

Article

Is Economic Connectedness Likely to Raise the Environmental Footprint?

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Abstract

Economic connectedness has been recently found to lower income inequality by rising intergenerational mobility, yet its environmental impacts are less well known. More well-known is the fact that the non-carbon footprint is easier to reach via regulations because its production is domestic. These two problems of income inequality and environmental pollution have echoed in public opinion polls as one of the major current problems in developed countries. We thereby look at the United States on the state level during the last two decades (2010–2020) with a Hausman–Taylor estimator for panel data. The choice of the estimator stems from its appropriateness for panel datasets with constant variables. We find that in the United States, economic connectedness between friends, whereby friendships were formed within the same group, may be blamed for the rising environmental (non-carbon) footprint. The non-carbon footprint is, therefore, explained by the bonding of social capital, which may restrict innovation. We document the case where social capital in the form of economic connectedness may be harmful to the public good, such as the environment, our main contribution. The negative effect of bonding social capital on environmental outcomes due to rigid social networks and particular network technology use is a novel addition to the prior research. The policy implications are discussed in more detail, and a call is made to distinguish social capital types and promote bridging social capital where bonding social capital is relatively strong.

Keywords: non-carbon footprint; economic connectedness; environment; social capital; Hausman–Taylor estimator



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1. Introduction

The footprint of grazing land, built-up land, fishing, and forest, namely the non-carbon footprint, puts pressure on the environment in the place of production [1]. With increased globalisation, international trade allows more affluent societies to outsource nature-based production in poorer countries through imports, thus enabling them to improve environmental quality at home and meet their ecological footprint empowered by efficient technology and pro-environmental attitudes [1]. Therefore, until low-income countries have reached income levels that yield environmental improvements and improve environmental conditions worldwide, it is necessary that researchers and policymakers investigate what drives the non-carbon footprint in developed economies and put regulations in place, starting with easier-to-regulate domestic production.

On a policy agenda level, environmental footprint has been addressed by the Sustainable Development Goals through promoting sustainable consumption and production patterns (Goal 12), transitioning to clean energy (Goal 7), and preserving terrestrial (Goal 15) and marine (Goal 14) ecosystems.

In the United States (US), the environmental footprint due to domestic production has not yet been linked to the economic connectedness. Economic connectedness is measured by the interaction across class lines, or defined as the degree of cross-socioeconomic status (SES) friendships (i.e., how much people with low SES are socially connected to people with high SES), and is the form of social capital most strongly associated with economic mobility in developed countries [2] of individuals, and a measure of social capital. With social capital being capable of being built up through public policymaking [3] and having positive effects, such as the promotion of socially minded behaviour and social spillover [4]. It is worthwhile to study its effects on the non-carbon footprint as a tool and determinant of the latter.

Thus, this investigation takes up a challenge to dissect social capital's effects on the United States' non-carbon footprint over the last two decades using the Hausman–Taylor estimator (see Section 3). Specifically, we ask: is economic connectedness affecting non-carbon footprint, and if so, in which direction? We aim to find out whether economic connectedness always has a positive, environment-enhancing effect, or if it may also be related to lower environmental performance. We find that economic connectedness is likely to raise the non-carbon footprint (see Section 4). Specifically, we have asked whether better economic connectedness leaves us with a lower non-carbon footprint. We hypothesise that more social capital in the form of economic connectedness is related to better management of environmental resources and industrial impacts and thus results in a lower non-carbon footprint.

However, the results confirm that the opposite may be true. While the symmetrical logic following this result would suggest that segregation of classes would aid in curbing the non-carbon footprint, we offer an alternative explanation (see Sections 5 and 6 for Discussion and Conclusions, respectively).

This investigation aligns with the work on sustainability planning and scale complexity. Rees [5] has suggested that humans, as social beings who live in extended groups, overwhelm local ecosystems and need a sense of belonging to the community to bring sustainability. This needs to be performed on bioregional levels. Selman [6] recites the idea of increased social capital as being able to curb losses in eco-capital. However, to this day, these ideas have found little support in the empirical research track.

Therefore, as the main contribution to the literature, we document the case where social capital in the form of economic connectedness may be harmful to the public good, such as the environment. We find that bonding ties with friends can decrease innovation and harm the environment. This is yet a less documented implication of social capital effects on environmental-related outcomes. Previously, social capital has been found to promote pro-environmental behaviour and enhance environmental knowledge [7], ease adaptation to climate change [8], and positively impact compliance with both compulsory and economic environmental policy instruments, as well as voluntary measures [9].

The article is organised as follows: Section 2 reviews the literature, Section 3 describes the data and methodology used, and Section 4 describes empirical results. Section 5 discusses the results, and Section 6 concludes.

2. Literature Review

We start by reviewing the past work on this subject to better explain the model we drew up (see Figure 1) and test it in later sections.

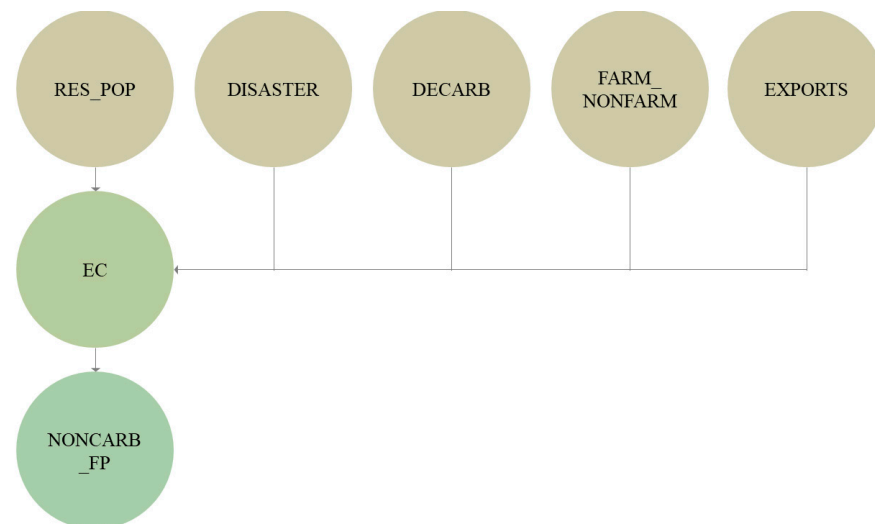


Figure 1. Instrumental variable model of non-carbon footprint. Note: RES_POP denotes resident population; DISASTER denotes disaster resiliency; DECARB denotes decarbonisation; FARM_NONFARM denotes farm-to-nonfarm production ratio; EXPORTS denotes high-technology exports; EC denotes economic connectedness; and NONCARB_FP denotes non-carbon footprint.

Whereas Figure 1 is specific and available data-restricted (further in brackets) in testing how globalisation (exports), the number of people living in the area, disaster resiliency, and industry type (decarbonisation, agriculture) affect economic connectedness, we first review the more abstract theoretical relations from general (social capital) to its specific measurement (economic connectedness) and reference some recent empirical work.

2.1. Social Capital—Economic Connectedness

Social capital can be defined as collective assets, such as norms, values, trust, networks, and others, that facilitate cooperation and collective action for mutual benefit [10]. Generally, two distinct types have been distinguished: bonding and bridging capital. Bridging capital bridges external actors to the focal one, where the focal actor can gain access to others' resources through new network connections. Bonding capital strongly ties the actors with similar backgrounds and interests [11]. Economic connectedness, measuring the interaction across class lines, is the form of social capital most strongly associated with economic mobility in developed countries [2]. It is due to mobility's positive income inequality outcomes, which are also some of the most salient ones. It can be seen as a bridging form of social capital, because there are *bridges* built between the high- and low-socioeconomic statuses. As defined by [2], economic connectedness is a measure of interaction between individuals and high and low social statuses, whereby social status is an index with variables used to predict socio-economic status in a machine learning model being age, city prediction, college attended, county prediction, gender, language, phone model, estimated phone price, mobile carrier and phone operating system type, average donation amount, graduate school attendance, among other variables. Economic connectedness in groups of friendships in which they were made can be understood as a measure of social interaction within the same-origin friendship groups.

2.2. Factors That Impact Non-Carbon Footprint via Economic Connectedness

Now we discuss what factors (used as the instruments in our benchmark model) impact the non-carbon footprint through economic connectedness. Similar to our large analyses, we have found that social capital has a carbon-diminishing effect, with the environmental Kuznets curve first rising and then dropping in emissions [12]. No current

evidence of carbon emissions affecting social capital exists. Yet, we hypothesise that more developed and emission-heavy environments have low social capital.

The other factor impacting economic connectedness is globalisation. Regarding globalisation and its proxy migration as the indicator, it theoretically affects social capital in both the sending and receiving countries. The social capital drops in the receiving developed country [13]. We know that with lower population density, there are higher levels of social capital in the US [14], and there are more resident populations where the population density is low. That is, immigrants are more concentrated in US cities and suburbs [15]. Thus, one may infer that the social capital levels are higher when there are more resident populations (the rural areas). This is partly approved by [16], who find that rural and urban region residents do not differ on aggregate. Yet, urban areas see less participation and trust than semi-urban and rural regions. The rural regions are also expected to have a higher farm-to-farm production ratio, such that rurality affects social capital.

Regarding disaster resiliency, economic, social, environmental, institutional, infrastructural, and community capital aspects of disaster resilience may univocally impact social capital, and assistance post-disaster has proven to enhance the growth in social capital [14]. Generally, disaster community literature states that increases follow consensus crisis shocks in social capital, while corrosive community shocks are in decline. Still, the strength and effect are also decisive factors [17]. We therefore hypothesise that disaster resilience, as a community's cumulative ability to cope with shocks, should be related to higher social capital in those states.

The more explored causality regarding high-technology exports asks how social capital may affect export growth. However, we wish to shed light on the opposite: how exports (which, along with interstate trade, relate to spatial cluster formation and natural and created comparative advantage) [18] affect the formation of social capital. We hypothesise that clusters attract immigrant workers because there is a lack of a specialised workforce at home, and thus, with immigration, social capital drops. However, contrary to the individual-level social capital, the firm-level social capital may rise; therefore, on aggregate, social capital is kept at the same level as before the cluster formation. This analysis focuses on individual-level social capital within the state.

Thus, we turn to the question of the investigated matter, that is, whether economic connectedness rises, diminishes, or does not impact the non-carbon footprint in a developed country setting. Based on the literature just reviewed, we assume that with a higher density of resident population, social capital rises, but at very high levels of population density, it drops, exhibiting an inverse U-curve relationship. This might be because of the fact that in high levels of population density, society becomes highly independent due to the division of work tasks and the short-termism of contacts and social contracts between inhabitants, whereas at very low levels of population density, the linkages between the actors are hard to establish. Therefore, the sign of the population density effect on economic connectedness varies by percentile. Next, the effect of disaster resiliency on social capital is rather positive, as seen in the post-disaster literature. Regarding decarbonisation, we repeat that the hypothesis goes as follows: more developed and emission-heavy environments have low social capital. Regarding the ratio of farm to non-farm labour, the rural regions where there is more farm-to-non-farm labour may see higher participation and trust, as evidenced in the literature. Finally, exports as the proxy for globalisation do not lead to high social capital, as discussed in the previous paragraphs.

Apart from signals just discussed affecting social capital itself, we consider the main question to lie in the linkage between social capital and environmental footprint, more specifically, a non-carbon footprint, which is characteristic of the local production activity (see Figure 2). We do not make any anterior hypothesis due to the lack of literature on the

subject and bring about novel results as a result. Indeed, there is no previous literature covering the question of social capital and environmental footprint in the highly developed country context.

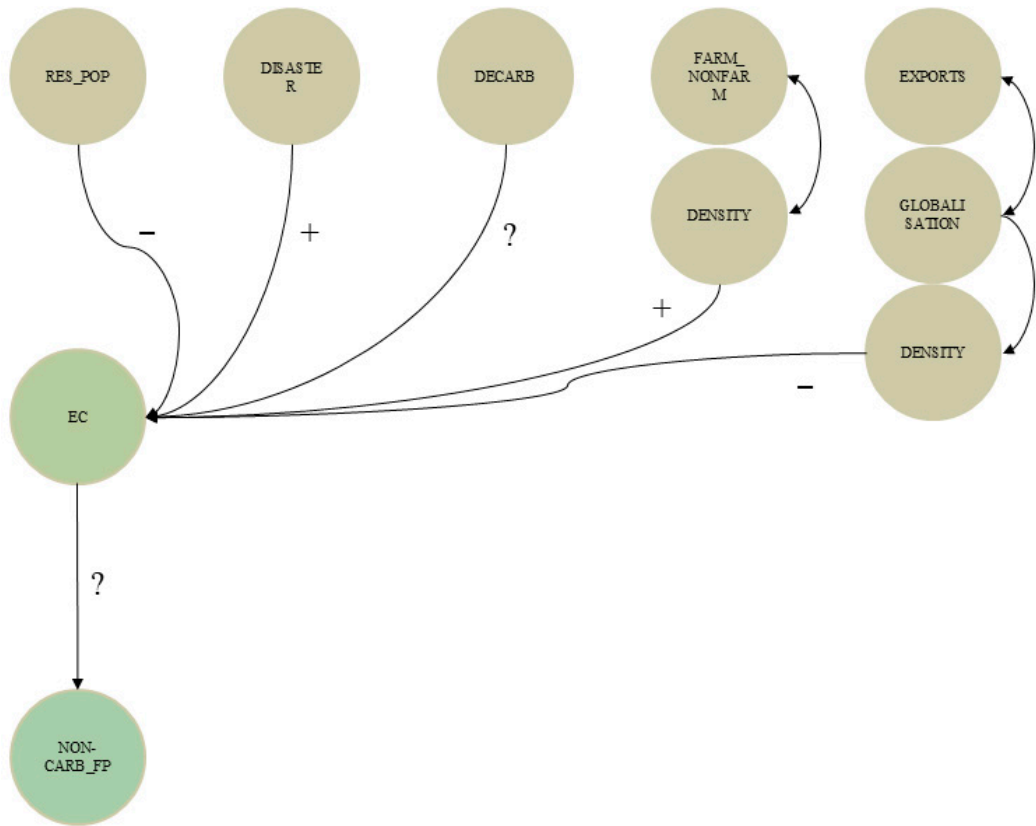


Figure 2. Conceptual framework.

3. Data and Method

The dataset is composed of variables listed in Table 1 for all states in the United States for the years 2010 and 2020, making it rather cross-sectional. The data is annual, and there are two instances for which it was collected: 2010 and 2020.

Table 1. Data description and sources.

Variable	Full Name	Source
NONCARB_FP	Non-carbon footprint	[19]
RES_POP	Resident population	[20]
DISASTER	Disaster resilience	[21]
DECARB	Decarbonisation	[22]
HT_EXPORTS	High-tech exports	[22]
FARM_NONFARM	The ratio of farm to non-farm production	[21]
FOREIGN	Foreign-born population	[20]
EC	Economic connectedness within group membership	[23]

Note: All variables were readily taken by state, and no transformations from levels of aggregation were made.

The non-carbon footprint represents the environmental impacts of production and consumption that exclude carbon emissions, including resource use, land transformation, water depletion, air pollution, and ecological degradation. Resident population is defined as the population who “usually resides” in the state, excluding residents of US territories, US military personnel stationed overseas, and US citizens living abroad. Disaster resilience measures a community’s ability to absorb and recover from disasters by assessing social vulnerability. The data uses American Community Survey and Population Estimates Program

data to analyse factors like income, age, education, disability, and internet access to generate resilience scores for neighbourhoods. Decarbonization is measured in CO₂ emission tons per capita. High-tech exports are measured in the total value added of exports between NAICS 333, 334, and 335. The ratio of farm to non-farm production is the total value of agricultural output relative to the output of all other industries in a region. The foreign-born population is anyone who is not a U.S. citizen at birth, which includes naturalised citizens, lawful permanent residents, temporary migrants (like students), humanitarian migrants (like refugees), and unauthorised migrants. Economic connectedness is defined as the degree of cross-socioeconomic status (SES) friendships (i.e., how much people with low SES are socially connected to people with high SES). The economic connectedness within group membership specifically is selected due to the fact that it reflects bonding social capital.

The variables used in the model aim to reflect the urbanisation rate and economic sophistication of the production, as well as environmental performance, such as disaster resilience and decarbonisation rate. The ratio of farm to non-farm production relates to the non-carbon footprint, as the non-carbon footprint is related to the place of production, and farming has a strong impact on the environmental performance. Lastly, the foreign-born population aims to capture the effects of internationalisation reflected in the population.

Due to the panel's short time span, there are only 95 observations (see Table 2). The most dispersed data are found for the resident population and farm-to-nonfarm production ratio, whereas the most concentrated variable is disaster resiliency, which signifies largely similar preparedness to disasters in all states.

Table 2. Descriptive Statistics.

Variable	Obs.	Min	Max	Mean	S-D
NONCARB_FP	95	1.649	1.943	1.788	0.1012
RES_POP	95	13.700	16.370	15.190	0.8830
DISASTER	95	−0.840	−0.584	−0.702	0.0887
DECARB	95	2.504	3.387	2.892	0.2849
HT_EXPORTS	95	−4.999	−3.533	−4.228	0.5121
FARM_NONFARM	95	−6.974	−3.361	−5.111	1.0903
FOREIGN	95	−3.409	−1.702	−2.616	0.5785
EC	95	−0.3041	0.1479	−0.0395	0.1481

Note: All variables are in logs and winsorised by the upper and lower 10%. Obs. and S-D denote the number of observations and standard deviation, respectively. Note 2: It is an unbalanced panel, i.e., $n = 8$, $T = 11$ – 12 , $N = 95$. There were two missings for HT_EXPORTS and DECARB, and three missings for FARM_NONFARM, making it less than 100 observations.

The steps of the empirical approach are depicted in Figure 3. The data on economic connectedness were first merged from county to state levels, and the county indices were averaged for the state.

The estimation method [24] was applied to assess its suitability for the time-invariant variables (in our case, the main regressant EC). The other variables are variables, and there are no quasi-invariant variables. It also handles models with unobserved heterogeneity and can be referred to as a regression technique that mixes random and fixed effects. We choose the Hausman–Taylor estimator in place of the other time effect estimators, as the autoregressive distributed lag (ARDL), due to its ability to handle EC invariance to time. The Hausman–Taylor estimator is an instrumental-variables-based panel data technique that identifies and consistently estimates coefficients on time-invariant and potentially endogenous regressors by exploiting the orthogonality between within- and between-individual variations. It constructs instruments internally from exogenous components of the model, thereby achieving efficiency gains over fixed effects while avoiding the biased parameter estimates characteristic of random effects in the presence of endogeneity. The

Hausman–Taylor estimator was summarised in [25]. It assumed orthogonality between the error term and individual effects, that is,

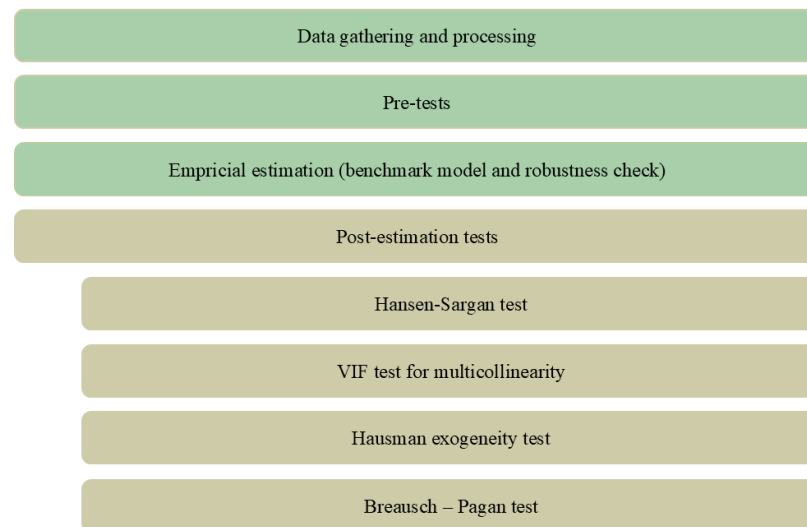


Figure 3. The empirical approach of the investigation.

The standard panel data model with time-invariant variables

$$y_{it} = X'_{it}\beta + Z_i\gamma + \mu_i + \varrho_{it} \quad (1)$$

where covariates X_1 and Z_1 denote exogenous variables, X_2 and Z_2 denote endogenous variables, and Z_i denotes time-invariant cross-sectional variables; we are left with

$$y_{it} = X'_{1it}\beta_1 + X'_{2it}\beta_2 + X'_{3it}\beta_3 + X'_{4it}\beta_4 + X'_{5it}\beta_5 + Z_{1i}\gamma_1 + \mu_i + \varrho_{it} \quad (2)$$

and in terms of the particular benchmark model, with

$$NONCARB_FP_{it} = RES_POP'_{1it}\beta_1 + DISASTER'_{2it}\beta_2 + DECARB'_{3it}\beta_3 + HT_EXPORTS'_{4it}\beta_4 + FARM_NONFARM'_{5it}\beta_5 + EC_{1i}\gamma_1 + \mu_i + \varrho_{it} \quad (3)$$

First, a within transformation is performed. All variables in regression are deducted from their group's individual mean, and within-group estimators and residuals are obtained. Then, the residual is regressed on time-invariant variables, using X_{1-6} exogenous variables as instruments, and a random effect estimation can be performed for each variable. Finally, a Hausman–Taylor estimator is obtained by instrumental variable regression.

We draw up similar OLS, FE, and RE models to supplement the Hausman–Taylor benchmark model. Different instruments are utilised for Hausman–Taylor estimation, as shown in Equation (4).

$$NONCARB_FP_{it} = RES_POP'_{1it}\beta_1 + DISASTER'_{2it}\beta_2 + DECARB'_{3it}\beta_3 + HT_EXPORTS'_{4it}\beta_4 + FOREIGN'_{5it}\beta_5 + EC_{1i}\gamma_1 + \mu_i + \varrho_{it} \quad (4)$$

Lastly, the assumptions of the absence of collinearity [26], exogeneity for the EC variable [27], and homoskedasticity [28] are tested. The Hansen–Sargan test is applied to test for instrument validity [29].

4. Empirical Results

Before estimating the benchmark model, we draw up a matrix of correlations, test for multicollinearity with VIF, and test for cross-sectional dependence. We depict the results in Table 3 below.

Table 3. Pre-test results.

Test Name	Statistics/Variables			
Exogeneity test (Hausman)	Chi ² 14.852	Df 4	p-value 0.0050	
Multicollinearity (VIF) test	EC 1.2663	FARM_NONFARM 1.1757	NASICI 1.5859	RES_POP 1.5895
Homoskedasticity test (Breusch–Pagan)	BP 5.2747	Df 4	p-value 0.2603	

Notes: H_0 for the Hausman test is that random effects are at work; this hypothesis is rejected in favour of fixed effects. VIF values are usually deemed to be high if the value is higher than 8. H_0 for Breusch–Pagan test is the presence of heteroskedasticity.

Next, we present the matrix of correlations between the variables that enter the Hausman–Taylor estimation, presented in Figure 4. Although the correlation between some variables, such as EC and NONCARB_FP, is quite high, we reinforce the idea that the two are highly different in nature and come from different sources with different natures.

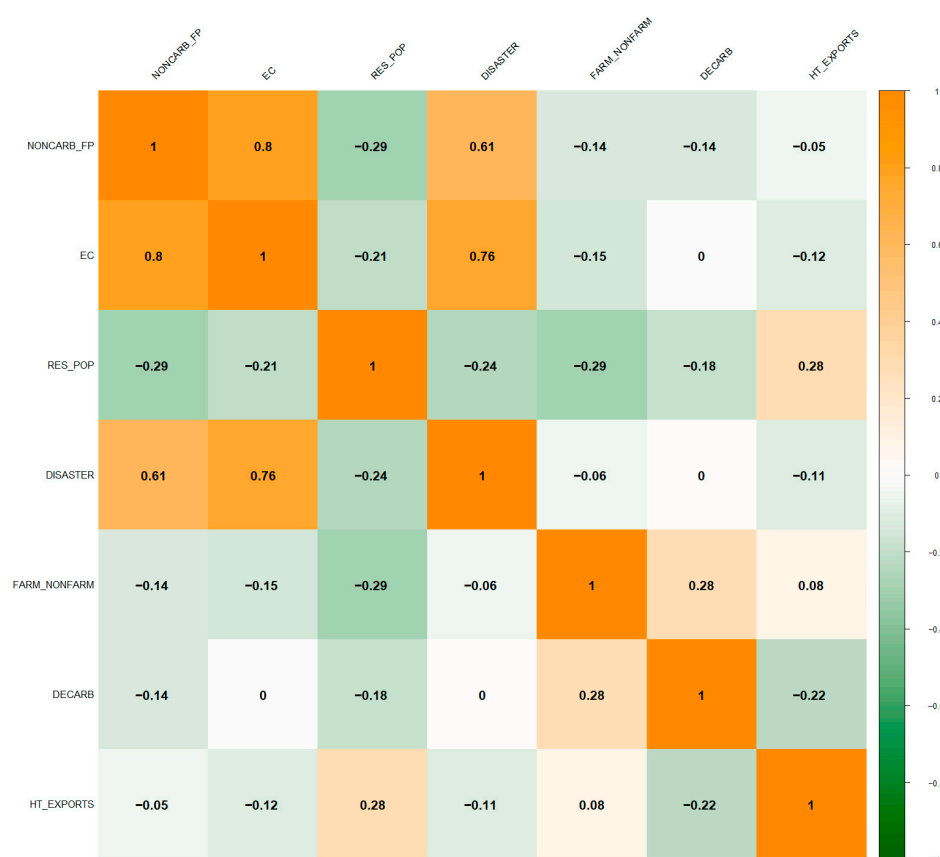


Figure 4. Correlation matrix. Source: authors' calculations.

We first estimate the benchmark model via the Hausman–Taylor estimator (instrumented by resident population, disaster resiliency, farm-to-nonfarm production, decarbonisation, and high-technology exports). Then, similar models involving the NASICI competitiveness index are tested via OLS, FE, and RE, as can be seen in Table 3. The

NASICI variable is included only in models other than the benchmark models because it is not likely to impact economic connectedness instrumentally. The other regressions are supplemented by variables that previously entered the Hausman–Taylor estimation as instruments, namely, resident population and farm-to-nonfarm production. The choice of not using all instruments as independent variables is due to the significance of the data-tested modelling, not as much due to the conceptual and theoretical considerations. However, we hold that farm-to-nonfarm production should directly impact the footprint from non-carbon emissions and, therefore, include it in OLS, FE, and RE models.

Estimation results in Table 4 (see Equation (3)) show that economic connectedness (EC) strongly predicts a non-carbon footprint (NONCARB_FP). The non-carbon footprint rises with a smaller resident population (RESID_POP) and a higher competitiveness index (NASICI). While the farm-nonfarm production ratio (FARM_NONFARM) is a valid instrument for economic connectedness, it is not a strong enough predictor of the non-carbon footprint. Because all the econometric estimations follow the same pattern, we declare the benchmark estimation to be robust. Next, we turn to estimations for robustness with different sets of instruments (see Equation (4)), focusing on globalisation and thus involving foreign-born population and competitiveness, but not farm-nonfarm production.

Table 4. Estimation results for instrumental variables of Equation (3).

Dependent: NONCARB_FP	Hausman–Taylor	OLS	FE	RE
<i>Time-varying exogenous</i>				
RESID_POP		−0.0350 ***	−0.0314 ***	−0.0334 ***
DISASTER				
FARM_NONFARM		−0.0034	−0.0078	−0.0053
DECARB				
HT_EXPORTS				
FOREIGN	-			
NASICI	-	0.1639 ***	0.1474 ***	0.1564 ***
<i>Time-invariant endogenous</i>				
EC	0.5489 ***	0.4517 ***	0.4245 ***	0.4406 ***
Constant	1.8094 ***	1.6723 ***		1.6676 ***
Number of observations	95	95	95	95
Total sum of squares	0.8537		0.7750	0.9221
Residual sum of squares	0.3137		0.2279	0.2563
R-squared	0.6334	0.7105	0.7060	0.7222
Adjusted R-squared	0.6294	0.6976	0.6670	0.7099
F-statistic	-	55.22 ***	49.821 ***	
Wald chi-square	100.321 ***			217.612 ***
Hansen–Sargan test	0.4107 ***			

Note: All variables enter regressions in logs and are winsorised to the upper and lower 10%. The R function “PLM” was used to obtain results for Hausman–Taylor and FE, RE estimation, and “lm” to obtain OLS estimates. The Hausman–Taylor model uses classical standard errors. Hereafter, *** denotes 1% significance level.

In Table 5, one can again notice that the general effects of economic connectedness (EC) on non-carbon footprint (NONCARB_FP) remain the same, but the effect is slightly larger in the case where we instrument for globalisation (FOREIGN). The resident population (RESID_POP) seems to have reduced its footprint, while more competitive industries (NASICI) in the state have raised it. These three main results remain largely intact. It must be kept in mind that coefficients should be interpreted as elasticities.

Table 5. Estimation results for instrumental variables of Equation (4).

Dependent: NONCARB_FP	Hausman–Taylor	OLS	FE	RE
<i>Time-varying exogenous</i>				
RESID_POP		−0.0351 ***	−0.0312 ***	−0.0342 ***
DISASTER				
FARM_NONFARM	-			
DECARB				
HT_EXPORTS				
FOREIGN		0.0072	0.0111	0.0078
NASICI	-	0.1546 **	0.1384 **	0.1512 **
<i>Time-invariant endogenous</i>				
EC	0.5718 ***	0.4514 ***	0.4242 ***	0.4463 ***
Constant	1.8103 ***	1.7467 ***		1.7450 ***
Number of observations	95	95	95	95
Total sum of squares	0.8579		0.7750	0.9489
Residual sum of squares	0.3178		0.2318	0.2682
R-squared	0.6335	0.7102	0.7009	0.7174
Adjusted R-squared	0.6296	0.6973	0.6613	0.7049
F-statistic		55.14 ***	48.6281 ***	
Wald chi-square	137.937 ***			217.988 ***

Note: All variables enter regressions in logs and are winsorised to the upper and lower 10%. The R function “PLM” was used to obtain results for Hausman–Taylor and FE, RE estimation, and “lm” to obtain OLS estimates. Hereafter, ***, ** denotes 1% and 5% significance levels, respectively.

We have tested our results after regressions (see Table 6).

Table 6. Post-estimation tests.

Equation (3) (Table 3)	Hausman–Taylor	OLS	FE	RE
Hansen–Sargan test	0.4107 ***			
VIF (max value)		1.5895		
Hausman exogeneity test			27.731 ***	
Breusch–Pagan test				5.2747
Equation (4) (Table 4)				
Hansen–Sargan test	1.9028 ***			
VIF (max value)		2.2822		
Hausman exogeneity test			24.344 ***	
Breusch–Pagan test				5.5672

Note: Hereafter, *** denotes 1% significance level.

The Hansen–Sargan tests’ [29] validity of the instrument choice, the shallow variance inflation factor values allow us to assume there is a lack of collinearity [26]. Durbin–Wu–Hausman [27] tests allow us to conclude that the RE alternative is the consistent estimator, and the Breusch–Pagan test [28] establishes that the variance of the errors from regression is dependent on the values of independent variables; that is, there is no significant homoskedasticity.

5. Discussion and Implications for Policy

The principal model of economic connectedness in groups of friendships in which they were made, bringing about a higher non-carbon ecological footprint, could be explained by the narrative of two existing research streams with respective results: rigid social networks and information technology use.

5.1. Rigid Social Networks

First, friendships that can be allocated to the group they were formed in suggest that individuals in question do not generally reallocate and maintain friendships within the same groups. This is because the further one lives, the less likely one is to form friendships with someone of a different age and race [30].

This suggests a rigid social network, where the more closely tied structures bring about constrained social behaviour and less innovation [30]. If this is the case, and social capital is of bonding (opposite of bridging as distinguished in [31] type, which is likely in the case of same-group social connectedness, as it is easier to maintain in the long-term [32]. Then friendships made and maintained in the same groups are less likely to bring about (economic and social) innovation. Less innovation is, in turn, related to more primary-sector-oriented economic activities where less technology is applied. This is due to the general finding in developed countries that patents (innovativeness) and value added are generally positively correlated [33], at the same time, abstaining from claiming industries to represent homogeneous technologies.

5.2. Information Technology Use

Another explanation of friendships maintained in the same group in which they were formed might be related to better and more widely used information technology and online social networks. While physical distance matters despite the internet, relationship persistence has changed. Nevertheless, most networks in the US are within driving distance [34].

The other minor findings from complementary models indicate that the amount of resident population and economy being knowledge-based, globalised and innovation-ready takes a front seat in determining the non-carbon footprint outcome. While the resident population has a footprint-relieving effect, we find that overall competitiveness raises footprint. This dynamic ties well with our previous observation that bonding social capital-driven states is less innovative, productive, and, therefore, less polluting. At the same time, competitiveness brings about a larger non-carbon footprint.

The policy implications of these findings, abiding still by the general result found in the literature of social capital generally bringing a positive impact on emission reduction or doing so in a Kuznets way, may imply that we need to find new ways to inject bridging social capital in states and communities where social capital of the bonding type is prevalent and strong. This is to be performed in order to revive innovation in closely tied groups, which may otherwise abide by know-how already embedded into the industry in which production takes place. This improvement could potentially bring new innovation from individuals of other income levels and, likely also, economic migrants, who may otherwise choose to immigrate into states with lower resident populations where the bridging social capital is already high (that is, they have an easier time developing bridges to climb the income ladder).

Although community action is predicted by bridging and bonding social capital, one form can compensate for weaknesses in the other [35]. We find that the bonding social capital undermines environmental outcomes and calls for careful actions that set bridging capital to emerging, as bonding capital may be hampered on the way [36]. Dispersed social housing programmes, school class composition programmes, and other actions aiming at closer interactions across socio-economic levels for individuals and families of all ages and races can inject bridging social capital in places with high bonding capital.

However, caution must be taken when interpreting the findings very strongly, as the research suffers from scarce data availability, drawing on a rather small set of observations available for two decades (2010 and 2020). We nevertheless maintain that the key relation-

ship between social capital and environmental footprint may not always be positive, as shown in this investigation.

6. Conclusions

We have established a possible interconnection between social capital and the non-carbon footprint, and we now call for further exploration of the mechanisms at work.

The hypothesis of social capital having a positive effect on the non-carbon footprint is not supported; bonding social capital may be, in fact, negatively related to the non-carbon footprint. This finding is supplemented by the fact that a higher resident population diminishes the footprint, while the higher competitiveness of the state increases it. They are relevant to the discussion on social capital-enhancing policies as a tool for collective, environmentally conscious action resulting in better environmental outcomes. Significantly, we may not always reach positive environmental outcomes when promoting bonding social capital. Therefore, distinguishing between social capital at all levels of policymaking is advised. That said, bonding social capital—social capital that is based on networks that are close-knit, continuous, and strong—may be harmful. To reach the benefits of high social capital, one may want to focus on bridging social capital, which characterises weaker ties applied across broad social networks. Such ties can be developed in large community groups, such as larger voluntary groups and broader school classes, and mingling activities in after-school interest education groups, to give a few examples for all age groups.

As for limitations of the study, these findings establish a research avenue and demand more inquiry with other developed country datasets or, when available, a longer time span inquiry in the United States. Indeed, the time span considered in this study does not allow for a high-precision study of changes in social capital and their effects on the non-carbon footprint. Neither does the limited number of cross-sections allow us to draw broader conclusions that would apply to developed countries in general.

As for future research prospects, in the future, therefore, upon the development of social capital measures for other developed countries, one may want to study other areas where economies and societies are highly developed. Moreover, one may want to track developments of social capital, natural resources, and environmental footprints in particular through the centuries, to reach better insights into the modes of operation of these two variables in relation to one another.

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