Banning wildlife trade can boost demand for unregulated threatened species

Abstract

Regulations on the harvest and use of natural resources might have unintended spillover impacts beyond the policy targets. Banning wildlife trade is an immediate measure to protect species from overexploitation. However, few causal inference studies have investigated the consequences of wildlife trade bans. We use the synthetic difference-in-differences approach to causal inference based on a 10-year online auction dataset to explore whether trade bans on three threatened species in Japan–giant water bugs, Tokyo salamanders, and golden venus chub–have spillover impacts on trades of substitutable non-banned species. We find conservation side effects of wildlife trade bans, leading to an increase in trade volume of non-banned species in each taxon. Our results raise concerns about the unintended consequences of trade bans and restate the importance of further efforts concerning consumer research, monitoring and enforcement beyond the target species, while minimizing costs by applying machine learning technologies and enhancing international cooperation.

1 Main

The unsustainable wildlife trade is a major threat to biodiversity conservation[1]. Commercial wildlife trade is a multi-billion dollar activity that supports millions of livelihoods worldwide[2, 3], but unsustainable trade causes population decline suggesting a sixth mass extinction[4, 5, 6]. The recent rise in internet usage and the move of online trade can fuel wildlife trades through online e-commerce platforms and social media, increasing the risk of illegal and/or unsustainable trade across the globe [7, 8, 9, 10].

To mitigate this risk, trade bans at both the domestic and international levels are one of the most common and immediate measures for governments to manage wildlife trade[11]. There is no doubt that trade bans play substantial roles toward sustainable wildlife trade. However, the introduction and existence of the bans might lead to unintended and/or negative consequences for species conservation[12, 13, 14, 15]. For example, the introduction of the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) trade ban increased the trade volume and price of wildlife and the products[12, 13]. This subsequently activated the underground market[16, 17]. Furthermore, the trade ban affected species distributions and ecological threats[18, 19].

However, most studies investigating the effect of trade ban policies have focused solely on banned species[12], while the scarcity of comprehensive datasets on wildlife trade have resulted in limited policy evaluation studies[20]. This indicates that governments and researchers might have overlooked the risk of unintended *spillover* impacts on unregulated (i.e., legally tradable) threatened species caused by trade bans. As disentangling the cause-effect relationships of policy interventions is at the heart of effective development of conservation policies and regulations[9, 20, 21], rigorous policy evaluations identifying causality are required.

This study explores the impacts of the trade ban regulation implemented in February 2020 in Japan[22, 23, 24]—one of the largest wildlife trade countries—by employing 10 years of online auction data. We answer the question “Do trade bans have spillover impacts on the demand for non-banned species?” by applying the recently developed causal inference approach, synthetic difference-in-differences (SDID)[25]. Advantages of the method enable us to identify policy impacts by considering global/national impacts, such as the COVID-19 pandemic (see Methods for details), and to provide extensive insights into the spillover mechanisms and raise caution to the fact that wildlife trade bans can present unintended dangers to other threatened species.

2 Results

2.1 Preliminary insights

Fig. 1 presents the quarterly trade sales volumes and mean prices of the policy target banned species (i.e., giant water bugs *Kirkaldyia deyrolli*, Tokyo salamanders *Hynobius tokyoensis*, and golden venus chub *Hemigrammocypris neglectus*) in the online auction market from February 2011 to February 2021. Banned species were not traded after the ban except for one giant water bug trade on February 22, 2020 and one golden venus chub trade on February 10, 2020. Prior to the ban, the trade volume of giant water bugs (n = 3037) was larger than those of the two (n = 307 for Tokyo salamanders; n = 503 for golden venus chub). The mean prices (price range) of each banned species prior to the ban were 33.3 (0.01-700), 32.8 (0.01-365), and 16.3 (0.01-350) USD for giant water bugs, Tokyo salamanders and golden venus chub, respectively. In this paper, Japanese yen (JPY) has been converted at 100 to the US dollar (USD). There was a price spike for giant water bugs (116.9 USD) during the fourth quarter of 2019 (November 10, 2019 - February 9, 2020: the last quarter before the ban), which includes the initial announcement day of this policy change (December 25, 2019).

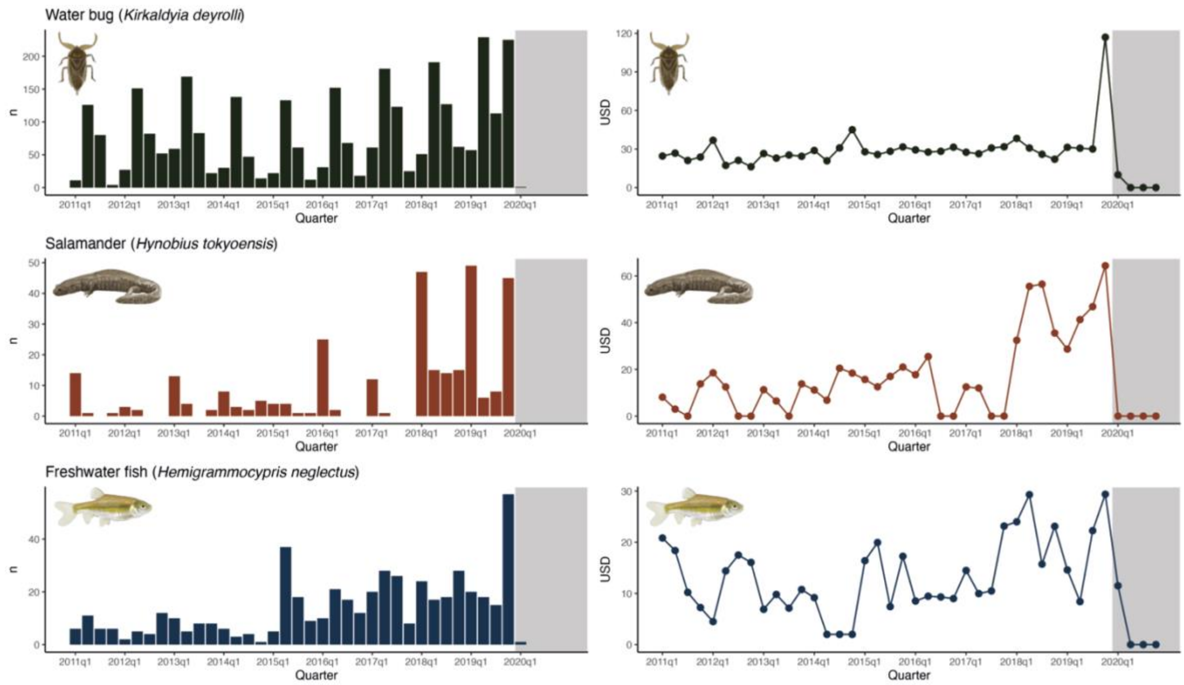

Fig. 1. The sales volumes of trade (Left) and the mean prices (Right) by quarter of each banned species: giant water bugs (Top), Tokyo salamanders (Middle), and golden venus chub (Bottom). When the species were not traded in a quarter, the prices are represented as zero. The shaded area is the trade-ban period (February 10, 2020 – February 09, 2021).

Fig. 2 shows the trade volumes and mean prices of the potential spillover species composed of three legally tradable species in each taxon, selected by considering the substitutability for the banned species (see section 4.3 Data for details of the substitutability). The details of trade volumes and mean prices associated with Fig. 1 and Fig. 2 are presented in the SI Appendix Datasets.

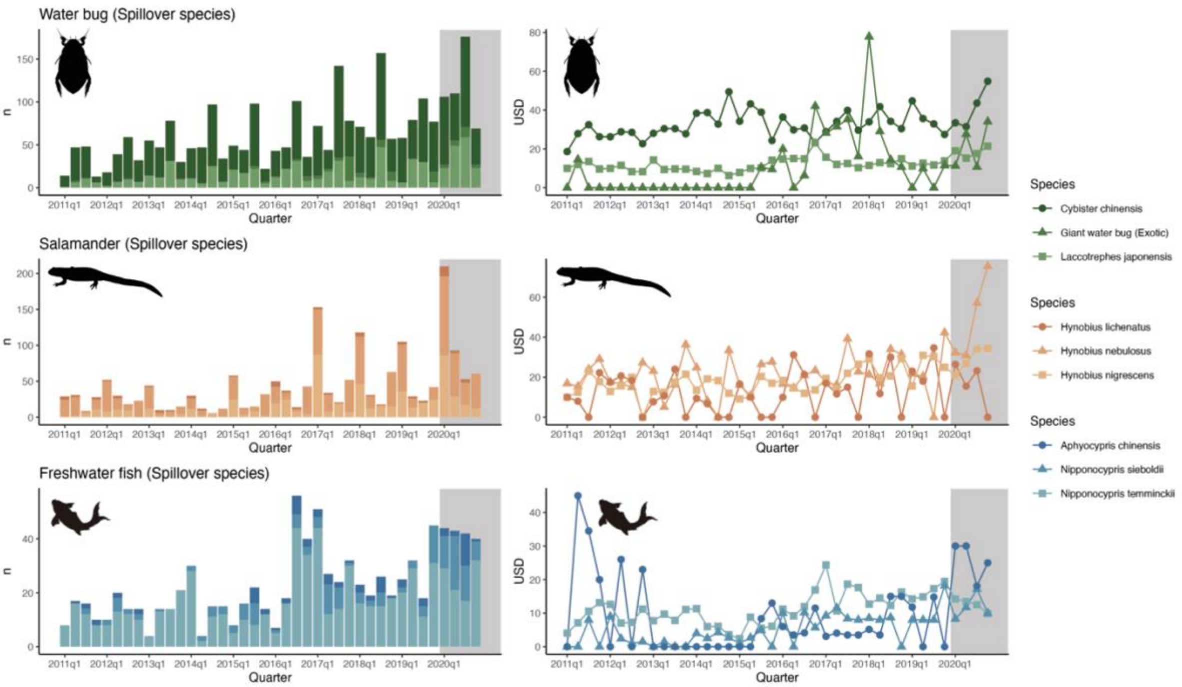

Fig. 2. The sales volumes of trade (Left) and the mean prices (Right) by quarter of each potential spillover species: the species in taxa of water bugs (Top), salamanders (Middle), and freshwater fish (Bottom). When the species were not traded in a quarter, the prices are represented as zero. The shaded area is the trade-ban period (i.e., February 10, 2020 – February 09, 2021).

2.2 Estimation of the impact of the ban

The SDID identified positive spillover impacts concerning sales volumes of trade in each taxon (water bug: +17.54 mean effect, 95% confidence interval (CI) = [14.03, 21.06]; salamander: +10.06 mean effect, 95% CI = [2.73, 17.39]; freshwater fish: +6.19 mean effect; 95% CI = [0.12, 12.25]; see Fig. 3). Our sensitivity and placebo analyses for robustness checks showed that the parameter signs and effects were virtually the same as our main results here (see Fig. S4-S8 and Table S4-S6 for details).

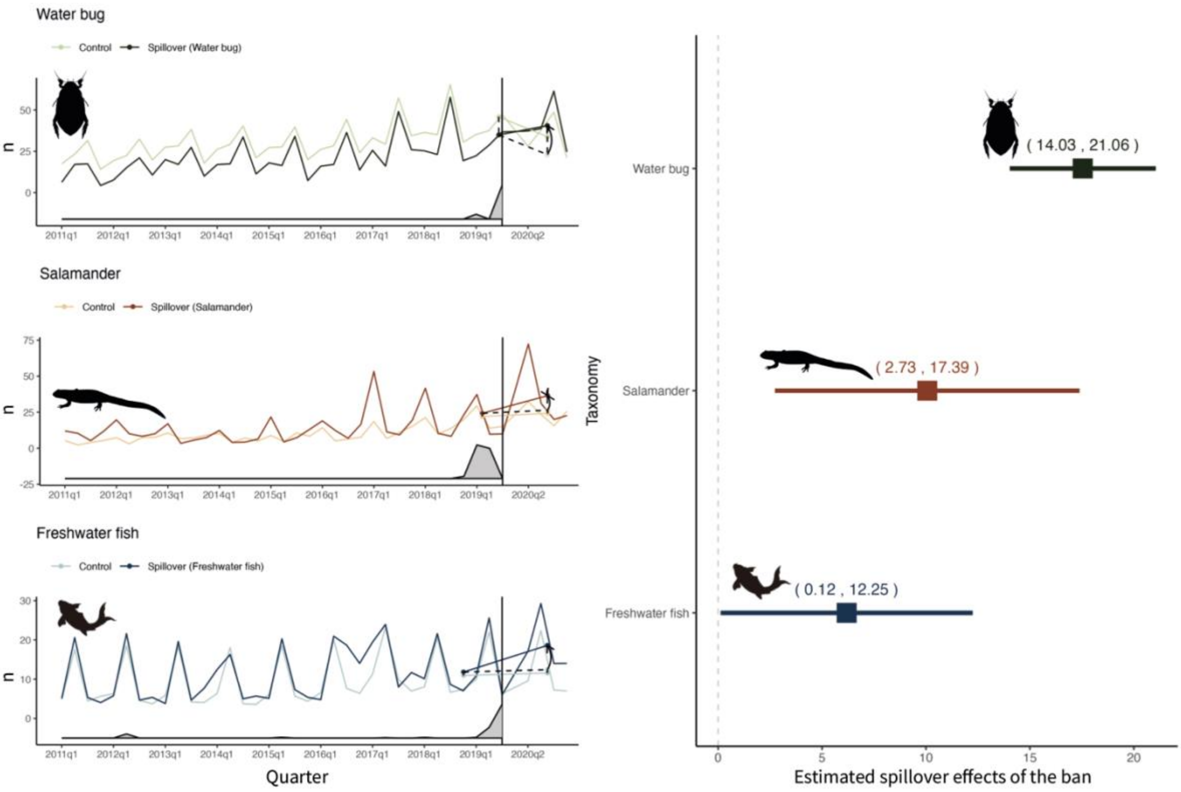

Fig. 3. Results of synthetic difference-in-differences (SDID) on the sales volumes of trade. To mitigate the announcement bias before the ban, 2019's fourth quarter was removed from the estimation. In the left column, each panel shows trends in relative sales volumes of trade by quarter over time for the spillover species and the relevant weighted average of control species. The arrows indicate the estimated spillover effects of the trade ban. The right column figure shows the estimated spillover effects with a 95% confidence interval (CI) in each taxon.

3 Discussion

Our findings show conservation side effects of wildlife trade bans on non-banned threatened species as substitutes of banned species. Bans on the three policy targeted species– giant water bugs, Tokyo salamanders, and golden venus chub–led to an increase in the trade volumes of non-banned species in each taxon, indicating that banning wildlife trade can bring unintended dangers to other threatened species.

The findings have several important insights into consequences. First, demand caused by the trade ban can reach non-banned threatened species in countries where the ban is implemented. For example, a substitute for the giant water bugs *Cybister chinensis* is designated as vulnerable in the Japanese Red List and is extinct in five prefectures[26]. This effect potentially harms conservation of many legally tradable threatened species currently sold online by driving up demand for the alternatives, which can activate wild harvest. This concern is not limited to the country implementing trade bans. Spillover effects are not necessarily limited to native species; they are also applicable to exotic species, such as giant water bugs, from other countries. An increase in exotic species trade can increase overexploitation risk in source countries and lead to population declines unless appropriate management is implemented[27]. Source countries, often developing countries, may face difficulties in meeting additional management needs because of the trade ban, as they often struggle to implement robust natural resource governance[4].

In addition to overexploitation risk, the imports and breeding of exotic species stimulated by the policy change raise concerns about the potential impacts of invasive species if exotic pet species are (un)intentionally released[27, 28]. Moreover, the more often exotic species in closely related taxa to the banned species are imported, the higher the risk of disease outbreaks that could affect the banned species[29]. Considering these concerns, we highlight the possibility of the existence of a feedback loop in which trade bans may accelerate threats to biodiversity conservation. Trade bans can stimulate demand for non-banned species, triggering new regulations, and stimulate demand for other non-banned species, thus creating a self-perpetuating loop. Indeed, the commercial trade of *Cybister chinensis,* for which we detected the positive spillover effects from the big water bug in this study, has been prohibited since January 2023. As these processes can occur with other feedback challenges like *Anthropogenic Allee Effect*[13], these multiple feedback loops may accelerate human-induced population decline of both banned and non-banned species[6, 30].

To mitigate the risk of the negative consequences, we note some policy and management implications. We first call for understanding market dynamics and recommend the use of behavioral science insights to manage demand prior to introducing a trade ban[15, 31, 32]. Our findings concerning heterogeneity of the effects across taxa note that an initial goal of interventions should be to reduce the demand for the species to be banned, therefore reducing the magnitude of any potential spillover. For example, the demand for and public interest in giant water bugs were considerably higher than the other species (see Fig. 1 and Fig. S1), which possibly led to higher potential leakage of the demand for the non-banned species following the ban. Following this, demand management should be aimed at redirecting any spillover demand towards legal and sustainable sources, either from well-managed wild populations or captive breeds, thus minimizing any threats to biodiversity. Identifying these potential substitute sources requires a detailed understanding not only of the conservation status and trade sustainability of different wildlife populations and species but also of consumer motivations and preferences, which are often context-dependent and culture-specific.

The complexity of understanding substitutability has been underlined by ongoing debates on the potential of farmed products as substitutes for wild-sourced products[33, 34]. This uncertainty regarding an issue that has received substantial research attention shows the importance of further research to avoid situations wherein substitutes are deemed either biologically unsuitable or not desirable by consumers[33]. This need for planning highlights the systemic risks of reactive bans—often the case in wildlife trade—imposed on a short notice and often without detailed knowledge of the systems they intended to influence. Additionally, we highlight the importance of understanding the mechanisms behind the supply side of trade. Supply volume can be affected by characteristics of wildlife and wildlife products such as accessibility and price elasticity. Due to the relatively low capture cost for the taxa in this study, their transaction volumes can be affected by the policy change[35]. Policy makers and researchers need to contribute to the development of market-based approaches[36, 37], for example, increasing the transaction costs of the potential spillover species via regulations.

To develop effective interventions to manage wildlife trade, further efforts concerning monitoring the volume, composition, and prices of species trade are needed. Specifically, our findings insist that the monitoring should be extended to unregulated threatened species. However, as demonstrated by the case of Japan, where the conservation budget has increased only marginally while the number of protected species has been increasing[38], it is essential to enhance monitoring efficiency and management capacity as conservation practices have faced substantial financial shortages[39]. There are several ways to improve monitoring efficiency and management capacity. The latest computer science technology can, for example, be utilized to identify traded species[40, 41]. Thus far, species identification has been challenging, even on online trade platforms, since species are traded using not only species names, but also common names and codified language designed to be understood only by those within specific pet owner and trader networks[42]. Our findings based on datasets processed using natural language processing (NLP) can, in part, showcase benefits of the technology.

Furthermore, the findings regarding cross-country spillovers from other countries calls for international cooperation beyond what currently occurs under CITES. We suggest the development of a database comprising the banned and non-banned traded/tradable species with common names in multiple languages; this can help disseminate information on policy interventions for the species across countries. Overcoming language barriers in conservation science and practice[43] will better identify species traded across borders and ensure more reliable trade monitoring.

At a time when biodiversity is being lost at an unprecedented rate, evidence-based policy evaluation is essential for effective measures. Policy evaluations ignoring spillover effects might overstate the benefits of trade ban policies in conservation. Our evidence raises concerns about the unintended consequences of wildlife trade bans through a feedback loop of spillover demand, which can threaten conservation status of non-banned species. This challenge is not limited to legislation aimed at conservation. Banning wildlife trade to cope with wildlife disease, which has been discussed during the COVID-19 pandemic, might also stimulate demand and lead to species extinction via this mechanism[14, 44, 45]. The introduction of legislation requires further consumer research, monitoring and enforcement that goes beyond the species targeted by the policy, while minimizing the costs vias the application of modern technologies and enhancing international cooperation.

4 Methods

4.1 Policy background

The Japanese government has enforced the law, "The Act on Conservation of Endangered Species of Wild Fauna and Flora (ACES)", to conserve endangered species (for details, see the description by the Ministry of the Environment, Japan: https://www.env.go.jp/nature/kisho/kisei/en/species/index.html). Under the ACES, threatened wildlife species in Japan are designated as Nationally Endangered Species of Wildlife Fauna and Flora. There is a ban on capture, trade, transfer, and export of these designated species. Further, one is not allowed to display or advertise such species for commercial trade. This regulation applies not only to living species, including both wild-taken and captive-bred, but also to dead biological specimens and products made from the designated species.

With the recent increase in demand for wildlife trade, there is a growing concern that mass capture for commercial purposes can cause species extinction. Particularly, semi-natural ecosystem species (for example water bugs, amphibians, and freshwater fishes) are now at risk of species extinction due to this commercial use in addition to the existing risk of habitat destruction. To regulate the commercial use of the species without discouraging the conservation activities, the Japanese government amended the law and created a new framework, called "Class II Designated Nationally Endangered Species of Wild Fauna and Flora". On February 10, 2020, the regulation of this framework was introduced on three species—giant water bugs, Tokyo salamanders, and golden venus chub—by considering their ecological status and characteristics. Accordingly, under this regulation, the capture, trade, and transfer of the three species for commercial activities have been prohibited since February 10, 2020 (For details, see the press release on the policy amendment: https://www.env.go.jp/press/107622.html).

4.2 Identification strategy

This study analyzed the introduction of the trade ban policy on the three species in Japan using online auction data to answer the question, "Do trade bans have spillover impacts on the demand for non-banned species?". We used SDID to estimate the causal impact of the wildlife trade bans on demand for non-banned species. SDID has several advantages over previous causal inference approaches[25]. For example, unlike synthetic control methods (SCM), SDID controls for individual specific fixed effects and constructs weights allowing for difference in the dependent variable prior to the treatment. Unlike difference-in-differences (DID), SDID weights observations to construct more credible synthetic control than DID, making it more plausible to satisfy the parallel trend assumption, which is crucial for unbiased identification of the treatment effect. These advantages enable us to identify policy impacts by considering common shock, such as the COVID-19 pandemic. Furthermore, while this modelling flexibility comes at the small cost of statistical efficiency when either SCM or DID is correctly specified, SDID is more robust than SCM and DID[25].

In this paper, we control for seasonal trend in the SDID framework (typically more trades are happening in the summer than winter; see Fig 1-2, for example). It has been shown that the two-step procedure developed by Kranz (2023) performs better than the original SDID method when there are other controls (here, seasonal dummies) other than individual fixed effects, year fixed effects, and the treatment variable[25, 46]. The two-step procedure works as follows:

First, we regress $Y_{i,y,q}$ on X (quarter dummies), individual fixed effects, and year fixed effects.

$$Y_{i,y,q} = \phi_q + \alpha_i + \gamma_y + v_{i,q,y} \qquad \text{(Eq. 1).}$$

$Y_{i,y,q}$ is the trade volume of species i in quarter q in year y; ϕ_q is the quarter fixed effects; α_i is species fixed effect; γ_y is year fixed effects； $v_{i,q,y}$ is the error term.

Once this model is estimated, we find the residuals of $Y_{i,y,q}$.

$$\tilde{Y}_{i,y,q} = Y_{i,y,q} - \hat{\phi}_q - \hat{\alpha}_i - \hat{\gamma}_y \qquad \text{(Eq. 2).}$$

We then apply the SDID framework[25], which solves the following minimization problem to identify the treatment effect:

$$Min_{\tau,\gamma,\alpha} \sum_i \sum_q (\tilde{Y}_{i,y,q} - \gamma_y - \alpha_i - \tau W_{i,y,q})^2 \times \omega_i \times \lambda_y \qquad \text{(Eq. 3).}$$

Our ultimate interest is estimating τ, which is the average treatment (causal) effect; $W_{i,y,q}$ is the treatment dummy; ω_i is the weight on species i; λ_y is the weight on year y.

We also excluded the last quarter of 2019 to mitigate the bias concerning the announcement of the policy change. Sensitivity and placebo analyses for robustness checks (e.g., including the last quarter of 2019) were also conducted (see details in Fig. S3-S8 and Table S3-6 in the SI Appendix). All analyses were conducted using R version 4.1.2. The R packages "*synthdid*" and "*xsynthdid*" were used for the estimation[46, 47].

4.3 Data

We used a 10-year dataset from Japan's leading online auction platform Yahoo! Auction (https://auctions.yahoo.co.jp/). The dataset included the nine years prior to the ban (February

2011–2020) and one year after the ban (February 2020–2021). The data was downloaded from the publicly accessible mirroring website Aucfan (https://aucfan.com/). The number of transactions composed of each taxon's banned, potential spillover, and control species is 333349, 22766, and 91879 for water bugs, salamanders, and freshwater fish, respectively (see Table S3 and Datasets in the SI Appendix for details). This dataset includes the following variables: traded dates, titles, traded categories, and final auction prices of each traded product. Traded categories, such as amphibian, were given by the auction website (i.e., https://auctions.yahoo.co.jp/list1/0-all.html). We applied NLP to extract the traded species' names using the information on the titles and categories; then, we manually confirmed the names of the banned and potential spillover species.

The outcomes of the identifications are the potential spillover species' trade volumes to clarify the spillover demands for non-banned species. The potential spillover species (i.e., treated units) were chosen based on three criteria as we suppose they are substitutable species relative to the banned species. First, we selected species expressed by the same Japanese names with those of the banned species but legally tradable in the market. These species were not under the trade ban because they were biologically different from the banned species (i.e., they had different scientific names from the banned species). Second, to find the similar characteristics through a lens of human preference and searchability, we queried Google Trends for the banned three species and sales in Japanese for the 10-year data period, and used related queries through the R package "gtrendsR"[48] (see Note S1 for details). Third, if no candidate species were available after considering the two criteria for each banned species, the three phylogenetically closest species in the market were selected using the phylogeny with reference to iNaturalist (https://www.inaturalist.org/) and OneZoom (https://www.onezoom.org/). As previous studies exploring substitutability in wildlife trade have mainly focused on traditional Chinese medicine[49], it is not possible to judge how well these criteria capture the similarities between banned and potential spillover species to consider substitutability. However, these procedures concerning criteria selection do not overestimate the spillover impacts even if there is misassignment concerning species in the SDID models (see Note S2 in the SI Appendix for details). Following this procedure, three species were chosen as potential spillover species for each banned species (see Table S1 in the SI Appendix for details), whereas we also conducted sensitivity analyses focusing on a species in each category to confirm the findings (see Table S4 in the SI Appendix for details).

The control units were the trades in the same categories given by the auction website as those of the banned species, excluding those of the potential spillover species. For example, the control units to identify the spillover effects of banning Tokyo salamander were trades in the amphibian category on the auction website excluding the trades of potential spillover species (*Hynobius nebulosus*, *Hynobius nigrescens*, and *Hynobius lichenatus*). Given the large volume of the datasets, not all species in the control units were identified by a scientific name; therefore, as a robustness check, we also analyzed the datasets with only the control units identified by the scientific names in the same taxonomic families as the trade banned species (see Fig. S3-4, S7-8 and Datasets in the SI Appendix for the details).

Considering seasonality and the balanced panel requirements of SDID, the data analysis was compiled on a quarterly basis, starting on the day the policy was implemented, February 10, 2020. Expressly, the pre-treatment period is from February 10, 2011, to February 9, 2020 and the post-treated period is from February 10, 2020 to February 9, 2021. The trade volume of each species was aggregated by quarter. Additionally, as a robustness check, we conducted sensitivity and placebo analyses with different datasets to confirm our findings (see Table S3-4 in the SI Appendix for details). Because of the discovery of new salamander species during this research, the species were aggregated into the oldest taxa[50] (see Table S2 in the SI Appendix for the details).

5 References

1. Maxwell SL, Fuller RA, Brooks TM, Watson JEM. Biodiversity: The ravages of guns, nets and bulldozers. *Nature* 2016, **536**(7615)**:** 143-145.

2. Cawthorn D-M, Hoffman LC. The bushmeat and food security nexus: A global account of the contributions, conundrums and ethical collisions. *Food Research International* 2015, **76:** 906-925.

3. UNODC. World wildlife crime report 2020: Trafficking in protected species. United Nations Office on Drugs and Crime Vienna, Austria; 2020.

4. Liew JH, Kho ZY, Lim RBH, Dingle C, Bonebrake TC, Sung YH*, et al.* International socioeconomic inequality drives trade patterns in the global wildlife market. *Science Advances* 2021, **7**(19)**:** eabf7679.

5. Feddema K, Nekaris KAI, Nijman V, Harrigan P. Re-evaluating the notion of value in wildlife trade research from a service marketing perspective. *Biol Conserv* 2021, **256:** 109060.

6. Scheffers BR, Oliveira BF, Lamb I, Edwards DP. Global wildlife trade across the tree of life. *Science* 2019, **366**(6461)**:** 71.

7. Alfino S, Roberts DL. Code word usage in the online ivory trade across four European Union member states. *Oryx* 2020, **54**(4)**:** 494-498.

8. Lavorgna A. Wildlife trafficking in the Internet age. *Crime Science* 2014, **3**(1)**:** 5.

9. Marshall BM, Strine C, Hughes AC. Thousands of reptile species threatened by under-regulated global trade. *Nature Communications* 2020, **11**(1)**:** 4738.

10. Wang Z, Chan W-P, Pham NT, Zeng J, Pierce NE, Lohman DJ*, et al.* One in five butterfly species sold online across borders. *Biol Conserv* 2023, **283:** 110092.

11. Oldfield S. *The trade in wildlife: regulation for conservation*. Routledge, 2003.

12. Rivalan P, Delmas V, Angulo E, Bull LS, Hall RJ, Courchamp F*, et al.* Can bans stimulate wildlife trade? *Nature* 2007, **447**(7144)**:** 529-530.

13. Courchamp F, Angulo E, Rivalan P, Hall RJ, Signoret L, Bull L*, et al.* Rarity Value and Species Extinction: The Anthropogenic Allee Effect. *PLOS Biology* 2006, **4**(12)**:** e415.

14. Eskew EA, Carlson CJ. Overselling wildlife trade bans will not bolster conservation or pandemic preparedness. *Lancet Planet Health* 2020, **4**(6)**:** e215-e216.

15. Challender DWS, Harrop SR, MacMillan DC. Understanding markets to conserve trade-threatened species in CITES. *Biol Conserv* 2015, **187:** 249-259.

16. Rosen GE, Smith KF. Summarizing the Evidence on the International Trade in Illegal Wildlife. *EcoHealth* 2010, **7**(1)**:** 24-32.

17. Underwood FM, Burn RW, Milliken T. Dissecting the Illegal Ivory Trade: An Analysis of Ivory Seizures Data. *PLOS ONE* 2013, **8**(10)**:** e76539.

18. Reino L, Figueira R, Beja P, Araújo MB, Capinha C, Strubbe D. Networks of global bird invasion altered by regional trade ban. *Science Advances* 2017, **3**(11)**:** e1700783.

19. Weber DS, Mandler T, Dyck M, Van Coeverden De Groot PJ, Lee DS, Clark DA. Unexpected and undesired conservation outcomes of wildlife trade bans—An emerging problem for stakeholders? *Glob Ecol Conserv* 2015, **3:** 389-400.

20. Challender DWS, Brockington D, Hinsley A, Hoffmann M, Kolby JE, Massé F*, et al.* Mischaracterizing wildlife trade and its impacts may mislead policy processes. *Conserv Lett* 2022, **15**(1)**:** e12832.

21. Natusch DJD, Aust PW, Shine R. The perils of flawed science in wildlife trade literature. *Conservation Biology* 2021, **35**(5)**:** 1396-1404.

22. McMillan SE, Dingle C, Allcock JA, Bonebrake TC. Exotic animal cafes are increasingly home to threatened biodiversity. *Conserv Lett* 2020, **14**(1)**:** e12760.

23. Tournant P, Joseph L, Goka K, Courchamp F. The rarity and overexploitation paradox: stag beetle collections in Japan. *Biodiversity and Conservation* 2012, **21**(6)**:** 1425-1440.

24. Andersson AA, Tilley HB, Lau W, Dudgeon D, Bonebrake TC, Dingle C. CITES and beyond: Illuminating 20 years of global, legal wildlife trade. *Glob Ecol Conserv* 2021, **26:** e01455.

25. Arkhangelsky D, Athey S, Hirshberg DA, Imbens GW, Wager S. Synthetic Difference-in-Differences. *American Economic Review* 2021, **111**(12)**:** 4088-4118.

26. Ohba S-y, Fukui M, Terazono Y, Takada S. Effects of temperature on life histories of three endangered Japanese diving beetle species. *Entomologia Experimentalis et Applicata* 2020, **168**(11)**:** 808-816.

27. Lockwood JL, Welbourne DJ, Romagosa CM, Cassey P, Mandrak NE, Strecker A*, et al.* When pets become pests: the role of the exotic pet trade in producing invasive vertebrate animals. *Front Ecol Environ* 2019, **17**(6)**:** 323-330.

28. Gippet JMW, Bertelsmeier C. Invasiveness is linked to greater commercial success in the global pet trade. *Proceedings of the National Academy of Sciences* 2021, **118**(14)**:** e2016337118.

29. O'Hanlon Simon J, Rieux A, Farrer Rhys A, Rosa Gonçalo M, Waldman B, Bataille A*, et al.* Recent Asian origin of chytrid fungi causing global amphibian declines. *Science* 2018, **360**(6389)**:** 621-627.

30. Ceballos G, Ehrlich PR, Barnosky AD, Garcia A, Pringle RM, Palmer TM. Accelerated modern human-induced species losses: Entering the sixth mass extinction. *Science Advances* 2015, **1**(5)**:** e1400253.

31. Greenfield S, Veríssimo D. To What Extent Is Social Marketing Used in Demand Reduction Campaigns for Illegal Wildlife Products? Insights From Elephant Ivory and Rhino Horn. *Soc Mark Q* 2018, **25**(1)**:** 40-54.

32. Veríssimo D, t Sas-Rolfes M, Glikman JA. Influencing consumer demand is vital for tackling the illegal wildlife trade. *People and Nature* 2020, **2**(4)**:** 872-876.

33. Hinsley A, t Sas-Rolfes M. Wild assumptions? Questioning simplistic narratives about consumer preferences for wildlife products. *People and Nature* 2020, **2**(4)**:** 972-979.

34. Davis EO, Veríssimo D, Crudge B, Sam SH, Cao DT, Ho PV*, et al.* How Will the End of Bear Bile Farming in Vietnam Influence Consumer Choice? *Conservation & Society* 2022, **20**(1)**:** 1-11.

35. Mialon Hugo M, Klumpp T, Williams Michael A. International trade and the survival of mammalian and reptilian species. *Science Advances* 2022, **8**(1)**:** eabh3442.

36. Cooney R, Jepson P. The international wild bird trade: what's wrong with blanket bans? *Oryx* 2006, **40**(1)**:** 18-23.

37. Phelps J, Biggs D, Webb EL. Tools and terms for understanding illegal wildlife trade. *Front Ecol Environ* 2016, **14**(9)**:** 479-489.

38. Ministry of the Environment, Japan. Scientific Committee of Experts on Rare Wild Fauna and Flora Species. 2018 (Available from: https://www.env.go.jp/nature/kisho/kagaku/gijishidai.html)

39. Dempsey J, Irvine-Broque A, Bigger P, Christiansen J, Muchhala B, Nelson S*, et al.* Biodiversity targets will not be met without debt and tax justice. *Nature Ecology & Evolution* 2022, **6**(3)**:** 237-239.

40. Di Minin E, Fink C, Tenkanen H, Hiippala T. Machine learning for tracking illegal wildlife trade on social media. *Nature Ecology & Evolution* 2018, **2**(3)**:** 406-407.

41. Hino M, Benami E, Brooks N. Machine learning for environmental monitoring. *Nature Sustainability* 2018, **1**(10)**:** 583-588.

42. Stringham OC, Toomes A, Kanishka AM, Mitchell L, Heinrich S, Ross JV*, et al.* A guide to using the internet to monitor and quantify the wildlife trade. *Conservation Biology* 2021, **35**(4)**:** 1130-1139.

43. Amano T, Rios Rojas C, Boum Ii Y, Calvo M, Misra BB. Ten tips for overcoming language barriers in science. *Nature Human Behaviour* 2021, **5**(9)**:** 1119-1122.

44. Roe D, Lee TM. Possible negative consequences of a wildlife trade ban. *Nature Sustainability* 2021, **4**(1)**:** 5-6.

45. Roe D, Dickman A, Kock R, Milner-Gulland EJ, Rihoy E, 't Sas-Rolfes M. Beyond banning wildlife trade: COVID-19, conservation and development. *World Development* 2020, **136:** 105121.

46. Kranz S. Package: xsynthdid 2022 (Available from: https://github.com/skranz/xsynthdid)

47. Arkhangelsky D, Athey S, Hirshberg DA, Imbens GW, Wager S. synthdid: Synthetic Difference in Differences Estimation. 2021 (Available from: https://github.com/synth-inference/synthdid)

48. Massicotte P, Eddelbuettel D, Massicotte MP. Package 'gtrendsR'. 2016.

49. Moorhouse TP, Zhou Z-M, Shao M-L, Zhou Y, Elwin A, D'Cruze NC*, et al.* Substitutes for wildlife-origin materials as described in China's "TCM" research literature. *Glob Ecol Conserv* 2022, **34:** e02042.

50. Matsui M, Okawa H, Nishikawa K, Aoki G, Eto K, Yoshikawa N*, et al.* Systematics of the Widely Distributed Japanese Clouded Salamander, *Hynobius nebulosus* (Amphibia: Caudata: Hynobiidae), and Its Closest Relatives. *Current Herpetology* 2019, **38**(1)**:** 32-90.

Supplementary Information (SI) Appendix for

"Banning wildlife trade can boost demand for unregulated threatened species"

<u>The SI includes:</u>

SI Notes and Figures

- **Note S1.** The use of Google Trends to find potential spillover species.
- **Fig. S1.** Google Trends statistics for sales of the policy targeted banned species.
- **Fig. S2.** Control unit contribution plot of the synthetic difference-in-differences associated with Fig. 3 in the article.
- **Fig. S3.** Results of synthetic difference-in-differences on sales volumes of trade (using the datasets with only the control units identified by the scientific names).
- **Fig. S4.** Control unit contribution plot of the synthetic difference-in-differences associated with Fig. S3.
- **Fig. S5.** Results of synthetic difference-in-differences on sales volumes of trade (including 2019's last quarter with the same dataset as the Fig. 3 in the article).
- **Fig. S6.** Control unit contribution plot of the synthetic difference-in-differences associated with Fig. S5.
- **Fig. S7.** Results of synthetic difference-in-differences on sales volumes of trade (using the datasets with only the control units identified by the scientific names and including 2019's last quarter).
- **Fig. S8.** Control unit contribution plot of the synthetic difference-in-differences associated with Fig. S7.
- **Note S2.** The implications of treatment-control designations.

SI Tables

- **Table S1.** Descriptions of the banned and potential spillover species.
- **Table S2.** Descriptions and references of the new salamander species.
- **Table S3.** Summary of the datasets concerning the synthetic difference-in-differences.
- **Table S4.** Estimation of robustness checks with dataset by single species.
- **Table S5.** Estimation of robustness checks with datasets by month.
- **Table S6.** Summary of placebo analyses.

Other SI Materials (Datasets / R codes)

SI References

SI Notes and Figures

Note S1. The use of Google Trends to find potential spillover species

We queried Google Trends for the banned three species and sales in Japanese—"タガメ 販売 (i.e., 'giant water bugs' sales)", "トウキョウサンショウウオ 販売 (i.e., 'Tokyo salamander' sales)", and "カワバタモロコ 販売 (i.e., 'golden venus chub' sales)")—for the 10- year data period (February 10, 2011–February 9, 2021) and used related queries. The analysis was implemented using the R package "gtrendsR"[1]. The trends of the relative number of search-term hits returned by Google Trends are presented in Fig. S1. Through this process, two potential spillover species were identified in the water bug taxon (see Table S1).

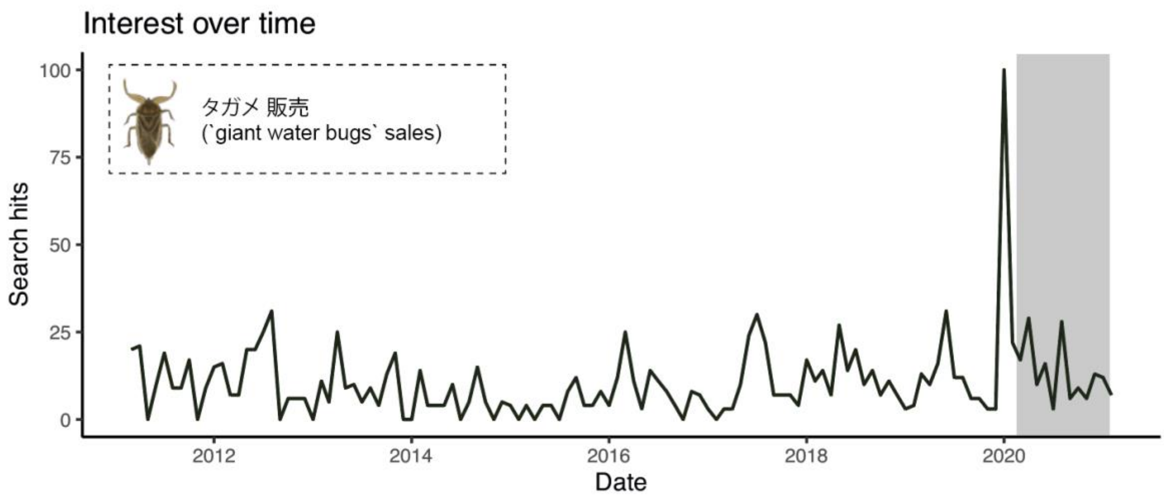

Fig. S1. Google Trends statistics for sales of the policy targeted banned species. Only "'giant water bug' sales" was detected and drawn in this figure; the trends of the other two species were not detected due to the limited search volume. The shaded area is the trade-ban period (i.e., February 10, 2020–February 09, 2021).

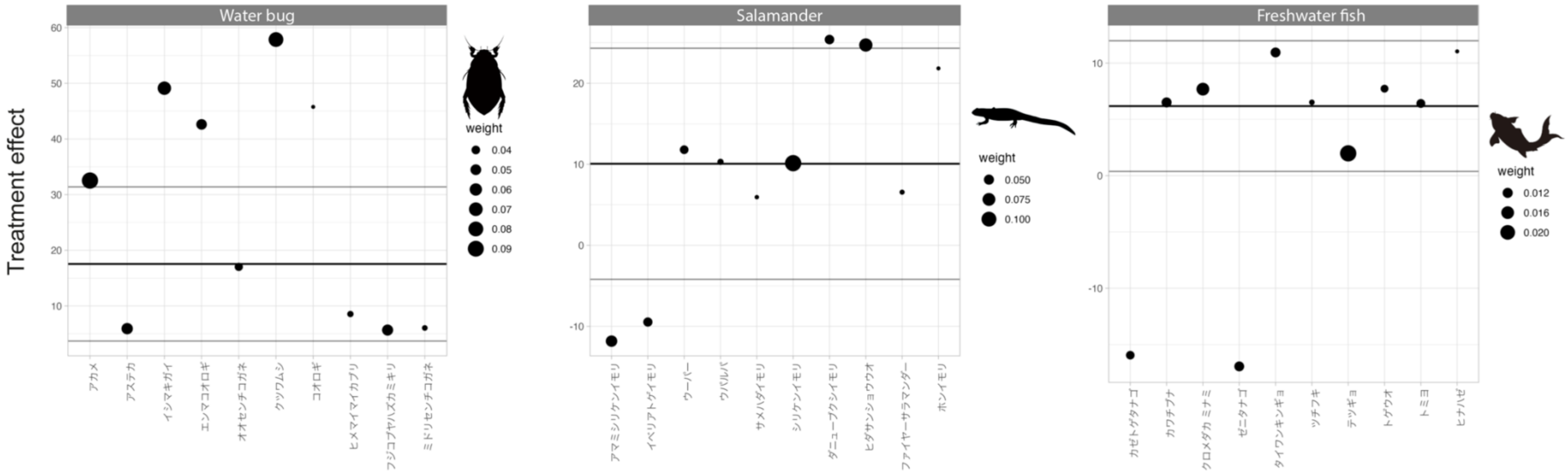

Fig. S2. Control unit contribution plot of the synthetic difference-in-differences associated with Fig. 3 in the article.

This figure shows the weight on each of the top 10 contributing control units with its size represented by circle size (see 4.2 section Identification strategy in the main and Arkhangelsky et al. 2021 for details). The names of control units are expressed in Japanese on the horizontal axis by following the estimation (see section 4.3 Data in the article and Other SI Materials for details). The treatment effect when the control unit is used as the sole control unit is represented on the vertical axis. The black line represents the synthetic difference-in-differences estimate, which is the weighted average of the treatment effects for the individual control units. The grey lines represent the upper and lower bound of the 95% confidence interval.

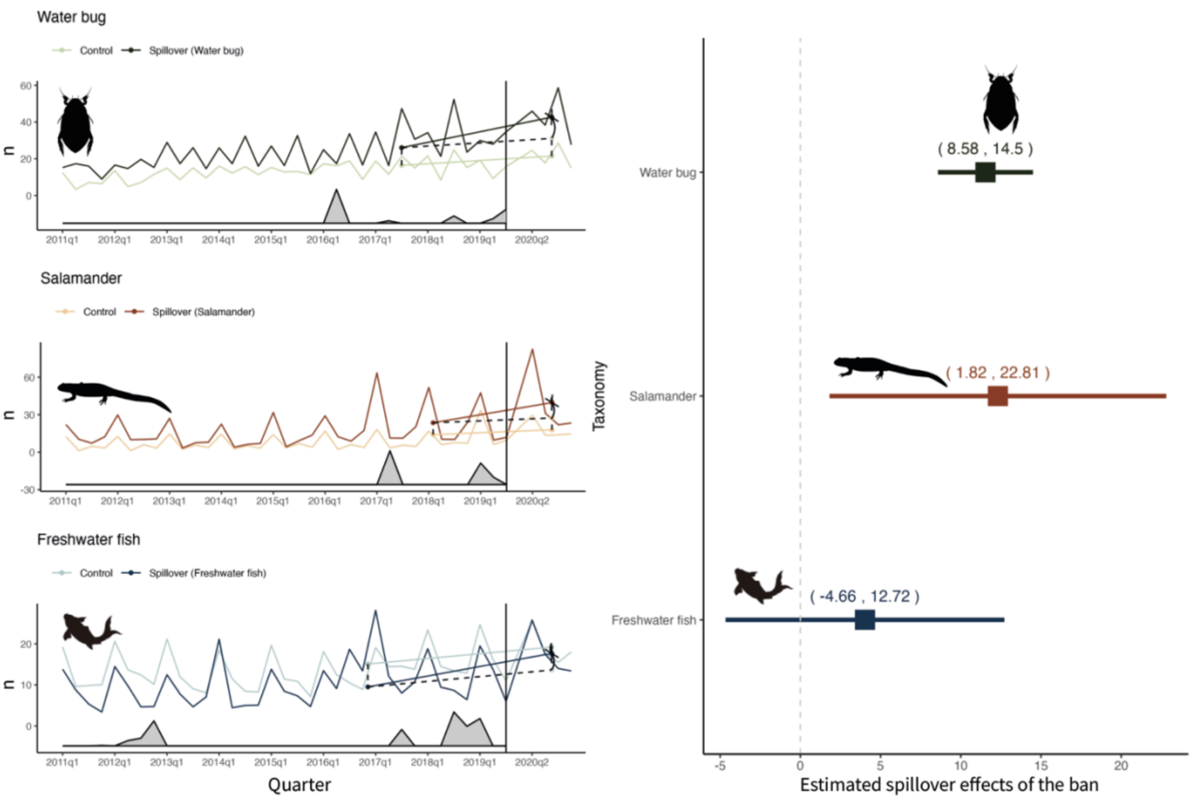

Fig. S3. Results of synthetic difference-in-differences on sales volumes of trade (using the datasets with only the control units identified by the scientific names). The estimation was conducted using the datasets with only the control units manually identified by the scientific names. In the left column, each panel shows trends in sales volumes of trade by quarter over time for the spillover species and the relevant weighted average of control species. The arrows indicate the estimated spillover effects of the trade ban. The right column figure shows the estimated spillover effects with a 95% confidence interval (CI) in each taxon.

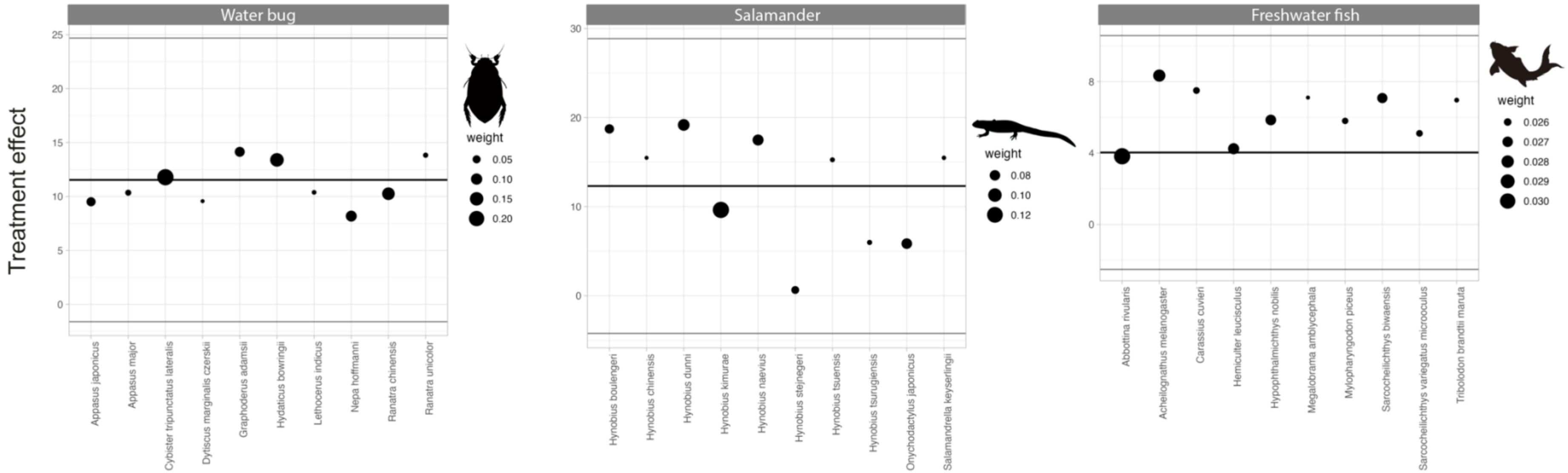

Fig. S4. Control unit contribution plot of the synthetic difference-in-differences associated with Fig. S3.

This figure shows the weight on each of the top 10 contributing control units with its size represented by circle size (see 4.2 section Identification strategy in the main and Arkhangelsky et al. 2021 for details). The names of control units are described in scientific names on the horizontal axis by following the estimation (see section 4.3 Data in the article and Other SI Materials for details). The treatment effect when the control unit is used as the sole control unit is represented on the vertical axis. The black line represents the synthetic difference-in-differences estimate, which is the weighted average of the treatment effects for the individual control units. The grey lines represent the upper and lower bound of the 95% confidence interval.

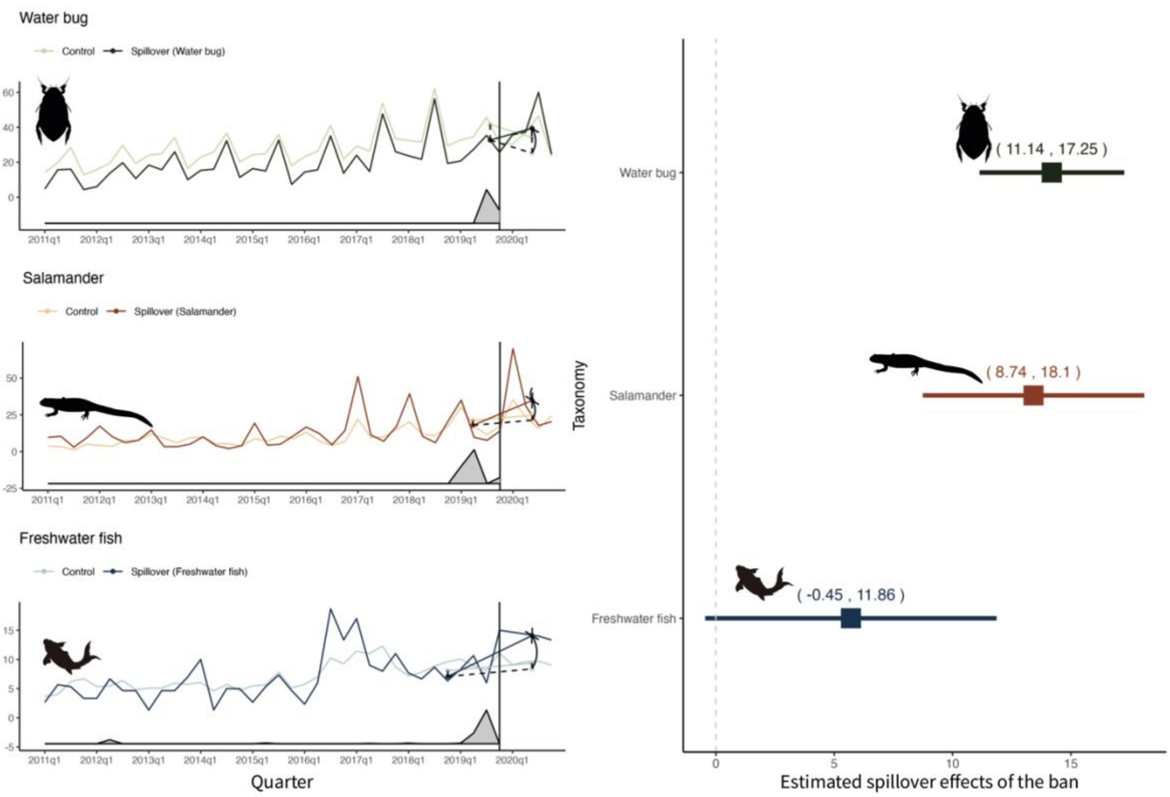

Fig. S5. Results of synthetic difference-in-differences on sales volumes of trade (including 2019's last quarter with the same dataset as Fig. 3 in the article).
This figure presents the results of synthetic difference-in-differences (SDID) on the sales volumes of trade. In the left column, each panel shows trends in sales volumes of trade by quarter over time for the spillover species and the relevant weighted average of control species. The arrows indicate the estimated spillover effects of the trade ban. The right column figure shows the estimated spillover effects with a 95% confidence interval (CI) in each taxon.

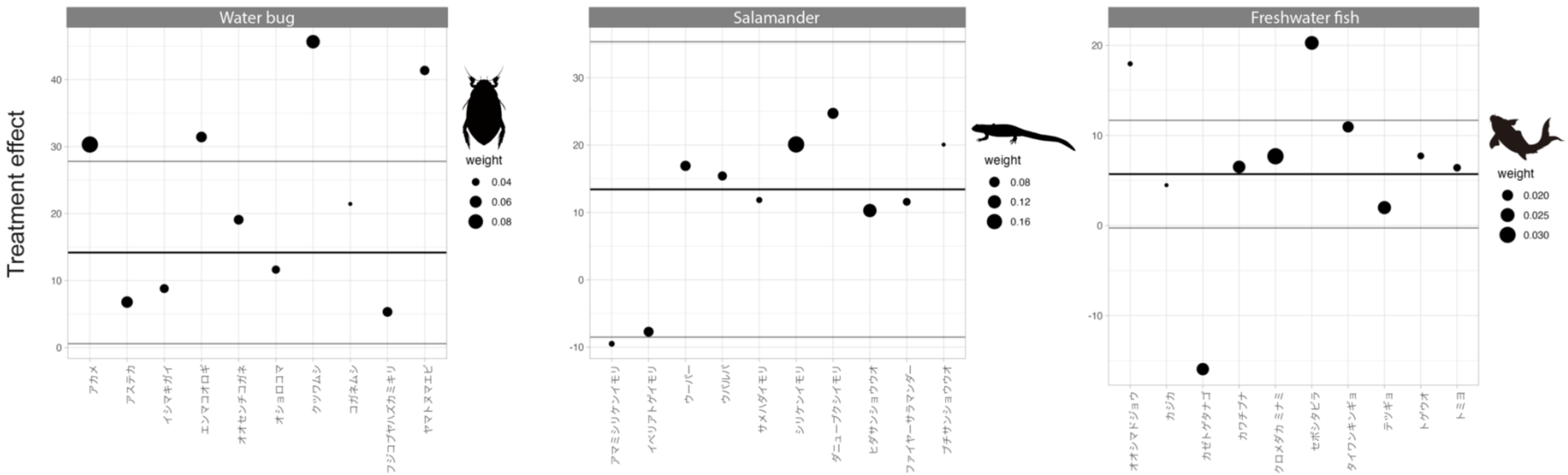

Fig. S6. Control unit contribution plot of the synthetic difference-in-differences associated with Fig. S5.

This figure shows the weight on each of the top 10 contributing control units with its size represented by circle size (see 4.2 section Identification strategy in the main and Arkhangelsky et al. 2021 for details). The names of control units are described in Japanese on the horizontal axis by following the estimation (see section 4.3 Data in the main and Other SI Materials for details). The treatment effect when the control unit is used as the sole control unit is represented on the vertical axis. The black line represents the synthetic difference-in-differences estimate, which is the weighted average of the treatment effects for the individual control units. The grey lines represent the upper and lower bound of the 95% confidence interval.

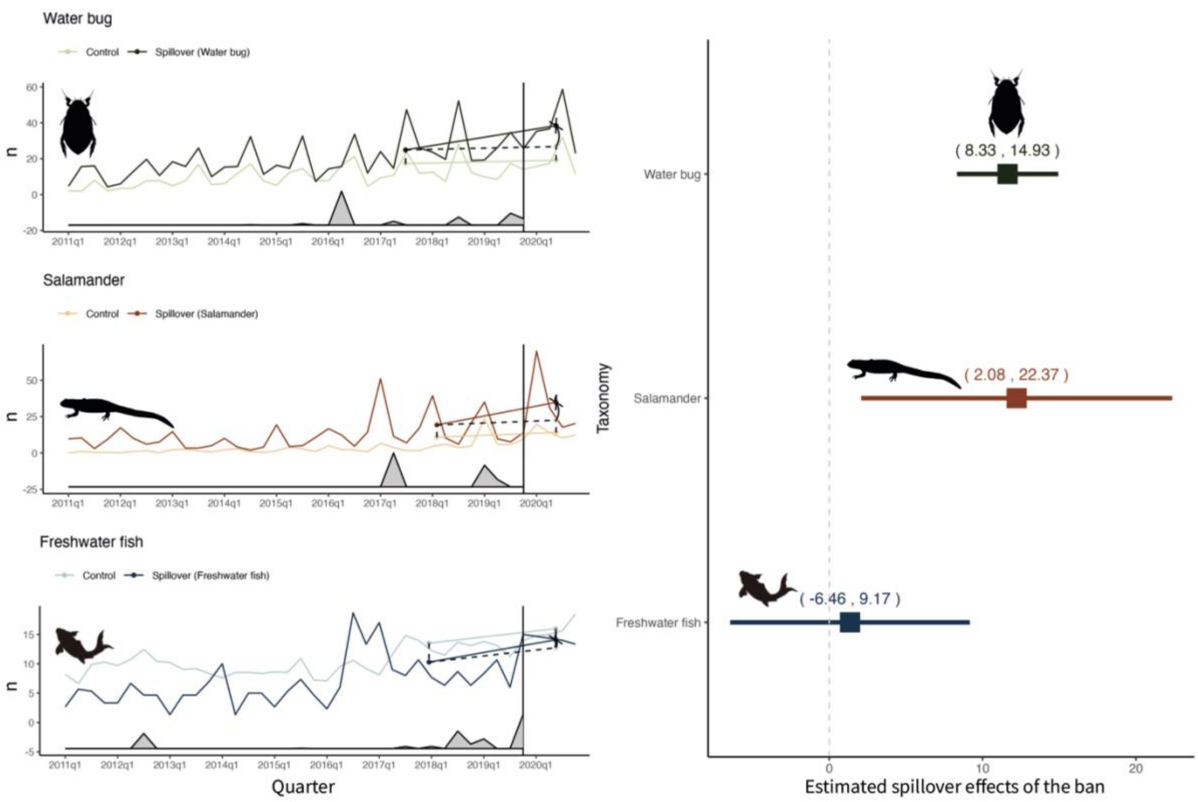

Fig. S7. Results of synthetic difference-in-differences on sales volumes of trade (using the datasets with only the control units identified by the scientific names and including 2019's last quarter).

The estimation was conducted using the datasets with only the control units manually identified by the scientific names. In the left column, each panel shows trends in sales volumes of trade by quarter over time for the spillover species and the relevant weighted average of control species. The arrows indicate the estimated spillover effects of the trade ban. The right column figure shows the estimated spillover effects with a 95% confidence interval (CI) in each taxon.

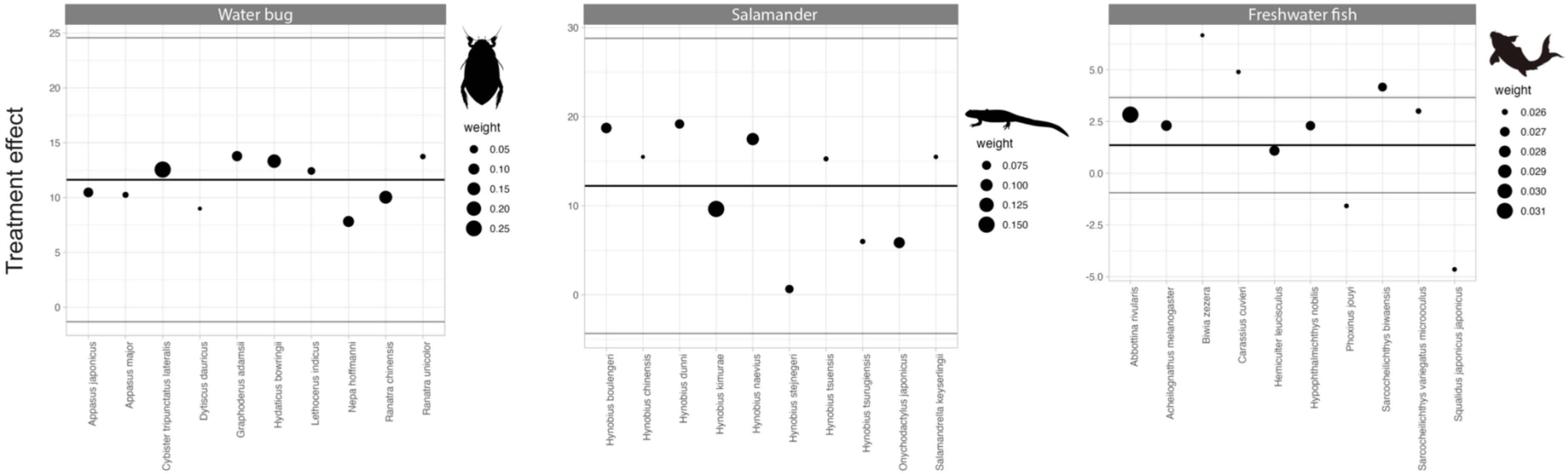

Fig. S8. Control unit contribution plot of the synthetic difference-in-differences associated with Fig. S7.

This figure shows the weight on each of the top 10 contributing control units with its size represented by circle size (see 4.2 section Identification strategy in the main and Arkhangelsky et al. 2021 for details). The names of control units are described in scientific names on the horizontal axis by following the estimation (see section 4.3 Data in the article and Other SI Materials for details). The treatment effect when the control unit is used as the sole control unit is represented on the vertical axis. The black line represents the synthetic difference-in-differences estimate, which is the weighted average of the treatment effects for the individual control units. The grey lines represent the upper and lower bound of the 95% confidence interval.

Note S2. The implications of treatment-control designations

The biggest challenge in identifying the impact of the regulation is to determine which control or treatment group non-banned species belong to. Here, we show that group mis-designation would result in the underestimation of treatment effect using an illustrative example. Below we assume that the spillover effect to other species should be positive since potential buyers can use the money they would have used for the banned species to other species when a species is banned.

Suppose you have 8 species: 4 treated and 4 untreated. Further suppose that the treatment effect is 50 trades for all the four treated species. When the treatment status is correctly assigned, the estimated treatment effect would be (4 * 50 – 4 * 0) / 4 = 50. However, suppose one of the treated species is assigned to the control group and one of the untreated species is assigned to the treated group. Then, the estimated impact would be [(3 * 50 + 0) – (3 * 0 + 50)] / 4 = 25. If two of the treated species are assigned to the control group and two of the untreated species are assigned to the treated group, then the estimated impact would be [(2 * 50 +2 * 0) – (2 * 0 + 2 * 50)] / 4 = 0. The impact of treatment can be estimated to be negative. If three of the treated species are assigned to the control group and three of the untreated species are assigned to the treated group, then the estimated impact would be [(1 * 50 + 3 * 0) – (1 * 0 + 3 * 50)] / 4 = -25. It is possible that some species are misassigned in this study. That is, we are likely to have a negative bias on our estimation of the impact of the regulation.

This implies that if we find a statistically significant positive treatment effect, then it is additional strong evidence that the impact of regulation is indeed positive. However, when we find a negative or statistically insignificant positive treatment, then that does not necessarily mean there was no positive spillover effect because of the inherent negative bias described above.

SI Tables

Table S1. Descriptions of the banned and potential spillover species.

Taxon	Banned / Spillover	Scientific names	Japanese name	Spillover criteria	Status in Red List (Japan[*1] / IUCN[*2])
Water bug	Banned	*Kirkaldyia deyrolli*	タガメ	–	VU / Not Evaluated
Water bug	Spillover	(Giant water bag (Exotic))	タガメ（海外）	1. Same name in the market	–
Water bug	Spillover	*Cybister chinensis*	ゲンゴロウ	2. Google Trends	VU / Not Evaluated
Water bug	Spillover	*Laccotrephes japonensis*	タイコウチ	2. Google Trends	Not Evaluated / Not Evaluated
Salamanders	Banned	*Hynobius tokyoensis*	トウキョウサンショウウオ	–	VU / VU
Salamanders	Spillover	*Hynobius nebulosus*	カスミサンショウウオ	3. Phylogenetically close	VU / LC
Salamanders	Spillover	*Hynobius nigrescens*	クロサンショウウオ	3. Phylogenetically close	NT / LC
Salamanders	Spillover	*Hynobius lichenatus*	トウホクサンショウウオ	3. Phylogenetically close	NT / LC
Freshwater fish	Banned	*Hemigrammocypris neglectus*	カワバタモロコ	–	EN / LC
Freshwater fish	Spillover	*Nipponocypris temminckii*	カワムツ	3. Phylogenetically close	Not Evaluated / Not Evaluated
Freshwater fish	Spillover	*Nipponocypris sieboldii*	ヌマムツ	3. Phylogenetically close	Not Evaluated / Not Evaluated
Freshwater fish	Spillover	*Aphyocypris chinensis*	ヒナモロコ	3. Phylogenetically close	CR / LC

[*1] Japanese National Red List 2020 (http://www.env.go.jp/press/files/jp/114457.pdf)
[*2] The IUCN Red List of Threatened Species (https://www.iucnredlist.org/)

Table S2. Descriptions and references of the new salamander species.

Scientific name (2020)	Japanese name 2020	Year of species description	Reference No.	Previous scientific name (2011)	Previous Japanese name (2011)
Hynobius tosashimizuensis	トサシミズサンショウウオ	2018	*(2)*	*Hynobius dunni*	オオイタサンショウウオ
Hynobius amakusaensis	アマクササンショウウオ	2014	*(3)*	*Hynobius boulengeri*	オオダイガハラサンショウウオ
Hynobius shinichisatoi	ソボサンショウウオ	2014	*(3)*	*Hynobius boulengeri*	オオダイガハラサンショウウオ
Hynobius akiensis	アキサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius abuensis	アブサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius iwami	イワミサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius setoi	サンインサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius setouchi	セトウチサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius utsunomiyaorum	ヒバサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius bakan	ヤマグチサンショウウオ	2019	*(4)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius vandenburghi	ヤマトサンショウウオ	2019	*(4, 5)*	*Hynobius nebulosus*	カスミサンショウウオ
Hynobius kuishiensis	イヨシマサンショウウオ	2019	*(6)*	*Hynobius yatsui*	コガタブチサンショウウオ
Hynobius tsurugiensis	ツルギサンショウウオ	2019	*(6)*	*Hynobius yatsui*	コガタブチサンショウウオ
Hynobius guttatus	マホロバサンショウウオ	2019	*(6)*	*Hynobius yatsui*	コガタブチサンショウウオ
Hynobius fossigenus	ヒガシヒダサンショウウオ	2018	*(7)*	*Hynobius kimurae*	ヒダサンショウウオ
Hynobius oyamai	チクシブチサンショウウオ	2019	*(8)*	*Hynobius naevius*	ブチサンショウウオ
Hynobius sematonotos	チュウゴクブチサンショウウオ	2019	*(8)*	*Hynobius naevius*	ブチサンショウウオ
Onychodactylus nipponoborealis	キタオウシュウサンショウウオ	2012	*(9)*	*Onychodactylus japonicus*	ハコネサンショウウオ
Onychodactylus kinneburi	シコクハコネサンショウウオ	2013	*(10)*	*Onychodactylus japonicus*	ハコネサンショウウオ
Onychodactylus fuscus	タダミハコネサンショウウオ	2013	*(11)*	*Onychodactylus japonicus*	ハコネサンショウウオ
Onychodactylus tsukubaensis	ツクバハコネサンショウウオ	2013	*(12)*	*Onychodactylus japonicus*	ハコネサンショウウオ
Onychodactylus Source *intermedius*	バンダイハコネサンショウウオ	2014	*(11)*	*Onychodactylus japonicus*	ハコネサンショウウオ

Table S3. Summary of the datasets concerning the synthetic difference-in-differences.

Dataset	Associated Figures	Unit of Treatments (n): Water bug / Salamander / Freshwater fish			Trade of Treatments (n): Water bug / Salamander / Freshwater fish (Quarter mean, med, and Sum)			Unit of Controls (n): Water bug / Salamander / Freshwater fish			Trade of Controls (n): Water bug / Salamander / Freshwater fish (Quarter mean, med, and Sum)		
NLP[*1, 2]	Fig 3, Fig S2	3	3	3	39.4 / 35.0 / 473	34.8 / 23.0 / 417	14.1 / 12.5 / 169	13649	440	766	0.596 / 0 / 317101	1.22 / 0 / 20936	2.97 / 0 / 88767
Manual[*2]	Fig S3-4	3	3	3	38.4 / 32.5 / 461	34.8 / 23.0 / 417	14.1 / 12.5 / 169	29	17	47	4.43 / 0 / 5642	4.68 / 0 / 3047	13.4 / 3.0 / 24437
NLP	Fig S5-6	3	3	3	39.4 / 35.0 / 473	34.8 / 23.0 / 417	14.1 / 12.5 / 169	13649	440	766	0.604 / 0 / 329838	1.25 / 0 / 22042	2.98 / 0 / 91204
Manual	Fig SI7-8	3	3	3	38.4 / 32.5 / 461	34.8 / 23.0 / 417	14.1 / 12.5 / 169	29	17	47	4.48 / 0 / 5855	4.78 / 0 / 3196	13.5 / 3.0 / 25173

[*1] NLP: Natural Language Processing

[*2] The announcement term (last quarter of 2019) has been excluded.

Table S4. Estimation of robustness checks with dataset by single species.
The single species model uses a species among the three potential spillover species in each taxon as treated units. The control units in the Japanese datasets were identified by the Natural Language Processing (NLP), whereas the units in the scientific names were identified manually and only composed of the species with the scientific names.

No.	Dataset	Taxon	Model Description[*1]	Coefficient	95% CI
1	Japanese (NLP)	Water bug	Single species (Giant water bug (Exotic）)	0.440	-11.5, 12.3
2	Japanese (NLP)	Water bug	Single species (*Cybister chinensis*)	26.7	14.3, 39.0
3	Japanese (NLP)	Water bug	Single species (*Laccotrephes japonensis*)	20.6	8.61, 32.5
4	Japanese (NLP)	Salamander	Single species (*Hynobius nebulosus*）	11.9	0.620, 23.1
5	Japanese (NLP)	Salamander	Single species (*Hynobius nigrescens*）	4.18	-7.11, 15.5
6	Japanese (NLP)	Salamander	Single species (*Hynobius lichenatus*）	1.82	-9.23, 12.9
7	Japanese (NLP)	Freshwater fish	Single species (*Nipponocypris temminckii*）	7.88	-2.90, 18.7
8	Japanese (NLP)	Freshwater fish	Single species (*Nipponocypris sieboldii*）	7.94	-3.30, 19.2
9	Japanese (NLP)	Freshwater fish	Single species (*Aphyocypris chinensis*）	1.39	-9.87, 12.7
22	Scientific name (Manual)	Water bug	Single species (Giant water bug (Exotic）)	2.14	-4.54, 8.81
23	Scientific name (Manual)	Water bug	Single species (*Cybister chinensis*)	8.33	1.87, 14.8
24	Scientific name (Manual)	Water bug	Single species (*Laccotrephes japonensis*)	5.07	-3.86, 14.0
25	Scientific name (Manual)	Salamander	Single species (*Hynobius nebulosus*）	17.2	-0.0661, 34.4
26	Scientific name (Manual)	Salamander	Single species (*Hynobius nigrescens*）	-28.8	-48.2, -9.40
27	Scientific name (Manual)	Salamander	Single species (*Hynobius lichenatus*）	-0.405	-25.6, 24.8
28	Scientific name (Manual)	Freshwater fish	Single species (*Nipponocypris temminckii*）	6.82	-10.2, 23.8
29	Scientific name (Manual)	Freshwater fish	Single species (*Nipponocypris sieboldii*）	6.65	-11.6, 24.9
30	Scientific name (Manual)	Freshwater fish	Single species (*Aphyocypris chinensis*）	-1.74	-19.5, 16.0

[*1] The announcement term(s) (i.e., from December 25 2019 to February 9 2020) has been removed in all models to mitigate the announcement bias.

Table S5. Estimation of robustness checks with datasets by month.

The monthly model compiles the data monthly rather than quarterly. The control units in the Japanese datasets were identified by the Natural Language Processing (NLP), whereas the units in the scientific names were identified manually and only composed of the species with the scientific names.

No.	Dataset	Taxon	Model Description[*1]	Coefficient	95% CI
10	Japanese (NLP)	Water bug	Monthly	2.98	2.00, 3.96
11	Japanese (NLP)	Salamander	Monthly	4.71	2.46, 6.97
12	Japanese (NLP)	Freshwater fish	Monthly	1.71	-0.551, 3.97
31	Scientific name (Manual)	Water bug	Monthly	2.29	0.765, 3.82
32	Scientific name (Manual)	Salamander	Monthly	4.29	0.0856, 8.49
33	Scientific name (Manual)	Freshwater fish	Monthly	1.29	-2.15, 4.74

[*1] The announcement term(s) (i.e., from December 25 2019 to February 9 2020) has been removed in all models to mitigate the announcement bias.

Table S6. Summary of placebo analyses.

We conducted 100 rounds of placebo analyses for each dataset type of taxonomy (six total combinations) to test if there any tendency to over-reject the null hypothesis of zero treatment effects. We first eliminate all the treated species from the sample. For each round, we then randomly selected three species as treated units, and then the rest of the species were designated as the control group (all the samples in the placebo analyses come from the control group of our main analyses). Finally, we applied SDID analyses to the data to estimate the impact of the fake treatment and test if the fake treatment has zero impacts at the 5% significant level. The table below shows the results of the 100 rounds of placebo analyses. As you can see in the table, for most of the combinations, the null hypothesis was rejected around five times (5% of 100 rounds). These results show that the SDID approach does not tend to excessively reject the null hypothesis of zero treatment effect of treatment that should indeed have zero impacts.

No.	Dataset[*1]	Taxon	Statistically significant cases per 100 estimations[*2]
1	Japanese (NLP)	Water bug	5
2	Japanese (NLP)	Salamander	10
3	Japanese (NLP)	Freshwater fish	5
4	Scientific name (Manual)	Water bug	2
5	Scientific name (Manual)	Salamander	4
6	Scientific name (Manual)	Freshwater fish	9

[*1]The control units in the Japanese datasets were identified by the Natural Language Processing (NLP), whereas the units in the scientific names were identified manually and only composed of the species with the scientific names.
[*2] The announcement term(s) (i.e., from December 25 2019 to February 9 2020) has been removed in all models to mitigate the announcement bias.

Other SI materials (Datasets / R codes)

All datasets and R codes used in this study will be publicly accessible when the manuscript is published (https://github.com/nies-consplan/wt_policy_spillover).

SI References

1. Massicotte, P., Eddelbuettel, D. & Massicotte, M. P. Package 'gtrendsR'. (2016).
2 Sugawara, H., Watabe, T., Yoshikawa, T. & Nagano, M. Morphological and Molecular Analyses of Hynobius dunni Reveal a New Species from Shikoku, Japan. Herpetologica 74, 159-168, doi:10.1655/Herpetologica-D-17-00002.1 (2018).
3 Nishikawa, K. & Matsui, M. Three new species of the salamander genus Hynobius (Amphibia, Urodela, Hynobiidae) from Kyushu, Japan. Zootaxa 3852, 203–226-203–226, doi:10.11646/zootaxa.3852.2.3 (2014).
4 Matsui, M. et al. Systematics of the Widely Distributed Japanese Clouded Salamander, Hynobius nebulosus (Amphibia: Caudata: Hynobiidae), and Its Closest Relatives. Current Herpetology 38, 32-90, doi:10.5358/hsj.38.32 (2019).
5 Dunn, E. R. The Salamanders of the Family Hynobiidae. Proceedings of the American Academy of Arts and Sciences 58, 445-523, doi:10.2307/20026019 (1923).
6 Tominaga, A., Matsui, M., Tanabe, S. & Nishikawa, K. A revision of Hynobius stejnegeri, a lotic breeding salamander from western Japan, with a description of three new species (Amphibia, Caudata, Hynobiidae). Zootaxa 4651, zootaxa. 4651.4653. 4651-zootaxa. 4651.4653. 4651, doi:10.11646/zootaxa.4651.3.1 (2019).
7 Okamiya, H., Sugawara, H., Nagano, M. & Poyarkov, N. A. An integrative taxonomic analysis reveals a new species of lotic Hynobius salamander from Japan. PeerJ 6, e5084, doi:10.7717/peerj.5084 (2018).
8 Tominaga, A., Matsui, M. & Nishikawa, K. Two new species of lotic breeding salamanders (Amphibia, Caudata, Hynobiidae) from western Japan. Zootaxa 4550, 525-544, doi:10.11646/zootaxa.4550.4.3 (2019).
9 Poyarkov Jr, N. A. et al. Review of the systematics, morphology and distribution of Asian Clawed Salamanders, genus Onychodactylus (Amphibia, Caudata: Hynobiidae), with the description of four new species. Zootaxa 3465, 1–106-101–106 (2012).

10 Yoshikawa, N., Matsui, M., Tanabe, S. & Okayama, T. Description of a new salamander of the genus Onychodactylus from Shikoku and western Honshu, Japan (Amphibia, Caudata, Hynobiidae). Zootaxa 3693, 441-464, doi:10.11646/zootaxa.3693.4.2 (2013).

11 Yoshikawa, N. & Matsui, M. Two new salamanders of the genus Onychodactylus from eastern Honshu, Japan (Amphibia, Caudata, Hynobiidae). Zootaxa 3866, 53-78, doi:10.11646/zootaxa.3866.1.3 (2014).

12 Yoshikawa, N. & Matsui, M. A New Salamander of the Genus Onychodactylus from Tsukuba Mountains, Eastern Honshu, Japan (Amphibia, Caudata, Hynobiidae). Current Herpetology 32, 9-25, doi:10.5358/hsj.32.9 (2013).