population, country-level dummy for being below poverty, country-level CO_2 emissions from electricity and heat production, country-level energy intensity, country-level mean temperature, and global CO_2 concentration. We do not estimate a transition density for oil price, but instead assume rational expectations for oil price and use the actual values for oil price in our structural model.

We use annual data from 1996-2014 for all 92 countries in our data set. We use several machine learning techniques to help us select the best-fit transition densities. These machine learning techniques include least angle regression, LASSO, K-fold cross-validation and h-step ahead rolling cross-validation for LASSO, square-root LASSO, adaptive LASSO, ridge regression, elastic net, stepwise regression, and backward elimination. We use coefficients that are significant at a 5% level in our structural model.

The results are presented in Table B6-B8 in Appendix B. We highlight several results from our transition densities.

First, when a country adopts a Kyoto target, this is associated with a decline in the future probability that that country is below poverty in years prior to the period when the target will be in effect (Table B6), but also potentially an increase in future mean temperature for that country in years prior to the period when the target will be in effect (Table B7).

During the period in which the COP3 targets were in effect (2008-2012), having adopted a COP3 Kyoto target is associated with a decline in future GDP for that country, but also a decline in the future probability that that country is below poverty (Table B6).

Since adopting a Kyoto target is associated with both a decline in future GDP for that country in years following a year during which the target is in effect and an increase in future mean temperature for that country in years prior to the period when the target will be in effect, this suggests that it may not be in a country's own private interest to adopt a Kyoto target.

For a country that adopts a Kyoto target, adopting a less stringent (higher) Kyoto target is associated with a higher future percentage of CO_2 emissions from electricity and heat production for that country (Table B7), which is perhaps as expected. For a country that adopts a Kyoto target, adopting a less stringent Kyoto target is also associated with a decrease in future mean temperature for that country in years prior to the period when the target will be in effect (Table B7), however, which suggests that it may not be in a country's own private interest to adopt a stringent Kyoto target.

The higher a country's CO2 emissions, the higher the country's future GDP (Table B6), which again suggests that it may not be in a country's own private interest to reduce CO2 emissions.

Our transition densities also show that the Kyoto Protocol has an impact on all countries in our data set, whether or not they adopt a Kyoto target. In the years following the first adoption of any Kyoto targets by any country, our preliminary results show that GDP is lower for all countries and the probability of being in poverty increases for all countries (Table B6). The more stringent the mean Kyoto target adopted by other countries, the higher the probability of a country being in poverty (Table B6).

We find that the more stringent the mean Kyoto target adopted, the higher the global CO_2 concentration (Table B8). For all countries, the global CO_2 concentration is higher following a year when the COP3 targets were in effect (Table B8). These results suggest that that Kyoto Protocol may have had unintended or perverse consequences.

The results of our transition densities therefore suggest that the Kyoto Protocol may have had unintended or perverse consequences.

7.3. Structural parameters

The structural parameters θ we estimate are the coefficients on each of the terms in the country-level per-period payoff function.

Since the per-period payoff is unit-less, and since the magnitudes of the coefficients and per-period payoff are not identified, we normalize the coefficient on "GDP PPP (trillion 2011$)" to be equal to 100. This enables us to pin down the magnitudes of the other parameters, since we can identify the relative magnitudes of all other coefficients with respect to the coefficient on GDP. This also enables us to interpret the per-period payoff in the same units as GDP PPP x 100 (i.e., in units of "10 billion 2011$"), and also interpret the coefficients in the per-period off as measuring trade-offs between GDP and other terms (such as CO2 emissions).

As explained above, we are unable to identify the coefficients on any terms that are exogenous and evolve exogenously, since their values would be the same regardless of action choice. We are therefore unable to identify the coefficients on any state variables that are exogenous and evolve exogenously, since their values would be the same regardless of action choice. State variables that are exogenous and evolve exogenously include any characteristic of countries that are fixed over time and/or exogenous (such as the EU dummy, ETS dummy, Annex I dummy); any global variable that is exogenous and evolves exogenously (time trend, oil price (since we assume rational expectations), period in which COP3 Kyoto targets are in place (2008-2012), dummy for any country having adopted before, and constant). If we want to include state variables that are exogenous and evolve exogenously in the per-period payoff, they need to be interacted with variables that are endogenous.

Tables B9a and B9b in Appendix B presents the structural parameter estimates from 12 different specifications of the per-period payoff function. In all specifications, we normalize the coefficient on "GDP PPP (trillion 2011$)" to be equal to 100. We therefore interpret the per-period payoff in units of "10 billion 2011$", and also interpret the coefficients in the per-period off as measuring trade-offs between GDP and other terms (such as CO_2 emissions).

In addition to GDP PPP (trillion 2011$), whose coefficient we normalize to 100, other terms we try including in various specifications of the per-period payoff include: a dummy for an Annex I country adopting a Kyoto target in a year that it has an option to adopt a Kyoto target (1997 or 2012); adopted before (dummy); the Kyoto target (%) adopted this year by a country that adopted a Kyoto target this year; the % change in CO_2 emissions from 1990 levels this year (%) minus the Kyoto target adopted this year by a country that adopted a Kyoto target this year (%), which is a measure how ambitious (and hard to meet) the Kyoto target adopted by this country this year is, since it is a measure of the % reduction in CO_2 emissions from 1990 levels needed by this country to meet the target it adopted; the latest Kyoto target adopted (%); a dummy for being a year in which the COP3 targets are in effect (1998-2012) and being a country that adopted a COP3 Kyoto target; the level of the Kyoto target adopted at COP3 (%) during a year in which the COP3 targets are in effect (1998-2012); the amount by which the % change in CO_2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) during a year in which the COP3 targets are in effect (1998-2012) for an EU country, calculated as "min{(% Change in CO2 emissions from 1990 levels (%)) minus (Kyoto_target_latest_lagged (%)), 0}" X Target period (dummy) X adopted before (dummy) X EU_dummy, and which measures any costs an EU country faces from exceeding (i.e., not meeting) its COP3 target during the COP3 target period; the amount by which the % change in CO_2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) during a year in which the COP3 targets are in effect (1998-2012) for a non-EU country, measures any costs a non-EU country faces from exceeding (i.e., not meeting) its COP3 target during the COP3 target period; the amount by which the % change in CO_2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) by an EU country, calculated as "min{(% Change in CO2 emissions from 1990 levels (%)) minus (Kyoto_target_latest_lagged (%)), 0}" X adopted before (dummy) X EU_dummy, which measures any costs an EU country faces from exceeding (i.e., not meeting) its Kyoto target at any time after adopting that Kyoto target (even if it's not during the target period); amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) by a non-EU country, measures any costs a non-EU country faces from exceeding (i.e., not meeting) its Kyoto target at any time after adopting that Kyoto target (even if it's not during the target period); CO_2 emissions (Mt); CO_2 emissions (Mt) for an EU country; CO_2 emissions (Mt) for a non-EU country; EU ETS dummy * CO_2 emissions (Mt), to capture in part the cost (price) of CO_2 permits in the EU ETS system; CO_2 emissions (Mt) for an EU country that adopted a Kyoto target before during a year in which the COP3 Kyoto targets are in place (1998-2012); CO_2 emissions (Mt) for a non-EU country that adopted a Kyoto target before during a year in which the COP3 Kyoto targets are in place (1998-2012); CO_2 emissions (Mt) for an EU country that adopted a Kyoto target; CO_2 emissions (Mt) for a non-EU country that adopted a Kyoto target; mean temperature; mean temperature squared; and global CO_2 concentration.

Across the many different specifications, we find the robust result that CO_2 emissions have a significant negative effect on the per-period payoff, particularly for non-EU countries (Specifications (8),(10),(11), and (12)), with a coefficient of around -0.075 to -0.058. We also find a significant positive coefficient in some specifications on the amount by which the % change in CO_2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) by an EU country, which suggests that an EU country may face a cost from exceeding (i.e., not meeting) its Kyoto target at any time after adopting that Kyoto target (even if it is not during the target period). None of the other terms appear to have a significant effect on the per-period payoff.

We use Specification (8) in Table B9b as our preferred specification. In Specification (8), the coefficient on CO_2 emissions for non-EU countries is statistically significant and negative. For non-EU countries, an increase in CO_2 emissions by 1 Mt decreases the per-period payoff by 0.73 billion real US dollars (2011$). In ongoing work, we are also conducting another set of counterfactual analyses using Specification (10) in Table B9b.

7.4. Welfare

We use our estimated structural parameters from Specification (8) of Table B9b in Appendix B to calculate the welfare generated from countries' decisions regarding whether to adopt a Kyoto target, the level of the Kyoto target, and CO_2 emissions. Welfare is the present discounted value of the entire stream of per-period payoffs over the period 1997-2014, and is in units of 10 billion real US dollars (2011$). Average annual welfare is welfare divided by the number of years.

For each country, we calculate the actual welfare generated based on the observed actions and state variables over the period 1997-2014, the model predicted welfare generated from 100 simulation runs of the 1997-2014 period, and the difference between model predicted and actual welfare. Both actual and model predicted welfare are calculated using the parameter estimates from the structural model. Actual welfare is calculated using actual values of actions and states in the data over the period 1997-2014. Model predicted welfare is calculated using model predicted actions and states generated from 100 simulation runs of the 1997-2014 period.

The mean, minimun, and maximum of model predicted and actual average annual welfare per country are presented in Table B10 of Appendix B. Model predicted and actual average annual welfare by country are presented in Table B11 of Appendix B. The model predicted average annual welfare per country is 227.2 billion real US dollars (2011$). Countries with high model predicted average annual welfare include the US (3.9 trillion 2011$), China (1.6 trillion 2011$), Japan (1.6 trillion 2011$), India (1.2 trillion 2011$), and Germany (1.2 trillion 2011$). Countries with low model predicted average annual welfare include Armenia (6.2 billion 2011$), Benin (7.9 billion 2011$), Estonia (7.6 billion 2011$), Iceland (5.0 billion 2011$), Kyrgyzstan (3.6 billion 2011$), Malta (4.7 billion 2011$), Mauritius (8.6 billion 2011$), Mongolia (7.9 billion 2011$), Mozambique (8.9 billion 2011$), Togo (3.8 billion 2011$), Turkmenistan (9.0 billion 2011$), and Zimbabwe (7.7 billion 2011$).

7.5. Model validation

To assess the goodness of fit of our structural econometric model, we first compare the action and state variables predicted by our model with the actual values in the data. The fit of our model for action and state variables is summarized in Tables B12a-B12d in Appendix B. When comparing the actual and model predicted action and states variables, our structural econometric model does a good job matching the actual data.

We also compare actual welfare and model predicted welfare. In Table B10 in Appendix B, we show the the mean, minimun, and maximum of model predicted and actual average annual welfare per country. In Table B11 in Appendix B, we show, for each country, the actual welfare generated based on the observed player actions and state variables, the model predicted welfare generated from 100 simulation runs of the open access period, and the difference between model predicted and actual welfare. Our model does a fairly good job of matching the welfare across countries based on actual values of actions and states.

Our econometric estimation entails finding the parameters θ that minimize any profitable deviations from the optimal strategy as given by the estimated policy functions. Table B13 in Appendix B presents each country's profitable deviations from their estimated optimal strategy under our estimated structural parameters, expressed as a percentage of their welfare. The profitable deviations less than 4.9 percent of welfare for 78 of the 92 countries, and less than 10 percent of welfare for all except 4 of the 92 countries. Our model of the open access dynamic game therefore does a good job explaining the climate change policy decisions of most of the 92 countries in our data set during the time period of our data set.

8. Counterfactual scenarios

We use the estimated parameters from Specification (8) of Table B9b in Appendix B to simulate the effects of counterfactual scenarios, situations, and institutions on climate change policy, emissions, economic outcomes, and welfare.

For each counterfactual scenario, we simulate the effects of a counterfactual change that takes place in the year 1997 on the actions, states, and welfare for 92 countries in the world over the years 1997 to 2014. We then compare the mean action and state variables, welfare per country per year, and welfare per year by country under that counterfactual scenario with those under the base-reference case of no change using two-sample t-tests. Our structural model therefore enables us to assess, for each counterfactual scenario, the combined effects of all the different channels, mechanisms, feedback effects, and feed-forward effects on the trajectories for the state and actions variables.

There are several channels through which each counterfactual change may affect country welfare. First, if the counterfactual change is a counterfactual change in a variable that appears in the per period payoff function, then may the counterfactual change affect country welfare directly. Second, the counterfactual change may affect Kyoto target adoption, Kyoto target, and CO_2 emissions decisions which affect country welfare. Third, the counterfactual change may affect other decisions of the country which may affect country welfare. Although we focus on explicitly modeling the Kyoto target adoption, Kyoto target, and CO_2 emissions decisions of the countries, our model implicitly captures other decisions made by the country by allowing other country-level variables to evolve endogenously conditional on state variables and actions via the transition densities. Fourth, the counterfactual change may affect decisions of other countries, which may then affect a country's welfare. Fifth, changes in actions and/or state variables resulting from the counterfactual change may affect future values of the state variables, which may affect future actions and/or welfare. Our estimates of the changes in welfare that arise in each counterfactual simulation capture all channels through which the counterfactual scenario may affect country welfare.

In analyzing the short-run effects of the counterfactual scenarios, we assume that the counterfactual changes we simulate are ones that countries neither anticipate nor expect to be permanent. Adapting the policy invariance assumption and approach of Benkard, Bodoh-Creed and Lazarev (2018), we therefore assume that the policy functions, transition densities of unaffected state variables, and structural parameters we estimate themselves do not change under the different counterfactual scenarios.

The counterfactual scenarios we simulate are scenarios in which certain countries are not members of the Conference of the Parties (COP), either because they have exited or have never joined. These countries are still in our 92-country game, but no longer have the option of adopting a Kyoto target. In particular, we simulate separate counterfactual scenarios in which (i) the US is not in COP, and (ii) the entire EU is not in COP.

For each of our counterfactual COP membership scenarios, we compare the mean action and state variables, welfare per country per year, and welfare per year by country under that counterfactual scenario with those under the base case of no change for all the other countries using two-sample t-tests. For example, for the counterfactual scenario in which the US is not a member of COP, we compare the mean action and state variables, welfare per country per year, and welfare per year by country under that counterfactual scenario with those under the base case of no change for all countries excluding the US using two-sample t-tests.

Figure 1 presents the results of two-sample t-tests of the effects of changes in COP membership on (a) the mean probability of Kyoto target adoption by non-EU countries remaining in COP, and (b) the mean Kyoto target adopted by those that adopt. Error bars indicate the 95% confidence interval. According to the results in Figure 1, the US exiting COP will decrease both the probability of Kyoto target adoption by non-EU countries remaining in COP, and the stringency of the Kyoto target adopted by those that adopt. In contrast, the EU exiting COP does not have a statistically significant effect on either the mean probability of Kyoto target adoption by non-EU countries remaining in COP or the mean Kyoto target adopted by those that adopt.

Figure 2 presents the results of two-sample t-tests of the effects of changes in COP membership on CO_2 emissions over the period 1997-2014 by (a) all 92 countries, (b) EU countries, and (c) non-EU countries. According to the results in Figure 2, the US exiting COP will decrease the mean CO_2 emissions from EU countries and increase the mean CO_2 emissions from non-EU countries, leading to a net increase in the mean CO_2 emissions over all 92 countries. The EU exiting COP will increase the mean CO_2 emissions from EU countries, leading to an increase in the mean CO_2 emissions over all 92 countries. Thus, CO_2 emissions will increase if either US or the EU exits COP.

Figure 3 presents the results of two-sample t-tests of the effects of changes in COP membership on the state variables for (a) EU countries and (b) non-EU countries. The US exiting COP will increase the mean temperature of EU countries and decrease aggregate CO_2 emissions from EU countries, but has not statistically significant effect on any of the state variables for non-EU countries. The EU exiting COP will increase mean temperatures for EU countries and GDP for non-EU countries. Thus, mean temperatures for EU countries will increase if either the US or the EU exits COP; and non-EU countries will benefit in terms of higher GDP if the EU exits COP.

Figure 4 presents the results of two-sample t-tests of the effects of changes in COP membership on the state variables for (a) countries that have adopted a Kyoto target either that year or in a previous year, and (b) countries that have not ever adopted a Kyoto target. If the US exits COP, the mean temperatures for countries that adopt a Kyoto target will increase, and the GDP for countries that do not adopt a Kyoto target will increase. The EU exiting COP will cause the mean temperatures of countries that adopt a Kyoto target to increase, but does not have a statistically significant effect on any of the state variables for countries that do not adopt a Kyoto target. Thus, mean temperatures for countries that adopt a Kyoto target will increase if either the US or the EU exits COP; and countries that do not adopt a Kyoto target will benefit in terms of higher GDP if the US exits COP.

Figure 5 shows the signs of changes in average welfare per year by country that are significant at a 5% level when COP does not include (a) US or (b) the EU. The countries in red are those that experience a statistically significant decrease in average welfare per year; the countries in green are those that experience a statistically significant increase in average welfare per year; and the countries in grey are those with no statistically significant change in average welfare per year. The magnitudes (as well as signs) of the changes for each country and their statistical significance for each counterfactual COP membership scenario are reported in Table B14 of Appendix B.

As seen in Figure 5, when the US is not in COP, the US, China, India, Canada, and some countries in Western Europe do not experience a statistically significant change in average welfare per year at a 5% level; while Russia, Australia, some countries in South America, some countries in Africa, some countries in the Middle East, some countries in Eastern Europe, and some Scandinavian countries experience a statistically significant decrease in average welfare per year. Only a few countries experience a statistically significant increase in average welfare per year when the US is not in COP: the Czech Republic, Estonia, Italy, Saudi Arabia, Senegal, Tanzania, and the Ukraine.

When the EU is not in COP, the US, China, India, and many EU countries in Western Europe do not experience a statistically significant change in average welfare per year at a 5% level; while Russia, some countries in South America, some countries in Africa, some countries in Eastern Europe, some countries in the Middle East, and some Scandinavian countries experience a statistically significant decrease in average welfare per year. Belarus, Bulgaria, Canada, Estonia, Jordan, Lithuania, Mongolia, Nigeria, Slovakia, Sudan, Tanzania, Tunisia, Turkmenistan, and Uruguay experience a statistically significant increase in average welfare per year when the EU is not in COP.

9. Conclusion

Climate change is a "tragedy of the commons" problem that has the potential to cause catastrophic damages worldwide. In this paper, we use machine learning and structural econometric modeling to develop and estimate a structural econometric model of the dynamic game among countries making dynamic and strategic decisions regarding whether to adopt a national greenhouse gas emissions target under the Kyoto Protocol, what target level to adopt, and how much CO_2 to emit. We use the parameters estimated from our structural econometric model to simulate the effects of counterfactual scenarios on climate change policy, emissions, economic outcomes, and welfare.

Results of our policy functions and transition densities are consistent with the presence of a free-rider problem, and also suggest that the Kyoto Protocol may have had some unintended or even perverse effects. When examined each in isolation, our policy functions and transition transitions do not fully capture all the different channels, mechanisms, feedback effects, and feed-forward effects of the actions and states of all countries in our dynamic game, however.

In contrast, our structural model of the dynamic climate policy game enables us to assess, for each counterfactual scenario, the combined effects of all the different channels, mechanisms, feedback effects, and feed-forward effects on the trajectories for the state and actions variables.

Across many different specifications of the per-period payoff, we find the robust result that CO_2 emissions have a significant negative effect on the per-period payoff, particularly for non-EU countries. We also find a significant positive coefficient in some specifications on the amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) by an EU country, which suggests that an EU country may face a cost from exceeding (i.e., not meeting) its Kyoto target at any time after adopting that Kyoto target (even if it is not during the target period). None of the other terms appear to have a significant effect on the per-period payoff. In our preferred specification, for non-EU countries, an increase in CO2 emissions by 1 Mt decreases the per-period payoff by 0.73 billion real US dollars (2011$).

We use our structural model to simulate counterfactual scenarios in which certain countries are not members of the Conference of the Parties (COP), either because they have exited or have never joined.

We find that the US exiting COP will decrease both the probability of Kyoto target adoption by non-EU countries remaining in COP, and the stringency of the Kyoto target adopted by those that adopt. The US exiting COP will decrease the CO_2 emissions from EU countries and increase the mean CO_2 emissions from non-EU countries, leading to a net increase in the mean CO_2 emissions over all 92 countries. The mean temperature will increase for EU countries and for countries that adopt a Kyoto target; and the GDP for countries that do not adopt a Kyoto target will increase.

When the US is not in COP, the US, China, India, Canada, and some countries in Western Europe do not experience a statistically significant change in average welfare per year at a 5%

level; while other countries experience a statistically significant decrease in average welfare per year. Only a few countries experience a statistically significant increase in average welfare per year when the US is not in COP.

In contrast, the EU exiting COP does not have a statistically significant effect on either the mean probability of Kyoto target adoption by non-EU countries remaining in COP or the mean Kyoto target adopted by those that adopt. The EU exiting COP will increase the mean CO_2 emissions from EU countries, leading to an increase in the mean CO_2 emissions over all 92 countries. The EU exiting COP will increase mean temperatures for EU countries and countries that adopt a Kyoto target; and will increase GDP for non-EU countries.

When the EU is not in COP, the US, China, India, and many EU countries in Western Europe do not experience a statistically significant change in average welfare per year at a 5% level; some countries experience a statistically significant decrease in average welfare per year; and some countries experience a statistically significant increase in average welfare per year.

Thus, results of our counterfactual simulations, which enable us to assess the combined effects of all the different channels, mechanisms, feedback effects, and feed-forward effects on the trajectories for the state and actions variables, provide evidence that that having the US and the EU as members of the Conference of the Parties (COP) is important for reducing aggregate CO_2 emissions and for reducing mean temperatures in EU countries, but at a cost to GDP. CO_2 emissions will increase if either US or the EU exits COP. Mean temperatures for EU countries and for countries that adopt a Kyoto target will increase if either the US or the EU exits COP. Non-EU countries will benefit in terms of higher GDP if the EU exits COP; countries that do not adopt a Kyoto target will benefit in terms of higher GDP if the US exits COP.

Our results have important implications for climate policy decision-making and the design of international environmental agreements, and will be of interest to academics, policy-makers, business practitioners, and environmental advocacy groups alike.

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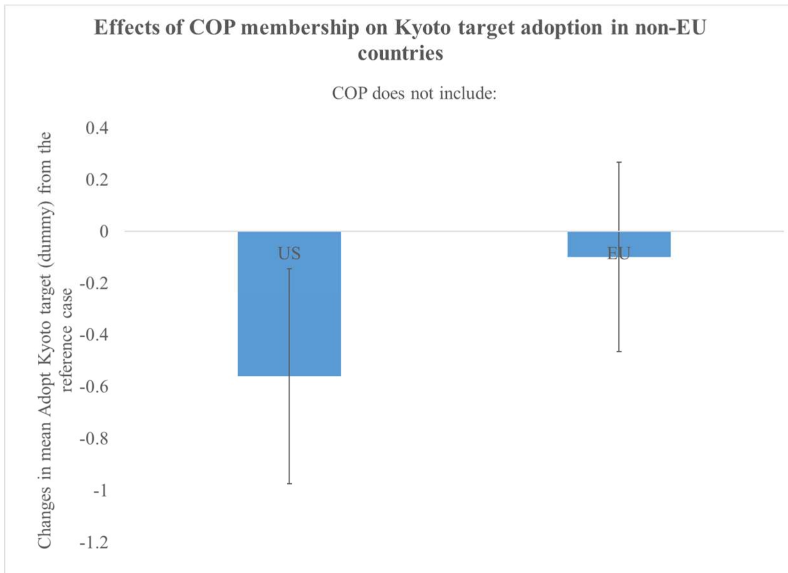
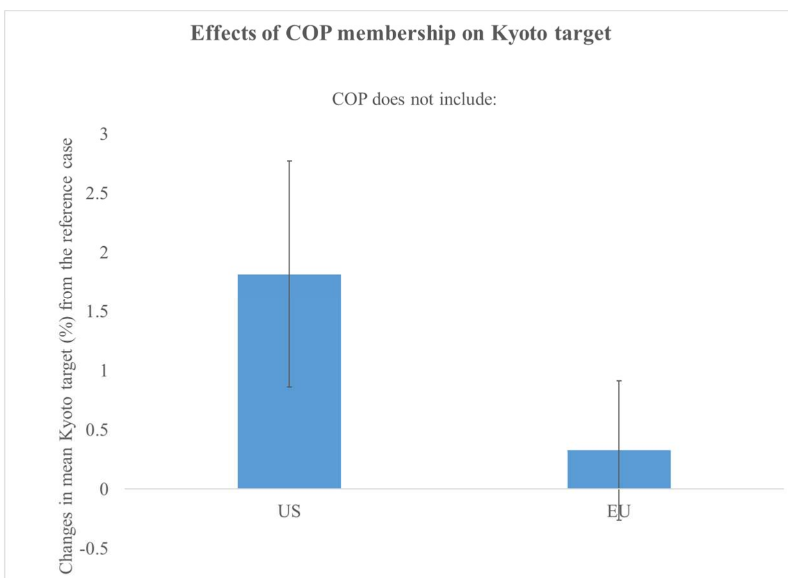
Figure 1. Effects of Changes in COP Membership on Adopt Kyoto Target and Kyoto Target Action Variables

(a)



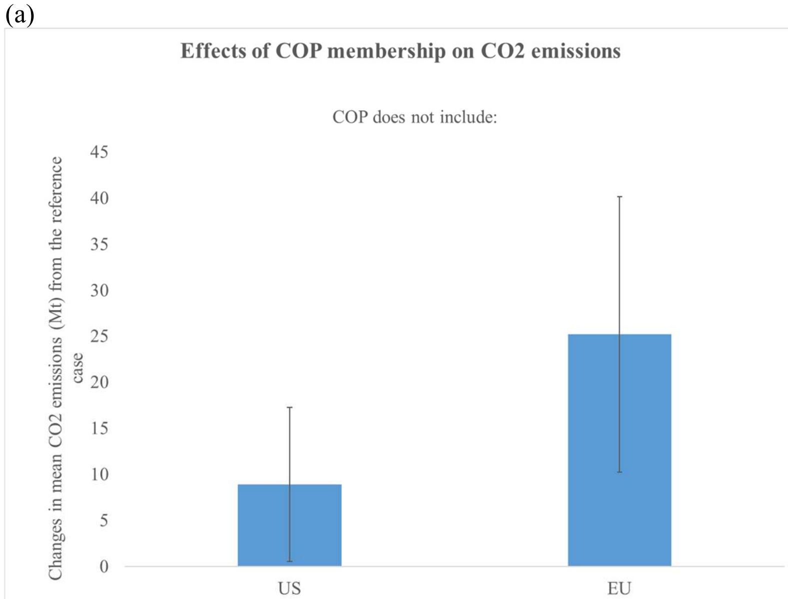
(b)



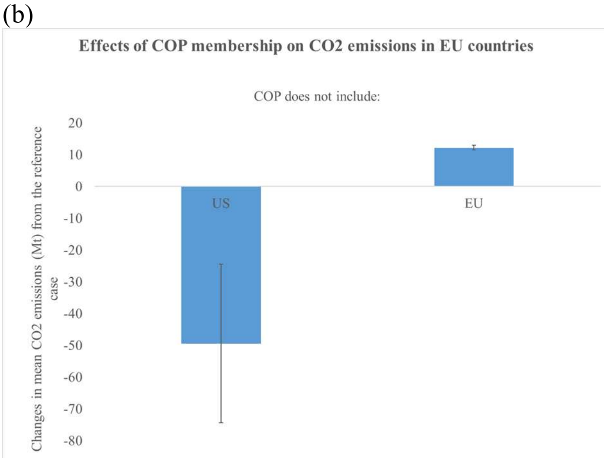
Notes: Figures show results of two-sample t-tests of the effects of changes in COP membership on the (a) mean probability of Kyoto target adoption by non-EU countries remaining in COP, and (b) mean Kyoto target adopted by those who adopt. Error bars indicate the 95% confidence interval.

Figure 2. Effects of Changes in COP Membership on CO_2 Emissions

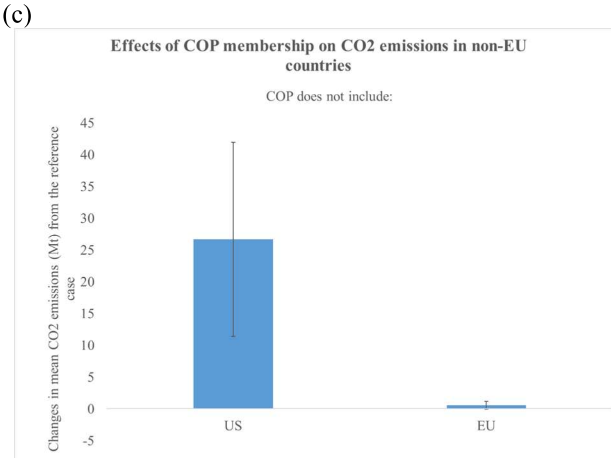
(a)



(b)



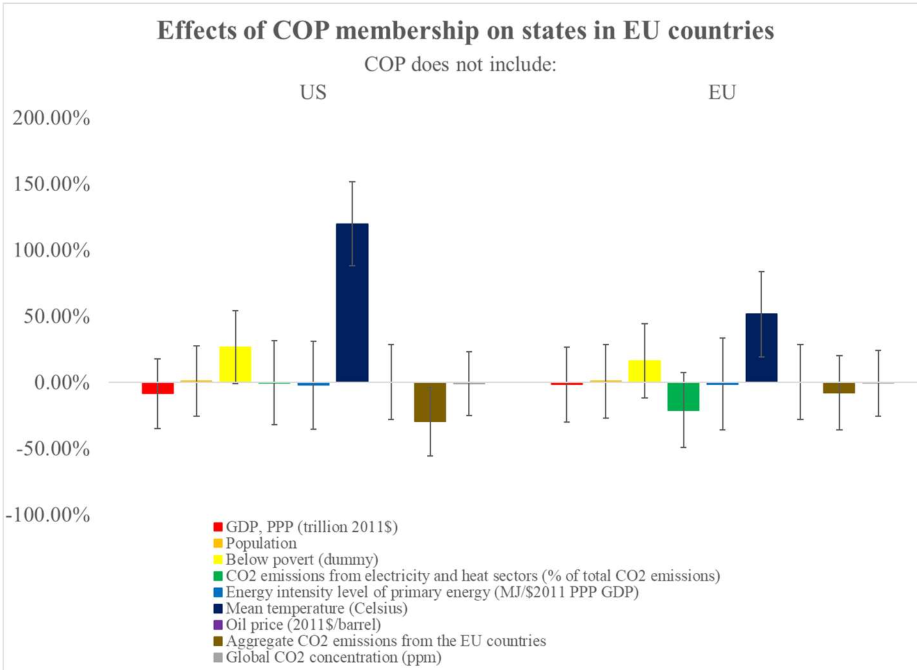
(c)



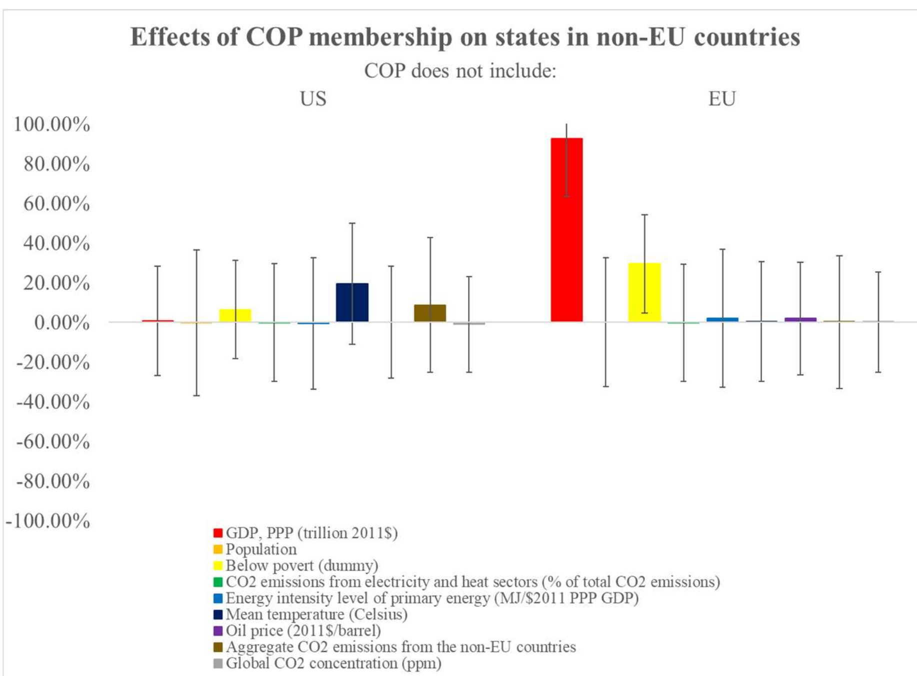
Notes: Figures show results of two-sample t-tests of the effects of changes in COP membership on mean CO_2 emissions over the period 1997-2014 from (a) all 92 countries, (b) EU countries, and (c) non-EU countries. Error bars indicate the 95% confidence interval.

Figure 3. Effects of Changes in COP Membership on State Variables for EU and non-EU Countries

(a)



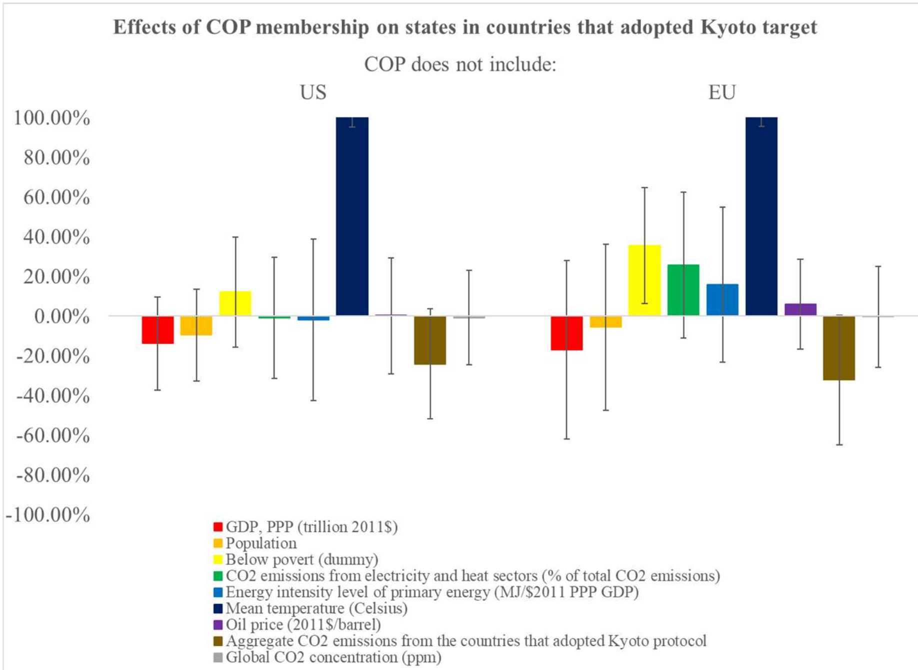
(b)



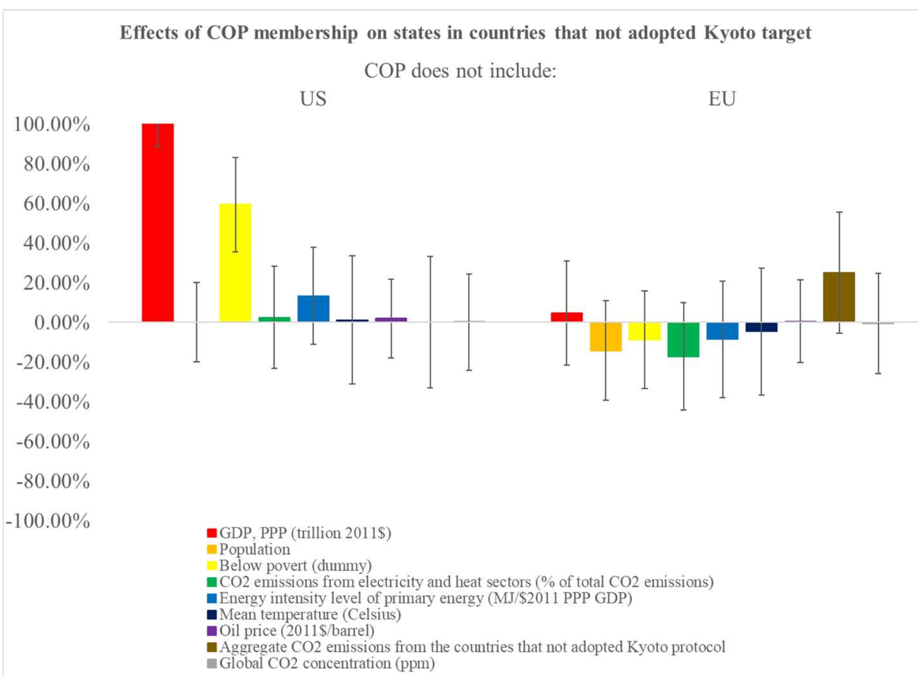
Notes: Figures show results of two-sample t-tests of the effects of changes in COP membership on state variables for (a) EU countries and (b) non-EU countries. Error bars indicate the 95% confidence interval.

Figure 4. Effects of Changes in COP Membership on State Variables by Whether the Country has Adopted a Kyoto Target

(a)



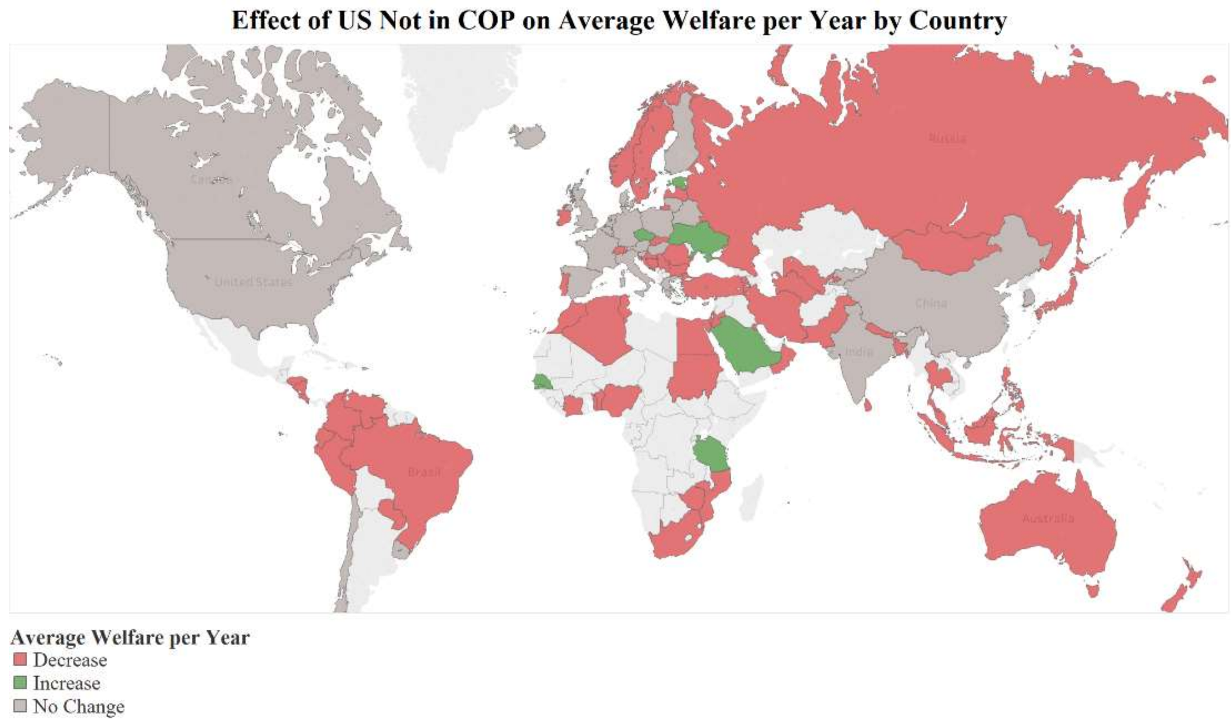
(b)



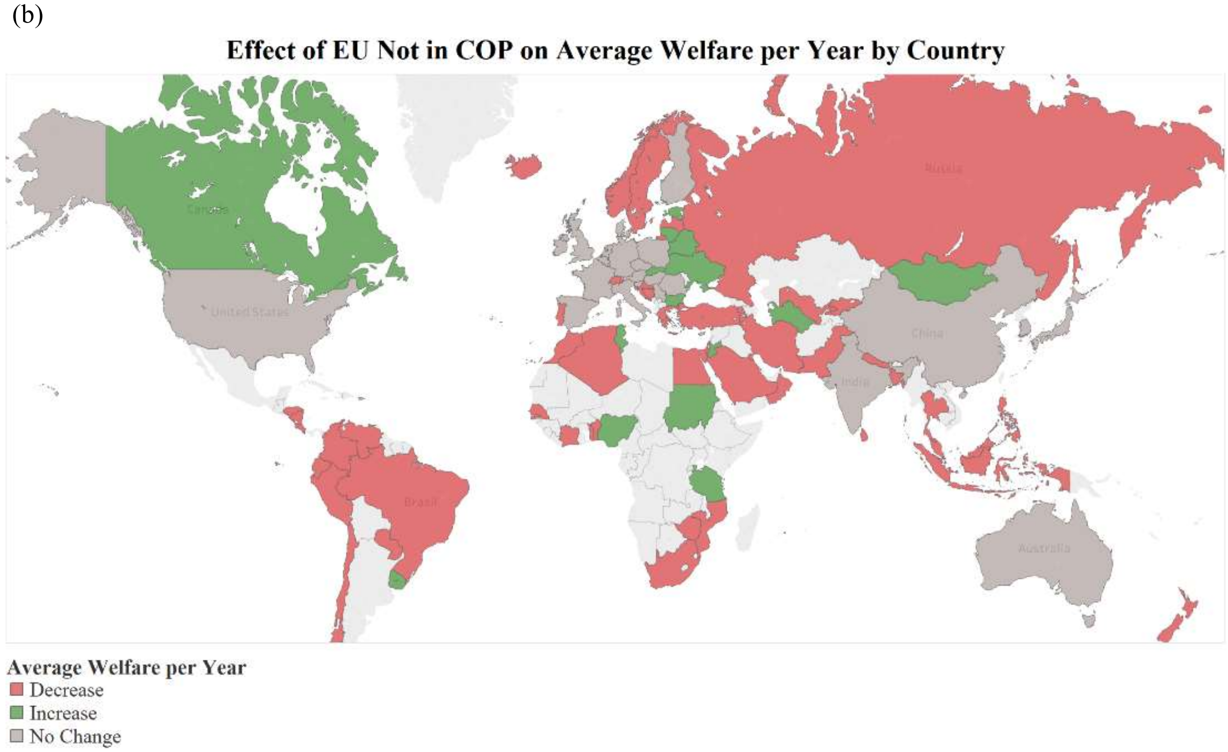
Notes: Figures show results of two-sample t-tests of the effects of changes in COP membership on state variables for (a) countries that have adopted a Kyoto target either that year or in a previous year, and (b) countries that have not ever adopted a Kyoto target. Error bars indicate the 95% confidence interval.

Figure 5. Effects of Changes in COP Membership on Welfare by Country

(a)



(b)



Note: Maps show signs of changes in average welfare per year by country that are significant at a 5% level when COP does not include (a) US or (b) EU.

Appendix

Appendix A. Supplementary Data Description

We collect and construct an annual country-level panel data set of an extensive set of variables relating to economic factors, energy, the environment, climate, and country-level economic, demographic, political, and social characteristics that includes all the observations we could find and collect of all these variables for all the countries in the world. In this Appendix, we describe the entire annual country-level panel data set of all the variables we collected and analyzed, from which we selected the 8 state variables we use in our structural model based on the machine learning results and also on data availability considerations.

We use data from different sources of International Energy Agency (IEA) including IEA statistics and IEA world energy balance for renewable energy consumption, fossil fuel energy consumption, energy use, net energy imports, alternative and nuclear energy, CO_2 emissions from electricity and heat production, CO_2 emissions from manufacturing industries and construction, CO_2 emissions from other sectors excluding residential buildings and commercial and public services, CO_2 emissions from residential buildings and commercial and public services, combustible renewables and waste, electric power consumption, electricity net generation, electricity production from coal sources, electricity production from hydroelectric sources, electricity production from natural gas sources, electricity production from nuclear sources, electricity production from oil sources, electricity production from oil, gas and coal sources, energy intensity level of primary energy, energy use per capita, energy use, energy use per $1,000 GDP, GDP per unit of energy use, renewable electricity output, renewable energy consumption, wind energy levelized cost, total primary energy consumption, total primary energy production, total electricity net consumption, total electricity net generation, total fossil fuels electricity net generation, total non-hydro renewable electricity net generation, wind electricity net generation, dummy variable for wind electricity net generation, solar electricity net generation, dummy variable for solar electricity net generation, nuclear electricity net generation, total primary coal production, gross natural gas production, total biofuels consumption, total biofuels production, total petroleum consumption, total oil supply, natural gas prices for industry, total coal consumption, heavy fuel oil price for electricity generation, domestic heating oil price, automotive diesel oil price, natural gas prices for households, natural gas price for electricity generation, fuel ethanol consumption, biodiesel consumption, gasoline price, total renewable electricity net consumption, total renewable electricity installed capacity, wind electricity installed capacity, electricity prices for households, heavy fuel oil prices for electricity generation, electricity prices for industry, gross marketed dry natural gas consumption, and R&D in renewables.

The total oil supply variable from the IEA includes the production of crude oil (including lease condensate), natural gas plant liquids, and other liquids, and refinery processing gain. Other Liquids includes biodiesel, ethanol, liquids produced from coal, gas, and oil shale, Orimulsion, and other hydrocarbons. Crude Oil data for Canada include oil processed from Alberta oil sands. Negative refinery processing gain data values indicate a net refinery processing loss. The Liquefied Petroleum Gases category includes, where data are available, pentanes plus. The Other Products category includes asphalt, coke, aviation gasoline, lubricants, naphthas, paraffin wax, petrochemical feedstocks, unfinished oils, white spirits, and blending components.

We use United Nations Population Division data for population and population growth, and United Nations Framework Convention on Climate Change information for greenhouse gas net emissions. Moreover, we use United Nations Comtrade database for high-technology exports, fuel export and import. We also gathered data for research and development expenditure, researchers in R&D, scientific and technical journal articles and technicians in R&D from United Nations Educational, Scientific, and Cultural Organization (UNESCO) institute for statistics.

We obtain CO_2 emissions, CO_2 emissions per GDP PPP, CO_2 emissions per capita, and CO_2 intensity data from Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory. Negative values of CO_2 emissions from other sectors excluding residential buildings and commercial and public services may arise because there are some sinks (the IPCC Sink Categories) for negative emissions. We also use NOAA Earth System Research Laboratory (ESRL) data base for the global CO_2 concentration.

We extract mean, maximum, and minimum temperatures from the National Oceanic and Atmospheric Administration (NOAA) Global Historical Climatology Network (GHCN) database.

We use Lazard's levelized cost of energy analysis (version 9) for levelized cost of solar and wind energy. We use International Renewable Energy Agency (IRENA) databases for crystalline solar price, onshore wind cost and wind turbine price. Photovoltaic (PV) efficiencies and cost are also taken from the Navigant report (Navigant, 2012). We use data from a report from the National Laboratory for Sustainable Energy (National Laboratory for Sustainable Energy, 2008) for wind turbine size.

We use Eurostat data for final energy consumption, and InflationData website[4] for global oil prices.

Coal rents, forest rents, mineral rents, natural gas rents, oil rents and total natural resources rents are estimated based on sources and methods described in the World Bank report "The Changing Wealth of Nations: Measuring Sustainable Development in the New Millennium" (World Bank, 2011).

We use World Bank national accounts data, and OECD National Accounts data for GDP per capita growth, GDP per capita growth squared, GDP per capita, GDP growth, GDP growth squared, GDP and inflation.

We use World Intellectual Property Organization (WIPO) patent report and world intellectual property indicators for residents and non-residents patent applications and total trademark applications.

World Development Indicators from the World Bank is used for GDP PPP, renewable electricity production excluding hydroelectric, total electricity production and total electricity consumption.

Finally, we calculate the Shannon-Wienner diversity index to quantify the energy security of each country/region (Jewell et al. 2014) as it is shown in the following formula:

$$ES = -\sum_i p_i \ln(p_i)$$

where p_i indicates the share of fuel i.

From our entire annual country-level panel data set of all the variables we collected and analyzed, we selected the 8 state variables and formed the balanced annual country-level panel data set we used in our structural model based on the machine learning results and also on data availability considerations.

While our entire annual country-level panel data set of all the variables we collected and analyzed includes all the observations we could find and collect of all the variables for all the countries in the world, the countries and years in the balanced annual country-level panel data set we used for our structural model were selected so that all countries had data on all the action and state variables for all years in our panel data set.

[4] http://inflationdata.com/Inflation/Inflation_Rate/Historical_Oil_Prices_Table.asp

Appendix B. Supplementary Tables and Figures

Table B1. Kyoto targets adopted

Country/region	**Kyoto target adopted (% change in emissions relative to 1990 level)**	
	COP 3 (target for 2008-2012)	COP 18 (target for 2013-2020)
Australia	8	-0.5
Austria	-13	-20
Belgium	-7.5	-20
Bulgaria	-8	-20
Canada*	-6	
Croatia	-5	-20
Cyprus		-20
Czech Republic	-8	-20
Denmark	-21	-20
Estonia	-8	-20
Finland	0	-20
France	0	-20
Germany	-21	-20
Greece	25	-20
Hungary	-6	-20
Iceland	10	-20
Italy	-6.5	-20
Ireland	13	-20
Japan**	-6	
Latvia	-8	-20
Liechtenstein	-8	-20
Lithuania	-8	-20
Luxembourg	-28	-20
Malta		-20
Monaco	-8	-20
Netherlands	-6	-20
New Zealand	0	
Norway	1	-16
Poland	-6	-20
Portugal	27	-20
Romania	-8	-20
Russia**	0	
Slovakia	-8	-20
Slovenia	-8	-20
Spain	15	-20
Sweden	4	-20
Switzerland	-8	-15.8

Ukraine	0	-24
United Kingdom	-12.5	-20

Sources: Delreux (2011); Olivier et al. (2011); Doha Climate Gateway (2012)
*In December 2011, Canada withdrew from the Kyoto Protocol.
**In December 2010, Japan and Russia indicated that they do not have any intention to be under obligation of the second commitment period of the Kyoto Protocol after 2012.

Table B2a. Summary statistics for adopt Kyoto target action variable

	# Annex I Countries in data set	# Countries that adopted
Adopt Kyoto target: 1997 (Kyoto Protocol, COP 3)		
Number of countries that adopted a Kyoto target in 1997	40	35
Number of EU countries that adopted a Kyoto target in 1997	15	15
Number of non-EU countries that adopted a Kyoto target in 1997	25	20
Adopt Kyoto target: 2012 (Doha Amendment, COP 18)		
Number of countries that adopted a Kyoto target in 1997	40	33
Number of EU countries that adopted a Kyoto target in 1997	27	27
Number of non-EU countries that adopted a Kyoto target in 1997	13	6

Table B2b. Summary statistics for Kyoto target action variable

	# Obs	Mean	Std. Dev.	Min	Max
Kyoto target adopted in 1997 (Kyoto Protocol, COP 3)					
Kyoto target (% change in emissions) in 1997	35	-3.2	11.4	-28	27
Kyoto target (% change in emissions) for EU countries in 1997	15	-2.1	16.5	-28	27
Kyoto target (% change in emissions) for non-EU countries in 1997	20	-4.1	5.5	-8	10
Kyoto target adopted in 2012 (Doha Amendment, COP 18)					
Kyoto target (% change in emissions) in 2012	33	-19.3	3.6	-24	-0.5
Kyoto target (% change in emissions) for EU countries in 2012	27	-20	0	-20	-20
Kyoto target (% change in emissions) for non-EU countries in 2012	6	-16.1	8.2	-24	-0.5

Notes: Kyoto targets are in units of % change in emissions relative to 1990 level.

Table B2c. Summary statistics for CO_2 emissions action variable

	# Obs	Mean	Std. Dev.	Min	Max
CO_2 emissions, 1997-2014					
CO_2 emissions (Mt)	1,656	265.1	868.6	0.7	9,190.5
CO_2 emissions (Mt) from EU countries	387	156.6	198.0	2.4	854.9
CO_2 emissions (Mt) from non-EU countries	1,269	298.2	983.9	0.7	9,190.5
% change in CO_2 emissions from 1990 levels, 1997-2014					
% change in CO_2 emissions from 1990 levels	1,656	0.65	1.47	-0.85	17.66
% change in CO_2 emissions from 1990 levels for EU countries	387	-0.01	0.31	-0.68	0.95
% change in CO_2 emissions from 1990 levels for non-EU countries	1,269	0.85	1.62	-0.85	17.66

Table B2d. Summary statistics for state variables

	# Obs	Mean	Std. Dev.	Min	Max
Country-level state variables					
GDP, PPP (trillion 2011$)	1,655	0.77	1.9	0.0	17.2
Population (million people)	1,656	60.00	182.00	0.27	1,360.0
Below poverty (dummy)	1,656	0.577	0.5	0.0	1.0
CO_2 emissions from electricity and heat production (% of total fuel combustion)	1,656	40.62	18.8	0.0	89.0
Energy intensity level of primary energy (MJ/$2011 PPP GDP)	1,656	6.63	4.6	2.0	37.2
Mean temperature (Celsius)	1,557	9.49	12.5	-26.4	28.5
Global state variables					
Oil price (2011$/barrel)	18	54.52	25.8	15.6	95.2
Global CO_2 concentration (ppm)	18	379.81	10.3	362.9	397.1

Table B3. Adopt Kyoto target policy function for Non-EU countries

	Dependent variable is probability of non-EU country adopting a Kyoto target
	(1)
Country-level state variables	
GDP, PPP (trillion 2011$) squared	0.0037*
	(0.0017)
CO_2 emissions (Mt)	-0.0002**
	(0.0001)
EU ETS (dummy)	0.4047*
	(0.1889)
Adopted Kyoto target before (dummy)	0.5216*
	(0.2014)
Global state variables	
Oil price (2011$/barrel)	-0.0131***
	(0.0014)
Constant	Y
# Observations	38

Notes: Robust standard errors are in parentheses. Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table B4a. Kyoto target policy function for EU countries

Dependent variable is the level of the Kyoto target adopted by EU country, conditional on adopting a Kyoto target that year	Level of target (1)	Difference in target from EU norm (2)
Country-level state variables		
CO_2 emissions (Mt)	-0.0156**	-0.0156**
	(0.0055)	(0.0055)
Mean temperature (Celsius)	0.8974**	0.8974**
	(0.2856)	(0.2856)
Global state variables		
Oil price (2011$/barrel)	-0.4945***	-0.2952**
	(0.0853)	(0.0853)
COP 18 (dummy)	10.8759***	10.8759***
	(2.2887)	(2.2887)
Constant	Y	Y
# Observations	42	42

Notes: Kyoto targets are in units of % change in emissions relative to 1990 level. Robust standard errors are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B4b. Kyoto target policy function for non-EU countries

Dependent variable is the level of the Kyoto target adopted by non-EU country, conditional on adopting a Kyoto target that year	(1)
Country-level state variables	
GDP, PPP (trillion 2011$)	-6.4188***
	(1.1974)
Below poverty (dummy)	-6.1289*
	(2.5080)
CO_2 emissions (Mt)	0.0185***
	(0.0023)
Energy intensity level of primary energy (MJ/$2011 PPP GDP)	0.0954
	(0.1943)
Mean temperature (Celsius)	0.3788***
	(0.0907)
Adopted before (dummy) * Previous Kyoto target adopted (% change in emissions)	0.0297
	(0.4497)
Global state variables	
Oil price (2011$/barrel)	-0.2570***
	(0.0539)
Constant	Y
# Observations	26

Notes: Kyoto targets are in units of % change in emissions relative to 1990 level. Robust standard errors are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B5a. CO_2 emissions policy function for EU countries

	Dependent variable is:	
	CO_2 emissions (Mt) (1)	% change in CO_2 emissions from 1990 levels (2)
Country-level state variables		
Lagged CO_2 emissions (Mt)	0.9889***	
	(0.0010)	
Lagged % change in CO_2 emissions from 1990 levels		0.9633***
		(0.0088)
CO_2 emissions from electricity and heat production (% of total fuel combustion)	0.0334***	
	(0.0134)	
Adopted before (dummy)		-0.0408***
		(0.0079)
Target period (dummy) * Adopted before (dummy) * Previous Kyoto target adopted (% change in emissions)		-6.32E-4*
		(2.53E-4)
Global state variables		
Oil price (2011$/barrel)	0.1532*	
	(0.0656)	
Global CO_2 concentration (ppm)	3.8538***	0.0248***
	(1.0285)	(0.0064)
Lagged aggregate CO_2 emissions (Mt)	-0.0061***	-3.65E-5***
	(0.0016)	(0.98E-5)
Any country adopted before (dummy)		0.0319*
		(0.0137)
Year (time trend)	-5.1724**	-0.0317**
	(1.5489)	(0.0107)

Constant	Y	Y
# Observations	402	402

Notes: "Lagged aggregate CO_2 emissions" are lagged CO_2 emissions (Mt) summed over all 92 countries. Kyoto targets are in units of % change in emissions relative to 1990 level. Robust standard errors are in parentheses. Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table B5b. CO_2 emissions policy function for non-EU countries

	Dependent variable is:	
	CO_2 emissions (Mt)	% change in CO_2 emissions from 1990 levels
	(1)	(2)
Country-level state variables		
Lagged CO_2 emissions (Mt)	1.1106***	
	(0.0122)	
Lagged % change in CO_2 emissions from 1990 levels		1.0559***
		(0.0029)
CO_2 emissions in 1990 (Mt)	-0.0581***	
	(0.0081)	
GDP, PPP squared (trillion 2011$)	-1.6271**	
	(0.5048)	
Adopted before (dummy)		-0.0201**
		(0.0061)
OECD dummy (dummy)		-0.0300***
		(0.0065)
Global state variables		
Oil price (2011$/barrel)	0.2029*	
	(0.0779)	
Lagged aggregate CO_2 emissions (Mt)	-0.0018**	
	(0.0006)	
Constant	Y	Y
# Observations	1,346	1,346

Notes: "Lagged aggregate CO_2 emissions" are lagged CO_2 emissions (Mt) summed over all 92 countries. Robust standard errors are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B6. Transition densities for the country-level socio-economic state variables

	Dependent variable is: GDP, PPP (trillion 2011$)	Population (million people)	Below poverty (dummy)
Lagged CO_2 emissions (Mt)	0.0002***	-654.05***	
	(0.0000)	(126.31)	
CO_2 emissions in 1990 (Mt)	-0.0001***	-416.73**	
	(0.0000)	(152.49)	
Adopted before (dummy)			-0.0215*
			(0.0092)
Lagged target period (dummy) x Adopt Kyoto target in 1997 (% change in emissions)	-0.0150***		0.0279**
	(0.0037)		(0.0095)
Lagged GDP, PPP (trillion 2011$)	0.9913***	-240548.52**	
	(0.0084)	(89,020.23)	
Lagged below poverty (dummy)		-164301.29**	0.9370***
		(58,396.79)	(0.0139)
Lagged energy intensity level of primary energy (MJ/$2011 PPP GDP)	-0.0004*		0.0014*
	(0.0002)		(0.0005)
Lagged population (million people)		1.0172***	
		(0.0001)	
Any country adopted before (dummy) x Lagged mean of Kyoto target adopted by other countries (% change in emissions)			-0.0020***
			(0.0005)
Annex I (dummy)		-190815.32***	-0.0343**
		(53,523.65)	(0.0113)
US (dummy)	-0.1068*	6532332.40***	
	(0.0434)	(404,349.63)	
China (dummy)	0.1132***	-7.7708E6***	
	(0.0255)	(0.3355E6)	
India (dummy)	0.1465***		0.0159**

	(0.0144)		(0.0047)
Any country adopted before (dummy)	-0.0142**		0.0296**
	(0.0053)		(0.0095)
Lagged global CO_2 concentration (ppm)	0.0022***		-0.0047**
	(0.0006)		(0.0014)
Lagged oil price (2011$/barrel)	-0.0008***		0.0013**
	(0.0002)		(0.0004)
Constant	Y	Y	Y
Observations	1,747	1,748	1,748

Notes: Robust standard errors clustered are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B7. Transition densities for the country-level energy- and climate-related state variables

	Dependent variable is: CO2 emissions from electricity and heat production (% of total fuel combustion)	Energy intensity level of primary energy (MJ/$2011 PPP GDP)	Mean temperature (Celsius)
Lagged CO_2 emissions (Mt)			-0.0003**
			(0.0001)
Lagged % change in CO_2 emissions from 1990 levels		0.0153*	0.0636*
		(0.0070)	(0.0304)
Adopted before (dummy)			0.5460***
			(0.1473)
Adopted before (dummy) x Lagged latest Kyoto target adopted (% change in emissions)	0.0247***		-0.0089*
	(0.0060)		(0.0040)
Lagged target period (dummy) x Adopted before (dummy)		0.1120***	-0.7376***
		(0.0294)	(0.1231)
Lagged target period (dummy) x Adopted before (dummy) x Lagged latest Kyoto target adopted (% change in emissions)			0.0354***
			(0.0061)
Lagged GDP, PPP (trillion 2011$)	0.1942**		0.0964*
	(0.0653)		(0.0394)
Lagged GDP, PPP (trillion 2011$), squared	-0.0137**		
	(0.0044)		
Lagged below poverty (dummy)		-0.0874*	
		(0.0418)	
Lagged CO_2 emissions from electricity and heat production (% of total fuel combustion)	0.9838***		
	(0.0040)		
Lagged energy intensity level of primary energy (MJ/$2011 PPP GDP)		0.9570***	-0.0181***
		(0.0105)	(0.0052)
Lagged mean temperature (Celsius)			0.9657***
			(0.0076)

Any country adopted before (dummy) x Lagged mean of Kyoto target adopted by other countries (% change in emissions)		0.0072***	
		(0.0018)	
Annex I (dummy)		-0.1439***	-0.7174***
		(0.0384)	(0.1849)
China (dummy)		-0.1296**	
		(0.0453)	
India (dummy)		-0.0679**	
		(0.0208)	
Lagged aggregate CO_2 emissions (Mt)			0.0003*
			(0.0001)
Lagged global CO_2 concentration (ppm)			-0.0791*
			(0.0361)
Constant	Y	Y	Y
Observations	1,748	1,748	1,599

Notes: Robust standard errors clustered are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B8. Transition density for the global CO_2 concentration

	Dependent variable is Global CO2 concentration (ppm)
Any country adopted before (dummy) x Lagged mean of Kyoto target adopted (% change in emissions)	-0.1072***
	(0.0000)
Lagged target period (dummy)	0.3162***
	(0.0000)
Lagged aggregate CO_2 emissions (Mt)	0.0001***
	(0.0000)
Lagged global CO_2 concentration (ppm)	-0.1039***
	(0.0000)
Lagged oil price (2011$/barrel)	-0.0300***
	(0.0000)
Lagged US CO_2 emissions (Mt)	-0.0018***
	(0.0000)
Lagged US GDP, PPP (trillion 2011$)	1.4321***
	(0.0000)
Lagged US CO_2 emissions from electricity and heat production (% of total fuel combustion)	0.5373***
	(0.0000)
Lagged US energy intensity level of primary energy (MJ/$2011 PPP GDP)	2.3059***
	(0.0000)
Lagged China CO_2 emissions (Mt)	0.0006***
	(0.0000)
Lagged China GDP, PPP (trillion 2011$)	0.0754***
	(0.0000)
Lagged China CO_2 emissions from electricity and heat production (% of total fuel combustion)	0.0038***
	(0.0000)
Lagged China energy intensity level of primary energy (MJ/$2011 PPP GDP)	0.0338***
	(0.0000)
Lagged India CO_2 emissions (Mt)	-0.0143***
	(0.0000)
Lagged India GDP, PPP (trillion 2011$)	2.9754***
	(0.0000)
Lagged India CO_2 emissions from electricity and heat production (% of total fuel combustion)	0.0472***
	(0.0000)
Lagged India energy intensity level of primary energy (MJ/$2011 PPP GDP)	3.4919***
	(0.0000)
Year (time trend)	2.4681***
	(0.0000)
Constant	Y
Observations	1,748

Notes: Robust standard errors are in parentheses. Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table B9a. Structural parameter estimates

	(1)	(2)	(3)	(4)	(5)
Coefficients in per-period payoff function on:					
GDP, PPP (trillion 2011$)	100 (normalization)	100 (normalization)	100 (normalization)	100 (normalization)	100 (normalization)
Mean temperature (Celsius)	-0.166 (0.754)				
Mean temperature (Celsius), squared	-0.006 (0.015)				
Global CO_2 concentration (ppm)	-0.838 (17.241)				
Adopt Kyoto target (dummy) * Country has option to adopt a Kyoto target this year (dummy)	138.682 (260.622)				
Adopted before (dummy)	-3.397 (41.397)				
Kyoto target adopted this year by a country that adopted a Kyoto target this year (%)	3.884 (40.102)				
% change in CO_2 emissions from 1990 levels (%) minus Kyoto target adopted this year by a country that adopted a Kyoto target this year (%)	0.645 (2.213)				
Latest Kyoto target adopted (%)	0.608 (2.080)				
Target period (dummy) x Adopted before (dummy)	-41.340 (176.121)				
Target period (dummy) x Lagged latest Kyoto target adopted (%)	-4.032 (21.316)				
Amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) during a year in which the COP3 targets are in effect x EU (dummy)	7.479 (22.786)	-4.695 (12.568)			
amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) during a year in which the COP3 targets are in effect x non-EU (dummy)	21.784 (19.511)	2.217 (14.845)			
amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) x EU (dummy)	-0.547 (4.224)	1.023 (2.277)	0.169 (0.270)	0.166 (0.251)	0.559* (0.271)
amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) x non-EU (dummy)	-1.571 (3.704)	0.692 (2.770)	0.789 (0.96)	0.642 (1.061)	0.572 (0.913)
CO_2 emissions (Mt)	-0.067*** (0.006)	-0.058*** (0.007)	-0.075*** (0.007)	-0.072*** (0.008)	-0.068*** (0.007)
EU ETS dummy X CO_2 emissions (Mt)	-0.021 (0.081)	0.062 (0.154)	-0.055 (0.132)	-0.144 (0.130)	0.051 (0.126)
CO_2 emissions (Mt) x target period (dummy) x adopted before (dummy) x EU (dummy)		-0.093 (0.297)	0.150 (0.219)		
CO_2 emissions (Mt) x target period (dummy) x adopted before (dummy) x non-EU (dummy)		-0.009 (0.027)	0.027 (0.023)		

CO_2 emissions (Mt) x adopted before (dummy) x EU (dummy)	0.081
	(0.075)
CO_2 emissions (Mt) x adopted before (dummy) x non-EU (dummy)	-0.002
	(0.008)

Notes: Standard errors are in parentheses. In all specifications, we normalize the coefficient on "GDP PPP (trillion 2011$)" to be equal to 100. This enables us to pin down the magnitudes of the other parameters, since we can identify the relative magnitudes of all other coefficients with respect to the coefficient on GDP. This also enables us to interpret the per-period payoff in the same units as GDP PPP x 100 (i.e., in units of "10 billion 2011$"), and also interpret the coefficients in the per-period off as measuring trade-offs between GDP and other terms (such as CO2 emissions).Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table B9b. Structural parameter estimates

	(6)	(7)	(8) BASE	(9)	(10)	(11)	(12)
Coefficients in per-period payoff function on:							
GDP, PPP (trillion 2011$)	100	100	100	100	100	100	100
	(normalization)	(normalization)	(normalization)	(normalization)	(normalization)	(normalization)	(normalization)
amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) x EU (dummy)					0.698***		
					(0.169)		
amount by which the % change in CO2 emissions from 1990 levels (%) exceeds the Kyoto target adopted at COP3 (%) x non-EU (dummy)					-0.117		
					(0.094)		
CO_2 emissions (Mt)	-0.065***	-0.072***		-0.06***			
	(0.007)	(0.007)		(0.008)			
CO_2 emissions (Mt) x EU (dummy)			-0.050		-0.070	-0.144	-0.055
			(0.095)		(0.128)	(0.089)	(0.144)
CO_2 emissions (Mt) x non-EU (dummy)			-0.073***		-0.069***	-0.056***	-0.055***
			(0.007)		(0.008)	(0.008)	(0.008)
EU ETS dummy X CO_2 emissions (Mt)	0.029						-0.122
	(0.109)						(0.177)
CO_2 emissions (Mt) x target period (dummy) x adopted before (dummy) x EU (dummy)							
CO_2 emissions (Mt) x target period (dummy) x adopted before (dummy) x non-EU (dummy)							
CO_2 emissions (Mt) x adopted before (dummy) x EU (dummy)	-0.013	-0.014				0.053	
	(0.061)	(0.045)				(0.049)	
CO_2 emissions (Mt) x adopted before (dummy) x non-EU (dummy)	-0.003	0.00002				-0.006	
	(0.007)	(0.00005)				(0.008)	

Notes: Standard errors are in parentheses. In all specifications, we normalize the coefficient on "GDP PPP (trillion 2011$)" to be equal to 100. This enables us to pin down the magnitudes of the other parameters, since we can identify the relative magnitudes of all other coefficients with respect to the coefficient on GDP. This also enables us to interpret the per-period payoff in the same units as GDP PPP x 100 (i.e., in units of "10 billion 2011$"), and also interpret the coefficients in the per-period off as measuring trade-offs between GDP and other terms (such as CO2 emissions).Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B10. Welfare

	Model Predicted	Actual
Average annual welfare per country (10 billion 2011$)		
Mean	22.72***	22.26***
	(1.072)	(1.273)
Min	-1.230	-0.120
	(4.299)	(11.372)
Max	394.15***	405.9***
	(16.475)	(15.318)

Notes: We use our estimated structural parameters from Specification (8) of Table B9b in Appendix B to calculate the welfare generated from countries' decisions regarding whether to adopt a Kyoto target, the level of the Kyoto target, and CO2 emissions. Welfare is the present discounted value of the entire stream of per-period payoffs over the period 1997-2014. Average annual welfare is welfare divided by the number of years. For each country, we calculate the actual welfare generated based on the observed actions and state variables over the period 1997-2014, the model predicted welfare generated from 100 simulation runs of the 1997-2014 period, and the difference between model predicted and actual welfare. Both actual and model predicted welfare are calculated using the parameter estimates from the structural model. Actual welfare is calculated using actual values of actions and states in the data over the period 1997-2014. Model predicted welfare is calculated using model predicted actions and states generated from 100 simulation runs of the 1997-2014 period. Standard errors are in parentheses. Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table B11. Welfare per year by country

Average annual welfare (10 billion 2011$)	Model predicted	Actual
Algeria	12.94***	13.29***
Armenia	0.62***	0.44***
Australia	22.83***	20.67***
Austria	13.49***	12.25***
Bahrain	1.71***	0.94***
Bangladesh	10.22***	10.15***
Belarus	2.47***	2.31***
Belgium	15.53***	14.37**
Benin	0.79***	0.48***
Bosnia and Herzegovina	1.2***	0.69***
Brazil	77.71***	84.74***
Bulgaria	2.89***	2.39***
Canada	37.06***	35.4***
Chile	9.91***	9.3***
China	161.05***	151.63***
Colombia	15.66***	14.77***
Costa Rica	2.42***	1.67***
Cote d'Ivoire	2.9***	1.96***
Croatia	3.62***	2.72***
Cyprus	1.05***	0.78***
Czech Republic	8.16***	6.95***
Denmark	9.64***	8.46***
Ecuador	5.7***	4.01***
Egypt	18.85***	21.13***
Estonia	0.76***	0.63**
Finland	7.52***	6.68**
France	79.36***	84.97***
Germany	115.86***	114.38***
Greece	12.39***	10.59**
Honduras	1.38***	0.89***
Hungary	7.66***	6.89***
Iceland	0.50***	0.38***
India	121.94***	112.63***
Indonesia	55.77***	54.19***
Iran	29.57***	28.08***
Ireland	6.77***	6.24***
Israel	7.17***	5.7***
Italy	79.18***	78.67***

Average annual welfare (10 billion 2011$)	Model predicted	Actual
Japan	156.47***	143.09***
Jordan	2.37***	1.46***
Kuwait	7.51***	5.89***
Kyrgyzstan	0.36***	0.33***
Latvia	1.59***	1.14***
Lithuania	2.21***	1.88***
Luxembourg	1.83***	1.4***
Malaysia	15.46***	14.46***
Malta	0.47***	0.35***
Mauritius	0.86***	0.55***
Mongolia	0.79***	0.3***
Morocco	7.36***	5.6***
Mozambique	0.89***	0.54***
Nepal	2.41***	1.64***
Netherlands	26.03***	25.52***
New Zealand	5.36***	4.12***
Nicaragua	1.08***	0.69***
Nigeria	14.23***	19.37***
Norway	12.24***	10.7***
Oman	5.46***	3.74***
Pakistan	19.75***	20.46***
Paraguay	2.25***	1.41***
Peru	8.79***	7.74***
Philippines	14.17***	14.28***
Poland	18.51***	18.04***
Portugal	11.61***	10.27***
Romania	9.1***	9.13***
Russia	44.4***	52.17***
Saudi Arabia	28.53***	29.5***
Senegal	1.18***	0.79***
Serbia	1.73***	1.46***
Singapore	9.42***	9.23***
Slovakia	3.95***	3.14***
Slovenia	2.02***	1.66***
South Africa	14.19***	10.46***
South Korea	33.52***	33.87***
Spain	45.43***	50.04***
Sri Lanka	5.74***	4.83***

Sudan	4.78***	3.87***
Sweden	14.28***	13.58***
Switzerland	15.68***	14.35***
Tanzania	3.34***	2.55***
Thailand	25.04***	23.57***
Togo	0.38***	0.26***
Tunisia	3.82***	2.94***
Turkey	32.95***	33.21***
Turkmenistan	0.90***	0.00***
Ukraine	-1.23	3.12***
United Kingdom	72.88***	76.23***
United States	394.15***	405.9***
Uruguay	2.51***	1.76***
Uzbekistan	1.08*	-0.12***
Venezuela	15.21***	12.67***
Zimbabwe	0.77***	0.79***

Notes: We use our estimated structural parameters from Specification (8) of Table B9b in Appendix B to calculate the welfare generated from countries' decisions regarding whether to adopt a Kyoto target, the level of the Kyoto target, and CO2 emissions. Welfare is the present discounted value of the entire stream of per-period payoffs over the period 1997-2014. Average annual welfare is welfare divided by the number of years. For each country, we calculate the actual welfare generated based on the observed actions and state variables over the period 1997-2014, the model predicted welfare generated from 100 simulation runs of the 1997-2014 period, and the difference between model predicted and actual welfare. Both actual and model predicted welfare are calculated using the parameter estimates from the structural model. Actual welfare is calculated using actual values of actions and states in the data over the period 1997-2014. Model predicted welfare is calculated using model predicted actions and states generated from 100 simulation runs of the 1997-2014 period. Standard errors are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table B12a. Model fit for adopt Kyoto target action variable

	Model Predicted	# Countries that adopted Actual	% Difference
Adopt Kyoto target: 1997 (Kyoto Protocol, COP 3)			
Number of countries that adopted a Kyoto target in 1997	33.20	35	-0.05
Number of EU countries that adopted a Kyoto target in 1997	15	15	0
Number of non-EU countries that adopted a Kyoto target in 1997	18.20	20	-0.09
Adopt Kyoto target: 2012 (Doha Amendment, COP 18)			
Number of countries that adopted a Kyoto target in 1997	32.83	33	-0.01
Number of EU countries that adopted a Kyoto target in 1997	27	27	0
Number of non-EU countries that adopted a Kyoto target in 1997	5.83	6	-0.03

Note: The percent difference of model predicted minus actual is calculated as the difference between model predicted and actual, divided by actual.

Table B12b. Model fit for Kyoto target action variable

	Mean		
	Model Predicted	**Actual**	**% Difference**
Kyoto target adopted in 1997 (Kyoto Protocol, COP 3)			
Kyoto target (% change in emissions) in 1997	-2.68	-3.2	-0.17
Kyoto target (% change in emissions) for EU countries in 1997	-2.17	-2.1	-0.03
Kyoto target (% change in emissions) for non-EU countries in 1997	-3.10	-4.1	0.13
Kyoto target adopted in 2012 (Doha Amendment, COP 18)			
Kyoto target (% change in emissions) in 2012	-15.78	-19.3	-0.18
Kyoto target (% change in emissions) for EU countries in 2012	-16.09	-20	-0.09
Kyoto target (% change in emissions) for non-EU countries in 2012	-14.34	-16.1	0.001

Notes: Kyoto targets are in units of % change in emissions relative to 1990 level. The percent difference of model predicted minus actual is calculated as the difference between model predicted and actual, divided by actual.

Table B12c. Model fit for CO_2 emissions action variable

	Mean		
	Model Predicted	Actual	% Difference
CO_2 emissions, 1997-2014			
CO_2 emissions (Mt)	275.2	265.1	0.04
CO_2 emissions (Mt) from EU countries	150.3	156.6	-0.04
CO_2 emissions (Mt) from non-EU countries	313.3	298.2	0.05

	Model Predicted	Actual	Model Predicted Minus Actual
% change in CO_2 emissions from 1990 levels, 1997-2014			
% change in CO_2 emissions from 1990 levels	0.66	0.65	0.01
% change in CO_2 emissions from 1990 levels for EU countries	-0.06	-0.01	-0.06
% change in CO_2 emissions from 1990 levels for non-EU countries	0.88	0.85	0.03

Notes: Kyoto targets are in units of % change in emissions relative to 1990 level. The percent difference of model predicted minus actual is calculated as the difference between model predicted and actual, divided by actual.

Table B12d. Model fit for state variables

	Mean		
	Model Predicted	Actual	% Difference
Country-level state variables			
GDP, PPP (trillion 2011$)	0.77	0.77	0.004
Population (million people)	59.88	60.00	-0.002
Below poverty (dummy)	0.551	0.577	-0.045
CO_2 emissions from electricity and heat production (% of total fuel combustion)	40.77	40.62	0.004
Energy intensity level of primary energy (MJ/$2011 PPP GDP)	6.64	6.63	0.001
Mean temperature (Celsius)	9.75	9.49	0.028
Global state variables			
Global CO_2 concentration (ppm)	378.56	379.81	-0.003

Note: The percent difference of model predicted minus actual is calculated as the difference between model predicted and actual, divided by actual.

Table B13. Profitable Deviations

	Expected profitable deviations
Algeria	0.026
Armenia	0.031
Australia	0.015
Austria	0.007
Bahrain	0.013
Bangladesh	0.011
Belarus	0.097
Belgium	0.012
Benin	0.013
Bosnia and Herzegovina	0.008
Brazil	0.000
Bulgaria	0.050
Canada	0.016
Chile	0.045
China	0.005
Colombia	0.009
Costa Rica	0.025
Cote d'Ivoire	0.006
Croatia	0.014
Cyprus	0.016
Czech Republic	0.024
Denmark	0.019
Ecuador	0.014
Egypt	0.019
Estonia	0.109
Finland	0.014
France	0.001
Germany	0.001
Greece	0.001
Honduras	0.022
Hungary	0.018
Iceland	0.010
India	0.001
Indonesia	0.001
Iran	0.004
Ireland	0.011
Israel	0.017
Italy	0.004
Japan	0.005

	Expected profitable deviations
Jordan	0.022
Kuwait	0.010
Kyrgyzstan	0.177
Latvia	0.009
Lithuania	0.055
Luxembourg	0.026
Malaysia	0.024
Malta	0.010
Mauritius	0.015
Mongolia	0.075
Morocco	0.005
Mozambique	0.010
Nepal	0.014
Netherlands	0.002
New Zealand	0.012
Nicaragua	0.010
Nigeria	0.031
Norway	0.000
Oman	0.010
Pakistan	0.006
Paraguay	0.004
Peru	0.026
Philippines	0.020
Poland	0.023
Portugal	0.009
Romania	0.031
Russia	0.022
Saudi Arabia	0.015
Senegal	0.042
Serbia	0.075
Singapore	0.021
Slovakia	0.038
Slovenia	0.068
South Africa	0.014
South Korea	0.024
Spain	0.004
Sri Lanka	0.064
Sudan	0.017
Sweden	0.002

Switzerland	0.001
Tanzania	0.074
Thailand	0.004
Togo	0.007
Tunisia	0.041
Turkey	0.002
Turkmenistan	0.124
Ukraine	0.489
United Kingdom	0.001
United States	0.004
Uruguay	0.048
Uzbekistan	0.057
Venezuela	0.008
Zimbabwe	0.099

Notes: Expected profitable deviations are expressed as a percentage of model predicted welfare. Since model predicted welfare for Ukraine is negative, expected profitable deviations for Ukraine are expressed as a percentage of actual welfare.

Table B14. Change in welfare per year by country from base-reference case under the COP membership counterfactual scenarios

	Change in average annual welfare relative to the Reference scenario (10 billion 2011$) When COP does not include:	
	US	EU
Algeria	-0.511***	-0.329***
Armenia	-0.026***	-0.090***
Australia	-0.905***	0.114
Austria	-0.441	0.495
Bahrain	-0.408***	-0.215***
Bangladesh	-0.565***	-0.407***
Belarus	-0.039	0.357***
Belgium	-0.066	0.165
Benin	-0.062***	-0.094***
Bosnia and Herzegovina	-0.121***	-0.116***
Brazil	-0.768***	-1.976***
Bulgaria	-0.296***	0.248***
Canada	0.021	0.999***
Chile	-0.038	-0.441***
China	-0.533	-1.646
Colombia	-1.277***	-1.039***
Costa Rica	-0.251***	-0.099***
Cote d'Ivoire	-0.109***	-0.154***
Croatia	-0.127***	-0.036***
Cyprus	0.004	0.003
Czech Republic	0.597***	0.372
Denmark	-0.340	-0.602
Ecuador	-0.450***	-0.516***
Egypt	-0.543***	-0.216***
Estonia	0.130***	0.152***
Finland	0.320	-0.446
France	-0.384	-0.899
Germany	1.697	0.637
Greece	-0.275	-1.143***
Honduras	-0.069***	-0.018***
Hungary	0.041	-0.017
Iceland	-0.001	-0.039***
India	-0.652	0.407
Indonesia	-2.041***	-0.503***
Iran	-0.961***	-0.573***
Ireland	-0.852***	0.219
Israel	-0.343***	-0.822***
Italy	1.373***	-0.201

Japan	-1.232***	0.104
Jordan	-0.296***	0.058***
Kuwait	-0.087***	-0.803***
Kyrgyzstan	0.007	-0.058***
Latvia	-0.112***	-0.092***
Lithuania	0.067	0.174***
Luxembourg	-0.059	0.056
Malaysia	-0.374***	-0.637***
Malta	-0.008	0.015***
Mauritius	-0.045***	-0.040***
Mongolia	-0.030***	0.043***
Morocco	-1.249***	-1.481***
Mozambique	-0.139***	-0.128***
Nepal	-0.220***	-0.085***
Netherlands	-1.336	-0.550
New Zealand	-0.318***	-0.258***
Nicaragua	-0.113***	-0.032***
Nigeria	-0.699***	0.295***
Norway	-0.931***	-1.179***
Oman	-0.108***	-0.379***
Pakistan	-0.947***	-0.613***
Paraguay	-0.236***	-0.190***
Peru	-1.360***	-0.819***
Philippines	-1.360***	-0.317***
Poland	-0.512	0.212
Portugal	-0.667***	-0.666***
Romania	-0.884***	0.196
Russia	-1.780***	-4.725***
Saudi Arabia	0.628***	-0.472***
Senegal	0.010***	-0.074***
Serbia	-0.536***	0.025
Singapore	-0.747***	-0.624***
Slovakia	-0.160***	0.741***
Slovenia	0.025	0.025
South Africa	-1.455***	-0.660***
South Korea	0.009	0.341
Spain	-0.278	0.260
Sri Lanka	-0.491***	-0.213***
Sudan	-0.377***	0.044***
Sweden	-1.307***	-0.865***
Switzerland	-1.088***	-0.872***
Tanzania	0.128***	0.307***
Thailand	-2.53***	-1.255***
Togo	-0.029***	-0.021***
Tunisia	-0.134***	0.055***

Turkey	-1.370***	-1.373***
Turkmenistan	-0.030***	0.075***
Ukraine	1.134***	1.517***
United Kingdom	-0.212	0.453
United States	2.989	-1.092
Uruguay	0.0004	0.018***
Uzbekistan	-0.879***	-0.739***
Venezuela	-0.780***	-0.291***
Zimbabwe	-0.111***	-0.125***

Notes: Significance codes: *** p<0.001, ** p<0.01, * p<0.05.