



Regimes, Not Averages: Tail-Concentrated Dependence Between Energy Carriers And Ecological Pressure In Colombia

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ABSTRACT

This study examines the distributional relationship between ecological footprint, economic output, hydroelectricity, oil, and coal consumption in Colombia using quarterly data from 1970Q1 to 2022Q4. A cross quantilogram framework and Fourier augmented quantile causality test are employed to capture dependence across the entire distribution. Hydroelectricity exhibits the strongest and most consistent negative association with ecological pressure, while coal is the only energy source showing a localized positive reversal at the highest consumption levels. The results reveal substantial heterogeneity across energy carriers that conventional mean based models fail to detect. These findings provide state dependent evidence to support more targeted environmental and energy policies.

Keywords: cross-quantilogram, ecological footprint, energy disaggregation, hydropower, quantile causality, Colombia.

1 INTRODUCTION

Most energy and environmental studies estimate the effects of individual energy sources using a single average coefficient, implicitly assuming that these relationships remain constant across all conditions. Such an approach may overlook important distributional heterogeneity and mask effects that emerge only under specific levels of ecological pressure. As a result, mean based estimates can provide an incomplete basis for environmental policy.

To address this limitation, this study examines the distributional dependence between ecological footprint, economic output, hydroelectricity, oil, and coal consumption using the cross quantilogram, complemented by a Fourier augmented quantile Granger causality test. Colombia offers a suitable case because its electricity sector is dominated by



The study investigates whether energy carriers exhibit heterogeneous ecological effects, whether the output, environment relationship varies across the distribution, whether hydropower's environmental benefits weaken at high reliance, and whether predictive causality is concentrated in the tails. The findings show that quantile based analysis uncovers heterogeneous relationships overlooked by conventional mean based models, identifies distinct ecological signatures across energy carriers, and demonstrates that hydropower provides the most consistent, though bounded, environmental benefits.

2 Related Work

2.1 Carrier-Level Evidence and Its Disagreements

The modal finding is that disaggregating fossil fuels does not rescue them: coal and oil each raise emissions. Evidence for it spans single countries and panels, from Turkish coal [5] to United States non-renewables under a dynamic ARDL specification [6]. Work that moves past emissions to the ecological footprint reports the same direction for oil in major consuming economies [7]. The counterexamples are what make the record interesting. Malaysian evidence has coal raising emissions while oil lowers them in the long run [8]. Bangladeshi evidence reverses the roles: oil raises emissions, coal registers no effect at all [9]. Neither result is usually treated as a puzzle; both are absorbed as country heterogeneity. We read them differently. A carrier that binds only in extreme states will look insignificant wherever a sample sits mostly away from those states, so disagreement about signs may be partly a disagreement about sampling position rather than about structure. Hydropower gives the sharper illustration, because the literature contains all three available verdicts. Panel work on BRICS economies finds hydro lowering emissions [10]. Against that, a G20 panel returns hydro as statistically insignificant [11], and Turkish evidence has it insignificant under ARDL [12] yet emission increasing under quantile-on-quantile estimation [13]. One country, two estimators, opposite signs. The three verdicts reconcile if hydro's benefit attenuates as reliance climbs: a low-reliance sample finds benefit, a high-reliance sample finds none, an average over both finds ambiguity. Growth is the case where

the field already concedes state dependence and then estimates at the mean anyway. Kuznets-type reasoning holds the growth-environment relation to change with development [14], and consumptionbased evidence from Mexico has output aggravating degradation [15], while Icelandic evidence has it improving environmental quality [16]. The concept is explicitly non-monotone. The estimator applied to it usually is not.

2.2 What Conditional-Mean Designs Cannot See

ARDL and its nonlinear and dynamic variants, FMOLS, GMM and PMG dominate this literature, and each returns a conditional-mean object: the average change in the outcome per unit change in the regressor, taken over the sample. Under state dependence that average is a frequency-weighted mixture of regimes. States that occur rarely contribute little to it, which is unfortunate, because those are the states in which regulators act.

The estimators used here were built for that failure. The quantilogram measures directional predictability at chosen quantiles rather than at the mean [17], and its bivariate extension reports dependence separately for every pair of quantile levels of two series together with a testing procedure for it [18]. Inference rests on the stationary bootstrap, which preserves the dependence structure of a series while resampling [19]. Applications in finance have shown the method recovering tail behaviour that mean-based designs miss entirely [20]. On the causality side, augmenting a quantile VAR with a trigonometric term lets gradual structural shift be absorbed rather than mistaken for dependence, with bootstrap critical values guarding against non-normality and conditional heteroskedasticity [21].

Table 1. Variable definitions and descriptive statistics of the logged series, 1970Q1-2022Q4 ($T = 212$).

	EF	COE	GDP	HEC	OEC
Unit	gha/person	EJ	2015 US\$ p.c.	EJ	EJ
Mean	0.339	-0.887	3.611	-0.605	0.995
Median	0.338	-0.899	3.603	-0.506	1.019
Maximum	0.396	-0.562	3.844	-0.275	1.202
Minimum	0.232	-1.287	3.378	-1.223	0.725
Std. dev.	0.032	0.160	0.122	0.259	0.121



Jarque-Bera	7.531	4.009	9.098	28.999	10.731
p-value	0.023	0.134	0.010	0.000	0.004

Units are stated before logging. EF: global hectares per person. EJ: exajoules. GDP: per capita, constant 2015 US dollars. These tools have reached the energy literature, but mostly one carrier at a time and mostly against carbon emissions. The comparative question, whether carriers differ in their distributional signature inside a single economy when the outcome is a broad measure of ecological demand [22], has not been put. That is the gap this paper occupies.

3 Data and Empirical Design

3.1 Data and Preliminary Diagnostics

The ecological footprint (EF), measured in global hectares per capita, is the dependent variable, while GDP per capita, hydroelectricity (HEC), oil (OEC), and coal (COE) consumption are the explanatory variables [23,24,25]. The sample spans 1970Q1 to 2022Q4, yielding 212 quarterly observations. Since the original data are annual, all series were converted to quarterly frequency using the quadratic match sum method and transformed into natural logarithms. This interpolation preserves annual totals while providing sufficient observations for estimating the dependence surfaces, although short run movements should be interpreted with caution. Table 1 shows that HEC exhibits the greatest variability, whereas EF is the least dispersed. Skewness is generally mild, kurtosis remains below three, and the Jarque Bera test rejects normality for most variables. Table 2 reports the unit root results, where both the Augmented Dickey Fuller and Phillips Perron tests indicate that all variables are integrated of order one after first differencing. The BDS test further rejects the null hypothesis of independent and identically distributed observations across all series, confirming nonlinear dependence. These diagnostic results justify the use of a distribution sensitive framework rather than conventional linear mean based models.

3.2 The Cross-Quantilogram

Let $\{x_{i,t}\}, i = 1, 2$, be stationary series with distribution function $F_i(\cdot)$ and density $f_i(\cdot)$. The α_i -quantile is $q_i(\alpha_i) = \inf\{v: F_i(v) \geq \alpha_i\}$, and a quantile pair is written $\{q_1(\alpha_1), q_2(\alpha_2)\}^\top$ with $\alpha = (\alpha_1, \alpha_2)^\top$. Writing $\psi_a(u) = \mathbf{1}[u < 0] - a$ for the quantile-hit indicator, the cross-quantilogram at lag k is



Table 2. Unit root tests and BDS independence tests.

	EF	COE	GDP	HEC	OEK
Panel A. Unit root tests					
ADF, level	-2.967	-2.685	-2.778	-0.900	-2.712
ADF, first difference	-5.256 ^a	-4.357 ^a	-3.291 ^c	-6.072 ^a	-8.532 ^a
PP, level	-7.721	-3.225	-2.177	-1.058	-1.645
PP, first difference	-11.429 ^a	-9.904 ^a	-6.937 ^a	-6.803 ^a	-7.723 ^a
Panel B. BDS statistics by embedding dimension					
$m = 2$	0.185	0.169	0.201	0.206	0.201
$m = 3$	0.309	0.276	0.340	0.350	0.341
$m = 4$	0.390	0.344	0.436	0.451	0.438
$m = 5$	0.445	0.385	0.503	0.522	0.504
$m = 6$	0.482	0.413	0.550	0.571	0.550

^a, ^c denote significance at 1% and 10%. No level statistic is significant at 5%. Every BDS entry rejects the i.i.d. null at 1%.

$$\rho_{\alpha}(k) = \frac{E \left[\psi_{\alpha_1} \left(x_{1,t} - q_1(\alpha_1) \right) \psi_{\alpha_2} \left(x_{2,t-k} - q_2(\alpha_2) \right) \right]}{\sqrt{E \left[\psi_{\alpha_1}^2 \left(x_{1,t} - q_1(\alpha_1) \right) \right]} \sqrt{E \left[\psi_{\alpha_2}^2 \left(x_{2,t-k} - q_2(\alpha_2) \right) \right]}}, \quad (1)$$

for $k = 0, \pm 1, \pm 2, \dots$, with sample quantiles $\hat{q}_i(\alpha_i)$ substituted in estimation [18]. Here $x_{1,t}$ is EF and $x_{2,t}$ is each regressor in turn. A Ljung-Box-Pierce statistic in the quantile domain tests the joint null $H_0: \rho_{\alpha}(k) = 0$ for all $1 \leq k \leq p$,

$$\hat{Q}_{\alpha}^{(p)} = T(T+2) \sum_{k=1}^p \frac{\hat{\rho}_{\alpha}^2(k)}{T-k}. \quad (2)$$

We fix $p = 4$ in advance rather than selecting it by AIC or BIC. The distinction matters: an information criterion picks the lag that best describes the series, whereas here the horizon is part of the question. Four quarters gives predictability over one year, which is interpretable and matches the data frequency. Standard errors and confidence bands come from the stationary bootstrap [19, 20].

3.3 Bootstrap Fourier Granger Causality in Quantiles

The second estimator conditions on what the first leaves unconditioned. Its quantile equation augments a VAR with one trigonometric pair,

$$y_t(\tau) = \alpha_0(\tau) + \gamma_1(\tau) \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2(\tau) \cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{p+d_{\max}} \alpha_i(\tau) y_{t-i} + \sum_{i=1}^{p+d_{\max}} \beta_i(\tau) x_{t-i} + \varepsilon_t, (3)$$

The Fourier Toda Yamamoto causality test incorporates sine and cosine terms to account for smooth structural shifts, reducing the risk of spurious dependence. Non causality is tested using a Wald statistic with 1,000 bootstrap replications, ensuring robust inference under non normality and heteroskedasticity [21]. The analysis uses a Fourier frequency of four and evaluates quantiles at 0.1, 0.3, 0.5, 0.7, and 0.9. Together with the cross quantilegram, this approach distinguishes descriptive dependence from predictive causality and strengthens the robustness of the findings

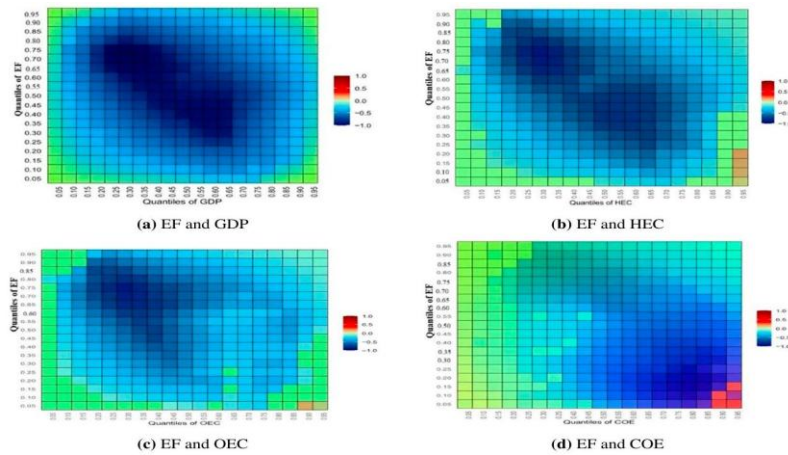


Figure 1. Cross-quantilogram dependence surfaces. Each panel presents a 19×19 quantile dependence surface between the explanatory variable and the ecological footprint. Blue indicates negative dependence, red indicates positive dependence, with coal being the only variable that exhibits a sign reversal.



4 Results

4.1 Dependence Surfaces

Fig. 1 Figure 1 presents the dependence surfaces for GDP and the three energy carriers. GDP shows a stable negative association with ecological pressure across the distribution. Hydropower exhibits the strongest and most consistent negative dependence, while oil maintains a weaker but distinct negative pattern. Coal is predominantly negative but displays a localized positive reversal at the highest consumption levels, revealing a distributional feature that conventional mean based approaches cannot detect

4.2 Predictive Causality Across Quantiles

Table 4 re-tests each relationship under (3).Hydroelectricity is the only regressor significant at every quantile examined, and its upper-tail statistic of 43.244 exceeds every other value in the table by more than a factor of two. Output clears significance at four of five quantilesTable 3. Cross-quantilogram surfaces: numeric summary. Locations are given as regressor quantile range $\times$ EF quantile range.

Pair	Bulk	Strongest region	Extremes
GDP-EF	-0.4/-0.9	0.25-0.65 $\times$ 0.35-0.75: -0.8 to -1.0	fades to -0.1/-0.3, both tails
HEC-EF	-0.2/-0.9	0.20-0.35 $\times$ 0.20-0.35 and 0.45-0.70 $\times$ 0.40-0.60: -0.8 to -1.0	≈ -0.1 at HEC 0.90-0.95
OEC-EF	-0.2/-0.9	0.20-0.35 $\times$ 0.65-0.80: -0.8 to -1.0; 0.35-0.55 $\times$ 0.40-0.55: -0.6 to -0.9	≈ -0.1 at OEC 0.90-0.95
COE-EF	-0.2/-0.9	0.45-0.85 $\times$ 0.15-0.60: -0.7 to -1.0	sign reversal to +0.4/+0.9

The coal reversal occurs at COE 0.90 – 0.95 $\times$ EF0.05 – 0.15. It is the only positive region across all four surfaces.



Table 4. Bootstrap Fourier Granger causality in quantiles: Wald statistics.

	Q0.1	Q0.3	Q0.5	Q0.7	Q0.9
GDP → EF	4.424 ^b (-)	3.715 ^c (-)	5.096 ^b (-)	2.246	17.776 ^a (-)
HEC → EF	7.471 ^a (-)	9.289 ^a (-)	7.580 ^a (-)	4.228 ^b (-)	43.244 ^a (-)
OEC → EF	6.297 ^b (-)	4.394 ^b (-)	2.443	2.043	16.761 ^a (-)
COE → EF	-0.204	-2.518	0.964	0.096	-7.633 ^a (-)

Critical values: 2.705 (10%), 3.841 (5%), 6.634 (1%). ^a, ^b, ^c denote significance at 1%, 5% and 10%. Signs in parentheses give the direction of the underlying estimated relationship. Negative entries in the COE row are reproduced as estimated; see the note in Section 3. and fails only at Q0.7. Oil is non-monotone in a way that a single test would hide: significant at the 5% level at Q0.1 and Q0.3, insignificant through the middle at Q0.5 and Q0.7, then significant at 1% again at Q0.9. Coal is insignificant at four quantiles and becomes significant only at Q0.9. One pattern cuts across all four rows. The largest statistic for every regressor occurs at Q0.9, and the smallest sits at Q0.5 or Q0.7. Causal evidence is a tail phenomenon here, not a central one, which is the same thing the surfaces say in a different language. The two estimators also agree on the ordering of robustness: hydro strongest and most uniform, output substantial but not uniform, oil state dependent, coal confined to the extreme. Agreement across estimators that condition on different things is what makes that ordering worth reporting. On the four claims of Section 1: the first holds, since coal and oil differ in location, strength and sign; the second and third hold, output being distribution sensitive and hydro bounded rather than proportional; the fourth holds for oil and coal and only partly for output, which keeps significance through most of the interior.

6 Conclusion

Holding country, sample and estimator fixed and varying only the energy carrier, we found four distinguishable distributional signatures and exactly one sign reversal.



Hydroelectricity was the most robust relationship in the system and also a bounded one. Oil was non-monotone across the distribution. Coal was quiet almost everywhere and then reversed in two cells of a 19×19 grid. The transferable claim is not about Colombia: it is that when dependence behaves this way, a conditional-mean estimate is not a noisy version of the answer but a different question, and reporting a surface costs little beyond the space to print it. Six limitations bound what the results support. The quarterly series were interpolated from annual observations, so genuine short-run variation is smoothed and short-horizon readings should be treated accordingly. No cointegration analysis is offered, because the design operates on stationary first differences and targets directional predictability rather than long-run equilibrium; the study therefore says nothing about level relationships among the variables. The framework is bivariate and omits urbanisation, globalisation, institutional quality and human development, which leaves the estimates exposed to omitted-variable bias. The ecological footprint captures demand-side pressure and misses supply-side burdens generated by domestic extraction, which matters in a country whose fossil carriers are principally export goods. The sample ends in 2022Q4, so the policy commitments discussed as context sit outside the estimation window and are not tested by these estimates. And single-country evidence limits external validity by construction. Two extensions follow directly. Conditioning the surfaces on institutional and structural covariates would separate carrier effects from the governance environment they operate in. Applying the same design to other fossil-exporting, hydro-dependent economies would establish whether the signature reported here is a Colombian fact or a structural one; the second would be the more useful result.

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