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Structural Vector Auto Regression Analysis of the Dynamic Effects of Shocks in Renewable Electricity Generation on Economic Output and Carbon Dioxide Emissions: China, India and Japan

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ABSTRACT

This paper investigates effects of shocks in the share of renewable electricity in total electricity generation on real output growth and carbon dioxide (CO_2) emissions in China, Japan and India from 1970 to 2011 using structural vector auto regression analysis. These economies are assumed to face exogenous correlated random shocks in the share of renewable electricity in total electricity generation (RT). The substantiality of the shocks' impact on real output growth and CO_2 emissions were examined using impulse responses and variance decompositions (VDC). The impulse responses show that positive shock in RT positively affects real output growth and reduces CO_2 emissions. Shocks in RT have long-lived impacts, but all countries show stability signs and absorb RT shocks with some delays. VDCs analysis corroborates the findings of impulse responses. These research findings support governmental initiatives that reduce CO_2 emissions through renewable power generation and ensure sustained economic growth.

Keywords: Renewable Electricity, Carbon Dioxide Emissions, Economic Growth
JEL Classifications: 013, Q5, Q42, Q43, Q56

1. INTRODUCTION

In recent years, the issue of global warming has gained prominence in the media and in policy and academic forums because of its deleterious effects on the environment, human health, and economic well-being. Burning fossil fuels, such as coal, oil and natural gas contributes to global warming and climate change because of the carbon dioxide (CO_2) it releases (IPCC, 2007). Combustion of fossil fuels to generate electricity and heat is the largest single source of CO_2 emissions, accounting for 41% of global CO_2 emissions in 2010 (IEA, 2012). Combustion of fossil fuels to transport people and goods and fossil fuels combustion allied with various industrial processes are the second and third largest sources of CO_2 emissions, accounting for 22% and 20%, respectively, of global CO_2 emissions in 2010.

During the past 20 years, in an effort to reduce the magnitude and rate of increase in CO_2 emissions, many countries have established policy targets for reducing the share of energy (electricity) generated from fossil fuels and increasing the share of renewable energy (defined broadly as energy generated from tide and wave, solar, wind, biomass and geothermal) in the overall energy supply. Renewable energy, unlike fossil fuels, can be regenerated; it is not susceptible to energy security issues the way oil, coal, gas and uranium are, and it does not directly have negative impact on global warming and climate change. Increased concern regarding issues related to global warming and energy supply security of countries dependent on fossil fuel imports suggests that in the future, renewable energy sources will feature significantly in the overall share of energy consumed worldwide. Furthermore, in the context of high and soaring costs of conventional energy, the price volatility of fossil fuels, and the significant technological innovation and cost reductions of renewable energy technologies in recent years, exploration of renewable energy as an alternative to the fossil fuels has become an area of increasing priority.

The growth of renewable energy technologies worldwide began in the 1990s and accelerated rapidly in the 2000s. Despite the recent global economic crisis and increased uncertainty over economic growth and policy priorities in developed countries, global investment in new renewable energy capacity increased from $104 billion in 2007 to $227 billion in 2010. Global new investment in renewable energy capacity attained a record high of $279 billion in 2011 but declined to $244 billion in 2012 (REN21, 2013). Average annual growth rates for the 5-year period 2007 to 2012 also showed significant gains - All forms of grid-connected solar photovoltaic capacity grew by 60%, solar thermal power increased by 43%, wind power grew by 25%, solar water heating capacity expanded by 15%, solid and gaseous biomass capacity increased at an average 8% annually, and hydropower and geothermal power expanded by 3-4% per year during this period. Renewable energy supplied an estimated 19% of global final energy consumption in 2011 and renewables made up just over half of total net additions to electric generating capacity from all sources in 2012. By end-2012, operating renewable capacity comprised more than 26% of global generating capacity and supplied approximately 21.7% of global electricity. The top investors in renewable energy capacity in 2012 included four developing countries and six developed countries[1] (REN21, 2013).

The preponderance of empirical research on the energy-economic growth nexus investigates the causal relationship between energy consumption and economic growth. Another substantive body of the literature examines the relationship between economic growth and greenhouse gas (GHG) emissions. Significantly, though, renewable electricity generation offers unique opportunities to reduce GHG emissions, enhance energy security, improve human health and economic well-being, support job creation, and expand rural energy access and development (REN21, 2013); however, empirical research specifically examining the expansion of renewable electricity production as possible remediation for GHG is considerably limited. Additionally, current research does not adequately address how exactly an expansion in the share of renewable electricity in total electricity generation might affect economic growth.

This study begins to address this deficit through its investigation of the relationship between renewable electricity generation, economic growth, and CO_2 emissions in China, India and Japan from 1970 to 2011. This study employs a structural vector auto regression (SVAR) model based on the identification technique developed by Blanchard and Perotti (2002). Specifically, this study aims to uncover the dynamic effects of innovations in the share of total electricity generation derived from renewable energy sources on CO_2 emissions and real output growth through impulse response function (IRF) and variance decomposition (VDC) analysis of the SVAR model in these Asian countries. The imperative for this analysis is clear. Following the March 2011 Fukushima Daiichi nuclear power plant disaster in Japan, governments worldwide are wary about the use of nuclear energy in order to meet their commitments to CO_2 reduction, improve their energy supply security, and achieve economic development goals; therefore, examining the ways in which an expansion in the share of renewable electricity in the total electricity generation affects economic growth and CO_2 emissions is warranted.

The efficacy of policies aimed at alleviating environmental degradation and ensuring sustainable development depends on the ability of policymakers to make an accurate assessment of the timing and effects of unexpected variations in renewable electricity supply on economic activities and emissions. Therefore, to design appropriate emissions mitigation strategies in general, and renewable energy policies in particular, policymakers need to have a clear understanding of the dynamic effects of renewable energy shocks on real output growth and emissions.

Table 1 presents some figures of the economic profiles, electricity production, CO_2 emissions, and energy intensity of gross domestic product (GDP) for China, India, and Japan. As a consequence of their status as signatories to both the 1992 United Nations Framework Convention on Climate Change and the 2002 Kyoto Protocol, these countries are the subject of this analysis. These countries have, for many years, recognized the importance of stabilizing the level of GHGs in the atmosphere and alleviating environmental degradation. These countries represent different income groups as classified by the World Bank and are at different stages of economic development in terms of population dynamics, social structure, income growth and institutional capacity. In 2011, China, India and Japan ranked among the top 10 largest economies in the world and are among the world's top 5 polluting countries in terms of CO_2 emissions (World Bank, 2012; IEA, 2012). As shown in Table 1, the combined population, GDP and electricity production of these countries are 2.71 billion, US$ 10,134.39 billion and 6797 TWh, which amount to about 39%, 19.31% and 30.04% of the world's 2011 population, GDP and total electricity production, respectively. These figures indicate that these countries produce huge amounts of electricity to meet increasing energy demands of their large populations and keep their economies growing.

Furthermore, Table 1 reveals that these countries started out with relatively high CO_2 intensity and energy intensity in 2000 but over time the ratios have generally fallen; this diminution has not been accompanied by a similar fall in total CO_2 emissions, which has generally trended upward. In response to growing international and domestic pressures to reduce emissions and because of policymakers' increased awareness of potential contributions renewable energy make towards development, China, India, and Japan are actively accelerating adoption of different renewable energy sources and increasing the share of renewable electricity in total electricity production, as shown in Table 1. As noted earlier, these countries ranked among the world's top 10 renewable energy investor countries in 2012. Due to the increasing awareness of global warming, this study has significant implications for the successful implementation of renewable energy policies and climate change mitigation strategies in these countries and elsewhere. These findings may prove valuable as a guide for designing policies that balance and mitigate the often-conflicting goals of higher economic growth and climate protection.

1 China, India, South Africa, Brazil, Japan, United States, Germany, Italy, United Kingdom and France.

Table 1: Economic profile and renewable electricity production indicators, various years

Country	Year	Population (millions)	GDP (billion constant $2005)	CO_2 emissions from fuel combustion ($MtCO_2$)	Total electricity production (TWh)	Share renewable electricity in electricity production (%)	GDP/capita at PPP (constant $2005)	CO_2 emissions/capita (ton)	Electricity consumption/capita (KWH)	CO_2 intensity of GDP at PPP ($kgCO_2$/$2005)	Energy intensity of GDP at PPP (toe/1000 $2005)	GDP growth (annual %)
China	2000	1262.65	1417.05	3310	1356	16.6	2667.46	2.62	0.99	0.98	0.356	8.4
	2005	1303.72	2256.90	5403	2502	16.1	4114.57	4.44	1.78	1.01	0.326	11.3
	2010	1337.83	3838.00	7253	4208	18.5	6819.31	5.42	2.94	0.80	0.265	10.4
	2011	1344.13	4194.94	7954	4701	16.1	7417.88	5.92	3.29	0.73	0.262	9.3
India	2000	1053.90	601.31	972	561	13.8	1741.32	0.92	0.39	0.54	0.254	3.9
	2005	1140.04	834.22	1164	698	15.8	2233.86	1.02	0.46	0.46	0.215	9.3
	2010	1224.61	1232.95	1710	960	14.2	3121.61	1.40	0.63	0.46	0.185	10.5
	2011	1241.49	1317.48	1745	1038	15.1	3277.01	1.41	0.67	0.44	0.190	6.3
Japan	2000	126.93	4308.10	1175	1059	10.9	28889.20	9.26	7.97	0.32	0.143	2.3
	2005	127.76	4571.88	1213	1100	10.4	30441.35	9.49	8.21	0.27	0.134	1.3
	2010	128.04	4648.48	1138	1119	11.1	31029.75	8.89	8.34	0.29	0.128	4.7
	2011	127.83	4621.97	1186	1058	11.9	30764.24	9.28	7.85	0.30	0.122	−0.6
Countries combined	2011	2713.45	10134.39	10885	6797							
The world	2011	6958.00	52485.86	31342	22619	20.9	10102.10	4.50	2.93	0.45	0.19	

Source: Authors own compilation/calculation using data from-World Development Indicator, World Bank (2012); IEA (2013); Enterdata Energy Statistical Yearbook (2013); CIA, World Fact Book (2012), GDP: Gross domestic product

In brief, our primary findings for the sampled countries indicate positive shock to the share of renewable electricity in total electricity generation enhances economic growth and reduces CO_2 emissions. Shocks in renewable electricity have long-lived impacts on economic growth and CO_2 emissions, but all the countries show stability signs and can absorb shocks with some delays. VDCs analysis also corroborates the findings of the IRFs.

The remainder of the paper is organized as follows: Section 2 provides a brief literature review. Section 3 discusses the statistical methodology and the time series properties of estimation data. Section 4 presents results of the IRF and VDC analysis. Section 5 concludes the paper.

2. LITERATURE REVIEW

The extant scholarship is replete with different empirical results regarding the relationship between energy consumption, economic growth and environmental quality (frequently measured by CO_2 emissions) but neglects the specific questions raised by examining renewable electricity production as possible remediation for GHG emission. It is important to point out that we do not intend to provide an extensive review of the literature because studies by Omri (2014), Bouoiyour et al. (2014), Payne (2010), and Ozturk (2010) provide exhaustive surveys and chronological listing of international scholarly research into the economic growth, energy consumption (electricity, nuclear, and renewable consumption), and environmental quality nexus till 2012. For this reason, we focus more on the post-2012 studies in the field of renewable energy consumption, carbon emissions and economic growth.

Contributing to the literature on the energy consumption - economic growth-environmental quality nexus, Chema and Javid (2015) applied panel data co-integration, fully modified ordinary least squares (OLS), and vector error correction model techniques to investigate the link between economic growth, disaggregate energy consumption (coal, petroleum, electricity, renewable energy consumption), economic growth and environmental quality for a panel of Asian developing countries. The analysis revealed a stable long-run relationship between economic growth, the different categories of energy consumption and the environment. Further, all forms of disaggregate energy consumption were found to have statistically significant positive impacts on growth. The authors therefore recommended enhancing the renewable energy sector to enhance economic growth and because its impact on environment degradation is low as compare to other sources.

Leitao (2014) used OLS and generalized method of moments time series techniques to investigate the correlation between economic growth, CO_2 emissions, renewable energy and globalization for Portugal over the period 1970-2010. The findings reveal that CO_2 emissions, globalization and renewable energy are positively correlated with economic growth. Results from the causality test indicate unidirectional causality from renewable energy to economic growth. Dogan (2014) examined the nature of the causal relationship between energy consumption and economic growth in four low-income Sub-Saharan Africa countries: Kenya, Benin, Congo and Zimbabwe for the period 1971-2011 using the econometrics in time-series methods. The findings reveal that the variables are not co-integrated. Further, there is a unidirectional causality running from energy use to economic growth in the case Kenya and no causal link between energy consumption and economic growth in Benin, Congo and Zimbabwe.

Tiwari (2011) used the SVAR approach to analyze the relationship between renewable energy, economic growth, and CO_2 emissions for India. The author found that positive shock in renewable energy increases output growth and decreased CO_2 emissions. Azgun (2011) applied the SVAR methodology to access the impact of innovations in aggregate electricity consumption and the sub-components of electricity consumption (industrial electricity consumption, residential and commercial, government offices and street illuminations) on real GDP for Turkey over the period 1968 and 2008. Both the results of structural factorization and impulse-response analysis reveal that while real GDP is invariant to shocks to aggregate electricity consumption as well as those to the sub-components of electricity consumption, perturbations to real GDP significantly affect total electrical energy consumption and the sub-components of electricity consumption. Silva et al. (2012) examined the impact of renewable energy sources on economic growth and CO_2 emissions in Denmark, Portugal, Spain and USA over the period 1960-2004 by using the SVAR. They found that although an increase in the renewable electricity generation may initially hinder economic growth for all countries except for the USA, it contributes to reduction in emissions. In a recent effort, Maslyuk and Dharmaratna (2013) applied the SVAR technique to 11 Asian developing countries. They found that for majority of countries in their sample of countries, there is a trade-off between economic growth and environment sustainability at least in the early years.

Pao and Fu (2013) examined the causal relationship between output growth, aggregated energy consumption, and four different categories of energy consumption: Non-hydroelectric renewable energy consumption (NHREC), total renewable energy consumption (TREC), non-renewable energy consumption (NREC) and the total primary energy consumption (TPEC) for Brazil over the period 1980-2010. The results of the co-integration test indicate a stable relationship between output growth and each of the four categories of renewable energy consumption. The results also indicate evidence of a one-way causality running from NHREC to economic growth in the long-run, bidirectional causality between economic growth and TREC, and unidirectional causality from economic growth to NREC and TPEC. Tugcu (2013) examined the causal relationships between total factor productivity growth and different categories of renewable energy for Turkey for the period 1970-2011 by using the autoregressive distributed lag (ARDL) bounds testing approach to co-integration and the Dolado and Lütkepohl's Granger causality test. The findings reveal that disaggregate energy consumption is co-integrated with total factor productivity growth and there exists bi-directional causal relationships among the variables in consideration. Further, the share of renewable energy consumption in total energy consumption was found to be the only energy type that positively affects total factor productivity growth in the Turkish economy. Ocal and Aslan (2013) used the ARDL approach and Toda-Yamamoto causality tests to examine the causal relationship between renewable energy use and economic growth in Turkey. In contrast to Tugcu (2013), the authors found that there exists a unidirectional causality running from economic growth to renewable energy consumption.

Al-Mulali et al. (2013) used the Canonical co-integrating regression technique to explore the causal relationship between energy consumption, CO_2 emission, and economic growth in Latin American and Caribbean countries over the period of 1980-2008. For 60% of the countries, they find bi-directional long-run causality between energy consumption, CO_2 emission, and economic growth. The results for the remaining 40% countries are mixed. Apergis and Payne (2012) examined the causal relationship between renewable energy consumption and economic growth in six Central American countries over the period of 1980-2006 and found one-way causality running from renewable energy consumption to economic growth in the short-run, but bidirectional causality in the long-run. Farhani and Rejeb (2012) applied panel unit root tests, panel co-integration methods and panel causality test to investigate the relationship between energy consumption, GDP and CO_2 emissions for 15 MENA countries over the period 1973-2008. In contrast to Apergis and Payne (2012), they find no causal link between economic growth and energy consumption; and between CO_2 emissions and energy consumption in the short-run and found evidence of a unidirectional causality running from income growth and CO_2 emissions to energy consumption in the long-run. Ozturk and Uddin (2012) investigate the long-run Granger causality relationship between energy consumption, CO_2 emission and economic growth in India over the period 1971-2007. The most important result is that there is feedback causal relationship between energy consumption and economic growth in India which implies that the level of economic activity and energy consumption mutually influence each other; a high level of economic growth leads to a high level of energy consumption and viz. The value of the error correction term confirms the expected convergence process in the long-run for carbon emissions and growth in India which implies that emission reduction policies will hurt economic growth in India if there are no supplementary policies which seek to modify this causal relationship.

In summary, the relationship between energy consumption, economic growth and environmental quality is not conclusive. The diverse results, among other things, may "arise due to the different data set, alternative econometric methodologies, and different countries' characteristics (Ozturk, 2010. p. 340)." The conflicting results show that the debate regarding the causal relationship between energy consumption, economic growth, and environment quality is unresolved. This study is not a resolution of the debate. Its intention is to contribute to the literature by ascertaining for policy implications, the timing and magnitude of the dynamic effects of shocks in the share of renewable electricity in total electricity generation on output growth and CO_2 emissions within a system approach that implicitly assumes that the economy faces unexpected shocks in share of renewable electricity in total electricity generation which can have substantial impact on the aggregate total of carbon emissions and economic growth.

3. METHODOLOGY AND DATA

This study implements a vector auto regression (VAR) based model to examine the effects of shocks in the share of renewable electricity in total electricity generation on CO_2 emissions and economic growth by analyzing IRFs and VDCs. Many scholars use VAR models to investigate the impacts of different types of random monetary, fiscal, and technology shocks on economic systems (Enders, 2010). VAR popularity derives from its ease of use. Often it is more successful than complex simultaneous models in predicting the dynamic impacts of different types of random disturbances on the variables in the model and, they are a priori non-restrictive (Ferreira et al., 2005; Sims, 1980).

VAR considers the variables' interactions and treats all variables as endogenous and as a function of all variables in lags. VAR's defect lies in its failure to consider the structural relationships among variables. Since different structural forms give the same reduced-form VAR, it is impossible to draw meaningful conclusions about the structural model from reduced-form VAR without identifying restrictions. SVAR analysis attempts to solve this identification problem. In contrast to VAR, the SVAR takes contemporaneous interaction of endogenous variables into account and, allows for the estimation of structural shocks and impulse responses from empirical data. Models of SVAR use restrictions based on economic theory to identify the system and obtain an economic interpretative function of the impulse response.

3.1. Specification of the SVAR Model

This study employs a SVAR framework as it compensates for the flaws of VAR. Three endogenous variables make up the specification depicting the relationship between CO_2 emissions, real GDP, and the share of renewable electricity in total electricity generation.

In the SVAR context, the trivariate VAR system of equations can, for simplicity, be written as a first-order VAR:

$$\begin{aligned} RT_t &= a_{13}E_t + d_{11}RT_{t-1} + d_{12}Y_{t-1} + d_{13}E_{t-1} + b_{12}\varepsilon_t^{Y} + \varepsilon_t^{RT} \\ Y_t &= a_{23}E_t + d_{21}RT_{t-1} + d_{22}Y_{t-1} + d_{23}E_{t-1} + b_{21}\varepsilon_t^{RT} + \varepsilon_t^{Y} \\ E_t &= a_{31}RT_t + a_{32}Y_t + d_{31}RT_{t-1} + d_{32}Y_{t-1} + d_{33}E_{t-1} + \varepsilon_t^{E} \end{aligned} \quad (1)$$

Where, RT denotes the share of total electricity generation derived from renewable energy sources per capita, Y corresponds to real GDP per capita, E refers to CO_2 emissions per capita. εt^{RT}, εt^{Y}, and εt^{E} denote mutually uncorrelated structural innovations; in other words RT shocks, Y shocks, and E shocks, respectively. Equation (1) can be expressed in matrix form as:

$$\underbrace{\begin{bmatrix} 1 & 0 & -a_{13} \\ 0 & 1 & -a_{23} \\ -a_{31} & -a_{32} & 1 \end{bmatrix}}_{A}\underbrace{\begin{bmatrix} RT_t \\ Y_t \\ E_t \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix}}_{D}\underbrace{\begin{bmatrix} RT_{t-1} \\ Y_{t-1} \\ E_{t-1} \end{bmatrix}}_{X_{t-1}} + \underbrace{\begin{bmatrix} 1 & b_{12} & 0 \\ b_{21} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{B}\underbrace{\begin{bmatrix} \varepsilon_t^{RT} \\ \varepsilon_t^{Y} \\ \varepsilon_t^{E} \end{bmatrix}}_{\varepsilon_t} \quad (2)$$

Where, matrix A and D, respectively, model current and past relationships between the variables; matrix B contains the structural form parameters of the model; ε_t is the vector of structural innovations and var $(\varepsilon_t) = \Omega$, where Ω is a diagonal matrix with the variance of structural innovations making up the diagonal elements.

From Equation (2) above it follows that the reduced-form VAR model is written in matrix notation as:

$$X_t = A^{-1}DX_{t-1} + A^{-1}B\varepsilon_t \quad (3)$$

Or, equivalently, as:

$$X_t = FX_{t-1} + U_t \quad (4)$$

Where, X_t is the vector [RT, Y, E] of endogenous variables and $F=A^{-1}D$:

$$\begin{bmatrix} RT_t \\ Y_t \\ E_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & -a_{13} \\ 0 & 1 & -a_{23} \\ -a_{31} & -a_{32} & 1 \end{bmatrix}\begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix}\begin{bmatrix} RT_{t-1} \\ Y_{t-1} \\ E_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & -a_{13} \\ 0 & 1 & -a_{23} \\ -a_{31} & -a_{32} & 1 \end{bmatrix}^{-1}\begin{bmatrix} 1 & b_{12} & 0 \\ b_{21} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} \varepsilon_t^{RT} \\ \varepsilon_t^{Y} \\ \varepsilon_t^{E} \end{bmatrix} \quad (5)$$

Equation (5) above suggests that the reduced-form innovations are a linear combination of the structural innovations of the form:

$$u_t = A^{-1}B\varepsilon_t \quad (6)$$

Innovations of reduced-form VAR can equivalently be written as:

$$\underbrace{\begin{bmatrix} u_t^{RT} \\ u_t^{Y} \\ u_t^{E} \end{bmatrix}}_{u_t} = \underbrace{\begin{bmatrix} 1 & 0 & -a_{13} \\ 0 & 1 & -a_{23} \\ -a_{31} & -a_{32} & 1 \end{bmatrix}^{-1}}_{A^{-1}}\underbrace{\begin{bmatrix} 1 & b_{12} & 0 \\ b_{21} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{B}\underbrace{\begin{bmatrix} \varepsilon_t^{RT} \\ \varepsilon_t^{Y} \\ \varepsilon_t^{E} \end{bmatrix}}_{\varepsilon_t} \quad (7)$$

Where the error terms ut^{RT}, ut^{Y}, and ut^{E} signify reduced-form residuals and, as before, εt^{RT}, εt^{Y}, and εt^{E} denote structural innovations.

3.2. Identifying Restrictions for the SVAR

Without imposing restrictions, structural innovations of the reduced-form VAR cannot be identified both in the short-run and the long-run and, therefore, studying the IRF—the dynamic responses of endogenous variables to a unit shock of some of the variables in the system—will not reveal anything about the response of the variables to structural shocks. This reality occurs because reduced-form residuals have no economic significance. They are a linear combination of structural innovations. Several techniques can be used to recover the structural innovations in vector ε_t and obtain estimates of the structural coefficients. This study employs the long-run restriction identification technique proposed by Blanchard and Perotti (2002) to identify structural innovations in reduced-form VAR and arrives at economically interpretative IRFs.

To recover the structural innovations and identify the underlying structural model, the estimation proceeds as follows: The VAR is estimated in its unrestricted form. Since all equations in the unrestricted VAR model share the same matrix of regressors, estimation of the reduced-form VAR model amounts to applying OLS separately to each Equation in (2) after carefully determining the optimal lag structure to eliminate serial correlation from the residuals. After the reduced-form VAR is estimated using OLS, long-run restrictions consistent with economic theory are imposed on the residuals of the reduced-form VAR in order to obtain structural innovations from reduced-form innovations.

The identification scheme assumes that the B matrix is a unit matrix while the A matrix is a lower triangular matrix. The order of variables in the vector of endogenous variables plays a crucial role in the identification process, because altering the order changes the relationship structure of innovations. The first variable in ordering should be that whose future periods' variance is best explained by its own structural innovations. The problem is that every order implies different VDC, and requires a significant effort to determine the optimal order. It is common practice to place the variables by the time-line of occurrence.

The sequence ordering of the variables used in this study is: The share of total electricity generation derived from renewable energy sources per capita (RT), real GDP per capita (Y), and CO_2 emissions per capita (E) (Silva et al., 2012). The long-run restrictions correspond to this ordering. The first shock associated to RT shock affects contemporaneously all variables; the second shock associated to Y shock affects contemporaneously all variables except RT. Finally, the shock associated to E shock affects this variable contemporaneously and the other variables only a period later.

3.3. Data

This study uses annual data for China, India and Japan on real GDP, CO_2 emissions, and the share of renewable electricity in total electricity generation during 1970-2011. Data is from World Development Indicators, International Energy Agency, US Energy Information Administration, and Global Energy Statistical Year Book. Data on renewable electric energy consumption is difficult to obtain, and so this study uses data on renewable electricity generation as a proxy for renewable electricity consumption[2] (Yoo and Kim, 2006; Silva et al., 2012).

This study calculates the share of total electricity generation derived from renewable energy sources per capita (RT) as the ratio of electricity generation derived from renewable energy sources per capita to the sum of electricity generation derived from non-renewable energy sources per capita and renewable energy sources per capita (Silva et al., 2012). All the variables are entered in per capita terms to facilitate easy and less-biased comparison among countries with different population dynamics, geographical factors, and renewable energy resources endowments. This study uses logarithmical differences of the series as proxy of the growing rates. All estimation was performed using EViews 6.0 software.

2 Carbon dioxide emissions per capita are measured as metric tons of carbon dioxide per capita. Real GDP is GDP per capita in constant 2005 US dollars. Renewable electricity production is measured in billions of kilowatt hours (KW-H).

4. EMPIRICAL RESULTS

4.1. Unit Roots Test Results

The literature substantiates linear combinations of non-stationary time series leads to spurious regression. SVAR studies show that if variables are non-stationary, shocks continue to accumulate over time and so have permanent effects (Shapiro and Watson, 1988; Blanchard and Quah, 1989). The presence of unit roots in the variables can give rise to spurious regression if the VAR is estimated in levels. Primarily, we examine unit roots properties of the data series using the Ng and Perron (2001) unit roots M-tests procedure in order to avoid drawing incorrect inferences that can result in misleading conclusions and in improperly conceived energy and environmental policies. This test is optimum because experience in the application of augmented Dickey-Fuller and Phillips-Perron unit roots tests procedures reveal that the procedures are affected by finite sample power and size problems (DeJong et al., 1992; Schwert, 1989). This step determines whether the variables are I(0) or I(1) and whether a reduced form representation in levels or in first differences is required. If variables include integrated processes, one should estimate a VAR in first difference or as vector error correction model (Guay and Pelgrin, 2004). The results of the Ng and Perron (2001) M-tests statistics, reported in Table 2, show that all variables are non-stationary in their level form, but become stationary after first difference. Since all variables were found to be integrated of order one, the VAR models are specified in first difference.

An important step in the specification of VAR/SVAR models is determination of the optimal lag order. This step is essential because all inferences in VAR/SVAR depend on correct model specification. This study determines optimal number of lags in the model using Akaike information criteria (AIC), Hannan-Quinn criteria (HQ), and Schwartz information criteria (SC). The results of the lag selection process (not reported here so as to conserve on space) show that with AIC and HQ, it is possible to select optimal lag lengths higher than three lags, while the SC suggested a lag length of three for the period studied. Because SC defines parsimonious specifications, with limited annual observations, this study uses the SC to set the maximum number of lags for each country at three lags.

Table 2: Results of Ng-Perron unit root tests

Country	Variables	Level		First difference	
		MZa	MZt	MZa	MZt
China	RT	0.638	0.656	−18.632*	−3.047*
	Y	−0.059	−0.027	−13.999*	−2.642*
	E	1.811	1.203	−13.407*	−2.585*
India	RT	2.032	2.262	−20.006*	−3.162*
	Y	−0.184	−0.074	−17.635*	−2.969*
	E	−0.174	−0.078	−18.858*	−2.995*
Japan	RT	−5.065	−1.398	−19.951*	−3.151*
	Y	0.451	0.395	−18.703*	−3.056*
	E	−2.770	−1.155	−18.763*	−2.839*

Note: All the variables are in natural logarithm. * and ** represent rejection of the null hypothesis at significance level of 1% and 5% for MZa critical values −13.800 and −8.100 with constant, and MZt critical values −2.580 and −1.980 with constant

4.2. Stability Test Results

Having identified the optimal lag structure of the VAR, as a simple indicator of the stability of the VAR model, the next step is to calculate the inverse roots of the characteristic polynomials. This step is a preliminary but important component of the empirical analysis, since the reduced form of a VAR model must be stable for it to be used as a valid statistical framework for formulation and testing of alternative structural hypotheses. If all the inverse roots of the VAR model have roots with modulus less than one and lie inside the unit circle, the model is considered stable (Lutkepohl, 2005). Results of the stability test show that the reported inverse roots of the VAR model for each of the countries has roots with modulus less than one and lies inside the unit circle, meaning that the VAR is variance and covariance stationary and, thus, satisfy the stability condition (Figure 1).

4.3. Results of SVAR IRFs Analysis

Because estimated structural shocks are assumed to have unit root variances in the SVAR, their sizes and adjustment speed can be deduced by examining the associated IRFs. Plotting IRFs is a practical way to represent the behavior of CO_2 emissions and real GDP in response to unexpected variations in the share of renewable electricity in total electricity generation.

Panels A to C of Figure 2 display the impulse responses of CO_2 emissions and real GDP to a positive shock from RT in the sampled countries across a 15-year forecast horizon. For a covariance stationary VAR, the effect of any shock given by the reduced form innovation dies out at some point in time in the future, apparent in Panels A to C of Figure 2. The dashed lines in the figures represent the confidence interval bands of plus/minus two-standard deviations, calculated using the Monte Carlo approach (Runkle, 1987). The middle lines represent the IRFs. The statistical significance of the impulse response is determined by the use of confidence interval bands. If the horizontal line is not within the bands, the impulse response is considered statistically different from zero. In other words, when the horizontal line falls into the confidence interval bands, then the null hypothesis that there is no effect of RT shocks on real GDP growth and CO_2 emissions cannot be rejected. The speed of adjustment after structural shock is measured by the number of periods before the IRFs cross the zero line and stays on the line.

Starting with the results for China depicted in Panel A, a one standard deviation shock in RT led to a sharp decline in real GDP growth for the first 2 years following shock, the response is positive and remained positive, though not statistically significant, till the end of year 5. It slowly dissipates and dies out in the 7th year. It takes about 7 years for real GDP to adjust back to its initial level following shock in RT. These results suggest that increases in the share of renewable electricity in the total electricity generation may initially harm economic growth; it ultimately leads to increased economic output.

Contextually, the result consists with the fact that significant economic growth in China is fueled by industry growth, requiring intensive use of electricity. In 2011, industry value added as percentage of GDP for China was 46.64% (World Bank, 2012). In addition to the direct effect of renewable electricity consumed for industrial use, which results in higher rates of economic growth, higher renewable electricity production results in an increase in total electricity production, having the indirect effect of generating employment and infrastructure in energy service. China's power generating and industrial sectors are currently heavily dependent on coal. The country's dependence upon coal occurs due to its abundant domestic stock and its reliance on coal as a contextually inexpensive energy source. Fossil fuels account for 81.5% of the country's electricity generation in 2011, but that dominance is challenged by competition from the country's renewable energy sectors. Jobs in the renewable energy sectors require different skills and qualifications compared to jobs in non-renewable energy sectors (Maslyuk and Dharmaratna, 2013. p. 238). Consequently, as resources divert from non-renewable electricity generation to renewable electricity supply, there could be disproportionate losses of jobs and income in the non-renewable energy sectors compared to jobs and income created in the renewable energy sectors. This

Figure 1: Inverse roots of the characteristic polynomial

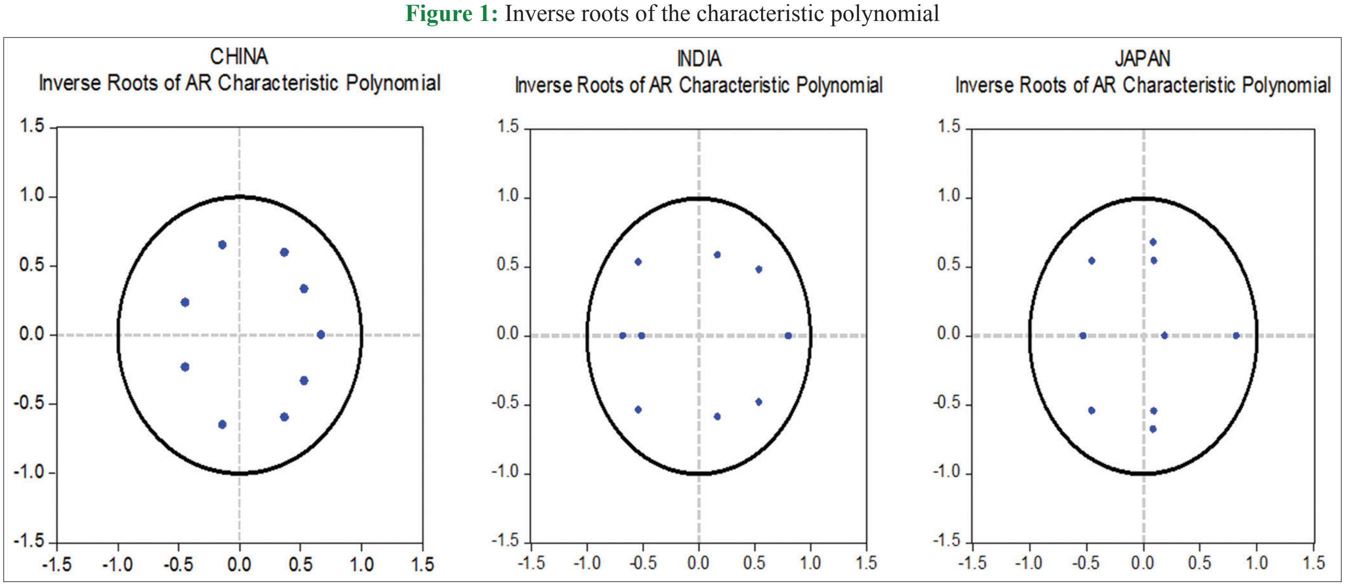
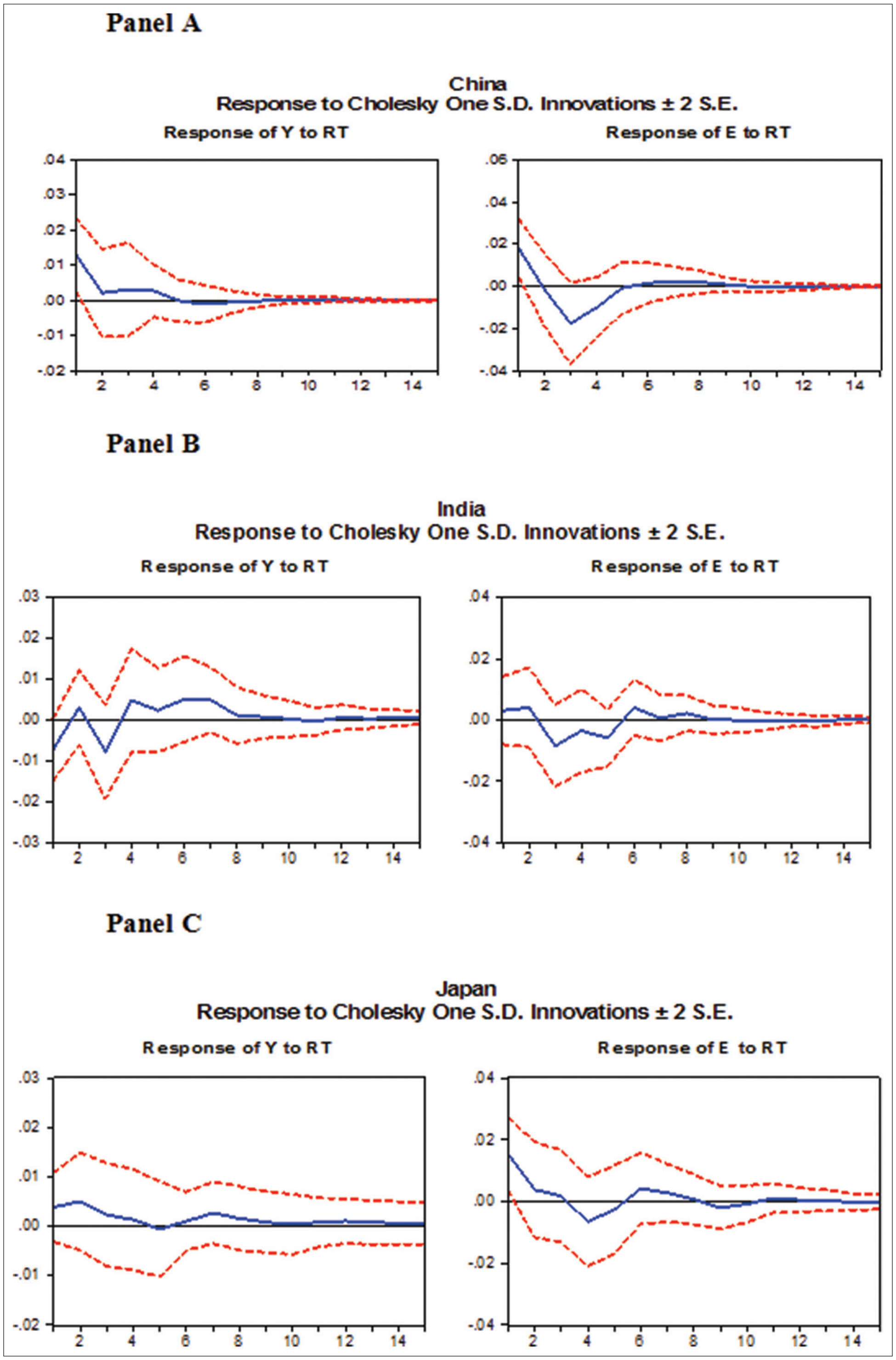


Figure 2: Structural vector autoregression impulse response functions



may explain why an increase in the share of renewable electricity initially reduces economic growth.

Panel A shows that in China, positive shock in RT resulted in a sharp decrease in CO_2 emissions in the first 4 years following the shock and that this result is not statistically significant. This response became positive in the 5th year and slowly dissipated in the 10th year. This finding suggests that it takes about 10 years for CO_2 emissions to adjust to equilibrium following shock in RT. These results are consistent with Silva et al. (2012) who, for three-out-of-the-four developed countries examined in their study find that an increase in the share of renewable electricity in total electricity generation may initially harm real output growth but decreases CO_2 emissions. This study's findings are also consistent with Tiwari (2011) for India but, conflict with Maslyuk and Dharmaratna (2013) for China, who report that shocks in renewable electricity production negatively affect real output growth and positively affects CO_2 emissions.

The results for India presented in Panel B, show that positive shock to RT increases real GDP for 2 years following shock. The response becomes negative in the 3rd year but turned positive in the 4th year. This positive response reached its maximum level in the 6th and 7th year following shock. The response dwindled and died in the 9th year. It takes about 9 years for real GDP to adjust to equilibrium following shock in RT. With regard to the response of CO_2 emissions to a positive shock from RT, in India, and unlike in China and Japan, a positive shock in RT increases CO_2 emissions for the first 2 years. The impulse response becomes negative in the 3rd, 4th, and 4th years after shock. In year 6, CO_2 emissions respond in a positive, though not statistically significant way, to the shock in RT. The response dissipated after the 9th year. This result might reflect the fact that, while India has actively promoted the development of renewables since the 1990s, India's electricity is still primarily generated by burning CO_2-emissions-intensive fuels, particularly coal. These results are consistent with Maslyuk and Dharmaratna (2013) for India who find that positive shock in renewable electricity generation leads to an increase in CO_2 emissions, and, on average, it takes more than 7 years for the target variables to adjust to equilibrium following shock.

The results of the IRFs for Japan, presented in Panel C, show that in Japan, like in China, and in contrast to India, the response of real GDP to positive shock in RT is consistently positive. The response petered out in the 12th year, indicating that it takes about 12 years for real GDP to adjust back to equilibrium following shock in RT. These results suggest sensitivity of economic output to changes in the energy supply mix and dependency of industrial output on energy input. The result makes sense considering the production side of the economy. Energy is vital to production of most goods and services. Efficient energy supply and availability, along with inputs of capital and labor, increases output.

In Japan, the shock in RT leads to gradual reductions in CO2 emissions in the first 4 years (Panel C). Response reached its minimum value in the 4th year, after which it reverts and oscillates close to the zero line, fizzling out in the 12th year. This finding is similar to Silva et al. (2012) and Tiwari (2011), who find that an increasing share of renewable electricity reduces CO_2 emissions.

4.4. Results of VDCs from the SVAR

VDC present an alternative method of interpreting the properties of SVARs. VDC reports the proportions of error of forecasts, generated by the SVAR, attributable to shocks to each of the variables in the model after some periods. Table 3 presents the VDCs for a 10-year horizon into the future for the sampled countries. Since SVAR assumes recursivity, VDC depends on ordering of the variables. The results in Table 3 correspond to the ordering: RT, Y, and E. Each column of the table reports, for a different target variable, the proportion of the forecast error explained by structural shocks to each of the three explanatory variables, listed in the second top most row of the table. This study focuses on real GDP per capita (Y) and CO_2 emissions per capita (E).

The VDC of real GDP per capita for China reveals that, apart from its own innovation that accounts for over 91% of the variation in real GDP, the remaining variation in the 1st year is accounted for by RT with about 8.8%. CO_2 emissions did not contribute anything in the first period to the variance in real GDP. Innovations to RT account for as much as 10.7% of the variation in the fourth period, while CO_2 emissions account for 5.5% of the variation in the same period. Over 12% of the variation in real GDP, from the 6th year upward, is due to variations in RT; the contributions of CO_2 emissions to real GDP variance averaged 6.8% between the 6th and 10th periods. The variance of real GDP attributed to its own shock, dampened over time. Even in the 10th period, 79.4% of real GDP variance is explained by its own innovations, with 8.5% and 12.1% explained by variations in CO_2 emissions and RT respectively. These findings imply that shocks to real GDP are long-lived.

With regard to CO_2 emissions variance, Table 3 shows that 55.8% of variation in CO_2 emissions in China is attributable to its own shock in the first period. The contribution of CO_2 emissions to its own variance in the remaining nine periods records an increasing trend, which stood at 60.84%, 61.17%, and 61.22% in the 5th, 6th and 10th periods respectively. RT and real GDP contribute

Table 3: VDCs of real GDP per capita (Y) and CO_2 emissions per capita (E) at various horizons

Horizon	Percentage of forecast error variance of Y explained by shocks to			Percentage of forecast error variance of E explained by shocks to		
	RT	Y	E	RT	Y	E
China						
1	8.757	91.242	0.000	15.884	28.314	55.801
2	8.565	87.228	4.206	12.403	22.392	65.203
3	8.286	87.485	4.228	18.317	19.552	62.130
4	10.683	83.788	5.528	19.758	18.971	61.269
5	11.920	80.652	7.426	19.984	19.167	60.848
6	12.190	79.959	7.850	19.822	19.006	61.170
7	12.179	79.942	7.878	19.686	18.985	61.327
8	12.114	79.600	8.284	19.707	19.035	61.256
9	12.084	79.399	8.516	19.721	19.056	61.221
10	12.080	79.385	8.533	19.721	19.056	61.221
India						
1	9.918	90.081	0.000	0.855	26.243	72.901
2	11.342	88.151	0.506	2.295	26.829	70.874
3	12.082	50.953	36.963	7.943	27.623	64.433
4	13.264	50.912	35.823	8.632	29.068	62.298
5	12.781	50.531	36.687	10.922	28.108	60.969
6	14.211	48.881	36.906	11.990	27.829	60.179
7	15.765	48.165	36.069	11.960	28.046	59.993
8	15.758	47.921	36.319	12.260	28.009	59.730
9	15.689	48.200	36.110	12.248	27.985	59.765
10	15.693	48.195	36.110	12.248	27.989	59.762
Japan						
1	3.957	96.042	0.000	19.447	18.290	62.262
2	3.158	94.963	1.878	18.294	22.720	58.985
3	3.483	93.389	3.127	15.599	32.657	51.742
4	3.586	86.808	9.604	15.656	32.878	51.465
5	3.544	85.637	10.818	15.262	34.963	49.773
6	3.589	85.926	10.484	15.338	34.712	49.948
7	3.608	85.559	10.831	15.403	34.741	49.855
8	3.584	85.061	11.353	15.359	34.690	49.949
9	3.567	84.901	11.530	15.400	34.675	49.923
10	3.544	84.860	11.594	15.379	34.753	49.866

VDC: Variance decompositions, GDP: Gross domestic product

15.8 and 28.3% respectively to variance in CO_2 emissions in the first period; however, the contribution of RT to the variation of CO2 emissions becomes increasingly significant throughout the remaining periods. In the fifth period, the peak contribution of RT was observed. It stood at 19.98%, while real GDP accounted for 19.16% of CO_2emissions variance in the same period.

The results for India show that real GDP variance explained by its own innovations in the first period is approximately 90%, while RT accounts for the remaining variation with about 9.9%. The contribution of shocks in CO_2 emissions to real GDP variance is 0% in the first period. The longer the horizon, the smaller the proportion of real GDP variance explained by its own shocks (50.9%, 48.8%, and 48.1% in the 3rd, 6th and 10th periods respectively); and the larger the proportion of the variation explained by shocks to RT and CO2 emissions. More specifically, the proportion of real GDP variance explained by CO_2 emissions is only 0.51% after two periods, but sharply increased to 36.9% after three periods and the contribution of RT to real GDP variance is 11.3% in the second period but steadily increased to 14.2% in the 6th period and to 15.7% in the 10th period. Between the 6th and 10th period innovations in RT and CO_2 emissions jointly account for approximately 51% of the variations in real GDP; implying that the changes of RT and CO_2 emissions are important determinants of real GDP growth in India in the long-run.

As shown in Table 3, over 72% of the variation in CO_2 emissions in India is attributed to its own shock in the first period. In the same period, shocks to RT and real GDP account for 0.85% and 26.24% respectively of the variations in CO_2 emissions. The contribution of CO_2 emissions to its own variance follows a decreasing trend and stood at 59.7% in the 10th period. RT and real GDP contribute 2.3% and 26.8% respectively to the variance of CO_2 emissions in the second period. Their contributions, however, become increasingly significant the longer the horizon, reaching 8.6% and 29.1% respectively in the fourth period and 12.2% and 27.9% respectively in the 10th period.

The results for Japan show that variations in real GDP is significantly explained by its own innovations, which accounts for about 96% in the first period; the contribution records a declining trend which stood at 93.3%, 85.9% and 84.8% in the 3rd, 6th and 10th period respectively. The contribution of CO_2 emissions to real GDP variance is 0% in the first period; however, this becomes increasingly significant throughout the remaining nine periods. The contribution of CO_2 emissions to real GDP variance reaches maximum value (11.59%) in the 10th period. It is revelatory that contribution of RT to real GDP variance in any period is minimal, with a contribution of <4% in any period. This finding suggests that renewable energy and output growth are contemporaneously correlated and is consistent with energy's attributes as both an input in the production of goods and services and as a final good at the microcosmic level of the individual household.

The results of VDC of CO_2 emissions is also quite revelatory as it shows that in Japan, like in China and India, variation in CO_2 emissions is significantly explained by its own perturbation, which accounts for about 62.3% in the first period. The variation in CO_2 emissions explained by own shock, dampened over time, and stood at 58.9%, 49.95% and 49.86% in the second, 6th and 10th periods respectively. The results show that shocks to RT and real GDP have an immediate and significant impact on CO_2 emission—RT and real GDP explain 19.5% and 18.3% respectively of CO_2 emissions variation in the first period; however, the longer the horizon, the smaller the proportion of CO_2 emissions variance explained by RT and the larger the proportion of the variance explained by real GDP. More specifically, the proportion explained by real GDP is only 22.7% in the second period but sharply increases to 34.9% after five periods. The proportion of RT is 18.29% in the second period but gradually decreases to 15.37% by the 10th period.

5. CONCLUSIONS AND POLICY IMPLICATIONS

In response to growing environmental threats posed by fossil fuels in the generation of electricity, many countries worldwide are taking the initiative to restructure their electricity production profile through investments in different renewable energy technologies designed to increase the proportion of renewables in total electricity generation. This paper aims to deepen the knowledge of the effects expansions in the share of renewable electricity in total electricity generation have on real output growth and CO_2 emissions. To this end, this study investigates the dynamic effects of shocks in the share of renewable electricity in total electricity generation on real output growth and CO_2 emissions in China, India and Japan from 1970 to 2011 using SVAR approach. The model is based on the long-run restrictions identification technique proposed by Blanchard and Perotti (2002). These restrictions were necessary to recover structural innovations from the reduced-form VAR model residuals, and to obtain the associated economic interpretative impulse responses. Tests of the inverse roots of VAR characteristics polynomial confirm the robustness of the SVAR model specification.

The results from the IRFs show that while positive shocks in the share of renewable electricity may initially decrease economic growth (China); in the long-run they increase output growth and reduce CO_2 emissions. The results reveal that the impact of shocks in RT on economic growth and CO_2 emissions are long-lived; it takes on average more than 7 years for the target variables to adjust back to equilibrium following shock to the system. The results of VDCs corroborate those of the impulse response analysis. The results indicate that innovations in the variables are mostly explained by their own shocks. These findings endorse the proposal that government policy aimed at speeding up the adoption of renewables and reducing the usage of fossil fuels lead to increased economic growth and may prove effective in reducing world-wide CO_2 emissions and mitigating climate change.

The findings of this paper provide valuable input, which may be used to design policy to balance and mitigate the often-conflicting goals of sustained economic growth and environmental protection. Indubitably, the most efficient strategies will be those that capitalize on the natural synergies between environmental protection and national development priorities in order to advance both simultaneously. It is, however, equally important to note that policy shocks to renewable energy do not always show immediate responses in the desired direction. Policy decision makers need to be cognizant of this lag to ensure timely implementation of effective and progressive strategic policies.

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