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Wildlife Trade Policy and the Decline of Wildlife

Abstract

The Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) is the international agreement that regulates international trade in wildlife to prevent its decline. Little is known about the effectiveness of its trade restrictions and bans. Combining the largest available panel database on wildlife population sizes of vertebrates with the history of species' inclusion into CITES, we find that populations increase by 20% after their species' inclusion into CITES. This effect is driven by populations in countries with thorough enforcement. Outright trade bans increase wildlife, but restrictions that incentivize sustainable use have more immediate positive effects.

JEL-Codes: F180, Q270, Q560.

Keywords: CITES, endangered species, wildlife decline, wildlife trade policy.

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1 Introduction

Wildlife is in decline. This decline in natural resources has direct economic consequences, e.g., for fisheries and agricultural production and, more generally, for ecosystem services. International wildlife trade is often seen as a major driver of wildlife decline (Scheffers et al., 2019). Although gauging the extent of international trade in wildlife products is difficult, estimates suggest that its volume is sizeable: Global wildlife trade was estimated at 249 billion € per year (Engler and Parry-Jones, 2007).

There is an ongoing debate whether and under which circumstances restrictions on wildlife trade are effective in protecting wildlife. On the one hand, restricting trade seems an intuitive policy measure to prevent unsustainable resource use and subsequent wildlife decline. Outright trade bans can stigmatize consumption of wildlife products, reducing their demand. Economists, on the other hand, tend to be sceptical about trade bans, as banning wildlife trade renders the legal economic value of wildlife to zero, reducing the incentive for local communities to protect or harvest resources at sustainable levels. Without costly monitoring and enforcement, poaching and illegal trade may replace legal trade, rendering trade bans ineffective. Summarizing the literature on wildlife trade restrictions, Fischer (2010) calls for an empirical evaluation of their effectiveness in preventing wildlife decline.[1] Similarly, 't Sas-Rolfes et al. (2019) highlight the need for evaluating the effectiveness of specific trade policy interventions in a recent survey on illegal wildlife trade.

Our paper provides such an evaluation using the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES). CITES is the international agreement that regulates and restricts international wildlife trade to prevent wildlife decline. It uses a system of export and import permits that applies to species listed in its appendices. The history of species' listings in CITES provides an ideal setting to identify the effects of international trade restrictions on wildlife.

It is unclear whether the current international wildlife trade policy regime represented by CITES effectively prevents the decline of wildlife.[2]

[1] So do Bulte and Barbier (2005) in an earlier survey of the effects of trade liberalization on welfare and wildlife stocks.

[2] For different viewpoints concerning the effectiveness of CITES, see, e.g., Hutton and

A naive test of CITES' effectiveness would compare the size of wildlife populations of species listed in CITES with non-listed species. A challenge in interpreting this means comparison causally is the endogeneous selection of individual wildlife species into CITES. For example, CITES listed species may be more likely to become extinct. Then, comparing population sizes of CITES listed and non-listed species would deliver biased results. Other confounding factors may correlate with both wildlife decline and CITES' listing decisions: Commercially valuable species may be less likely to see their international trade restricted or banned (Stokstad, 2010). Moreover, CITES' listings may be more likely for well-known, charismatic species, reflecting a more general "taxonomic bias" in wildlife conservation efforts (Clark and May, 2002).

Our paper overcomes these challenges by using a geo-referenced unbalanced panel of 7379 populations in 158 countries from 1950 to 2015, the largest publicly available database on vertebrate population sizes over time. We combine these wildlife population data with the detailed history of species' inclusion into CITES and with data from the IUCN Red List of Threatened Species, the world's most comprehensive inventory of species' extinction risk. Our panel data allow us to control for unobserved species' characteristics that drive the non-random selection of species into CITES. This enables us to identify the causal effect of CITES' trade restrictions on wildlife population sizes once a species gets listed in CITES, and determine whether CITES effectively prevents the decline of wildlife.

We find that wildlife populations increase after their corresponding species is listed in CITES, but only with considerable lag. This result is driven by populations located in CITES' member countries with strong enforcement of its rules. Populations increase by about 20% 11 to 15 years after the species is listed in CITES, and by about 50% for species that benefit from CITES' protection for more than 20 years. Frank and Wilcove (2019) find that, on average, species are listed in CITES more than 10 years after they have been identified as threatened by international trade. Our results, combined with this finding, highlight the importance of reducing the time lag between new scientific evidence and species' inclusion into

Dickson (2000); Ginsberg (2002); Bulte et al. (2004); Fischer (2010); Challender et al. (2015).

CITES to effectively prevent wildlife decline.

We explore whether populations of different types of species are affected differently after their CITES' listing. Species with high economic value, which are intentionally harvested, vulnerable species with high extinction risk, highly-studied species, well-known species, and species with a large body mass do not seem to benefit differently from CITES protection in countries with strong enforcement. For large species such as elephants, rhinos, and whales, CITES protects effectively populations of listed species even in member countries with weak enforcement.

Our results are robust to controlling for time-varying country-specific confounding factors that may affect both CITES' listing decisions and wildlife decline such as habitat loss, corruption, or armed conflicts.

We explore the two main mechanisms through which species benefit from CITES' protection: 1.) outright trade bans or 2.) more nuanced trade restrictions that are meant to ensure the sustainable use of species. This allows us to quantify the relative effectiveness of these mechanisms, which are represented by CITES' two main appendices: Species listed in Appendix I are not allowed to be traded internationally for commercial purposes. Species listed in Appendix II may be traded internationally but their trade is restricted to ensure that trade is sustainable and does not threaten a species' survival. Our results show that wildlife populations increase by a similar magnitude for species in both Appendix I and Appendix II. Contrary to views that question the effectiveness of international wildlife trade bans (see, e.g., Smith et al., 2003b), we find that trade bans prevent wildlife decline. However, restrictions that incentivize sustainable use have more immediate positive effects.

As a consistency check, we use an alternative identification strategy by exploiting quasi-natural variation in trade bans for wild birds due to bird flu outbreaks across countries over time. We find that bird populations increase after trade bans. In a placebo test, we do not find an effect of bird trade bans on other species. We interpret these results as corroborating evidence that strict enforcement of trade bans help to prevent wildlife decline, particularly if bans are applied for a wide range of species so that they are more easily enforceable by customs officials.

Our paper relates to various strands of the literature. A broad theoretical literature discusses the circumstances under which trade restrictions can alleviate or exacerbate the overharvesting of renewable resources. Whether trade bans are effective in protecting wildlife populations depends on the assumptions chosen such as whether wildlife trade is imperfectly competitive, whether models allow species to be illegally traded or stockpiled, whether they consider the possibility of legal trade allowing the laundering of poached specimens, and how the behavior of the regulator is modelled, e.g., if it can sell or destroy seized specimens of poached species. Much of this theoretical literature focuses on the ivory trade ban, see, e.g., Khanna and Harford (1996), Bulte and van Kooten (1999), Burton (1999), Fischer (2004), Heltberg (2001), and Kremer and Morcom (2000). These studies highlight the importance of country-specific institutional factors such as a government's ability to enforce wildlife trade regulations for proper management of common property resources, see, e.g., Copeland and Taylor (2009). Our results document the importance of countries' enforcement capability for CITES' effectiveness.

Several studies quantify the effectiveness of other international environmental agreements. Aichele and Felbermayr (2012) study whether the Kyoto Protocol, which attempts to reduce carbon dioxide emissions of its member countries, has led to a reduction in countries' carbon footprint, i.e., the emissions embodied in domestic consumption and investment. They find that the Kyoto Protocol has been ineffective, as it has not reduced global emissions. Kellenberg and Levinson (2014) analyze the effectiveness of the Basel Convention, which intends to reduce the generation of hazardous waste by restricting its shipment to countries with inadequate environmental regulation. They find no evidence of a reduction in the overall level of international trade in waste. Contrary to the evidence in this literature, we find that CITES is effective in its goal of preventing wildlife decline. More generally, our paper highlights that international cooperation helps to prevent *local* environmental degradation caused by *global* threats such as international wildlife trade.

Our paper also relates to the literature that analyzes the effects of domestic regulations concerning endangered species. A large part of this literature focuses on the U.S. Endangered Species Act (ESA). Similar to CITES, ESA's protection relies on listing endangered species. ESA implements CITES' regulations in domestic law, but has more far-reaching powers. Whereas CITES only regulates international wildlife trade, ESA protects species by effectively preventing any economic development of areas with populations of listed species, see the survey by Brown and Shogren (1998). Metrick and Weitzman (1996) document that species' characteristics determine the probability of receiving protection by ESA: Charismatic species, particularly large mammals, the so-called "charismatic megafauna", are more likely to be protected, highlighting the importance of the non-random selection of species. Ferraro et al. (2007) evaluate the effectiveness of ESA's listings by studying their impact on the change in an index of a species' endangerment status between 1993 and 2004 using 430 species from the US. Similar to our results for CITES, they find that implementation is crucial for ESA's effectiveness. Ando and Langpap (2018) provide a recent survey on empirical studies of ESA's effectiveness, as well as on similar regulations in Australia and Canada. The literature surveyed finds only little evidence for the effectiveness of domestic regulations that intend to protect endangered species. Our study identifies a positive effect of international wildlife trade regulation on populations using data from 158 countries over 66 years.

We also relate to a literature that empirically analyzes the consequences of international trade bans using case studies of individual species. Hsiang and Sekar (2016) study the effect of a temporary removal of the trade ban for ivory for a one-off international legal sale. Using an unbalanced panel of illegal elephant killings across 38 countries, they find that the temporary removal of the trade ban led to an increase in elephant poaching. Chimeli and Soares (2017) study the effects of the introduction of a ban on mahogany exports in Brazil in 2001. They find that illegal exports of mahogany increase after the introduction of the trade ban and decrease with improved monitoring and enforcement of trade bans. Taylor (2011) documents that international trade and the absence of trade restrictions in wildlife products explain the virtual extinction of the North American bison. Complementing these studies of individual species, we study the impact of CITES' effectiveness for more than 2000 vertebrate species.

More broadly, our paper relates to the literature on environmental effects of international trade, see the review by Cherniwchan et al. (2017).

This literature focuses mostly on local pollution and global emission effects of changes in trade policies for manufacturing goods, whereas we focus on the effects of wildlife trade policy on wildlife.

The rest of the paper is organized as follows. Section 2 provides institutional background and describes the data. Section 3 describes our identification strategy. Section 4 presents results. Section 5 concludes.

2 Institutional background and data

2.1 Wildlife protection under CITES

CITES is the multilateral trade agreement that regulates wildlife trade in endangered species. It aims at ensuring species' survival by prohibiting or regulating international wildlife trade and the commercial use of wildlife and its products. Species covered by CITES are listed in two appendices, according to their degree of protection. International commercial trade in species listed in Appendix I is prohibited, but may be allowed for species listed in Appendix II if it does not endanger the survival of the species.[3]

With its entry into force in 1975, CITES protected a large number of species. In subsequent years, species were included into CITES at one of the Conferences of the Parties (CoPs), the bi-annual meeting of representatives of CITES' member countries. We present the distribution of entry years of the species in our data in Figure 1. The majority of species were first listed into CITES until the mid eighties, and since then the inclusion of species has slowed down.

Once a species is listed, CITES monitors its international trade via a system of import permits (for Appendix I and II) and export permits (for Appendix I). CITES member countries are expected to control all international trade in species listed in CITES, even imports of species from non-member countries. We show the evolution of the number of member countries over time in Figure 2. Today, CITES' membership is almost universal, with 183 country members, more than the World Trade Organization's 164 members.

[3]For an overview of CITES, see, e.g., Hutton and Dickson (2000); Ginsberg (2002); Reeve (2006); Challender et al. (2015).

Figure 1: Distribution of year of first entry into CITES (species)

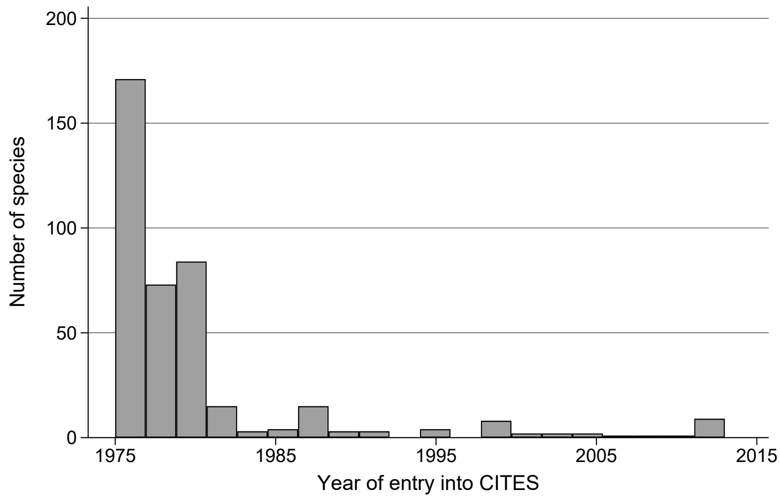


Figure depicts the distribution of the first year a species entered into one of CITES' appendices in our data.

CITES classifies member countries into three categories, according to the quality of their enforcement and compliance procedures. The classification takes into account four criteria: First, that the country has designated, at least, one Management Authority and one Scientific Authority. Second, that the country prohibits trade in specimens in violation of CITES. Third, that the country penalizes such trade; and, finally, that the country confiscates specimens illegally traded or possessed. Countries are then classified as Category 1 (those that have legislation that meet all four requirements for effective implementation of CITES), Category 2 (those countries that have legislation that is believed generally to meet one to three of the four requirements for effective implementation of CITES), and Category 3 (those that have legislation that is believed generally not to meet any of the four requirements for effective implementation of CITES). In our analysis, we will make use of the variation across species, time, member countries, as well as their classifications to identify the effect of CITES on wildlife.

2.2 Data

Our focus is measuring CITES' effectiveness in terms of its ultimate goal, the prevention of wildlife decline. We therefore use wildlife population size

Figure 2: Year of entry into CITES (countries)

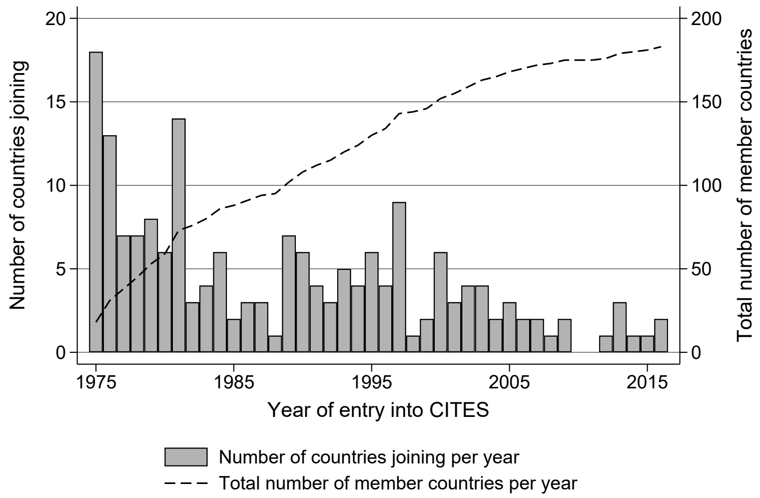


Figure depicts number of countries in which CITES entered into force per year.

as our dependent variable.

Wildlife population size data.—We focus on the evolution of the population size of a (sub-)species s at a geographic location l at time t, i.e., population refers to the tuple (s, l). We use the raw data underlying the Living Planet Index (LPI) by World Wildlife Fund (2016).[4] These data are the largest publicly-available database providing information on wildlife population sizes over time and are routinely used to monitor the progress of biodiversity conservation targets (see, e.g., Butchart et al., 2010 and Tittensor et al., 2014).[5]

[4]For a description of the data, see Loh et al. (2005); Collen et al. (2009). The data can be downloaded from `http://www.livingplanetindex.org/projects?main\_page\_project=LivingPlanetReport\&home\_flag=1` (downloaded 10 January 2017).

[5]Note that wildlife trade data for species included in the LPI raw data are not available. Available databases such as the CITES Trade Database only contain trade in species listed in CITES, preventing before-and-after comparisons of species becoming listed in CITES. Furthermore, the CITES Trade Database is derived from the number of import and export permits CITES' members submit through annual reports. These data are measured with considerable error, and no clear rules exist on how to calculate trade volumes from the underlying records on permits, see, e.g., Berec et al. (2018). As pointed out by Chan et al. (2015), standard merchandise trade classifications such as the Harmonized System do not distinguish trade in individual species. Even if trade data were available, many species, including those that are regulated under CITES, are traded illegally and hence their trade is not documented, see, e.g., 't Sas-Rolfes et al. (2019).

Population size data are ideal for our purpose as they react more quickly to changes in wildlife protection than data on species' endangerment status and whether species are (close to becoming) extinct. Extinction is a long-run process and it can be difficult to determine whether a species is actually extinct.[6] Declines in population sizes are directly linked to reduced ecosystem services and ultimately, e.g., fisheries and agricultural production. Particularly, wildlife populations can become so small that they are functionally extinct, i.e., they cease to provide economic benefits, even when complete extinction can be avoided, see Sekercioglu et al. (2004).[7]

Population size data in the LPI are unbalanced and not necessarily available for consecutive years. For example, the population of Cape vultures (*Gyps coprotheres*) in Namibia is only observed for the years 1975, 1980, 1990, and 2000. Hence we cannot calculate annual (log) growth rates for all populations. In our empirical analysis, we therefore use a within estimator instead of a first difference transformation to control for unobserved population fixed effects. This allows us to incorporate the information from those populations whose size is not observed every year.

The LPI data report population size in a variety of units, depending on the study from which the raw data are collected: Population sizes may be simple counts of individuals in a given geographic location, or the number of breeding pairs; sometimes, population size is measured as the amount of biomass in a population, i.e., in kilograms, or as the number of individuals per a given area. In our empirical analysis, we use a log-linear regression with species-location (i.e., population) fixed effects that control for these differences in units of measurements across the different populations.[8]

[6]For a discussion of these issues, see, e.g., Ceballos and Ehrlich (2002); Butchart et al. (2006).

[7]In our final dataset, 3682 observations report a population size of zero, about 3% of our final dataset. Note that population sizes of 0 do not necessarily imply that a population has gone extinct, as population size data are measured with considerable measurement error, see, e.g., Meir and Fagan (2000), and the recent upward revisions of population size data for *Gorilla gorilla gorilla* by Strindberg et al. (2018). In our dataset, of the 951 populations which record a zero population size in one year, 83 percent report a non-zero population size afterwards. We therefore assume that zeros are due to random measurement error. If measurement errors are specific to certain populations, the fixed effects we include in our regressions will control for this.

[8]By way of illustration, imagine that there are just two different measurement units used, individuals and pairs. In this case, the difference in measurement units is a factor of 2. By multiplying our dependent variable by this factor for all observations

CITES data.—We combine the wildlife population size data with information about which species are listed in CITES' Appendices I and II from the *Checklist of CITES Species* by UNEP-WCMC (2017). We get the year in which countries became CITES members from the CITES Secretariat website.[9] Data on the classification of member countries according to the quality of their enforcement and compliance procedures is from the CITES official document "Status of Legislative Progress for Implementing CITES", CoP17 Doc. 22 Annex 3 (Rev. 1).

Corruption at the border data.—CITES being an international trade agreement, its rules have to be implemented by national governments and enforced by customs officials. In countries with high levels of customs corruption, CITES may therefore be less effective. As a proxy for corruption at the border, we use the share of a country's population that answered "yes" to the question "in the last 12 months anyone living in a household paid a bribe in any form to customs" (variable "Paid Bribe: Customs") in the Global Corruption Barometer by Transparency International as reported in the Quality of Government Basic Dataset (version Jan17) by Dahlberg et al. (2017).

CITES' sanctions data.—CITES allows to impose sanctions on countries that are not compliant with CITES regulations. If a country is sanctioned, all commercial trade in CITES-listed species is suspended. Sanctions are indicative of a lack of enforcement of CITES. It is likely that CITES is not effective in sanctioned countries. In a subsample analysis, we therefore exclude all populations in sanctioned countries for those years where the sanctions are applied. To do so, we rely on the historical data on suspensions of all commercial trade in CITES-listed species that is avail-

measured in pairs, we can transform all observations measured in pairs to individuals. This factor is constant over time, as the measurement unit for a population does not change over time in our dataset, and is not affected by CITES. It is hence perfectly captured by a population fixed effect μ_{sl}. More generally, all observations can be converted to the same unit of measurement by multiplying by b_{sl}, a population-specific, time-invariant scale factor ($N_{slt}^{same\ unit} = b_{sl}N_{slt}$). Taking the natural logarithm, this becomes ($\ln N_{slt}^{same\ unit} = \ln b_{sl} + \ln N_{slt}$). Hence, including a population-specific fixed effect in combination with using the dependent variable in logs controls for the different units of measurement problem and we can then interpret regression coefficients in the usual way, as a semi-elasticity that is independent of the unit of measurement.

[9]The "List of Contracting Parties" is available at `https://www.cites.org/eng/disc/parties/chronolo.php`.

able from Sand (2013). Sand lists sanctions for the period 1985-2013. We update sanctions data until 2016 by using the information provided on the CITES webpage regarding "Countries currently subject to a recommendation to suspend trade".[10]

IUCN Red List data.—We estimate separate species-type specific treatment effects because CITES may be more or less effective for different types of species. For example, the protection offered by CITES may be more effective for species with commercial value (or species with "intentional use"), as it may prevent overharvesting. We use data on intentional use from the IUCN-CMP Unified Classification of Direct Threats (version 3.2), which is a refined version of the classification introduced by Salafsky et al. (2008).[11] We also estimate a separate effect for species that are vulnerable. We use the IUCN Red List of Threatened Species classification on extinction risk and consider as vulnerable all species that are classified as "critically endangered", "endangered", and "vulnerable", i.e., species facing extremely or very high risk of extinction in the wild.[12]

Citizen science data (iNaturalist).—We estimate a separate treatment effect for well-known species. To identify these species, we use citizen science data on users' identifications for species from *iNaturalist*.[13] This database contains information about exemplars of species identified by the community, mostly by photos, going back to 1970. Today, users can upload their photos via a smartphone app.

Species traits data.—We estimate a separate treatment effect for large species, i.e., species with larger than average body mass. We use data from the EltonTraits 1.0 dataset, a species-level compilation from various sources of species' attributes of birds and mammals by Wilman et al. (2014).[14]

[10]This information is available at `https://www.cites.org/eng/resources/ref/suspend.php`, but is updated with frequency, hence countries that are no longer subject to a recommendation to suspend trade, are removed from the list. We update the sanctions data with the help of the *Wayback Machine - Internet Archive*.

[11]We downloaded these data from the IUCN Red List API-v3 (`http://apiv3.iucnredlist.org/api/v3/docs`) on 20 February 2019.

[12]We downloaded these data from the IUCN Red List API-v3 on 8 November 2017.

[13]Data downloaded from the *iNaturalist* webpage `https://www.inaturalist.org/home`. Data downloaded are for taxa on amphibians, birds, fishes, mammals, and reptiles. Data downloaded on 12 and 13 November 2019.

[14]The main sources for the body mass data are Smith et al. (2003a) for mammals and Dunning (2007) for birds.

Data on spread and scope of avian influenza ("bird flu").—To confirm the mechanisms underlying our results, we consider whether country-specific trade bans unrelated to CITES have an impact on wildlife. Trade bans on birds were imposed following the outbreak of the bird flu in South-East Asia in late 2003 and its subsequent spread to other continents. We use notifications and follow-up reports notified by World Organisation for Animal Health (OIE) member countries of local bird flu outbreaks to identify countries affected by trade bans.[15]

3 Research design and identification

We estimate the causal effect of CITES' listings on the size of species' populations. Figure 3 shows the evolution of the average population size for species that are listed in CITES at some point of time within our sample period and those which are not, respectively, i.e., the graph does *not* take into account that different species enter in different years. The figure shows predicted log population size per year for these two groups. To calculate predicted population sizes, we run a regression of log population sizes on a population fixed effect to control for the difference in measurement units, and different year effects for CITES listed and non-listed (never listed) species. Figure 3 shows the average of the predicted values from this regression excluding the population fixed effect to ensure that we use the same measurement unit for all observations. Species protected by CITES have smaller populations before CITES entered into force in 1975, i.e., there are pre-existing differences in listed and non-listed species which we will control by the inclusion of population fixed effects. The figure also shows a dashed line with the evolution of the difference in population size between listed and non-listed species. This line allows a coarse comparison of the relative pre-existing trends for the period before any species are treated, i.e, before 1975. We see that population size seems to move on parallel

[15]We use countries' notifications and follow-up reports of highly pathogenic avian influenza due to H5 and H7 serotypes available at `https://www.oie.int/en/animal-health-in-the-world/update-on-avian-influenza/`. These notifications are used to impose trade bans on wild birds originating in countries with a notified outbreak, see, e.g., the corresponding legislation of the European Union (European Commission 2005).

Figure 3: Average population size: Listed and never listed species by year

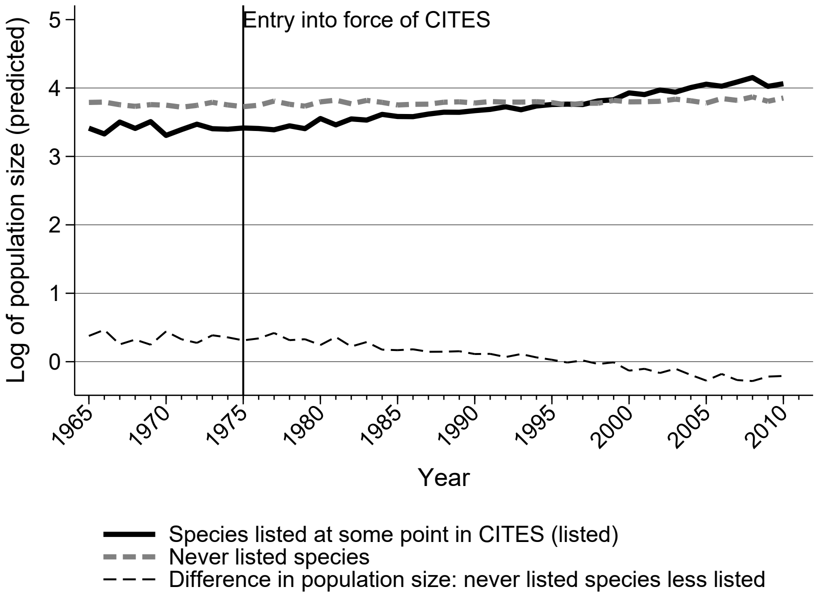


Figure depicts the (predicted) population size per year for species that have ever been listed in CITES versus species that have never been listed in CITES.

trends before CITES entered into force.[16] After 1975, species start to get listed in CITES' appendices and trends start to diverge.

The intuition derived from eyeballing Figure 3 is also borne out when using a formal statistical test for equality of trends following the approach by Antwi et al. (2013). As species start to be included into CITES with its entry into force in 1975, we only use data of populations observed before 1975 for this test (N = 14418). We then regress population size on population (species-location) and year fixed effects, and an interaction term of the linear time trend with $EVERCITES_s$, $EVERCITES_st$, where $EVERCITES_s$ indicates whether species s is part of the treatment group, i.e., a species included into CITES' appendices at some point in time in our dataset. There is no significant difference in the trends of treatment and control groups prior to the entry into force of CITES.[17]

[16]Note that the number of observations included in the "treated" group is considerably lower than the number of observations included in the "control" group, which explains the larger variance in the average population size for listed species.

[17]The estimated coefficient for $EVERCITES_st$ is 0.016 ($s.e.$ = 0.010, p-value = 0.108).

One of the reasons for pre-existing differences between listed and non-listed species is that the probability of being listed in CITES is different across species. Metrick and Weitzman (1996) document that different types of species have different probabilities of getting listed in the U.S. Endangered Species Act. We confirm their result for CITES. In Appendix A, we show that large mammals (the so-called "charismatic megafauna"), vulnerable species, and species used intentionally have a higher probability of being listed in CITES. Similarly, we find higher probabilities of getting listed for mammals, birds, and reptiles than for fishes. This provides evidence of a selection bias driven by species' time-invariant characteristics.

The probability of a species getting listed may change over time because new scientific evidence on the status of a species becomes known. For every population in our data, the LPI data reference the source of the population size data in the scientific literature. This allows us to construct a balanced panel dataset for all species for the years 1950 to 2015 where we count the accumulated number of studies available in a given year for a specific species, $ACCUMULATEDSTUDIES_{st}$. We run the following regression:

$$CITES_{st} = \alpha_s + \beta ACCUMULATEDSTUDIES_{st} + \delta t + \varepsilon_{st}, \qquad (1)$$

where $CITES_{st}$ is an indicator variable which is one if species s is listed in CITES in year t and zero otherwise, δt is a time trend, and α_s is a species fixed effect that controls for all time-invariant species characteristics influencing the selection into CITES as documented in Appendix A. We cluster standard errors at the species level. We present results in Table 1.

We find a significant time trend, with the probability of being listed in CITES increasing by 0.3 percentage points per year. Importantly, we do not find a significant effect of the number of accumulated studies. Accordingly, the explanatory power of the regressor is weak, which together with the time trend contributes only 5% percentage points to the overall R^2 of the pooled regression. Comparing the two columns reveals that the majority of the variation in $CITES_{st}$ is explained by the species fixed effect.

These results inform our identification strategy to estimate the effect of CITES' listings on wildlife populations. Including population-specific fixed effects remedies the documented time-invariant selection bias by fo-

Table 1: Determinants of CITES listings (panel)

	(1)	(2)
accumulated number of studies available	0.005	−0.001
	(0.003)	(0.002)
trend	0.003	0.003
	(0.000)	(0.000)
R^2	0.05	0.59
N	156420	156420

Notes: Table 1 reports estimated coefficients from a panel linear probability model. The dependent variable is a dummy variable that equals one when the species is listed in CITES in year t and zero otherwise. As regressors we use a variable that measures the accumulated number of published studies in our dataset in t on a specific species and a time trend. Column (1) estimates Equation (1) using pooled OLS. Column (2) adds a species fixed effect. Standard errors are in parentheses and are clustered at the species level.

cusing on within-population variation for a given species. In addition, our population fixed effect eliminates the time-invariant taxonomic bias. It also controls for systematic time-invariant differences between species that have been listed early on in CITES and those that have been listed later. We control for the trend in the probability of species becoming listed by including year fixed effects. Our baseline regression is given by:

$$\ln N_{slt} \quad = \quad \mu_{sl} + \eta_t + \beta(\text{in CITES})_{st} + \varepsilon_{slt}, \tag{2}$$

where N_{slt} is the size of the population of a species s in location l in year t.[18] $(\text{in CITES})_{st}$ is a dummy variable that is one when a species is listed in one of CITES' appendices in a given year, and zero otherwise. μ_{sl} is a time-invariant species-location-specific (i.e., population-specific) fixed effect that controls for factors such as, e.g., habitat suitability, which determine population size of a species in a given location. Even in a world without any loss of wildlife caused by human activity, species are unevenly distributed across space according to their habitat. For example, red fox (*Vulpes vulpes*) populations vary considerably across their geographical range, which is the largest within the order Carnivora, see Hoffmann and Silero-Zubiri (2016). This highlights the importance of allowing for different base levels of a species' abundance in different populations. In addition, species differ in terms of both their abundance and their extinction risk due to factors such

[18] Note that population refers to a given species s in location l. Hence, for a given year, there may be several species in the same location, and the same species may occur in several locations.

as body weight, size, attractiveness to humans, economic value and reproductive rates, see Hutton and Dickson (2000); Cardillo et al. (2005); McClenachan et al. (2016). η_t is a year-specific fixed effect that controls for time-varying factors that influence treatment and control species in a similar way. Finally, ε_{slt} is an error term that measures random fluctuations in population size. This regression is equivalent to a generalized differences-in-differences approach where species protected by CITES are the treatment group and the control group comprises species that are not included in the CITES appendices.[19] We keep all populations with at least four observations over time. Our final sample includes 7379 populations of 2370 species in 158 countries over 66 years (from 1950 to 2015). We follow the suggestion of Bertrand et al. (2004) and cluster standard errors at the species level to allow for correlation within species which may be introduced as our treatment variable is defined at the species level.

We later relax the assumption of constant treatment effects over time by estimating the following event study specification:

$$\ln N_{slt} = \sum_{\substack{\tau \in \{-10,-5,0,5\\ 10,15,20,>20\}}} \beta_\tau \mathbf{1}(t = t_s^{CITES} + \tau)_{st} + \mu_{sl} + \eta_t + \varepsilon_{slt}. \quad (3)$$

We regress the log population size on a set of relative time dummies that indicate the number of years before or after a species' listing in either CITES Appendix I or II. Our interest lies in estimating the treatment effect β_τ on population size τ years after a species is included into CITES' appendices.[20] The set of time dummies allows the treatment effect to vary with time τ since the year a species was listed into CITES' appendices, t_s^{CITES}. We consider different effects for the year of inclusion ($\tau = 0$), the first five years after listing, and then, in five year intervals up to 20 years. We also consider a separate treatment effect for species listed for more than 20 years.

We estimate leading values of the treatment to test the reliability of

[19]For our estimation, we use the Stata package `reghdfe` by Correia (2016).

[20]We write $\tau = -10$ for years 6 to 10 years before a species' CITES listing, $\tau = -5$ for years 1 to 5 before a species' CITES listing, $\tau = 0$ for the year of a species' CITES listing, $\tau = 5$ for years 1 to 5 after a species' listing into CITES, $\tau = 10$ for years 6 to 10, $\tau = 15$ for years 11 to 15, $\tau = 20$ for years 16 to 20, and $\tau > 20$ for more than 20 years after a species' CITES listing.

our identification strategy. A statistical significant effect for $\tau = -10$ or $\tau = -5$ indicates pre-existing differences in the trends between listed and non-listed species, which may cast doubt on the common trend assumption underlying our approach.

As an additional test of the parallel trend assumption, we follow the recommendation by Bilinski and Hatfield (2019) and estimate a model that uses the same treatment variables as in Equation (3) but we include $EVERCITES_s t$ instead of placebo treatments in the years before inclusion into CITES. Note that in this specification with a full set of treatment dummies for all years after treatment starts, $\theta EVERCITES_s t$ directly measures a violation of the parallel trend assumption prior to treatment, i.e., inclusion into CITES. We estimate $\hat{\theta} = 0.009$ ($s.e. = 0.006$, p-value $=$ 0.118). Hence we can rule out a violation of the parallel trend assumption of trend differences larger than the bounds of the 95% confidence interval of $\hat{\theta}$, $[-0.002, 0.021]$, validating our identification strategy.

4 Results

4.1 Effect of CITES listings on wildlife population sizes

Species listed in CITES.—We present results of Equation (2) in column (1) of Table 2. After a species is listed in CITES, the populations of this species increase by 21%.[21] Most of the species in our sample were included into CITES in 1975 (see Figure 1). There may be a difference in CITES' effectiveness between the species listed in 1975 and those that were listed later. We therefore estimate separate treatment effects for these two groups of species.[22] In column (2), we define treatment only for those species that were included into CITES in 1975. We estimate a similarly sized effect as in column (1) but with low precision. In column (3), we define treatment only for those species included after 1975. The effect is again of similar size, and is now precisely estimated. In column (4), we include both dummies

[21] We calculate marginal effects of variable k as $(e^{\beta_k} - 1) \times 100$.

[22] This also checks for the similarity of treatment effects for early and late treated species, in the spirit of Goodman-Bacon (2019). Note that it is unclear how the decomposition of difference-in-differences estimates in balanced panels proposed by Goodman-Bacon (2019) applies in our case since we use an unbalanced panel.

Table 2: Effect of CITES on population size (species listed in CITES)

	(1)	(2)	(3)	(4)
in CITES	0.193			
	(0.073)			
in CITES in 1975		0.214		0.224
		(0.125)		(0.125)
in CITES after 1975			0.173	0.179
			(0.084)	(0.085)
N	111292	111292	111292	111292

Notes: Table 2 reports estimated regression coefficients from a panel regression of log of population size on a dummy variable that equals one when the population is listed into CITES, along with a set of population and year fixed effects. Standard errors are in parentheses and are clustered at the species level. Column (1) estimates a regression in which the treatment dummy equals one for species listed in CITES. Column (2) includes a variation of the treatment dummy that equals one for species listed in CITES in 1975. Column (3) includes a variation of the treatment dummy that equals one for species listed in CITES after 1975. Column (4) includes both treatment dummies for species listed in CITES in 1975 and after 1975, separately.

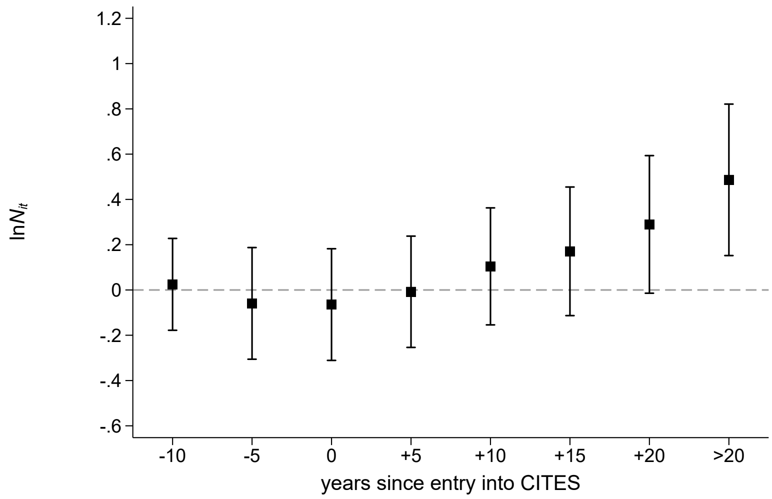
simultaneously, with similar results. We cannot reject the null hypothesis that the effect for species listed in 1975 and after 1975 is the same (p-value $= 0.754$), but their effect is jointly significant (p-value $= 0.031$).

We allow the treatment effect of CITES listings to vary over time in our event study specification given in Equation (3). We present estimates in Figure 4. Results confirm that CITES listings have a positive effect on species' population sizes, however, the effect of CITES does not occur immediately, as it takes about 16 to 20 years until populations of CITES-listed species increase in size as a consequence of the species' listings in CITES. In addition, the pre-trend variables are not significant, validating the common trend assumption.

As in Table 2, we allow for separate effects of species listed in 1975 and after 1975. We present results in Appendix Figure 1. We find a similar pattern of the estimated coefficients for both species listed in 1975 and those listed after 1975. It takes about 16 to 20 years until populations of CITES-listed species increase. Again, precision of the estimates is considerably lower when singling out 1975, probably because we observe the majority of populations after 1975. The effect of CITES on population sizes increases over time, as wildlife populations slowly recover. We therefore stick to the event study specification in the following.

CITES' member countries.—Until now, the set of treatment dummies takes the same values for all populations of a given species. Some populations of protected species in our data are located in a country which was

Figure 4: Effect of CITES on population size (species listed in CITES)

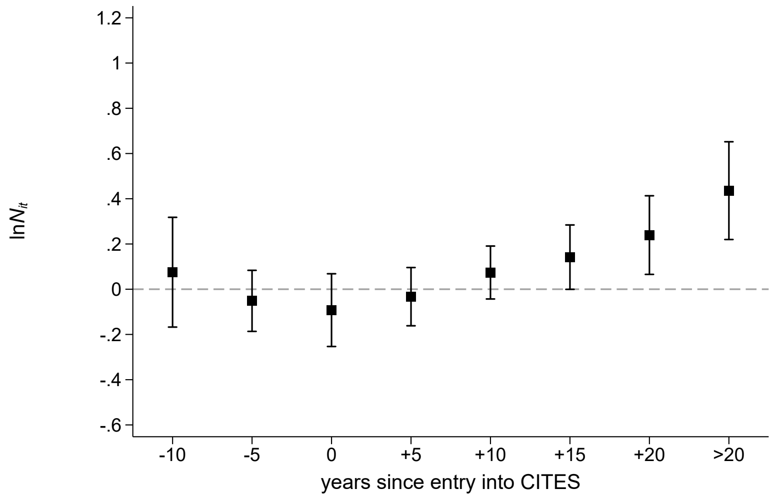


This figure shows coefficient estimates from Equation (3), i.e., a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES, along with a set of population and year fixed effects. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 111292.

not a CITES member country at the time of observation. CITES members are expected to apply CITES regulations also to wildlife trade originating from non-member countries (see Article X of CITES). Therefore, CITES in principle should also protect species in non-member countries. If the protection of a species is only partly enforced, our baseline estimates can be interpreted as the intention-to-treat effect of the inclusion in CITES. Still, CITES' listings may be more effective to protect wildlife populations in member countries. We therefore map each population to the country in which it is located. This allows us to interact our species-specific treatment variable with a dummy variable indicating whether the country in which the population is located is a member of CITES that year.

Results are presented in Figure 5. Pre-trends are not significant. Judging by the confidence intervals, results are similar to the event study results presented in Figure 4, i.e., membership of the country where a population is located does not seem to matter much. Point estimates are slightly smaller and more precisely estimated. This is not surprising. Article X of CITES stipulates that trade with non-member countries is only allowed

Figure 5: Effect of CITES on population size (species listed in CITES, in CITES' member countries)



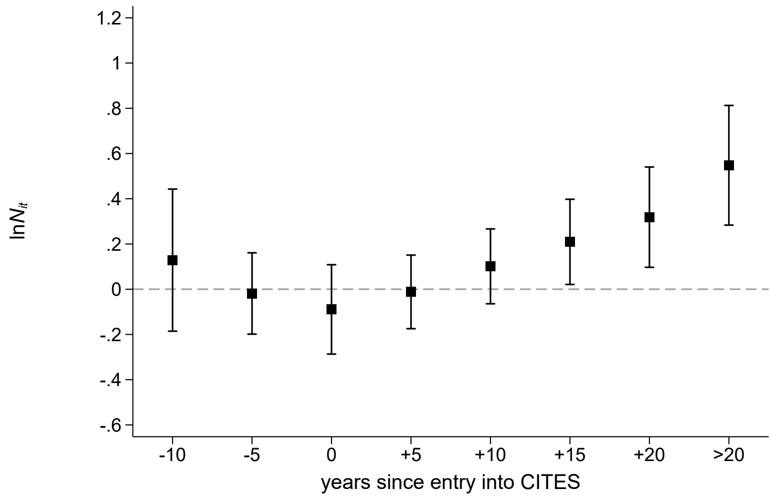
This figure shows coefficient estimates from a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES interacted with a variable indicating whether the country is a CITES member in year t, along with a set of population and year fixed effects. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 111292.

when essentially equivalent documentation, particularly export permits, are provided by any potential trader, and countries explicitly are allowed to even apply stricter standards to non-member country trade. Therefore, the slightly lower coefficients could be interpreted as evidence that CITES membership of countries may actually facilitate trade with subsequent negative effects on population sizes, as it allows for an easier provision of export permits compared to non-member countries.[23] Results confirm the lagged and persistent positive effect of CITES listing on population sizes. Because these results are more conservative and more precisely estimated, we proceed in the rest of this section and in Section 4.2 with this variable, i.e., considering species listed in CITES and CITES' member countries.

Corruption at the border.—Countries with high levels of corruption may limit the success of conservation projects by reducing effective funding levels

[23]Given the size of the confidence intervals, one should not overinterpret these results. We explore the effects of country-specific enforcement of CITES further below. For a detailed discussion of the provisions of Article X and their implementation, see Sand (2013) and Wijnstekers (2011), particularly pages 339-342.

Figure 6: Effect of CITES on population size, considering corruption in countries (species listed in CITES, in CITES' member countries)

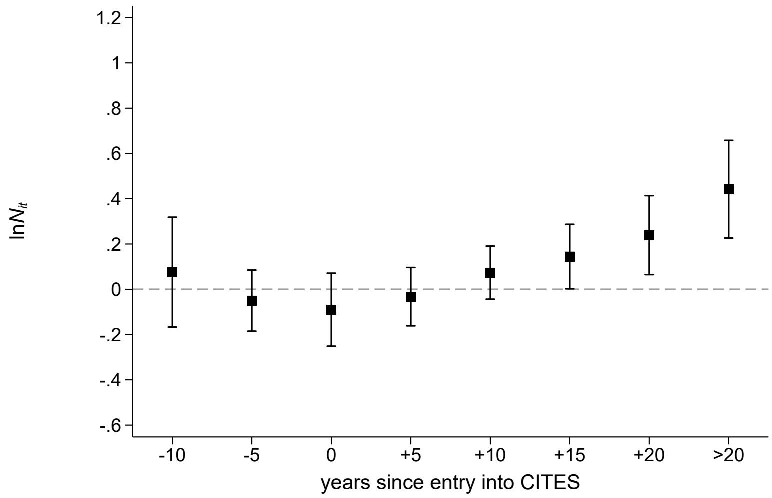


This figure shows coefficient estimates from a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES interacted with a variable indicating whether the country is a CITES member in year t, and the interaction of one minus a variable indicating the share of population in country c answering "yes" to the question "in the last 12 months anyone living in a household paid a bribe in any form to customs", along with a set of population and year fixed effects. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 100728. The difference in the number of observations compared to Figure 5 arises from missing data in the corruption variable for some countries with wildlife populations.

and distorting priorities (see Smith et al., 2003b). The relationship between (bad) governance and wildlife (decline) has been discussed in, e.g., Barrett et al. (2006). We interact the set of dummy variables indicating the years since entry into CITES with a variable indicating whether the country is a CITES member in year t, and the interaction of one minus a variable indicating the share of population in country c answering "yes" to the question "in the last 12 months anyone living in a household paid a bribe in any form to customs" (variable "Paid Bribe: Customs", see Dahlberg et al., 2017). Hence, we allow corruption at the border to vary the "dosage" of the effectiveness of CITES. Results obtained in Figure 6 confirm the lagged positive effects of CITES on species' population size for less corrupt countries.

Sanctions.—Under Article XIV.1(a) of CITES, member countries can sanction other countries if they do not comply with CITES regulations,

Figure 7: Effect of CITES on population size, for non-sanctioned countries (species listed in CITES, in CITES' member countries)



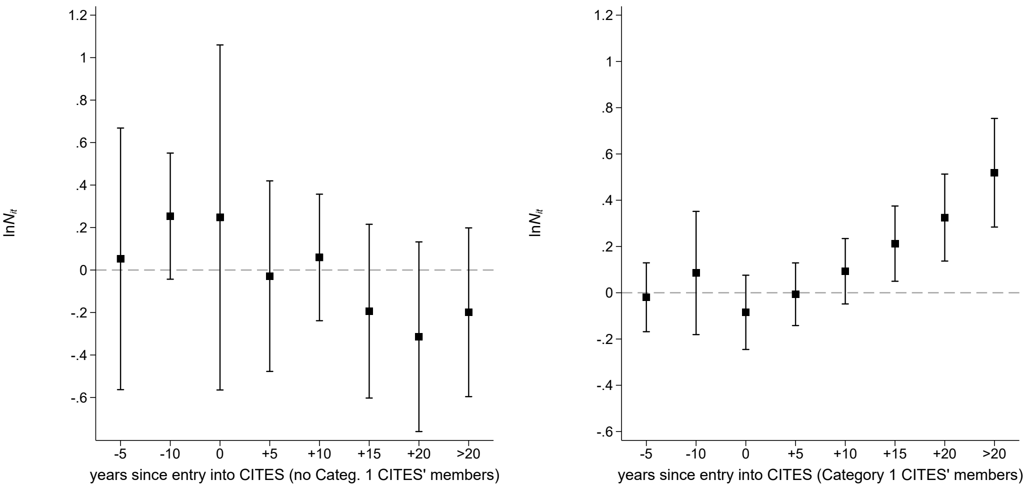
This figure shows coefficient estimates from a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES interacted with a variable indicating whether the country is a CITES member in year t, along with a set of population and year fixed effects. The sample drops populations in sanctioned countries for those years in which the sanctions were applied. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 110852.

e.g., by not passing local legislation to implement CITES.[24] We identify the populations located in countries and observed during years when the sanctions were in place and drop them from the sample. In the remaining sample of populations located in countries without sanctions, the lagged positive effect of CITES is confirmed, see Figure 7.

Member countries' implementation and enforcement.—Some countries may implement and enforce CITES more stringently than others. Following the previous results that CITES' listings are effectively protecting species in countries that are less corrupt and that are non-sanctioned, we analyze whether the effectiveness of CITES might differ by a country's implementation and enforcement level. If a country is not implementing or enforcing CITES regulations properly, we should not expect CITES to have an impact on the populations located in these countries. To check this, we create two dummy variables, one that identifies populations in Category

[24] For an overview of CITES' sanction regime, see Sand (2013).

Figure 8: Effect of CITES on population size for species listed in CITES and populations in CITES' member countries



This figure shows results from a panel regression of log of population size on a set of treatment dummies, along with a set of population and year fixed effects. The left panel shows the coefficient estimates of dummy variables indicating the years since a species' entry into CITES interacted with a variable indicating whether the country is a CITES member in year t for non-"Category 1" countries. The right panel shows the coefficient estimates of dummy variables indicating the years since entry into CITES interacted with a variable indicating whether the country is a CITES member in year t for "Category 1" countries. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 111292.

1 CITES' member countries, i.e., countries whose national legislation fully complies with the requirements of CITES, and the other for no Category 1 countries. We interact these dummies with the interaction of each of the treatment dummies with the dummy variable for CITES' members. Our results in Figure 8 show that CITES has a significant lagged effect on population sizes in Category 1 countries only, stressing the importance of proper implementation of CITES. These results show evidence of heterogeneous treatment effects at the country level, as CITES is effective in countries with strong enforcement. In what follows, we analyze whether species with different characteristics benefit differently from CITES protection.

4.2 Species-type specific treatment effects

We have seen in the previous section that CITES is effective in countries that properly implement and enforce CITES, but its effect occurs mostly with a 16 to 20 year lag. To shed more light on the effectiveness of CITES, we explore whether treatment effects differ across different types of species. For ease of exposition, we only include the last treatment dummy ($\tau > 20$) in these regressions instead of the full set of lags. We estimate separate effects for non-"Category 1" member countries (i.e., where CITES is poorly implemented or enforced) and for "Category 1" countries (i.e., where CITES is effectively implemented or enforced). We present results in Appendix Table 2. We consider the following different groups of species:

Intentionally-used species.—Some species have a direct economic value as they are used for different purposes, and as a consequence they are intentionally harvested with potential negative effects on their population sizes. We create an indicator variable for species with intentional use, i.e., where the species is the target of economic activity. Population size increases for species listed in CITES for "Category 1" countries only. We estimate a negative coefficient for the interaction term, but due to the lack of precision, it is not statistically significant, see column (1).

Vulnerable species.—The IUCN Red List provides an evaluation of the extinction risk of species using different categories. We identify species that are classified as either "critically endangered", "endangered", or "vulnerable" by the IUCN Red List as vulnerable species and create the according interaction term, see column (2). We find that CITES only increases population size in "Category 1" member countries. The interaction term for vulnerable species is not precisely estimated.

Highly-studied species.—Some species receive more funding for their conservation and hence are more studied by researchers (see, e.g., Brambilla et al., 2013; Colléony et al., 2017). This may be because some species are more well-known and have particularly desirable features in the view of the general public, e.g., the "cuteness" of koalas (*Phascolarctos cinereus*).[25] CITES' effectiveness may be different for these highly-studied species. Our

[25] More generally, the less similar a particular taxonomic order is to humans (i.e., the larger its phylogenetic distance), the lower the number of scientific studies on this species (Martín-López et al., 2009).

population data contain information about the scientific study from where the population data are obtained. We therefore count the number of studies per species and year and create a dummy variable for those species for which the number of studies is larger than the sample average. We present results in column (3). We do not find evidence that CITES effectiveness changes for highly-studied species.

Well-known species.—The number of scientific studies may not fully reflect how well-known a species is in the general public. We therefore use a more direct proxy by using data from the citizen science project *iNaturalist*. Contributors to *iNaturalist* can identify the species of the animal they have seen using their smartphone and have the possibility to corroborate the data by confirming the species identified by other users in the *iNaturalist* app. Different users should agree more often on a species the more well-known it is. We calculate the average number of identification agreements by species and year. We interpret a higher than average number of agreements as an indication that a species is well-known. Column (4) shows that CITES' effectiveness does not depend on how well-known a species is.

Large species.—We consider species-type specific treatment effects for "charismatic megafauna" as a species' charisma may be a function of its physical size (see Metrick and Weitzman, 1996). We create a variable for large species as a dummy that equals one for those species with a higher than average body mass in our sample, and zero otherwise.[26] Results in column (5) show that CITES' effectiveness is not influenced by how large a species is. According to our results, CITES increases population size in "Category 1" member countries for both large and other species. In non-"Category 1" member countries, CITES increases the population size only of large species.

While our results show evidence of heterogeneous treatment effects across countries as CITES is only effective in countries with strong enforcement,[27] species with different characteristics do not seem to benefit differently from CITES. We therefore explore the impact of unobserved time-varying country-level confounding factors in the next section.

[26] In this group, our sample includes species that are well-known under their common names buffalo, elephant, giraffe, hippopotamus, manatee, rhino, walrus, and whale.

[27] Excluding the case of megafauna, as CITES is effective for large species in non-"Category 1" member countries.

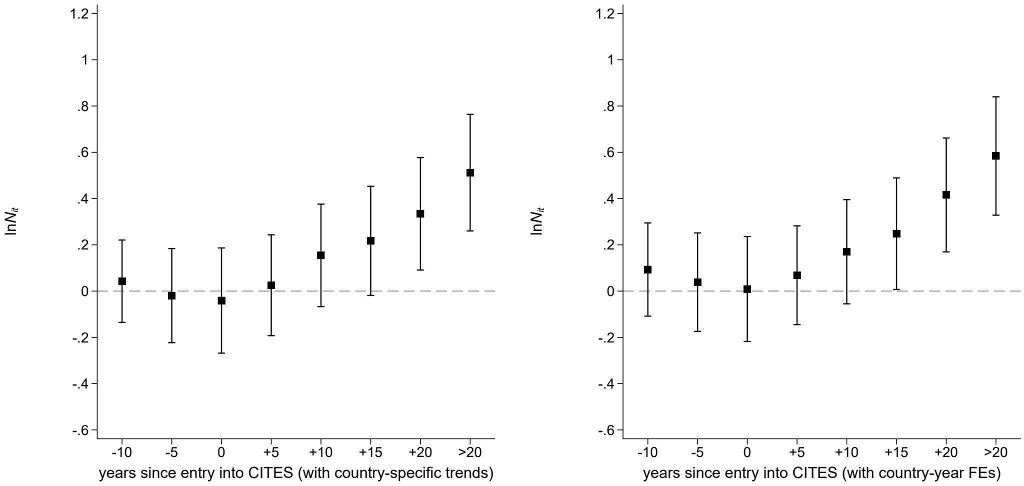
4.3 Controlling for country-specific time-varying confounding factors

Our results have shown the importance of countries' implementation and enforcement. More generally, countries' attitudes towards protecting wildlife, the size of their wildlife populations, and voting in favor of listing further species at one of the CoPs are likely correlated. Over time, these attitudes may change due to changes in countries' governments as well as changes in societal attitudes and awareness concerning environmental issues. These and other time-varying country-specific factors that affect both the probability of a species' listing in CITES and its population size may bias our results. For example, a country's level of corruption and the occurrence of (civil) wars correlate with wildlife decline (see Smith et al., 2003b and Daskin and Pringle, 2018). The extent of agricultural production also varies across countries, and increases in agricultural production are a key driver of habitat loss and subsequent wildlife decline (see Green et al., 2005).

To control for these and other unobserved country-specific time-varying factors, in a first step, we include country-specific trends by augmenting Equation (3) with $\delta_c t$. To check robustness, we consider several specifications that account for different functional forms of the country-specific time trends. Following Neumark et al. (2014), we consider polynomials of orders 2 to 5 for country-specific trends, and we compare results with our main specification (i.e., without country-specific trends). Results in Appendix Table 3 show the robustness of our baseline results. Across all specifications, pre-trends are not significant. For all specifications, we obtain a positive and significant effect of CITES on population sizes 16 to 20 years after species' listing. We also obtain a positive and significant effect of CITES after 11 to 15 years of listing the species in CITES at a 10% of significance level for all specifications, except for our main specification (i.e., without country-specific trends).

In a second step, instead of country-specific time trends, we include country-year fixed effects into our model to control for arbitrary shocks across countries and time, e.g., time-varying enforcement and compliance patterns over CITES signatory and non-signatory parties.

Figure 9: Effect of CITES on population size, including country-specific trends, or country-year FEs (species listed in CITES)



This figure shows coefficient estimates from an event study specification, i.e., a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES, along with a set of population fixed effects. The left panel shows the coefficient estimates of a specification that includes country-specific time trends. The right panel shows the coefficient estimates of a specification that includes country-year fixed effects. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 111292 (left panel) and 109961 (right panel).

Figure 9 displays results for our event study specification augmented with the country-specific linear trends (in the left panel) and country-year fixed effects (in the right panel). Obtained results are consistent with our main findings and confirm that listing species in CITES has a positive effect on species population size. This effect is, however, lagged and starts to be significant from 16 to 20 years after listing.

4.4 Is CITES effective because it bans wildlife trade or because it enables sustainable wildlife trade?

We have established that inclusion into CITES leads to an increase in the size of wildlife populations. Until now, our analysis has remained silent on a key debate concerning CITES. The main way how CITES offers protection for species is via inclusion into either its Appendix I or Appendix II. These two appendices represent two different approaches to wildlife conservation.

Species listed in Appendix I cannot be traded internationally for commercial purposes, i.e., it imposes an international trade ban. Species listed in Appendix II can be traded internationally as long as this trade is sustainable and does not endanger the survival of the species ("sustainable use"). Which of these two approaches is more effective in protecting wildlife is debated among conservationists, policy makers, and the wider community. Economic theory as well as case studies provide conflicting arguments.

On the one hand, prohibiting trade may have negative effects as it reduces the (international) legal value of wildlife to zero, reducing economic incentives to protect wildlife. Also, enforcing wildlife trade bans is difficult. Bans reduce the legal supply of goods from wildlife, but do not directly affect demand. Hence, prohibiting trade creates incentives for poaching and trade may be diverted to illegal channels, rendering bans ineffective. At the same time, bans may stigmatize the purchase and possession of goods derived from endangered species, and hence may reduce demand as well, see Fischer (2004).

On the other hand, sustainable use of species listed in Appendix II allows local communities to generate income from their legal use in the long run (Rivalan et al., 2007; Challender et al., 2015). However, it may increase demand by legitimizing the consumption of wildlife goods. Consumers may interpret certificates which assure goods are produced in accordance with CITES as a go-ahead without any negative environmental consequences. It may also allow poachers to launder illegally harvested specimens in the legal market, see Fischer (2004).

To disentangle which mechanism, trade bans or sustainable use, dominates the positive effect of CITES on wildlife population sizes, we distinguish species listed in Appendix I and species listed in Appendix II. In Equation (3) we have defined t_s^{CITES} as the year when a species s is included in either Appendix I or II for the first time, whichever year comes first. We now distinguish whether a species has ever been listed in Appendix I or Appendix II. We show the distribution of years when a species in our sample is first listed in one of the two appendices in Figure 10. There has been a movement away from Appendix I in recent years and species now enter CITES via its Appendix II.[28]

[28]Note that the number of species entering into any of CITES' appendices depicted in

Figure 10: Distribution of year of first entry into CITES' Appendix I and Appendix II

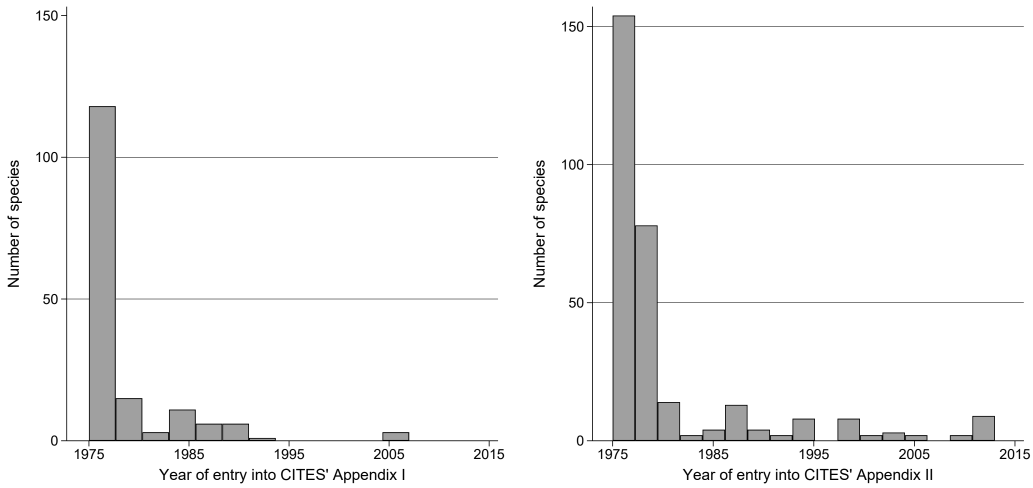


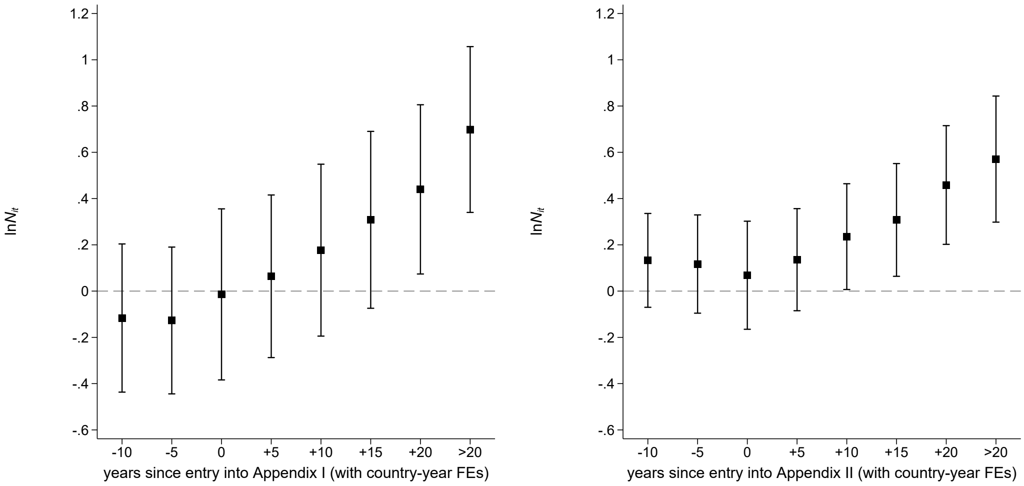
Figure depicts the distribution of the year a species entered into Appendix I (left panel) and Appendix II (right panel) in our data.

We show the results of two regressions in Figure 11. The left panel shows coefficients of an event study where we define treatment as the year when a species is listed in Appendix I. The right panel shows the results for a regression where we define treatment as the year when a species is listed in Appendix II. We find that population sizes of species included into either Appendix I or II increase by similar amounts. However, the positive effect on wildlife population sizes is significant after 6 to 10 years of inclusion into Appendix II, whereas we find a positive and significant effect for species included into Appendix I after 16 to 20 years. Encouraging sustainable use seems to be effective sooner than trade bans. This may be due to incomplete enforcement of trade bans that need strict species-specific controls to be effective, whereas sustainable use is to some extent self-enforcing, as it creates incentives to protect wildlife to ensure revenues in the long-run.

Some species may move from Appendix II to Appendix I (they get "uplisted") or from Appendix I to Appendix II (they get "downlisted"). The

Figure 1 is not the sum of species entering in Appendix I and Appendix II as species can have been uplisted or downlisted over time. For example, the Mauritius kestrel (*Falco punctatus*), a falcon from Mauritius, was included into Appendix II in 1975 and uplisted to Appendix I in 1977, hence it appears in both the left and right panel of Figure 10, but only once in Figure 1.

Figure 11: Effect of CITES on population size (App. I vs. App. II), including country-year FEs (species listed in CITES)



The left panel shows coefficient estimates from an event study specification, i.e., a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES' Appendix I. The right panel shows coefficients from a separate estimation where dummy variables indicate the years since entry into CITES' Appendix II. Both regressions include population and country-year fixed effects. 95% percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 109961.

previous regressions ignored these dynamics. We therefore take into account a species' history of being uplisted or downlisted as a robustness check. For example, the bald eagle (*Haliaeetus leucocephalus*) was downlisted from Appendix I to Appendix II in 2005, while the African elephant (*Loxodonta africana*) was first listed in CITES' Appendix II in 1977, and uplisted to Appendix I in 1990. Listings in CITES appendices can occur at any taxonomic level, i.e., either individual (sub-)species are included in an appendix or a whole taxonomic group (genus, family, order) is included, i.e., groups of related species. The sturgeon, the source of sought-after caviar, is a good example. The common name sturgeon refers to 27 species which are part of the family Acipenseridae, which itself is part of the larger order Acipenseriformes. In 1975, the species *Acipenser oxyrinchus* was included in Appendix I. In 1979, this species was downlisted to Appendix II. In 1998, the whole order Acipenseriformes was included in Appendix II. The family Lemuridae, a group of primates found primarily in Madagascar, was included in Appendix I in 1975, except the probably best known lemur species, the ring-tailed lemur (*Lemur catta*), which was included in Appendix II. *Lemur catta* was then uplisted into Appendix I in 1977. We take into account changes like these in Figure 12, where we drop populations of species that have ever been listed in *both* Appendix I *and* Appendix II during the period available for those populations in the sample ("switchers").[29]

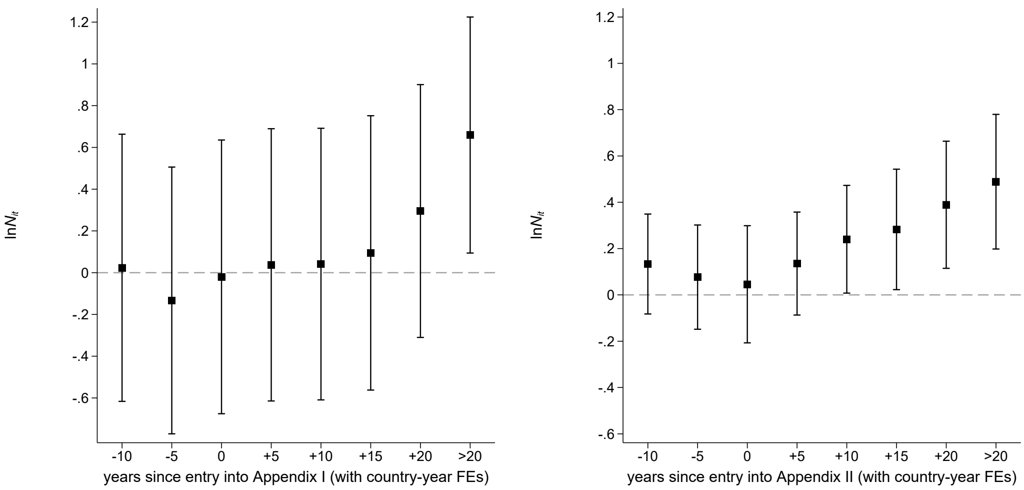
Figure 12 confirms that trade bans and sustainable use are both effective in the long-run. We find significant positive effects on wildlife populations of incentivizing sustainable use six to ten years after inclusion into Appendix II. However, it seems that identification of positive effects for trade bans, i.e., Appendix I, in Figure 11 stems mostly from "switchers". The low precision of the effect of Appendix I listings implies that we cannot rule out positive effects of trade bans in the early years after their imposition. One of the reasons for this may be the relatively low number of affected species who are not "switchers" in Appendix I. To shed light on the effectiveness of trade bans in the short- to medium-run, we turn to exogenous variation in country-specific trade bans due to "bird flu" outbreaks, i.e., bans that are independent of CITES listings.

4.5 Quasi-natural evidence on the effectiveness of trade bans due to "bird flu" outbreaks

Following the outbreak of the bird flu in South-East Asia in 2003, countries imposed trade bans on birds from the affected countries to stop its spread. These bans have significantly reduced trade in birds, see Nicita (2008), in-

[29]Specifically, we drop from our regressions 4238 observations that correspond to populations of 38 (sub-)species. Their common names are: Addax, African elephant, American alligator, American crocodile, Bald eagle, Black caiman, Black rhinoceros, Bonobo, Chimpanzee, Common spider tortoise, Dalmatian pelican, Dugong, Fin whale, Flatback turtle, Forest elephant, Green turtle, Grey wolf, Grizzly bear, Guadalupe fur seal, Gyrfalcon, Indus blind dolphin, Insular flying-fox, Irrawaddy dolphin, Leatherback turtle, Loggerhead sea turtle, Markhor, Mauritius kestrel, Mongolian saiga, Olive ridley, Peregrine falcon, Ring-tailed lemur, Saltwater crocodile, Samoa flying fox, Sei whale, Southern white rhinoceros, Tiger, and Vicuna. Of these, 6 were downlisted from Appendix I to Appendix II of CITES: American alligator, Bald eagle, Black caiman, Mongolian saiga, Southern white rhinoceros, and Vicuna; different populations of 5 (sub-)species were listed in different CITES' appendices (I and II) the same year: Dugong, Fin whale, Grizzly bear, Markhor, and Sei whale. For example, all populations of Dugong were listed in Appendix I in 1975, except those of Australia that were listed in Appendix II. The remaining (sub-)species correspond to species that were uplisted from Appendix II to Appendix I of CITES.

Figure 12: Effect of CITES on population size (App. I vs. App. II), including country-year FEs (species listed in CITES), excluding "switchers"



The left panel shows coefficient estimates from an event study specification, i.e., a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES' Appendix I. The right panel shows coefficients from a separate estimation where dummy variables indicate the years since entry into CITES' Appendix II. Both regressions include population and country-year fixed effects. 95% percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 105872.

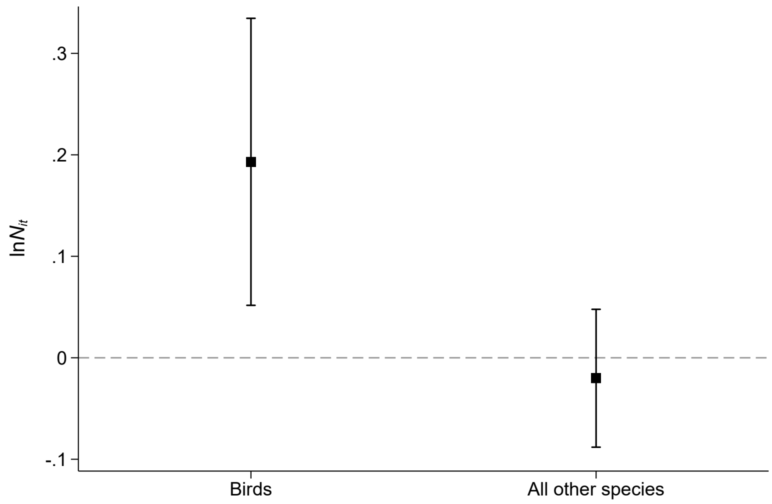
cluding domestic trade of birds caught in the wild, see Brooks-Moizer et al. (2009). If trade bans are an effective tool to increase wildlife populations, trade bans should have an impact on wildlife in the countries affected by the outbreak. These bans are unrelated to a species' listing in Appendix I of CITES, so concerns about potential time-varying selection bias of species into CITES do not affect this alternative identification strategy.

We construct a dummy variable $BIRDFLU_{ct}$ that equals one when country c reports any notification or follow-up on a bird flu outbreak in year t, and equals zero otherwise. We take these notifications as indicative of the existence of a trade ban imposed on birds originating from country c. We estimate the following equation:

$$\ln N_{slt} \quad = \quad \alpha BIRDFLU_{ct} + \mu_{sl} + \eta_t + \varepsilon_{slt}, \tag{4}$$

where μ_{sl} is a species×location (i.e., population) fixed effect and η_t a year fixed effect. We now cluster standard errors at the country-level as

Figure 13: Effect of bird flu trade bans



This figure shows coefficient estimates from Equation (4), i.e., a panel regression of log of population size on a variable indicating whether the country provided immediate notifications and follow-up reports of highly pathogenic avian influenza (types H5 and H7) in year t, along with a set of population and year fixed effects. Number of observations for birds: 64474; for all other species: 55064. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the country level.

$BIRDFLU_{ct}$ varies at the country(-year) level. We estimate Equation (4) for all bird species in our dataset. Other species should not be affected by trade bans on birds. We therefore estimate Equation (4) for all other species (i.e., for fishes, mammals, reptiles, and amphibians) as a placebo test.[30] We present results in Figure 13. We find that trade bans of birds increase birds' population sizes, whereas they do not affect population sizes of all other species. This result suggests that wildlife trade bans effectively increase wildlife, even in the short-run.

5 Conclusion

Wildlife is in decline. One driver of this decline is international wildlife trade. CITES' goal is to protect endangered species from extinction either

[30] For both regressions, the common trend assumption holds: When we include a pre-trend term (one year lead) in Equation (4), it is insignificant, indicating that countries do not anticipate a trade prohibition on birds. Specifically, in the regression for birds, the coefficient for this pre-trend term equals 0.23 ($s.e.$ = 0.139, p-value = 0.102) and in the regression for all other species equals -0.037 ($s.e.$ = 0.046, p-value = 0.418).

by restricting their international trade to sustainable levels or by banning their international trade altogether. We provide the first global assessment of CITES' effectiveness by combining geo-referenced panel data on wildlife population sizes for 7379 populations across 158 countries with their history of inclusion into CITES. In our baseline results, we find that CITES is effective: Wildlife populations increase by 20% after their inclusion into CITES. This effect accrues slowly over time. We find significant and positive effects 16 to 20 years after species are listed in CITES.

While our results show that CITES does prevent wildlife decline, our approach remains silent on whether other approaches would be more efficient to protect wildlife than regulating wildlife trade via CITES. Neither does our approach determine whether the effect of CITES is strong enough to prevent the eventual extinction of a population or of the whole species, or whether CITES merely postpones its extinction. Wildlife decline is not only caused by the harvesting and consumption of endangered species, the focus of CITES. The production of merchandise goods for foreign consumption in biodiversity hotspots has been shown to have large detrimental effects on wildlife due to its impact on habitat loss, see Lenzen et al. (2012). Identifying and monitoring the effects of international merchandise trade on wildlife may well be needed to effectively prevent the extinction of endangered species.

Our results reveal that CITES is effective at protecting wildlife populations in CITES member countries that properly implement and enforce its rules, highlighting the important role of national governments for wildlife protection. Focusing on mechanisms, we find that both wildlife trade bans and restrictions that incentivize sustainable use of endangered species increase wildlife. However, the effects of sustainable wildlife trade materialize more quickly than those of trade bans: Whereas we find significant increases in wildlife 16 to 20 years after CITES banned their international trade, wildlife trade restrictions that incentivize sustainable use significantly increase wildlife already after 6 to 10 years. A reason for this may be that enforcing trade bans for individual species protected by CITES by customs agents is challenging as species may be difficult to identify and most merchandise trade is not inspected, allowing illegal wildlife smuggle to circumvent trade bans. In line with this reasoning, we find that relatively easy to enforce blanket trade bans for birds imposed as a response to bird flu outbreaks do indeed increase populations of wild birds. Given that blanket trade bans and stringent controls of all international goods trade are unlikely, incentivizing sustainable use of endangered species seems to be the most effective mechanism how wildlife trade policy can protect wildlife.

References

Aichele, R. and Felbermayr, G. (2012). Kyoto and the carbon footprint of nations. *Journal of Environmental Economics and Management*, 63(3):336–354.

Ando, A. W. and Langpap, C. (2018). The Economics of Species Conservation. *Annual Review of Resource Economics*, 10(1):445–467.

Antwi, Y. A., Moriya, A. S., and Simon, K. (2013). Effects of federal policy to insure young adults: Evidence from the 2010 Affordable Care Act's dependent-coverage mandate. *American Economic Journal: Economic Policy*, 5(4):1–28.

Barrett, C. B., Gibson, C. C., Hoffman, B., and McCubbins, M. D. (2006). The complex links between governance and biodiversity. *Conservation Biology*, 20(5):1358–1366.

Berec, M., Vršecká, L., and Šetlíková, I. (2018). What is the reality of wildlife trade volume? CITES Trade Database limitations. *Biological Conservation*, 224(May):111–116.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119(1):249–275.

Bilinski, A. and Hatfield, L. A. (2019). Nothing to see here? Non-inferiority approaches to parallel trends and other model assumptions. *arXiv:1805.03273v5 [stat.ME]*.

Brambilla, M., Gustin, M., and Celada, C. (2013). Species appeal predicts conservation status. *Biological Conservation*, 160:209–213.

Brooks-Moizer, F., Roberton, S. I., Edmunds, K., and Bell, D. (2009). Avian influenza H5N1 and the wild bird trade in Hanoi, Vietnam. *Ecology and Society*, 14(1):28.

Brown, G. M. and Shogren, J. F. (1998). Economics of the Endangered Species Act. *Journal of Economic Perspectives*, 12(3):3–20.

Bulte, E., Damania, R., Gillson, L., and Lindsay, K. (2004). Space - The final frontier for economists and elephants. *Science*, 306(5695):420–421.

Bulte, E. H. and Barbier, E. B. (2005). Trade and Renewable Resources in a Second Best World: An Overview. *Environmental & Resource Economics*, 30:423–463.

Bulte, E. H. and van Kooten, G. C. (1999). Economics of Antipoaching Enforcement and the Ivory Trade Ban. *American Journal of Agricultural Economics*, 81(2):453–466.

Burton, M. (1999). An assessment of alternative methods of estimating the effect of the ivory trade ban on poaching effort. *Ecological Economics*, 30(1):93–106.

Butchart, S., Walpole, M., Collen, B., van Strien, A., Scharlemann, J., Almond, R., Baillie, J., and ... (2010). Global Biodiversity: Indicators of Recent Declines. *Science*, 328(5982):1164–1169.

Butchart, S. H., Stattersfield, A. J., and Collar, N. J. (2006). How many bird extinctions have we prevented? *Oryx*, 40(3):266–278.

Cardillo, M., Mace, G. M., Jones, K. E., Bielby, J., Bininda-emonds, O. R. P., Sechrest, W., Orme, C. D. L., and Purvis, A. (2005). Multiple Causes of High Extinction Risk in Large Mammal Species. *Science*, 309:1239–1241.

Ceballos, G. and Ehrlich, P. R. (2002). Mammal Population Losses and the Extinction Crisis. *Science*, 296(5569):904–907.

Challender, D. W. S., Harrop, S. R., and MacMillan, D. C. (2015). Towards informed and multi-faceted wildlife trade interventions. *Global Ecology and Conservation*, 3:129–148.

Chan, H. K., Zhang, H., Yang, F., and Fischer, G. (2015). Improve customs systems to monitor global wildlife trade. *Science*, 348(6232):291–292.

Cherniwchan, J., Copeland, B. R., and Taylor, M. S. (2017). Trade and the Environment: New Methods, Measurements, and Results. *Annual Review of Economics*, 9(1):59–85.

Chimeli, A. B. and Soares, R. R. (2017). The Use of Violence in Illegal Markets: Evidence from Mahogany Trade in the Brazilian Amazon. *American Economic Journal: Applied Economics*, 9(4):30–57.

Clark, J. and May, R. (2002). Taxonomic Bias in Conservation Research. *Science*, 297(5579):191–192.

Collen, B., Loh, J., Whitmee, S., McRae, L., Amin, R., and Baillie, J. E. M. (2009). Monitoring Change in Vertebrate Abundance: the Living Planet Index. *Conservation Biology*, 23(2):317–327.

Colléony, A., Clayton, S., Couvet, D., Saint Jalme, M., and Prévot, A. C. (2017). Human preferences for species conservation: Animal charisma trumps endangered status. *Biological Conservation*, 206:263–269.

Copeland, B. R. and Taylor, M. S. (2009). Trade, Tragedy, and the Commons. *American Economic Review*, 99(3):725–749.

Correia, S. (2016). A Feasible Estimator for Linear Models with Multi-Way Fixed Effects. *Working paper*.

Dahlberg, S., Holmberg, S., Rothstein, B., Khomenko, A., and Svensson, R. (2017). The Quality of Government Basic Dataset, version Jan17. *University of Gothenburg: The Quality of Government Institute*.

Daskin, J. H. and Pringle, R. M. (2018). Warfare and wildlife declines in Africa's protected areas. *Nature*, 553(7688):328–332.

Dunning, J. B. (2007). *CRC Handbook of Avian Body Masses (2nd ed.)*. CRC Press.

Engler, M. and Parry-Jones, R. (2007). Opportunity or threat: The role of the European Union in global wildlife trade. Technical report, Brussels, Belgium.

European Commission (2005). COMMISSION DECISION of 27 October 2005 concerning certain protection measures in relation to highly pathogenic avian influenza in certain third countries for the import of captive birds. *Official Journal of the European Union*, pages L 285/60–L 285/62.

Ferraro, P. J., McIntosh, C., and Ospina, M. (2007). The effectiveness of the US Endangered Species Act: An econometric analysis using matching methods. *Journal of Environmental Economics and Management*, 54(3):245–261.

Fischer, C. (2004). The complex interactions of markets for endangered species products. *Journal of Environmental Economics and Management*, 48(2):926–953.

Fischer, C. (2010). Does trade help or hinder the conservation of natural resources? *Review of Environmental Economics and Policy*, 4(1):103–121.

Frank, E. G. and Wilcove, D. S. (2019). Long delays in banning trade in threatened species. *Science*, 363(6428):686–688.

Ginsberg, J. (2002). CITES at 30, or 40. *Conservation Biology*, 16(5):1184–1191.

Goodman-Bacon, A. (2019). Difference-in-difference with variation in treatment timing. *Working paper.*

Green, R. E., Cornell, S. J., Scharlemann, J. P. W., and Balmford, A. (2005). Farming and the fate of wild nature. *Science*, 307(5709):550–555.

Heltberg, R. (2001). Impact of the ivory trade ban on poaching incentives: A numerical example (commentary). *Ecological Economics*, 36(2):189–195.

Hoffmann, M. and Silero-Zubiri, C. (2016). Vulpes vulpes. *The IUCN Red List of Threatened Species 2016.*

Hsiang, S. and Sekar, N. (2016). Does Legalization Reduce Black Market Activity? Evidence from a Global Ivory Experiment and Elephant Poaching Data. *NBER Working Paper 22314.*

Hutton, J. and Dickson, B., editors (2000). *Endangered Species Threatened Convention: The Past, Present and Future of CITES, the Convention on International Trade in Endangered Species of Wild Fauna and Flora.* Earthscan Publications Ltd, London.

Kellenberg, D. and Levinson, A. (2014). Waste of Effort? International Environmental Agreements. *Journal of the Association of Environmental and Resource Economists*, 1(1/2):135–169.

Khanna, J. and Harford, J. (1996). The ivory trade ban: Is it effective? *Ecological Economics*, 19(2):147–155.

Kremer, M. and Morcom, C. (2000). Elephants. *American Economic Review*, 90(1):212–234.

Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., and Geschke, A. (2012). International trade drives biodiversity threats in developing nations. *Nature*, 486:109–112.

Loh, J., Green, R. E., Ricketts, T., Lamoreux, J., Jenkins, M., Kapos, V., and Randers, J. (2005). The Living Planet Index: using species population time series to track trends in biodiversity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1454):289–295.

Martín-López, B., Montes, C., Ramírez, L., and Benayas, J. (2009). What drives policy decision-making related to species conservation? *Biological Conservation*, 142(7):1370–1380.

McClenachan, L., Cooper, A. B., and Dulvy, N. K. (2016). Rethinking Trade-Driven Extinction Risk in Marine and Terrestrial Megafauna. *Current Biology*, 26(12):1640–1646.

Meir, E. and Fagan, W. F. (2000). Will observation error and biases ruin the use of simple extinction models? *Conservation Biology*, 14(1):148–154.

Metrick, A. and Weitzman, M. L. (1996). Patterns of Behavior in Endangered Species Preservation. *Land Economics*, 72(1):1–16.

Neumark, D., Salas, J. M. I., and Wascher, W. (2014). Revisiting the minimum wage and employment debate: Throwing out the baby with the bathwater? *Industrial and Labor Relations Review*, 67(3):7.

Nicita, A. (2008). Avian Influenza And The Poultry Trade. *World Bank Policy Research Working Paper 4551.*

Reeve, R. (2006). Wildlife trade, sanctions and compliance: Lessons from the CITES regime. *International Affairs*, 82(5):881–897.

Rivalan, P., Delmas, V., Angulo, E., Bull, L. S., Hall, R. J., Courchamp, F., Rosser, A. M., and Leader-Williams, N. (2007). Can bans stimulate wildlife trade? *Nature*, 447(7144):529–530.

Salafsky, N., Salzer, D., Stattersfield, A. J., Hilton-Taylor, C., Neugarten, R., Butchart, S. H., Collen, B., Cox, N., Master, L. L., O'Connor, S., and Wilkie, D. (2008). A Standard Lexicon for Biodiversity Conservation: Unified Classifications of Threats and Actions. *Conservation Biology*, 22(4):897–911.

Sand, P. H. (2013). Enforcing CITES: The rise and fall of trade sanctions. *Review of European, Comparative and International Environmental Law*, 22(3):251–263.

Scheffers, B. R., Oliveira, B. F., Lamb, I., and Edwards, D. P. (2019). Global wildlife trade across the tree of life. *Science*, 366(October):71–76.

Sekercioglu, C. H., Daily, G. C., and Ehrlich, P. R. (2004). Ecosystem consequences of bird declines. *Proceedings of the National Academy of Sciences*, 101(52):18042–18047.

Smith, F. A., Lyons, S. K., Ernest, S. K. M., Jones, K. E., Kaufman, D. M., Dayan, T., Marquet, P. A., Brown, J. H., and Haskell, J. P. (2003a). Body mass of late Quaternary mammals. *Ecology*, 84(12):3403.

Smith, R. J., Muir, R. D. J., Walpole, M. J., Balmford, A., and Leader-Williams, N. (2003b). Governance and the loss of biodiversity. *Nature*, 426(6962):67–70.

Stokstad, E. (2010). Trade trumps science for marine species at international meeting. *Science*, 328(5974):26–27.

Strindberg, S., Maisels, F., Williamson, E. A., Blake, S., Stokes, E. J., Aba'a, R., and ... (2018). Guns, germs, and trees determine density and distribution of gorillas and chimpanzees in Western Equatorial Africa. *Science Advances*, 4(4):eaar2964.

't Sas-Rolfes, M., Challender, D. W., Hinsley, A., Veríssimo, D., and Milner-Gulland, E. (2019). Illegal Wildlife Trade: Scale, Processes, and Governance. *Annual Review of Environment and Resources*, 44(1):201–228.

Taylor, M. S. (2011). Buffalo hunt: International trade and the virtual extinction of the North American Bison. *American Economic Review*, 101(7):3162–3195.

Tittensor, D. P., Walpole, M., Hill, S. L. L., Boyce, D. G., Britten, G. L., Burgess, N. D., Butchart, S. H. M., and ... (2014). A mid-term analysis of progress toward international biodiversity targets. *Science*, 346(6206):241–245.

UNEP-WCMC (2017). The Checklist of CITES Species Website. *CITES Secretariat, Geneva, Switzerland. Compiled by UNEP-WCMC, Cambridge, UK. Available at: http://checklist.cites.org. (Accessed 19 April 2017).*

Wijnstekers, W. (2011). *The Evolution of CITES. 9th edition.* International Council for Game and Wildlife Conservation, Budapest.

Wilman, H., Belmaker, J., Simpson, J., de la Rosa, C., Rivadeneira, M. M., and Jetz, W. (2014). EltonTraits 1.0: Species-level foraging attributes of the world's birds and mammals. *Ecology*, 95(October 2013):2027.

World Wildlife Fund (2016). *Living Planet Report 2016. Risk and resilience in a new era.* WWF International, Gland.

For Online Publication
Appendix for "Wildlife Trade Policy and the Decline of Wildlife" by Benedikt Heid and Laura Márquez-Ramos

A Determinants of CITES listings

In this Section, we provide evidence that different types of species are not selected randomly to be listed in CITES, creating a selection bias. We investigate a number of factors that may affect the probability of a particular species being listed into CITES. For example, more charismatic species that are well-known and studied more often, or species with a higher extinction risk may have a higher probability of being listed.

We use the LPI data in combination with the CITES listing data, data on the average body mass of a species from the EltonTraits 1.0 dataset, as well as IUCN Red List extinction risk data, data on whether a species is used intentionally, and whether the species is threatened by fishing, both intentionally (the species is the target of the fishing activity) or unintentionally (e.g., by-catch).

As regressors, in addition to including dummies for the taxonomic class (mammal, bird, reptile, and amphibian; fishes are the baseline category), we consider whether the species is vulnerable (*vulnerable*) and whether there is intentional biological resource use of the species (the species is the target), i.e., including hunting and collection of terrestrial animals, fishing and harvesting aquatic resources (*intentional use*). We also include separately any direct threat of fishing, which includes unintentional effects, i.e., the species is not the target (*fishing*). The last regressor is the log of the average of the body mass of the species (*log of body mass*).

We present results of an OLS regression in which the dependent variable is a dummy variable that equals one when the species has ever been listed in CITES and zero when the species has never been listed in CITES in Appendix Table 1. As regressors, we use the variables described above. Columns (1) to (4) show that mammals, birds, and reptiles are more likely to be listed in CITES than fishes. This is consistent with Metrick and

Appendix Table 1: Determinants of CITES listings (cross-section)

	(1)	(2)	(3)	(4)	(5)
mammal	0.412	0.372	0.365	0.326	0.047
	(0.025)	(0.023)	(0.022)	(0.024)	(0.023)
bird	0.129	0.134	0.184	0.152	
	(0.011)	(0.011)	(0.013)	(0.013)	
reptile	0.273	0.214	0.261	0.228	
	(0.039)	(0.037)	(0.037)	(0.037)	
amphibian	−0.015	−0.025	0.032	−0.000	
	(0.008)	(0.011)	(0.012)	(0.013)	
vulnerable		0.244	0.196	0.192	0.194
		(0.022)	(0.022)	(0.022)	(0.033)
intentional use			0.158	0.181	0.129
			(0.016)	(0.019)	(0.034)
fishing				−0.099	
				(0.019)	
log of body mass					0.038
					(0.004)
R^2	0.15	0.21	0.24	0.24	0.26
N	2838	2838	2838	2838	1647

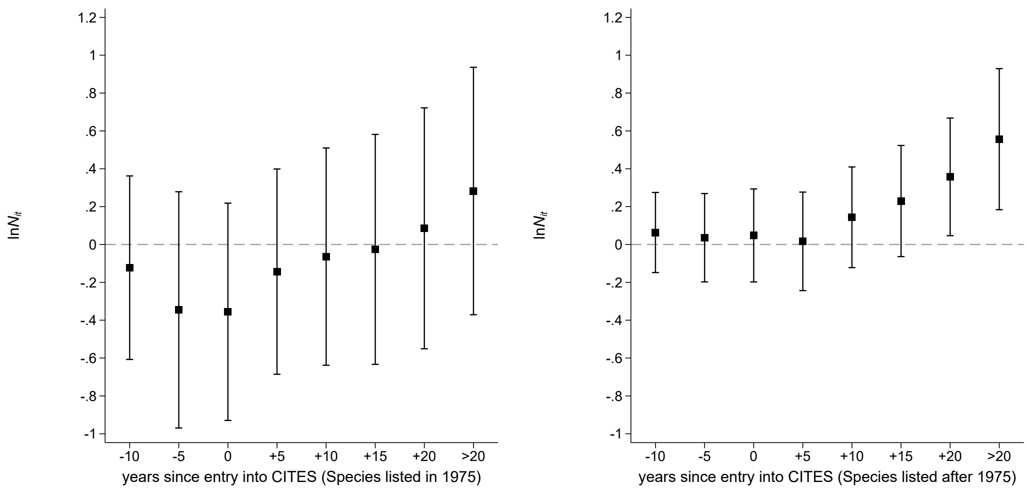
Notes: Appendix Table 1 reports estimated regression coefficients from an OLS regression of a dummy variable that equals one when the (sub-)species has ever been listed in CITES (and zero when it has never been listed in CITES) on a number of variables affecting the probability of being listed. Standard errors are in parentheses and are clustered at the species level. Data are for a cross-section of the subsample of species from the LPI data for which the IUCN Red List reports information on threats. Regressions in columns (1)-(4) include dummies for the taxonomic class of the species: mammal, bird, reptile, and amphibian; fishes are the baseline category. Columns (2)-(5) include variables that measure whether the species is vulnerable and whether the species is used intentionally. Column (4) also includes a variable that measures whether there is any threat of fishing. Column (5) includes a variable for body mass of the species. Data on body mass is only available for mammals and birds, therefore column (5) includes a dummy for the taxonomic class mammals only; birds are the baseline category.

Weitzman (1996) who analyze listing decisions for the Endangered Species Act in the United States. A species is more likely to be listed if it is more vulnerable, i.e., it has a higher extinction risk, see columns (2) to (5); if a species is used intentionally, see columns (3) to (5); and it is less likely to be listed if there is any direct threat of fishing, see column (4). Finally, column (5) shows that large species (i.e., with a higher body mass) are more likely to be listed.[31]

[31] Because data on body mass is only available for mammals and birds, this regression only includes a dummy for the taxonomic class mammals; birds are the baseline category.

B Separate effects for species listed in 1975 and after

Appendix Figure 1: Effect of CITES on population size (species listed in CITES). Species listed in 1975 vs. species listed after 1975



This figure shows coefficient estimates from Equation (3), i.e., a panel regression of log of population size on a set of dummy variables indicating the years since a species' entry into CITES, along with a set of population and year fixed effects. The left panel shows the coefficient estimates of dummy variables indicating the years since entry into CITES interacted with a variable indicating whether the species was listed in CITES in 1975. The right panel shows the coefficient estimates of dummy variables indicating the years since entry into CITES interacted with a variable indicating whether the species was listed in CITES after 1975. 95% confidence intervals are displayed around each point estimate. Standard errors are clustered at the species level. Number of observations: 111292.

C Species-type specific treatment effects

Appendix Table 2: Effect of CITES on population size. Species-type specific treatment effects for species listed in CITES in CITES' member countries

	(1)	(2)	(3)	(4)	(5)
for non-"Category 1" member countries					
$>$ 20 years later	0.076	−0.070	−0.092	−0.098	−0.164
	(0.176)	(0.230)	(0.111)	(0.090)	(0.120)
...for species with intentional use	−0.170				
	(0.209)				
...for vulnerable species		0.009			
		(0.256)			
...for highly-studied species			0.125		
			(0.129)		
...for well-known species				0.133	
				(0.082)	
...for large species					0.359
					(0.154)
for "Category 1" member countries					
$>$ 20 years later	0.394	0.370	0.272	0.311	0.334
	(0.106)	(0.090)	(0.061)	(0.069)	(0.077)
...for species with intentional use	−0.162				
	(0.132)				
...for vulnerable species		−0.185			
		(0.123)			
...for highly-studied species			0.144		
			(0.098)		
...for well-known species				0.062	
				(0.047)	
...for large species					−0.025
					(0.127)
N	96318	93799	111292	111292	111292

Notes: Appendix Table 2 reports coefficient estimates of a regression which uses $\ln N_{slt}$ as the dependent variable and includes separate treatment dummies that indicate populations of species listed at least 21 years in CITES' appendices and located in member countries classified as non-"Category 1" countries and "Category 1" countries, as well as interaction terms of these dummies with species-level dummies which identify different types of species. Column (1) estimates the regression including an interaction term of the separate treatment dummies with a dummy variable that equals one for species with intentional use. Column (2) includes an interaction for vulnerable species, i.e., when they are classified as either "critically endangered", "endangered", or "vulnerable" by the IUCN Red List. Column (3) includes an interaction with highly-studied species, i.e., with a higher than average number of studies per species and year. Column (4) includes an interaction with well-known species, i.e., with a higher than average number of identification agreements by the users of *iNaturalist* per species and year. Column (5) includes an interaction with large species, i.e., with a higher than average body size. All regressions contain population and year fixed effects. Standard errors are in parentheses and are clustered at the species level.

D Alternative specifications for country-specific trends

Appendix Table 3: Effect of CITES on population size

	(1)	(2)	(3)	(4)	(5)	(6)
6-10 years before	0.025	0.043	0.043	0.064	0.068	0.060
	(0.103)	(0.091)	(0.091)	(0.090)	(0.092)	(0.093)
1-5 years before	−0.059	−0.020	−0.019	0.012	0.016	0.008
	(0.126)	(0.104)	(0.104)	(0.102)	(0.103)	(0.104)
year of listing in CITES	−0.064	−0.041	−0.041	−0.016	−0.012	−0.021
	(0.126)	(0.116)	(0.116)	(0.112)	(0.114)	(0.114)
2-5 years later	−0.008	0.025	0.026	0.039	0.043	0.032
	(0.125)	(0.111)	(0.111)	(0.109)	(0.110)	(0.111)
6-10 years later	0.104	0.154	0.155	0.157	0.156	0.144
	(0.132)	(0.113)	(0.113)	(0.111)	(0.113)	(0.114)
11-15 years later	0.171	0.217	0.217	0.229	0.232	0.221
	(0.145)	(0.120)	(0.120)	(0.118)	(0.120)	(0.120)
16-20 years later	0.290	0.334	0.334	0.359	0.365	0.356
	(0.155)	(0.124)	(0.124)	(0.123)	(0.124)	(0.124)
$\geq$ 21 years later	0.487	0.512	0.512	0.538	0.547	0.539
	(0.171)	(0.128)	(0.129)	(0.128)	(0.128)	(0.128)
order of polynomial of time	0	1	2	3	4	5
N	111292	111292	111292	111292	111292	111292

Notes: Appendix Table 3 reports estimated regression coefficients and standard errors in parentheses. Standard errors are clustered at the species level. Dependent variable $\ln N_{slt}$. All regressions contain population and year fixed effects. For comparison, column (1) presents results of Equation (2). Columns (2)-(6) include country-specific (non-)linear trends modelled as polynomials of order 1 to 5 of time, respectively.

References

Metrick, A. and Weitzman, M. L. (1996). Patterns of Behavior in Endangered Species Preservation. *Land Economics*, 72(1):1–16.