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Environmental regulation, taxes, and activism.

Abstract

Social activism is a burgeoning human response to pressing problems around the world, and nowhere is this response more apparent than in the ongoing global push back against environmental externalities. In this paper, we explore – for the first time – whether there are degrees of activism that relate to degrees of regulatory stringency. Using data on environmental conflicts resulting from fossil fuel production across 68 countries over the period 1995-2014, we find that, for a given tax rate, a move from a lax to more stringent regime lowers the rate of environmental conflicts. These findings underscore the contingent role of policy stringency as a trigger for intense social movements.

Keywords: Social activism, interest groups, fossil fuel, regulatory stringency, Poisson count model.

JEL Classification: D74, H23, L71, L78

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1. Introduction

In recent years, citizens and social interest groups have increasingly clashed with firms and governments in their quest for solutions to pressing problems. Such conflicts are particularly apparent in the ongoing social response[2] to the 'ultimate commons problem' (Stavins, 2011, p.82) associated with global climate change. Central to social activism around climate change is a deep concern that governments and firms are moving too slowly to address the 'climate emergency'[3]. This notion was espoused most forcefully by climate activist Greta Thunberg during her address to the US Congress in 2019: 'I know you are trying but just not hard enough.'[4]

Whilst climate change activism is a response to a perceived inadequacy in government actions, in this research we explore – for the first time – whether there are degrees of activism that relate to degrees of government action. Using the case of environmental conflicts resulting from fossil fuel production, we investigate the effect of environmental regulation on the intensity of social activism. Our study is therefore situated at the intersection of social activism, climate change, the natural resource curse, and regulation. Investigating the relationship between regulatory stringency and the intensity of social activism[5] in the context of fossil fuel production offers a

[2] For instance, the activities of 'Extinction Rebellion' – a socio-political environmental group that uses civil disobedience and non-violent resistance to draw attention to issues regarding climate change and environmental degradation.
[3] https://www.unep.org/explore-topics/climate-change/facts-about-climate-emergency
[4] https://www.theguardian.com/environment/2019/sep/17/greta-thunberg-to-congress-youre-not-trying-hard-enough-sorry
[5] The existing literature has widely studied the impact of regulatory stringency on firms' strategic behaviour in the context of negative externalities and allied matters (Ederington et al., 2005; Bazillier et al., 2017). However, evidence on the impacts of externality regulation on social movements is scarce.

relevant and timely analysis of an industry that is front and centre in climate change, the world's foremost challenge.

In addressing this issue, our contribution is three-fold. First, understanding the behaviour of social activist groups and their conflict strategies has become imperative in a world that is witnessing an upsurge in the use of social activism as a behavioural response to a wide range of social issues and concerns in general, but in the context of climate change in particular. One activity particularly that is prone to conflict is natural resource exploitation, as often highlighted by the natural resource curse hypothesis. These conflicts arise for a range of reasons, such as claims to resource windfall or rent (Angrist and Kugler, 2008; Cotet and Tsui, 2013), the impacts of commodity price shocks (Dube and Vargas, 2013; Berman et al., 2017), resource discovery/location (Maystadt et al., 2014; Morelli and Rohner, 2015). Such research as does exist is yet to explore the peculiarities of social movements in response to climate change, including the regulation of the environmental externalities arising from natural resource extraction.

Second, we present a conceptual framework to analyse the interaction between firms and activist groups when the firms' production activities generate negative externalities. This approach, which is based on a regulatory contest framework where the firm and the activist group treat regulation exogenously as part of the neutral context allows us to generate testable hypotheses on the relationship between environmental conflict and regulatory stringency. Thus, within this framework, we address a hitherto unexplored research gap on the role of policy stringency as a determinant of the intensity of social activism, in the presence of negative externalities. However, we acknowledge that by focusing on the effect of environmental regulations on social activism/environmental conflicts, our study says little about the circular mechanisms between the two variables. Although we address this potential reverse causality within our empirical analysis, the nature and extent of this circular relationship are outside the scope of this paper.

Our third contribution is methodological. We have employed an approach that captures the intensity, incidence, and persistence of environmental conflicts. We therefore extend a sparse but recently emerging conflict literature that models the above mechanisms (e.g., Bluhm et al., 2021). First, we explore the intensity of environmental conflict by computing an environmental conflict variable that is based on the number of conflict events in a country during each given year. Second, we capture the incidence of environmental conflicts using a binary coding for nonzero environmental clashes across sampled countries. Third, we model conflict persistence using a dynamic panel modelling approach.

Our paper is related to the social activism literature as developed by Baron (2001, 2003) who assumes that activists pursue social objectives. It is also close to Daubanes and Rochet (2019) who explain the rising influence of NGO activists, but without considering the effect of regulatory stringency - the central focus in our setting. Other close relatives to our study include the theoretical work by Baik and Shogren (1994) which explores conflicts between a firm and a citizens' group by investigating how symmetric and asymmetric reimbursement of legal expenditures in environmental court cases shape effort levels. Similarly, Heyes (1997) considers the case of environmental regulation being passed on to activists, exploring whether the state is willing to tax/subsidise the activists' activities, and characterising the optimal subsidy/tax. A more recent strand of the literature focuses on how the optimal tax affects the probability of conflict while also stimulating collaboration (Stathopoulou and Gautier, 2019). These are in addition to our contribution to the literature on the resource curse.

Our results indicate that, for a given tax rate, a move from a lax to more stringent regime lowers the rate of environmental conflicts. Specifically, in lax regimes, we estimate a tax elasticity of 0.241. Conversely, in stringent regimes, the tax elasticity is estimated at -0.244. Both findings indicate that, for a given tax rate, tax hikes are complemented by increased social agitation about environmental damage in lax regimes. By contrast, similar tax increases tend to reduce the intensity of environmental clashes between EGs and fossil-fuel firms when environmental stringency is strong. As far as we know, the contingent role of policy stringency as a factor determining the intensity of social activism has not been pinned down in the extant literature.

The remainder of the paper is structured as follows. Section 2 presents our conceptual framework. In section 3, we describe the testable hypotheses and our empirical framework. Section 4 describes the dataset we used for the analysis. Section 5 presents the empirical results. Section 6 concludes.

2. Conceptual framework

In this section, we analyse a pared-down model of the possible conflict between a fossil fuel firm and an interest group. The group and the firm choose how much effort to put into this conflict, and this can be modelled as a regulatory contest (game) in continuous strategies. There are two players, the firm undertaking activities that produce environmental damage D and an interest group (e.g., an NGO or an environmental group, hereafter EG), which can oppose the firm's operation and hence the damage[6]. There is a regulatory context in the form of a known tax rate on the damage produced[7], t. The form of opposition mounted by the EG is simply left open and may include a range of public domain activity and lobbying but not include the capacity to unilaterally alter the damage tax rate. The utility function of the firm has two arguments: first, the net of tax profit from production, and second, the effort

[6] The value of the damage is common knowledge. There is a large volume of national public domain literature and databases on many kinds of environmental damage together with work done by supranational bodies such as the Intergovernmental Panel on Climate Change (IPCC).

[7] Neither the regulator's behaviour nor the tax rate is endogenous to the game. Both players treat the regulation as part of the neutral context. We deliberately choose this simple game framework because the main focus of the paper is to derive a clear testable set of propositions and to avoid putting impracticable demands on the public domain data at our disposal. In a sense, by allowing the tax to condition the location of the firm's best response function so that two of the possible four Nash equilibria are eliminated, the tax will have set the regulatory context before the start of the game and hence the choice of the tax rate is unlikely to be correlated with the error terms in the determination of the best responses of the firm and EG within the game. Nevertheless, given the relatively long time-series of our empirical data, there is scope for EG behaviour to coalesce over time, in response to perceived regulatory stringency. Therefore, we treat this potential reverse causality in our regression analysis.

expended to play the game; utility is increasing in profit and decreasing in effort. The utility function of the interest group likewise contains two arguments: it is decreasing in both the common knowledge level of damage and the effort expended in playing the game.

The subjective probability that the firm wins the contest is shared by both the firm and the EG since each believes that their respective efforts are the only factors that can determine the outcome. The probability that the firm wins is:

$$p(e_F, e_G) = e_F/(e_F + e_G) \qquad [1]$$

where e_F, e_G are the respective efforts by the firm and the group which capture the monetary costs incurred to win the contest. The action strategies of the players are the efforts that they use.

The firm puts in effort e_F to maximise the expected profits net of the effort costs given the effort of the group, $\bar{e}_G$:

$$\max_{e_F} \Pi = p(e_F, \bar{e}_G)\pi - e_F \qquad [2]$$

where $\pi = v - tD$, i.e., variable profits minus the tax liability set by the government or regulator on the environmental damage caused, tD. The interest group wishes to minimise the expected externality or damage[8] plus the cost of its effort, given the effort of the firm to win the game, $\bar{e}_F$.

$$\min_{e_G} E = p(\bar{e}_F, e_G)\, D \; + \; e_G. \qquad [3]$$

To solve for the Nash-equilibria in [2] and [3], we look for the best response functions for each player, given the effort level of the other. The firm's optimisation problem requires the maximisation of [2] which implies

$$d\Pi/de_F = 0 \Rightarrow [e_G/(e_F + e_G)^2]\,(v - tD) - 1 = 0$$

$$\Rightarrow e_G(v - tD) = (e_F + e_G)^2. \qquad [4]$$

$$d^2\Pi/de_F^2 = (v - tD)[(e_F + e_G)^2(0) - e_G 2(e_F + e_G)/(e_F + e_G)^4] < 0 \; if (v - tD) > 0 \; and \; e_F > 0 \; and \; e_G > 0$$

Therefore, the second-order condition $d^2\Pi/de_F^2 < 0$ is satisfied if profit, and the respective effort strategies, are all positive.

For the group, minimisation of [3] gives

$$d\mathrm{E}/de_G = 0 \Rightarrow - \; [e_F/(e_F + e_G)^2]\, D + 1 = 0$$

$$\Rightarrow e_F D = (e_F + e_G)^2. \qquad [5]$$

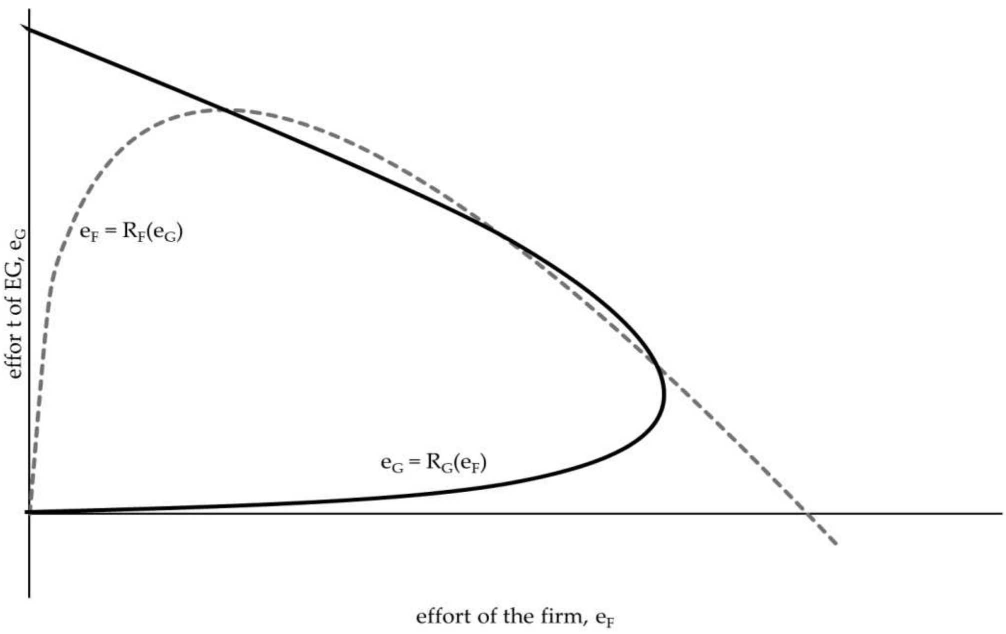
$$d^2E/de_G^2 = -D[(e_F + e_G)^2(0) - e_G 2(e_F + e_G)/(e_F + e_G)^4] > 0 \; if D > 0 \; and \; e_F > 0 \; and \; e_G > 0$$

[8] The level of environmental damage is perceived analogously by the group and the firm. This is standard in the literature (see Heijnen and Schoonbeek, 2008; van der Made, 2014, amongst others).

The second-order condition $d^2E/de_G^2 > 0$ is satisfied if damages are positive and effort strategies are positive.

Equations [4] and [5] are the best response functions of the players, and these are quadratic in form, suggesting multiple Nash equilibria. This is illustrated in Figure 1, where the solid curve represents the best response or reaction function of the environmental group, and the dashed line represents the best response or reaction function of the firm[9].

Fig.1. Reaction curves for the two-player firm-environmental group contest



The intuition behind the firm's best response function is that if the interest group expends zero effort, then the firm needs to expend zero effort; but then it must initially expend more effort itself if the interest group expends more effort. However,

[9] The sketch in figure 1 was created using the following values: $v = 1, D = 0.4, t = 0.1$

if the interest group can expend effort equal in value to $v - tD$, the firm will return to expending zero effort since all its gains from the game will have dissipated. Hence the firm's best response function has the parabolic shape shown in Figure 1. The best response function of the firm is dependent on the tax rate as well: the higher the tax rate, the less effort it will expend for any given effort level of the interest group. The intuition behind the interest group's best response function is somewhat similar - it expends zero effort if the firm expends zero effort but must then initially increase its effort as the firm expends more effort. However, if the firm is able or willing to expend effort equal to the value of the damage, D then the interest group will return to expending zero effort. Otherwise, it would be required to spend more than the value of the damage it opposes. Hence, the best response function of the interest group also has the parabolic shape shown in Figure 1.

With multiple intersections of the nonlinear reaction functions, not all the Nash equilibria are dynamically stable. These first-order conditions for a Nash equilibrium also mean that the ratio of the respective effort cost is equal to the ratio of each player's objective function payoff.

$$e_F/e_G = (v - tD)/D = r(t); r'(t) = -1 \quad [6]$$

We interpret $r(t)$ as the ratio of perceived profit to perceived damages. It equals the ratio of efforts. The perceptions are shared by the firm and the group. However, because they are perceptions, they are subject to errors due to behavioural agents as suggested by Farhi and Gabaix (2020). This could lead to an inefficient Nash equilibrium among the multiple equilibria. Besides, Farhi and Gabaix (2020) identify misperceptions in the form of agents paying limited attention to the tax or the value of the damages. In other words, myopia and hyperbolic discounting may also be characteristics of long-lived decisions about resource depletion, damage control, and environmental activism.

Using [6] in [4] and [5] respectively, we obtain:

$$e_F = D/\big(1 + (1/r)\big)^2 \tag{7}$$

together with:

$$e_G = (v - tD)/(1 + r)^2 \tag{8}$$

More explicitly, from [7] we obtain the best response function of the firm in the form of a reaction curve conditional on the effort of the group:

$$e_F = R_F(e_G) = -e_G + \sqrt{(v - tD)}\sqrt{e_G}$$

Hence the firm's effort is directly increasing in the profit net of the tax paid on the level of damages. From [8] we obtain the best response function of the environmental group as a reaction curve conditional on the effort of the firm:

$$e_G = R_G(e_F) = -e_F + \sqrt{D}\sqrt{e_F}$$

Therefore, the environmental group's effort is directly increasing in the level of environmental damages. It is these reaction curves that are illustrated in Figure 1.

Thus, we state the first part of our first proposition:

Proposition 1a: *The firm always responds to a higher tax rate with weaker effort and vice versa*.

Proof. Differentiate the Nash equilibrium solution for the firm's effort with respect to the rate of environmental tax:

$$de_F/dt = -\,2D(1/r^2)/\big(1 + (1/r)\big)^3 < 0$$

The assumptions required for the second-order conditions: $D > 0$, $r = e_F/e_G > 0$, $r'(t) = -1$, establish the proof. A rise in the tax rate penalises the firm and reduces the payoff from additional effort to win the regulatory game. This leads to the second part of proposition 1:

Proposition 1b: *The response of the EG to a rise in the tax is ambiguous in sign*.

Proof. Differentiate the Nash equilibrium solution for the EG's effort with respect to the tax rate:

$$de_G/dt = [-D(1 + r)^2 + 2(v - tD)(1 + r)]/(1 + r)^4$$

The assumptions required for the second-order conditions: $(v - tD) > 0$, $r = e_F/e_G > 0$, $r'(t) = -1$, establish the proof that the sign of de_G/dt depends on the level of the tax rate imposed, *t*, given the values of the residual profit, $(v - tD)$, and the damages, *D*. Therefore, there is a critical value of *t* which will define the response of the EG to a change in the stringency of the regulatory regime as embodied in changing the tax rate.

A lax regime is represented by a low environmental damage tax rate t, if

$$t < v/D - \left((1/2)(1+r)\right)$$

then $de_G/dt > 0$ – the EG strategy is complementary to regulation. An increase in a low rate of environmental tax leads the EG to increase its effort, thereby complementing the regulatory decision when the tax change is in an upward direction. However, in the same setting, a decrease in the tax would result in much larger environmental damage in the already lax regime such that the group's effort would not compensate for such an increase in damage. This implies lower efforts by the group (and thus complementarity between the group and the regulator's efforts), leading to lower efforts by the firm as it finds winning the contest to be easier. In the limit, this leads the outcome to the Nash equilibrium at the origin of the effort space, with zero effort by both the firm and environmental group. In such a situation, the EG may abandon its legitimate and costly effort that we have modelled here and be tempted to turn to extra-legal activity.

Consequently, in the case of a lower than the threshold tax rate, i.e., in a lax regime, the relationship between the tax and the group's effort is positive. The mechanism behind this result lies in the minimisation of the objective function of the group[10] as presented in eq. [3]. A higher tax will reduce the firm's damage while the group will reduce the probability that the firm wins the contest by exerting more effort

[10] This is of the standard form used in the literature (Heijnen and Schoonbeek, 2008).

(eq. [1]). By implication, fossil fuel production will likely cease, resulting in a further reduction in environmental damage. These two effects will suppress the first term in the group's objective function (Eq. [3]). Hence, in a lax regime, the efforts by the group and regulator can be considered complements[11].

In contrast, a stringent regulatory regime is represented by a high environmental damage tax rate, t; if

$$t > v/D - \left((1/2)(1+r)\right)$$

then $de_G/dt < 0$. Now, the EG strategy is a substitute for regulation. Recall, proposition 1b) which sheds light on the interplay between the tax and the group's effort. In a stringent regime, a higher tax rate would decrease the optimal effort required by the group, implying that the roles of the government and the group are substitutes. On the other hand, in a lax regime, a higher tax rate would make the group exert stronger efforts implying that the EG adopts an approach that complements and reinforces the government's position[12]. This is evident from the proof of proposition 1b) where we have shown that if $t < (>)\, v/D - \left((1/2)(1+r)\right)$ then $de_G/dt > 0 (< 0)$.

Subsequently, in the case of a higher than the threshold tax rate, the relationship between the tax and the group's effort is negative i.e., an increase in the

[11] In the same setting, a decrease in the tax would result in an even larger environmental damage in the already lax regime and hence the group's effort would not compensate such an increase implying lower efforts by the group (and thus complementarity between the group's and the regulator's efforts).

[12] Here, we examine the non-cooperative game. Another possibility is that the regulator and environmental groups participate in a coalitional game or lobbying. The literature is substantial on such games; see Damania (2001) and Fredriksson et al. (2007). However, we believe that this would not be an appropriate setting to explore this topic as empirical evidence suggests that the group and the regulator act independently.

tax rate would lower the efforts by the EG and vice versa. In other words, in a more stringent regulatory setting, the environmental damage would be lower and hence for a higher tax, the group's optimisation problem would not require higher levels of effort. Intuitively, this result suggests that the group can 'free-ride' to some extent on the stringency of the regulation[13] thereby economising on effort levels.

It is also interesting that the tax rate t does not affect the position of the EG's best response function, but it does determine the position of the firm's best response function. In this sense, the regulator or government body setting the tax rate does have a role to play since the choice of the tax rate can determine the number of potential Nash equilibria outcomes. A rise in the tax rate shifts the firm's best response function downwards in terms of Figure 1. This has the effect of eliminating two of the four equilibria illustrated, leaving only the equilibrium with zero efforts at the origin, and equilibrium at the intersection on the negative slope of the firm's response function and the positive slope of the EG's response function. It is the second of these two equilibria which are encapsulated in our testable propositions.

Finally, looking at Proposition 1b, we can also observe that an increase in the environmental damage D implies that the R.H.S. of the inequality, i.e., $v/D - \left((1/2)(1+r)\right)$ would decrease. This implies that the threshold t will be lower and now more likely to be in the interval above the threshold, such that the roles of the EG and the regulator are likely to be substitutes. In this case, an increase (decrease) in

[13] The idea of free riding in environmental regulation is well-established in the literature (Heyes, 1997).

policy stringency would lower (raise) the optimal activism effort by the group. For an increase in the variable profits, *ceteris paribus*, we can see that the R.H.S. of the inequality would increase, making it more likely that the group's and the regulator's efforts are complementary.

The efforts levels of the firm and environmental group map directly onto the intensity and incidence of environmental conflicts. Measuring the intensity of conflict by the number of environmental conflicts, designated y, our propostion 1b becomes:

$\partial y/\partial t < 0$ in *stringent* regimes, and $\partial y/\partial t > 0$ in *lax* regimes. In summary, we argue that, for a given tax rate, a move from a lax to more stringent regime would lower the rate of environmental conflict. It is this step change which captures the non-monotonicity aspect of our theoretical argument.

3. Data

We construct an unbalanced panel dataset spanning 68 countries for the period 1995-2014. Thus, our unit of analysis is at the country × year level. The sample is the result of data availability, following our data matching exercise across different sources namely the Environmental Justice Atlas (EJAtlas) (Temper, et al., 2015), OECD environmental tax database, World Input-Output (WIOD), and the 10-Sector database.

3.1. *Constructing an environmental conflict variable*

In the empirical conflict literature, studies often explore common datasets such as the Armed Conflict Location & Event Data (ACLED) and the UCDP Georeferenced Event Dataset (GED) (Maystadt et al., 2014; Hodler and Raschky, 2014; Berman et al., 2017). Other prior studies have focused on social conflicts using the Social Conflict Analysis Database (SCAD) (e.g., Henderson et al., 2017). However, these datasets are unsuitable for the analysis of environmental conflicts for two main reasons. First, the ACLED and UCDP datasets are focused on political and organised violence, respectively. Hence, both datasets largely exclude environmental conflicts, which often take milder forms of intensity such as media campaigns, demonstrations, civil disobedience, boycotts, etc. Second, SCAD covers social conflicts across Africa and Latin America only. Given that a significant proportion of global fossil production is concentrated in the Middle East, North America, and the Commonwealth of Independent States (CIS), SCAD certainly underreports environmental conflicts.

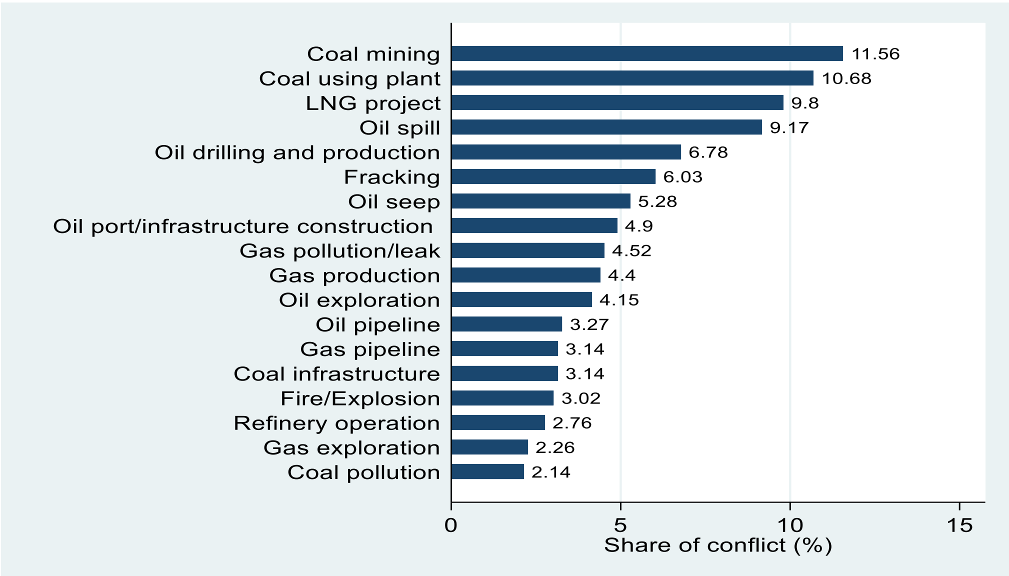
Thus, we follow the recently emerging literature on ecological conflicts (e.g., Aydin et al., 2017. Pérez-Rincón et al., 2019) by using georeferenced event-based information on over 3000 environmental clashes between firms and EGs (e.g., local communities, NGOs), available from the Environmental Justice Atlas (EJAtlas).[14] As a specialized database, the EJAtlas overcomes the coverage limitations of the above three data sources. Nevertheless, a major limitation of the EJAtlas is that information on each conflict is only available in text and image formats. As such, the compilation

[14] https://ejatlas.org/

of a usable dataset required enormous efforts to hand collect information from maps and the associated written reports one by one, for each conflict. Consequently, creating our dataset constitutes an additional layer of contribution in this study.

Our dependent variable is the intensity or incidence of environmental conflicts in country i in year t. Conflict intensity is the annual number of conflicts by country, while the incidence measure is a dummy variable coded as 1 for conflict events and zero otherwise[15]. Figure 2 shows that the most common causes of environmental conflict are coal mining, LNG projects, and oil spills. In Figure 3, we present a world map of environmental conflicts, depicting that these conflicts have become a global phenomenon, as evidenced by their spatial distribution across the different continents.

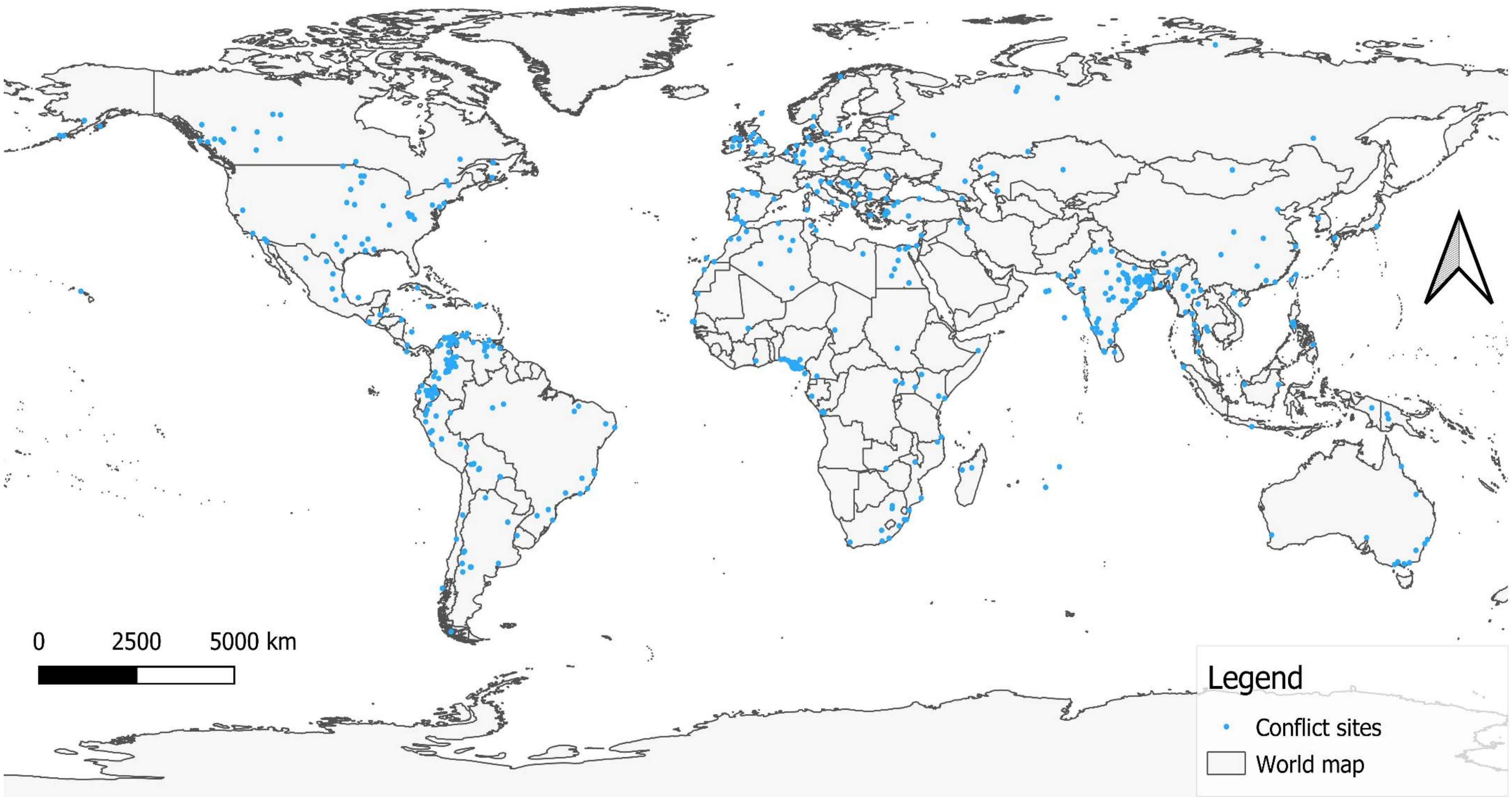
Fig 2: Sources of environmental conflict



Source: Authors' calculation based on EJAtlas

[15] This coding approach is suitable for our available data. Unlike the violent conflict literature that often derives the conflict dummy using thresholds on the number of deaths, the conflicts captured in the EJAtlas are mainly qualitative, lacking outcomes like the number of deaths associated with a conflict. Additionally, due to the lack of consistent data on conflict episodes, our coding is based on conflict onset. This simplification is appropriate since we do not observe cases of multiple conflicts regarding the same environmental issue. We thank an anonymous referee for useful guidance regarding our coding exercise.

Table 1 provides a more focused x-ray of the distribution of conflicts by geographic region and level of development. Panels A and B show that conflict events are more concentrated in developing countries that are mostly found in Latin America, Sub-Saharan Africa, and the Asian regions. Notable hotspots include India, Nigeria, and Colombia. While the Indian conflicts are mainly driven by grievances about coal production, the Nigerian and Colombian conflicts mainly relate to oil and gas production. In terms of the developed countries, the US and Canada are shown to have a relatively high number of conflicts, reflecting their large oil and gas sectors.



Note: Points represent the location of environmental conflicts. In some cases, multiple instances of conflict were observed for certain locations.

Fig 3: Spatial distribution of environmental conflict

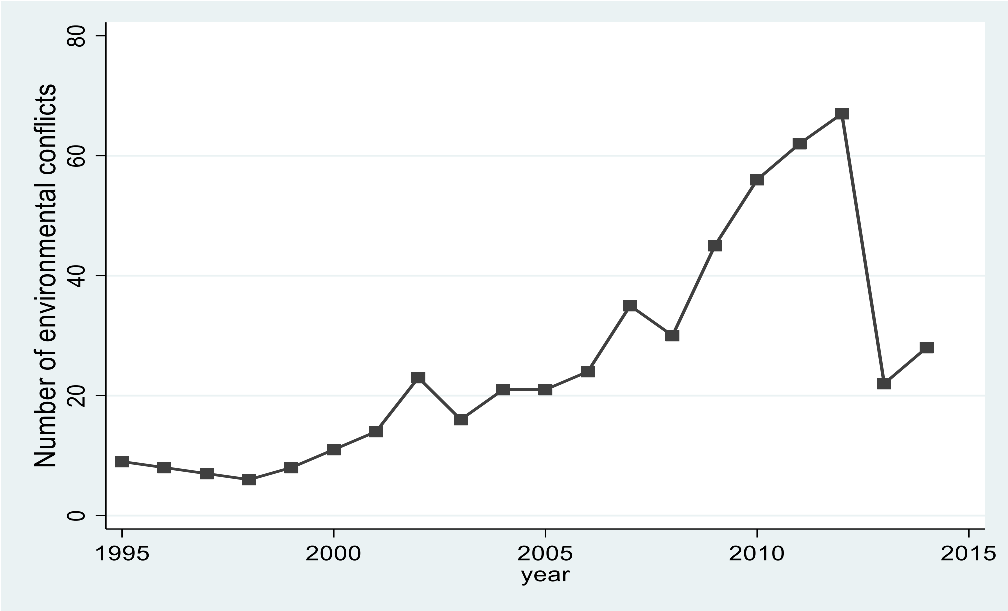
Table 1: Environmental conflicts by region and income

PANEL A: Environmental conflict by regions	**Number**	**Share of total (%)**
East Asia & Pacific	51	10%
Europe & Central Asia	88	17%
Latin America & Caribbean	134	26%
Middle East & North Africa	11	2%
North America	41	8%
South Asia	83	16%
Sub-Saharan Africa	105	20%
PANEL B: Environmental conflict by income level		
OECD	160	31%
Non-OECD	353	69%

Source: Authors' calculation based on EJAtlas

Figure 4 plots the trend in the sum of environmental conflicts for our data sample. As illustrated, there is a clear upward trend in environmental conflicts. Around 130 conflicts were recorded between 2011 and 2012 across sampled countries, compared to only 9 in 1995. This trend seems consistent with the notion of the rising number of environmental campaigns. Although we observe a spike in the number of conflicts in 2012, the upward trend in conflicts continued between 2014 and 2015.

Fig. 4: Trends in environmental conflicts



3.2. *Main independent variable*

Our key independent variable is environmental taxes, which we compute as the ratio of sectoral environmental taxes to pollution. To achieve this, we obtain data on the total environmental tax levied on the petroleum and mineral mining sector (in million USD) from the OECD environmental policy database.[16] The sector-level pollution (kilotonne CO2-equivalent) information is collected from the IEA database.

3.3. *Production Function Data*

To compute the shadow price of fossil sector pollution, we estimate a distance function (see online appendix), using production data for the mining sector[17] available from the World Input-Output Database (WIOD) and the 10-Sector Database. We collect raw

[16] The OECD tax data covers all OECD member countries and 67 non-OECD countries.
[17] The industrial classification in both datasets is based on the NACE rev 1 (ISIC rev 2) where the sectoral composition includes three activities namely (i) oil and gas extraction (ii) mineral and coal mining and (iii) ancillary support services for the above two activities.

data on value-added (Y), capital stock (K)[18], and Number of employees (L). The monetary values in local currency at current prices are normalised in two steps. First, we deflate the nominal values using GDP deflators from the WDI database, using 2011 as the base year. Second, we converted the local currency values into internationally comparable values using the purchasing power parity (PPP) exchange rates from the Penn World Table (PWT10.0). Finally, pollution[19] from the petroleum sector is collected from the IEA database.

3.4. Control variables

We control for economic, social, climatic factors in our econometric estimations. For instance, we follow prior studies (e.g., Hodler and Raschky, 2014) by controlling for the impact of income (GDP per capita in constant 2011 PPP $) and population on conflict. The data are obtained from the Penn World Table version 10.0. Further, we include annual average temperature in our estimations considering that climatic shocks elevate the risk of conflicts. (Miguel et al, 2004). This is downloaded from World Bank Climate Change Knowledge Portal.

Because weak institutions are generally known to increase the likelihood of conflict, we employ the rule of law index from the World Governance Indicators (WGIs) as a control variable. Additionally, because the resource conflict literature

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[18] In a few countries where we encountered missing data for the capital stock variable, we use sectoral gross fixed capital formation data from UNdata. Alternatively, we apply the proportional Denton process to data on sectoral contribution to GDP, to interpolate the available aggregate capital stock data in the Penn World Tables.

[19] The activities generating these pollutants include production/exploitation activities, flaring, venting, accidental discharge, and deliberate distribution losses.

suggests that the civil conflicts are often shaped by resource endowment (Maystadt et al., 2014; Berman et al., 2017) our model also includes a fossil fuel reserve variable, which is the sum of crude oil, natural gas, and coal reserves, collected from the BP Annual Statistical Bulletin. Similarly, we control for commodity price effects using the composite energy price index from the IMF commodity price database.

We expect the response of environmental conflict to vary depending on the magnitude of environmental damage(s). While the EJAtlas does not report measures of pollution damage, it reports the size (in hectares) of the affected area for each clash. Thus, we use the total affected land area as a proxy for environmental damage. Finally, we include information on the instrumental variables covering colonial history, neighbouring country regulations, and trade partner characteristics. Table 2 provides descriptive statistics for our panel dataset which contains 1,310 country-year observations.

Table 2. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Environmental conflict (count)	0.392	1.412	0	32
Environmental conflict (dummy)	0.202	0.401	0	1
Environmental tax (real USD per ktoe emission)	6.098	11.039	0	106.14
Per capita income (2011 PPP $)	23230.34	17255.46	577.477	97864.18
Population (in millions)	76.185	212.321	0.376	1390.113
Temperature (degrees Celsius)	15.106	8.479	-7.077	29.201
Rule of law (index)	0.601	0.929	-1.69	2.1
Fossil reserves (barrel of oil equivalent, bbl)	6.465	22.121	0.2	211.87
Energy price (index)	123.4	70.642	37.344	234.787
World Economic Forum (WEF) stringency index (ranges from 1-7)	4.286	1.068	2.305	6.292
Value-added (real million USD)	21918.39	54511.36	9.348	581902.1
Pollution (ktoe)	3572.83	12801.80	0.2	126159.2
Capital stock (real million USD)	89836.68	250885.1	2.08	3326053
Employment (thousand employees)	344523.8	1690235	3	1.94e+07
Total area size of damage (hectares)	2805477	1.99e+07	0	3.42e+08
Colonial tax (real USD per ktoe emission)	5.011	5.825	0	48.71
Neighbour's environmental legislative proposals	0.177	0.487	0	4
Trade partner's weighted population (million persons)	72.59	261.02	0	1364.27
Trade partner's weighted industrial share (%)	3.659	1.368	1.077	8.519
Trade partner's weighted tariffs (%)	3.061	4.350	0	40.58

4. Empirics

4.1. *Hypotheses*

Our theoretical propositions yield two testable hypotheses:

> *Testable hypothesis 1*: The intensity of environmental conflict is decreasing in environmental tax *t*, for stringent regulatory regimes.

To verify this relationship, we expect a negative coefficient in a regression of the number of environmental conflicts on environmental taxes at higher levels of regulatory stringency.

> *Testable hypothesis 2*: The intensity of environmental conflict is increasing in environmental tax *t*, for regimes with weaker environmental stringency.

We expect a positive coefficient in a regression of the number of environmental conflicts on environmental taxes at lower levels of environmental standards.

4.2. *Measuring regulatory stringency*

Our theoretical predictions (and hypothesis) embody different stringency thresholds, but stringency is not observable. To overcome this challenge, we use a production approach that is well-grounded in theory to identify the shadow price of the petroleum sector's pollution. Stringency is then estimated as the wedge between environmental taxes and the shadow price of pollution. Van Soest et al (2006) proposed such a stringency approach and Färe and Grosskopf (1990) and Färe et al.

(1993) demonstrate the production function estimation of shadow costs in the input and output dimensions, respectively. Following the above studies, we estimate the shadow price of the pollution arising from the fossil fuel sector. See the online appendix for a detailed econometric methodology of our shadow cost analysis.

4.3. *Modelling conflicts*

Our dependent variable is the number of times EGs clashed with fossil fuel producers in country i in year t. The discrete non-negative feature of this data means that it is best described as a count variable exhibiting a skewed distribution with a significant number of zeros (79% of our observations), as shown in Figure 5. Consequently, the natural candidate for our analysis is the Poisson regression:

$$\Pr(y_i = j|x_i) = \exp(-\lambda)\lambda^j/j!\,,\ j = 0, 1, 2, \ldots \qquad [9]$$

where λ is specified as

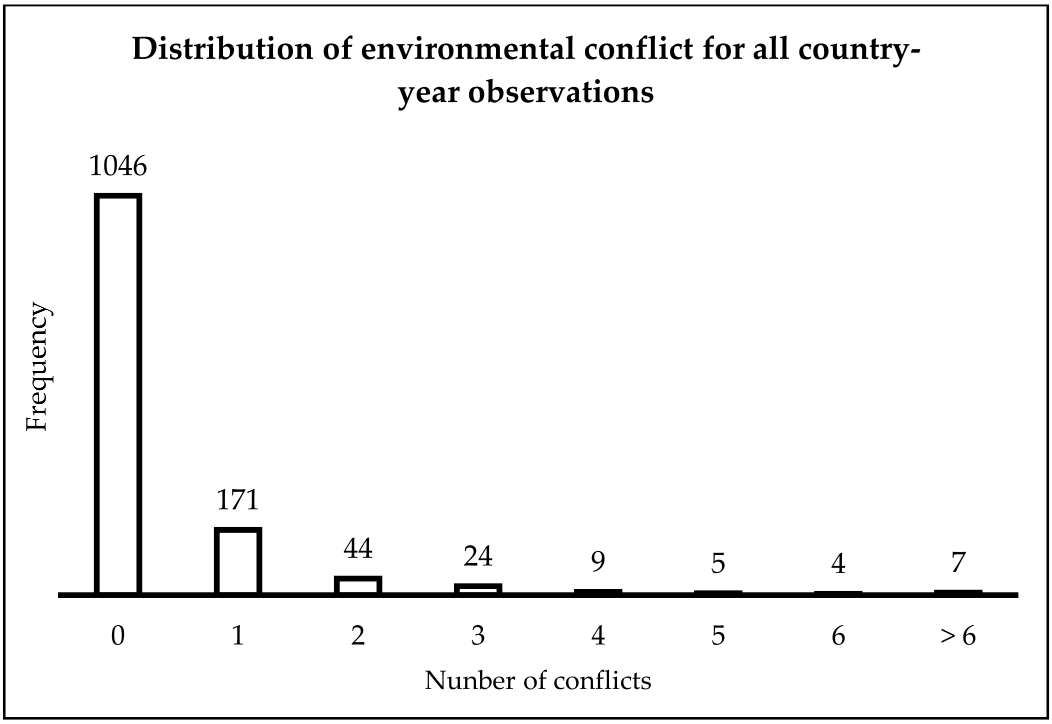
$$\lambda = \exp(x_i'\beta) = \exp(\beta_0 + \beta_1 x_{1i} + \ldots) \qquad [10]$$

where β is the vector of parameters. However, given its underlying assumption of the equality between data mean and variance, the Poisson model may be susceptible to the problem of overdispersion in the face of excessive zeros in the data (Deb and Trivedi, 1997)[20]. This results in the conditional variance being larger than the

[20] A common alternative approach to address overdispersion is the negative binomial model. However, the efficiency gains from employing the negative binomial instead of the Poisson model are limited in practice, even when the observed overdispersion follows a negative-binomial distribution (Cameron and Trivedi, 2014). Furthermore, the negative binomial model is not adept at handling fixed effects and potential endogeneity issues (Gillingham and Tsvetanov, 2019).

conditional mean, leading to consistent but inefficient estimates, often evidenced by downward biased standard errors and spuriously low p-values (Wooldridge 2002). We address this problem by using robust standard errors rather than the classical standard errors from the Poisson model (*Ibid*).

Fig 5: Distribution of environmental conflicts



Finally, to test our study hypotheses, we need to isolate the impact of environmental taxes on conflicts across weak and strong stringency thresholds. We achieve this in three steps. First, we compute a time-varying measure of environmental stringency as the difference between environmental taxes and the estimated shadow prices across countries. This stringency measure allows us to capture the reality that environmental taxes and shadow costs vary across countries and time[21]. Second, we capture 'LAX' and 'STRINGENT' thresholds by isolating observations at both tails of the stringency distribution using two dummies STR_{q25} and STR_{q75}, respectively[22]. The dummy variables take the values of 1 when a data observation falls in the bottom (or top) quantile of the stringency distribution, and zero otherwise.

Identifying the stringency of environmental taxes as the difference between taxes and shadow cost of pollution is more appropriate than using the initial level of taxes to approximate environmental stringency (i.e., to assume that countries with higher (lower) environmental taxes are more stringent (lax)). The reason is threefold. First, the level of a tax (on its own) tells us little about its stringency since a tax rate may rise but still not be stringent and vice versa. Second, the level of taxes only is insufficient because social damage or the shadow cost of pollution varies across countries and over time. Ignoring environmental tax adjustments in the context of time-varying social pollution damage will likely distort our stringency estimates. Third, the tax-shadow cost difference approach is consistent with the textbook treatment of environmental stringency which suggests an efficiency criterion where regulators set and adjust taxes to match the marginal social cost of pollution (e.g., see Perman et al., 2003, pp 547; Tietenberg and Lewis, 2018, pp 376-377).

[21] While this approach allows the time-varying changes in environmental taxes and shadow costs to affect stringency, using a constant stringency threshold (i.e., the first sample year's stringency) does not qualitatively affect our model results. Moreover, employing an alternative (constant) survey-based measure of environmental stringency yields similar results to our baseline. Hence, our underlying findings are not affected by the variations in taxes and shadow costs.

[22] We test the sensitivity of our results to the choice of stringency distribution. See robustness tests.

Finally, we augment our model with interaction terms between Tax_{it} and stringency dummy variables:

$$Tax_{it} \times STR_q \qquad [11]$$

where the dummy variables STR_q depict the quantiles above.

4.4. *Econometric specification and estimation issues*

The theoretical literature emphasizes the potential for a protracted conflict, as often exemplified in cycles of continuing conflicts (Acemoglu and Wolitzky, 2014; Bluhm et al., 2021). Thus, capturing the persistence of conflicts is appropriate for our empirical analysis. Consequently, we employ a dynamic modelling framework[23]. However, there are three major challenges to estimating a dynamic relationship within a count dataset. First, the nonlinearity of our discrete and non-negative count data confines us to a Poisson distribution, making a linear regression model unsuitable. Second, there is potential for reverse causality running from conflict to environmental regulation since regulators may also respond to the EG campaigns. Third, fixed unobservable country characteristics may shape the probability of experiencing environmental conflicts, and these may also be correlated with other explanatory variables. Fourth,

[23] The closest relative to our study in terms of modelling the dynamics of social conflicts is Bluhm et al. (2021). However, while they model conflict dynamics using an ordered probit approach, we employ a dynamic count data approach. The difference in empirics is due to the nature of Bluhm et al's multiple data sources that embody a broad set of thresholds for civil conflicts, permitting the coding of conflict dummy variables spanning 25 battle-related deaths (BDs) to 1000 BDs. Unlike their information on BDs, our dataset pertains to the number of environmental clashes, ranging from 0 to 32 across sampled countries. This narrower data span, along with our count data setting, make an ordered probit approach unsuitable for our analysis.

the lagged dependent variable is a source of bias since it is correlated with the country-specific effects.

To deal with the above issues, we control for unobserved country heterogeneity and endogeneity by using the Pre-sample Mean (PSM) GMM Poisson estimator proposed by Blundell et al. (2002). Under this approach, we account for unobserved heterogeneity by using the pre-sample history of conflicts to control for the fixed country effects. Moreover, the PSM[24] model is known to exhibit better finite sample properties and greater consistency than the standard FE-Poisson estimator (Hausman et al., 1984) and the quasi-differenced estimator (Chamberlain, 1992; Wooldridge, 1997). The PSM values of conflict are derived as:

$$\bar{y}_{ic} = (1/TP) \sum_{r=0}^{TP-1} y_{i,0-r} \tag{12}$$

where TP denotes the pre-sample periods. We can then jointly capture unobservable heterogeneity and panel dynamics by introducing the PSM and lagged dependent variable, respectively into the Poisson model:

$$y_{it} = \rho y_{it-1} + \exp(x_{it}\beta + \gamma \bar{y}_{ic}) + \varepsilon_{it} \tag{13}$$

The above PSM model includes a linear feedback which enables us to separate the short- and long-run effects of environmental regulation on conflict (see Blundell et al.,

[24] See Nesta et al. (2014) and Lazkano et al. (2017) for some empirical application in the context of energy and environmental regulation.

2002). The linear feedback imposes a lower bound on the expected conflict variable at ρy_{it-1} since $\exp(x_{it}\beta + \gamma \bar{y}_{ic})$ is always positive. Therefore, this approach overcomes the limitations of the exponential feedback specification which can yield explosive series. Moreover, unlike the quasi-differenced models, the PSM estimator does not assume strict exogeneity of the right-hand side variables. Thus, due to the endogeneity concerns about environmental taxes, we note that a GMM estimator allows us to use within-sample instruments, which can be derived as:

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} \boldsymbol{Z}_{it}\left(y_{it} - \rho y_{it-1} - \exp(x_{it}\beta + \gamma \bar{y}_{ic})\right) = 0 \tag{14}$$

In this case, we can define exclusion restrictions using $\boldsymbol{Z}_{it} = (1, \tilde{x}_{it}, y_{ic}, Tax_{it-\tau}, IV_{it-\tau})$, where $\tilde{x}_{it}$ contains exogenous variables, $Tax_{it-\tau}$ denotes the lagged environmental tax variable while IV contains instrumental variables which act as additional moment restrictions to address the endogeneity of environmental taxes. Besides taxes, we note additional sources of endogeneity arising from other RHS variables in our model. For example, per capita income can be endogenous to conflicts, especially in resource-rich economies. Similar arguments apply to institutional quality, which may be susceptible to the resource curse (Aghion et al., 2004). Resource endowment is also plausibly endogenous since reserves are endogenously depleted by fossil production, which in turn depends on the tranquility afforded by the lack of conflict (Arezki et al., 2017). In addition to the above endogenous regressors, the interaction terms between taxes and the stringency thresholds are also contaminated by the endogenous tax variable.

Given the foregoing, we exploit the relatively long time-series dimension of our data sample by using lags of environmental taxes and other endogenous variables as instruments. Further, we call on exogenous instruments which we discuss as follows.

4.4.1. *Instrumental variables*

Before proceeding to the issue of conflict persistence, we wish to shed light on our identification strategy for pinning down the causal effect of regulation on conflict. To achieve this, we first explore the 2SLS estimator by instrumenting for the endogenous tax variable and the stringency thresholds.[25] We set out the instrumental variables and identifying assumptions as follows.

Colonizer's environmental regulation

A large body of empirical research documents that a country's regulations can be strongly influenced by its colonial origins (Glaeser and Shleifer, 2002; La Porta et al., 2008; Anderson, 2018). Even after attaining independence, the colonial influence on regulation persists across many former colonies (Anderson, 2018). Recent literature

[25] Before estimating our GMM model, initially stripping down our identification strategy to the endogeneity of environmental taxes and the stringency thresholds allows us to offer insight on the source of identification of a causal effect between environmental regulation and conflict.

confirms this colonial path dependence in environmental policies (see Fredriksson and Wollscheid, 2015; Ang and Fredriksson, 2017).

Thus, we consider the environmental taxes of colonizers[26] to be suitable instruments for the taxes of their former colonies. In addition to the correlation documented in the above literature, our identifying assumption is that the colonizer's environmental regulation is orthogonal to the error term in a second-stage regression. The reason is twofold. First, colonization is usually imposed involuntarily through military conquests (McNeill and McNeill, 2003). Thus, the absence of colonists' choice or self-selection into colonization makes a strong case for the exogeneity of this instrument. Second, the period of colonization and subsequent political independence of all countries in our data sample pre-date our study period. Hence, the colonial origin is predetermined and should not directly affect conflict, except through its historical impact on domestic environmental regulation.

Neighbour's environmental reforms

Studies on regulation (Persson and Tabellini, 2009; Giuliano et al., 2013) argue that policy reforms in neighbouring countries tend to shape domestic policies. The idea underlying this approach is that peer pressure effects cause domestic environmental policies to respond to reforms in neighboring countries (Kellenberg, 2009). Building on this idea, we employ environmental policy reform in a neighbouring country that

[26] We identify each country's colonizer using information from Mayer and Zignago (2011). Where a country was never colonised, we use the information on its periodic invasion or conquest from foreign adversaries. For instance, we use the information on the Norman invasion of Britain to identify a pseudo colonist for the UK.

is excluded from our data sample as an instrument. First, we identify all neighbours for each country in our sample using the distance data from Head et al. (2010). We then collect information on the total number of legislative environmental proposals across all countries from the Climate Change Laws of the World database.[27]

Our identifying assumption is that changes to environmental regulations are by-products of the legislative process (Hazilla and Kopp, 1990). This process is long-winded and complex, and its outcomes are strongly influenced by pre-determined and exogenous social and political factors (e.g., electoral margins/swings, party ideology, gender composition of the legislature, etc.) (Ashworth et al., 2006; Gouglas et al., 2018). Thus, this instrument should provide information on the peer effect of environmental reforms in excluded neighbouring countries, which will affect domestic taxes but should not be correlated with the error term.

Bilateral trade instruments

While the stringency dummy measures are time-invariant, they are also endogenous[28]. A major source of this endogeneity is that the dummies emanate from the social (shadow) cost of pollution, and pollution level is endogenously determined by technology, innovation, etc. (Stern and Stiglitz, 2021). Moreover, the regulators' perception of pollution costs can be distorted by endogenous discounting (Weitzman,

[27] https://climate-laws.org/

[28] We econometrically test the time-invariant stringency variables using the Hausman endogeneity test, under the null hypothesis that they are exogenous. The value of the test statistic is 15.91 with 2 degrees of freedom (p-value 0.0005), strongly indicating that environmental stringency is endogenous.

2013; Lemoine, 2021). Therefore, we also instrument for the stringency interactions using the well-established textbook assumption that trade is a channel for external pressure on domestic pollution and stringency (Perman et al., 2003, p. 340-342; Tietenberg and Lewis, 2018, p. 585-586). Following several empirical applications (e.g., Frankel and Rose, 2005; Kellenberg, 2009; Roy, 2017), we use relevant exogenous/predetermined characteristics of trade partners as instruments.

First, we identify each country's major trade partners using the 'Bilateral Trade Historical Series'[29]. Second, we use three of their exogenous factors as instruments: size (population), structure (manufacturing share of value added), and barriers (average primary product tariffs to other countries). The identifying assumption is that the above variables exogenously originate from external jurisdictions that do not directly impact conflict but are good candidates that affect domestic pollution. For instance, trade partners with large populations or high manufacturing emissions may discount pollution more aggressively, plausibly signalling a lax view about pollution externalities to firms. This is because regulators often worry about broader social objectives such as avoiding job losses and upholding the international competitiveness of emission-intensive sectors (Martin et al., 2014; Cui et al., 2021). These considerations usually shape the cross-border convergence of pollution via stringent trade standards/requirements or lack of it (Kellenberg, 2009). To mitigate concerns that trade connections may be driven by strategic choices, we use pre-

[29] http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=32

determined geographic and historic ties of country-pairs as weights for identifying trade partners: (i) distance between country pairs, (ii) pre-historic language ties, and (iii) area size. These factors are outside the control of all countries, ensuring that our instruments embody ties that predate any potential strategic interactions.

5. Results

5.1. Test of exogenous instruments

We initially follow the suggestion of Miguel et al (2004) who analysed armed civil conflict using a linear IV-2SLS approach with a dichotomous dependent variable (coded one for incidence of battle deaths)[30]. We do this to check for the importance of the IV approach, but we recognise that our count data will necessitate a subsequent Poisson estimation model. The estimates from the linear model will not of course be comparable in magnitude to those from the exponentiated Poisson approach but may be indicative of sign properties. To conserve space, we present only the second stage and first stage (tax) estimates in Table 3, providing the full results containing the reduced form and first stage interaction estimates in the online appendix. In column 1, we fit the pared-down model where we include the tax variable only using the Neighbour's and colonial master instruments. The result suggests that higher taxes reduce the intensity of environmental conflict. The first stage estimates have the right signs, and they are statistically significant.

[30] We are grateful to an anonymous reviewer for suggesting the relevance of Miguel et al (2004).

Table 3. 2SLS test of exogenous instruments

Dep var: Environmental conflict	(1)	(2)	(3)
PANEL A: 2nd Stage regression	2SLS	2SLS	2SLS
Log (Tax per emission)	-0.163***	-0.087	0.115
	(0.055)	(0.321)	(0.357)
Log (Per capita income)		0.575	
		(0.525)	
Log (Energy price)		-0.376*	-0.344
		(0.211)	(0.212)
Rule of law (Index)		-0.600	
		(0.393)	
Log (Population)		3.263***	3.957***
		(1.267)	(1.353)
Temperature		-0.035	-0.076
		(0.069)	(0.079)
Log (Fossil reserves)		0.238*	
		(0.133)	
Log (Area size)		0.050***	
		(0.013)	
Tax x LAX		1.253**	1.342**
		(0.578)	(0.599)
Tax x STRINGENT		-0.750**	-1.046**
		(0.343)	(0.421)
PANEL B: 1st Stage Tax regression			
Neighbor's legislative proposals	1.182***	1.158***	1.182***
	(0.180)	(0.182)	(0.183)
Colonial master's tax per emission	0.448***	0.428***	0.402***
	(0.081)	(0.095)	(0.094)
Partner's population		-1.771**	-1.435**
		(0.730)	(0.724)
Partner's industrial share		0.024	0.048
		(0.089)	(0.087)
Partner's tariffs		0.039***	0.029***
		(0.011)	(0.010)
Elasticities			
Tax x LAX elasticity	**-**	**2.978**	**3.721**
Tax x STRINGENT elasticity	**-**	**-2.137**	**-2.377**
Time effect	Y	Y	Y
Country effect	Y	Y	Y
F-test of tax instruments	44.53	15.63	15.09
Under-id test (*p*-value)	0.000	0.001	0.003
Over id Hansen *J* test (*p*-value)	0.297	0.126	0.243
Observations	1310	1310	1310

Notes: The dependent variable in the second stage (Panel A) is environmental conflicts. Panel B contains the first stage OLS regressions in which the dependent variable is environmental tax. Heteroskedasticity-robust standard errors are presented in parentheses. ***, **, and * indicate significance at 1, 5 and 10%-level, respectively. See online appendix F for elasticity calculations.

In column 2, we add the stringency interactions and all control variables. We instrument for the interaction terms using the trade partner instruments. The tax coefficient remains negative but loses statistical significance while the LAX and STRINGENT interactions are positive and negative, respectively[31]. They are also significant at the 5% level. Given the loss of statistical significance in the tax variable, the regulatory regimes captured by the threshold interactions seem important in explaining conflict. Additionally, the under-identification and Hansen *J* tests suggest that the instruments are relevant, and the over-identifying restrictions are valid.

In column 3, we drop the other potentially endogenous controls.[32] The tax variable turns positive but fails to attain statistical significance. The interaction terms remain qualitatively and quantitatively stable in terms of their signs and statistical significance, supporting our theoretical prediction of the non-monotonic effect of regulation on environmental activism. It seems that two effects are at play in these estimates. On the one hand, ignoring the simultaneity bias arising from the dropped controls in column 2 means that we are not able to mitigate their endogeneity. On the other hand, dropping them in column 3 results in omitted variable bias, leading us to attribute their effects to the remaining variables in the model, as shown by the larger

[31] Instead of interpreting the estimated coefficient directly, we derive the elasticities implied by the coefficient at the bottom of the table.
[32] As shown in section 4.4, income, institutional quality, resource reserves, and damages are endogenous to conflicts, especially in resource rich countries.

coefficient magnitudes in column 3 relative to column 2. We attempt to mitigate these issues within the GMM-Poisson framework.

5.2. *Main results*

Having explored an IV strategy that enables us to identify the causal effect of environmental regulation on environmental conflict, we now turn to our baseline analysis where we jointly address the endogeneity of regulation and the persistence of environmental conflicts using a Poisson GMM estimator. Table 4 reports the baseline regression results. Where possible, we take the natural logarithm of the regressors, as shown in Table 4.[33]

Column (1) contains coefficient estimates of a standard Poisson model, but without any unobservable country effects. Our coefficients of interest, the interaction terms between environmental taxes and stringency indicate a positive (negative) coefficient on Tax x LAX (Tax x STRINGENT). Both coefficients are statistically significant at the 1% and 5%-level, respectively. We add country effects in column (2) using the exponential feedback model (EFM). In this specification, both coefficients retain their signs and statistical significance. In column (3), we present our preferred model where we capture the unobservable country effects using the PSM. The coefficients on both interaction terms retain their qualitative implications and they attain statistical significance at the 1%-level. We now focus on the PSM model.

[33] To avoid dropping data observations, we follow previous studies by adding a small constant of 0.01 to the average of variables with zero values before taking the natural logarithm (Michalopoulos and Papaioannou 2013, 2014; Hodler and Raschky, 2014).

Table 4. Baseline results

	Poisson (1)	Poisson GMM-EFM (2)	Poisson GMM-PSM (3)
Lagged conflict/Linear ρ	0.078**	0.089***	0.425***
	(0.036)	(0.015)	(0.019)
Log (PSM)	-	-	0.097***
			(0.027)
Log (Tax per emission)	0.031	0.050	0.078***
	(0.042)	(0.031)	(0.024)
Log (Per capita income)	-0.494***	-0.668***	-1.001***
	(0.151)	(0.137)	(0.143)
Log (Energy price)	-0.118	-0.044	-0.291***
	(0.194)	(0.084)	(0.098)
Rule of law (Index)	0.306**	0.316***	0.446***
	(0.143)	(0.118)	(0.153)
Log (Population)	0.116	0.114**	0.136***
	(0.072)	(0.047)	(0.032)
Temperature	0.047***	0.043***	0.052***
	(0.013)	(0.009)	(0.009)
Log (Fossil reserves)	0.307***	0.333***	0.495***
	(0.063)	(0.053)	(0.071)
Log (Area size)	0.076***	0.089***	0.051***
	(0.018)	(0.015)	(0.014)
Tax x LAX	0.157***	0.171***	0.163***
	(0.057)	(0.051)	(0.046)
Tax x STRINGENT	-0.193**	-0.339***	-0.322***
	(0.097)	(0.093)	(0.065)
Elasticities			
Tax x LAX	**0.188**	**0.221**	**0.241**
Tax x STRINGENT	**-0.162**	**-0.289**	**-0.244**
Time effect	Y	Y	Y
Country effect	N	Y	Y
Moments	-	34	47
Hansen *J* statistic		19.63	32.97
Hansen *p*-val		(0.545)	(0.468)
F-test of slopes (T_LAX = T_STRINGENT)	12.80***	27.30***	27.06***
p-val	(0.000)	(0.000)	(0.000)
Observations	1242	1242	1106

Notes: The dependent variable is the number of environmental conflicts between EGs and firms. '*LAX*' is a dummy variable that takes the value of 1 if the gap between a country's environmental tax to pollution shadow price falls in the bottom quantile, zero otherwise. '*STRINGENT*' is a dummy variable that takes the value of 1 when the difference falls in the top quantile but zero otherwise. GMM estimates in columns 2 and 3 use as instruments, three lags of endogenous variables, along with the five exogenous instruments. Standard errors in parentheses are clustered at the county level. ***, **, and * indicate significance at 1, 5 and 10%-level, respectively. See online appendix F for elasticity calculations.

Our dependent variable is a count of environmental conflicts while our key independent variable is the environmental tax and its interaction with the stringency dummies. However, for ease of interpretation, and to aid comparison with the 2SLS results, we compute the tax elasticties indicated by the estimated coefficients at the bottom of Table 4. In lax regimes, we obtain an elasticity of 0.241. However, in a stringent regime, the tax elasticity is -0.244. These estimated effects suggest that, for a given tax rate, tax hikes are complemented by increased social agitation about environmental damage when environmental regulation is lax. However, moving from such lax regimes to strigent regimes, similar tax increases tend to reduce the intensity of environmental clashes between EGs and fossil-fuel firms. Encouragingly, the sign patterns across both the 2SLS and GMM-Poisson models are the same, confirming the non-monotonic effect of environmental taxes across both regimes. However, the 2SLS yields larger absolute tax elasticities (2.978 and -2.137) relative to the Poisson specification (0.241 and -0.244). This magnitude difference is unsurprising for the following reasons.

In count data environment, the substantial specification bias in the linear estimators relative to IV-Poisson estimators is well-recognised in the literature (Silva and Tenreyro, 2006; 2011; Gillingham and Tsvetanov, 2019). This problem commonly results in considerable magnitude difference in the empirical comparison of linear and Poisson estimators (e.g., Chappell et al., 1990; Brülhart et al., 2012; Bernstein, 2015; Gillingham and Tsvetanov, 2019). Moreover, while the 2SLS more easily accommodates fixed effects and allows for the straightforward treatment of endogeneity, it generally mis-specifies the underlying count data process, often predicting negative and noninteger outcome values (King, 1988; Wooldridge, 2002; Gillingham and Tsvetanov, 2019). Considering that the values taken by our conflict variable are clustered around zero, the 2SLS result does not account for the censoring and the integer nature of conflicts. Theoretically, the excess zeros in our data depict two natural processes or observation types (positive and zero conflicts) and the 2SLS estimator is unsuited for analyzing this. Expectedly, this data truncation yields biased and inefficient 2SLS estimates.

On the one hand, the nonnegative nature of conflicts implies that, as $E[Conflict_i|x]$ approaches zero, the probability of conflict being positive also approaches zero. Hence, the conditional variance of environmental conflicts vanishes as $E[Conflict_i|x]$ tends to zero. On the other hand, when $E[Conflict_i|x]$ is far from the lower bound, significant deviations (in both directions) from the conditional mean causes greater dispersion such that the error terms are heteroskedastic (see Silva and Tenreyro, 2006). Thus, given the specification bias of the 2SLS and the qualitative similarities across both the 2SLS and GMM Poisson estimators, we treat our 2SLS results as indicative of our IV strategy at best. We now rely on the GMM-Poisson estimator for the remainder of our analysis.

Turning to the findings from our preferred model, we note that the F-tests of the equality of parameters on both interaction terms strongly reject the null that the coefficient estimates are statistically analogous across the estimated models. Taken together, both coefficients support our hypotheses that environmental activism and environment taxes are strategic substitutes (complements) in strong (weak) regulatory settings.

The pre-sample mean (PSM) of conflict has a positive sign and is statistically significant at the 1%-level. This result suggests that unobserved individual differences across sampled countries (e.g., culture or behavioural propensity for confrontation) have stimulated environmental clashes. The finding underscores how country-specific initial conditions can trigger conflicts. Additionally, we estimate the coefficient on the lagged dependent variable at 0.43, suggesting that environmental conflicts exhibit significant persistence in time: when a location experiences conflicts, it has a 43% higher likelihood of experiencing the same in the following year. Finally, we note that they mostly have the right signs and they are statistically significant.

5.3. Robustness

We conduct a range of sensitivity tests[34] in Table 5. First, the regulation-activism relationship may vary across fuel types since their extraction and processing differ in significant ways that lead to variations in their environmental impacts. Thus, we re-estimate our baseline model separately for the three different fossil fuels: oil, gas, and coal. In columns 1-3, the results across the fuels are consistent with our baseline finding, albeit the coefficient on the LAX interaction loses statistical significance in the coal regression.

[34] See online appendix for a few more additional robustness tests.

In column 4, we employ an alternative stringency measure that is based on the World Economic Forum (WEF) stringency index. An alternative stringency measure is necessary since environmental taxes are less common in less developed regions of the world where traditional command-and-control policy instruments are more prevalent (see Xie, et al., 2017). Therefore, the WEF index allows us to capture other non-tax regulations. The index is based on an opinion survey across 150 countries, which asks respondents to rate the environmental stringency on a scale of 1 (very lax) to 7 (most stringent). Due to missing values for some countries during some years in the sample period, we use the constant average of the available data. The alternative stringency dummy variables is then derived by identifying the quantile where these average values fall. The re-estimation in column 4 suggests that our results are robust to the use of an alternative stringency measure.

In column (5), we check the sensitivity of our findings to the stringency thresholds by squeezing the tails on our dummy variables to the bottom decile (for LAX) vs the top decile (for STRINGENT). The results from the squeezed thresholds remain economically and statistically consistent with our baseline findings. Finally, we use conflict per capita as a dependent variable in column 6. The results remain qualitatively unchanged.

Table 5. Sensitivity tests

	Commodity			WEF	Squeezed	Conflict
	Oil	Gas	Coal	Threshold	Threshold	Per Head
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged conflict/Linear ρ	0.429***	0.214***	0.457***	0.408***	0.387***	0.157***
	(0.029)	(0.013)	(0.040)	(0.019)	(0.036)	(0.025)
Log (PSM)	0.074***	0.205***	-0.114	0.152***	0.043	-0.172***
	(0.026)	(0.045)	(0.135)	(0.044)	(0.064)	(0.057)
Log (Tax per emission)	0.021	-0.055*	0.277***	0.005	0.082**	0.099**
	(0.024)	(0.030)	(0.065)	(0.033)	(0.037)	(0.040)
Tax x LAX	0.285***	0.135**	0.806	0.073**	0.229**	0.068
	(0.053)	(0.052)	(1.076)	(0.034)	(0.112)	(0.049)
Tax x STRINGENT	-0.321***	-0.134	-0.623***	-0.253***	-0.369***	-0.689***
	(0.062)	(0.103)	(0.198)	(0.050)	(0.131)	(0.214)
Time effect	Y	Y	Y	Y	Y	Y
Country effect	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Moments	47	47	47	47	33	47
Hansen *J* statistic	35.55	32.04	26.60	32.11	26.08	37.50
p-val	(0. 493)	(0.514)	(0.114)	(0.511)	(0.128)	(0.270)
T_LAX = T_STRINGENT	69.62***	6.01**	1.73	48.31***	12.08***	14.47***
p-val	(0.000)	(0.014)	(0.189)	(0.000)	(0.001)	(0.000)
Observations	1106	1106	1106	1106	1106	1106

Notes: In columns 1-3, the conflict count differs by commodity type. The dependent variable in columns 4-5 is the number of environmental conflicts between EGs and firms. The dependent variable in column 6 is total conflict divided by total population in each country-year. '*LAX*' is a dummy variable that takes the value of 1 if the gap between a country's environmental tax to pollution shadow price falls in the bottom quantile, zero otherwise. '*STRINGENT*' is a dummy variable that takes the value of 1 when the difference falls in the top quantile but zero otherwise. For the WEF stringency, we use the quantile distribution of the WEF index to create the dummy variables. Controls are the same as those in Table 4. GMM estimates use as instruments, three lags of endogenous variables, along with the two exogenous instruments. Standard errors in parentheses are clustered at the county level. ***, **, and * indicate significance at 1, 5 and 10%-level, respectively.

5.4. *Conflict incidence and alternative estimators*

In columns 1-5 of Table 6, we explore conflict incidence using a binary coding for nonzero environmental conflicts across our data sample. In columns 6-9, we employ alternative model estimators (i.e., Logit, LPM, and FE Poisson) to further aid our result comparison. In the incidence regressions, we estimate linear and logit models, using both static and dynamic specifications. In general, we note that the coefficients on the interaction terms (especially the stringent interaction) lose statistical significance, although their signs confirm the pattern observed in our baseline results: for any given tax rate, rising environmental taxes are associated with lower (higher) conflict intensity when environmental stringency is strong (weak).

Focusing on the linear IV model where we account for tax endogeneity, the tax coefficient is positive albeit it fails to attain statistical significance at conventional levels. Additionally, considering the lack of statistical significance of the stringent interaction in the IV incidence model, we tentatively conclude that the non-monotonic relationship between regulation and environmental activism is stronger for conflict intensity than conflict incidence[35]. We think the main reason is that the impact of regulation on conflict is plausibly easier to detect in larger samples than ours. This is especially the case when using macro-level data in which civil environmental conflicts are relatively rare events such that the low number of switches in the dependent indicator variable leads to a significant loss of efficiency (Bazzi and Blattman, 2014; Berman and Couttenier, 2015).

[35] Berman and Couttenier (2015) find similarly stronger results for the effects of external income shocks on conflict intensity compared to conflict incidence.

Table 6. Alternative model estimators

	Incidence (Dummy dep variable)					Intensity (Count dep variable)			
	Static Models			Dynamic Models		Static Models		Dynamic Models	
	LPM	2SLS	Logit	LPM	Logit	Poisson	OLS	Poisson	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Conflict				0.130**	0.319			0.044**	0.126**
				(0.061)	(0.220)			(0.018)	(0.059)
Log Tax	-0.046***	0.040	-0.182	-0.038***	-0.128	-0.049	-0.350***	-0.010	-0.295***
	(0.015)	(0.089)	(0.160)	(0.013)	(0.175)	(0.074)	(0.107)	(0.080)	(0.096)
T x LAX	0.068***	0.179***	0.479***	0.057***	0.425***	0.125	0.490***	0.103	0.412***
	(0.014)	(0.087)	(0.150)	(0.013)	(0.154)	(0.083)	(0.102)	(0.083)	(0.089)
T x STRINGENT	-0.007	-0.189	-0.226	-0.003	-0.187	-0.278*	-0.037	-0.234	-0.013
	(0.021)	(0.123)	(0.240)	(0.019)	(0.257)	(0.155)	(0.147)	(0.159)	(0.134)
Time effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1310	1310	884	1242	819	902	1310	836	1242

Notes: The dependent variable in the incidence regressions is a dummy variable taking the value 1 if at least conflict occurs in the country in year *t*; for the intensity regressions, the dependent variable in the Poisson models is the number of environmental conflicts between EGs and firms. In the linear/OLS models, the dependent variable is the log of conflict, derived by adding a small constant of 0.01. In columns 1, 2, 5, 6, we estimate static models while columns 3, 4, 7, 8 introduce conflict dynamics using a lagged dependent variable. '*LAX*' is a dummy variable that takes the value of 1 if the gap between a country's environmental tax to pollution shadow price falls in the bottom quantile, zero otherwise. '*STRINGENT*' is a dummy variable that takes the value of 1 when the difference falls in the top quantile but zero otherwise. Controls are the same as those in Table 4. Standard errors in parentheses are clustered at the county level. ***, **, & * indicate significance at 1, 5 & 10%-level, respectively.

6. Discussion and conclusion

In this study, we take a first step towards understanding the relationship between social activism and regulation in the presence of negative externalities. We build a regulatory contest model of the interaction between firms and interest groups. Motivated by the rising incidence of environmental activism around the world, we empirically test our model prediction using data on clashes between environmental groups and fossil fuel firms across 68 countries over the period 1995-2014.

We find that, for a given tax rate, a move from a lax to more stringent regime lowers the rate of environmental conflicts. The evidence suggests two alternative implications on how EGs may condition their conflict strategies to fit their regulatory regimes, even when faced with similar levels of environmental taxes. On the one hand, EGs are likely to intensify their anti-pollution campaign efforts to compensate for lax policy stringency, such that environmental activism and environmental taxes can be viwed as substitutes. On the other hand, EGs can conserve their efforts by free-riding on more stringent regulation, suggesting that environmental activism and environmental taxes are complements.

An obvious policy implication of our results is that activists can perceive the stringency of regulation to the extent that it informs the intensity of their environmental activism. Therefore, the design of a regulatory instrument alone may not be sufficient to satisfy the concerns of social interest groups. Considering the rising wave of environmental activism around the world, a more specific implication of our results is that activists' behaviour in terms of their campaign intensity and approach will likely be shaped by their perception of regulatory stringency. Hence, our findings are particularly relevant for predicting EGs' responses to pollution externalities across different regulatory contexts.

We also offer three significant implications for research. First, we offer a theoretical framework that directly explores the connection between natural resource abundance, conflicts, and regulatory stringency. Second, we provide an original attempt to shed much-needed light on these interactions by carefully constructing a unique dataset on environmental conflicts using comprehensive textual information on clashes between activist groups and fossil fuel firms. Third, we extend the validity of the resource curse hypothesis by incorporating environmental activism as a novel behavioural mechanism within this literature.

There are several fruitful avenues for further research. For example, it would be interesting to look at different sectors other than fossil fuels, exploring whether the non-monotonic relationship between regulation and activism holds for externalities arising from other non-resource-based production. This is especially important for exploring the nature of social activism in different production settings where governments may exhibit a different attitude to regulation.

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Appendix

A. Data sample

Table A1 contains the sampled countries in our study. The sample is the result of a data matching exercise across our three main data sources. First, after extracting detailed information on each conflict from the EJAtlas maps, arrive at a conflict database spanning 106 countries. Meanwhile, the OECD environmental policy database covers around 102 countries of the world. Furthermore, the production data only covers around 71 countries. After matching country information across these three datasets, we obtain a final database of 68 (33 OECD and 35 non-OECD) countries with consistent information during the period 1995-2014.

Table A1: Countries in the data sample

Classification	Country
OECD	Australia, Austria, Belgium, Canada, Chile, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, United Kingdom, United States.
Non-OECD	Argentina, Bolivia, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Croatia, Egypt, Ethiopia, Ghana, Hong-Kong, India, Indonesia, Kenya, Malawi, Malaysia, Malta, Mauritius, Morocco, Nigeria, Peru, Philippines, Romania, Russia, Senegal, Singapore, South Africa, Taiwan, Tanzania, Thailand, Turkey, Venezuela, Zambia

B. The shadow price of pollution from the fossil fuel sector

We consider pollution as an undesirable output. However, modelling these environmental externalities in a production function environment requires that the undesirable output is constrained to be treated as an input, as in Färe et al. (1993) where a linear programming methodology is used. To implement an econometric methodology, we treat the undesirable output of pollution as an unpriced input and derive its shadow input price. This formulation has a long history in environmental economics (Fullerton, 2001), permitting us to adopt the methodology suggested by Färe and Grosskopf (1990).

We begin with the standard cost function where $\mathbf{p}^{\mathbf{s}\prime} = (p_1^s, \dots, p_k^s)$ is a vector of shadow prices. Some of these will be equal to the market prices of traded inputs, but one or more represents the shadow prices of unpriced inputs which could be undesirable by-products of production. Let $I(\mathbf{y}) = \{\mathbf{x}: \mathbf{x} \text{ can produce } \mathbf{y}\}$ be the convex input requirement set for the production of outputs $\mathbf{y}' = (y_1, \dots, y_R) \in \mathbb{R}_+^R$ from inputs: $\mathbf{x}' = (x_1, \dots, x_K) \in \mathbb{R}_+^K$. An alternative representation of the technology is the input distance function:

$$D_I(\mathbf{y}, \mathbf{x}) = \max_{\theta}\{(1/\theta)\mathbf{x}: \mathbf{x} \in I(\mathbf{y}), for\ given\ \mathbf{y}\} \qquad \text{[A1]}$$

The input distance function has the properties:

a. $D_I(\mathbf{y}, \mathbf{x}) \geq 1$ so that it represents the maximum contraction in $\mathbf{x}$ that maintains feasibility of the production of outputs, $\mathbf{y}$
b. $D_I(\mathbf{y}, \mathbf{x})$ is homogeneous of degree $+1$ in inputs, $\mathbf{x}$
c. $D_I(\mathbf{y}, \mathbf{x})$ is nondecreasing in $\mathbf{x}$
d. $D_I(\mathbf{y}, \mathbf{x})$ is nonincreasing in $\mathbf{y}$
e. $D_I(\mathbf{y}, \mathbf{x})$ is a concave function in $\mathbf{x}$ if $I(\mathbf{y})$ is a convex set.

Therefore, $\mathbf{x} \in I(\mathbf{y})$ if and only if $D_I(\mathbf{y}, \mathbf{x}) \geq 1$. Thus, the shadow cost function is

$$C(\mathbf{y}, \mathbf{p}^s) = \min_{\mathbf{x}}\{\mathbf{p}^{s\prime}\mathbf{x}: \mathbf{x} \in I(\mathbf{y})\} = \min_{\mathbf{x}}\{\mathbf{p}^{s\prime}\mathbf{x}: D_I(\mathbf{y}, \mathbf{x}) \geq 1\} \qquad \text{[A2]}$$

Färe and Grosskopf (1990) show that, if the input requirement set is convex, an alternative and equivalent definition of the input distance function is

$$D_I(\mathbf{y},\mathbf{x}) = \min_{\mathbf{q}}\{\mathbf{q}'\mathbf{x}: C(\mathbf{y},\mathbf{q}) \geq 1\} \qquad [A3]$$

In equation [A3] $\mathbf{q}' = (q_1, \dots, q_K) = \left((p_1^s/C(\mathbf{y},\mathbf{p}^s)), \dots, (p_K^s/C(\mathbf{y},\mathbf{p}^s))\right)$, the vector of cost-normalised input prices. Färe and Grosskopf are now able to show that the shadow prices that we are looking for, to measure the impact of the undesirable output, can be estimated from the form of the input distance function given in [A1], i.e., having information only on inputs and outputs. The argument uses the pair of duality relationships given in [A2] and [A3], where [A2] chooses inputs to minimise technologically feasible cost and [A3] chooses cost normalized input prices to minimise economically feasible input contraction.

Solving [A2], the first-order conditions on the efficient frontier are, where λ is the Lagrange multiplier for the problem

$$p_k^s = \lambda(\partial D_I(\mathbf{y},\mathbf{x})/\partial x_k); k = 1, \dots, K$$
$$D_I(\mathbf{y},\mathbf{x}) = 1$$

[A4]

Invoking homogeneity, (for the full proof see Färe et al (1993)), it is shown that

$$\lambda = C(\mathbf{y},\mathbf{p}^s) \qquad [A5]$$

Now consider the problem in [A3] and write the Lagrangean function with multiplier μ as

$$L = \mathbf{q}'\mathbf{x} + \mu\left(1 - C(\mathbf{y},\mathbf{q})\right)$$

[A6]

The solution yields: $q_k = q_k(\mathbf{y}, \mathbf{x})$, $k = 1, \dots, K.$, with the optimised value of the Lagrangean equal to: $L^* = D_I^*(\mathbf{y}, \mathbf{x}) = \mathbf{q}^*(\mathbf{y}, \mathbf{x})'\mathbf{x}.$ Applying the envelope theorem to [A6] we obtain Shephard's dual lemma:

$$\partial L/\partial x_k = q_k(\mathbf{y}, \mathbf{x}) = \partial D_I(\mathbf{y}, \mathbf{x})/\partial x_k \,; k = 1, \dots, K \tag{A7}$$

Then using [A4], [A5] and [A7], we obtain:

$$p_k^s/C(\mathbf{y}, \mathbf{p}^s) = \partial D_I(\mathbf{y}, \mathbf{x})/\partial x_k \,; k = 1, \dots, K \tag{A8}$$

Summing up we find that the cost normalised shadow prices are measurable by the first-order derivatives of the input distance function [A3] equivalently [A1]. The version in [A1] requires knowledge only of the levels of the inputs and the outputs, including the undesirable outputs represented as unpriced inputs. The input distance function [A1] can be fitted as a translog function using properties a and b.

From property a),

$$D_I(\mathbf{y}, \mathbf{x}) \geq 1$$

Then

$$\ln D_I(\mathbf{y}, \mathbf{x}) \geq 0 \Rightarrow \ln D_I(\mathbf{y}, \mathbf{x}) - u = 0, u \geq 0$$

From property b),

$$D_I(\mathbf{y}, k\mathbf{x}) = kD_I(\mathbf{y}, \mathbf{x})$$

Let $k = 1/x_K$, then

$$D_I(\mathbf{y}, (1/x_K)\mathbf{x}) \equiv D_I(\mathbf{y}, \tilde{\mathbf{x}}) = (1/x_K)D_I(\mathbf{y}, \mathbf{x})$$

So that

$$\ln D_I(\mathbf{y}, \tilde{\mathbf{x}}) = -\ln x_K + \ln D_I(\mathbf{y}, \mathbf{x})$$

Rearrange this result using property a) above and representing the left-hand side of the equation by a translog function in $(\mathbf{y}, \tilde{\mathbf{x}})$, i.e., $TL(\mathbf{y}, \tilde{\mathbf{x}})$, plus a random error term, v.

$$-\ln x_K = TL(\mathbf{y}, \tilde{\mathbf{x}}) + v - \ln D_I(\mathbf{y}, \mathbf{x}) = TL(\mathbf{y}, \tilde{\mathbf{x}}) + v - u$$

[A9]

Interpreting u as a one-sided random error measuring the distance to the efficient frontier means that $exp(\hat{u}) = \widehat{D}_I$, and [A1] can be fitted as a stochastic frontier analysis translog regression with the composed error term $(v - u)$. Technological progress can be estimated through terms in time, t.

Write $\mathbf{lx}' = (\ln(x_1/x_K), \dots, \ln(x_{K-1}/x_K))$ and $\mathbf{ly}' = (\ln y_1, \dots, \ln y_R)$, then

$$TL\big((\mathbf{y}, \tilde{\mathbf{x}}, t)\big) = \alpha_0 + \boldsymbol{\alpha}'\mathbf{ly} + \tfrac{1}{2}\mathbf{ly}'\mathbf{A}\mathbf{ly} + \boldsymbol{\beta}'\mathbf{lx} + \tfrac{1}{2}\mathbf{lx}'\mathbf{B}\mathbf{lx} + \mathbf{ly}'\boldsymbol{\Gamma}\mathbf{lx} + \delta_1 t + \tfrac{1}{2}\delta_2 t^2 + \boldsymbol{\mu}'\mathbf{ly}t + \boldsymbol{\eta}'\mathbf{lx}t + v - u$$

Elasticity effects are

$$\begin{pmatrix} \boldsymbol{e_y} \\ \boldsymbol{e_x} \\ \boldsymbol{e_t} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\alpha} & \mathbf{A} & \boldsymbol{\Gamma} & \boldsymbol{\mu} \\ \boldsymbol{\beta} & \boldsymbol{\Gamma}' & \mathbf{B} & \boldsymbol{\eta} \\ \delta_1 & \boldsymbol{\mu}' & \boldsymbol{\eta}' & \delta_2 \end{pmatrix} \begin{pmatrix} 1 \\ \mathbf{ly} \\ \mathbf{lx} \\ t \end{pmatrix}$$

Here $\boldsymbol{e_y}' = \big(e_{y1}, \dots, e_{yR}\big) = \big((\partial \ln D_I/\partial \ln y_1), \dots, (\partial \ln D_I/\partial \ln y_R)\big)$

And $\boldsymbol{e_x}' = (e_{x1}, \dots, e_{xK}) = \big((\partial \ln D_I/\partial \ln x_1), \dots, (\partial \ln D_I/\partial \ln x_K)\big)$

Consequently, the estimates of cost normalised shadow prices are recovered as

$$SP = (\partial \ln D_I/\partial \ln x_k)\big(\widehat{D}_I/x_k\big) = e_{xk}\big(\widehat{D}_I/x_k\big)$$

[A10]

C. Distance function coefficients and shadow cost estimates.

In Table A2, we present the parameter estimates from three distance function formulations using the commonly adopted flexible transcendental logarithmic (translog) functional form (Christensen et al., 1973). The translog functional form offers a better fit, especially in terms of offering a good first-order approximation to the production function, relative to the more common Cobb–Douglas specification, which is restrictive in its imposition of constant elasticity of substitution (see Kumbhakar & Wang, 2005).

Table A2: Distance function coefficients

	(1) Pooled	(2) TVD	(3) TFE
Output	-1.0107***	-0.2300***	-0.1403***
	(0.0144)	(0.0198)	(0.0000)
Pollution	0.0392***	0.3195***	0.6186***
	(0.0115)	(0.0156)	(0.0000)
Capital	0.5794***	0.2557***	0.1641***
	(0.0160)	(0.0142)	(0.0000)
Output-square	0.0514***	0.0297***	0.0066***
	(0.0055)	(0.0043)	(0.0000)
Pollution-square	-0.0075**	-0.0231***	-0.0282***
	(0.0035)	(0.0028)	(0.0000)
Capital-square	0.0395***	0.0278***	0.0150***
	(0.0058)	(0.0033)	(0.0000)
Pollution x capital	-0.0017	0.0359***	0.0335***
	(0.0072)	(0.0044)	(0.0000)
Output x pollution	-0.0833***	-0.0314***	-0.0308***
	(0.0063)	(0.0046)	(0.0000)
Output x capital	0.0476***	-0.0579***	-0.0238***
	(0.0069)	(0.0058)	(0.0000)
Time	0.0007	0.0282***	-0.0018***
	(0.0043)	(0.0057)	(0.0000)
Time-square	-0.0009	-0.0011***	0.0001***
	(0.0008)	(0.0002)	(0.0000)
Output x time	-0.0004	0.0030**	-0.0023***
	(0.0023)	(0.0012)	(0.0000)
Pollution x time	-0.0011	0.0017***	0.0006***
	(0.0016)	(0.0006)	(0.0000)
Capital x time	0.0087***	0.0061***	0.0049***
	(0.0022)	(0.0007)	(0.0000)
μ		4.3610***	
		(0.5017)	
η		-0.0081***	

		(0.0013)	
Log likelihood	-1622.519	-83.128	495.041
Observations	1310	1310	1310
Country FE	No	Yes	Yes
Heteroscedasticity adjustment	No	No	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In column 1, we estimate a pooled distance function. Because the output and inputs are in mean-corrected logarithms, they can be interpreted as elasticities at the sample mean. All the first-order coefficients on inputs and output have the right signs[1] and they are all statistically significant at the 1% level. In column two, we control for the panel structure of our data by using the time-varying decay (TVD) model specification proposed by Battese and Coelli (1992). The model estimates are qualitatively consistent with the pooled model and they retain their statistical significance. In column 3, we address two issues namely country-fixed effects and heteroscedasticity in the model errors. We address the former using the True Fixed Effects (TFE) model proposed by Greene (2005a,b). Finally, we address the problem arising from panel heteroscedasticity following the error adjustment suggested by Stevenson (1980) and Hadri (1999). This third model is our preferred model since it permits the estimation of time-varying efficiency estimates while allowing the inclusion of fixed effects, along with a heteroskedasticity adjustment in the model errors. The estimates from the model retain the qualitative implications and statistical significance from the two prior model specifications.

In table A3, we briefly present estimates of the shadow cost of pollution, focusing on some notable economies and resource-rich economies within our sample. As shown in Table 2, the lowest shadow prices ($ per ktoe) are found for Canada, China, India, Indonesia,

[1] The positive (negative) signs on the inputs (output) elasticities reflect that the input distance function attempts to proportionally contract the input vector, holding the output vector fixed.

Nigeria, and Russia, where the incentive for strict restrictions on fossil extraction may be low due either to their resource reliance/abundance, or their status as emerging economies. In contrast, the estimates in Finland, Spain, and the UK appear consistent with the observed levels of regulation in these countries.

Table A3. Shadow cost estimates

	Country	Estimated SC	Std. Error
1	Argentina	0.00028***	0.00003
2	Australia	0.00023***	0.00001
3	Brazil	0.00023***	0.00001
4	Canada	0.00010***	0.00000
5	Chile	0.00248***	0.00043
6	China	0.00002***	0.00000
7	Colombia	0.00037***	0.00003
8	Finland	4.50788***	0.07540
9	India	0.00015***	0.00000
10	Indonesia	0.00005***	0.00000
11	Malaysia	0.00017***	0.00001
12	Netherlands	0.01854***	0.00118
13	Nigeria	0.00001***	0.00000
14	Norway	0.00050***	0.00005
15	Russia	0.00000***	0.00000
16	Spain	4.61044***	0.01435
17	Sweden	0.36280***	0.00762
18	United Kingdom	1.11851***	0.06262
19	United States	0.54459***	0.07413
20	Venezuela	0.00100***	0.00000

Notes: This table contains the shadow price estimates from the estimated distance function in Table A2 above.

D. Environmental stringency estimates

We briefly present the stringency measures used in identifying the tax thresholds in our empirical analysis in Table A4. In Panel A, we present the estimated stringency (i.e., the difference between the environmental tax variable and the estimated shadow cost of pollution)[2]. To aid comparison, we present the survey-based WEF measure in Panel B. Both

[2] See the online appendix for a full presentation of the panel distance function underlying the shadow cost estimates.

measures are somewhat consistent in their ranking of countries at the top and bottom of the threshold. Hence, we obtain a correlation coefficient of 0.347*** between both measures.

Table A4. Ranking of countries by environmental stringency

PANEL A		**PANEL B**	
Tax - estimated shadow cost		**Average WEF index**	
Top Performers		**Top Performers**	
Country	Stringency	Country	WEF Index
Cyprus	38.93	Switzerland	6.29
India	31.84	Finland	6.26
Latvia	29.12	Sweden	6.14
Luxembourg	27.79	Germany	6.13
Hungary	22.26	Luxembourg	5.97
France	13.91	Belgium	5.95
Belgium	12.61	Japan	5.83
Germany	11.01	Denmark	5.66
Slovenia	10.54	Slovenia	5.54
Italy	8.71917	France	5.52
Bottom Performers		**Bottom Performers**	
Ethiopia	-3.37	Ethiopia	3.02
Hong Kong	-3.43	Nigeria	3.00
Singapore	-3.63	Colombia	3.00
Costa Rica	-3.82	Tanzania	2.97
Mauritius	-4.09	China	2.95
Croatia	-4.19	Costa Rica	2.94
Taiwan	-4.45	Morocco	2.91
Zambia	-4.47	Senegal	2.89
Malawi	-4.47	Argentina	2.74
Bulgaria	-4.49	Croatia	2.60

E. Full IV-2SLS results

Table A5. 2SLS test of exogenous instruments

Dep var: Environmental conflict **PANEL A: 2nd Stage regression**	(1)	(2)	(3)
Log (Tax per emission)	-0.163***	-0.087	0.115
	(0.055)	(0.321)	(0.357)
Log (Per capita income)		0.575	
		(0.525)	
Log (Energy price)		-0.376*	-0.344
		(0.211)	(0.212)
Rule of law (Index)		-0.600	
		(0.393)	
Log (Population)		3.263***	-3.957***
		(1.267)	(1.353)

Temperature		-0.035	-0.076
		(0.069)	(0.079)
Log (Fossil reserves)		0.238*	
		(0.133)	
Log (Area size)		0.050***	
		(0.013)	
Tax x LAX		1.253**	1.342**
		(0.578)	(0.599)
Tax x STRINGENT		-0.750**	-1.046**
		(0.343)	(0.421)
PANEL B: 1st Stage Tax regression			
Neighbor's legislative proposals	1.182***	1.158***	1.182***
	(0.180)	(0.182)	(0.183)
Colonial master's tax per emission	0.448***	0.428***	0.402***
	(0.081)	(0.095)	(0.094)
Partner's population		-1.771**	-1.435**
		(0.730)	(0.724)
Partner's industrial share		0.024	0.048
		(0.089)	(0.087)
Partner's tariffs		0.039***	0.029***
		(0.011)	(0.010)
PANEL B: 1st Stage Tax x LAX			
Neighbor's legislative proposals		0.460***	0.485***
		(0.120)	(0.122)
Colonial master's tax per emission		0.106	0.067
		(0.068)	(0.066)
Partner's population		-0.203	0.141
		(0.629)	(0.619)
Partner's industrial share		-0.434***	-0.424***
		(0.115)	(0.117)
Partner's tariffs		0.018*	0.012
		(0.009)	(0.009)
PANEL B: 1st Stage Tax x STRINGENT			
Neighbor's legislative proposals		0.941***	0.962***
		(0.077)	(0.077)
Colonial master's tax per emission		0.321***	0.294***
		(0.063)	(0.062)
Partner's population		-1.617***	-1.410***
		(0.426)	(0.422)
Partner's industrial share		-0.141***	-0.144***
		(0.043)	(0.043)
Partner's tariffs		-0.014*	-0.018**

		(0.008)	(0.008)
PANEL C: Reduced form estimates			
Neighbor's legislative proposals	-0.215***	-0.280***	-0.323***
	(0.084)	(0.077)	(0.091)
Colonial master's tax per emission	-0.271***	0.020	0.060
	(0.064)	(0.076)	(0.079)
Partner's population		2.982***	2.539***
		(1.001)	(0.951)
Partner's industrial share		-0.428**	-0.439**
		(0.213)	(0.214)
Partner's tariffs		0.015	0.027**
		(0.011)	(0.011)
Time effect	Y	Y	Y
Country effect	Y	Y	Y
F-test of instruments	44.53	15.63	15.09
Over id Hansen J test (p-value)	0.297	0.126	0.243
Observations	1310	1310	1310

Notes: The dependent variable in the second stage (Panel A) is environmental conflicts. Panel B contains the first stage OLS regressions in which the dependent variable is environmental tax. Heteroskedasticity-robust standard errors are presented in parentheses. ***, **, & * indicate significance at 1, 5 & 10%-level, respectively.

F. Elasticity calculations

We have two models:

Linear IV-2SLS

Strictly this is a linear-log model regressing (CONFLICT) COUNT against log(TAX). COUNT is treated as an unrestricted sample of observations on a continuous variable.

$$COUNT = y = \beta_0 + \beta_{tax}(\ln tax) + \beta_{taxLAX}\big((\ln tax) * (LAX = 1)\big)$$
$$+ \beta_{taxSTR}\big((\ln tax) * (STR = 1)\big) + \cdots$$

Elasticity of COUNT with respect to tax in LAX regimes:

$$\partial E(y|\mathbf{x})/\partial\big((\ln tax)\big)\big(E(y|\mathbf{x})\big)^{-1} = [\beta_{tax} + \beta_{taxLAX}]/\hat{E}(COUNT)$$

And in stringent regimes:

$$\partial E(y|\mathbf{x})/\partial((\ln tax))(E(y|\mathbf{x}))^{-1} = [\beta_{tax} + \beta_{taxSTR}]/\hat{E}(COUNT)$$

We use $\overline{COUNT}$ for $\hat{E}(COUNT)$ = 0.3916031, i.e., the overall sample mean.

***Poisson Model*.**

We have the same regression form but a different data generating process imposing the restrictions of the Poisson model on the dependent variable, i.e., COUNT can take only nonnegative integer values, including an arbitrary number of zeros. This in effect is a log linear model or a log log model if the RHS variable is in log form which ours is, i.e., $COUNT = \mathbf{x}'\boldsymbol{\beta} = \ln(exp(COUNT)) = \ln(e^{\mathbf{x}'\boldsymbol{\beta}})$. In this case, elasticity is

$$[\beta_{tax} + \beta_{taxLAX}]$$

or

$$[\beta_{tax} + \beta_{taxSTR}]$$

G. Linear split-sample specification

Given the strong correlation between the level of taxes and environmental stringency (Table A6), we consider one final analysis to explore the linear effect of taxes on conflict (Table A7)

Table A6. Correlation matrix for tax and strigency thresholds

	Tax	**STRINGENCY**
Tax	1.000	
STRINGENCY	0.570*** (0.000)	1.000

***Denotes statistical significance at 1%

In Table A7, we perform split sample OLS and 2SLS regressions using the mean of the tax distribution. The 2SLS results are qualitatively similar to our main findings, albeit the LAX sample fails to attain statistical significance at conventional levels.

Table A7. Linear effect of environmental taxes on conflit using split samples

	(1)	(2)	(3)	(4)
	Split sample regressions based on sample mean			
	LOW/LAX		HIGH/STRINGENT	
	OLS	2SLS	OLS	2SLS
Tax	-0.211	1.896	-0.107	-0.326***
	(0.158)	(1.656)	(0.105)	(0.111)
Country effect	Y	Y	Y	Y
Year effect	Y	Y	Y	Y
Other controls	Y	Y	Y	Y
R-squared	0.056	0.720	0.157	0.149
N	526	526	784	783

Notes: The dependent variable is the number of environmental conflicts between EGs and firms. Controls are the same as those in baseline estimates. LOW/LAX and HIGH/STRINGENT samples are based on the mean value of taxes. Robust errors in parentheses. ***, **, & * indicate significance at 1, 5 & 10%-level, respectively.

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