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RESEARCH ARTICLE

Does democratic transition reduce carbon intensity? Evidence from Indonesia using the synthetic control method

Yimin Mao[1]

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Abstract
Despite growing concern about the low-carbon economic development, little is known about the role of political institutions, democracy, or the absence thereof, in controlling carbon intensity (carbon dioxide emissions per unit of GDP). This paper estimates the causal effects of democratic transition in Indonesia on its national carbon emission intensity. The synthetic control method is adopted to handle both time-invariant and time-variant confounding heterogeneity. Results show that Indonesia's democratic transition increases on average 0.24 kg carbon dioxide emissions per constant 2005 US dollar in the post-transition period (1999–2010), a rise of approximately 25.34%. The placebo tests indicate this causal effect is significant and the leave-one-out sensitivity check also demonstrates its robustness. The evidence of Indonesia suggests that democratic transition may serve to intensify, rather than mitigate, the emissions of carbon dioxide. Therefore, policymakers should pay more attentions to the contextual fit of democratic transition.

Keywords Democracy · Carbon intensity · Synthetic control method · Indonesia

Introduction

The rapid growth of carbon dioxide (CO2) emissions is widely recognized as the major cause of global warming. The Intergovernmental Panel on Climate Change (IPCC) reports that CO2 emissions from fossil fuel combustion and industrial processes contributed about 78% of the total greenhouse gas emission increase from 1970 to 2010.[1] Therefore, the reduction of CO2 emissions has been a focal issue on the global climate policy agenda.

Carbon intensity, i.e., *CO2 emissions per unit of economic output (CO2/GDP)*, is one of the most commonly used indicators to evaluate climate policy performance in recent decades. For example, China, the world's top CO2 emitter in total, has pledged to lower the carbon intensity of GDP by 60–65% from the 2005 level by 2030 in December 2015 Paris Agreement on climate change. As a ratio, the value of carbon intensity depends on two factors: CO2 emissions and GDP. Therefore, carbon intensity can be reduced if the growth rate of CO2 emissions is smaller than the growth rate of GDP, even if the total amount of CO2 emissions is still increasing. Herzog et al. (2006) argue that the goal of reducing carbon intensity is to generate a maximum of economic wealth with a minimum of carbon emissions.

Existing literature has shown that multiple socio-economic factors, including economic growth, energy intensity, industrial structure, and urbanization, can affect the trajectory of carbon intensity in a country (Roberts and Grimes 1997; Guan et al. 2014; Thomakos and Alexopoulos 2016; Chang et al. 2017). For example, Roberts and Grimes (1997) find that the relationship between carbon intensity and the level of economic development has changed from essentially linear in 1962 to strongly curvilinear in 1991. Zhu et al. (2014) investigate the reduction rate of carbon intensity among 89 countries and find that (1) countries with high initial conditions of carbon intensity tend to have higher decline rate and (2) keeping fast and steady economic growth increases the total amount of carbon emissions, but it can significantly reduce carbon intensity.

[1] This report can be downloaded from the official website of IPCC. See https://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_summary-for-policymakers.pdf.

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✉ Yimin Mao
mym@zjgsu.edu.cn

[1] College of Public Administration, Zhejiang Gongshang University, No.18, Xuezheng Str., Xiasha University Town, Hangzhou 310018, China

Energy intensity is considered as another important contributor to carbon intensity. Fan et al. (2007) reveal that the decline of real energy intensity is the overwhelming contributor to the reduction of energy-related carbon intensity in China from 1980 to 2003. Ebohon and Ikeme (2006) adopt the Laspeyres index method to investigate the carbon intensity in sub-Saharan African countries and find that the intensity and structure of energy use as well as economic growth exert great impact on carbon intensity. Moreover, after reviewing 80 peer-reviewed papers on this issue, Xu and Ang (2013) conclude that reducing energy intensity can facilitate reduction of carbon intensity in both developing and developed countries.

In addition, many studies investigate the role of industrial structure and urbanization in reducing carbon intensity (Bhattacharyya and Ussanarassamee 2004; Zhang et al. 2014; Dong et al. 2016). For example, by using the logarithmic mean Divisia index decomposition method, Bhattacharyya and Ussanarassamee (2004) find that the relationship between energy intensity and carbon intensity is moderated by the national economic conditions, industrial structure, and the structure of fuel in Thailand from 1981 to 2000. Zhang et al. (2014) show that China's economic growth and the share of tertiary industry are conducive to its reduction of carbon intensity, while urbanization may intensify the CO2 emissions.

However, little is known about the effects of political institutions, democracy, or the absence thereof on carbon intensity. It seems to be surprising because the literature on environmental politics has claimed that political regime type exerts great impact on the design and enforcement of national environmental policy (Buitenzorgy and Mol 2010; Steinberg and VanDeveer 2012; Adams et al. 2016). Specifically, many scholars advocate that democracy can cure environmental degradation as it brings public accountability, civic participation, free medias, and information transparency (Payne 1995; Barrett and Graddy 2000; Winslow 2005; Farzin and Bond 2006; Li and Reuveny 2006; Bernauer and Koubi 2009), while some studies suggest that democracy is unable to save the environment because of collective action problems, interest capture, frequent election, budget restraints, etc. (Heilbroner 1974; Ophuls 1977; Midlarsky 1998; Beeson 2010; Arvin and Lew 2011; Gaarder and Vadlamannati 2017).

Recently, some researchers have investigated the relationship between democracy and CO2 emissions. For example, Mayer (2017) finds that democracy decreases total CO2 emissions in a modest degree. You et al. (2015) find that the impact of democracy on CO2 emissions per capita is heterogeneous across quantiles (positive for the least emissions countries while negative for the most emissions countries). *However, the outcome they are interested in is total CO2 emissions or CO2 emissions per capita, instead of carbon intensity (CO2/GDP).* As carbon intensity is sensitive to economic, social, and technical change, its trajectory may be quite different from that of total carbon emissions. Thomakos and Alexopoulos (2016) argue that it may show opposite trends over time between carbon intensity and total CO2 emissions. Therefore, with the increased use of carbon intensity as an indicator to set carbon policy target, it is meaningful to reveal the effects of democratic transition on carbon intensity.

To be specific, this paper examines the causal effects of democratic transition on carbon intensity in Indonesia by using the synthetic control method (SCM) (Abadie and Gardeazabal 2003; Abadie et al. 2010, 2015). As a new method for causal inference, SCM can control confounding factors, both observable and unobservable, by using panel data with time series information. The contributions of this paper are twofold. Theoretically, it investigates carbon intensity from political perspective and reveals the causal effects of democratic transition on carbon intensity in Indonesia. Methodologically, it establishes a quasi-experimental design and adopts SCM to improve causal inference.

This paper is organized as follows: Section 2 provides an instruction of methods, variables, and data sources; Section 3 presents the empirical results, including placebo test and robustness check; and Section 4 concludes with contributions, policy implications, limitations, and further research directions.

Method and data

Identification of causal effects

In causal inference research, causal effects are defined as the difference between the actual observed outcome and the outcome that would have been observed had treatment not taken place.[2] In brief, the estimation of causal effects, by its nature, is a comparison of potential outcomes (Rubin 1974). Specifically, each unit i in the sample has two potential outcomes, that is, the potential outcome if it is treated, $Y_i(1)$, and the potential outcome if it is not treated, $Y_i(0)$. Then, the causal effects of treatment on the unit i are the gap between $Y_i(1)$ and $Y_i(0)$. However, it is impossible to observe both potentials in reality because each unit i will receive either treatment or control. For example, $Y(0)$ is counterfactual for a treated unit. Thus, a prerequisite for estimating causal effects is to handle the missing data problem of potential outcomes, which has

[2] It needs to be mentioned that causal inference research is not to prove causation, but to identify the impact of exposure to a particular treatment or program. For example, Rothman and Greenland (2005) discuss the causality and causal inference in epidemiology and argue that "philosophers agree that causal propositions cannot be proved, and find flaws or practical limitations in all philosophies of causal inference. Hence, the role of logic, belief, and observation in evaluating causal propositions is not settled. *Causal inference in epidemiology is better viewed as an exercise in measurement of an effect rather than as a criterion-guided process for deciding whether an effect is present or not.*"

been identified as the "fundamental problem of causal inference" (Holland 1986).

Randomized experiment is the common way to cope with this fundamental problem. It achieves the balance of covariates between the treated and control groups, which means "the treated and control groups are guaranteed to be only randomly different from one another on all background covariates, both observed and unobserved" (Roberts and Grimes 1997). However, it is usually unfeasible to conduct randomized experiments in social science research because of the implementation cost or unethical issues (Morgan and Winship 2014). In observation studies, treatment is not randomly assigned and cofounders can lead to selection bias. Therefore, to make causal inference in observation studies, some key assumptions must be posited. One assumption is ignorability, which means that, given pretreatment covariates X, treatment assignment is independent from the potential outcomes (Rosenbaum and Rubin 1983). It can be formally presented as $Y(0)$, $Y(1) \perp \text{Treatment} \mid X$. Under this assumption, the treatment can be seen as randomly assigned among the units given the balance of X. An additional assumption is the stable unit treatment value assumption (SUTVA), indicating that units do not interfere with each other (Rubin 1980). This assumption ensures the potential outcome for one unit in terms of only that unit's treatment.

Under these assumptions, matching has become widely used to balance the properties of the treated and control groups in observation studies (Stuart 2010). By using propensity score or weighting techniques, matching methods can make the treated and control groups as similar as possible; then, the causal effects of treatment can be calculated with a simple comparison. However, traditional matching methods require a big sample of observations and cannot deal with the unobservable cofounders (Imbens and Rubin 2015). As such, their capabilities for causal inference are limited if the analysis is conducted at the aggregate level (country, region, etc.).

Synthetic control method

SCM, as a new matching method for causal inference based on the panel data, has been elaborated by some scholars in recent decade (Abadie and Gardeazabal 2003; Abadie et al. 2010; Abadie et al. 2015). The key advantages of SCM are as follows. First, SCM can control both time-invariant and time-variant confounders. Second, SCM can be applied to the small sample with one or a few treated units, which is useful if we want to estimate causal effects at the aggregate level. Third, as a data-driven method, SCM is objective and transparent. For example, the weight distributed to every control unit in the donor pool can be clearly seen.

Here, this paper gives a brief description of SCM. Suppose that there are $J+1$ units and only the first unit is exposed to the treatment of interest (e.g., democratic transition), so we observe J remaining units as controls. Let T be the number of whole time period and T_0 be the number of pretreatment period, with $1 \leq T_0 < T$. And then let y_{it}^{I} be the outcome that would be observed for unit i at time t if unit i is exposed to the treatment in periods T_0+1 to T, while let y_{it}^{N} be the outcome that would be observed for unit i at time t without treatment, with $i = 2, \ldots, J+1$, and $t = 1, \ldots, T$. The treatment effect on the first unit, for $t > T_0$, can be written as $\alpha_{1t} = y_{1t}^{I} - y_{1t}^{N} = y_{1t} - y_{1t}^{N}$. However, y_{it}^{N} is counterfactual. To deal with this problem, SCM suggests that, for $t > T_0, y_{it}^{N}$ can be estimated with $\hat{y}_{1t}^{N} = \sum_{j=2}^{J+1} w_j^* y_{jt}$. An optimal vector of weights $W^* = \left(w_2^*, \ldots, w_{J+1}^*\right)$ is chosen to minimize the distance between pretreatment characteristics and outcomes for the treated unit (X_1) and for the control units (X_0). The penalty function is formally given by $\|X_1 - X_0 W\|_{v} = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$, with $0 \leq w_j \leq 1$ for $j = 2 \ldots, J+1$, and $w_2 + \ldots + w_{J+1} = 1$. Specifically, V denotes a diagonal positive semidefinite identity matrix of dimension ($k \times k$) that minimizes the root mean squared prediction error (RMSPE). In other words, this algorithm can help us minimize the properties of discrepancy between the treated unit and its synthetic control counterpart in the pretreatment period. Once the synthetic control is constructed, the estimation of treatment effect is just a matter of comparing the post-treatment outcomes of the treated unit and the synthetic control.

Due to the small sample, the common inferential techniques, such as T test, are not allowed to assess the significance of the SCM results. However, this limitation can be conquered by running a series of placebo tests, that is, applying the SCM to all untreated units in the donor pool as if they were treated and then comparing trajectories of the placebo with that of the baseline result (Abadie et al. 2010). These tests allow us to judge whether the estimated effect on the treated unit is observed by chance. The basic idea of the placebo tests is that the treatment effect can be seen as significant only if the effects observed in those untreated units are rarely larger than the effect observed in the treated unit.

The robustness of the SCM results is checked by running the leave-one-out tests. Researches can iteratively estimate the baseline model but omit in each iteration one of the control units that received a positive weight (Abadie et al. 2015). This sensitivity check evaluates to what degree the estimated effect is resulted from any one of control units. The estimated effect can be seen as robustness only if it is insensitive to the leave-one-out design.

In short, SCM constructs a synthetic control by assigning weights to control units according to their similarity to the treated unit in the pretreatment period. Then, the causal effects of treatment can be obtained by calculating the discrepancy of the actual and synthetic outcomes in the post-treatment period. The basic steps of SCM can be summarized as follows.

1. Identify the outcome and treatment according to your research question;
2. Identify a treated unit and a set of potential control units;
3. Select a series of characteristics that are important in determining the outcome;
4. Estimate the synthetic control by assigning weights to control units according to their similarity to the treated unit in the pretreatment period;
5. Check the balance of characteristics between the treated unit and its synthetic counterpart;
6. Use weighted average of the control units to create the counterfactual outcome in the post-treatment period;
7. Estimate the causal effects by comparing the outcomes of the treated unit and its synthetic counterpart;
8. Use placebo tests to check the significance of the estimated causal effects; and
9. Use leave-one-out tests to check the robustness of the estimated causal effects.

Treated unit and potential controls

In this study, the treatment is democratic transition. Treated cases are countries that experienced democratic transition in the period from 1980 to 2010, while controls are countries that remain non-democratic during this time period. The question here is how to identify democratic transition. To cope with the measure bias, I adopt two dichotomous democracy indexes simultaneously: one is from Boix et al. (2013) and the other is provided by Freedom House (2017).[3] According to Boix et al. (2013), a country is defined as democratic if it satisfies conditions for both contestation and participation. Specifically, "democracies feature political leaders are chosen through free and fair elections and a threshold value of suffrage is satisfied" (Boix et al. 2013). As they only focus on the election and male suffrage rate, their index is in fact to set the minimal level of "electoral democracy." Freedom House measures each country on political rights and civil liberties. A country can be recognized as electoral democracy if it has met certain minimum standards for political rights. Freedom House's term electoral democracy differs from "liberal democracy" in that the latter also implies the presence of a substantial array of civil liberties. Therefore, free countries can be considered both electoral and liberal democracies, while some partly free countries qualify as electoral, but not liberal, democracies. Based on these dichotomous indexes of democracy, the year of democratic transition is identified by examining the changes of coding values.

This research takes Indonesia as the treated case for three seasons. First, with the fall of Suharto, the first free and legislative election in Indonesia was held on June 7, 1999. Both Boix et al. (2013) and Freedom House (2017) regard the year 1999 as the beginning of democratic regime in Indonesia. Moreover, the democratic regime in Indonesia has not been severely interrupted since 1999. Second, as a developing country with large population, Indonesia is one of the greatest CO2 emitters in the world, with estimated CO2 emissions of 428,760 kt in 2010. Moreover, the carbon intensity in Indonesia is also relatively high, with 1.15 kg per constant 2005 US$ of GDP. Therefore, the reduction of CO2 emissions in Indonesia has been widely concerned in recent decades. Third, many empirical studies have examined the multifaceted effects of democratic transition in Indonesia (Antlöv et al. 2010; Bandiera and Levy 2011; Aspinall 2014), which can provide this study with a huge background knowledge.

According to the above two indexes, 24 countries remain non-democratic from 1980 to 2010, namely, Algeria, Bahrain, Cameroon, China, Congo, Democratic Republic of the Congo, Cote d'Ivoire, Egypt, Gabon, Haiti, Iran, Iraq, Jordan, Kuwait, Malaysia, Morocco, Myanmar, Qatar, Singapore, Syria, Tunisia, United Arab Emirates, Vietnam, and Zimbabwe. These non-democratic countries are used as controls.

Variables and data sources

The outcome of interest is carbon intensity, i.e., CO2 emissions per GDP (kg per constant 2005 US$ of GDP). The data are obtained from the World Development Index (WDI). As for predictors, SCM suggests that we should control the influencing factors as many as possible, so as to achieve the balance of properties between the treated case and its synthetic counterpart. If the characteristics of synthetic control are almost the same as that of the treated unit before treatment, then the treatment can be seen as randomly assigned. According to the existing literature, this research includes 12 predictors in five main categories (see Table 1). All data, except the electoral democracy index from Freedom House, are gained from the standard QOG dataset (version Jan 2017) provided by the Quality of Government Institute (Teorell et al. 2017).

The first category is the initial level of carbon intensity. Zhu et al. (2014) find that higher level of initial intensity means higher potential of reduction. The aim of including this predictor is to ensure the approximately same level of carbon intensity in the actual and synthetic Indonesia before democratic transition.

The second category is about state capacities, which contains two predictors. One is quality of government, measured

[3] The methodology report and dataset can be downloaded from the official website of Freedom House. https://freedomhouse.org/report/freedom-world/freedom-world-2017

Table 1 The definition of variables

Variables	Definition	Sources
Dependent variable		
Carbon intensity	CO_2 emissions per constant 2005 US$ of GDP	WDI
Treatment		
Democratic transition	A country as electoral democracy if it satisfies conditions for both contestation and participation (Boix et al. 2013) and meets the minimal standards of political rights (Freedom House 2017)	Boix et al. (2013) and Freedom House (2017)
Predictors		
The initial level of carbon intensity	CO_2 emissions per constant 2005 US$ of GDP	WDI
Quality of government	Mean value of three indicators: "Corruption," "Law and Order," and "Bureaucracy Quality"	The International Country Risk Guide
Political stability	Political stability and absence of violence index	Worldwide Governance Indicators
GDP per capita GDP per capita (squared)	Natural logarithm of GDP per capita (constant 2005 US$)	WDI
Industrial structure	The added value of services (% of GDP)	WDI
Trade openness	Sum of the imports and exports of goods and services (% of GDP)	WDI
Fossil fuel energy consumption	Fossil fuel energy consumption (% of total)	WDI
Energy intensity	Energy use per constant 2005 US$ of GDP	WDI
Urbanization	Urban population (% of total)	WDI
Total population	Natural logarithm of total population	WDI
Education	Average schooling years, both female and male (25+)	Educational Attainment Dataset(Barro and Lee 2013)

by the mean value of the International Country Risk Guide variables, i.e. "Corruption," "Law and Order," and "Bureaucracy Quality," scaled 0–1. Higher values indicate higher quality of government. A large body of literature has advocated that quality of government is positively associated with environment policy performance (Holmberg et al. 2009). The other is political stability, measured by political stability and absence of violence index in Worldwide Governance Indicators. Some authors have mentioned that political stability can affect the stringency of environmental regulation (Fredriksson and Svensson 2003).

The third category is economic factors (Roberts and Grimes 1997; Kretschmer et al. 2013; Zhang et al. 2014): (1) natural logarithm of GDP per capita (constant 2005 US$) and its squared value; (2) industrial structure, measured by the added value of services (% of GDP); and (3) trade openness, measured by summing the imports and exports of goods and services (% of GDP).

The fourth category is related to the structure and intensity of energy use: (1) fossil fuel energy consumption (% of total); the consumption of fossil fuel energy is a key source of CO_2 emissions; and (2) energy intensity, measured by total energy use per GDP (kg per constant 2005 US$ of GDP). Many scholars have argued that higher energy intensity will lead to higher carbon intensity (Ebohon and Ikeme 2006; Dong et al. 2016).

And the last category is concerned with three social-demographic factors: (1) urbanization, measured by urban population (% of total); (2) natural logarithm of total population; and (3) education, measured by average schooling years, both female and male (25+). The source of education data is the Educational Attainment Dataset (Barro and Lee 2013).

Results and discussion

Constructing synthetic Indonesia as weighted averages

Using the techniques of SCM, this paper constructs a synthetic Indonesia with the weighted combination of control countries from the donor pool.[4] Table 2 shows the weights assigned to every control country. Specifically, 7 countries have positive weights, while remaining 17 countries are zero. The maximum weight, 41.30%, is assigned to Congo, Democratic Republic, which means it is the most similar country to Indonesia according to the predictors and outcome in the pre-treatment period. The RMSPE is quite small, 0.057, indicating

[4] This research implements SCM with the R package "MSCMT" (Becker and Klößner 2018).

Table 2 Synthetic weights for Indonesia

Country	Weight (%)	Country	Weight (%)
Algeria	0	Kuwait	0
Bahrain	0	Malaysia	12.41
Cameroon	0	Morocco	0
China	5.97	Myanmar	0
Congo	7.63	Qatar	0
Congo, Democratic Republic	41.30	Singapore	0
Cote d'Ivoire	0	Syria	0
Egypt	29.00	Tanzania	0
Gabon	0	Tunisia	0
Haiti	0	United Arab Emirates	0
Iran	0	Vietnam	0
Iraq	2.47	Zimbabwe	0
Jordan	1.20		

that the synthetic Indonesia is closely resembling the actual Indonesia in the period before democratic transition.

Table 3 checks the balance of characteristics between actual Indonesia and its synthetic counterpart. Columns 1 and 2 are names of predictors and relevant years before treatment. Columns 3 and 5 are the simple averages of each predictor in the treated country (Indonesia) and all the control countries in the donor pool before 1999, while column 4 is the weighted averages of each predictor in synthetic Indonesia. It can be observed that large differences exist in each predictor between columns 3 and 5. For example, the quality of government, the degree of political stability, and the level of economic development in Indonesia are much lower than the average level of all control countries. However, if we compare columns 3 and 4, these differences have been effectively eliminated. By using weighted averages, SCM achieves a good balance of characteristics of the actual Indonesia and its synthetic counterpart. Thus, the synthetic Indonesia is reasonably constructed by SCM. The next step is to compare the actual and synthetic trajectory of carbon intensity in Indonesia during the post-treatment period.

The causal effects of democratic transition on carbon intensity

The upper half of Fig. 1 illustrates the trajectories of carbon intensity in Indonesia and its synthetic counterpart from 1980 to 2010. During the pretreatment period (1980–1998), the carbon intensity in synthetic Indonesia is quite close to that in actual Indonesia. However, their trajectories of carbon intensity diverge apparently after democratic transition in 1999 (the dotted vertical line). Specifically, the actual trajectory of carbon intensity presents an upward trend, while the synthetic trajectory of carbon intensity experiences an apparent decline with fluctuation. The bottom half of Fig. 1 shows the gap in carbon intensity between actual and synthetic Indonesia. The value of gap hovered at 0 before 1999, while it shot up to the peak value of 0.37 in 2002. After a 4-year decline, the intensity gap increased again, reaching a high value of 0.33 in 2009. The average gap in carbon intensity during these 12 years is 0.24, which suggests that democratic transition in Indonesia increases nearly 0.24 kg CO_2 emissions per constant 2005 US$ of GDP, a rise of approximately 25.34%.

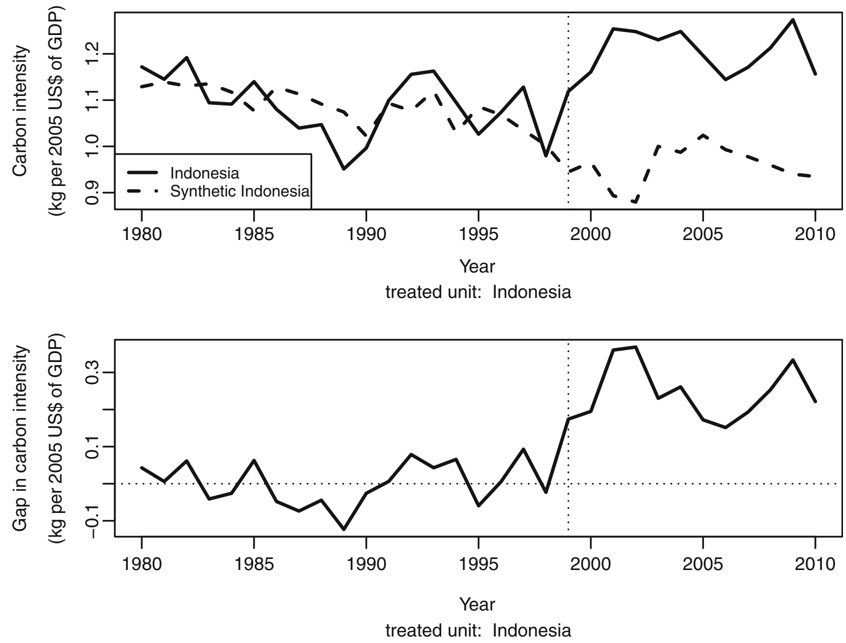
The placebo tests are employed to evaluate the significance of estimated causal effects in SCM applications (Abadie et al. 2010). Specifically, it works by iteratively assigning the treatment to the control units and proceeding with the same synthesizing algorithm as if they were treated in the same time. Then, researchers compare those placebo effects of control

Table 3 Balancing properties

Predictors	Year	Treated	Synthetic	All donors
Carbon intensity	1980–1998	1.09	1.09	1.20
Quality of government	1985–1998	0.33	0.35	0.48
Political stability	1996, 1998	− 1.47	− 1.45	− 0.46
Log (GDP per capita)	1980–1998	6.68	6.68	7.65
Log (GDP per capita) squared	1980–1998	44.71	45.18	60.65
Industrial structure	1990–1998	40.69	41.29	46.19
Trade openness	1985–1998	52.30	64.85	81.03
Fossil fuel energy consumption	1990–1998	58.37	51.58	66.45
Energy intensity	1980–1998	0.63	0.68	0.59
Urbanization	1980–1998	30.13	39.50	52.99
Log (total population)	1980–1998	18.99	17.36	16.13
Education	1985, 1990, 1995	3.57	3.56	4.15

This table reports the characteristics of the treated country (Indonesia), its synthetic control, and all the countries in the set of donors before 1999. The weights used to build the synthetic control are presented in Table 2

Fig. 1 The gap in carbon intensity between actual and synthetic Indonesia

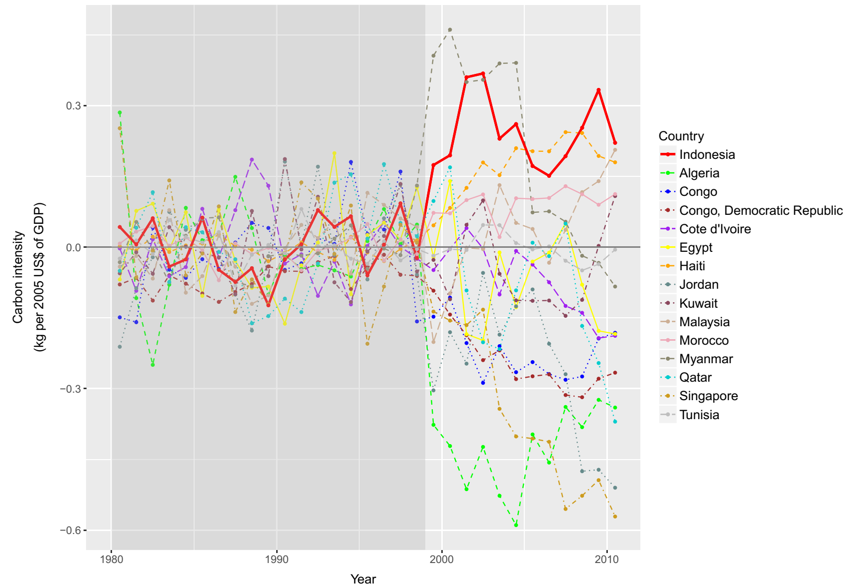


units with the effects observed in the treated units. "The intuition behind this test is that if the results are significant, there will be a low probability of observing an effect larger in a non-treated unit than the effect observed in the treated unit" (Birdsall 2016). In this research, placebo tests are implemented by iteratively assigning the treatment, i.e., democratic transition in 1999, to the countries in the donor pool. Abadie et al. (2010) suggest that those control countries with large RMSPE in the pretreatment period should be discarded because their poor fit may artificially produce misleading gaps observed in the post-treatment period. Following their recommendation, some donor countries are omitted as their values of RMSPE are more than two times larger than that of Indonesia. Only 14 control countries are left and Fig. 2 shows the results of placebo tests. The red solid line represents the gap of carbon intensity observed in Indonesia, while the remaining dash lines indicate the intensity gaps observed in those control countries. Apparently, no much difference exists among these countries in the pretreatment period, but in the post-treatment period, the red solid line is among the highest and goes above all dash lines at the end, indicating the intensity gap in Indonesia is unusually large relative to the distribution of intensity gaps in those remaining 14 countries. Approximately, its probability of occurrence is $1/(1 + 14) = 0.067$. Therefore, the placebo tests indicate this estimated causal effect is significant.

As the weighted average of control units, the synthetic trajectory of carbon intensity may be sensitive to the changes in the weights of these countries. Abadie et al. (2015) suggest that the robustness of the SCM results can be checked by using a series of leave-one-out tests. Specifically, the baseline model is re-estimated iteratively to construct the synthetic Indonesia, but in each iteration, one of the control units that received a positive weight in baseline model is excluded. If a major change appears in the trajectory of synthetic Indonesia when one of control countries is omitted, then the SCM results are to some degree driven by this particular country. Figure 3 shows the results of robustness check. The solid and dash black lines represent the trajectories of carbon intensity in Indonesia and its synthetic counterpart, while the gray lines represent the leave-one-out estimates. It shows that almost all of gray lines are below the black line and share the same trend with the dash line, suggesting that the previous SCM results are quite robust to the exclusion of any particular countries with positive weights. Additionally, the figure shows that one gray line exceeds the black line during the period from 2004 to 2006. It happens when China is excluded in the leave-one-out test. However, even this smallest effect is still quite large in substantive terms: the average carbon intensity in the period 1999–2010 is increased by 0.075 kg per constant 2005 US dollars, approximately 6.67%. Therefore, this estimated causal effect is robust.

It seems to be abnormal that democratic transition leads to a significant increase, rather than a reduction, in the carbon intensity in Indonesia, because many studies have advocated that democratization will lead to a better environment. Here, this paper attempts to discuss this result from the three aspects. First, although the causal effect of democratic transition on carbon intensity is negative, this result does indicate that the type of political regime, which has been overlooked by those environment and energy economists, plays an important role in the change trajectory of carbon intensity in Indonesia. It will be meaningful to explore carbon intensity reduction from the environmental politics perspective. Second, as Table 3 shows,

Fig. 2 The placebo tests of estimated causal effects

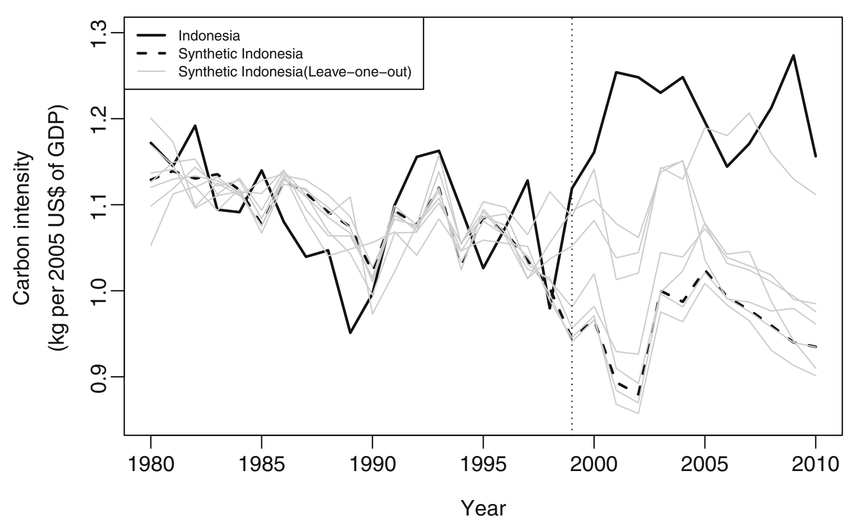


the pre-transition Indonesia features poor quality of government and low level of political stability, with the value much lower than the average level of 24 non-democratic countries, indicating that the capacities of state are relatively weak. Fukuyama (2014) argues that state capacities and democracy are mutually supportive and democratization may be destructive without being supported by a relatively strong state. Moreover, Fukuoka (2013a, b) finds that democratization leads Indonesia to "oligarchy" rather than "liberty," which facilitates a decentralized patronage networks and redistributing spoils within the state towards elites that had been excluded from Suharto's inner circle. Therefore, a lack of state capacities may make democratic transition harmful to the environment. Third, the post-transition period in this study is 12 years, which is relatively short, so it may not capture the lagged effects of regime change. For example, Policardo (2016) finds that the beneficial effects of democracy on the environment are lagged and small, detectable only in the long run. This study shows that the negative effect of democratic transition reaches its peak in the third year after transition and then shows a small downward trend with fluctuation. Therefore, the optimistic outcome is that the negative effect of democratic transition is just a short-term phenomenon; it will change to the opposite in the long run.

Conclusion and policy implications

The reduction of carbon intensity has become an issue of worldwide concern in recent years. This paper examines the causal effects of democratic transition on carbon intensity in Indonesia by using SCM. The main finding is that democratic transition in Indonesia increases carbon intensity by approximately 25.34%. The placebo tests indicate the estimated causal effect is significant and the leave-one-out check also

Fig. 3 Robustness check with leave-one-out tests



demonstrates its robustness. Therefore, democratic transition intensifies, rather than mitigates, CO2 emissions in Indonesia.

This paper makes two contributions to the exiting knowledge of carbon intensity reduction. First, it reveals that political institutions do affect carbon intensity. Existing literature has explored multiple influencing factors of carbon intensity, such as economic development, energy intensity, industrial structure, and urbanization. However, the role of political institutions is surprisingly overlooked. Focusing on democratic transition, this paper opens the political horizons on carbon intensity research. Second, it shows that causal inference is very useful to uncover the impact of major events, such as regime transition, policy change, and natural disasters, on the environmental performance. By using SCM, this paper reveals the negative impact of democratic transition on carbon intensity in Indonesia.

The policy implication of this paper is that policymakers should pay more attention to adverse effects of democratic transition. Under the waves of global democratization, more and more developing countries are likely to experience the transition of political regime. The evidence of Indonesia reminds policymakers to be cautious because democratic transition is not a quick cure for environmental degradation. It will be helpful if policymakers can consciously rethink the contextual fit of democratic regime and enhance state capacity to eliminate its possible adverse effects.

Some limitations exist in this research. First, only one treated country, Indonesia, is examined, so the generalizability of conclusion is limited. Future studies can improve causal inference by taking more countries that experience democratic transition as the treated group. Second, it only reveals the causal "effects" of democratic transition on carbon intensity; the causal "mechanisms" behind them are still unexplored. Some qualitative methods, such as longitudinal case study and process tracing, can be adopted to obtain mechanism-based explanations.

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Compliance with ethical standards

Conflict of interest The author declares that there is no conflict of interest.

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