INTERNATIONAL MONETARY FUND

Time-Varying Impacts of Government Spending on CO2 Emissions

Stefano Di Bucchianico, Mario Di Serio, Matteo Fragetta and Giovanni Melina

WP/25/132

2025
JUL

WORKING PAPER

 WP/25/132

IMF Working Paper
Research Department

Time-Varying Impacts of Government Spending on CO2 Emissions*

Prepared by Stefano Di Bucchianico, Mario Di Serio, Matteo Fragetta and Giovanni Melina

Authorized for distribution by Florence Jaumotte
July 2025

ABSTRACT: A Bayesian factor-augmented interacted vector autoregression framework purified of expectations is employed to analyze how government spending shocks have impacted CO2 emissions in the United States from the 1980s to the pre-pandemic period. Consumption-generated emissions are found to have generally risen following fiscal expansions, although their elasticity to government spending has declined substantially over time—with the five-year elasticity dropping from about 0.5 in the early 1980s to 0.1 by 2019. In contrast, positive government spending shocks increased production-generated emissions in the early 1980s—with a five-year elasticity near 0.4—but reversed course by the 1990s, eventually reaching an elasticity of –0.5 by the end of the sample. Examination of time-varying interaction variables suggests that environmental regulation, tertiarization, and a larger share of spending on public goods can mitigate—or even reverse—the emissions growth associated with economic expansions driven by government spending. Furthermore, government consumption, rather than investment, is chiefly responsible for these shifts in emissions elasticities.

RECOMMENDED CITATION: Di Bucchianico S., M. Di Serio, M. Fragetta and G. Melina (2025). “Time-Varying Impacts of Government Spending on CO2 Emissions,” IMF Working Paper No. 25/132, International Monetary Fund, Washington, D.C.

JEL Classification Numbers:	C32, C38, E62, Q54, Q58
Keywords:	government spending; fiscal policy; CO2 emissions

Author’s E-Mail Address:	mdiserio@unisa.it; mfragetta@unisa.it; gmelina@imf.org

* Stefano Di Bucchianico acknowledges funding from the Italian MUR through the PRIN 2022 PNRR project Disentangling the Environmental and energy efficiency impact of public innovation investment for a green transition (DEMETRA) (P2022SRW8N, CUP D53D23017910001) financed by the European Union. The authors thank Giovanni Angelini, Matteo Ciccarelli, Marwil Dàvila, Andreas Dibiasi, Sergio Destefanis, Giovanni Pellegrino, and Peter Skott for useful comments.

WORKING PAPERS

Time-Varying Impacts of Government Spending on CO2 Emissions

Prepared by Stefano Di Bucchianico, Mario Di Serio, Matteo Fragetta and Giovanni Melina

Contents

List of Tables

List of Figures

1 Introduction

While a substantial body of research has examined the link between economic activity and CO_2 emissions (Dinda, 2004; Stern, 2017; Cohen et al., 2018), the specific impact of government spending on emissions has been understudied. The few studies on the topic often report conflicting findings (Bernauer and Koubi (2013); Chishti et al., 2021; Halkos and Paizanos, 2016a; López et al., 2011), and this lack of consensus highlights the inherent complexity of the fiscal policy–emissions nexus. On one hand, higher government spending can stimulate aggregate demand and consequently increase energy use and emissions. On the other hand, such spending has the potential to finance cleaner technologies, drive shifts in consumption patterns, and enforce more robust environmental standards. These countervailing forces suggest that the net effect of fiscal policy on emissions is far from straightforward (Halkos and Paizanos, 2013), warranting a deeper investigation into the mechanisms at play.

Four key channels appear especially relevant for understanding how government spending may influence emissions: (1) income, (2) tertiarization, (3) environmental regulation, and (4) spending composition. The income channel, proxied by per-capita GDP, underlies the Environmental Kuznets Curve (EKC) argument, whereby increases in income can initially raise emissions but later may foster environmental improvements (Grossman and Krueger, 1995). The tertiarization channel highlights that a shift toward service-oriented activities generally lowers carbon intensity (Sanchez and Stern, 2016). Environmental regulation—including policies, taxes, and enforcement—exerts a critical influence on whether fiscal expansions translate into higher or lower emissions (Kruse et al., 2022). Finally, the spending composition channel captures how government allocations to expenditures aimed at fixing market failures such as in education, health, and the environment can reduce its carbon footprint (López and Galinato, 2007; Halkos and Paizanos, 2013; Halkos and Paizanos, 2016a; Islam et al., 2015). Crucially, these channels are dynamic: their strength may fluctuate with evolving technologies, shifting policy priorities, and changing societal preferences, rendering the net effect of fiscal policy on CO_2 emissions sensitive to both time and context.

Building on these theoretical insights, this study addresses three research questions empirically, using data on the U.S. economy from the early 1980s to the pre-pandemic period (1981Q1-2019Q1). First, how do government spending shocks affect consumption-generated and production-generated CO_2 emissions, once the responses are non-linearly conditioned on the aforementioned channels? Second, has the relationship changed over time? Third, is the evolution in the relationship consistent with the theoretical mechanisms highlighted in the literature?

The analysis focuses on the United States for several reasons. As a major advanced economy with a significant share of global emissions, the U.S. has undergone significant fiscal policy shocks, experienced rapid technological change, and seen notable shifts in industrial structure and environmental governance over recent decades. Moreover, the U.S. has reliable and relatively long time series at a quarterly frequency of both macroeconomic and environmental variables required by a study of this kind. The investigation examines CO_2 emissions, as they remain the principal greenhouse gas driving climate change, making it a critical metric for evaluating the environmental consequences of public spending.

The results reveal that government spending shocks have markedly different effects on consumption-generated versus production-generated CO_2 emissions, and these effects have evolved significantly over time. For consumption-generated emissions, fiscal expansions led to a five-year elasticity of approximately 0.5 in the early 1980s; however, by 2019, this elasticity had declined to around 0.1. Five-year partial correlations of the elasticities with each of the four interaction variables indicate a positive association of government-spending-driven emissions with real GDP per capita. In contrast, environmental regulation and structural shifts toward the service sector exhibit a negative correlation. Evidence on the role of the spending composition is mixed. These findings suggest that rising income levels do not account for the declining effect of government spending shocks on consumption-generated emissions, while tertiarization and environmental regulation appear to have contributed to the decline.

Production-generated emissions exhibited a five-year elasticity of about 0.4 at the beginning of the sample period. Yet, by the 1990s, this relationship reversed, and by the end of the sample, the elasticity had reached approximately –0.5. In this case, there is mixed evidence for the income effect, while tertiarization, spending composition, and environmental regulation all show a negative association with the emission elasticity.

Moreover, the evidence points to government consumption as the main driver behind both the gradual decline in consumption-generated CO_2 elasticities and the post-1990 shift in production-generated elasticities from positive to negative, while government investment plays a more limited role, helping to dampen production-generated elasticities but not accounting for their reversal.

The estimates are derived from a Bayesian factor-augmented interacted vector autoregressive model purified of expectations (FAIVAR-X), an extension of the I-VAR framework proposed by Caggiano et al. (2017), which has been recently employed to estimate state-dependent fiscal multipliers (Amendola et al., 2020; Di Serio et al., 2021; Di Serio et al., 2024). This framework offers three key advantages. First, the incorporation of interaction terms allows capturing nonlinearities and estimating the responses of the variables of interest to government spending shocks, conditional on proxies for the theoretical channels posited to influence how fiscal shocks affect emissions. These proxies are treated as endogenous variables in the empirical model, hence they react to shocks and the movements of the other variables in the system. Second, by augmenting the specification with factors extracted from a broad set of macroeconomic variables, concerns related to limited information are mitigated. This approach ensures that important information, which might be implicitly used by economic agents in making decisions, is effectively incorporated (see Bernanke et al., 2005; Stock and Watson, 2005; Fragetta and Gasteiger, 2014). Third, including forecasts of government spending formed over the quarter as an exogenous variable purges a substantial portion of the anticipated component of government spending shocks, thereby mitigating the issue of fiscal foresight (see, e.g., Forni and Gambetti, 2010).

The paper links two distinct strands of the literature. The first strand investigates the relationship between economic activity, fiscal policy, and environmental outcomes. A substantial body of research presents mixed evidence on the relationship between output and CO_2 emissions via the income effect. In contrast, advancements in environmental regulation, technological progress, and structural shifts—such as tertiarization— are consistently associated with reductions in emissions (Stern, 2017). Moreover, recent research has examined the role of the government in influencing air pollution and the direct impact of fiscal shocks on emissions, finding mixed evidence. While some findings suggest that the government can reduce emissions by fixing market failures and fostering human capital accumulation (López et al., 2011), other studies indicate that larger government size may exacerbate pollutant concentrations (Bernauer and Koubi, 2013). As a result, there are both studies claiming that expansionary fiscal policy exerts a beneficial effect in terms of emissions reduction (Halkos and Paizanos, 2016b) and others showing the opposite effect (Chishti et al., 2021).

The second strand focuses on the state dependency of fiscal multipliers, with research showing that the effects of government spending depend on the state of the business cycle (Sá et al., 2014; Auerbach and Gorodnichenko, 2012b; Batini et al., 2012; Caggiano et al., 2015; Ramey and Zubairy, 2018), supply-versus-demand-driven recessions (Ghassibe and Zanetti (2022); Di Serio et al. (2024); Jo and Zubairy (2025)), monetary policy regimes (Miyamoto et al., 2018; Amendola et al., 2020; Bonam et al., 2022), and levels of government debt (Kirchner et al., 2010; Nickel and Tudyka, 2014), among others. Our paper bridges these two strands for the first time by linking the elasticity of CO_2 emissions in response to government spending shocks to time-varying proxies for four channels posited to govern the relationship. Differently from other studies employing stochastic time-varying coefficients in contexts unrelated to the emission impacts of fiscal shocks (see, e.g., Primiceri, 2005), the econometric approach adopted in this paper models time variation as a function of the interaction terms (as, e.g., in Sá et al., 2014). This specification allows for an assessment of how observable structural factors shape the effects of fiscal policy on emissions over time.

The remainder of the paper is structured as follows. Section 2 explains the empirical methodology and the econometric specification. Section 3 reports the results. Section 4 makes a distinction between government consumption and investment. Finally, Section 5 concludes. Data sources are appended to the paper.

2 Methodology

2.1 Empirical Model

The empirical model is based on a factor-augmented interacted vector autoregressive framework purified of expectations (FAIVAR-X) relying on the approach of Caggiano et al. (2017), Di Serio et al. (2021) and Di Serio et al. (2024). This method is well-suited for incorporating multiple interaction terms. The objective is to identify the exogenous variation of government spending, G_t, while capturing its links with other endogenous variables, as suggested by theoretical considerations. The model's reduced-form specification is outlined by the following equation:

$$Y_t = c + \sum_{k=1}^{p} A_k Y_{t-k} + \sum_{k=1}^{p} \sum_{j=1}^{n} A_k^j G_{t-k} \times X_{t-k}^j + V f_{(t|t-1)} + u_t. \tag{1}$$

In this context, $t = 1, ..., T$ denotes the time dimension, p represents the number of lags, and n represents the number of interaction terms. The vector of endogenous variables, denoted by Y_t, the interaction terms, expressed as $G_{t-k} \times X_{t-k}^j$, where each X_{t-k}^j is an endogenous variable contained in a subset of vector Y_t, and the exogenous variable $f_{(t|t-1)}$, are discussed in Subsection 2.2. Coefficient c represents the constant term. Matrix A_k, with $k = 1, \ldots, p$, contains the autoregressive coefficients associated with the endogenous variable, while A_k^j captures the coefficients linked to each interaction term. Vector V comprises the coefficients attached to the exogenous variables, and u_t represents a vector of normally distributed residuals with mean zero and covariance matrix Σ. We restrict the analysis to a two-quarter lag structure, as increasing the number of lags would lead to pervasive instability in the estimates. This instability arises from the rapid increase in the number of interaction terms (an issue also highlighted by Caggiano et al., 2017), along with a general increase in the number of parameters to be estimated.

The interacted VAR approach offers a distinct way to analyze regime dependency compared to methods like threshold VAR, which require estimating separate sets of coefficients for different regimes. Instead, the interacted VAR estimates a single set of coefficients while incorporating interaction terms, enabling an assessment of how the level of certain endogenous variables influences the transmission of a given shock. As a result, unlike binary approaches, this methodology allows for conditioning shock propagation across a continuum of regimes rather than being confined to discrete thresholds.

2.2 Data and Baseline Specification

The dataset comprises quarterly U.S. data covering the period from 1981Q1 to 2019Q1, which is dictated by the availability of the news-based environmental and climate policy index produced by Noailly et al. (2024). The description below provides a rationale for the choice of the main variables included in the specification. For details on the construction of the dataset, see Appendix A.

The vector of endogenous variables reads as follows:

$$Y_t = \left[G_t, GDP_t, T_t, CO^P_{2,t}, CO^C_{2,t}, EP_t, EC_t, \Pi_t, R_t, F_t, SERV_t, ENVP_t, PG_t\right]'. \qquad (2)$$

Variables G_t, GDP_t and T_t are the three variables traditionally used in the fiscal-VAR literature since Blanchard and Perotti (2002) and represent real government purchases (the sum of government gross fixed capital formation and government consumption), real gross domestic product, and real net taxes, respectively. These variables are included in per-capita terms. Several other endogenous variables are added to the specification due to the reasons discussed below.

First, the objectives of the analysis require including production- and consumption-generated CO_2 emissions—$CO^P_{2,t}, CO^C_{2,t}$—as endogenous variables, which are obtained from the U.S. Environmental Protection Agency[1] and are included in per-capita terms for consistency with the other variables.

Second, the year-on-year growth rate of the oil price, used as a proxy of energy prices, EP_t, and energy consumption (per capita total energy consumed across residential, commercial, industrial, and transportation sectors), EC_t, are included, given that energy prices are a significant determinant of energy consumption (Halkos and Paizanos, 2016b;Li et al., 2020), which in turn is closely associated with carbon emissions (Waheed et al., 2019).[2]

Third, inflation and monetary policy's endogenous responses are captured by the inclusion

[1] Production-generated CO_2 emissions includes *Total Industrial Sector CO2 Emissions*, while in line with Halkos and Paizanos (2016a) consumption-generated CO_2 emissions is constructed as the sum between *Total Energy Residential Sector CO2 Emissions* and *Total Energy Transportation Sector CO2 Emissions.*

[2] In the specific case of the US, Soytas et al. (2007) state that accounting for energy consumption aids in explaining the drivers of emissions, as it Granger causes long-term pollution from CO_2.

of the year-on-year CPI inflation rate, Π_t, and the one-year government bond rate, R_t.[3]

Fourth, common factors, F_t, are extracted through principal components from a large number of macroeconomic time series and added to the vector of endogenous variables. Indeed, VAR models are characterized by a trade-off between parsimony and the omission of relevant variables, which can lead to nonfundamentalness of the identified shocks (see, e.g., Forni and Gambetti, 2010). By extracting information from a broad set of macroeconomic variables, this approach addresses a limited information problem, because the principal components serve as proxies for the unobserved factors influencing most macroeconomic variables (see Fragetta and Gasteiger, 2014 for further details). A two-step estimation procedure is employed, following Bernanke et al. (2005). In the first step, a set of common factors is extracted, with the number determined by the Bai and Ng (2007) ICp2 information criterion, which selects three factors in this case. The second step incorporates these factors into the vector of endogenous variables. Appendix A lists all the macroeconomic time series employed to extract the factors.

Fifth, three additional variables are added among the endogenous variables. These are (1) the share of service providers over the total number of government and private employees, $SERV_t$; (2) the news-based environmental and climate policy index produced by Noailly et al. (2024), $ENVP_t$; and (3) the share of government spending on public goods—that is, education, housing, income security, health, and recreation—PG_t. These three variables, together with per-capita GDP, GDP_t, are used as interaction terms with government spending to account for four key channels governing the impact of fiscal policy on CO_2 emissions. It is important to note that, by adopting a generalized impulse response framework (explained in Subsection 2.3), all the variables interacting with government spending can be endogeneized. Consequently, these variables simultaneously respond to government spending shocks, and concurrently, influence the impact of the shock on all endogenous variables, including CO_2 emissions. The four channels governing the impact of fiscal policy on CO_2 emissions are outlined below:

- *Income.* This channel, proxied by real per capita GDP, is linked to the Environmental Kuznets Curve (EKC), whereby emissions initially rise with income but decline as economies develop (Grossman and Krueger, 1995; Dinda, 2004). The effect of fiscal expansions on emissions depends on a country's EKC position, as rising income tends to increase both production and demand for environmental quality (McConnell, 1997; Stern, 2017).

[3]Following Gertler and Kiyotaki (2015) and Jarociński and Karadi (2020), the one-year government bond rate is preferred over the federal funds rate as it incorporates forward guidance effects, offering a more reliable indicator of monetary policy stance, particularly when the federal funds rate is constrained by the zero lower bound.

- *Tertiarization.* This channel is captured by the share of service workers in the economy. Rodrik (2016) highlights that many advanced economies transitioned to a post-industrial structure following decades of deindustrialization, particularly evident in the declining share of manufacturing employment, offering a possible link between (de)industrialization and emissions. In addition, given its service-oriented nature, a government's expansion—assuming other factors remain constant—can foster a more tertiarized economy.

- *Environmental regulation.* This channel is captured by the environmental and climate policy index. Environmental regulation—including policies, taxes, and enforcement—plays a crucial role in determining whether fiscal expansions result in higher or lower emissions (Kruse et al., 2022). The index reflects the extent to which a government prioritizes environmental issues, which in turn likely influences the sectors targeted by government spending and standards adopted for public procurement.

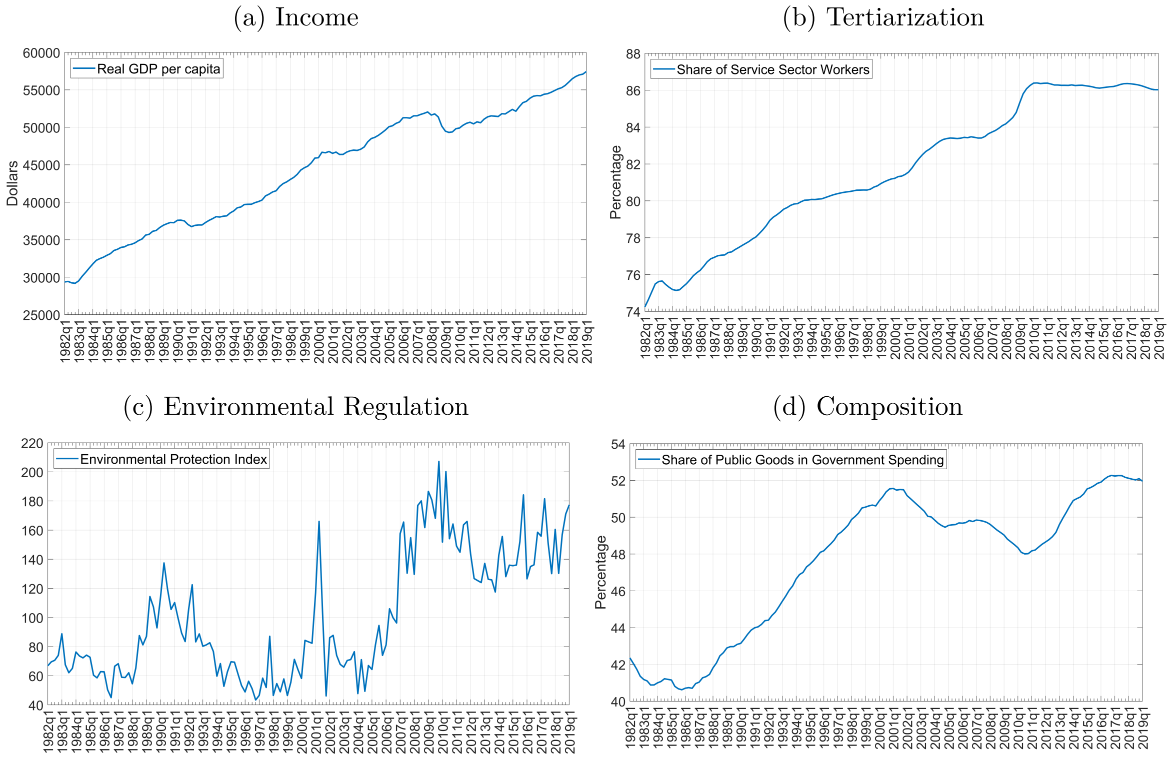
- *Spending composition.* This channel is captured by the share of government spending on public goods. A higher allocation of government expenditure toward public goods can contribute to lower emissions (López et al., 2011; Galinato and Islam, 2017). The classification of public goods follows López and Galinato (2007) and includes education and culture, health, social welfare, housing, and transportation. These spending items are thought of mitigating market failures, such as pollution externalities and credit market imperfections that obstruct access to healthcare and human capital accumulation.

Figure 1 illustrates the four proxies representing the channels through which fiscal policy affects CO_2 emissions. While both income per capita and the degree of tertiarization follow a positive trajectory, their recent patterns differ notably. For example, real per capita income has continued to rise steadily, yet tertiarization has remained relatively flat over the past decade. Environmental regulation has generally strengthened over the sample period, though its progression has not been linear. A noticeable upward shift occurred in the mid-2000s, followed by considerable fluctuations. The spending composition channel also gained prominence between the mid-1980s and early 2000s and has shown volatility in the past two decades. These distinct patterns highlight the importance of examining each channel to unpack the relationship between fiscal policy and environmental outcomes.

Finally, the $f_{(t|t-1)}$ series is included as an exogenous variable. This represents the forecast of time-t growth of real government spending over the past three months based on the Survey of Professional Forecasters (SPF).[4] The addition of this variable helps purge the structural

[4]See appendix A for further details.

Figure 1: Proxies for Channels Governing the Impact of Fiscal Policy on CO_2 Emissions



government spending shocks from the change in government spending already anticipated by economic agents in the past quarter, mitigating the problem known in the literature as fiscal foresight. Although this device does not control for anticipated movements in government spending beyond the three-month horizon, it alleviates the issue of anticipation insofar as a considerable share of variation of government spending is attributable to expectations formed over the past quarter.

2.3 Inference, Identification, and Computation of Cumulated CO_2 Elasticities

The FAIVARX model presented in equation (1) is estimated, and the cumulative CO_2 elasticities are computed, through the following four steps.

1. Estimate the reduced-form model using a Bayesian strategy for inference. Specifically, a Minnesota prior is employed for the coefficients, consistent with a broad literature, while the variance-covariance matrix is treated as known and set to its OLS estimate. In the spirit of Giannone et al. (2013), a hierarchical approach is adopted for the choice of Minnesota priors, by optimizing the hyperparameters through grid search. The grid

search maximizes the model's marginal likelihood by seeking the optimal combination of values for the priors. In other words, the hyperparameter values are not imposed but are estimated within the Bayesian framework by selecting hyperparameter values that maximize the marginal likelihood.

2. Draw the posterior distribution and derive generalized impulse response functions (GIRFs) following the methodology of Koop et al. (1996) and Caggiano et al. (2017). This approach allows endogenizing the variables in the interaction terms and, consequently, conditioning the response of the other endogenous variables also on their evolution.[5] Specifically, GIRFs are derived as the following difference:

$$GIRF_y(h, \delta, \omega_{t-1}) = E\left[y_{t+h}|\delta, \omega_{t-1}\right] - E\left[y_{t+h}|\omega_{t-1}\right]. \tag{3}$$

   where, $E\left[y_{t+h}|\delta, \omega_{t-1}\right]$ represents the expected value of the response of the endogenous variables y to a shock of size δ, at horizon $t+h$, conditional on an initial history ω_{t-1}; and $E\left[y_{t+h}|\omega_{t-1}\right]$ represents the expected value of the endogenous variable y at horizon $t+h$ conditional on an initial history ω_{t-1}. This step requires the following sub-steps:

   (a) choose an initial condition ω_{t-1};
   (b) simulate the residuals series starting from its empirical distribution $\tilde{u}^r_{t+h}$;
   (c) for each simulation of residuals r, recover the path $E\left[y_{t+h}|\omega_{t-1}\right]^r$;
   (d) simulate the path $E\left[y_{t+h}|\delta, \omega_{t-1}\right]^r$ starting from the residuals obtained in sub-step (b) perturbed by a government spending shock identified using a Cholesky decomposition[6] (as in Kilian and Vigfusson (2011) and Caggiano et al. (2017));
   (e) compute the GIRF as shown in equation (3);
   (f) calculate the average GIRF across $R = 500$ simulations to obtain consistent estimates.

3. Repeat step 2 for 10,000 draws from the posterior distribution. Then, consider the median IRFs across the 10,000 parameter draws. Parameter uncertainty is considered by saving the 16th and 84th percentiles of the distribution as an error band.

[5]While GIRFs are traditionally based on reduced form residuals, in the case of Caggiano et al. (2017) GIRFs are based on structural shocks derived from a Cholesky decomposition inserted in a GIRF algorithm with the advantage of endogenizing states that can be influenced by the shocks.

[6]Following Blanchard and Perotti (2002), we order government spending as the first endogenous variables. The assumption behind this choice is that, due to implementation and legislation lags, government spending does not respond contemporaneously to other endogenous variables within the same quarter.

4. Calculate the cumulative CO_2 emissions elasticities, E_h, analogously to the method to compute cumulative fiscal multipliers. In other words, cumulative CO_2 emissions elasticities are determined as the ratio of the discrete approximations of the integral of the median impulse response functions (IRFs) of the natural logarithm of CO_2 and the natural logarithm of government purchases over a specified time horizon *h = 0, 1, ..., H:*

$$E_h = \frac{\sum_{h=0}^{H} d\ln CO2(h)}{\sum_{h=0}^{H} d\ln G(h)}. \tag{4}$$

3 Results

3.1 Cumulative CO2 Elasticities to Government Spending

The FAIVAR-X framework enables us to derive impulse responses of consumption- and production-generated CO_2 emissions to government spending shocks while conditioning on the contemporaneous values of all four interaction variables. Concretely, for each quarter in the sample, impulse responses are computed based on the realized values of the interaction variables at the time of the shock. Subsequently, all endogenous variables—including the interaction variables—evolve according to the system's dynamics. This procedure allows calculating time series of cumulative CO_2 elasticities at specified horizons, following the methodology described in Subsection 2.3. In practice, if CO_2 emissions change by x percent and government spending changes by y percent over a given horizon H in response to a government spending shock, the elasticity is defined as the ratio x/y.

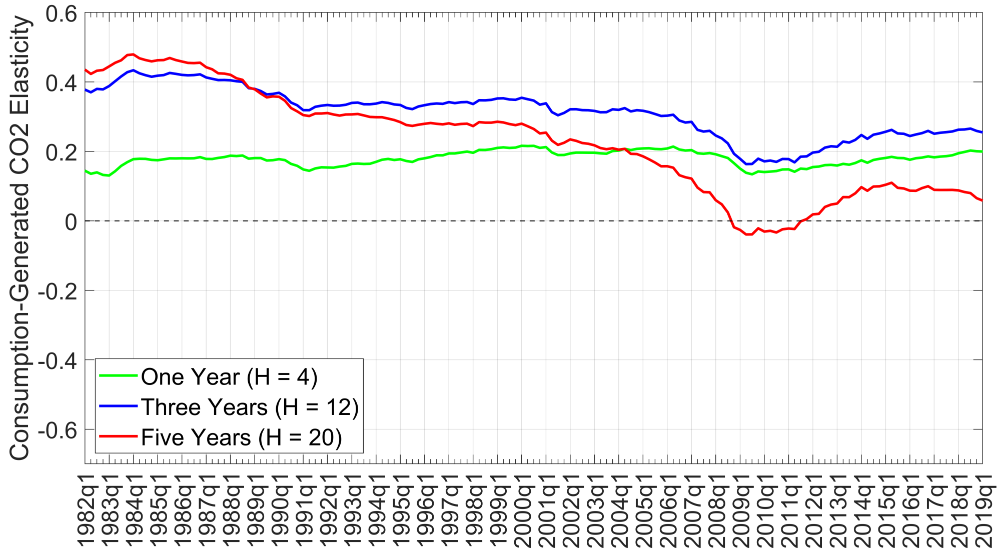
Results are presented in Figure 2, which displays the cumulative consumption-generated (Subfigure 2-(a)) and production-generated (Subfigure 2-(b)) elasticities at horizons $H = \{4, 12, 20\}$ (i.e., one, three, and five years) for each quarter in the estimation sample, spanning 1982 to 2019 (after adjusting for the lag structure).

Consumption-generated CO_2 emissions generally rise in response to a positive government spending shock, with the cumulative effect growing stronger over the medium term compared to the short term. Notably, however, this effect has diminished over the past four decades: at a five-year horizon, the associated elasticity has declined from nearly 0.5 in the early 1980s to about 0.1 in 2019.

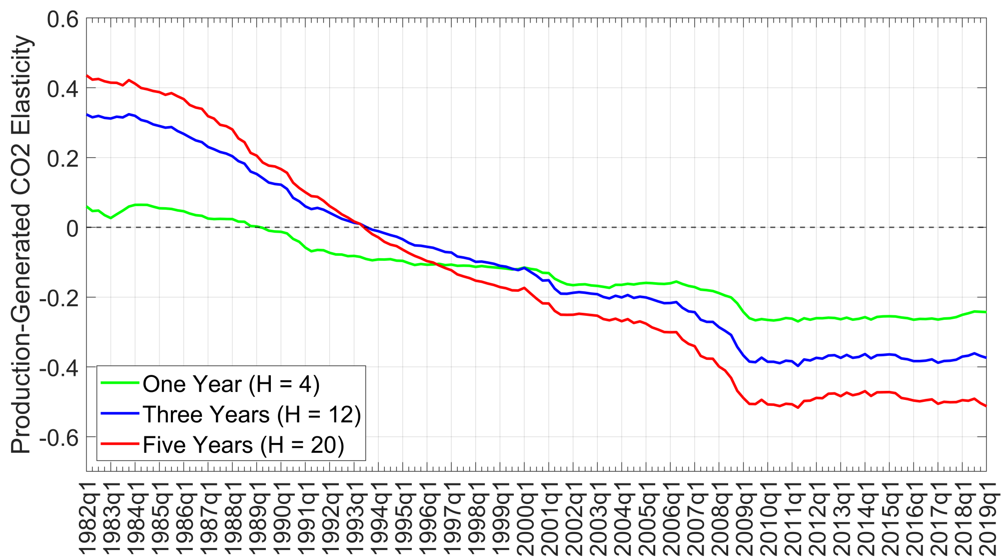
A similar pattern of increasing absolute magnitudes with the time horizon also applies to production-generated CO_2 emission elasticities, but with a key difference in how the relationship has evolved over time. In the early 1980s, a positive government spending shock raises production-generated emissions, with the effect weakening in subsequent years. By the 1990s, the sign of the elasticity has reversed, indicating that government spending begins to

Figure 2: Cumulative CO_2 Emission Elasticities

(a) Consumption-Generated



(b) Production-Generated



Notes: Elasticities are computed as in Equation (4). H identifies the number of quarters after the shock.

reduce production-generated CO_2 emissions. Indeed, at a five-year horizon, the cumulative elasticity falls from around 0.4 at the start of the sample to approximately -0.5 at its end, remaining relatively stable over the most recent decade.

Table 1 reports the average cumulative CO_2 elasticities for the first and second halves of the estimation sample, using the year 2000 as the cut-off point. In general, the absolute magnitude of these elasticities increases at longer horizons, except for consumption-generated

Table 1: Average Cumulative CO_2 Emission Elasticities

		Consumption-Generated		
Horizon	H	[A] Pre-2000q3	[B] Post-2000q3	Prob([B]<[A])
1 year	4	0.18	0.18	0.47
2 years	8	0.32	0.28	0.64
3 years	12	0.37	0.26	0.72
4 years	16	0.37	0.19	0.76
5 years	20	0.35	0.10	0.78
		Production-Generated		
Horizon	H	[A] Pre-2000q3	[B] Post-2000q3	Prob([B]<[A])
1 year	4	-0.04	-0.22	0.99
2 years	8	0.04	-0.27	0.98
3 years	12	0.09	-0.31	0.97
4 years	16	0.11	-0.36	0.96
5 years	20	0.12	-0.41	0.94

Notes: Elasticities are computed as in Equation (4) for the pre- and post-2000q3 periods. The table reports average values. H identifies the number of quarters after the shock.

CO_2 emissions in the post-2000 period. Importantly, the five-year elasticity for consumption-generated CO_2 emissions exceeds 0.35 in the first 20 years but drops to 0.1 thereafter. For production-generated CO_2 emissions, the five-year elasticity shifts from 0.12 in the earlier sub-sample to -0.14 in the later one.

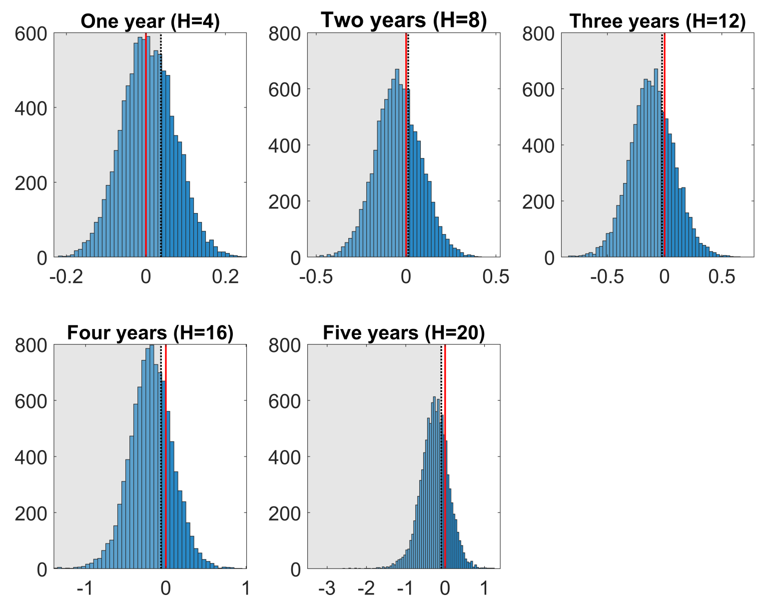
A natural question is whether these differences in elasticities between the second and first part of the sample are statistically smaller than zero. Because Bayesian inference does not allow for the usual frequentist hypothesis testing, a Bayesian-compatible procedure similar to Caggiano et al. (2015) and Amendola et al. (2020) is employed. For each of the 10,000 draws from the posterior distribution, the elasticities (as in Equation (4)) for the two subperiods are computed and their difference is taken. Figure 3 shows the distributions of these differences at various horizons, along with their 68 percent credible sets.

The results indicate that, for horizons beyond three years in the case of consumption-generated CO_2 emissions and for all horizons in the case of production-generated CO_2 emissions, at least 68 percent of the respective difference distributions lie below zero. This suggests that the sub-sample difference in elasticities is negative with high probability. As shown in Table 1, for consumption-generated emissions, the probability of a negative difference increases from 47 percent at a one-year horizon to 78 percent at a five-year horizon, while for production-generated emissions it remains above 90 percent across all horizons.

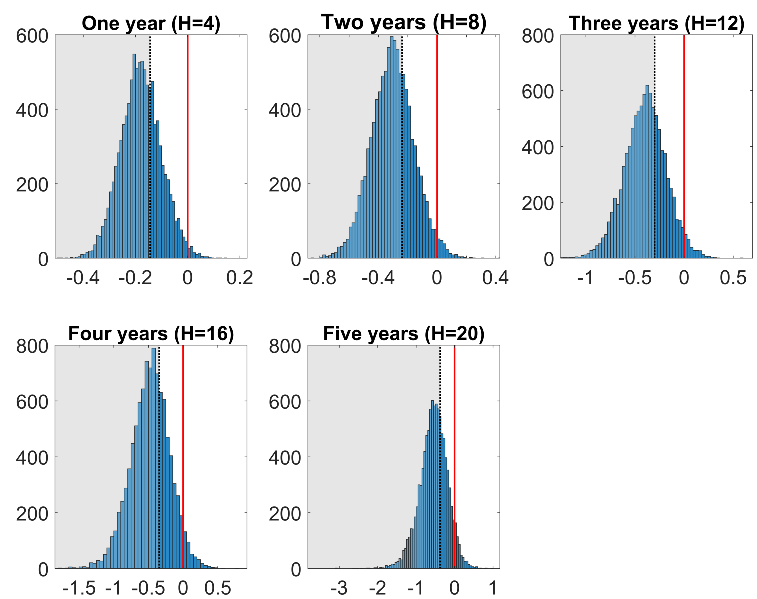
In sum, the FAIVAR-X analysis reveals distinct dynamics for consumption- and production-generated CO_2 emissions following government spending shocks. Consumption-generated

Figure 3: Distributions of Differences in Cumulative Emission Elasticitied Between the Pre- and Post-2000q3 Periods

(a) Consumption-Generated



(b) Production-Generated



Notes: Empirical distributions of the differences are computed as average cumulative emission elasticities in the pre-2000q3 period minus average cumulative emission elasticities in the post-2000q3 period. Elasticities are computed as in Equation 4 for each of the 10,000 parameter draws from the posterior distribution. The shaded area delimited by the vertical dotted line represent 68 percent of the distribution of differences. The vertical red line denotes zero. H identifies the number of quarters after the shock.

emissions show a generally positive response that weakens considerably over the past four decades, while production-generated emissions initially increase in the early 1980s but switch to a negative relationship by the 1990s. Subsample comparisons indicate large differences in the emission elasticities before and after the year 2000. Furthermore, a Bayesian-compatible inference procedure confirms that the elasticity reductions across time are highly probable, underscoring the evolving nature of the fiscal policy–CO_2 emissions nexus.

3.2 Drivers of CO_2 Emission Elasticities

To investigate the potential mechanisms driving the observed evolution of both consumption- and production-generated CO_2 emission elasticities to government spending, this subsection explores how these elasticities vary with each of the four interaction variables. Specifically, ten-year rolling windows of partial correlations between the elasticities and each interaction variable— real GDP per capita level, share of service-providing workers, environmental regulation, and spending composition—are computed, while controlling for the remaining three variables each time. Two clarifications are in order. First, the use of a ten-year rolling window implies that partial correlations can only be computed over the period from 1992Q1 to 2019Q1. Second, although these partial correlations offer valuable insights in the individual contribution of each channel, they should not be read as causal relationships.

The partial correlations for consumption-generated CO_2 elasticities (Figure 4) show a negative relationship with both the environmental protection index and the share of workers in service-providing activities, echoing the notion that stricter environmental regulations and the tertiarization of the economy moderate the link between fiscal expansions and household carbon emissions (Galinato and Islam, 2017; Stern, 2017). In contrast, the relation with GDP tends to be positive—albeit not uniformly so— which provide indication about the fact that greater economic activity raises consumption and thus emissions (Grossman and Krueger, 1995). Lastly, relationship with the share of public goods in government spending appears more nuanced, switching signs across subperiods. This variability is consistent with studies suggesting that while certain categories of public spending may encourage cleaner consumption, other forms—particularly those boosting disposable income—might lead to higher emissions depending on household preferences and market conditions (Galinato and Islam, 2017).

For production-generated CO_2 elasticities (Figure 5), both the environmental protection index and the share of workers in service activities exhibit consistently negative correlations, in line with the effects of structural change toward a more stringent regulatory framework and a service-dominated economy (Panayotou, 1993; Sanchez and Stern, 2016). By contrast, the GDP level generally shows a positive association, likely reflecting that a higher income level intensifies pollution unless counteracted by regulatory or technological advancements (Stern, 2017).[7] The share of public goods in government spending also shows a predominantly negative correlation, in line with the view that fiscal allocations in favor of social programs like education and health may reduce the emissions intensity of production (this mechanism is often referred to in the literature as the "technique effect") (López and Galinato, 2007; Halkos and Paizanos, 2016b). However, this negative association weakens at times, possibly highlighting shifts in fiscal priorities that may have environmental repercussions.

3.3 Cumulated CO_2 Emission Elasticities to Government Consumption and Investment

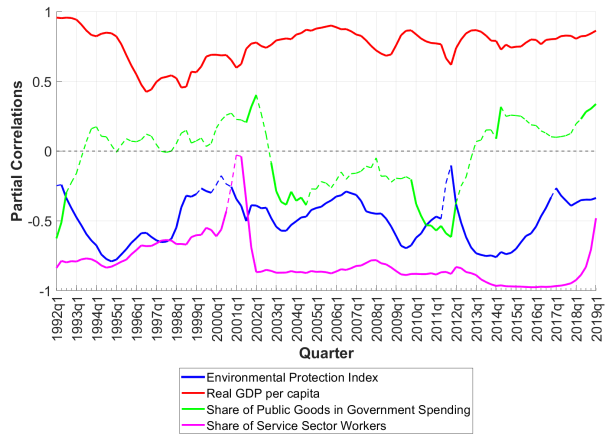
A closer look at the composition of public outlays helps explain the aggregate relationship between fiscal policy and CO_2 emissions over time. Government consumption and investment differ in both scale and nature: the former is the larger, more routine component, heavily oriented toward wages, intermediate inputs, and service delivery; the latter is smaller but capital intensive, tied to infrastructure cycles and long lived assets. Replicating the baseline estimation exercise for each of the two items—computing cumulative elasticities for emissions generated on the consumption and production side—reveals that the two spending categories have left very different carbon footprints over the sample under investigation.

Figure 6 traces CO_2 emission elasticities to government consumption. Given that consumption accounts for the largest part of total outlays, its elasticities unsurprisingly echo those found for total government expenditures. Consumption-generated elasticities begin the sample at about 0.3–0.5, then trend downward but remain positive throughout the four decade window; even five years after a shock, a one percent rise in government consumption still lifts household level emissions by roughly 0.1–0.2 percent toward the end of the sample. Just like for total expenditures, on the production side, the picture changes qualitatively around the early 1990s. Until then, production-generated elasticities related to government consumption are mildly positive, reflecting the carbon intensive nature of public procurement during the manufacturing heavy 1980s. From the mid 1990s onward, the sign flips and the elasticities settle in negative territory, reaching –0.3 to –0.5 in the late 2000s. Table 2 formalizes this visual break: the probability that post 2000 Q3 production-generated elasticities are smaller than their pre 2000 counterparts is at least 95 percent at every horizon, while the corresponding probabilities for consumption-generated elasticities range between

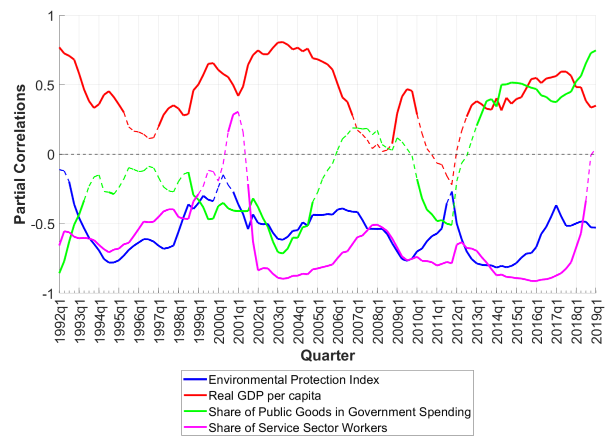
[7] Note that in this case, unlike the five-year-horizon results on the consumption-generated emissions, the five-year-horizon results on production-generated emissions several times display windows in which the relationship with real GDP per capita is negative.

Figure 4: Cumulative Consumption-Generated CO_2 Emission Elasticities: Rolling-Window Partial Correlations with Proxies of Key Determinants

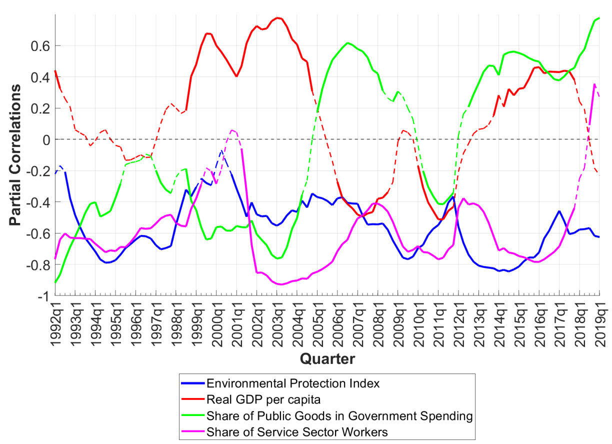
(a) 1-Year Horizon ($H = 4$)



(b) 3-Year Horizon ($H = 12$)



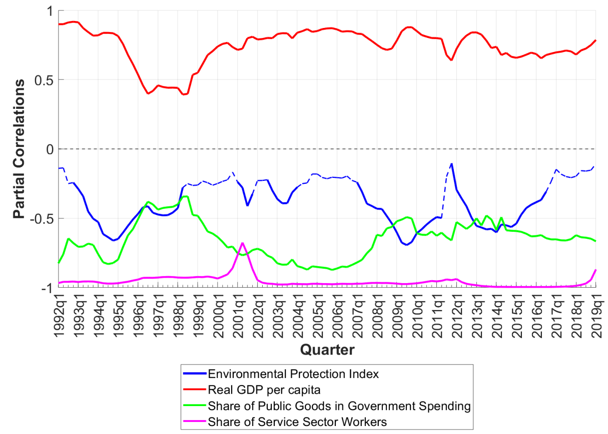
(c) 5-Year Horizon ($H = 20$)



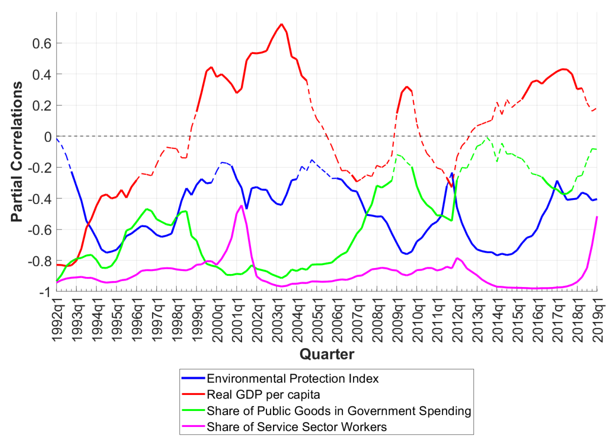
Notes: Charts report ten-year rolling windows of partial correlations between the elasticities and each interaction variable—environmental protection, GDP level, share of public goods, and share of service-sector workers—while controlling for the remaining three variables each time.

Figure 5: Cumulative Production-Generated CO_2 Emission Elasticities: Rolling-Window Partial Correlations with Proxies of Key Determinants

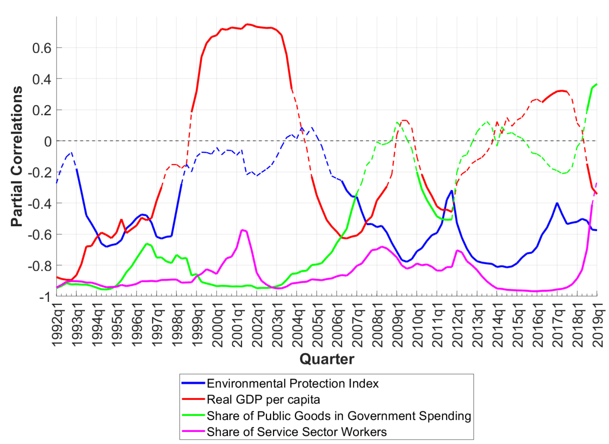
(a) 1-Year Horizon ($H = 4$)



(b) 3-Year Horizon ($H = 12$)



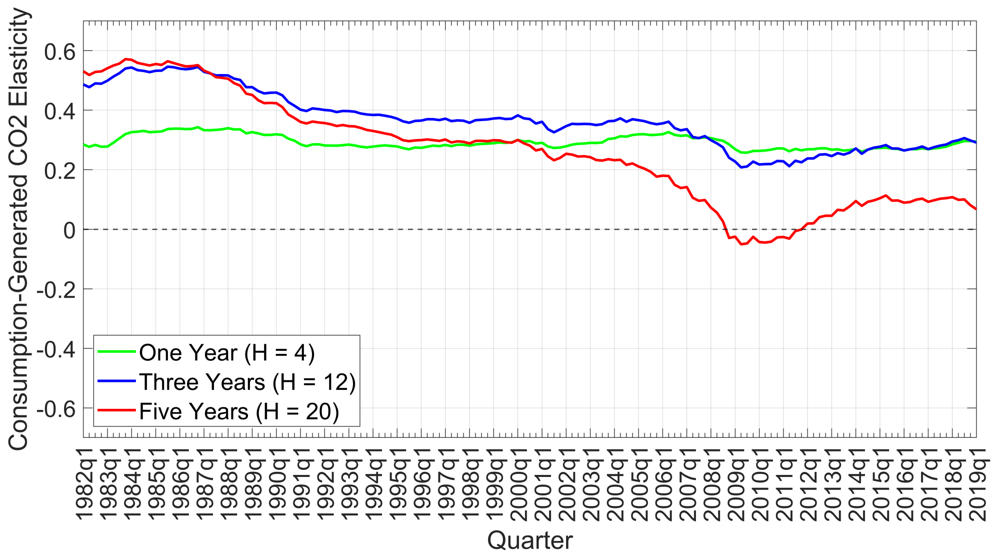
(c) 5-Year Horizon ($H = 20$)



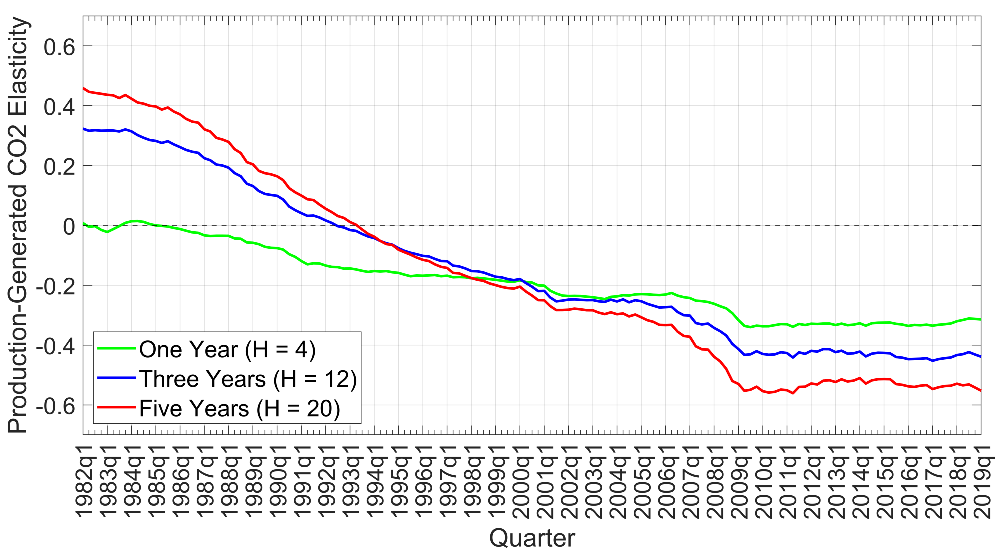
Notes: Charts report ten-year rolling windows of partial correlations between the elasticities and each interaction variable—environmental protection, GDP level, share of public goods, and share of service-sector workers—while controlling for the remaining three variables each time.

Figure 6: Cumulative CO_2 Emission Elasticities—Government Consumption

(a) Consumption-Generated



(b) Production-Generated



Notes: Elasticities are computed as in Equation (4). H identifies the number of quarters after the shock.

59 and 81 percent.

Government investment, depicted in Figure 7, tells a more cyclical story. Both consumption- and production-generated CO2 elasticities related to government investment rise sharply in the early 1980s, fall through the 1990s, rebound during the infrastructure push of the early 2000s, dip again after the global financial crisis, and edge upward toward the end of the sample. Importantly, although production-generated elasticities decline on average after

Table 2: Average Cumulative CO_2 Emission Elasticities—Government Consumption

		Consumption-Generated		
Horizon	H	[A] Pre-2000q3	[B] Post-2000q3	Prob([B]<[A])
1 year	4	0.30	0.29	0.59
2 years	8	0.41	0.34	0.73
3 years	12	0.44	0.29	0.77
4 years	16	0.43	0.21	0.79
5 years	20	0.41	0.11	0.81
		Production-Generated		
Horizon	H	[A] Pre-2000q3	[B] Post-2000q3	Prob([B]<[A])
1 year	4	-0.10	-0.29	0.99
2 years	8	-0.01	-0.34	0.99
3 years	12	0.07	-0.36	0.98
4 years	16	0.10	-0.40	0.96
5 years	20	0.11	-0.44	0.95

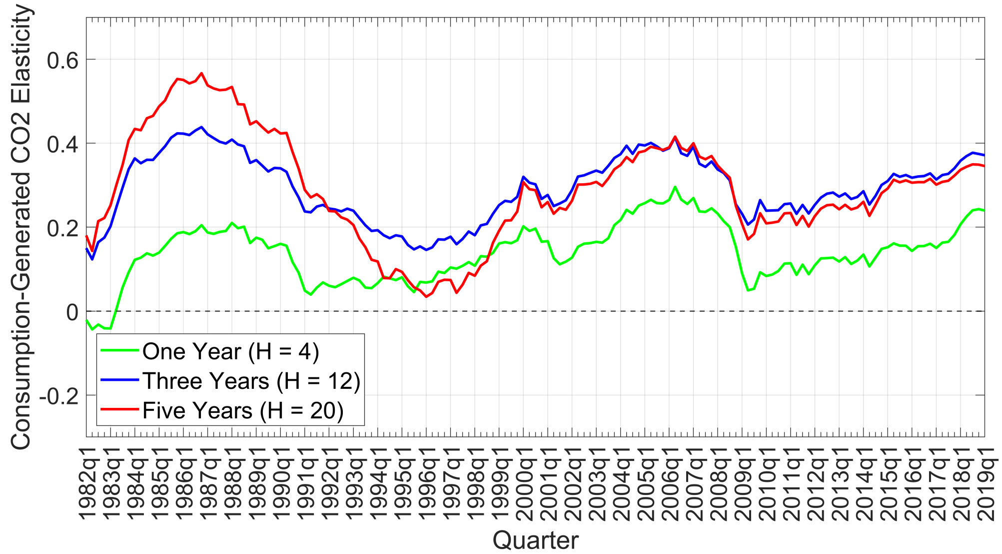
Notes: Multipliers are computed as in Equation (4) for the pre- and post-2000q3 periods. The table reports average values. H identifies the number of quarters after the shock.

2000 Q3 (Table 3), their sign remains on average positive, with short-lived drops below zero. A possible explanation is that investment projects, even when greener than in the past, still relied on materials, heavy equipment, and energy intensive construction processes. By contrast, consumption-generated CO2 elasticities for government investment show no significant change across the 2000 Q3 breakpoint, ranging between 0.1–0.4 regardless of horizon. In other words, the indirect boost to household emissions stemming from higher public capital spending is less time varying than the boost associated with government consumption. Specifically, the probability that post 2000 Q3 consumption-generated elasticities related to government investment are smaller than their pre 2000 counterparts ranges between 12 and 48 percent, while the corresponding probabilities for production-generated elasticities range between 45 and 74 percent.

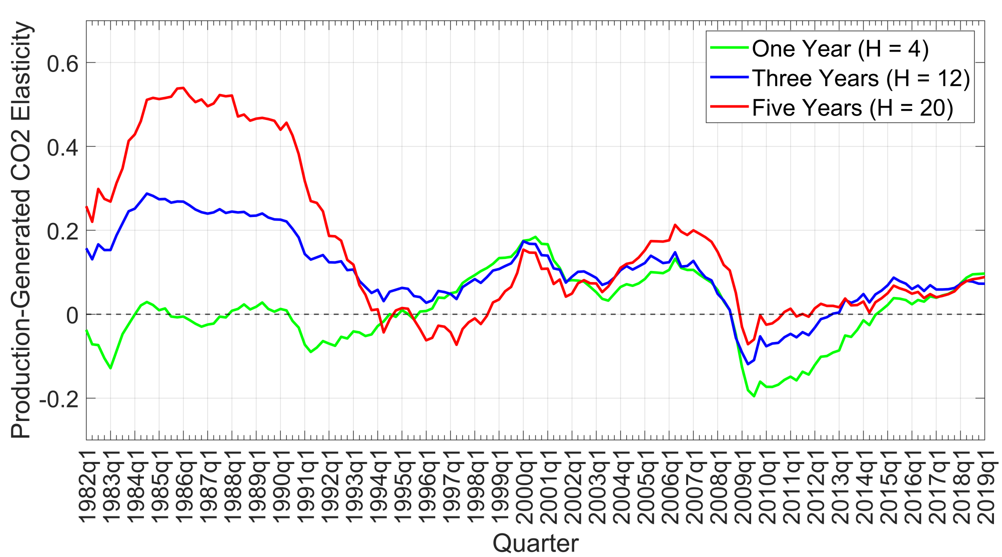
Taken together, the evidence shows that government consumption is chiefly responsible for the gradual reduction in consumption-generated CO_2 elasticities to government spending and for the post 1990 shift of production-generated elasticities from positive to negative. Government investment plays little role in the decline in consumption-generated elasticities and, while it helps lower production-generated elasticities, it is not the main responsible driver of their sign change in the more recent part of the sample.

Figure 7: Cumulative CO_2 Emission Elasticities—Government Investment

(a) Consumption-Generated



(b) Production-Generated



Notes: Elasticities are computed as in Equation (4). H identifies the number of quarters after the shock.

4 Conclusions

Government spending exerted heterogeneous and time-varying effects on U.S. carbon emissions. Using a Bayesian factor-augmented interacted VAR purified of expectations, this paper shows that consumption-generated CO_2 emissions responded positively to fiscal expansions throughout 1981–2019, yet the medium-term elasticity has declined from roughly

Table 3: Average Cumulative CO_2 Emission Elasticities—Government Investment

		Consumption-Generated		
Horizon	H	[A] Pre-2000q3	[B] Post-2000q3	Prob([B]<[A])
1 year	4	0.11	0.17	0.12
2 years	8	0.22	0.27	0.26
3 years	12	0.28	0.31	0.36
4 years	16	0.29	0.32	0.43
5 years	20	0.29	0.29	0.48
		Production-Generated		
Horizon	H	[A] Pre-2000q3	[B] Post-2000q3	Prob([B]<[A])
1 year	4	0.01	0.01	0.45
2 years	8	0.09	0.02	0.72
3 years	12	0.16	0.05	0.76
4 years	16	0.22	0.07	0.75
5 years	20	0.26	0.07	0.74

Notes: Multipliers are computed as in Equation (4) for the pre- and post-2000q3 periods. The table reports average values. H identifies the number of quarters after the shock.

0.5 to 0.1. Production-generated emissions, by contrast, moved from an elasticity close to 0.4 in the early 1980s to about –0.5 by the late 2010s. Rolling correlations with structural and policy indicators reveal that while the income effect may have prevalently contributed positively to emissions, stricter environmental regulation, a rising service share, and greater allocations to public goods show a negative association. Decomposing outlays underscores the pivotal role of government consumption: it accounted for most of the downward trend in consumption-generated elasticities and drives the post-1990 sign switch on the production-generated side, whereas government investment contributed only marginally.

These findings advance the fiscal-environmental literature in two respects. First, the elasticity of emissions is highly state dependent, a feature that reconciles seemingly conflicting empirical results reported earlier in the literature. Second, the analysis clarifies the mechanisms that shape the environmental impact of fiscal policy, highlighting that spending composition and regulatory context, together with the structure of production, all play a pivotal role.

The greening of procurement standards, the expansion of public investment in clean infrastructure, and the tightening of environmental regulation can strengthen the downward pressure on both household and industrial emissions induced by government spending shocks. Extending this framework to other greenhouse gases, alternative tax-spending mixes, and cross-country settings represents a fruitful direction for future research.

References

Amendola, A., M. Di Serio, M. Fragetta, and G. Melina (2020). The euro-area government spending multiplier at the effective lower bound. *European Economic Review 127*, 103480.

Auerbach, A. J. and Y. Gorodnichenko (2012a). Fiscal multipliers in recession and expansion. In *Fiscal policy after the financial crisis*, pp. 63–98. University of Chicago Press.

Auerbach, A. J. and Y. Gorodnichenko (2012b). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy 4*(2), 1–27.

Bai, J. and S. Ng (2007). Determining the Number of Primitive Shocks in Factor Models. *Journal of Business and Economic Statistics 25*(1), 52–60.

Batini, N., G. Callegari, and G. Melina (2012). Successful austerity in the united states, europe and japan. *IMF Working Paper 190*.

Bernanke, B. S., J. Boivin, and P. Eliasz (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly journal of economics 120*(1), 387–422.

Bernauer, T. and V. Koubi (2013). Are bigger governments better providers of public goods? evidence from air pollution. *Public Choice 156*, 593–609.

Bonam, D., J. De Haan, and B. Soederhuizen (2022). The effects of fiscal policy at the effective lower bound. *Macroeconomic Dynamics 26*(1), 149–185.

Caggiano, G., E. Castelnuovo, V. Colombo, and G. Nodari (2015). Estimating fiscal multipliers: News from a non-linear world. *The Economic Journal 125*(584), 746–776.

Caggiano, G., E. Castelnuovo, and G. Pellegrino (2017). Estimating the real effects of uncertainty shocks at the zero lower bound. *European Economic Review 100*, 257–272.

Chishti, M. Z., M. Ahmad, A. Rehman, and M. K. Khan (2021). Mitigations pathways towards sustainable development: Assessing the influence of fiscal and monetary policies on carbon emissions in BRICS economies. *Journal of Cleaner Production 292*, 126035.

Cohen, G., J. T. Jalles, P. Loungani, and R. Marto (2018). The long-run decoupling of emissions and output: Evidence from the largest emitters. *Energy Policy 118*, 58–68.

Di Serio, M., M. Fragetta, E. Gasteiger, and G. Melina (2024). The euro area government spending multiplier in demand-and supply-driven recessions. *Oxford Bulletin of Economics and Statistics 86*(6), 1342–1372.

Di Serio, M., M. Fragetta, and G. Melina (2021). The impact of r-g on euro-area government spending multipliers. *Journal of International Money and Finance 119*, 102493.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association 74*(366), 427–431.

Dinda, S. (2004). Environmental kuznets curve hypothesis: A survey. *Ecological Economics 49*(4), 431–455.

Forni, M. and L. Gambetti (2010, May). Fiscal Foresight and the Effects of Goverment Spending. CEPR Discussion Papers 7840, C.E.P.R. Discussion Papers.

Fragetta, M. and E. Gasteiger (2014). Fiscal foresight, limited information and the effects of government spending shocks. *Oxford Bulletin of Economics and Statistics 76*(5), 667–692.

Galinato, G. I. and A. Islam (2017). The challenge of addressing consumption pollutants with fiscal policy. *Environment and Development Economics 22*(5), 624–647.

Gertler, M. and N. Kiyotaki (2015). Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review 105*(7), 2011–2043.

Ghassibe, M. and F. Zanetti (2022). State dependence of fiscal multipliers: the source of fluctuations matters. *Journal of Monetary Economics 132*, 1–23.

Grossman, G. M. and A. B. Krueger (1995). Economic growth and the environment. *The quarterly journal of economics 110*(2), 353–377.

Halkos, G. E. and E. A. Paizanos (2013). The effect of government expenditure on the environment: An empirical investigation. *Ecological Economics 91*, 48–56.

Halkos, G. E. and E. A. Paizanos (2016a). The effects of fiscal policy on CO2 emissions: Evidence from the USA. *Energy policy 88*, 317–328.

Halkos, G. E. and E. A. Paizanos (2016b). Environmental macroeconomics: Economic growth, fiscal spending and environmental quality. *International Review of Environmental and Resource Economics 9*(3–4), 321–362.

Islam, A. M., R. E. López, et al. (2015). Government spending and air pollution in the us. *International Review of Environmental and Resource Economics 8*(2), 139–189.

Jarociński, M. and P. Karadi (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics 12*(2), 1–43.

Jo, Y. J. and S. Zubairy (2025, January). State-dependent government spending multipliers: Downward nominal wage rigidity and sources of business cycle fluctuations. *American Economic Journal: Macroeconomics 17*(1), 379â413.

Kilian, L. and R. J. Vigfusson (2011). Are the responses of the US economy asymmetric in energy price increases and decreases? *Quantitative Economics 2*(3), 419–453.

Kirchner, M., J. Cimadomo, and S. Hauptmeier (2010). Transmission of government spending shocks in the euro area: Time variation and driving forces. *Working Paper Series 1219, European Central Bank*.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics 74*(1), 119–147.

Kruse, T., A. Dechezleprêtre, R. Saffar, and L. Robert (2022). Measuring environmental policy stringency in OECD countries: An update of the oecd composite eps indicator. *OECD Economic Department Working Papers* (1703), 0_1–56.

Kwiatkowski, D., P. C. B. Phillips, P. Schmidt, and Y. Shin (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics 54*(1-3), 159–178.

Li, B., L. You, M. Zheng, Y. Wang, and Z. Wang (2020). Energy consumption pattern and indoor thermal environment of residential building in rural China. *Energy and Built Environment 1*(3), 327–336.

López, R. and G. I. Galinato (2007). Should governments stop subsidies to private goods? Evidence from rural latin america. *Journal of Public Economics 91*(5-6), 1071–1094.

López, R., G. I. Galinato, and A. Islam (2011). Fiscal spending and the environment: Theory and empirics. *Journal of Environmental Economics and Management 62*(2), 180–198.

McConnell, K. E. (1997). Income and the demand for environmental quality. *Environment and development Economics 2*(4), 383–399.

Miyamoto, W., T. L. Nguyen, and D. Sergeyev (2018, July). Government spending multipliers under the zero lower bound: Evidence from japan. *American Economic Journal: Macroeconomics 10*(3), 247–77.

Nickel, C. and A. Tudyka (2014). Fiscal Stimulus in Times of High Debt: Reconsidering Multipliers and Twin Deficits. *Journal of Money, Credit and Banking 46*(7), 1313–1344.

Noailly, J., L. Nowzohour, M. van den Heuvel, and I. Pla (2024). Heard the news? Environmental policy and clean investments. *Journal of Public Economics 238*, 105190.

Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development. *ILO Working Papers*.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies 72*(252), 821–852.

Ramey, V. A. and S. Zubairy (2018). Government spending multipliers in good times and in bad: Evidence from US historical data. *Journal of political economy 126*(2), 850–901.

Sá, F., P. Towbin, and T. Wieladek (2014). Capital inflows, financial structure and housing booms. *Journal of the European Economic Association 12*(2), 522–546.

Sanchez, L. F. and D. I. Stern (2016). Drivers of industrial and non-industrial greenhouse gas emissions. *Ecological economics 124*, 17–24.

Soytas, U., R. Sari, and B. T. Ewing (2007). Energy consumption, income, and carbon emissions in the United States. *Ecological economics 62*(3-4), 482–489.

Stern, D. I. (2017). The environmental kuznets curve after 25 years. *Journal of Bioeconomics 19*, 7–28.

Stock, J. H. and M. W. Watson (2005). Implications of dynamic factor models for VAR analysis. *NBER Working Papers 11467*.

Waheed, R., S. Sarwar, and C. Wei (2019). The survey of economic growth, energy consumption and carbon emission. *Energy Reports 5*, 1103–1115.

Appendix

A Data

A.1 Endogenous Variables

The analysis is conducted using quarterly U.S. data from 1981Q1 to 2019Q1. Baseline specification includes the following endogenous variables:

- G_t: real per capita government consumption expenditures and gross investment;
- GDP_t: real per capita gross domestic product;
- T_t: real per capita government current tax receipts, constructed as the sum of real per capita federal government current tax receipts and real per capita state and local government current tax receipts;
- $CO_{2,t}^P$: per capita production-generated CO_2 emissions, measured as per capita Total Industrial Sector CO2 Emissions;
- $CO_{2,t}^C$: per capita consumption-generated CO_2 emissions, constructed as the sum between per capita total energy residential sector CO2 emissions and per capita total energy transportation sector CO2 emissions;
- EP_t: yearly real oil price growth rate (real crude oil domestic first purchase price);
- EC_t: per capita total energy consumed by residential, commercial, industrial, transportation sectors;
- π_t: year-on-year CPI inflation rate;
- R_t: market yield on U.S. Treasury securities at 1-year constant maturity;
- $SERV_t$: share of service-providing employees over total government and private employees;
- $ENVP_t$: environmental and climate policy news-based index, developed by Noailly et al. (2024);
- PG_t: share of government spending in education, housing, income security, health, recreation.

$G_t, GDP_t, T_t, \Pi_t, PG_t$ are downloaded from the U.S. Bureau of Economic Analysis (BEA), while $CO_{2,t}^P, CO_{2,t}^C, EP_t, EC_t$ data are downloaded from the U.S. Energy Information Administration (EIA). R_t is retrieved from the Federal Reserve Bank of St. Louis database (FRED). $SERV_t$ is constructed using U.S. Bureau of Labor Statistics (BLS) data. Variables are transformed in natural logarithms where appropriate.

A.2 Exogenous Variable

The exogenous variable is the forecast of time-t growth of real government spending over the past three months based on the Survey of Professional Forecasters (SPF) available from Federal Reserve Bank of Philadelphia. As in Auerbach and Gorodnichenko (2012b,a), the annualized growth rate of real government purchases forecast for time t at time $t-1$ is computed as $f_{(t|t-1)} = \left[\left(\frac{G^e_{t|t-1}}{G^e_{t-1|t-1}}\right)^4 - 1\right] \times 100$, where $G^e_{t|t-1}$ and $G^e_{t-1|t-1}$ are the sum of the forecasts for the Real Federal Government Consumption Expenditures & Gross Investment (RFEDGOV) and Real State and Local Government Consumption Expenditures & Gross Investment (RSLGOV).

A.3 Informational Dataset

The informational dataset used to extract common factors is composed by 64 series downloaded from the Federal Reserve Bank of St. Louis database. Specifically the following variables were downloaded:

- *National Account.* Real Personal Consumption Expenditures; Real Exports of Goods and Services; Real Imports of Goods and Services; Gross Private Domestic Investment; Gross Saving.

- *Government Statistics.* Federal Debt: Total Public Debt.

- *Output and income.* Industrial Production Index; Business Sector: Unit Labor Cost; Nonfarm Business Sector: Unit Labor Cost; Average Hourly Earnings of Production and Nonsupervisory Employees, Construction; Average Hourly Earnings of Production and Nonsupervisory Employees, Total Private; Change in Private Inventories; Corporate Inventory Valuation Adjustment; Corporate Net Cash Flow with IVA; Corporate Profits After Tax (without IVA and CCAdj); Real Final Sales of Domestic Product;

- *Employment and hours.* Business Sector: Real Compensation Per Hour; All Employees, Manufacturing; All Employees, Nondurable Goods; All Employees, Service-Providing;

All Employees, Education and Health Services; All Employees, Financial Activities; All Employees, Government; All Employees, Information; All Employees, Leisure and Hospitality; All Employees, Professional and Business Services; All Employees, Total Private; All Employees, Other Services; All Employees, Trade, Transportation, and Utilities; All Employees, Retail Trade; All Employees, Wholesale Trade; Number Unemployed for 15 Weeks & Over; Number Unemployed for 15-26 Weeks; Number Unemployed for 27 Weeks & Over; Number Unemployed for 5-14 Weeks; Number Unemployed for Less Than 5 Weeks; Average Weekly Hours of Production and Nonsupervisory Employees, Manufacturing; Nonfarm Business Sector: Hours of All Persons.

- *Money and credit quantity aggregates.* Currency Component of M1; Commercial and Industrial Loans, All Commercial Banks; Consumer Loans, All Commercial Banks; Total Nonrevolving Credit Owned and Securitized, Outstanding; Total Consumer Credit Owned and Securitized, Outstanding; Bank Credit, All Commercial Banks; Loans and Leases in Bank Credit, All Commercial Banks; Real Estate Loans, All Commercial Banks; Securities in Bank Credit, All Commercial Banks; Other Securities, All Commercial Banks; Treasury and Agency Securities, All Commercial Banks.

- *Interest Rates.* 3-Month Treasury Bill: Secondary Market Rate, Moody's Seasoned Aaa Corporate Bond Yield.

- *Prices.* Consumer Price Index for All Urban Consumers: All Items in U.S. City Average; Consumer Price Index for All Urban Consumers: Food in U.S. City Average; Consumer Price Index for All Urban Consumers: All Items Less Food in U.S. City Average; Producer Price Index for All Commodities; Producer Price Index by Commodity for Final Demand: Private Capital Equipment; Producer Price Index by Commodity Fuels and Related Products & Power; Producer Price Index by Commodity for Final Demand: Finished Consumer Foods; Producer Price Index by Commodity for Final Demand: Personal Consumption Goods (Finished Consumer Goods); Producer Price Index by Commodity for Final Demand: Finished Goods; Producer Price Index by Commodity Industrial Commodities; Gross Domestic Product: Chain-type Price Index; Spot Crude Oil Price: West Texas Intermediate (WTI)

Where appropriate variables differenced to guarantee stationarity tested by the Dickey and Fuller (1979) and Kwiatkowski et al. (1992) tests.

PUBLICATIONS

Time-Varying Impacts of Government Spending on CO2 Emissions
Working Paper No. WP/2025/132