

## Peer-reviewed research

# The Role of Technology in Emission Reduction Effect of Carbon Pricing: A Predictive Approach

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We employ a predictive approach to assess the combined effects of carbon pricing and technological advancements on the predictability of carbon emissions. Our model, which integrates both carbon pricing and technological innovation, demonstrates remarkable accuracy in forecasting emissions. The strength of our findings—supported by both in-sample and out-of-sample forecasts across various time horizons—suggests that the synergistic effects of carbon pricing and technological progress could be crucial for substantially reducing global CO<sub>2</sub> emissions.

### I. Introduction

Carbon pricing is an instrument that captures the external costs of greenhouse gas (GHG) emissions. A clear price signal from carbon pricing encourages investors to allocate capital toward low-carbon technologies. This suggests a possible interplay between carbon pricing and technology in achieving effective climate action. However, the existing literature has focused mainly on the direct effects of carbon pricing on emissions, often neglecting the role of technology (see Isah et al., 2024; Yan et al., 2020). It is suggested that firms striving to reduce their liabilities under carbon pricing frameworks are likely to innovate or adopt new technologies that further lower emissions (see M. Chen & Wang, 2023). The extent to which technology influences the effectiveness of carbon pricing in emission reduction remains an unresolved question. To address this, the current study seeks to contribute to the literature by examining the moderating role of technology in the relationship between carbon pricing and carbon emissions.

The economic theory that most effectively clarifies the impact of technology on the emission reduction effects of carbon pricing is the “induced innovation theory.” This theory posits that imposing a price on pollution motivates businesses to invest in and develop new technologies aimed at reducing emissions (see X. Chen & Lin, 2021). While this suggests that technological innovation is a critical factor in realizing the emission reduction effects of carbon pricing, existing studies have continued to address the relationship between carbon emissions and carbon pricing (see Rafatya

et al., 2020; Wu & Wang, 2022; Xiao et al., 2021), as well as between carbon emissions and technological innovations (Huang & Yang, 2021; Onifade & Alola, 2022), separately. It remains unclear whether the cooperative effects of carbon pricing and technological innovation are positive or negative.

The first contribution of this study is to investigate the interaction between carbon pricing and technology in the pursuit of the global objective of low-carbon emissions. Some academic efforts have been made to analyze the combined effects of carbon pricing and technological innovation on emissions (see M. Chen et al., 2023). However, much of the existing literature focuses primarily on impact assessments. Nonetheless, there is a belief that precise forecasting of carbon emissions can significantly enhance the effective implementation of emissions control policies. Therefore, another key contribution of this study to the literature is the application of a predictive model to examine the forecasting power of the combined effect of carbon pricing and technology when predicting low carbon emissions. In this context, we present results that underscore the robustness of technology’s moderating role in the emission reduction efficacy of carbon pricing, supported by both in-sample and out-of-sample analyses.

In addition to this introductory section, the remainder of the paper is organized as follows: Section II presents the data and methodology, Section III discusses the results, and Section IV provides the conclusion.

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**Table 1. Preliminary results**

| Summary Statistics                           |                    |           |                   |                               |                                 |           |          |
|----------------------------------------------|--------------------|-----------|-------------------|-------------------------------|---------------------------------|-----------|----------|
|                                              | Mean               |           | Std. Dev.         |                               | COV                             | Skewness  | Kurtosis |
| Climate change (CO2)                         | 406.78             |           | 8.95              |                               | 0.02                            | 0.00      | 1.88     |
| Carbon Prices (CP)                           | 28.63              |           | 29.44             |                               | 1.03                            | 1.03      | 2.49     |
| Technological Innovation (TI)                | 691.75             |           | 663.69            |                               | 0.10                            | -0.25     | 2.43     |
| Heteroscedasticity and Autocorrelation tests |                    |           |                   |                               |                                 |           |          |
|                                              | ARCH LM test       |           | Ljung-Box Q-stat. |                               | Ljung-Box Q <sup>2</sup> -stat. |           |          |
|                                              | k=5                | k=10      | k=5               | k=10                          | k=5                             | k=10      |          |
| Climate Change (CO2)                         | 451.17***          | 325.37*** | 633.55***         | 113.0***                      | 457.21***                       | 701.68*** |          |
| Carbon Price (CP)                            | 216.09***          | 102.37*** | 705.78***         | 131.1***                      | 581.64***                       | 936.97*** |          |
| Technological Innovation (TI)                | 61.55***           | 21.75***  | 455.75***         | 614.54***                     | 260.98***                       | 284.41*** |          |
| Persistence & Endogeneity tests              |                    |           |                   |                               |                                 |           |          |
|                                              | Carbon Prices (CP) |           |                   | Technological Innovation (TI) |                                 |           |          |
| Persistence test                             | 0.996***           |           |                   | 0.934***                      |                                 |           |          |
| Endogeneity test                             | 0.921***           |           |                   | 0.943***                      |                                 |           |          |

Note: The asterisk \*\*\*, \*\*, and \* implies statistical significance at 1%, 5%, and 10% levels, respectively. The values reported in parenthesis are the standard error.

## II. Data and Methodology

### A. Data

The European Union Emissions Trading System (EU-ETS) forms the cornerstone of the world's climate strategy, with European Allowance (EAU) futures contracts on the Intercontinental Exchange (ICE) used here as the measure of carbon prices (CP). Technological innovation (TI) is represented by the FTSE Environment Technologies Index, while carbon emissions are gauged by the global atmospheric CO<sub>2</sub> mole fraction in parts per million (PPM) per tonne. Emissions data are sourced from the National Oceanic and Atmospheric Administration (NOAA)<sup>1</sup>, and both CP and TI data are gathered from [investing.com](https://www.investing.com), covering the period from January 2012 to May 2024.

Descriptive statistics, shown in Table 1, indicate that the average atmospheric CO<sub>2</sub> concentration is 406.78 PPM. The mean carbon allowance price is €28.6 per tonne, while the environmental technology index averages 6911.75 points. The coefficient of variation (COV) highlights that CP is more volatile than TI. All series display platykurtic distributions, with CO showing positive skewness and TI negative skewness. The summary statistics in Table 1 further demonstrate the presence of heteroscedasticity, autocorrelation, persistence, and endogeneity, which validate the estimation technique employed in this study.

### B. Methodology

We adopt the bivariate predictive framework proposed by Westerlund and Narayan (2015), which accounts for im-

portant statistical properties commonly observed in time series data such as heteroscedasticity, autocorrelation, and high persistence thereby improving the robustness and reliability of predictive regressions (see Tables 1).

$$CO2_t = \alpha + \beta CP_{t-1} + \varepsilon_t \quad (1)$$

$$CO2_t = \alpha + \beta TI_{t-1} + \varepsilon_t \quad (2)$$

Equations (1) and (2) serve as our baseline predictive models, in which we assess the separate predictive power of higher carbon prices and increasing technological innovation in advancing the global goal of emissions reduction. Both the dependent and independent series are expressed in their natural logarithms. However, given our hypothesis that progress toward a low-carbon economy is more accurately predicted when combining the effects of carbon price and technological innovation, we further consolidated Equations (1) and (2) into a multifactor predictive model as follows.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 TI_{t-1} + \varepsilon_t \quad (3)$$

Based on our preliminary results, there appears to be a correlation between the error term and the predictor series in the predictive equations discussed above. To address this issue, Lewellen (2004) modified the OLS estimator to account for potential endogeneity.

$$CO2_t = \alpha + \beta'_{adj} x_{t-1} + \lambda(x_t - \delta x_{t-1}) + \varepsilon_t \quad (4)$$

The term  $\beta_{adj}$  in Equation (4) represents the adjusted OLS estimator,  $\beta_{adj} = \hat{\beta} - \lambda(\hat{\delta} - \delta)$ , while the probability of endogeneity bias caused by correlation between  $\varepsilon_{t-1}$  and  $x_t$  is addressed by including an additional term  $\lambda(\delta - \delta x_{t-1})$ . Here  $\delta$  and  $\hat{\delta}$  are fitted coefficients of one period-lagged values ( $x_{t-1}$ ) are denoted accordingly, and the vector represents carbon price (CP) and technological innovations in

<sup>1</sup> [https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series/3/tavg/all/1/1950-2022?base\\_prd=true&beginbaseyear=1901&endbaseyear=2000](https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series/3/tavg/all/1/1950-2022?base_prd=true&beginbaseyear=1901&endbaseyear=2000)

**Table 2. Predictive regression results**

| Predictive model type | Predictor            |                    |                        |                       |
|-----------------------|----------------------|--------------------|------------------------|-----------------------|
|                       | Single Predictor     |                    | Multi-Predictors       |                       |
|                       | CP                   | TI                 | CP                     | TI                    |
| Restricted model      | -0.0030*<br>(0.0016) | 0.6798<br>(0.4587) |                        |                       |
| Unrestricted model    |                      |                    | -0.0142***<br>(0.0038) | -0.6844**<br>(0.2379) |

Note: The values reported in parenthesis are the standard errors. \*\*\*, \*\*, and \* imply statistical significance at 1%, 5%, and 10% levels, respectively.

the predictive model. To address conditional heteroscedasticity - common in time-series data - Narayan and Westerlund (2015) recommend pre-weighting all data by  $\frac{1}{\sigma_v}$  before applying OLS model. This method, Feasible Quasi Generalized Least Square (FQGLS), is defined below:

$$\beta_{adj}^{FQGLS} = \frac{\sum_{t=qm+2}^T \hat{\tau}_t^2 p_t^d x_{t-1}^d}{\sum_{t=qm+2}^T \hat{\tau}_t^2 (x_{t-1}^d)^2} \quad (5)$$

where  $\hat{\tau}_t = \frac{1}{\hat{\sigma}_{v,t}}$  is used to weigh all the data in the bias-adjusted predictive model represented by Equation (4), while  $p_t^d = p - \sum_{p=2}^T \frac{p_t}{T}$  and  $x_t^d = x_t - \sum_{z=2}^T \frac{x_t}{T}$ .

We utilize both single and pairwise methods, recognized for their reliability, to assess the in-sample and out-of-sample forecasting accuracy of carbon emissions. Our objective is to compare the effectiveness of predictive models that use either carbon price or technological innovations alone against an unrestricted model that combines both variables. For this purpose, we calculated the Root Mean Square Error (RMSE) and its Mean Squared Error (MSE) variant to evaluate forecasting performance. To further strengthen our results, we applied two commonly used pairwise tests: the Campbell and Thompson (C-T, 2008) test and the Clark and West (C-W, 2007) test, which are standard measures for assessing nested models in our analysis.

### III. Empirical Results

The predictive estimates in Table 2 indicate that when predictors are considered individually, only the predictor CP leads to a rejection of the hypothesis of predictability. This suggests a potential benefit of using a combined approach. For instance, both CP and TI are statistically significant predictors of emissions reductions when included together in a multi-factor predictive model. Previous studies, such as Cui et al. (2021) and Kohlscheen et al. (2021), have identified a direct emission reduction effect from carbon pricing. In this analysis, the emission reduction effect becomes more pronounced when carbon pricing is considered alongside technological innovations, which points to the relevance of considering both factors together in efforts to achieve a low-carbon economy.

Previous research has predominantly focused on ex-post impact analysis. Building on this foundation, we extend the analysis to assess the forecasting capabilities of the combined dynamics of carbon prices (CP) and technological innovation (TI) in predicting carbon emissions. For our methodology, 75% of the total sample is utilized for in-

sample analysis, with the remaining 25% reserved for out-of-sample forecasts across various horizons. Evaluation using standard single-method forecast performance metrics indicates that the model incorporating both CP and TI yields lower RMSE and MSE values, as presented in Table 3, compared to models considering these predictors individually. Alternative pairwise approaches to assessing forecast accuracy consistently demonstrate that the integration of CP and TI provides the most reliable pathway for projecting progress toward global emission reduction targets. These findings reinforce the conclusion that the synergistic effects of carbon pricing and technological innovation offer the most effective strategy for achieving emissions reductions globally. Furthermore, the robustness of this result persists across both in-sample and out-of-sample forecasts, as well as across different forecast horizons.

### IV. Conclusion

We utilized a predictive approach to analyse the combined impact of carbon pricing and technological innovation on achieving a global low-carbon economy. Our integrated model, incorporating both carbon pricing and technological advancements, demonstrates superior accuracy in forecasting carbon emissions. The robustness of our results - consistent across both in-sample and out-of-sample forecasts, as well as various forecast horizons - indicates that the synergistic effects of carbon pricing and technological innovation are likely to play a crucial role in substantially reducing global CO<sub>2</sub> emissions.

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**Table 3. In-sample and out-of-sample forecast results**

| Single-method based forecast performance evaluation       |           |               |        |        |           |               |          |          |
|-----------------------------------------------------------|-----------|---------------|--------|--------|-----------|---------------|----------|----------|
| Predictive model type                                     | RMSE      |               |        |        | MSE       |               |          |          |
|                                                           | In-sample | Out-of-sample |        |        | In-sample | Out-of-sample |          |          |
|                                                           |           | h=4           | h=8    | h=12   |           | h=4           | h=8      | h=12     |
| Restricted model [CP]                                     | 2.1639    | 2.1412        | 2.1284 | 2.1322 | 4.6828    | 4.5848        | 4.5301   | 4.5464   |
| Restricted model [TI]                                     | 0.0549    | 0.0520        | 0.0532 | 0.0526 | 0.0030    | 0.0027        | 0.0028   | 0.0027   |
| Unrestricted model [CP:TI]                                | 0.0544    | 0.0491        | 0.0526 | 0.0518 | 0.0029    | 0.0024        | 0.0027   | 0.0026   |
| Pairwise-method based forecast performance evaluation     |           |               |        |        |           |               |          |          |
|                                                           | C-T test  |               |        |        | C-W test  |               |          |          |
|                                                           |           |               |        |        |           |               |          |          |
| Unrestricted model [CP:TI]<br>Vs<br>Restricted model [CP] | 0.99      | 0.99          | 0.99   | 0.99   | 13.11***  | 16.90***      | 13.44*** | 13.94*** |
| Unrestricted model [CP:TI]<br>Vs<br>Restricted model [TI] | 0.02      | 0.11          | 0.02   | 0.03   | 1.90**    | 4.55***       | 2.15***  | 2.41***  |

Note: Lower RMSE and MSE indicate better predictor accuracy. A positive C-T value means the unrestricted model [CP:TI] outperforms [CP] or [TI]; a negative value indicates the opposite. For the C-W test, use t-statistics of 1.28, 1.64, and 2.00 for 10%, 5%, and 1% significance levels.



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