What are the structural determinants of US carbon dioxide emissions? An econometric approach*

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Abstract

The role played by technological progress to reduce aggregate carbon dioxide (CO_2) emissions is not yet clear within the applied literature. This paper addresses this issue by developing two different recursive Vector Autoregressive (VAR) methodologies to investigate the short-run dynamic interactions between aggregate carbon dioxide emissions and a set of macroeconomic variables for the US economy over the 1949–2018 period. Existing empirical procedures do not involve identification strategies solely based on economic theory, and this study does so through two main theoretical elements: an extended Kaya identity, including renewable energy consumption and the number of employed workers, and the green growth hypothesis, which ranks technological change as one of the leading drivers of an absolute decoupling process. In both VAR estimations, I compute aggregate CO_2 emissions responses to technology, non-renewable and renewable energy use, population, and output structural shocks. Most results indicate that technology and non-renewable energy use shocks positive and significantly affect emissions over the short-run. Contrary to a current belief within the theoretical literature, our results indicate that technology shocks positively affect energy demand, while the latter's effect on the former is either negative or not significant. Finally, the US historical technological progress path does not support an absolute decoupling scenario among energy use, income, and emissions.

Keywords: Carbon emissions, technology, energy consumption, vector autoregressions, impulse-response functions

JEL Classification Codes: E32, O33, Q56, Q57

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1 Introduction

Economic growth sustained by fossil fuels is incompatible with environmental sustainability. Increased population, consumption, and development levels require rising energy demands, and achieving these standards in a sustainable way is the main global challenge for the next decades. Several institutional efforts evaluate diverse scenarios with the aim of mitigating greenhouse gas emissions, while still maintaining economic growth. The green growth hypothesis takes center stage in this debate. Its central claim is that technological progress and resource substitution are the key mechanisms for a potential absolute decoupling between economic growth and the natural environment. In other words, these would allow for an aggregate reduction in greenhouse gas emissions, while still promoting growth. A simultaneous achievement of higher employment and output levels with climate change mitigation is supposed to be possible with the application of new and improved low-emission production methods.

This paper addresses one of these mechanisms: does technological progress lead to reductions in emissions in the short-run, in the US post-war macroeconomy? It develops two different Vector Autoregressive (VAR) strategies that aim to estimate what are the main structural shocks affecting carbon dioxide (CO_2) emissions in the US economy over the 1949–2018 period. Among these, I highlight technology, non-renewable and renewable energy use, population, and output shocks as the main potential determinants of carbon emissions. This identification procedure follows from an extended Kaya identity, based on energy intensity, population growth, employment, and technology variables, emphasizing the latter's role in promoting both economic growth and environmental sustainability, as claimed by recent institutional views on green growth. Firstly, I propose a single-step VAR model, where I directly evaluate the dynamic interactions between emissions and other macroeconomic variables through Impulse-Response Functions (IRFs). Secondly, I estimate a two-step VAR, initially not accounting for emissions. Following a novel methodology developed in Kilian (2009), I retrieve its structural shocks and, in a second step, compute responses of CO_2 emissions to each of these exogenous shocks via regression models.

This paper aims to fill an important gap within the applied literature on the relationship between macroeconomic and environmental variables: providing a simple model identification solely based on economic theory. Macroeconometric models, such as Vector Autoregressions and Vector Error Correction (VEC) Models require a causal ordering involving its endogenous variables, so that the model's dynamic interactions can be properly identified. The strategies that several contributions have adopted so far involve either an identification procedure that does not require a specific ordering (Soytas et al. 2007; Ertugrul et al. 2016; Hossain 2011) or through machine learning algorithms (Bruns et al. 2019). This study proposes an empirical assessment of aggregate technological progress and other macroeconomic variables on CO_2 emissions guided by theory, so that its results can be critically confronted with theoretical positions.

Key results can be summarized as follows. The baseline procedure involves estimating the one- and two-step VAR models with variables in levels. For the one-step procedure, only a non-renewable energy use shock significantly affects carbon emissions over the short-run. On the other hand, the two-step VAR confirms the latter and also a technology shock positive and significantly impacting CO_2 production. In addition, I run several robustness checks, including using variables in first differences and also de-trended with the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997), as well as using two other proxy variables denoting a technology shock: the aggregate capital stock and total factor productivity. Most of the models verify both non-renewable energy use and technology as the main structural shocks positively affecting aggregate carbon dioxide emissions in the US economy over the short-run. Thus, this paper's contribution is twofold: (*i*) I identify VAR models based on theoretical assumptions, derived from an extended Kaya identity and the recent institutional claims for green growth; and (*ii*) historically, the US economy's technological progress path does not support reductions in emissions. In contrast, it increases environmental harm.

In addition to these central results, the impulse-response analyses also render other relevant inferences contrasting with the theoretical literature on technological change and its environmental effects. While theoretical models state that a faster labor productivity growth is predicated on using more energy (Taylor 2009; Semieniuk 2018; Bruns et al. 2019), the present analysis indicates the opposite: technological shocks positively affect (non-renewable) energy demand, while the latter's effect on the former is either negative or not statistically significant. Even though exploring short-run horizons at different frequencies, these results provide relevant input for both theoretical and applied works in the field. Finally, although the US economy has experienced increasing rates of labor and energy productivity over this sample period, such technological progress path has not been translated into the development of more sustainable techniques that effectively reduce carbon emissions. Conversely, not only has technological progress promoted heavier use of non-renewable energy sources, but also increased emissions over time.

Lastly, it is worth pointing out that the empirical literature may be broadly categorized into policy-driven and multivariate backward-looking analyses. The former would imply that only a big push with public investments towards renewable energy sources and increased carbon taxes can trigger such a shift. In contrast, the latter uses historical data to investigate short- and long-run dynamic linkages between environmental and macroeconomic variables. This paper does not assess potential future policy programs. Instead, it narrowly investigates whether aggregate technical change in the short-run implies sufficient improvements in energy use that could support a reduction in CO_2 emissions. The central finding suggests the opposite: improvements in technology increase emissions, rather than decrease them.

The rest of the paper is organized as follows. Section 2 reviews the interactions between greenhouse gas emissions and the macroeconomy throughout different strands of the literature. Section 3 outlines the empirical strategy by first motivating the theoretical priors, and then describing the two different VAR estimation procedures. Section 4 briefly illustrates the data set and the historical evolution of its variables. Section 5 presents and discusses results from the econometric models, also applying several robustness checks. Finally, Section 6 summarizes the paper's main findings and suggestions for future research.

2 Literature review

Economic growth sustained by fossil fuels is incompatible with environmental sustainability. In both theoretical and empirical grounds, growing interdisciplinary research agendas investigate a possible decoupling between growth, energy consumption, and greenhouse gas emissions. This section reviews this literature and its different emphases. I do not attempt to exhaustively cover all relevant research, but to touch upon its major themes and their insights for framing the next section's empirical methodology. Broadly speaking, the applied literature may be divided into policy-oriented and multivariate, backward-looking analyses, whose main branches will be further explored. Finally, it is important to mention that these agendas are connected by the necessity of decoupling. I thus define this term first, then circumscribing how decoupling is approached (*i*) in the dominant policy-oriented, long-run modeling framework and its critiques; (*ii*) within the institutional view on green growth; (*iii*) in backward-looking, applied works using decomposition and time-series methodologies.

The evolution of industrial operation scales and aggregate income over the past decades can be summarized by how well energy inputs could respond to higher production demands. The seminal note by Kraft and Kraft (1978) empirically tests the association between energy use and Gross National Product (GNP) for the US economy between 1947 and 1974. Through a simple Vector Autoregressive (VAR) analysis, the authors find a unidirectional causation relationship from GNP to energy use. While corroborated by later works, there is no empirical consensus on this issue, especially due to data and geographical reasons.[1] While, on one hand, scale demands were met, on the other, reliance on fossil fuels as the main energy source brought along the unintended consequence of increased damage to the biosystem, escalating to the current levels of global warming (Ayres and Warr 2010). To address this issue, studying the interactions between greenhouse gases with other macroeconomic variables is imperative.

From this setting, a possible decoupling between growth and environmental damage arises as a crucial question (Jorgenson and Clark 2010). Whether in absolute (i.e., when aggregate carbon emissions or energy use decrease over time) or relative terms (when the ratio between emissions and output or between energy and output decrease over time), such concept appears either explicit or implicitly within the literature as a unifying criterion connecting economy and environment. Although theoretical priors and empirical methods may diverge, decoupling is a focal point within the literature. I start with policy-oriented works on mainstream and alternative approaches.

[1] See Akarca and Long II (1979), Yu and Choi (1985), and Erol and Yu (1987), for instance.

2.1 Long-run policy-oriented analyses

The Dynamic Integrated models of Climate and the Economy (DICE) presented in Nordhaus (2008) and Nordhaus (2014), as well as its other revisions, are benchmark neoclassical general equilibrium models, serving as a foundation for several long-run simulation and policy-oriented studies.[2] Its theoretical backbone lies on the assumption that economies invest in education, capital, and technological improvements, while reducing present consumption. Moreover, the environment is considered a component of the aggregate capital stock, and these investments aim to reduce greenhouse gas emissions, so that overall consumption can be increased in the future.

Inspired by the DICE setting, Heutel (2012) addresses how tax and cap policies should adapt to business-cycle fluctuations caused by total factor productivity shocks. According to the author's Dynamic Stochastic General Equilibrium (DSGE) model, both policies, at their optimal levels, allow emissions to be procyclical: increased in expansions, and decreased in recessions. Lemoine and Rudik (2017) design possible cost-effective paths to sustain the increase in global average temperature below 2°C, relative to pre-industrial levels, as indicated by the 2015 Paris Agreement (UNFCCC 2015). According to the authors, delaying abatement policies (such as carbon pricing) may be the most cost-effective measure, since warming does not simultaneously respond to greenhouse gas concentration. Therefore, leveraging on this supposed inertia would make future carbon prices lower than in the present, while still being feasible to control the increase in the average global temperature.

A critique to this latter analysis is made by Mattauch et al. (2019). It is argued that the above conclusion is based on non-conventional atmospheric modeling approaches, mainly relative to the carbon cycle and the response of global temperature to increased emissions. Appealing to standard atmospheric science, the authors consider this inertial behavior an *ad hoc* device. Moreover, by modifying these definitions, they reach an initial price of US$ 5.60 per ton of carbon dioxide, and propose cutting emissions to zero by the second half of the present century to achieve the 2°C target.[3]

Using dynamic features from the DICE model, Rezai et al. (2018) shift from a supply to a demand-driven approach, highlighting the interdependence of economic growth, productivity, climate change, and income distribution. Their medium- to long-run analysis involves three scenarios: one with no mitigation policies, one with a 2°C target, and a full-abatement strategy. Furthermore, the model is calibrated to maintain an output growth of 3% in all scenarios. In the first, faster growth implies faster net emissions, with an increase in global temperature of 4°C by the end of the century, and a 7°C peak in 300 years. Abatement policies, on the other hand, also avoid economic stagnation: considering historical evidence, it is still possible to increase economic activity

[2]As an exception, Fischer and Springborn (2011) use a Real Business Cycle (RBC) model to evaluate different environmental policies, abstracting from DICE references. For an empirical response to neoclassical simulation studies, see Doda (2014).

[3]For more on carbon pricing, see van der Ploeg and Rezai (2019).

and employment, while mitigating greenhouse gas emissions. The further challenge, however, lies on managing the possible tension on the existing institutional framework allowing such changes to take place.

Still on the 2°C target, Marquetti et al. (2019) evaluate the Paris Agreement's proposed distribution of abatement efforts by outlining the stylized facts of output production, technological progress, and carbon dioxide (CO_2) emissions for 84 countries between 1980 and 2014. Among other points, the authors conclude that several developed countries have low emission rates, with some presenting absolute decoupling, such as France, Italy, and the United Kingdom. On the other hand, developing economies with high output growth have also high rates of emission. Therefore, maintaining increasing rates of labor productivity with decreases in the energy-labor ratio will require fast upticks in energy efficiency, which will unlikely be sufficient to achieve this target.

Semieniuk et al. (2021) analyze an even more optimistic scenario outlined by the Intergovernmental Panel on Climate Change (IPCC) 2018 report, aiming to keep average global temperature below 1.5°C (IPCC 2018). The authors emphasize the asymmetry between rich, deindustrializing economies and middle- and low-income, fast-growing countries with respect to absolute decoupling requirements. On one hand, it may be plausible to assume that absolute decoupling is feasible in the first group (as already shown by the aforementioned European economies), on the other, the fast growth paths shown by the second group are mainly triggered by industrialization, fueled by intensive non-renewable energy consumption.

At the core of this long-run policy-oriented literature lies the necessity of radical shifts in countries' macroeconomic planning, as well as an unprecedented coordination that no institutional or political efforts have been able to promote until now. In spite of the relevance of critically assessing official reports on mitigation scenarios, these studies do not concentrate on short-run mitigation effects for the current "business-as-usual" setting of both developed and developing economies. Furthermore, absolute decoupling is not yet a stylized fact for rich countries, especially due to their reliance on fossil energy sources. The present study investigates this latter point over the short-run for the United States, a developed economy whose historical technical progress pattern does not support a consistent decarbonization trajectory.

2.2 The green growth hypothesis

Several of the latter critiques to official reports on mitigation policies subscribe to the recent Ecological Macroeconomics research agenda (Rezai and Stagl 2016). By unifying macroeconomic theory with environmental sustainability, works in this strand have gained prominence since the Great Recession. Among different stimulus policies, those promoting ecological conservation, such as investing in pollution mitigation, renewable energy sources, and increased energy efficiency have become more widespread, relative to previous years (Pollin et al. 2008). At a more general institutional viewpoint, the concept of green growth has gained prominence in multilateral organizations, such as the United Nations, the World Bank, and the Organization for Economic Cooperation and Development (OECD). These have issued reports containing different definitions of an economic growth regime that is compatible with minimizing environmental damage, while also allowing for increased levels of well-being and poverty reduction (OECD 2011; UNEP 2011; World Bank 2012).

Furthermore, these reports agree on the two key mechanisms that are able unfold this scenario: technological change and resource substitution (Hickel and Kallis 2020). Assuming rising population and consumption levels over future generations, stronger negative environmental impacts are imminent, unless technology and input use adapt to such scenario. It is also argued that green growth initiatives may create new jobs in low-carbon and renewable energy sectors, such as wind, solar, and recycling fields (Jacobs 2013). Despite its audacity, it is still not clear how such changes will take place over the next decades, and, more importantly, such claims must also be empirically evaluated.

So far, the green growth hypothesis has not been sustained by evidence (Semieniuk 2018; Hickel and Kallis 2020). In addition, energy efficiency, either derived from technological improvements or input substitution, does not solely entail an automatic mitigation of greenhouse gas emissions. As a general rule, efficiency gains and energy savings do not imply not a zero-sum game. This so-called "rebound effect" occurs when energy savings are less than energy efficiency improvements (Gillingham et al. 2016). The Structural Vector Autoregressive (SVAR) modeling approach of Bruns et al. (2019) estimates an aggregate rebound effect of 100% for the US economy, implying that energy efficiency shocks do not produce significant short-run changes in overall energy use. As a consequence, energy-related improvements cannot be taken for granted when assessing the interactions between energy, technology, and emissions. Though using a different identification strategy,[4] this paper adopts similar macroeconometric techniques to further examine these linkages.

2.3 Decomposition and time-series approaches

A different analytical strategy from forward-looking policy-oriented studies are decomposition and time-series exercises. In gereneral, these backward-looking studies analyze historical data in order to highlight stylized facts and empirical linkages between environmental and macroeconomic variables. A common starting point is the Kaya identity. In its standard version, greenhouse gas emissions are related to energy use, population, and economic growth (Kaya 1990). A few examples are O'Mahony (2013), Shahiduzzaman and Layton (2015), and Tol et al. (2009). The first concentrates on Ireland's economy between 1990 and 2010, investigating the main drivers of CO_2 production through an extended Kaya identity (by including renewable energy sources), utilizing a Log Mean Divisia Index (LMDI) approach. It is found that renewable energy penetration is still nascent, while energy intensity (the ratio between the energy input and output) improvement and fossil fuel substitution are capable of countering

[4] While Bruns et al. (2019) identify their models based on statistical theory, this paper's approach follows from economic priors.

population and affluence (income) growth, the two main determinants of local carbon emissions.

The second, applied to the US economy, broadens the previous analysis by scrutinizing the asymmetrical behavior of carbon emissions during business cycle expansions and recessions. Also with an LMDI approach, and using yearly data from 1949 to 2014, as well as monthly data starting in 1973, it is found that that emissions, both in aggregate and intensity measures, decrease faster during recessions than increase over expansions. Also, during the most recent post-crisis period, emissions per capita are still declining, at a similar rate to that of reduction during contraction years. Finally, the third study proposes thinking beyond population growth and economic performance to evaluate CO_2 emissions over the long-run, also considering energy supply, technological, and behavioral changes. For three subperiods (1850–1917, 1917–1960, and 1960–2002), and dismembering emissions intensity (i.e., the ratio between emissions and output) into six components[5] through a multiplicative mean divisia index, it is shown that the first subperiod experienced a rise in emissions intensity, due to population and economic growth, as well as intensive electrification and a switch from wood to coal within industrial production. Energy intensity peaked in 1917, and, after this year, emissions intensity have fallen. In addition to the previous determinants, there was no net shift from fossil to non-fossil energy sources.[6]

Beyond the usual elements of decomposition analyses, globalization and international trade have gained prominence within environmental macroeconomic studies. Within this literature, the Environmental Kuznets Curve (EKC) hypothesis is a relevant theoretical feature. At initial stages of development, agriculture and resource extraction tend to deplete nature at a higher rate than its recovering capabilities, increasing waste and pollution. Then, as development advances, environmental awareness, technological progress, and economic integration tend to slowly decelerate these externalities and improve environmental quality.[7] These two distinct phases would then produce an inverted U-shaped association between pollution and income. Soytas et al. (2007) test a long-run Granger causality between energy use and emissions within an EKC setting. While the former is found significant, no evidence supports causality between the emissions and income growth for the 1960–2004 period. These results are based on generalized impulse-response functions and variance decomposition analyses, thus not offering a theory-based identification strategy (Pesaran and Shin 1998).

Relating international trade to a possible decline in the environmental quality of poorer countries, the "pollution haven" and "race to the bottom" hypotheses are commonly considered in these studies. The former states that poorer econom-

[5] These are (*i*) changes in population, (*ii*) income per capita, (*iii*) energy intensity, (*iv*) primary-final energy consumption ratio, (*v*) fossil-non fossil fuels mix, and (*vi*) in the ratio between emissions and fossil primary energy use.

[6] For different identity uses on the relationship between energy and the environment, see York et al. (2003).

[7] For a thorough survey of theoretical and empirical works on the subject, see Dinda (2004).

ies with lax environmental standards may act as attractors of heavy polluters from rich countries. According the the second proposition, as liberalization increases international competition, poorer countries may experience income increases by hosting external industry relocation; however, if part of this income is not invested in stronger environmental policy, the EKC scenario does not move beyond its initial stage (Wheeler 2000).

Empirical results, however, do not indicate significant impacts of international trade on increased emissions. Neoclassical general equilibrium models of Antweiler et al. (2001) and Copeland and Taylor (2004), cross-country regression models of Frankel and Rose (2005), and the probit estimation of Javorcik and Wei (2004) do not find empirical support neither for the pollution haven nor the race to the bottom conjectures. An exception is the multivariate time-series analysis of Hossain (2011), that, for a panel of nine newly industrialized economies between 1971 and 2007, finds several short-run causal relationships — the most relevant being economic growth and trade openness Granger-causing carbon emissions —, but no long-run panel causal association among the variables. Similar causality inferences are presented by Ertugrul et al. (2016), who apply the same method for the top-ten emitters among developing economies between 1971 and 2011, also finding support for the EKC hypothesis for Turkey, India, China, and South Korea. These latter two analyses, however, also do not offer theory-based identification strategies for their multivariate models.

In essence, detaching increased environmental damage from economic growth permeates all strands of literature hitherto discussed. It is widely agreed within these reviewed studies that, in addition to globally coordinated mitigation policies over the long-run, technological and energy improvements play the most critical role to reduce the use of non-renewable energy and improve the use of renewable sources, while cutting down aggregate energy use and maintaining economic growth. From this literature review, I piece together the set of elements that are at the core of this paper's contribution.

This study concentrates on the dynamic interactions between carbon dioxide emissions, the greatest contributor to the greenhouse effect, and a set of macroeconomic variables. Contrary to forward-looking policy-oriented works, I concentrate on the short-run, using historical data to empirically estimate what are the statistically significant shocks affecting CO_2 emissions for the US economy over the post-war period. As already highlighted, multivariate time-series and panel analyses lack theoretically-based identification strategies for their empirical models, and this paper provides it by using an extended Kaya identity and motivating a VAR model with causal relationships as informed by the green growth hypothesis. This way, it is possible to further assess the aggregate roles of technological progress and energy use to the dynamic behavior of carbon emissions.

3 Empirical strategy

This study's main purpose is to investigate what are the main structural shocks affecting aggregate carbon dioxide emissions in the US economy over the post-war period. In this section, I motivate the empirical methodology to answer this question.

Initially, I propose a theoretical framework inspired by the Ecological Macroeconomics literature, along with the recent institutional view on green growth analyzed in the last section. The first helps us in setting up an extended Kaya decomposition to explore the linkages between macroeconomic variables and carbon emissions. The second allows for a closer evaluation of the role played by technological progress to simultaneously promote economic growth and environmental sustainability.

I use these theoretical priors to identify recursive Vector Autoregressive (VAR) models, whose impulse-response functions will inform the main shocks affecting CO_2 emissions. This will be done in two ways. First, with a single-step VAR procedure. Second, I estimate a two-step VAR model, initially computed without emissions. Then, by retrieving its structural shocks, I quantify the response of CO_2 production to these exogenous shocks via regression models in a second step.

3.1 Overview

This paper's interest lies on the dynamic linkages between CO_2 emissions and macroeconomic variables over the short-run. I first define emissions, Φ_t, as an unintended outcome of economic activity, derived from anthropogenic influence on the natural environment. These are a product of the interactions of several variables, among which are considered the state of the business cycle, Y_t, aggregate primary energy demand (including both renewable and non-renewable sources), E_t, population growth, P_t, and the number of employed workers, L_t. Given the addition of this latter variable, we have an extended Kaya identity:

$$\Phi_t \equiv \frac{Y_t}{L_t} \cdot \frac{E_t}{Y_t} \cdot \frac{\Phi_t}{E_t} \cdot \frac{L_t}{P_t} \cdot P_t \tag{1}$$

where Y_t/L_t is output per worker, or aggregate labor productivity; E_t/Y_t is the energy intensity of output; Φ_t/E_t is the emissions share of energy use; and L_t/P_t is the employment rate, all at time t.

The main source of pollution and waste comes from the use of fossil fuels, such as coal, petroleum, and other chemicals, employed to generate output. Carbon dioxide, along with other greenhouse gases, such as methane and nitrous oxide, scatters and concentrates in the atmosphere, yielding higher levels of global warming. To overcome this scenario, green growth theory proposes that technological progress and resource substitution are the leading drivers of an absolute decoupling between economic growth and environmental harm.[8] In other words, shifting from "dirty" to cleaner technologies, as well as improving energy efficiency, may reduce aggregate greenhouse gas emissions while still improving production and economic growth.

More specifically, green growth theory argues that that rising technological progress correlates with a reduced acceleration, or even a decrease, in energy intensity. Semieniuk (2018) stresses that such view credits models of embodied technical change, where improvements in technological capacity can only be implemented via investments in new equipment (Jorgenson 1966; Berndt et al. 1993). Such improvements are, then, materialized into new capital goods, either fueled by renewable energy or using traditional sources more efficiently, reducing waste and pollution.[9] Thus, upticks in productivity tend to make older and more energy-consuming (i.e., more pollutant) techniques be replaced by newer, energy-saving ones, offsetting increases in energy intensity. Following Taylor (2009), energy intensity may be decomposed into two factors:

$$\frac{E_t}{Y_t} \equiv \frac{L_t}{Y_t} \cdot \frac{E_t}{L_t} \tag{2}$$

where L_t/Y_t is the inverse of labor productivity, and E_t/L_t is the energy-labor ratio, or the energy-deepening degree of production. Log-differentiation of (2) yields

$$\hat{\eta} \equiv \hat{\epsilon} - \hat{\xi} \tag{3}$$

with "ˆ" symbols meaning growth rates. Equation (3) illustrates that when aggregate productivity growth ($\hat{\xi}$) is faster than the degree of energy-deepening ($\hat{\epsilon}$), there is a relative decoupling between output and energy use ($\hat{\eta} < 0$). In other words, (3) shows that if the rate of technical change grows faster than the proportion between energy and labor inputs used, the rate of energy use relative to output growth decreases.

Next, the emissions intensity of energy use are decomposed in the following way:

$$\frac{\Phi_t}{E_t} \equiv \frac{\Phi_t}{L_t} \cdot \frac{L_t}{E_t} \tag{4}$$

where Φ_t/L_t are emissions per worker. From (2), we have $L_t/E_t = L_t/Y_t \cdot Y_t/E_t$. Then, canceling out energy use on both sides, we end up with

[8] Resource substitution will not be further studied in this paper.

[9] For an induced view of technical change concerning climate policy, see Wing (2006).

$$\hat{\Phi} \equiv \hat{\mu} + \hat{Y} - \hat{\xi} \tag{5}$$

Equation (5) shows that the growth rate of aggregate carbon emissions ($\hat{\Phi}$) are positively associated with the growth rates of emissions per worker ($\hat{\mu}$), output growth ($\hat{Y}$), and negatively with labor productivity growth. In other words, there is an absolute decoupling ($\hat{\Phi} < 0$) whenever the rate of labor productivity grows faster than the sum of the growth rates of emissions per worker and output.

The extended Kaya identity from (1) assumes a positive relationship between aggregate labor productivity and emissions, while equation (5) offers a negative association between technological progress and emissions. This paper's methodology aims to cast light on the empirical nature of this relationship. Along with equation (3), I emphasize the role played by technology for both relative and absolute decoupling relationships, as suggested by green growth advocates. Obviously, it is beyond the scope of this paper to infer causality from technological progress to decoupling on the basis of the above identities, though these help to motivate the intuitive appeal of green growth. As a final remark, both Kaya and macroeconomic identity approaches outlined in this subsection are generally used to motivate long-run relationships. However, given this paper's empirical methodology, its main interest lies on short-run linkages among the aforementioned variables. Doing so for the long-run requires a more sophisticated theoretical apparatus, such as assuming equilibrium conditions, which are beyond the intended contribution. I further investigate the empirical linkages between technology and emissions over the short-run using the econometric techniques I outline next.

3.2 VAR identification strategies

To empirically investigate the relationships outlined in equations (1), (3), and (5) over the short-run, Vector Autoregressive models are a well-suited econometric technique. It consists of a linear model where each variable of the system is explained in terms of its present and lagged (past) values, as well as of present and past values of other terms (Sims 1980). From its estimates, we are able to study how variables react to shocks to other variables in the system, through a procedure known as Impulse-Response Functions (IRFs).[10]

I study how aggregate carbon dioxide emissions react to macroeconomic shocks in two ways. First, I motivate a recursive VAR model in a single step, following an identification strategy inspired by the relations explored in the previous subsection. Second, I follow the methodology adopted by Kilian (2009) and Mendieta-Muñoz et al. (2020), by estimating a recursive VAR without CO_2

[10] It is important to highlight that such responses to shocks cannot be considered causal relationships, due to the correlation among the variables. Such fact may generate shocks are that contemporaneously correlated with themselves. In order to produce interpretable innovations, we must estimate orthogonal shocks, contemporaneously uncorrelated with all other shocks.

emissions.[11] On the premise that the structural shocks derived from this second model are exogenous and predetermined, I evaluate the response of emissions to these innovations in a second step.

3.2.1 One-step procedure

A VAR(p) model can be represented by

$$Av_t = \alpha + \sum_{i=1}^{p} A_i v_{t-i} + u_t \tag{6}$$

where the A matrix captures the contemporaneous linkages among the variables; the A_i matrices carry the connections between current and past values; the row vector v_t compresses the set of variables present in the system; p is the lag length (order) of the VAR model; α is a vector of intercept terms; and u_t is a vector of serially uncorrelated structural innovations (shocks).

Due to endogeneity, the structural innovations enclosed in u_t are not directly observable. Hence, it requires the estimation of reduced-form residuals, denoted by $\varepsilon_t = A^{-1}u_t$. I then proceed to an identification strategy, guided by theoretical priors. To estimate a reduced-form VAR, as in equation (7), we need enough restrictions (i.e., zero entries) in the A^{-1} matrix. For n endogenous variables, we need at least $n(n-1)/2$ restrictions.

$$v_t = \beta + \sum_{i=1}^{p} B_i v_{t-i} + \varepsilon_t \tag{7}$$

where now the B_i matrices denote the interactions among the variables within the system, and β is an intercept vector.

In order to identify the VAR model, I adopt a recursive strategy, based on a particular causal ordering of contemporaneous effects from one variable to the others. In these cases, the mathematical representation of the A^{-1} matrix involves either an upper or lower triangularization reflecting contemporaneous effects. This fact guarantees a unique solution, which is an advantage of recursive over Structural VAR (SVAR) models (Enders 2008).

Theory must guide an identification strategy. In this paper, I combine the interactions from equation (1) and the central role played by technology from the green growth hypothesis illustrated in equations (3) and (5). Initially, I assume that the current technological setup is exogenously given, and it contemporan-

[11] In these two works, their identification strategies are developed through Structural VAR (SVAR) models.

eously affects both CO_2 emissions and output growth.[12] As prescribed by the embodied technical change paradigm, technological progress can either (both) increase energy efficiency or (and) develop newer processes using renewable sources, as well as creating more jobs with the development of cleaner industries. As a general result, technology allows for a more efficient energy use, with the benefit of increasing output in a more sustainable way.

In light of this description, I identify this VAR model by employing the $X_t \rightarrow E_t \rightarrow P_t \rightarrow Y_t \rightarrow \Phi_t$ short-run causal ordering. In other words, technology contemporaneously affects energy use, whose short-run population effects translate into higher employment levels. Then, output is contemporaneously affected by all previous variables, and emissions are assumed to contemporaneously respond to all covariates in this causal chain. My identification strategy thus reflects adjustment speeds: given its exogeneity, technology is not contemporaneously affected by any other variable, being the slowest to adjust to shocks coming from other covariates. On the other hand, the last variable in this ordering, emissions, responds contemporaneously to shocks from all variables, thus showing the fastest adjustment to system disturbances.

Finally, for a broader analysis of energy use, I decompose it into non-renewable (henceforth E_t) and renewable sources (R_t). Since theory is unclear on the causal ordering between these two, I allow for both specifications, i.e., $E_t \rightarrow R_t$ and $R_t \rightarrow E_t$. I call the former *first ordering*, and the latter, *second ordering*. Unlike other time-series studies in this field, I offer a causal ordering to identify the VAR models based on theoretical claims.[13]

Finally, this VAR identification will not be a literal translation of the extended Kaya identity, which is built on ratios. It guides us in the choice of system variables, but my procedure will be based on variables in levels. The only exception will be the population component, given that the focus lies on the short-run. My solution will be working with the employment-to-population ratio, thus incorporating all variables present in equation (1). The next section brings more details on variable description.

Equations (8) and (9) illustrate the $\varepsilon_t = A^{-1}u_t$ relation from equations (6) and (7) for the first and second orderings, respectively. These reflect the imposed restrictions for the row vector $v_t = (X_t, E_t, R_t, P_t, Y_t, \Phi_t)'$. In other words, zero entries in the A^{-1} matrix imply no contemporaneous effect from the column to the row variable.

[12]This motivation resembles empirical works within the Real Business Cycle literature, where technology is considered an external source of output dynamics. Here, I extend such view to environmental issues. See Cogley and Nason (1995).

[13]It is outside the scope of this paper to discuss the trade-off between renewable and non-renewable energy sources. The central interest lies on aggregate emissions, and variables such as relative energy prices are thus not considered. Bruns et al. (2019) estimate identified SVAR models focusing on the relationship between energy efficiency and energy savings, where prices play a key role. See also Kilian (2009).

$$\varepsilon_t \equiv \begin{bmatrix} \varepsilon_t^X \\ \varepsilon_t^E \\ \varepsilon_t^R \\ \varepsilon_t^P \\ \varepsilon_t^Y \\ \varepsilon_t^\Phi \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 \end{bmatrix} \begin{bmatrix} u_t^{\mathrm{X}} \\ u_t^{\mathrm{E}} \\ u_t^{\mathrm{R}} \\ u_t^{\mathrm{P}} \\ u_t^{\mathrm{Y}} \\ u_t^{\Phi} \end{bmatrix} \tag{8}$$

$$\varepsilon_t \equiv \begin{bmatrix} \varepsilon_t^X \\ \varepsilon_t^R \\ \varepsilon_t^E \\ \varepsilon_t^P \\ \varepsilon_t^Y \\ \varepsilon_t^\Phi \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 \end{bmatrix} \begin{bmatrix} u_t^{\mathrm{X}} \\ u_t^{\mathrm{R}} \\ u_t^{\mathrm{E}} \\ u_t^{\mathrm{P}} \\ u_t^{\mathrm{Y}} \\ u_t^{\Phi} \end{bmatrix} \tag{9}$$

From these two orderings, one is able to estimate how a shock to one variable affects the other system covariates via Impulse-Response Functions (IRFs).

3.2.2 Two-step procedure

A novel methodology to evaluate the effects of exogenous shocks to variables of interest have been developed by Kilian (2009) and Mendieta-Muñoz et al. (2020). Since, by definition, shocks derived from a VAR specification are exogenous, it is possible to assume these shocks as predetermined regressors to study their impacts on a dependent variable. One may argue that a single-step VAR model, as the one in the previous subsection, allows for endogenous interactions between CO_2 emissions and the other system variables. To avoid these effects, that may potentially affect the impulse-response analysis, I set up a second recursive VAR model, following the same identification strategy as before, this time leaving Φ_t out of v_t.

This two-step VAR model for the first and second orderings, as in equations (10) and (11), respectively, delivers five structural shocks: u_t^X, a technology shock u_t^E, a non-renewable energy use shock, u_t^R, a renewable energy use shock, u_t^P, a population shock, and u_t^Y, an activity/production shock.[14] These are, by definition, orthogonal, exogenous, and unknown disturbances to the endogenous regressors. Furthermore, these innovations summarize the main structural drivers assumed to affect carbon dioxide emissions, and, by not including it in the first step, I avoid its potential endogenous influence in the system.

[14]Regarding u_t^P, one may assume that employment disturbances are endogenously captured by the VAR model, thus defining its exogenous component as population shocks.

$$\varepsilon_t \equiv \begin{bmatrix} \varepsilon_t^X \\ \varepsilon_t^E \\ \varepsilon_t^R \\ \varepsilon_t^P \\ \varepsilon_t^Y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} \begin{bmatrix} u_t^{\mathrm{X}} \\ u_t^{\mathrm{E}} \\ u_t^{\mathrm{R}} \\ u_t^{\mathrm{P}} \\ u_t^{\mathrm{Y}} \end{bmatrix} \tag{10}$$

$$\varepsilon_t \equiv \begin{bmatrix} \varepsilon_t^X \\ \varepsilon_t^R \\ \varepsilon_t^E \\ \varepsilon_t^P \\ \varepsilon_t^Y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} \begin{bmatrix} u_t^{\mathrm{X}} \\ u_t^{\mathrm{R}} \\ u_t^{\mathrm{E}} \\ u_t^{\mathrm{P}} \\ u_t^{\mathrm{Y}} \end{bmatrix} \tag{11}$$

I then use the innovations derived from this first step as exogenous regressors, in the following regression model:

$$\Phi_t = \gamma_j + \sum_{i=1}^{h} \delta_{j,i} \hat{u}_{j,t-i} + v_{j,t} \tag{12}$$

where $v_{j,t}$ are classical error terms; the $\delta_{j,i}$ terms encapsulate the effects of each structural innovation on the dependent variable over a time horizon h; and $\hat{u}_j$ are the estimated shocks from the first step, with $j = 1, 2, 3, 4, 5$. I also assume no feedback from emissions to these structural innovations.

In summary, I investigate what are the main shocks affecting carbon dioxide emissions over the short-run by employing two VAR strategies. In the first, I use a single-step VAR, inspired by the theoretical framework described in the beginning of this section. In the second, still using the same identification as the first model's, I retrieve the structural shocks from a VAR without accounting for Φ_t. By using these shocks as exogenous and predetermined covariates in a second step, I estimate regression models with emissions as the dependent variable. The next section briefly describes the data.

4 Data

This section briefly describes the data set and the evolution of its variables over the post-war period. I use seasonally adjusted annual data for the US economy between 1949 and 2018. Data for carbon dioxide emissions (Φ_t), measured in million metric tons of carbon dioxide, comprehend emissions from coal, natural gas, petroleum, and biomass consumption (wood, waste, fuel ethanol, and biodiesel), as well as from the electric power sector derived from geothermal and non-biomass sources. For the 1949–2011 interval, data were obtained from the US Energy Information Administration (US EIA)'s 2012 *Annual Energy Overview*, Table 11.1: "Carbon dioxide emissions from energy consumption by source." For the 2012–2018 period, emissions data were obtained from EIA's *Monthly*

Energy Review, Tables 11.1:"Carbon dioxide emissions from energy consumption by source," Table 11.6: "Electric power sector," and 11.7: "Biomass."[15]

Data for non-renewable (E_t) and renewable energy consumption (R_t) were obtained from US EIA's March 2019 *Monthly Energy Review*, Table 1.1: "Primary energy overview." Renewable energy comprehends the following sources: hydroelectric, geothermal, solar, wind, and biomass. The remaining are accounted for as non-renewable sources: fossil fuels and nuclear energy. These variables are measured in Quadrillion Btu. From the Federal Reserve Bank of St. Louis Economic Database (FRED), I obtained time series for the population (P_t), output (Y_t), and aggregate technology (X_t) variables: the civilian employment-to-population ratio (%), real GDP (billions of chained 2012 dollars), and labor productivity (real output per hour of all persons for the business sector), respectively.

Finally, for robustness purposes I have also performed estimations using two other variables as technology proxies: the aggregate capital stock and total factor productivity. These come from the Penn World Table 9.1 (Feenstra et al. 2015), with the first being the capital stock at constant national prices for the United States, measured in millions of 2011 US dollars, not seasonally adjusted (1950–2017), and the second is total factor productivity at constant prices for the United States (2011=1), not seasonally adjusted (1954–2017).

In the next figures, I briefly describe how the magnitudes of these variables have evolved over the post-war period.[16] In addition, I also show first differences and the cyclical components of the series. These filtering techniques help in breaking down important higher-frequency and business-cycle features of the data, and these transformed series will also be used for robustness checks in the next section. Lastly, I present some important ratios from equations (2) and (4). These will help us better visualize the relevant components for decoupling relationships explored in the last section.

Figures 1–3 are divided into three main groups. In the first, I include the two "activity" variables from the system: real GDP and the employment-to-population ratio. In the second, the three "environmental" variables: CO_2 emissions, non-renewable, and renewable energy use. Finally, the third comprehends the three "technology" variables: labor productivity, total factor productivity, and the aggregate capital stock. The right panels illustrate the series in first differences (gray) and their cyclical components extracted with the Hodrick-Prescott filter (black).[17]

Real output experienced an average annual growth rate of 3.15% in this period. From the filtered series, we observe the main recession periods: the

[15] In order to make the data sets from annual and monthly reviews consistent, I have excluded emissions from LPG (liquefied petroleum gases, which are not explicitly accounted for in monthly data sets), and excluded emission from hydrocarbon gas liquids (which are not accounted for in annual tables). Moreover, data from the annual overview are whole numbers. In order to be more precise, I have used data between 1949 and 1972 from this table, and the rest from the monthly overview tables. To reach similar amounts as the annual overview table, I have added total CO_2 emissions data from Table 11.1 (excluding hydrocarbons), and added geothermal and non-biomass emissions from Table 11.6, and biomass emissions from Table 11.7.

[16] Data were log-transformed, that is, $100 * ln(X_t)$, and so on.

[17] Its smoothing parameter (λ) was set to 100, as recommended for annual data (Enders 2008).

Eisenhower recession in the late 1950s, the first oil shock in 1973, the Volcker-shock throughout the 1980s, the Dotcom bubble in the late 1990s, and the Great Recession in 2008-09. The employment-to-population ratio has the lowest growth rate among all variables considered (0.12%), and also reflects the state of the business cycle. In both panels, we observe its increasing trend since mid-1970s, with increasing female participation in the labor force, and its major decrease during the financial crisis.

[FIGURE 1 ABOUT HERE]

CO_2 emissions grew 1.25% per year over this sample period. Since 2007, we observe a slight decline, close to 1% per year, in its historical trend. Non-renewable energy consumption grew, on average, 1.63% per year, and renewables use, 1.96%. The two main declining periods in non-renewable energy consumption followed from the two oil shocks in the 1970s, correlating with a similar behavior in the emissions series. These episodes paved the way for investments in renewable energy sources, with robust budget increases in the second half of the 1970s, abruptly stopping before 1980. Furthermore, the Gulf War in the beginning of the 1990s contributed to a resurgence of renewable policies, which were abandoned by the end of that decade. Finally, since 2000 renewable energy use has been growing at larger rates than non-renewables, though at a much lower magnitude (Laird and Stefes 2009).

[FIGURE 2 ABOUT HERE]

Lastly, labor productivity experienced a relatively stable growth path over this sample period, registering an annual rate of 2.09%. TFP and the capital stock grew, respectively, 0.69% and 2.75% per year.[18] From the filtered series, we observe that labor productivity and TFP show similar paths over higher frequencies, with the major decreases occurring between the late 1970s and the beginning of the 1980s. Such behavior reflects the recession period experienced by the US economy prior to the Great Moderation, with major losses in productivity (Stock and Watson 2002; Mendieta-Muñoz et al. 2020).

[FIGURE 3 ABOUT HERE]

Figure 4 illustrates the remaining components of equations (2) and (4). On the left panels, energy intensity (E_t/Y_t) and the energy-labor ratio (E_t/L_t). On the right, emissions intensity of energy consumption (Φ_t/E_t) and emissions per worker (Φ_t/L_t). For this figure, I use the sum of non-renewable and renewable energy for total primary energy use, and L_t is the number of employed workers for the US business sector.[19]

Energy intensity declined 1.48% per year over this period, with a slight uptick prior to 1970. After that, it showed a stable decrease. Since, by definition,

[18] Since TFP and the capital stock are indexes, these series are not presented in logs.

[19] These seasonally adjusted data were extracted from the US Bureau of Labor Statistics (BLS, PAYEMS series).

energy intensity is the inverse of energy productivity, the US economy has shown an energy-saving pattern of technical change over this sample period. The emissions-energy ratio also declined, with three different periods: the first, until the first oil shock shows a sharp decrease; the second, stable with a slight decline until mid-2000s; and the last with a more acute reduction until 2018. The energy-labor ratio grew until the first oil shock, experiencing a decline since this crisis. This pattern was reinforced after the second oil shock, as we see a slight prior increase in the series. Finally, emissions per worker showed a similar behavior, with the turning point for its decrease also being the first oil embargo, and emphasized after the second.

[FIGURE 4 ABOUT HERE]

Overall, we observe a relative decoupling between energy use and output, as well as between emissions and energy use. Furthermore, the two oil shocks of the 1970s represented a turning point in the behavior of the energy-labor ratio and emissions per worker. This last result shows that, historically, neither emissions nor energy consumption increase with rising employment. However, except for energy intensity, the decreasing annual rates of the remaining variables are below 1%. When comparing the energy-labor ratio between the first and last years, it has barely changed. Countries experiencing absolute decoupling, such as France, Italy, and the United Kingdom, have registered more robust negative rates for these variables over time (Marquetti et al. 2019). Furthermore, even though the last figures show positive growth rates of both labor and energy productivity, such technological change pattern has not been translated into reduced use of non-renewable energy sources, nor in reduced CO_2 emissions. These facts will be further developed in the next section.

5 Results

This section provides technical details and interpretations for the econometric estimations. I begin with the first procedure, with a single-step VAR. Next, I explore the two-step strategy, where I retrieve structural innovations from a VAR without emissions, then estimating the latter's response to these exogenous shocks in a second step. Lastly, I implement several robustness checks, by both testing different technology variables and applying filtering methods. By the end of this section, we will be able to verify what are the main structural shocks affecting aggregate carbon emissions over the post-war era, and whether there are relevant quantitative differences between these two methodologies. Lastly, for compactness purposes, the paper only presents results for the first causal ordering, as in equations (8) and (10), since similar findings are verified for both cases.

The implementation of VAR models with its covariates in levels has become more widely accepted in empirical time-series studies, given the low power of unit-root tests (Enders 2008; Basu and Gautham 2019; Mendieta-Muñoz et al. 2020). Adding the fact that results are robust to both data in levels, as well as using either first differences and the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) for both orderings, I opt for having the baseline VAR models in levels, letting the data "speak for itself," and leaving these other two transformations as robustness checks.

5.1 One-step VAR estimation

Following the recursive identification strategies from Section 3, I estimate VAR models for the row vector $v_t = (X_t, E_t, R_t, P_t, Y_t, \Phi_t)'$. All variables were log-transformed (i.e., $100 * ln(X_t)$, and so on) for interpretation easiness. According to Lagrange Multiplier-type tests, a lag length of 3 yields well-specified models, that is, without serial correlation at all lags. Furthermore, the models do not present heteroskedastic residuals, according to a White test.

Following these tests, I evaluate the short-run interactions within this system via Impulse-Response Functions (IRFs) for a horizon h of 10 years, through a Cholesky decomposition method. Figure 5 illustrates results for this VAR model, with dashed lines denoting 95% bootstrapped standard errors generated via 5,000 replications of Monte Carlo simulations. For compactness, the "→" symbol denotes the response of the row variable to a one-standard deviation orthogonalized shock to the column variable, with the main diagonal panels corresponding to own-shock responses. For instance, "$E_t \rightarrow X_t$" designates the response of labor productivity to a one-standard deviation non-renewable energy use structural shock.

Firstly, all variables respond positive and significantly to their own shocks, as expected. Secondly, the IRFs do not show statistically significant effects of a technology shock on non-renewable energy use and on the employment-to-population ratio. On the other hand, output reacts positively to a 1% technology shock for the first three years, beginning at 0.7%, increasing to 1.1% in the last significant period. Finally, despite a technology shock not significantly impacting the use of non-renewable sources, renewable energy demand responds negative and significantly in the first (-2%) and third (-3.4%) years. Overall, the technology shock only significantly impacts the use of renewable sources and output.

A non-renewable energy shock does not produce significant effects on renewable energy demand, but positively affects employment and output, which are the key business cycle variables in this system. These effects are more prominent in the first year for output and in the second for employment, with responses vanishing in the second year for output and in the third for the employment-to-population ratio. In the sequence of this cyclical process, when such effects to employment and output decay, we observe a minor, but still significant, negative effect of this energy shock on labor productivity in the second year (-0.8%). Furthermore, we observe a similar response of productivity to a population shock, reinforcing this cyclical behavior and the assumption that technology has the slowest adjustment to exogenous disturbances.

Output reacts positive and significantly to all shocks, except for emissions and renewable energy use innovations. The latter do not significantly impact any of the endogenous variables, reflecting the historical low share of renewable sources in the US energy mix. Despite its recent upward trend, renewables still do not produce robust effects in these variables.

Finally, the only statistically significant response of CO_2 emissions is to a non-renewable energy use shock. A 1% shock in “dirty” energy use positively impacts emissions by 2.5% in the first year. This effect stays positive and significant until the fifth year, with a 1.4% response. In this specification, technology shocks do not generate significant impacts to pollution. On the other hand, we observe a mildly negative, but significant, response of non-renewables to an emissions shock in the third year (-0.9%). Moreover, neither emissions nor non-renewable energy consumption increase with a population shock. Indeed, it decreases the use of non-renewable sources, while not significantly affecting pollution. Considering that this short-run setting mostly captures population dynamics through changes in employment, we observe that increases in the labor input do not increase the use of non-renewable sources and pollution.

In summary, this one-step estimation renders relevant features relative to this paper’s theoretical background. While we observe a positive impact on output, there is no statistically significant impact of a technology shock on CO_2 emissions. As expected, these react positively to non-renewable energy use shocks. Furthermore, the negative response of non-renewables to an emissions shock takes three years to be significant, with a much smaller magnitude than the reverse impulse-response relation. This fact, along with the negative impact of an output shock to the use of non-renewable sources, does not support an absolute decoupling trajectory for the US economy, based on post-war data. Finally, technology shocks do not have a significant impact on the use of non-renewables, but negatively affect renewable energy demand, while a “dirty” energy use shock negatively impacts aggregate labor productivity.

[FIGURE 5 ABOUT HERE]

5.2 Two-step VAR procedure

I begin the two-step VAR procedure following the same identification strategy as before, but this time excluding carbon dioxide emissions from the baseline model. Next, I retrieve the structural shocks from this model, using these as exogenous regressors for the second step. Then, I compute IRFs to quantify the response of emissions to the five structural innovations estimated in the first step. Finally, I compare the differences between the two adopted methodologies.

In both orderings, a lag length of 4 yields well-specified models. In addition, both models do not suffer from heteroskedasticity, using the same aforementioned tests. Figure 6 illustrates the impulse-response functions for the first step. As in the prior model, we observe similar reactions from the endogenous variables. Both quantitative impacts and statistical significance measures remain similar to the one-step procedure.

[FIGURE 6 ABOUT HERE]

This two-step VAR models delivers five structural shocks: a technology shock, a non-renewable energy use shock, a renewable energy use shock, a population shock, and an output shock. From equation (12), I verify the response of Φ_t to each of these shocks separately. Given that this second step uses generated covariates from the previous stage, I follow Kilian (2009) by testing whether these residuals can be considered predetermined relative to Φ_t. This was done by, first, estimating an AR(4) model for emissions[20] and, secondly, computing the contemporaneous correlation between this AR(4) model's residuals and the other five structural shocks. All linear association coefficients were low (below 15%), with the only exception being the one between Φ_t and the non-renewable energy use shock (77%). This was expected, given that emissions mostly derive from these sources. Furthermore, all IRFs were generated with 95% bootstrapped confidence intervals, also derived from 5,000 Monte Carlo simulations.

Figure 7 illustrates the effects of a one-standard deviation shock to each of the five structural innovations on Φ_t.[21] This time, technology and non-renewable energy use shocks have significant effects on aggregate CO_2 emissions. A 1% technology shock produces a 0.71% increase in emissions in the first year, increasing to 1.25% in the following period. For the next years, the effect is no longer significant. In addition, a 1% non-renewable energy demand shock increases emissions by 2.10% in the first year, decreasing to 1.71% in the subsequent year, also vanishing for the other periods.

[FIGURE 7 ABOUT HERE]

This two-step procedure provides an additional significant shock to aggregate carbon dioxide emissions. From the single-step VAR, only a non-renewable energy consumption shock had a statistically significant impact on emissions, with the highest effect, 2.5%, happening in the first year. From the second step, this impact is slightly lower (2.1%) in the first year. And the positive impact of a technology shock to emissions renders an additional evidence on the dynamic interactions between energy use and the technological profile of the US economy over this period. In spite of the downward historical trends of energy intensity and the emissions intensity of energy use, energy efficiency gains have not been sufficient to mitigate emissions. Along with the low participation of renewable sources within production, technological improvements have strongly favored the use of non-renewables, with both factors supporting increases in carbon dioxide emissions.

5.3 Robustness checks

Here, I briefly present results for different specifications of the VAR models. In addition to the baseline, I have estimated recursive VAR models for both one- and two-step procedures with variables in first differences and de-trended with the HP filter. Moreover, these models have also been estimated with two

[20] The AR model's order was selected reflecting the same lag length as the first step model's.

[21] As suggested by Kilian (2009), I introduced 3 lags, incorporating three years of data, to estimate (12). None of the models (including robustness checks) present serial correlation problems at 5% of significance.

different technology variables: the aggregate capital stock (K_t) and total factor productivity (TFP_t), replacing the baseline model's aggregate labor productivity.

Based on a battery of unit-root tests, it is possible to infer that all used variables are integrated of order 1.[22] Hence, for VAR models in first differences, all variables were differenced once to achieve stationarity. Furthermore, to de-trend the series with the HP filter, I set its smoothing parameter (λ) to 100, as recommended for annual data (Enders 2008).

Figures 8, 9, and 10 illustrate responses of CO_2 emissions to each of the structural shocks for the single-step VAR specification with labor productivity, the capital stock, and total factor productivity, respectively. For compactness, these figures only present emissions responses, and the full impulse-response systems are available in the Appendix. Moreover, responses from single-step VAR models estimated with the HP filter will only be discussed in text.[23]

In general, these alternative specifications produce similar responses to the ones verified in the baseline single-step VAR estimation, with a few exceptions. All models in first differences and with the HP filter return a positive and significant response of non-renewable energy demand to technology shocks, which is not significant in the baseline model. Furthermore, only models with labor productivity as the technology variable show a negative and significant response of renewable energy use to technology shocks. In the other specifications, such effect is not statistically significant. Lastly, in models with the capital stock and TFP, a technology shock positively affects the employment-to-population ratio, which was not verified before. This response is also verified in all models with the HP filter.

After these general observations, I concentrate on the response of CO_2 emissions to all structural shocks for the single-step VAR methodology. Figure 8 presents similar results to the baseline procedure, with only non-renewable energy use shocks significantly affecting emissions, in addition to its own shock. In the first year, a 1% non-renewable energy use shock produces a 2.8% increase in aggregate emissions. This same specification, this time estimated with all variables de-trended with the HP filter confirms the latter effect, but also returns a significant and positive impact of a technology shock on emissions, of 0.7% in the first, and 1.3% in the second year.

[FIGURE 8 ABOUT HERE]

Figures 9 and 10 present similar responses of CO_2 emissions to these structural shocks. In both cases, technology and non-renewable energy use shocks positive and significantly affect emissions. Models with the capital stock both in first differences and with the HP filter return technology shocks more strongly

[22] I have implemented four different unit root tests: Augmented Dickey-Fuller (ADF) (Said and Dickey 1984) , Dickey-Fuller with GLS de-trending (ADF-GLS) (Elliot et al. 1996), Ng and Perron's Modified Phillips (M-P) (Ng and Perron 1995), and the Kwiatowski-Phillips-Schmidt-Shin (KPSS) (Kwiatowski et al. 1992).

[23] The lag lengths for these single-step VAR models are 4, 4, and 3, respectively. In addition, lag lengths for VAR models with variables de-trended with the HP filter are 4, 3, and 2, respectively. None of these models present serial correlation or heteroskedasticity.

affecting Φ_t than non-renewable energy use shocks, while TFP specifications show the contrary. In summary, most single-step VAR estimations verify both technology and non-renewable energy use shocks positive and significantly affecting aggregate carbon emissions, similarly to the two-step methodology findings.

[FIGURE 9 ABOUT HERE]

[FIGURE 10 ABOUT HERE]

Next, I present results for the two-step VAR procedure. For compactness, I only present the statistically significant shocks affecting CO_2 emissions. Once again, technology and non-renewable energy use shocks positively affect Φ_t over the short-run. This result is robust to data in first differences and de-trended with the HP filter, for all three different technology proxy variables.

Figure 11 illustrates these results, with upper panels illustrating results for the data in first differences, and the lower for de-trended data with the HP filter. I also separate responses by the technology variable used in each model: labor productivity (left), capital stock (center), and total factor productivity (right). Solid black lines represent non-renewable energy use shocks, with dot-and-dashed lines denoting its standard errors. Solid and dashed gray lines stand for the technology shocks and standard errors, respectively.

In the upper panels, I show cumulative impulse-response functions (CIRFs) of CO_2 emissions relative to these two structural shocks.[24] Except for the baseline specification with labor productivity, the two other panels show a higher cumulative effect of the technology shock on emissions. Furthermore, in all cases the latter shock is more permanent, significantly lasting from the first to the sixth year in the left panel, until the fifth in center panel, and until the eighth year in right panel. The non-renewable energy shock also significantly persists until the eighth year in the left panel, but only until the second in the other two.

The bottom panels present IRFs for models with the variables de-trended by the Hodrick-Prescott filter. This time, emissions do not respond as permanently as before, and such behavior resembles baseline results. Only in the specification with the capital stock the response to a technology shock is higher than to a non-renewable energy use shock, with both effects being statistically significant for the first and second years. For two-step specifications with these other technology variables in levels, the same results are verified.

[FIGURE 11 ABOUT HERE]

The robustness checks reinforce the positive response of CO_2 emissions to technology and non-renewable energy consumption shocks. By using first differences and de-trended series with the HP filter, higher frequencies of the data become more prominent, with increased importance to immediate short-run and business-cycle effects. Both for the one- and two-step procedures, similar

[24] Since these results are based on data in first differences, presenting results for this second step through cumulative IRFs is recommended (Mendieta-Muñoz et al. 2020).

results are also verified for the different technology variables, the capital stock and total factor productivity. Finally, contrasting with the one- and two-step baseline results, we observe a positive impact of a technology shock on the use of non-renewable sources, along with a non-significant effect on renewables. In addition, there is no significant impact of both energy use shocks on the technology variables. Therefore, the impulse-response analyses do not verify faster aggregate productivity growth predicated on stronger energy demand, as noted by previous works (Taylor 2009; Semieniuk 2018; Bruns et al. 2019). On the contrary, when statistically significant, technology shocks positively affect non-renewable energy demand, while negatively impacting non-renewable energy sources.

6 Conclusion

This paper investigated the main structural shocks affecting aggregate carbon dioxide emissions in the US economy over the post-war era. Its main contribution to the recent Ecological Macroeconomics literature is twofold: first, on the employed empirical methodology, and second, on the resulting evidence concerning the linkages between technological progress and emissions mitigation. Based on two different Vector Autoregressive (VAR) strategies, with recursive identifications based on an extended Kaya identity and on current claims for green growth, I emphasize the role of technological progress to achieve an absolute decoupling between CO_2 emissions and output. Firstly, by estimating a single-step VAR model including labor productivity, non-renewable and renewable energy consumption, the employment-to-population ratio, real GDP, and carbon emissions, one directly observes the latter's response to structural shocks. Secondly, adopting a novel two-step VAR procedure, where initially, I estimate a VAR without emissions, retrieving its structural shocks. Then, after ensuring that these innovations could be considered predetermined, I compute the response of CO_2 emissions to each of these shocks via regression models. The main conclusions are summarized as follows:

1. For the baseline VAR models with variables in levels, the one-step procedure shows that only non-renewable energy use shocks significantly affect CO_2 emissions over the short-run. On the other hand, the two-step procedure includes a technology shock as positive and statistically significant. In both cases, non-renewable use shocks also have a positive impact on emissions.

2. Robustness checks included estimating both one- and two-step VAR models with data in first differences and de-trended with the Hodrick-Prescott filter. In addition, these models were also computed with different technology proxy variables, the aggregate capital stock and total factor productivity. Except for a single-step VAR with the baseline identification in first differences, which confirms baseline one-step results, all other

specifications support positive and significant effects of technology and non-renewable energy use shocks to carbon dioxide emissions.

3. Contrary to the belief that a faster labor productivity growth is predicated on heavier energy use, the results present the opposite: technological shocks positively affect non-renewable energy demand and decrease renewable energy demand, while these latter's effects on aggregate technology measures are either negative or not statistically significant.

4. All conclusions for the one- and two-step procedures, including robustness checks, are also verified for the second causal ordering.

5. In addition to these results, key decoupling variables have shown weak growth trajectories over the sample period. In spite of decreasing historical trends, energy intensity, output intensity of energy use, emissions per worker, and the energy-labor ratio levels are far from those observed by countries experiencing absolute decoupling, such as France, Italy, and the United Kingdom. The US economy experienced rising labor and energy productivity over the post-war era, but this progress was not translated into significant effects macroeconomic effects of renewable energy use, or less pollutant techniques. On the contrary, technological progress in the US economy still leads to higher use of "dirty" sources and increased CO_2 emissions, thus not supporting a mitigation scenario. On the basis of this historical relationship between aggregate technology and emissions, only aggressive macroeconomic, energetic, and institutional shifts may lead to an effective absolute decoupling path.

This contribution suggests several avenues for future research. In addition to longer-run analyses, the inclusion of price variables may help to further address the relationship between renewable and non-renewable energy sources throughout US history. Furthermore, extending the present analysis to a panel of countries is suitable for a comparison with other economies, with possibly different energy supply compositions. Lastly, these aggregate findings may also pave the way to microeconomic approaches, at both sectoral and firm levels.

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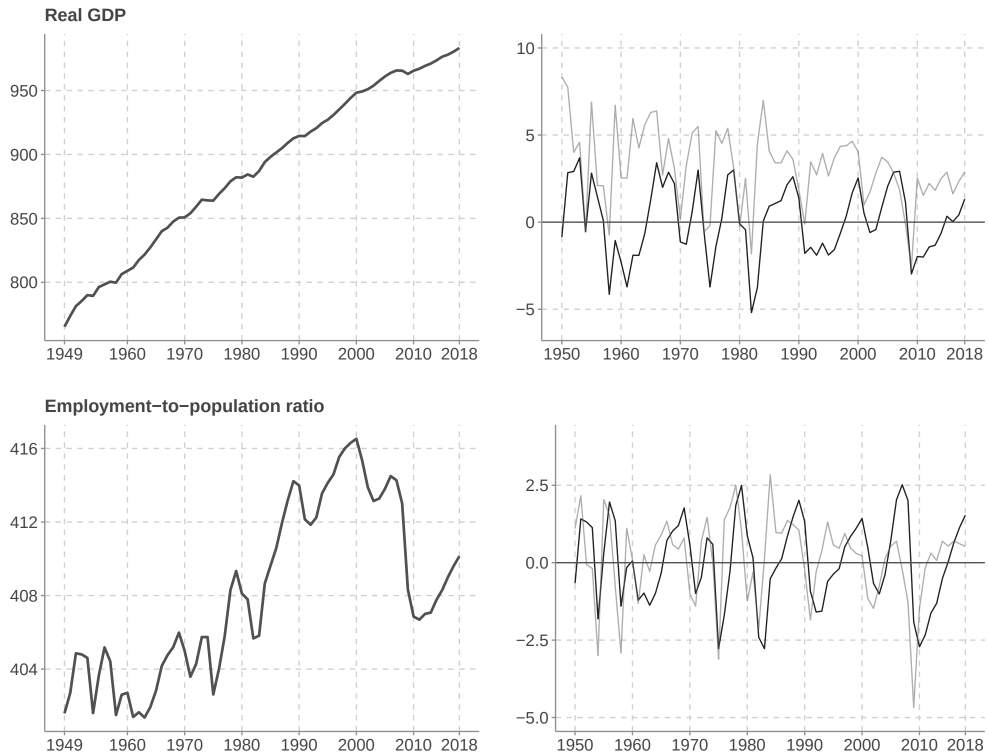

Figure 1: **Activity variables, 1949–2018**. Left panels: series in natural logarithms. Right panels: first differences (gray), de-trended series with the HP filter (black).

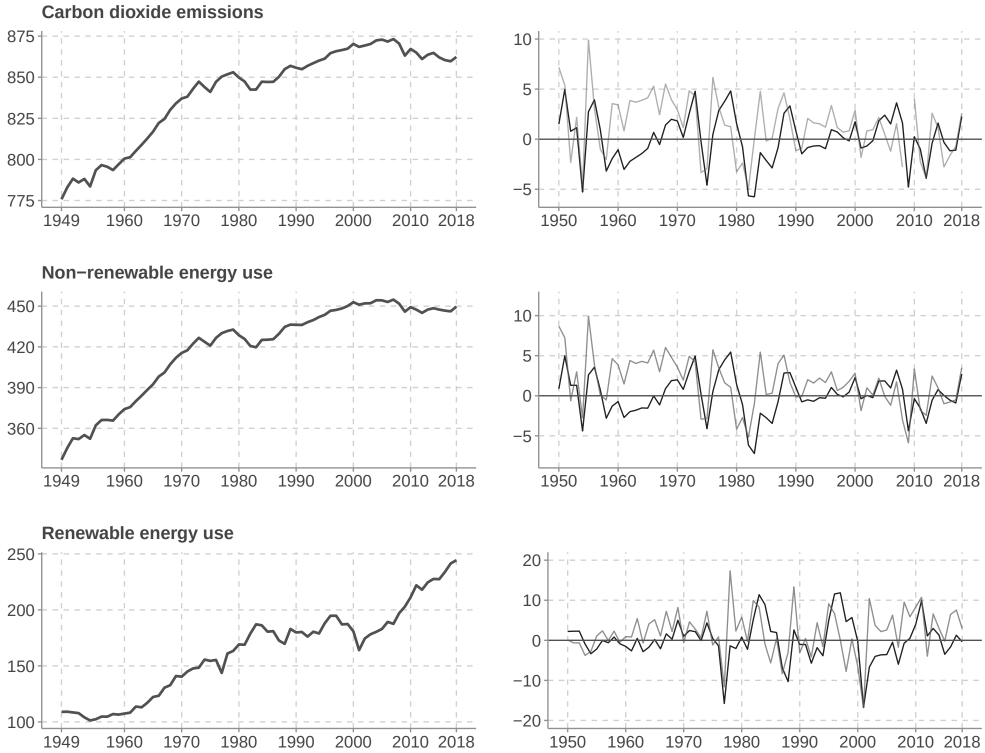

Figure 2: **Environmental variables, 1949–2018.** Left panels: series in natural logarithms. Right panels: first differences (gray), de-trended series with the HP filter (black).

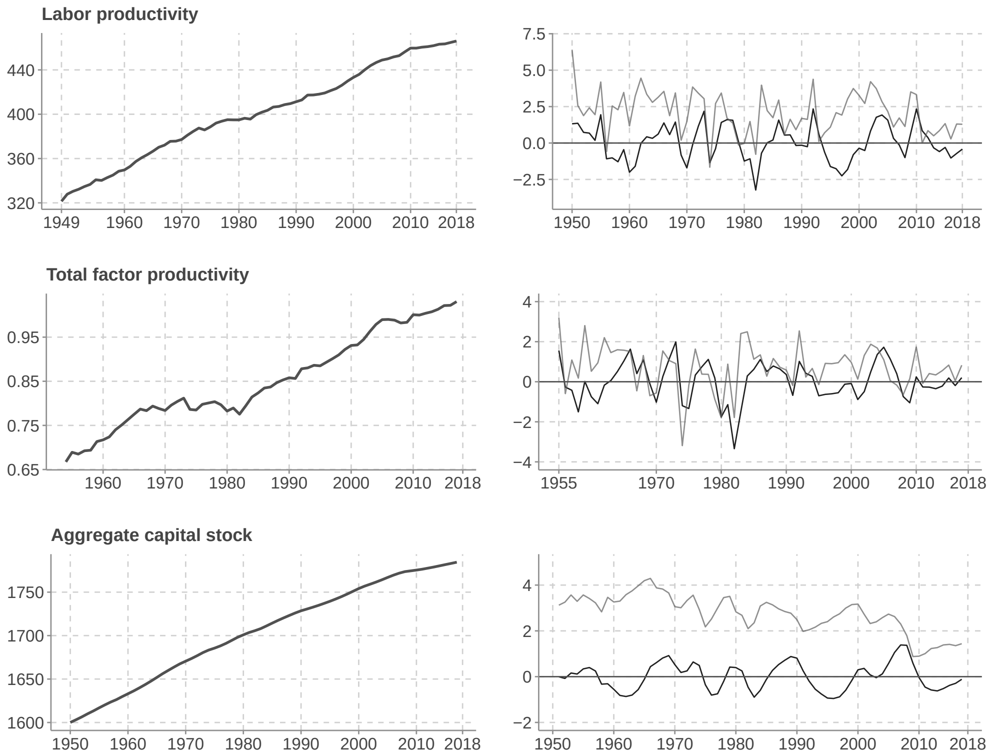

Figure 3: **Technology variables, 1949–2018.** Left panels: original series, except for labor productivity (in natural logarithms). Right panels: first differences (gray), de-trended series with the HP filter (black).

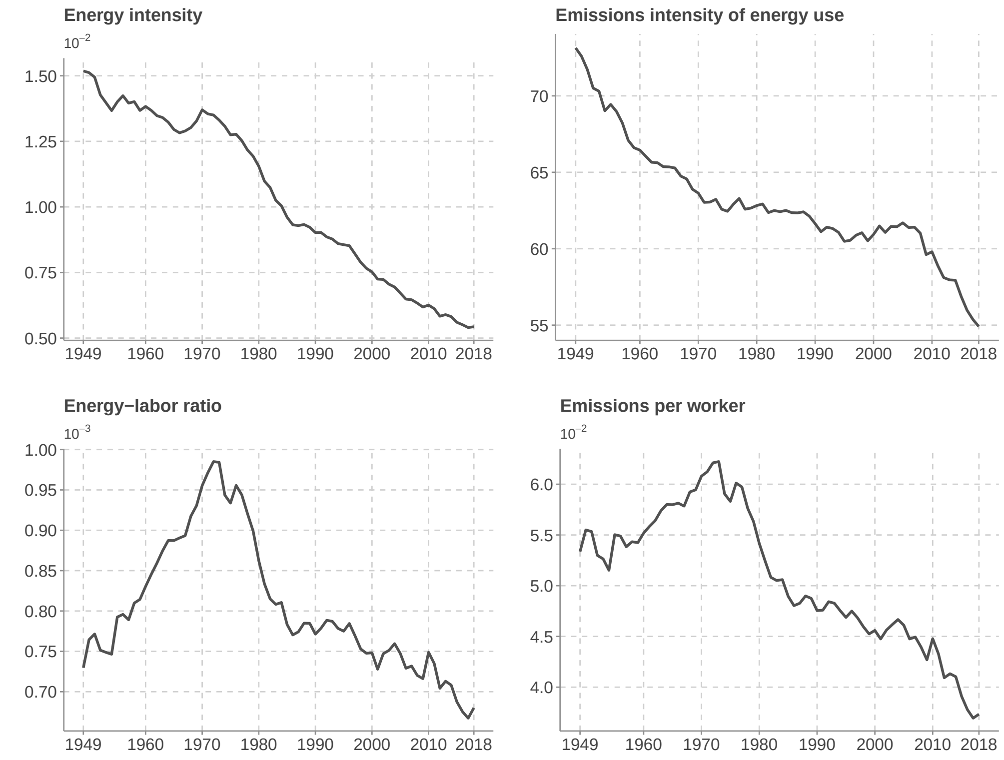

Figure 4: **Ratios from decoupling equations (2) and (4)**. Energy intensity is measured in Quadrillion Btu/billions of chained 2012 dollars; emissions intensity of energy used are measured in million metric tons of CO_2/Quadrillion Btu; the energy-labor ratio is measured in Quadrillion Btu/thousands of workers; and emissions per worker are measured in million metric tons of CO_2/thousands of workers.

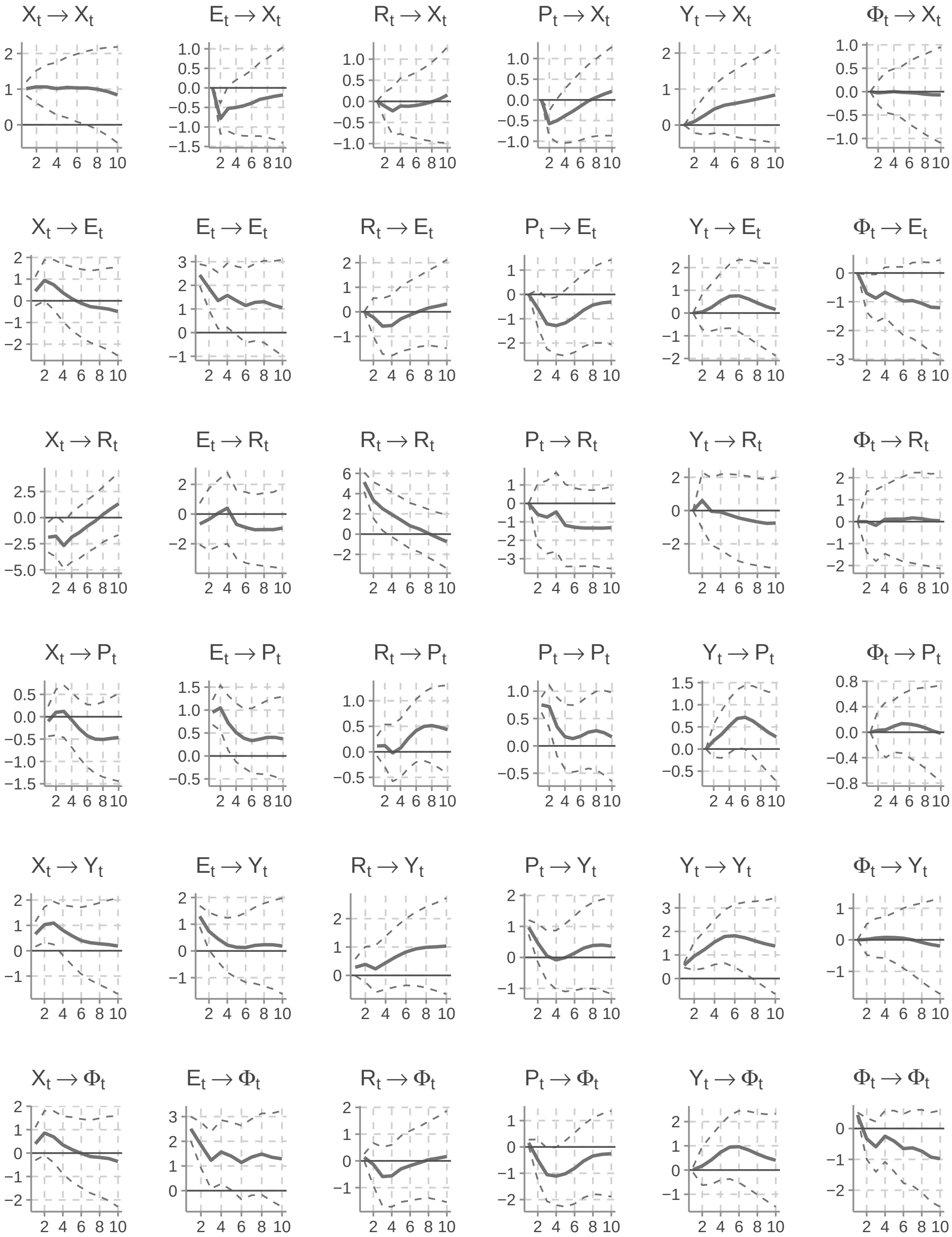

Figure 5: **Impulse-Response Functions, single-step VAR, first ordering**. Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

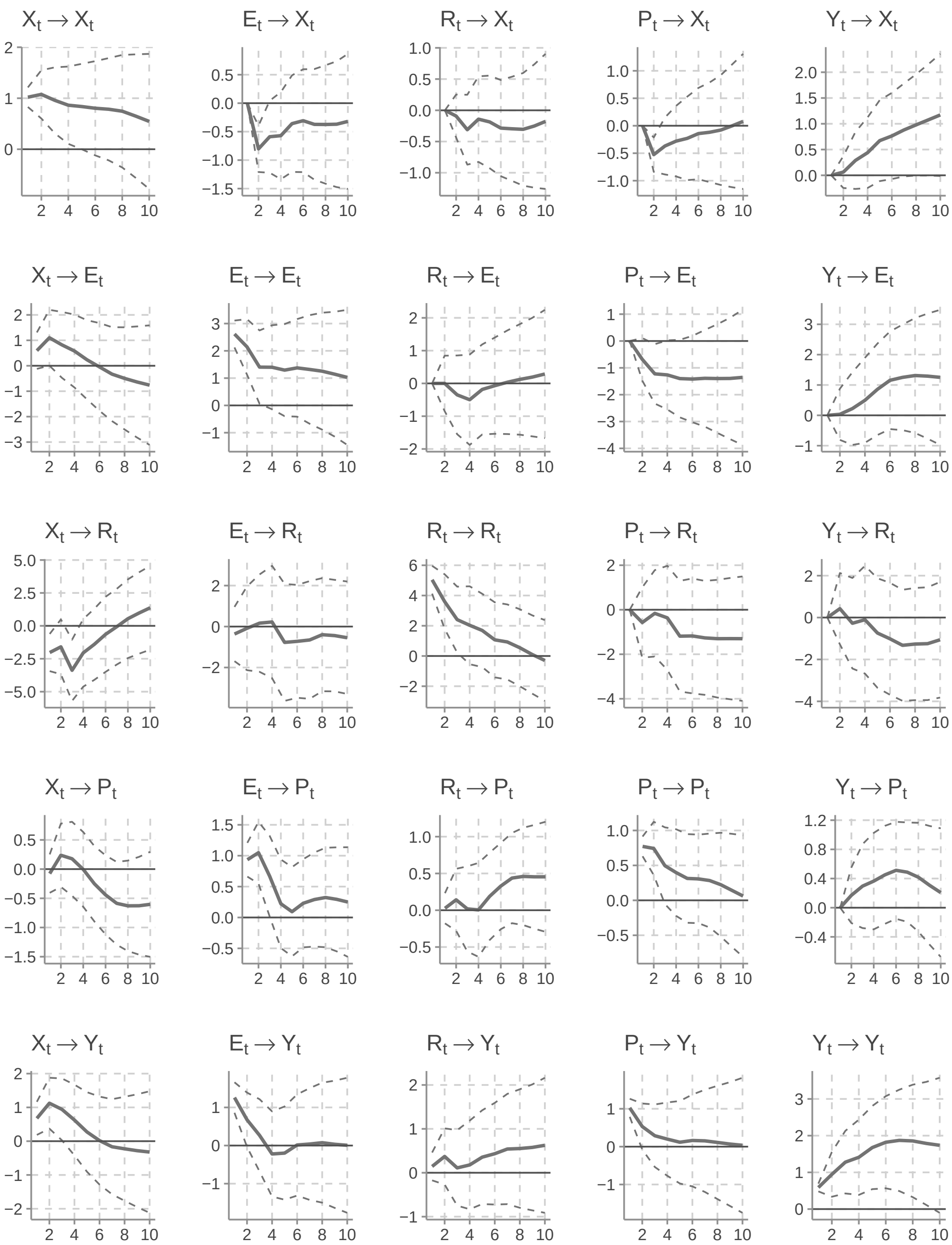

Figure 6: **Impulse-response functions, two-step VAR, first step, first ordering**. Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

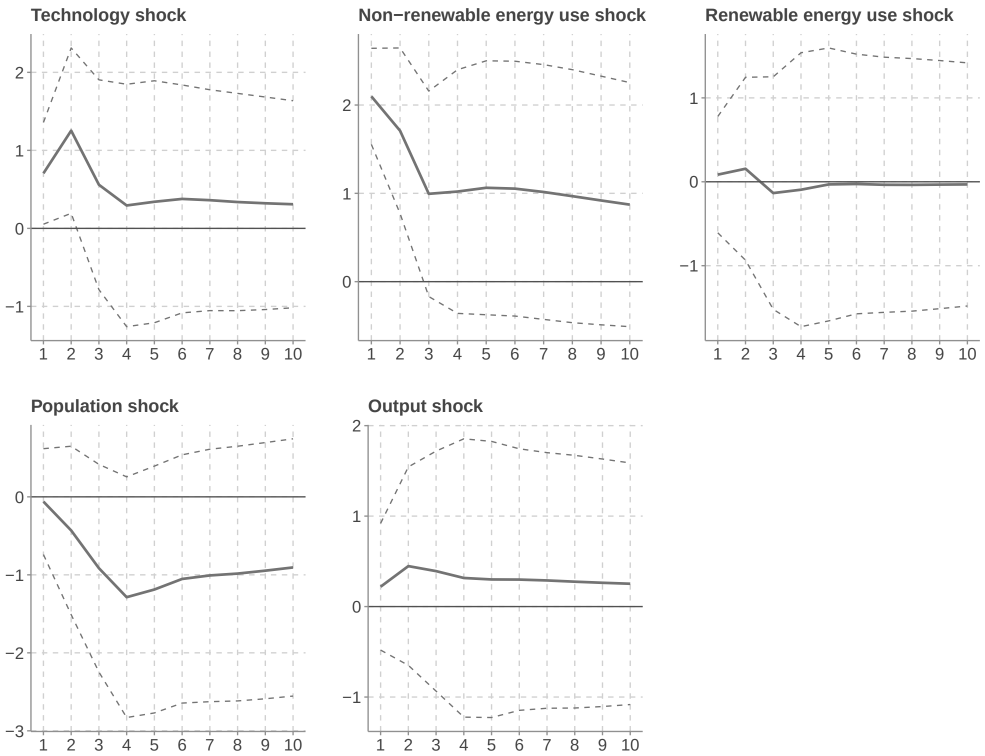

Figure 7: **Responses of aggregate carbon dioxide emissions to structural shocks, second step, first ordering**. Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

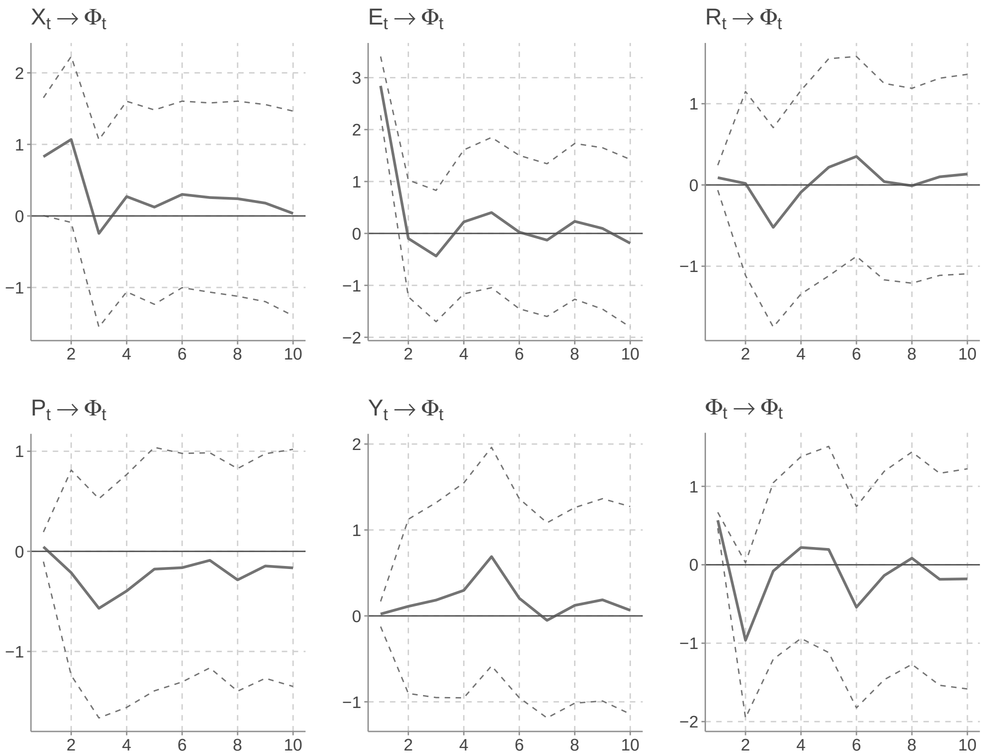

Figure 8: **Response of CO_2 emissions to structural shocks, one-step VAR in first differences and with labor productivity, first ordering**. Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

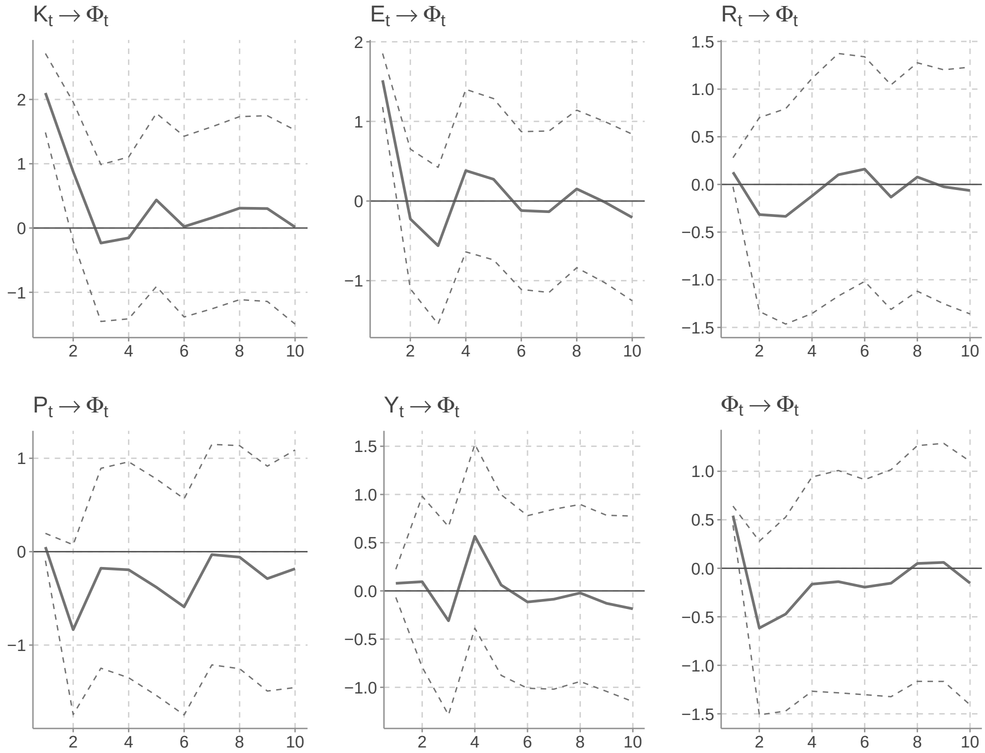

Figure 9: **Response of CO_2 emissions to structural shocks, one-step VAR in first differences and with the capital stock, first ordering.** Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

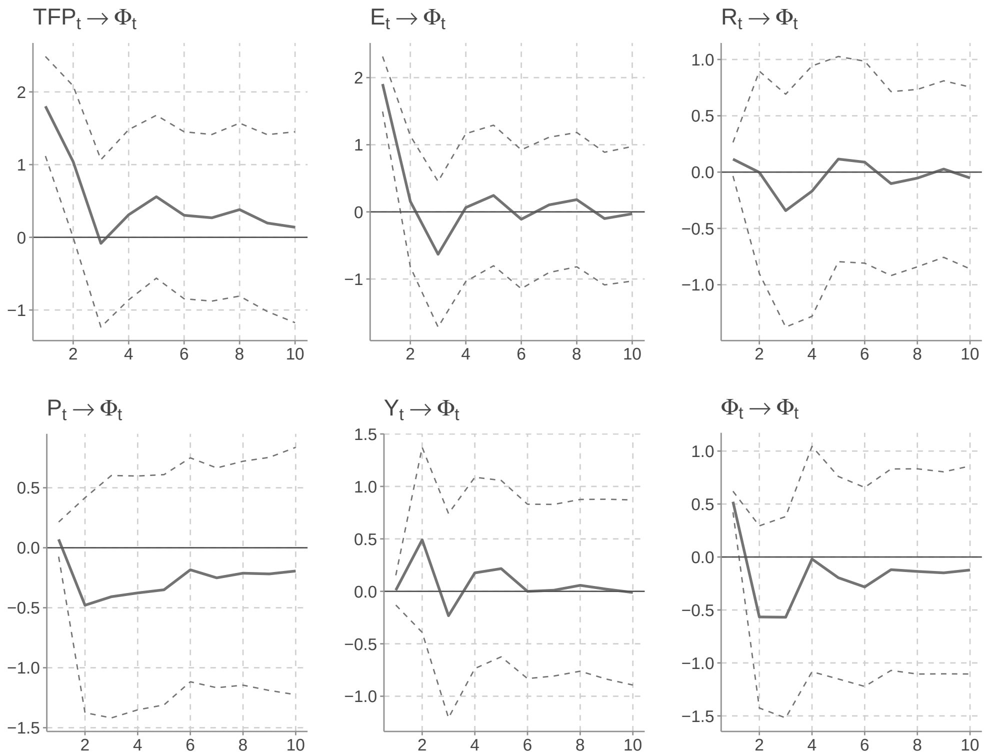

Figure 10: **Response of CO_2 emissions to structural shocks, one-step VAR in first differences and with total factor productivity, first ordering.** Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

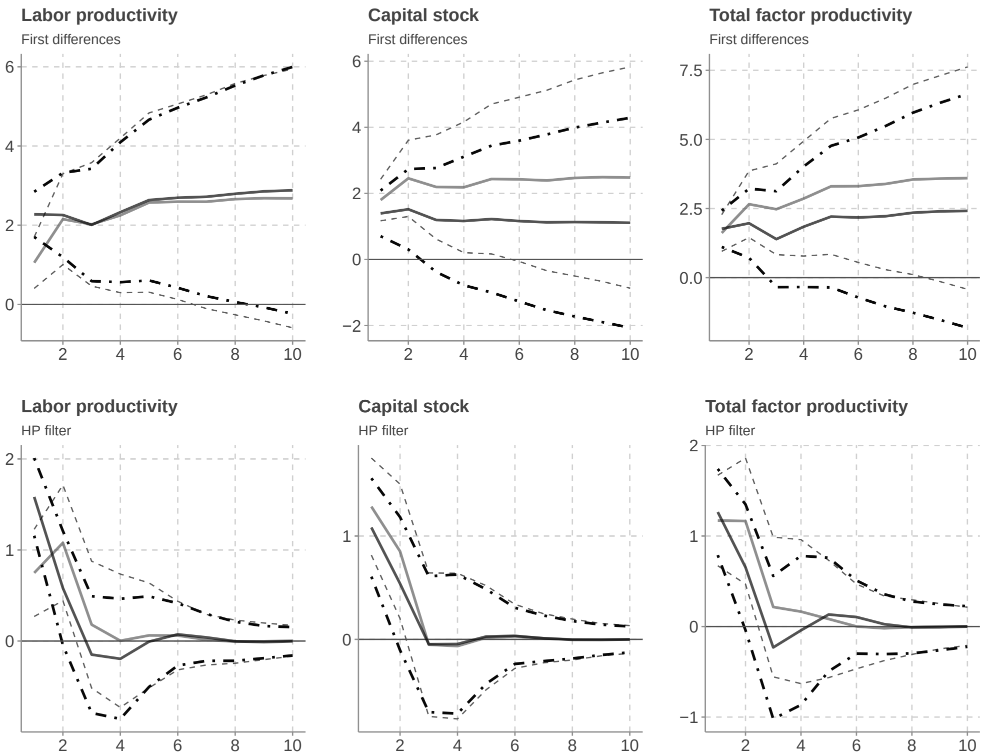

Figure 11: **Responses of carbon dioxide emissions to non-renewable energy use and technology structural shocks, first differences and de-trended series with the HP filter, first ordering**. Upper panel: cumulative responses to technology shocks (solid gray lines), with 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications (dashed gray lines), and non-renewable energy use shocks (solid black lines), with 95% bootstrapped confidence intervals (dot-and-dashed black lines) for VAR models with variables in first differences. Lower panel: responses to technology and non-renewable energy use shocks for VAR models with variables de-trended by the Hodrick-Prescott filter.

A Appendix

Below, the full impulse-response diagrams for the one-step VAR robustness checks.

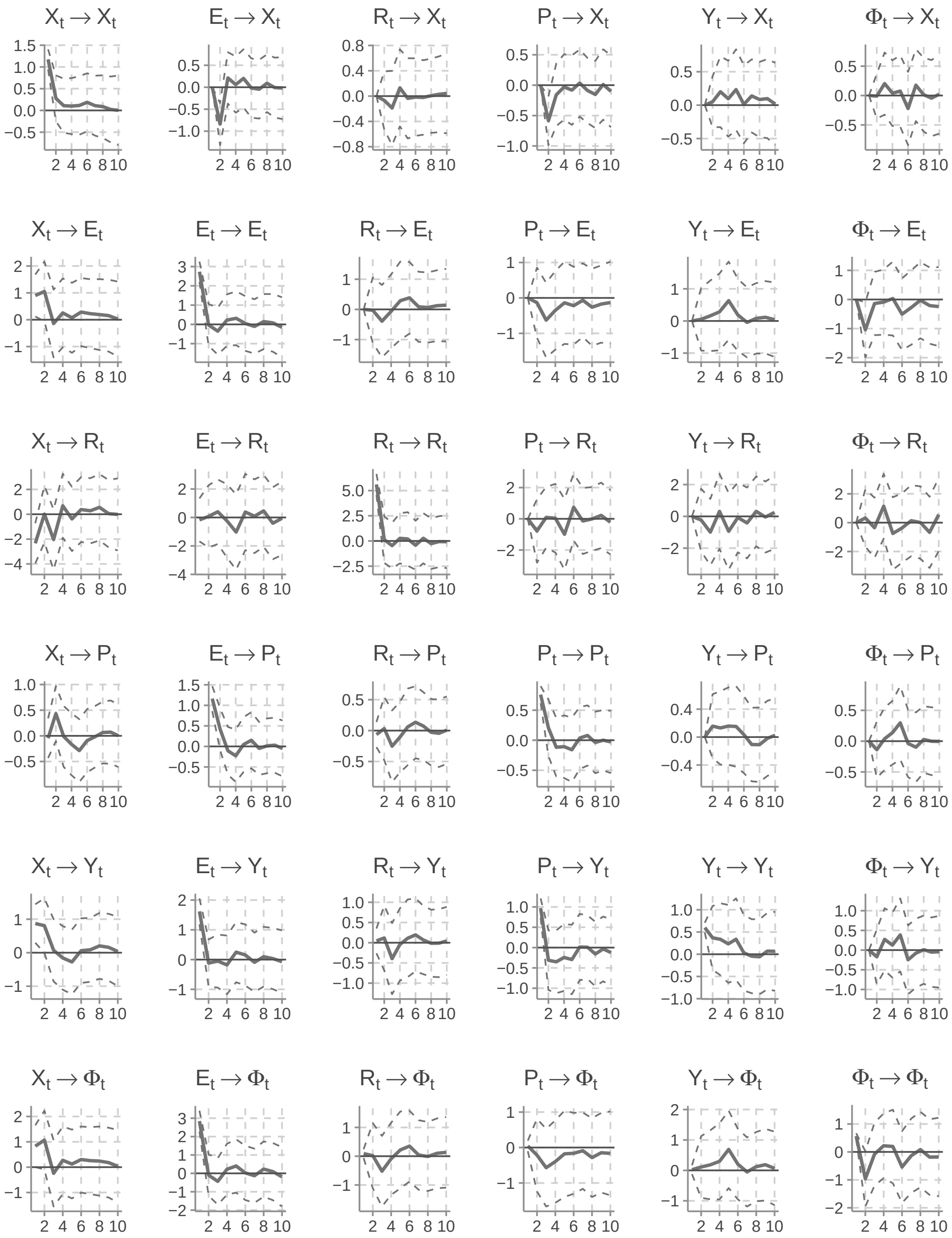

Figure 12: **Impulse-Response Functions, single-step VAR in first differences and with labor productivity, first ordering.** Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

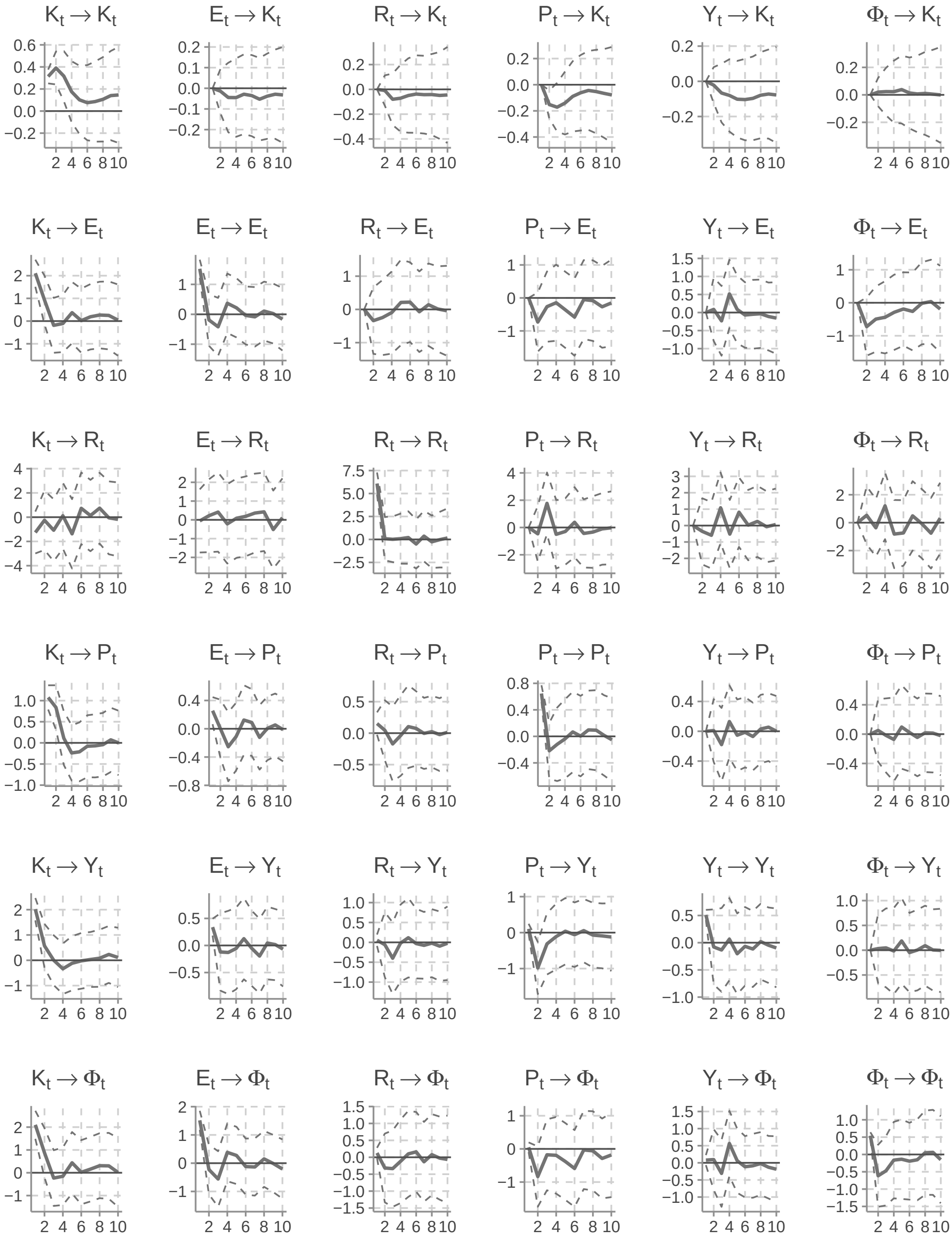

Figure 13: **Impulse-Response Functions, single-step VAR in first differences and with the capital stock, first ordering**. Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.

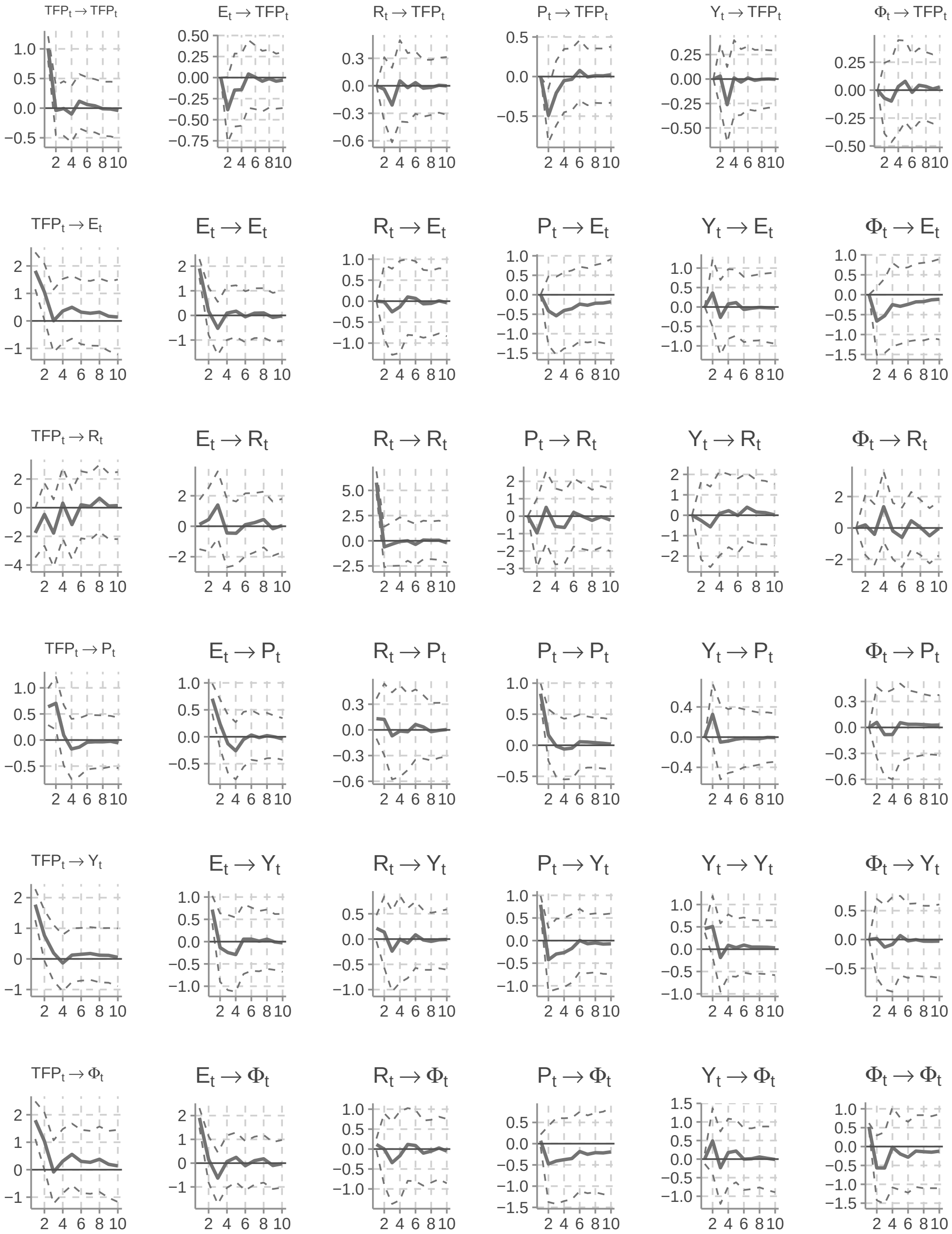

Figure 14: **Impulse-Response Functions, single-step VAR in first differences and with total factor productivity, first ordering**. Solid lines indicate estimated responses, while dashed lines are 95% bootstrapped confidence intervals obtained via 5,000 Monte Carlo replications.