# TESTING FOR CAUSALITY BETWEEN CLIMATE POLICIES AND CARBON EMISSIONS REDUCTION

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# Testing for Causality between Climate Policies and Carbon Emissions Reduction⋆

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**Abstract**

In this paper, we evaluate the causal effects of climate policies on carbon emissions reduction. Specifically, we investigate the properties of the Granger causality test in the frequency domain, assuming that the dependent variables include a binary variable and a continuous variable (resp. treatment and outcome variables). Monte Carlo simulations confirm that: (i) this test is valid under this assumption; and (ii) it has more power than its time-domain counterpart. Then, using Sweden as a case study, we evaluate the impact of the Kyoto Protocol, the Swedish carbon tax, and the European Union Emissions Trading System (EU ETS) on carbon emissions reduction over the period 1964–2021. Our empirical results indicate that only the carbon tax Granger causes carbon emissions reduction in the long run. Our methodological framework offers policymakers a useful toolbox for climate policy evaluation as well as new insights into the outcomes of international treaties and carbon pricing policies.

*Keywords:* *Granger causality; Spectral analysis; Climate policy; Carbon pricing.*

*JEL Classification: C12; C32; Q54; Q58.*

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## 1. Introduction

In this paper, we evaluate the causal effects of climate policies on carbon emissions reduction. Based on the Granger causality approach, we implement unconditional and conditional causality tests to evaluate the average, short-, and long-term impacts of climate policies on carbon emissions reduction. Specifically, we investigate the properties of the related tests in the time and frequency domains, assuming that the dependent variables include a binary variable and a continuous variable (resp. treatment and outcome variables). Monte Carlo experiments confirm that both tests present satisfactory size and power properties in this mixed model. Furthermore, our findings indicate that the Granger causality test in the frequency domain exhibits better power to detect abrupt and smooth structural breaks than its time domain counterpart. Then, using Sweden as a case study, we evaluate the impact of the Kyoto Protocol, the Swedish carbon tax, and the European Union Emissions Trading System (EU ETS) on carbon emissions reduction over the period 1964–2021. Our empirical results indicate that only the carbon tax Granger causes carbon emissions reduction in the long run. These findings are robust to different econometric specifications that control for macroeconomic and other climate policy variables.

The contribution to the literature is twofold. First, we propose a new methodological framework based on the Granger causality test in the frequency domain to evaluate the impact of climate policies in the short and long run, assuming that the dependent variables include binary and continuous variables. Our findings indicate that, under this assumption, this test is more appropriate to capture climate policy outcomes than its time domain counterpart. Finally, our empirical results advocate for a carbon tax to mitigate climate change. The rest of this paper is organized as follows. Section 2 surveys the key contributions to climate policy evaluation and related methods. Section 3 is devoted to the description of our innovative methodology, including the econometric framework and Monte Carlo investigation. Section 4 describes the dataset, empirical results, and robustness checks. Finally, Section 5 concludes the paper and highlights some policy implications.

## 2. Literature Review

The empirical literature related to climate policies aimed at reducing carbon emissions has been growing since the 2010s (Zhang et al., 2019). A consensus has emerged: policies based on carbon pricing are the most effective (if not the only ones) in terms of carbon emissions reduction. Among the recent contributions in the field, the most commonly used approaches to evaluate the consequences of a treatment on some outcome variable are the difference-in-differences (DID) and synthetic control methods (Athey and Imbens, 2017). Other methods have emerged recently, such as machine learning, network, and time-series econometric methods. Table 1 reports the most significant contributions in the recent literature, providing details about the methods and treatment variables.

Notably, less emphasis has been placed on time-series econometrics approaches. The reasons explaining this lack in the literature are related to: (i) the lack of hindsight and therefore of historical data allowing the use of econometric methods such as Granger causality; and (ii) the fact that the treatment variable is commonly defined as a binary variable. Indeed, in the related literature, the treatment variable is often defined as a binary variable that takes on the value of one if country $i$ has a policy commitment in period $t$ and zero otherwise. Such a binary dependent variable can be an issue in econometric models, and the related literature is scarce.

However, some recent empirical works use the Granger causality approach to evaluate climate policy effectiveness. For instance, Nakhli et al. (2022), Razzaq et al. (2023), and Liu et al. (2023) use Granger (1969)'s original test or Troster (2018)'s test for Granger causality in quantiles (see Table 1). The renewal interest in this econometric approach has its roots in White and Pettenuzzo (2014)'s work, who present a methodological framework for eco-

**Table 1:** Recent contributions about the evaluation of climate policies

| Authors | Methods | Treatment variables |
|---|---|---|
| Abrell et al. (2019) | Machine learning techniques | Variation in the relative market prices for coal and natural gas |
| Aichele and Felbermayr (2013) | DID estimation with matching | Kyoto commitment (dummy) |
| Aichele and Felbermayr (2015) | DID estimation | Kyoto commitment (dummy) |
| Akinlo and Apanisile (2023) | Nonlinear ARDL and Granger causality test | Stock market development |
| Andersson (2019) | Synthetic control method | Kyoto commitment (dummy) |
| Bartram et al. (2022) | DID estimation | Enactment of the California cap-and-trade program (dummy) |
| Chen and Lin (2021) | Data envelopment analysis and synthetic control method | Energy-carbon performance index |
| Chen et al. (2023) | Cointegration and causality | International environmental agreements |
| Gao et al. (2020) | DID and DDD estimation | Time of policy adoption, pilot regions and industries (dummies) |
| Jaraite-Kažukauske and Di Maria (2016) | DID estimation with matching | EU ETS membership (dummy) |
| Klemetsen et al. (2020) | DID estimation | EU ETS membership EU ETS phases (dummies) |
| Lépissier and Mildenberger (2021) | Synthetic control method | Enactment of the UK's 2001 Climate Change Programme |
| Liu et al. (2023) | Granger Causality-in-quantiles test | |
| Nakhli et al. (2022) | Granger causality | Economic policy uncertainty |
| Petrick and Wagner (2014) | DID estimation with matching | Propensity score |
| Razzaq et al. (2023) | Granger Causality-in-Quantiles | |
| Wagner et al. (2014) | DID estimation | EU ETS membership (dummy) |

**Notes**: This table provides a non-exhaustive list of recent contributions about the evaluation of climate policies. This list includes the references, methods, and treatment variables.

nomic policy analysis based on Granger causality. These authors reexamine the equivalence of structural and Granger causality, and they revisit the effectiveness of US Federal Reserve policy. However, these empirical works are constrained to Granger causality in the time domain, which does not allow us to disentangle short- and long-run causality.

## 3. Methodology

### *3.1. Econometric framework*

To investigate potential Granger causality in the relation between carbon emissions reduction and climate policies, we base our analysis on a bivariate vector autoregressive (VAR) model. Specifically, this model incorporates information from continuous and discrete variables (resp., carbon emission and climate policy proxies). A bivariate mixed-VAR(1) model is written as follows:

$$\begin{cases} ICO2_t = \alpha_{1,1} ICO2_{t-1} + \alpha_{1,2} D_{t-1} + \beta_1 X_{t-1} + c_1 + \epsilon_{1,t} \\ D_t = \alpha_{2,1} ICO2_{t-1} + \alpha_{2,2} D_{t-1} + \beta_2 X_{t-1} + c_2 + \epsilon_{2,t}, \end{cases} \tag{1}$$

where $ICO2_t$ represents the carbon intensity (i.e., carbon emissions scaled by GDP) and $D_t$ is the climate policy dummy variable ($D_t = 1$ if the policy is effective at time $t$ and $D_t = 0$ otherwise) at time $t$, both being $1 \times T$ vectors. $X_t$ is a set of $k$ control variables and is therefore a $K \times T$ matrix. $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are two uncorrelated iid normally distributed residuals.

The impact of climate change policies on carbon emissions can be simply tested in this framework with a Granger causality test, i.e., $H_0 : \alpha_{1,2} = 0$. More recently, Breitung and Candelon (2006) have extended the Granger causality test in the frequency domain, allowing us to evaluate the time horizon of the causal effect.

*3.2. Granger causality tests*

Let us consider $\mathbf{Y}_t = (x_t, y_t)'$ to be a covariance-stationary vector time series that can be represented by a finite-order VAR($p$) process,

$$\Theta(L)\mathbf{Y}_t = \varepsilon_t, \tag{2}$$

where $\Theta(L) = \mathbf{I}_2 - \Theta_1 L - \Theta_2 L^2 - \cdots - \Theta_p L^p$ is a $2 \times 2$ lag polynomial with the lag operator $L^i\mathbf{Y}_t = \mathbf{Y}_{t-i}, \boldsymbol{\Theta}_i i = 1, 2, \ldots, p$, is a $2 \times 2$ coefficient matrix associated with lag $i$, and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ denotes a vector white-noise process, with $E(\varepsilon_t) = \mathbf{0}$ and positive-definite covariance matrix $\boldsymbol{\Sigma} = E(\varepsilon_t\varepsilon_t')$. Applying Cholesky factorization, $\mathbf{G}'\mathbf{G} = \Sigma^{-1}$ (where $G$ is a lower-triangular matrix), we can write a moving-average representation of the system in (1) as

$$\begin{aligned}\begin{bmatrix} x_t \\ y_t \end{bmatrix} &= \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \\ &= \boldsymbol{\Psi}(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}.\end{aligned}$$

where $\boldsymbol{\eta}_t = \mathbf{G}\varepsilon_t$, $E(\boldsymbol{\eta}_t\boldsymbol{\eta}_t') = \mathbf{I}$, $\boldsymbol{\Phi}(L) = \Theta(L)^{-1}$, and $\Psi(L) = \Phi(L)\mathbf{G}^{-1}$.

The causality from $y_t$ to $x_t$ is therefore $H_0 : \Phi_{12}(L) = 0$ vs. $\mathrm{H}_0 : \Phi_{12}(L) \neq 0$.

Then, using the Fourier transformations of the moving-average polynomial terms, we can write the spectral density of $x_t$ as

$$f_x(\omega) = \frac{1}{2\pi}\left\{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2 + \left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2\right\}.$$

Geweke (1982)'s measure of linear feedback from $y_t$ to $x_t$ at frequency $\omega$ is defined as

$$M_{y\to x}(\omega) = \log\left\{\frac{2\pi f_x(\omega)}{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2}\right\} = \log\left\{1 + \frac{\left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2}{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2}\right\}.$$

If $|\Psi_{12}(e^{-i\omega})| = 0$, then $M_{y\to x}(\omega)$ will be 0. This means that $y_t$ does not Granger-cause $x_t$

at frequency $\omega$. Breitung and Candelon (2006) show that testing for noncausality from $y$ to $x$ can be done via $|\Psi_{12}(e^{-i\omega})| = 0$.

It therefore signifies that $y_t$ does not Granger-cause $x_t$ at frequency $\omega$ if the following condition is satisfied:

$$\left|\Theta_{12}\left(e^{-i\omega}\right)\right| = \left|\sum_{k=1}^{p} \theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p} \theta_{12,k}\sin(k\omega)\mathrm{i}\right| = 0.$$

Here, $\theta_{12,k}$ is the $(1,2)$-element of $\Theta_k$. In this case, the necessary and sufficient conditions for $|\Theta_{12}(e^{-i\omega})| = 0$ are

$$\sum_{k=1}^{p} \theta_{12,k}\cos(k\omega) = 0$$
$$\sum_{k=1}^{p} \theta_{12,k}\sin(k\omega) = 0.$$

Breitung and Candelon (2006) reformulate these restrictions by rewriting the equation for $x_t$ in the VAR($p$) system,

$$x_t = c_1 + \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_{1t}, \tag{3}$$

where $\alpha_j = \theta_{11,j}$ and $\beta_j = \theta_{12,j}$. The null hypothesis of $M_{y\to x}(\omega) = 0$ is equivalent to

$$H_0 : \mathbf{R}(\omega)\boldsymbol{\beta} = 0,$$

where $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)'$ and $\mathbf{R}(\omega)$ is a $2 \times p$ restriction matrix.

$$\mathbf{R}(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \ldots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \ldots & \sin(p\omega) \end{bmatrix}.$$

Because these are simple linear restrictions, standard empirical procedures (LR, LM and Wald tests) can be used to test this hypothesis. In the seminal paper, Breitung and Candelon

(2006) opt for a Wald statistic. [1] Let $\gamma = [c_1, \alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_p]'$ be the $q = (2p+1) \times 1$ vector of parameters, and let $\mathbf{V}$ be a $q \times q$ covariance matrix from the unrestricted regression (2). Then, the Wald statistic is

$$W = (\mathbf{Q}\gamma)' \left(\mathbf{Q}\mathbf{V}\mathbf{Q}'\right)^{-1} (\mathbf{Q}\gamma) \sim \chi^2_2,$$

where $\mathbf{Q}$ is the $2 \times q$ restriction matrix such that

$$\mathbf{Q} = \left[\mathbf{0}_{2\times(p+1)} \vdots \mathbf{R}(\omega)\right].$$

This test has paved the way for many studies. Yamada and Yanfeng (2014) have shown its validity at the frequency borders when $\omega = 0$ or $\pi$. Farnè and Montanari (2022) propose a bootstrap version to deal with the potential nonnormality properties of the residuals, whereas Breitung and Schreiber (2018) have extended it to test for a frequency range $[\underline{\omega}, \bar{\omega}]$.

*3.3. Testing Granger causality in mixed VAR*

There is still no literature on the validity of causality tests when the VAR is mixed, i.e., composed of continuous and discrete variables as Model (1). Testing for Granger causality in the context of such a bivariate mixed VAR raises two econometric issues related to (i) the estimation of the mixed VAR model and (ii) the validity of the Granger (1969)'s and Breitung and Candelon (2006)'s causality tests.

On the one hand, the literature about mixed VAR models is scarce. This framework was pioneered by Dueker (2005), who introduced the qual VAR model to include qualitative vari-

[1] Farnè and Montanari (2022) prefer the simple F test. A robustness check will be proposed in the empirical application.

ables in dynamic forecasting models of recessions. Since then, Candelon et al. (2013) have shown that a multivariate VAR model simultaneously constituted by discrete and continuous variables can be estimated via maximum likelihood.[2]

On the other hand, the question of the validity of causality tests in this context is not trivial, even if the literature partially answers it. Indeed, Candelon et al. (2013) have shown that Granger (1969)'s test is valid in a multivariate mixed VAR framework, but the assessment of whether Breitung and Candelon (2006)'s test is valid is far less straightforward, especially for low frequencies. Nevertheless, Stoffer (1991) have proven that Fourier transforms can be extended to cases with discrete- and categorical-valued time series and cases where the time series contain sharp discontinuities and, more recently, Yamada and Yanfeng (2014) have shown its validity at the frequency borders when $\omega = 0$ or $\pi$.

### *3.4. Simulation Analysis*

To better grasp the properties of the Breitung and Candelon (2006) causality test in mixed models, three different data-generating processes (DGPs) are generated to mimic the carbon intensity return. In the first one ($DGP_1$), carbon emissions follow an iid normal distribution with an unconditional mean ($\mu = 0$) and standard error ($\sigma = 0.5$), which corresponds to the estimates obtained for the whole sample. A structural break is included in the middle of the sample $t = 29$ of amplitude $\tau = (0, 0.5, 1, 2, 5)$. It is worth noting that, when $\tau = 0$, there is no break and that, therefore, we are under the null hypothesis of no causality. In $DGP_2$, instead of imposing an "abrupt" structural break, carbon emissions exhibit a deterministic trend with a negative constant slope ($\beta = 0.00, -0.05, -0.10, -0.15, -0.20, -0.25, -0.30$). Again, iidness is imposed around the trend. $DGP_3$ is similar to $DGP_1$, but instead of iidness being imposed, the residuals follow an AR(1) process, where the autoregressive coefficient

[2]Recently, such a mixed VAR approach has been considered by Belkhir et al. (2022) to analyze the direct and indirect interaction between economic growth and macroprudential regulations.

($\rho$) corresponds to the one estimated from historical data ($\rho = 0.96$). In each case, $5,000$ replications are simulated with $T = 57$, corresponding to our empirical sample period. An initial burn-off of 10 observations is considered to limit the dependence on initial observations. In each case, time and frequency domain tests are implemented. In Table 2, the rejection frequency of the null hypothesis of noncausality is reported. For the other rows (the power experiments), the rejection is calculated from the 95% quantile obtained in the simulations in the first row (the size experiments). Therefore, these rejection frequencies represent the size-adjusted power.

**Table 2:** Rejection rates – $DGP_1$ – $\sigma = 0.5$

| | Causality test in the time domain | Causality test in the frequency domain | | | |
|---|---|---|---|---|---|
| | | 0 | $\pi/4$ | $\pi/2$ | $3\pi/4$ |
| Break size | | | | | |
| $\tau = 0$ | 5.4 | 11.7 | 7.6 | 5.7 | 4.3 |
| $\tau = 0.5$ | 36.0 | 47.6 | 4.9 | 2.9 | 2.2 |
| $\tau = 1$ | 78.1 | 89.7 | 10.0 | 4.9 | 3.0 |
| $\tau = 2$ | 99.4 | 99.7 | 27.9 | 14.6 | 8.9 |
| $\tau = 5$ | 99.8 | 100.0 | 64.9 | 63.2 | 38.3 |

**Notes**: This table provides the rejection frequency of the noncausality test in the frequency domain for different frequencies $\omega$ and different break sizes $\tau$. For $\tau$=0, the asymptotic critical value of the distribution (5.99) is used. The 5% nominal size obtained is used for the other values of $\tau$. The results are computed by means of a Gretl procedure and Breitung and Schreiber (2018)'s Gretl package *"BreitungCandelonTest"*. The code is available upon request from the authors.

Several findings can be drawn from this simulation exercise. First, the causality tests in both the time and frequency domains are able to detect the presence of a structural break, confirming earlier findings in the literature (inter alii Bianchi, 1995). Nevertheless, the frequency domain test provides more information, as it unambiguously indicates that the presence of causality in the long run, not in the short run. The rejection frequency is therefore the highest at $\omega = 0$ for abrupt structural breaks and smooth breaks when residuals are iid (resp. Table 2 and Table 3) or autoregressive (Table 4). Second, it is observable that the rejection frequency under the null is close to the nominal size even if the sample size is relatively small.In addition, as in Breitung and Candelon (2006), we notice a small size

**Table 3:** Rejection rates – $DGP_2$ – $\sigma = 0.5$

| | Causality test in the time domain | Causality test in the frequency domain | | | |
|---|---|---|---|---|---|
| | | 0 | $\pi/4$ | $\pi/2$ | $3\pi/4$ |
| Slope size | | | | | |
| $\beta = 0.00$ | 5.4 | 11.7 | 7.6 | 5.7 | 4.3 |
| $\beta = 0.05$ | 12.8 | 13.0 | 2.5 | 1.7 | 1.5 |
| $\beta = 0.10$ | 13.7 | 13.9 | 0.9 | 1.9 | 1.9 |
| $\beta = 0.15$ | 20.8 | 27.0 | 2.3 | 2.5 | 2.1 |
| $\beta = 0.20$ | 33.6 | 44.2 | 2.6 | 1.9 | 1.7 |
| $\beta = 0.25$ | 48.5 | 63.5 | 2.4 | 1.6 | 2.0 |
| $\beta = 0.30$ | 64.8 | 81.8 | 4.8 | 3.0 | 2.1 |

**Notes**: This table provides the rejection frequency of the noncausality test in the frequency domain for different frequencies $\omega$ and different slopes of the deterministic trend $\beta$. For $\beta$=0, the asymptotic critical value of the distribution (5.99) is used. The 5% nominal size obtained is used for the other values of $\beta$. The results are computed by means of a Gretl procedure and Breitung and Schreiber (2018)'s Gretl package *"BreitungCandelonTest"*. The code is available upon request from the authors.

**Table 4:** Rejection rates – $DGP_3$– AR 0.96 – $\sigma = 0.5$

| | Causality test in the time domain | Causality test in the frequency domain | | | |
|---|---|---|---|---|---|
| | | 0 | $\pi/4$ | $\pi/2$ | $3\pi/4$ |
| Break size | | | | | |
| $\tau = 0$ | 5.4 | 11.7 | 7.6 | 5.7 | 4.3 |
| $\tau = 0.5$ | 20.9 | 31.8 | 0.5 | 0.6 | 0.3 |
| $\tau = 1$ | 61.4 | 77.5 | 4.0 | 1.1 | 0.7 |
| $\tau = 2$ | 97.7 | 98.3 | 15.9 | 7.5 | 2.6 |
| $\tau = 5$ | 99.8 | 100.0 | 43.1 | 43.9 | 18.8 |

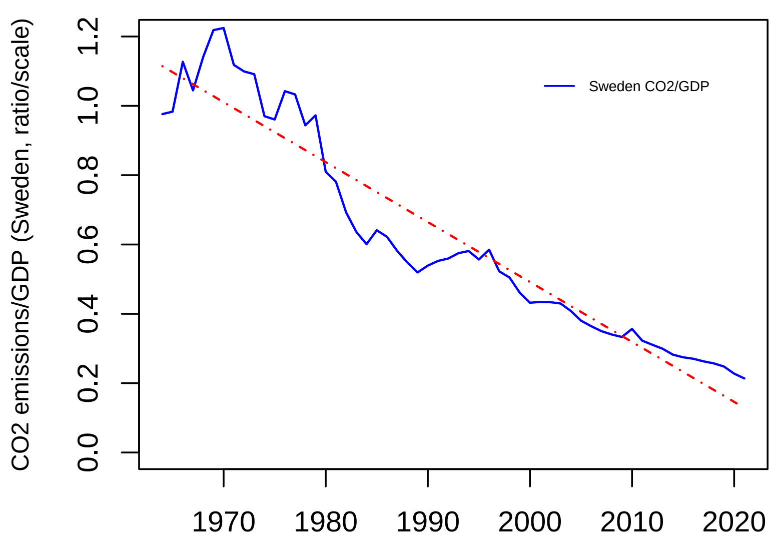
**Notes**: This table provides the rejection frequency of the noncausality test in the frequency domain for different frequencies $\omega$ and different break sizes $\tau$. For $\tau$=0, the asymptotic critical value of the distribution (5.99) is used. The 5% nominal size obtained is used for the other values of $\tau$. The results are computed by means of a Gretl procedure and Breitung and Schreiber (2018)'s Gretl package *"BreitungCandelonTest"*. The code is available upon request from the authors.

distortion at frequency $\omega = 0$. Nevertheless, as shown in Yamada and Yanfeng (2014), Breitung and Candelon (2006)'s test is useful even when the null hypothesis is noncausality at a frequency close to 0 or $\pi$. In addition, as the process is stationary, the spectral density is defined at $\omega = 0$, which would not be the case if it were nonstationary. Third, the size-adjusted power increases relatively quickly, as it is almost 100% in all cases with $\tau$ larger than 2.

## 4. Data

Nordhaus (2019) argues that the CO2/GDP ratio, also called the carbon intensity of production, is the best single measure of decarbonization. This indicator measures the trend in the ratio of carbon dioxide emissions to output. Figure 1 replicates for Sweden the trend in decarbonization illustrated in Figure 6 (p. 2009) in his paper.

**Figure 1:** Trend in Global Decarbonization, Sweden, 1964–2021




**Notes**: This figure illustrates the European CO2/output ratio from 1964 to 2021 along with a trend curve. The global average intensity declined by 1.7% per year over this period.

Following Nordhaus (2019), our dataset includes 4 variables at annual frequency over the period 1964–2021: (i) Swedish carbon intensity (first difference), (ii) a Kyoto Protocol dummy (taking value 1 from 1997 and 0 otherwise), (iii) a Swedish carbon tax dummy (taking value 1 from 1991 and 0 otherwise) and (iv) an EU ETS dummy (taking value 1 from 2005 and 0 otherwise). Each of these variables is included alternatively in Eq. (1) as an endogenous and an exogenous variable. The idea is to use the nontargeted policy dummies as policy control variables. The unemployment rate and a business cycle indicator are also included as economic control variables, as in Andersson (2019).

**Table 5:** Description of the dataset

| Variable | Description | Code | Source |
|---|---|---|---|
| Carbon intensity | Annual CO2 emissions over GDP (kg per $PPP) | ICO2 | ICOS |
| Kyoto Protocol | Dummy 1997–2021 budget period | KPRO | |
| Carbon Tax | Dummy 1991–2021 period | CTAX | |
| EU ETS | Dummy 2005–2021 period | ECTS | |
| Unemployment | Percentage of total labor force | UNPL | ECB |
| Business Cycles | Dummy for recessions | REC | OECD |

**Notes**: This table provides each variable's name, description, code and source. The panel dataset covers Sweden over the period 1964 to 2021.

The carbon intensity data are published by Global Carbon Budget (v2022) via ICOS's website.[3] Table 1 reports the variable names and descriptions and sources. The GDP per capita and unemployment rate time series were downloaded from the World Bank's and European Central Bank's (ECB's) databases, respectively. Last, the recession indicator from the OECD was downloaded from the Federal Reserve Economic Data (FRED) website.[4]

[3]ICOS's website: `https://www.icos-cp.eu/science-and-impact/global-carbon-budget/2022`.

[4]See Hasse and Lajaunie (2022) for a discussion about the differences between the NBER, ECB and OECD recession indicators.

## 5. Results and discussion

In this section, we illustrate the use of Breitung and Candelon (2006)'s test as an innovative case study methodology with an application to climate policies. Among potential countries, we choose to focus on Sweden for two reasons. First, emission reductions in Sweden are unbiased because of its geographical location, which limits potential carbon leakage from the transport sector. Second, Sweden implemented a carbon tax as early as 1991, ratified the Kyoto Protocol in 1997 and has been a part of the EU ETS system since the beginning in 2005. So Sweden is a relevant country case study providing the necessary historical data and the hindsight to perform both causality tests in the time and in the frequency domain. See Andersson (2019) for an extensive discussion about to the choice of Sweden as a case study. Of course, our results are replicable for other countries and other public policies. The purpose of this empirical section is mainly to illustrate the use of Breitung and Candelon (2006)'s test as a tool for policy impact evaluation.

### *5.1. Empirical results*

Elaborating on Nordhaus (2019)'s argument, the causal effect of climate policies on domestic carbon emissions reductions was tested in two steps. First, Granger (1969)'s and Breitung and Candelon (2006)'s original tests were used to evaluate the effect of the Swedish carbon tax, the Kyoto Protocol and the EU ETS on carbon emissions reductions. Table 5 reports the results estimated at low frequencies, i.e., $\omega = \{0.035, 0.25, 0.5\}$ and high frequencies, i.e., $\omega = \{1, 3\}$, for permanent and temporary effects, respectively.[5]

These empirical results indicate that the time series form of the Granger causality test is

[5]The formula for the period is $T = \frac{2\pi}{\omega}$, with $T$ being the period and $\omega$ being the frequency. For instance, the frequency $\omega = 0.25\ rad.s^{-1}$ corresponds to $T = 25\ years$.

**Table 6:** Empirical results: Granger causality tests – Time and frequency domains

| | Time domain | Frequency domain | | | | |
|---|---|---|---|---|---|---|
| Policy | | $\omega = 0.035$ | $\omega = 0.25$ | $\omega = 0.5$ | $\omega = 1$ | $\omega = 3$ |
| Swedish Carbon Tax | 1.02 | **5.44*** | **5.06*** | **4.63*** | 0.54 | 2.24 |
| Kyoto Protocol | 0.69 | 0.51 | 0.06 | 0.33 | 1.13 | 0.34 |
| EU ETS | 0.49 | 1.46 | 0.89 | 1.45 | 1.27 | 2.17 |

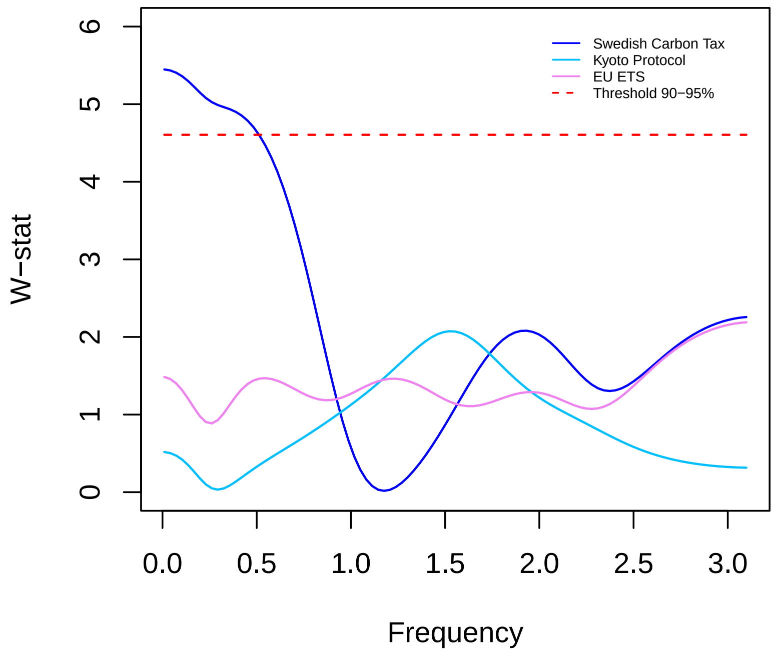
**Notes**: This table reports causality test statistics in both the time frequency domains. Test statistics are calculated at low frequencies ($\omega = \{0.035, 0.25, 0.5\}$) and high frequencies ($\omega = \{1, 3\}$) for permanent and temporary effects, respectively. The results are computed by means of Breitung and Schreiber (2018)'s Gretl package *"BreitungCandelonTest"*. The labels $***$, $**$ and $*$ indicate significance at the 99%, 95% and 90% levels, respectively.

not able to detect the effects of the Kyoto Protocol, the EU ETS or the carbon tax in Sweden. In contrast, the frequency domain causality test performs quite well, as it reveals a long-term impact of the carbon tax implementation in Sweden. This difference in results is in line with the outcomes of the simulation exercise and with the empirical results of Metcalf and Stock (2020). Second, it is worth noting that the empirical exercise assumes the imposition of a carbon tax but cannot provide the results corresponding to a higher or lower tax rate on carbon emissions. Nevertheless, the simple carbon tax setup indicates a positive impact on carbon emission reductions. Then, focusing on Breitung and Candelon (2006)'s test results, the main empirical findings are illustrated in Figure 2.

Figure 2 indicates that there exists a significant Granger causal relation between the Swedish carbon tax and domestic carbon emission reductions only. This causal effect is significant at low frequencies, lower than 0.5, indicating that the effect of the $CO2$ tax on emissions appears over the relatively long term, i.e., a period less than or equal to 12 years. It is also possible to calculate the Geweke (1982) intensity measure at this frequency, which lies at 2%.[6] In contrast, the Kyoto Protocol has had no significant impact, even in the long run, on carbon emissions in Sweden.

[6] As in Geweke (1982), the intensity is reported here in absolute values, but its signs appear to be negative, indicating that the policies implemented are reducing carbon emissions.

**Figure 2:** Granger causality – Frequency analysis




**Notes**: This figure illustrates the Granger causality between the CO2/output ratio, the carbon tax reform of 1991 in Sweden (in blue), the development of the EU ETS since 2005 (in violet) and the Kyoto Protocol of 1997 (in cyan). The results are computed using Breitung and Schreiber (2018)'s Gretl package *"BreitungCandelonTest"*.

### *5.2. Robustness checks*

Then, for robustness purposes, the Granger causality analysis in the frequency domain was replicated, including economic and policy control variables, in line with Andersson (2019). The economic control variables include the unemployment rate and a recession indicator for Sweden. The climate policy control variables include two dummies related to the periods corresponding to the Kyoto Protocol and the EU ETS. Table 6 reports the results.

We also perform a double statistical robustness check. Specifically, instead of using a Wald test for testing the frequency restriction as in Breitung and Candelon (2006), the test is based on an F test as in Farnè and Montanari (2022). Furthermore, several lag orders are considered (optimal lag order from 3 to 6 as indicated by the AIC). The frequencies $\omega$ considered are $\{0.035; 0.25; 0.5\}$. The resulting test statistics and significance levels are reported in Table 7. These results are equivalent to those reported in Table 5, thus confirming the long-run

**Table 7:** Empirical results: Robustness check – Conditional Granger-causality tests in the frequency domain at various frequencies

| Conditional Granger causality tests in the frequency domain | Policy $\mapsto$ CO2 $\omega = 0.035$ | $\omega = 0.25$ | $\omega = 0.5$ | $\omega = 1$ | $\omega = 3$ |
|---|---|---|---|---|---|
| Swedish Carbon Tax | | | | | |
| (a) Economic control variables | **4.76*** | **4.63*** | 4.39 | 1.64 | 1.28 |
| (b) Policy control variables | **5.02*** | **5.01*** | **4.65*** | 0.96 | 2.62 |
| (c) All control variables | **5.63*** | **5.77*** | **6.25**** | **4.77*** | 0.17 |
| Kyoto Protocol | | | | | |
| (a) Economic control variables | 0.50 | 0.30 | 0.58 | 1.24 | 1.98 |
| (b) Policy control variables | 0.90 | 0.97 | 0.96 | 0.07 | 0.74 |
| (c) All control variables | 2.57 | 2.50 | 2.52 | 2.06 | 3.80 |
| EU ETS | | | | | |
| (a) Economic control variables | 0.29 | 0.07 | 0.15 | 0.85 | 0.57 |
| (b) Policy control variables | 1.08 | 0.81 | 1.44 | 0.93 | 1.89 |
| (c) All control variables | 1.78 | 1.46 | 0.54 | 0.63 | 2.55 |

**Notes**: This table reports conditional Granger causality tests statistics in the frequency domain, including economic and policy control variables. The test statistics are calculated at low frequencies ($\omega = \{0.035, 0.25, 0.5\}$) and high frequencies ($\omega = \{1, 3\}$) for permanent and temporary effects, respectively. The results are computed by means of Breitung and Schreiber (2018)'s Gretl package *"BreitungCandelonTest"*. The labels $***$, $**$ and $*$ indicate significance at the 99%, 95% and 90% levels, respectively.

impact of carbon tax implementation in Sweden.

**Table 8:** Empirical results: Robustness check – Granger causality tests in the frequency domains with various lags and frequencies

| Swedish Carbon Tax | Causality test in the frequency domain $p = 3$ | $p = 4$ | $p = 5$ | $p = 6$ |
|---|---|---|---|---|
| $\omega = 0.035$ | **3.40**** | **3.08*** | **3.64**** | 2.83 |
| $\omega = 0.25$ | 0.29 | 0.20 | 0.14 | 0.33 |
| $\omega = 0.5$ | 0.09 | 0.00 | 0.02 | 0.061 |

**Notes**: This table reports causality tests statistics in both the time frequency domains considering different lags ($p = \{3, 4, 5, 6\}$). The test statistics are calculated at low frequencies ($\omega = \{0.035, 0.25, 0.5\}$) for permanent effects. The results are computed by means of Farnè and Montanari (2019)'s R package *"grangers"*. The labels $***$, $**$ and $*$ indicate significance at the 99%, 95% and 90% levels, respectively.

## 6. Conclusion and Policy Implications

As argued by Nordhaus (2019), *"climate change is the ultimate challenge"* for economists. In the failure of the Kyoto Protocol, it has become crucial to design and evaluate the policy tools available to mitigate the consequences of climate change. The outcomes of international treaties and carbon pricing policies, including carbon taxes and carbon markets, have been evaluated via different approaches such as difference-in-difference regressions and synthetic control methods, to name a few (Athey and Imbens, 2017). However, among the methodological approaches commonly used in the literature, none can disentangle the short- and long-run outcomes of a given climate policy. The Granger causality test in the frequency domain could fill this gap.

Therefore, we propose using an innovative approach based on Breitung and Candelon (2006) test. Recent contributions in econometrics indicate that using such a test to evaluate the impact of climate policies on carbon emissions reduction would be valid. Monte Carlo simulations confirm that testing Granger causality in the frequency domain with dependent variables including a binary variable and a continuous variable is valid. Moreover, we show that the test in the frequency domain has more power than its time domain counterpart. We illustrate the added value of our methodological framework with an application to climate policy evaluation. Using Sweden as a case study, we evaluate the impact of the Kyoto Protocol, the Swedish carbon tax, and the EU ETS on carbon emissions reduction. Our empirical results indicate that only the carbon tax Granger causes carbon emissions reduction in the long run.

In summary, our methodological framework offers policymakers a useful toolbox for climate policy evaluation. Furthermore, our findings could renew the interest of Granger causality tests for public policy evaluation or, more broadly, event analysis. Some limitations, such as the fact that our framework is constrained to a given country, call for further research.

Extending our econometric framework to a panel setting could be a promising solution to take into account potential interactions with other countries (e.g., carbon leakages, policy spillovers). Finally, despite these limitations, our findings pave the way for new research opportunities.

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