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Do Innovation in Environmental-Related Technologies and Renewable Energies Mitigate the Transport-Based CO_2 Emissions in Turkey?

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Given the unprecedented level of air pollution in urban areas, green transport systems has been a subject to an important debate in academic and policymaking circles. Despite the considerable outputs of the attendant literature, most of empirical studies to date have relied on conventional econometric models in which structural shocks are not controlled. This study, therefore, aims to offer a new perceptive of the dynamic connection between renewable energy, environment-related technological innovation, and transport-based CO_2 emissions in Turkey during 1990Q1 to 2014Q1 by applying the Structural Vector Autoregressive approach (SVAR). Furthermore, to explore the co-movements and the lead-lag interrelations among the study variables, the wavelet coherence technique was used. The wavelet coherence technique circumvents the other traditional causality approaches by detecting the causal interrelation between the underlying series at different frequencies. The findings disclose that environment-related technological innovation has no reliable power to explain the variation in CO_2 emissions from the transport sector. Solar energy is found to impact the CO_2 emissions positively in the long run, while biofuels hold the same effect in short run. Moreover, per capita GDP and urbanization significantly impact the carbon emissions from the transport system in the long run with a negative sign. The wavelet analysis reveals that renewables and environmental-related technological innovation lead the transport-based CO_2 emissions. The fourth and 16th periods are the most dominant frequencies. Accordingly, the study suggests that innovation in environment-related technologies is not enough to mitigate the pollution that stemming from the transport system in Turkey, it should be accompanied by strong and effective environmental measures. These policies might include environmental taxations, carbon pricing and trading schemes, which aim not only to prevent the pollution and over-extraction of resources, but also to promote the public revenues from different activities that related to environmental purposes and other applications such as energy product and vehicle fuels. In addition, it is suggested to strengthening the transportation system through the deployment of renewables and high-tech eco-friendly modes of transportation.

Keywords: green transportation, renewable energy, technological innovation, Turkey, SVAR model, and wavelet coherence technique

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INTRODUCTION

In recent decades, the natural disasters caused by global climate change have been increasing, and economic vulnerability due to uncertain global climate security is also a growing cause of concern. More extreme weather, rising sea levels, decreasing Arctic Sea ice, and other changes allow us to witness the consequences of global warming of the temperature 1°C (T. Yang and Wang, 2020). The climate change that stems from an increase in greenhouse gas emissions has become a serious problem that requires an urgent response and top priority. This persistent rise in the average global temperature will cause unpredictable changes in nature and environmental structures, which will negatively affect human lives and cause huge biodiversity losses. Moreover, global warming is another negative externality or by-product stemming from production activities for the ecosystem (Devi and Gupta, 2019).

Overdependence on fossil fuel energies, namely crude oil, natural gas, and coal contributes greatly to the contamination of the environment and the release of carbon dioxide emissions, causing a serious increase in risks to public health. Based on the 10th annual report of the "Carbon Emissions Gap 2019" released by the UN Environment Program (UNEP, 2019), to realize the goal set by the 2015 Paris Agreement, that is, to control global warming within 2°C, and during 2020–2030, global carbon emissions need to be reduced by 2.7% every year; and to achieve the goal of limiting temperature rise to 1.5°C, global carbon emissions need to be reduced by 7.6% per year between 2020 and 2030.

Transportation is one of the leading sectors that plays an essential role in achieving socio-economic development in any community, as it improves the mobility of citizens and the traffic of goods and offers employment opportunities (Ševčenko-Kozlovska and Čižiūnienė, 2022). Despite its great contribution to economic development, it is also ranked as the second-largest carbon emitter (Giannakis et al., 2020) due to its over-reliance on traditional fossil fuels. Annually, the transport sector consumes around 30% of total world energy, making it the second-largest energy consumer after the industrial sector (Zhou et al., 2014; Liang et al., 2017) resulting in a huge volume of gaseous emissions, causing severe environmental damage and health problems (Shah et al., 2021a). These undesirable effects constitute major obstacles that restrain efforts toward environmental sustainability and healthy societies. With the unprecedented level of urban population growth, the growth of the transport system has received considerable attention from researchers and policymakers, and the term "green transportation" has been a central subject of an important debate among scholars, outlining that the expansion of urban transportation must be carefully planned to achieve a green transport-system.

What is meant by sustainable and/or green transportation?

Within the context of the sustainable development agenda, sustainable transportation can be defined as the capacity to meet the mobility needs of today's society in such a way that preserving the environment and the mobility needs of future generations are not impaired (Shah et al., 2021b). Meanwhile, green transportation refers to a transport system with low negative effects on the environment and human health compared to available systems (Björklund, 2011). Given its significant impact economically, socially, and environmentally (**Figure 1**), green transport (GT) aims to contribute to economic growth through high productivity in green transport systems, increasing public transportation, increasing travel systems, and vehicle efficiency. The GT also aims to contribute to social welfare through a safe, secure, and less risky transport system. In terms of the environment, GT aims to improve environmental

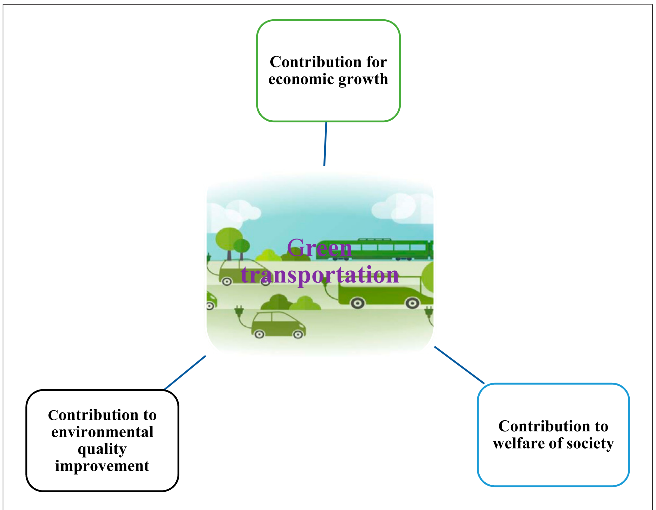

FIGURE 1 | Key parameters of green transportation to achieve sustainable mobility.

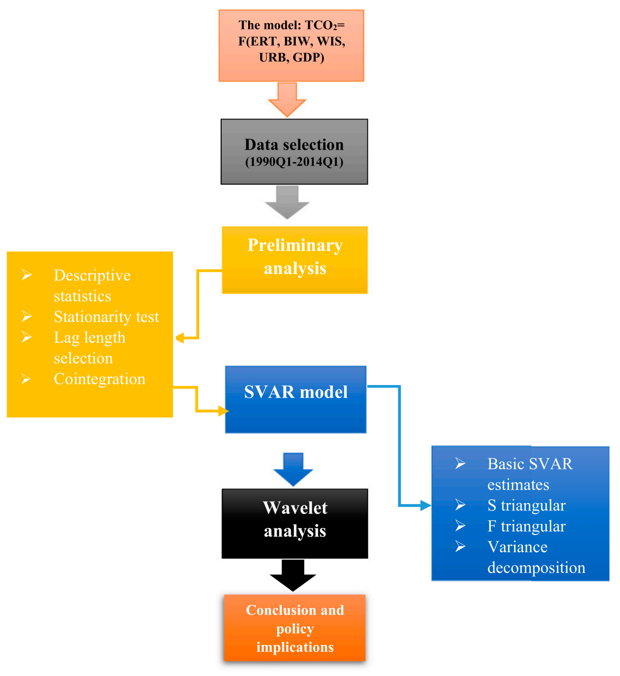

FIGURE 2 | Analysis flowchart.

quality through energy efficiency and low air emissions, travel and vehicle efficiency, reduced congestion, and time saving.

What strategies have been proposed for building green transport systems?

To date, conventional (supply-side-oriented) approaches have been implemented for dealing with substantial increases in transportation demands, which require additional road space to construct new and/or vast infrastructure. This approach is less efficient due to high traffic congestion and greenhouse gas emissions. The newly proposed strategy (Avoid-Shift-Improve (A-S-I)) focuses on the demand-side rather than the supply-side. The A-S-I, which is also sometimes called Reduce-Maintain-Improve (R-M-I), was introduced by German Services Providers in the field of International Cooperation. The A-S-I approach is built on three dimensions that aim at achieving a vast reduction in greenhouse gas outflow, decreasing energy utilization, creating less congestion, and decent urban societies (GIZ, 2004). The first aspect (Avoid) aims to promote the effectiveness of the transport system and decrease traveling demands. This is done by urban planning and involves reducing the distance between the facilities required for daily activities (*social sustainability*). The second aspect (Shift) refers to the promotion of trip efficiency, which can be accomplished by upgrading the public transport system and non-motorized vehicles, such as walking and cycling (*economic sustainability*). The third aspect (Improve) concentrates on improving fuel and vehicle efficiency and the optimization of transport infrastructure (*environmental sustainability*). This can be achieved through the deployment of clean and renewable energy, and energy technology as well as by what is called push-and-pull measures, which assign incentives and penalties to influence the citizens' behavior for better use of transport infrastructure. Within the context of environmental sustainability (improve strategy), this study aims to model the dynamic implications of renewable energy and environment-related technological innovation on transport-based carbon emissions in Turkey.

What motivates the current study?

The motivation of this study is based on two fundamental frameworks in academic and policymaking circles: notably 1) the ever-growing level of air pollution problems in major urban cities and the resulting severe impact on the environment and human health, and 2) current literature limitations. First, over recent decades, several nations have experienced tremendous demographical changes with an increasingly disparate distribution of urbanization, leading to a number of socio-economic and environmental problems (Kassouri, 2021a). These uncontrolled and unplanned urbanization processes poses a direct threat to the sustainability of the natural environment and human societies, given the predominant role of energy-intensive-based economic activities (Sanderson et al., 2018). Following urban transition theories and compact city theory, urban population growth leads to an increase in energy-intensive activities and several economic and structural changes. As cities become more urbanized the factors of production tend to move from the agricultural sector to the industrial sector. Roser (2013) reported that due to urbanization growth, a significant decline in GDP from agriculture (27–10%) and growth in industrial GDP (32–43%) have been recorded. This reallocation poses further challenges for governments, given the conflict between urban management and natural resource stock preservation. Furthermore, some critics stress that higher urban densities are likely to increase demand for land at the periphery, with changes in water-use and land-use patterns (Kassouri, 2021a). This increases the construction sector which generates between 30 and 40% of the worldwide environmental burden in terms of raw materials, direct and indirect energy consumption, waste, and CO_2 emissions (Marrero et al., 2020).

contrast, the ecological modern theory posits that urbanization may have some significant economies of scale for urban density infrastructure, resulting in several environmental benefits such as a reduction in energy use and greenhouse gas emissions (Kassouri, 2021a). However, this argument cannot withstand given the contemporaneous level of environmental damage caused by urban activities from carbon emissions to biodiversity loss. These environmental costs may eventually outweigh the claimed benefits of ecological modern theory. Salehi et al. (2017) describe how transportation alone emits around 15% of global CO_2 emissions, and it is expected to reach around 30–50% by 2050. As the urban population grows, so do mobility needs, which leads to high demand for personalized and motor-based vehicles. Shah et al. (2021a) documented that the number of registered vehicles increased from 200 M in the 1960's last century to 1431 M in 2018 worldwide. Therefore, studying transportation sustainability is an essential step for an effective response to the environmental challenges stemming from the transport system.

Second, within the context of transportation sustainability, there is a growing body of literature modeling the role of renewable energy and technological innovation in the reduction of carbon emissions from the transport sector. Despite their inconclusive outputs, one can report several limitations in the attendant literature, notably; a) given the methodological weaknesses, almost all empirical studies (**Table 1**) employed conventional approaches in which structural shocks are not controlled, and b) the existing literature also remains silent on the aggregation data bias. The aggregated data could raise the issue but are less effective in solving it, as they do not clearly indicate respective distinct impacts. Therefore, the major contribution of this study lies in addressing these literature shortcomings.

How current research incorporates the emerging literature drawbacks?

For (a), this study applies the Structural Vector Autoregressive model to monitor the structural impulse responses by decomposing shocks through relevant matrices, and composite shocks through recursive impulse responses by a triangular matrix. Furthermore, the research uses the wavelet coherence technique to identify the co-movements and the lead-lag relationships among the variables of interest. For (b), the study considers separately biofuels/waste and solar/wind energies. Biofuel energy which is one of the noteworthy alternative energy sources has been growing very fast in recent years. It is liquid fuels generated from organic materials and

TABLE 1 | Related previous studies.

Authors	Time interval	Nations	Methods	Results
Hassan et al., 2022	1985–2018	China	Dynamic ARDL	NEC$\rightarrow^{(-)}$ TCO2e
Zeng et al. (2022)	Cross-section	China	Case study–Feasibility	REC$\rightarrow^{(-)}$ TCO2e
Desta et al. (2022b)	Cross–section	Ethiopia	WTW analysis	REC$\rightarrow^{(-)}$ TGHGe
Maji and Adamu, (2021)	1989–2019	Nigeria	FMOLS	REC$\rightarrow^{(-)}$ TCO2e
(Danish I Godil et al., 2021)	1990–2018	China	QARDL	REC$\rightarrow^{(-)}$ TCO2e
Hasanov et al. (2021)	1990–2017	BRICS countries	CSA ARDL	REC$\rightarrow^{(-)}$ CO2e
Ulucak, (2021)	1980–2016	China and United States	DARDL	REC$\rightarrow^{(-)}$ CO2e
Amin et al. (2020)	1980–2014	14 EU-countries	DOLS	REC$\rightarrow^{(-)}$ TCO2e
Cepoi et al. (2020)	2010–2016	17 EU-countries	Panel S Transition	REC$\rightarrow^{(-)}$ CO2e
Magazzino et al. (2022)	1990–2018	Scandinavian countries	Dumitrescu and Hurlin (2012) panel pairwise	REC$\rightarrow^{(-)}$ CO2e
Dias et al. (2019)	Cross–section	Portugal	Integrated and flexible modelling	REC$\rightarrow^{(-)}$ TNOxe
Simionescu et al. (2017)	2010–2015	European Union	Dynamic panel, panel VAR	REC$\rightarrow^{(\times)}$ TGHGe
Singh et al. (2014)	Cross section	Norway	Life cycle assessment	B EC$\rightarrow^{(-)}$ TGHGe
Tsai et al. (2008)	1990–2005	Taiwan	Analytical description	REC$\rightarrow^{(-)}$ TCO2e
Alataş, (2021)	1977–2015	15 EU-countries	AMG	TECH$\rightarrow^{(\times)}$TCO2e
Chatti, (2021)	2002–2014	43 countries	GMM	TECH$\rightarrow^{(-)}$TCO2e
Demircan Çadslukar et al. (2021)	1997–2017	14 MEDC	PMG and DFE methods	TECH$\rightarrow^{(+)}$TCO2e
(A. N. Khan et al., 2020)	1991–2017	Pakistan	Quantile regression	TECH$\rightarrow^{(-)}$TCO2e
(D. Khan and Ulucak, 2022)	1990–2017	China	Dynamic ARDL	R&D$\rightarrow^{(-)}$ CO2e
Li et al. (2021)	1995–2017	China	Augmented ARDL	R&D$\rightarrow^{(-)}$ CO2e
Ahmed et al. (2021)	1974–2017	Japan	ARDL and NARDL	R&D$\rightarrow^{(-)}$ CO2e
Xu et al. (2021)	2007–2013	China	Spatial model	R&D$\rightarrow^{(-)}$ CO2e
Ma et al. (2021)	1995–2019	China	CS-ARDL	R&D$\rightarrow^{(-)}$ CO2e
Jiao et al. (2021)	1980–2018	India	NARDL	R&D$\rightarrow^{(+)}$ CO2e
Ganda, (2019b)	2000–2014	26 OECD countries	GMM	R&D$\rightarrow^{(-)}$ CO2e
(X. Wang et al., 2022)	1995–2017	China	VECM	ENPT $\rightarrow^{(-)}$CO2e
Shan et al. (2021)	1990–2018	Turkey	Bootstrapping ARDL	ENPT $\rightarrow^{(-)}$CO2e
Xin et al. (2021)	1990Q1-2016Q4	United States	FMOLS	ENPT $\rightarrow^{(-)}$CO2e
He et al. (2021)	2002–2015	China	Panel threshold model	ENPT $\rightarrow^{(-)}$CO2e
Cheng and Yao, (2021)	2000–2015	China	PMG and DFE	ENPT $\rightarrow^{(-)}$CO2e
(Z. Wang and Zhu, 2020)	2001–2017	China	Spatial model	ENPT $\rightarrow^{(-)}$CO2e
(B. Wang et al., 2018)	2001–2015	China	Spatial model	ENPT $\rightarrow^{(-)}$CO2e
Kassouri, (2021b)	2000–2017	28 of sub-Saharan Africa	STIRPAT mode	*URB* $\rightarrow^{(+)}$ *CO2e*
Iheonu et al. (2021)	1990–2016	Sub-Saharan Africa	Panel quantile regression	*URB* $\rightarrow^{(+)}$ *CO2e*
Chenghu et al. (2021)	2001–2018	China	AMG estimator	*URB* $\rightarrow^{(+)}$ *CO2e*
(X. Yang and Khan, 2022)	1992–2016	IEA member countries	Multivariate P. function	*URB* $\rightarrow^{(+)}$ *EFP*
Du, (2020)	1998–2012	China	STEPRAY model	*URB* $\rightarrow^{(+)}$ *CO2e*
Fang et al. (2020)	1990–2016	China	ARDL-ECM model	*URB* $\rightarrow^{(\pm)}$ *CO2e*
Bekhet and Othman, (2017)	1971–2015	Malaysia	VECM	*URB* $\rightarrow^{(-)}$ *CO2e*
Zhang et al. (2015)	2006–2015	China	DME model	*URB* $\rightarrow^{(-)}$ *CO2e*
Effiong, (2016)	1990–2010	49 African countries	STIRPAT	*URB* $\rightarrow^{(-)}$ *CO2e*
Alnour, (2021a)	1971–2015	Sudan	ARDL	*GDP*$\rightarrow^{(+)}$*CO2e*
Ganda, (2019a)	1980–2014	South Africa	ARDL	*GDP*$\rightarrow^{(-)}$*CO2e*
Rasool et al. (2019)	1971–2014	Pakistan	ARDL	*GDP*$\rightarrow^{(-)}$*TCO2e*
Magazzino, (2016b)	1960–2013	six GCC countries I	ARDL	PRGDP $\Leftrightarrow$ *CO2e*
Peng et al. (2020)	2001–2016	China	STIRPAT model	*GDP*$\rightarrow^{(+)}$*CO2e*
Alnour, (2021b)	1970–2017	Turkey	ARDL	*GDP*$\rightarrow^{(+)}$*CO2e*
Kizilkaya, (2017)	1970–2014	Turkey	ARDL	*GDP*$\rightarrow^{(+)}$*CO2*
Doğanlar et al. (2021)	1965–2018	Turkey	RALS-EG	*GDP*$\rightarrow^{(-)}$*CO2*
Magazzino, (2016a)	1992–2013	South Caucasus, Turkey	Panel VAR	*RGDP*$\rightarrow^{(-)}$*CO2*

Notes: TCO2e: Transport-based carbon emissions. REC: renewable energy consumption. TGHGe: transport-based greenhouse gas emissions. TECH: Technology innovation. TNO_xe: Transport-based nitrogen oxides emissions. BEC: Biomass-based electricity. TECN: Transport-based environmental contamination. NEC: Nuclear energy consumption. MEDC: Mediterranean countries. ENPT: Energy patent. RE, ET: Renewable energy and environmental technologies. $\Leftrightarrow$: Cointegration. GCC: gulf cooperation council.

wastes like wood scraps and farm crops. It provides wide-ranging forms of energy such as biodiesel and bioethanol which are largely used in diesel-engine vehicles. This potential makes biofuels important field of study to explore their possible role in combating CO_2 emissions from the transport sector (Taheripour et al., 2010; Dash and Lingfa, 2017; Ohia et al., 2020). On the other hand, a solar vehicle has been widely used in many countries, it is an electronic vehicle where solar energy is used as a fuel source. It utilizes photovoltaic cells to convert solar energy into electricity (Shah et al., 2021b). Regarding technology innovation, the study focuses on environment-related technology (green technology) and not on the total patent as the literature does.

The earlier literature that employed SVAR has mostly run the estimation based on basic A and B matrices, by deviating from the attendant literature, this paper offers a new perspective for the dynamic effect of structural shocks by relying on the recursive short run and long run impulse response functions (S and F triangular matrices). By using the recursive short-run and long run impulse response functions, the current study finds that green technology has insignificant effect on transport-based pollution. Solar energy is found to generate more pollution in long run, while biofuels hold the same effect in the short run. Interestingly, the experiment also uncovers that urbanization and economic growth reduce the transport-based environmental deterioration in long run. These outcomes justify the argument of the ecological modernization hypothesis, and partially the EKC postulation. The wavelet analysis discloses that environment-related technology and renewable energy lead the transport-based CO_2 emissions.

As many developed nations have cut long-term goals towards achieving green transportation, one cannot lose sight on the current state of many developing and some emerging economies. Therefore, the second major contribution of this paper is examining the potential of renewable energy consumption and environment-related technological progress in greening the transport sector in Turkey.

Why Turkey?

Turkey is one of the world's most important tourism destinations. Regrettably, it is also ranked 16th among the world's most polluted countries in terms of carbon emissions. Globally, tourism and travel industry activities, for example, transportation and accommodation, account for 4.4% of the total CO_2 emissions. The high energy consumption of transportation causes a significant amount of CO_2 emissions. Approximately 90% of the energy consumption in the tourism and travel sector is caused by air (43%), road (42%), sea, and railway (15%) transportation (Eyuboglu and Uzar, 2020). Therefore, exploring the role of environment-related technological progression and renewable energies in transportation sustainability will illuminate the policymakers of Turkey in formulating more plausible policies for better and sustainable transport infrastructure. To the best of our knowledge, this is the first empirical study on green transportation in Turkey.

The rest of the paper is structured as follows: part two presents important literature on the topic, part three highlights the data and methodology, part four portrays the findings and discussion, and lastly, part five presents the conclusion and policy recommendations.

LITERATURE REVIEW

Renewable energy and technological innovation are considered key items to meet sustainable development goals. They are a fundamental aspect of energy planning and policymaking for attaining a sustainable transport system. This research is related to four spectra of literature. The first spectrum examines the nexus between renewable energy and transport-based CO_2 emissions. The second spectrum explores the links between technological innovation and CO_2 emissions. Finally, as control variables, the third and fourth spectra discuss the association between economic growth, urbanization, and environmental quality. **Table 1** details previous research.

First, the growing urban population worldwide and its resulting environmental consequences, shift the attention to renewable energy sources which are thought to be less pollutant than traditional fossil fuels. Surveying literature on the renewable energy-transport-based CO_2 emissions nexus, one can capture three strands of research: the first strand focuses on cointegration to explore the long-term relationship between renewables and transport-based CO_2e (Cepoi et al., 2020; Maji and Adamu, 2021; Hassan et al., 2022). The second strand regards both long-term relationship and causality between renewables and TCO_2e (Simionescu et al., 2017; Amin et al., 2020; Danish I; Godil et al., 2021). The causality analysis between renewables and TCO_2e is examined within the scope of four hypotheses. First, the renewable energy-led TCO_2e hypothesis, which indicates that there is one-way causation running from renewable energy to TCO_2e. It suggests that renewable energy use can mitigate TCO_2e by decreasing carbon discharges. Second, the TCO_2e-led renewable energy hypothesis, which reveals that there is one-way causation flowing from TCO_2e to renewable energy. This reveals that TCO_2 emanations influence the deployment of green energy. Third, the feedback hypothesis is valid if there is a two-way causal link between renewable energy and TCO_2e, which reveals that the deployment of renewables causes TCO_2 discharges and therefore TCO_2 emanations induce renewable energy. Finally, the neutrality hypothesis reveals that no causal link exists between renewable energy and TCO_2e. In a such case, renewable energy consumption does not play a pivotal role in curbing TCO_2e. The third strand of research applies a cross-section analysis based on country provinces or sectoral-based analysis (Singh et al., 2014; Dias et al., 2019; Desta et al., 2022a; Zeng et al., 2022). However, after an in-depth search of the literature on the renewable energy-TCO_2e nexus, despite mixed results, one can claim that there are very limited empirical studies especially on biofuels and solar energy, which calls for a fresh look through a novel approach or intuitively appealing methodological innovation.

From the theoretical perspective, the ecological modernization theory holds that human-induced environmental pollution can be neutralized by rising resource efficiency through the development of green technology (Liddle, 2018). Given this argument, many governments and enterprises around the world have invested a considerable amount of resources in research and development to create new green technologies or improve the available technologies (Ding et al., 2021). Theoretically, the implementation of carbon-neutral energies through the development of green technology can significantly reduce GHG emissions by decreasing the dependence on carbon-intensive fuels (Altıntaş and Kassouri, 2020). Furthermore, the allocation of resources to energy R&D investment may create initial market conditions which motivate the private sector to invest in green technology, hence driving up the deployment of renewable energy in the transport sector at the expense of other polluting sources of energy (Mowery et al., 2010).

Within this context, myriad peer-reviewed research has studied the link between technological progress and carbon emissions. However, the findings are inconclusive. These conflicting results could be attributed to the utilization of different measures of green technology and econometric models. For instance, several studies utilize the total patent index as a proxy for technology innovation (Khan et al., 2020; Alataş, 2021; Chatti, 2021; Demircan Çakar et al., 2021). Other groups of research consider R&D expenditure as a proxy for green technology innovation (Ganda, 2019b; Ahmed et al., 2021; Jiao et al., 2021; Li et al., 2021; Ma et al., 2021). The energy patent index has also been widely used as an indicator of technological progress (Wang et al., 2018; Wang and Zhu, 2020; Cheng and Yao, 2021; He et al., 2021; Shan et al., 2021). **Table 1** provides more details on each study. Given the complexities of economic and environmental structures, the inferences of the aggregated indices such as total patent or total R&D investment may limit the policy's ability to understand the effectiveness of technology innovation in mitigating pollution. Therefore, there is a strong need to articulate exactly the role of technological progress in carbon emissions reduction. This is based on the belief that formulating environmental policies is much more complicated than what the total indicators might suggest. Therefore, unlike the existing literature, this study focuses on the green technology index, which is the patent indicator for the diffusion of environment-related technologies, providing important insights into ongoing discussions on the subject.

Third, this spectrum examines the dynamic effect of urbanization on environmental quality. The net impact of urbanization on the quality of the environment is still ambiguous. Supporters of the compact city hypothesis and urban transition theories claim that urbanization increases environmental pollution, however, supporters of ecological modernization theory argue that urbanization holds some benefit to the environment. Based on these arguments, myriad studies have been conducted to calculate the net implications of urban population growth on the quality of the environment. In agreement with the arguments of compact city and urban transition theories, Kassouri (2021a) employed the STIRPAT model to study the spatial effect of urbanization on the environmental quality in 28 sub-Saharan African countries, the author found that urbanization contributes to environmental deterioration. Similarly, Iheonu et al. (2021) employed a panel quantile regression to test the dynamic relationships between international trade, urbanization, and CO_2 emissions in Sub-Saharan Africa. The researchers mention that there is a positive relationship between urbanization and carbon emissions. Yang and Khan (2022) studied the effect of urbanization on the ecological footprint in IEA countries by using a multivariate production function. Their outcomes reveal that urbanization deteriorates environmental sustainability in the long run. Several other studies (Zhang et al., 2015; Du, 2020; Fang et al., 2020) found the same results in China by using the STEPRAY, ARDL-VECM, and DME models. In contrast, some authors have reported evidence supporting ecological modernization theory. For example, Bekhet and Othman (2017) applied VECM in Malaysia. The researchers found that the elasticity of CO_2–urbanization is negative at the higher urbanization stage. By using the STIRPAT model, Effiong (2016) found that urbanization contributes to environmental deterioration in 49 African countries.

Finally, this section explores the link between economic growth and pollution. Literature on environmental economics seldom finds an issue that captures the attention of economists more than the growth-pollution nexus. Since the pioneering work of Kuznets (1955) and later by Grossman and Krueger (1991), a large volume of empirical research has tested the impact of economic growth on environmental deterioration based on the Environmental Kuznets Curve (EKC) hypothesis. The EKC theory postulates that economic growth initially exacerbates the quality of environment as growth requires more resources to produce and consume (scale effect), which results in more waste and pollution. When the economy progresses, it brings a structural change from energy intensive-based activities to services and less pollutant technology-based activities replacing the old technologies with cleaner ones, which eventually improves the quality of environment (Ulucak and Bilgili, 2018). These desirable effects (composition and technique) have been confirmed by many authors (Magazzino, 2016a; Ganda, 2019a; Rasool et al., 2019; Doğanlar et al., 2021). By contrast, some authors provide evidence against the EKC hypothesis (Kizilkaya, 2017; Peng et al., 2020; Alnour, 2021a, 2021b). Although a large body of evidence has explored the dynamic relationship between economic growth and overall carbon emissions, its impact on carbon stemming from transport, has not been given enough attention.

DATA AND METHODOLOGY

The primary objective of this research is to explore whether environment-related technological development and renewable energy have reliable power to explain the variations in transportation-based carbon emissions in Turkey. As control variables, economic growth and urbanization have been added to the model. Economic growth and urbanization are widely accepted as factors that significantly determine the quality of transport infrastructure. Economic growth may better reflect the ability to finance the green projects planned in the transport sector. Furthermore, nations are presently confronted by two major challenges; accomplishing high growth and preserving the environment (Alnour, 2021a). This dilemma has raised some policy concerns, especially in developing and some emerging economies, where development plans are mistakenly built on the so-called pro-growth strategies, in which environmental regulation is neglected unintentionally to quickly attain a higher economic growth rate or capital accumulation.

On other hand, urbanization is considered the determinant of a transport system that influences environmental quality. In other

TABLE 2 | Definitions and the sources of the variables.

Variable	Description	Source
TCO_2	CO_2 emissions from transport (% of total fuel combustion)	World Bank (World Development Indicators)
ERT.	Patent indicator for diffusion of environment-related technologies	OECD
BIW.	Biofuel and waste, measured in thousands kg of oil equivalent (ktoe).	International Energy Agency (IEA)
WIS.	Wind and Solar, measured in thousands kg of oil equivalent (ktoe)	International Energy Agency (IEA)
URB.	Urban population growth (annual %)	World Bank (World Development Indicators)
GDP.	GDP per capita growth (annual %)	World Bank (World Development Indicators)

words, transport is the channel through which urbanization can impact the environment. As reported by Amin et al. (2020), the movement of a rural labor force to urban cities dramatically changes the settlement patterns, resulting in increased energy consumption, for instance, it increases energy consumption for transportation hubs, food, and electric devices, and increases the road use. Therefore, for more policy guidance, incorporating economic growth and urbanization in the current analysis is inevitable, as development cannot be realized without an influence on surroundings. Annual data from 1990 to 2014 on the study variables were collected from different sources and then transformed into quarterly data to overcome the sample size problems encountered in previous studies (Shahbaz et al., 2019; Godil et al., 2020b; Alnour and Atik, 2021; Godil et al., 2021). The period was selected based on the data availability. **Table 2** reports the definition and the description of each variable in our VAR system and their sources. Each of the variables has gone through normal logarithmic change to avoid the problem of extreme values (**Figure 2**).

To achieve the study objectives, the present research applies the Structural Vector Autoregressive (SVAR) model. Previous studies used the VAR model as a powerful method of analyzing the dynamic interaction of shocks within the impulse-response function. However, when the traditional or unrestricted VAR is utilized, the researcher does not rely on any identification restriction. This is basically due to the assumption that all variables in the VAR system are jointly endogenous and must be treated symmetrically. In this respect, Enders (2015) outlined that this assumption makes the traditional VAR model almost mechanic since it lacks any direct economic interpretation by the time there is a possibility to rely on the relevant economic theories to impose restrictions on the errors. Therefore, this study employs a structural vector autoregressive (SVAR) approach to utilize the relevant economic theories and empirical evidence to impose identifying restrictions. Following the work of others (Ibrahim and Sufian, 2014; Oryani et al., 2020; Bilgili et al., 2021a), the SVAR model can be specified as follows:

$$AX_t = C + A_t X_{t-1} + \ldots + A_p X_{t-p} + Be_t \tag{1}$$

X is an n × 1 dimensional variables' vector, C is an n × 1 vector of the constant term, A is an n × n matrix describing the contemporaneous correlations of the underlying variables, A_i for i = 1 . . ., p is an n × n matrix of parameters; p is the order of the vector autoregression model, and e is an n × 1 vector of structural shocks where $E(e) \sim (0, I_n)$. If we initially multiply **Eq. 1** with A^{-1} and eliminate the constant terms, the reduced-form VAR of **Eq. 1** can be obtained as follows:

$$X_t = \Gamma_1 X_{t-1} + \ldots + \Gamma_p X_{t-P} + u_t \tag{2}$$

Where $\Gamma_i = A^{-1}A_i$ and u is the reduced-form error terms. Following **Eqs 1**, **2**, the relationship between the structural and reduced-from error terms or shocks can be written as follows:

$$u_t = A^{-1}Be_t \quad or \quad Au_t = Be_t \tag{3}$$

Eq. 3 is called the AB model. When testing the dynamic effect of structural shocks on the variables in X, the reduced-from in **Eq. 2** is firstly estimated since the SVAR as exhibited in **Eq. 1** cannot be estimated directly due to the existence of contemporaneous correlations between the structural error terms and values of the variables, otherwise, the model would suffer from the simultaneous equation bias (Enders, 2015). The identification of structural shocks from reduced-from innovation is constructed by imposing identifying restrictions on matrix A and B as the reduced-form error terms are composites of structural shocks. Generally, most of the studies that utilized the SVAR approach have adopted the traditional strategy of Sims (1980) recursive approach, which has the foundation of Cholesky decomposition. However, this approach has some limitations in that it requires ordering specification of the variables as a prerequisite, and the outcomes may be sensitive to the way the variables are ordered. Therefore, unlike the traditional method, this study follows an alternative approach by applying relevant economic theories and empirical findings to impose identifying restrictions on A and B matrices. Our main vector autoregressive system includes economic growth (GDP PC), urbanization (URB), wind/solar energy (WIS), biofuel/waste energy (BIW), environment-related technology (ERT), and transportation-based carbon emission (TCO_2e). Based on **Eq. 3**, to identify the structural shocks the following restrictions on A and B matrices are imposed:(4)

$$\begin{bmatrix} 1 & \alpha_{12} & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ \alpha_{31} & 0 & 1 & 0 & 0 & 0 \\ \alpha_{41} & 0 & 0 & 1 & 0 & 0 \\ \alpha_{51} & 0 & 0 & 0 & 1 & \alpha_{56} \\ -\alpha_{61} & \alpha_{62} & -\alpha_{63} & -\alpha_{64} & -\alpha_{62} & 1 \end{bmatrix} \begin{bmatrix} \mathrm{u}_t^{LnGDP} \\ \mathrm{u}_t^{LnURB} \\ \mathrm{u}_t^{LnWIIS} \\ \mathrm{u}_t^{LnBIW} \\ \mathrm{u}_t^{LnERT} \\ \mathrm{u}_t^{LnTCO2} \end{bmatrix} = \begin{bmatrix} \beta_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & \beta_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & \beta_{66} \end{bmatrix} \begin{bmatrix} \mathrm{e}_t^{LnGDP} \\ \mathrm{e}_t^{LnURB} \\ \mathrm{e}_t^{LnWIS} \\ \mathrm{e}_t^{LnBIW} \\ \mathrm{e}_t^{LnERT} \\ \mathrm{e}_t^{LnTCO2} \end{bmatrix} \tag{4}$$

The first row in Eq. 4 can be viewed as the economic growth equation. It is drawn from recent work by (Bai et al., 2012; Bakirtas and Akpolat, 2018; M. Chen et al., 2014; Nguyen, 2018). It posits that economic growth responds to the rest of the variables in the system with lag except for urbanization, which is expected to positively (α_{12}) influence the GDP per capita. This assertion stems from ecological modern theory, which claims that higher urban densities may have significant economies of scale (Kassouri, 2021a). This is also in line with the argument that urbanization is an important factor in reducing regional income disparities and balancing development levels among a country's provinces. It is also in agreement with the notion that big cities tend to gain more income. For the sake of clarity, a restriction on the influences of other variables in the system on economic growth is guided by the study objectives. In the second row of Eq. 4, it is assumed that urbanization reacts to the impulse of other variables in the system with the lag. This is also motivated by the study objectives in which the determinants of urbanization are not the focus of the current analysis. In the third and fourth rows, energy consumption is assumed to respond contemporaneously to shocks in economic growth with positive signs (α_{51}, α_{41}). The fifth row can be seen as the environmental technology reaction. It is assumed that environment-related technology adjusts instantaneously to innovations in economic growth (α_{41}) and carbon emissions (α_{56}). This is based on the theoretical plausibility that higher pollution instigates and compels legislatures to allocate higher resources for R&D investment to develop specific energy and/or environment technologies. The last row in Eq. 4, which will be the focus of subsequent analysis, shows the response of transport-based carbon emissions to the impulse of other variables in the VAR system. The impulse in environment-related technology is assumed to mitigate the pollution from transport ($-\alpha_{62}$). From the theoretical view, ecological modernization theory holds that environmental concerns stemming from human activities can be neutralized by rising resource efficiency, through the development of green technology (Liddle, 2018).

Following the work of (Mowery et al., 2010; Murshed and Alam, 2021), a transformation to a clean energy system can promote countries to become carbon-neutral in the future and realize their environmental targets, it is, therefore, assumed that both biofuel ($-\alpha_{64}$) and wind/solar ($-\alpha_{63}$) respectively, can be helpful in mitigating carbon emissions. Following the compact city theory and urban transition theories, we assumed that the carbon emissions react positively (α_{62}) to the innovations in urbanization. It is well established that as cities become more urbanized, the energy intensive-based activities increase, which directly impact the environment given the predominant role of polluting fossil fuels (Kassouri, 2021a). Lastly, within the framework of the EKC hypothesis, it is assumed that initially, economic growth can exacerbate the pollution from the transport system, in long run, however, it can help mitigate pollution ($-\alpha_{61}$).

Apart from the SVAR approach, the current research also applies the wavelet coherence technique to detect the time-frequency and to identify the lead-lag interaction among series. Time-frequency is an important analysis for better understanding the dynamic relationship between variables, and how the relationship varies from one frequency to another becomes essential and strategic in policy formulation. The wavelet approach combines time-frequency domain-based causality approaches, which enables us to evaluate the degree of the correlation concurrently at different frequencies over time. The wavelet-based approach is a relatively new area of human knowledge, which is found to be useful for decomposing signals that have a cyclical behavior. In this study, the Morlet wavelet function is employed since it offers good results in terms of balance between time and frequency (Magazzino and Mutascu, 2019; Zhao et al., 2021) and it can be specified as follows:

$$W(\mathrm{n}) = \pi^{-\frac{1}{4}} e^{-iwn} e^{-\frac{1}{2}n^2} \tag{5}$$

Where the non-dimensional frequency (W) is six and i refers to $\sqrt{-1\, p(n)}$. For feature extraction, the continuous wavelet transformation is preferable (Magazzino and Mutascu, 2019). Bilgili et al. (2021b) outline that the CWT provides a redundant representation of a function in terms of scaled and translated wavelets. There is indeed a time transition to the time-frequency domain that corresponds to the wavelet change. W is transformed; thus, it progressed into $w_{k,f}$. This explanation is illustrated in **Eq. (6)**.

$$w_{k,f}(n) = \frac{1}{\sqrt{h}} w\left(\frac{n-k}{f}\right),\ k,\ f \in \mathbb{R},\ f \neq 0 \tag{6}$$

Where k denotes time and f indicates frequency. The CWT is the ground of cross-wavelet approaches, which allows two variables to interrelate, by using time and space, with n = 0,1,2,3 . . .N-1. The continuous wavelet transformation of the time series equation is written as follows:

$$\mathrm{w}_p(k,f) = \int_{-\infty}^{+\infty} p(n) \frac{1}{\sqrt{f}} \left(\overline{\frac{n-k}{f}}\right) dn, \tag{7}$$

Where the $p(n)$ which is the time-series data is incorporated. The local variance was revealed using the wavelet power spectrum (WPS) (Zhao et al., 2021). A cone of influence is considered to illustrate the edge effects of the observations. Herein, the observations are influenced by the edge effects below the cone. The statistical significance of wavelet power is tested by the null hypothesis, which claims that the data generating process is the result of a stationary process with a certain background power spectrum (Mutascu, 2018). The wavelet power spectrum (WPS) that captures the vulnerability of series is illustrated in the equation below:

$$WPS_p(k,f) = \left|W_p(k,f)\right|^2 \tag{8}$$

To examine the co-movement between two time series, the wavelet coherence approach (WTC) is used. The wavelet coherency (WTC) is the ratio of the cross-spectrum to the product of the spectrum of each series and can be thought of as the local correlation, both in time and frequency, between two time series. The cross-wavelet power yields the regions in the time-frequency space where the time series exhibit a strong common power, e.g., it explores the local covariance between

TABLE 3 | Descriptive statistics.

	TCO_2	ERT	BIW	WIS	URB	GDP
Mean	18.86241	7.171392	5811.170	1533.062	43315166	7187.521
Median	18.15293	7.130000	6006.000	1158.000	42978998	6509.902
Maximum	23.17876	11.34000	7211.000	5193.000	56436828	10549.68
Minimum	15.44296	4.440000	3508.000	461.0000	31923298	5303.010
Std. Dev	2.151555	1.228469	1253.102	1153.727	7044528	1498.439
Skewness	0.653483	0.742959	−0.402818	1.474804	0.139700	0.629248
Kurtosis	2.204914	4.375854	1.764172	4.315668	1.849507	2.247738
Jarque-Bera. 9.458797	16.57458	8.795963	42.15931	5.665195	8.688418	
Probability	0.008832	0.000252	0.012302	0.000000	0.058860	0.012982
Sum	1829.654	695.6250	563683.5	148707.0	4.20E+09	697189.5

the time series at each scale. Although relevant literature outlines many formulas that specify the approach of wavelet coherence, generally, the specification can be given in the following equation:

$$R^2(k,f) = \frac{\left|S\left(f^{-1}W_{pj}(k,f)\right)\right|^2}{S\left(f^{-1}\left|W_p(k,f)\right|^2\right)S\left(f^{-1}\left|W_j(k,f)\right|^2\right)} \tag{9}$$

Where S indicates the time and scale smoothing operators with $0 \leq R^2(k,f) \leq 0$. Particularly, if the $R^2(k,f)$ nears 1, indicates either the time-series indicators are correlated or that there is a causal interaction between the time-series indicators at a particular level. Furthermore, whenever $R^2(k,f)$ nears 0, it indicates that there is no proof of association or causality between the two variables. According to Bilgili et al. (2021b), the phase difference analysis monitors the phase relationships between components. It observes the positive or negative causality direction and lead-lag relation. The phase difference between the time series of {xg and {yg can be expressed as:

$$\Delta_{xy} = arctan\left[\left(\Phi_{xy}(m,n)\right)\Big/\left(\Phi_{xy}(m,n)\right)\right],\ \Delta_{xy} \in [-\pi,\pi] \tag{10}$$

Given a complex wavelet transformation, (Φ_{xy}) and (Φ_{xy}) exhibit the imaginary and real parts of the smooth power spectrum, respectively. If $\Delta_{xy} \in (0, \frac{\pi}{2})$, then the series move in phase, but the y(t) series leads to x(t). if $\Delta_{xy} \in (\frac{-\pi}{2}, \pi)$, then x(t) is leading. A phase difference of π (or −π) indicates an anti-phase relation. If $\Delta_{xy} \in (\frac{\pi}{2}, \pi)$, then x(t) is leading. if $\Delta_{xy} \in (-\pi, \frac{-\pi}{2})$, then x(t) is lagging. A zero-phase difference indicates that the observed time series move together at the specified frequency.

FINDINGS AND DISCUSSION

Before a preliminary analysis, the descriptive statistic properties are investigated. **Table 3** outlines some important descriptive statistics. Between 1990Q1 to 2014Q1, the transport CO_2e varied between 15.44296 and 23.17876, with average and standard deviation of 18.86241 and 2.151555 correspondingly. The renewable energy sources show dramatic movements. Particularly, wind/solar energy increased from 461.0000 to 5193.000 with a mean and standard deviation of 1533.062 and 1153.727 respectively. Similarly, biofuel energy also shows a considerable increase from 3508.000 to 7211.000 with an average of 5811.170 and a standard deviation of 1253.102. Within the same sample period, energy technology fluctuated slightly from 4.440000 to 11.34000 with average and standard deviation of 7.171392 and 1.228469. Economic growth also shows a significant increase from 5303.010 to 10549.68 with an average of 7187.521. Overall, urbanization demonstrates the highest average. The normal distribution evaluated by Kurtosis confirms that only biofuels/waste and urbanization demonstrate normal distribution. Only biofuels/waste show negative Skewness. All the variables are demonstrated not follow a normal distribution, as evidenced by the Jarque-Bera test.

As the most of time series data are nonstationary, it is necessary to investigate their stationary properties to avoid the presence of the second-order variables. According to Bilgili (2003), even if the underlying variables might individually be first-order integrated I (1), one more linear combination of those might be stationary I (0). In a such case, the underlying series are said to be cointegrated and there exists a long-run relationship among them. In the literature, (Dickey and Fuller, 1979; Phillips and Perron, 1988) tests are commonly used to examine the stationarity of the variables. The null hypothesis of the ADF and PP tests indicates a unit root.

Table 4 indicates that all the variables are tested for the presence of unit root at level as well as first-difference. The results of the ADF and PP tests are quite similar since none of the variables are integrated into the second-order or I (2). In particular, the ADF test reveals that only environment-related technology is stationary at a level, while the PP test shows that only urbanization reveals stationarity at a level. The rest of the variables are integrated at I(1). These disparate stochastic stationarity properties raise an important issue for SVAR specification, whether it should be specified in level or first difference. The current study follows a common approach used by other studies (Kim and Roubini, 2000; Mehrotra, 2007; Ibrahim and Sufian, 2014) which claim that there is no need to use differencing nonstationary variables because the statistic of interest often has a distribution that is robust to non-stationarity. Moreover, the VAR approach is not aiming at parameter estimates but explores the dynamic interrelations between the variables. Thus, for the concreteness of VAR results, the overall stationery of a system is a matter rather than individual variables' stochastic properties (Lütkepohl, 2005).

TABLE 4 | Stationarity tests.

Variables	Level I (0)		First-difference I(I)	
C	C&T	C	C&T	
Dickey and Fuller (1979) (ADF) unit root tests				
$LnTCO_2$	−2.138186 (0.230)	−2.653530 (0.258)	−3.584053 (0.007)*	−3.603787 (0.034)**
LnERT	−2.996202 (0.038)**	−2.985680 (0.141)	−3.381547 (0.014)*	−3.593506 (0.035)**
LnBIW	0.731279 (0.992)	−2.049708 (0.565)	−2.185654 (0.213)	−2.637924 (0.265)
LnWIS	1.815239 (0.999)	−0.136007 (0.993)	−2.555724 (0.105)	−3.204164 (0.08)***
LnURB	−0.124556 (0.942)	−3.045429 (0.126)	−1.431176 (0.563)	−4.096952 (0.097)*
LnGDP	0.187483 (0.970)	−2.584705 (0.288)	−2.903495 (0.048)**	−4.505626 (0.002)*
Phillips and Perron (PP) unit root test				
LnTCO2	−1.702590 (0.426)	−1.087645 (0.925)	−3.884227 (0.003)*	−3.931631 (0.014)*
LnERT	−1.663338 (0.426)	−1.616027 (0.925)	−4.546421 (0.003)*	−4.633961 (0.014)*
LnBIW	1.564986 (0.999)	−1.783750 (0.705)	−4.060790 (0.001)*	−4.399666 (0.003)*
LnWIS	3.488760 (1.000)	0.768178 (0.999)	−2.579944 (0.100)	−3.315040 (0.070)***
LnURB	−2.822735 (0.058)**	−3.419439 (0.054)**	−3.742857 (0.004)*	−2.848530 (0.184)
LnGDP	0.672169 (0.991)	−1.862037 (0.666)	−4.118420 (0.001)*	−4.167184 (0.007)*

*1% 5% 10% level of significance are illustrated by *, ** and *** correspondingly. C and C&T refer to constant and constant and trend respectively. In () are* p-values. *The lag order of ADF, and PP, unit root tests are based on Schwarz information criterion (SCI).*

TABLE 5 | VAR lag order selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	571.0263	NA	1.23e-13	−12.69722	−12.52945	−12.62959
1	1914.735	2476.048	2.13e-26	−42.08394	−40.90953	−41.61057
2	2129.005	365.9435	3.93e-28	−46.09000	−43.90895*	−45.21088*
3	2139.813	17.00161	7.11e-28	−45.52389	−42.33620	−44.23902
4	2162.125	32.08876	1.02e-27	−45.21629	−41.02196	−43.52567
5	2245.646	108.8588	3.83e-28	−46.28418	−41.08321	−44.18781
6	2332.109	101.0357*	1.42e-28*	−47.41818	−41.21057	−44.91607
7	2360.053	28.88556	2.09e-28	−47.23714	−40.02289	−44.32928
8	2408.034	43.12890	2.14e-28	−47.50637*	−39.28548	−44.19277

*Notes: * indicates lag order selected by the criterion. LR: sequential modified LR, test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information.*

To explore the cointegrating equation, the optimal lag was chosen to be 2 based on the Schwarz information criterion (SC) (see **Table 5**), given the basic concern of selecting a relatively smaller lag. Some literature argues that SC dominates all other criteria. **Table 6** portrays the findings of the Johansen cointegrating approach. The Trace test indicates 2 cointegrating equations at a 0.05% level. The standard error reveals that all the estimated coefficients are significant at 5 and 10% levels. The adjustment coefficient is found to be −0.045231 which implies the short-run dynamic and reveals the speed of adjustment of the variable in reaction to the standard deviation from long-run equilibrium. In other words, the adjustment coefficient is seen to facilitate long-run convergence, the TCO_2 emissions response to a 1-unit deviation from long-run equilibrium by −0.045231, for the system to return to the long-run equilibrium, the movements of at least some variables must respond to the magnitude of disequilibrium, and at least one of the adjustment parameters must be statistically different from zero, otherwise, there would be no error correction.

Before moving onto the basic SVAR estimates, it should be noted that in Eq. 4, the estimated parameters of A were expressed on the same side of the equation, therefore, they should be explained in reverse, meaning that the negative sign should be read as positive and vice versa. **Table 7** presents the findings of the SVAR model. The first row reveals that shocks in urbanization have an insignificant impact on economic growth, 10.03937 (0.1258). In contrast to our expectations, the second row indicates that economic growth responds negatively to innovation in wind/solar energy, 0.352331 (0.0006). However, as shown in the fourth row the shocks in biofuel energy seem to have no significant effect on economic growth 0.152551 (0.1781). In the fifth row, the impulse of economic growth enters negatively in the environment-related technology equation 0.022212 (0.0007). Similarly, environment-related technology reacts negatively to the shocks in transport-based carbon emissions 2.015876 (0.0541). Finally, in row six, only biofuel energy significantly influences the transport-based carbon emissions with a positive sign.

As most of the estimated contemporaneous coefficients display limited significant implications, the present study further examines the short-run (S triangular) and long-run (F triangular) recursive impulse response function. This procedure is often neglected in the literature, and researchers are usually satisfied with the basic SVAR estimates (A and B

TABLE 6 | Johansen cointegration test.

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.319135	108.0673	95.75366	0.0054
At most 1 *	0.266547	71.93456	69.81889	0.0336
At most 2	0.183460	42.79537	47.85613	0.1376
At most 3	0.133172	23.74347	29.79707	0.2115
At most 4	0.062014	10.30947	15.49471	0.2577
At most 5 *	0.044629	4.291590	3.841465	0.0383
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
None	0.319135	36.13272	40.07757	0.1302
At most 1	0.266547	29.13919	33.87687	0.1658
At most 2	0.183460	19.05191	27.58434	0.4105
At most 3	0.133172	13.43400	21.13162	0.4131
At most 4	0.062014	6.017879	14.26460	0.6109
At most 5 *	0.044629	4.291590	3.841465	0.0383

Cointegrating Equation(s): Log likelihood 2185.998

Normalized cointegrating coefficients (standard error in parentheses)

LNGDP	LNURB	LNWIS	LNBIW	LNERT	LNTCO2
1.000000	2.956524	−0.798568	0.618776	0.072540	0.142284
(0.69661)	(0.16049)	(0.17309)	(0.07130)	(0.14316)	

Adjustment coefficients (standard error in parentheses)

D (LNGDP)	−0.046025 (0.01817)
D (LNURB)	−0.001065 (0.00027)
D (LNWIS)	−0.006100 (0.01927)
D (LNBIW)	−0.000346 (0.02027)
D (LNERT)	−0.028632 (0.09225)
D (LNTCO2)	−0.045231 (0.02603)

*Notes: Trace test indicates 2 cointegrating equation at the 0.05 level. Max-eigenvalue test indicates no cointegration at the 0.05 level. * Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999)* p-values.

matrices) to conclude the dynamic interaction among the variables at hand. We believe that short-run and long-run recursive impulse response analyses will show the interrelations between the variables from a more holistic perspective. **Tables 8**, **9** correspondingly outlines the short-run and long-run recursive impulse-response results. To conserve space, the focus is only on the transport-based CO_2 emissions equation (row 6). To simplify the evaluation, both short-run and long-run results are highlighted with coinciding colors in **Tables 8**, **9**. Starting from the first parameter, the transport-based CO_2 emissions respond negatively to GDP in the short and long terms, the responses are given by parameter C (6). The equation also indicates that in the short run, urbanization does not affect the carbon emissions from the transportation sector, however, in the long run, urbanization can mitigate pollution. These responses are provided by parameter C (11). Moreover, in the short run, solar energy does not influence carbon emission, however, it increases emissions in the long run. The responses are yielded in parameter C (15). The biofuels are found to impact TCO_2 with a positive sign only in the short run, C (18). Lastly, environment-related technological development has no significant implications on transport carbon emissions, the result is given in C (20). For robustness, we assessed the relative contribution of the variables to the fluctuation in transport-based carbon emissions. We analyzed the forecast variance of the variables over different time intervals. The generated variance decompositions (**Table 10**) indicate that after its own shocks the biofuel energy shocks are the most dominant factor accounting for the variation in the TCO_2e over the time horizon. The results also reveal that GDP per capita and urbanization shocks respectively are the second source of variation in transport-based carbon emissions. Lastly, the innovations of environment-related technology and solar/wind energy display the lowest contribution to the variation of TCO_2. The VAR model is further evaluated by the diagnostic tests. **Table 11** reports the diagnostic test results. VAR Residual Serial Correlation LM Test reveals that the model is free of serial correlation as the null hypothesis of no serial correlation cannot be rejected. Similarly, the VAR Residual Heteroskedasticity Tests (Joint test) and VAR Residual Normality Tests (Skewness) show that our model does not suffer from Heteroskedasticity and normality issues correspondently. Moreover, the Ramsey Reset test indicates that the model is free of specification error. In addition, the stability of the model is assessed using the CUSUM and CUSUMSQ tests. **Figures 3**, **4** illustrate the outcomes of CUSUM and CUSUMSQ for our VAR model. Both CUSUM and CUSUMSQ tests show a slight

TABLE 7 | Structural Vector Autoregressive estimatesst.

Model: Ae = Bu where E [uu'] = I					
A =					
1	10.03937	0	0	0	0
	(0.1258)				
0	1	0	0	0	0
0.352331	0	1	0	0	0
(0.0006)					
0.152551	0	0	1	0	0
(0.1781)					
2.022212	0	0	0	1	2.015876
(0.0007)					(0.0541)
-0.025661	4.632758	−0.088154	−0.628049	0.146579	1
(0.9001)	(0.6359)	(0.5761)	(0.0001)	(0.1303)	
B =					
0.007613	0	0	0	0	0
(0.0000)					
0	0.000119	0	0	0	0
	(0.0000)				
0	0	0.007711	0	0	0
		(0.0000)			
0	0	0	0.008509	0	0
			(0.0000)		
0	0	0	0	0.038336	0
				(0.0000)	
0	0	0	0	0	0.010977
					(0.0000)

Notes: the estimation method: Maximum likelihood via Newton-Raphson (analytic derivatives). The SVAR, lag = 2 according to Schwarz information criterion (SC). Log likelihood = 2191.042. Convergence achieved after 25 iterations.

TABLE 8 | Recursive short-run impulse response (S triangular).

Model: e = Su where E [uu'] = I					
S =					
C (1)	0	0	0	0	0
C (2)	C (7)		0	0	0
C (3)	C (8)	C (12)	0	0	0
C (4)	C (9)	C (13)	C (16)	0	0
C (5)	C (10)	C (14)	C (17)	C (19)	0
C (6)	C (11)	C (15)	C (18)	C (20)	C (21)

	Coefficient	Std. Error	z-Statistic	Prob
C (1)	0.007707	0.000559	13.78405	0.0000
C (2)	−1.85E-05	1.21E-05	−1.521667	0.1281
C (3)	−0.002715	0.000815	−3.330587	0.0009
C (4)	−0.001176	0.000877	−1.340339	0.1801
C (5)	−0.010949	0.003692	−2.965680	0.0030
C (6)	−0.002299	0.001076	−2.137894	0.0325
C (7)	0.000118	8.54E-06	13.78405	0.0000
C (8)	0.000900	0.000788	1.141995	0.2535
C (9)	0.000437	0.000872	0.501453	0.6161
C (10)	0.001965	0.003603	0.545290	0.5856
C (11)	9.69E-05	0.001062	−0.091213	0.9273
C (12)	0.007658	0.000556	13.78405	0.0000
C (13)	−0.001246	0.000867	−1.436503	0.1509
C (14)	0.005342	0.003579	1.492664	0.1355
C (15)	0.000676	0.001061	−0.636786	0.5243
C (16)	0.008406	0.000610	13.78405	0.0000
C (17)	−0.008049	0.003510	−2.293456	0.0218
C (18)	0.004099	0.001018	4.028424	0.0001
C (19)	0.033732	0.002447	13.78405	0.0000
C (20)	−0.000614	0.000972	−0.631540	0.5277
C (21)	0.009465	0.000687	13.78405	0.0000

Notes: The estimation method: Maximum likelihood via Newton-Raphson (analytic derivatives). The SVAR, lag = 2 according to Schwarz information criterion (SC). Log likelihood = 2194.485. Convergence achieved after 44 iterations.

deviation from the critical boundaries at the 5% level of significance.

Given the time-frequency analysis, **Figures 5A–F** present the wavelet coherence among the underlying variables between 1990Q1 to 2014Q1. The horizontal and vertical axis in each figure indicates the time and frequency respectively. The yellow and blue colors denote high and low dependency between the variables. The rightward and leftward arrows correspondingly show the in-phase and out-of-phase interrelations. Furthermore, the rightward-down or leftward-up indicates that the first variable is lagging. Whereas rightward-up (leftward-down) indicates the first series is leading. The curved lines drawn by using the Monte Carlo simulation with a 5% level refer to the statistically significant region.

Panel (A) computes the wavelet coherence between TCO_2e and environment-related technological development. The local correlation was very high up to 40 periods of scale and displayed statistical significance. At various frequencies, most of the arrows were leftward-up indicating that environment-related technology negatively derives carbon emissions from the transportation sector. However, this relation is reversed in upcoming periods with low correlation. Herein, the correlation is positive but still, the carbon emissions are lagging in environmental technology as the arrows are oriented rightward-down. Panel (B) presents the wavelet coherence between TCO_2e and biofuel energy. Initially, the yellow color reveals a high positive correlation between the two series with biofuel energy leading till period 20 (around 4–5 years of scale). At the medium frequencies, the biofuel energy still derives the TCO_2e but with low and negative correlation up to period 50. From that period on, biofuels started to influence carbon emissions negatively with TCO_2 leading. The figure also shows that the most dominant periods are the fourth and eighth periods.

Panel (C) plots the wavelet coherence between TCO_2 and solar/wind energy. In contrary to panel (B), the figure shows that there was a high negative correlation between the two variables till period 30 (around 5-6 first years). As arrows were pointed leftward-up, it means that the TCO_2 is lagging in solar/wind energy. At the medium frequency, the solar energy still derives the TCO_2 but with a positive sign. From the 60 scales, the TCO_2 started to lead the solar energy with a positive sign as most arrows were oriented to the rightward-up. Panel (D) outlines the wavelet coherence between TCO_2 and urbanization. At various frequencies, the transport-based carbon emissions were lagging in urbanization with a negative correlation up to period 20 (around 4–5 years). At the medium frequency, the figure displayed almost no correlation between the two series. In the long term, however, the TCO_2 started to derive urbanization with positive signs.

Panel (E) computes the wavelet coherence transformation between TCO_2 emissions and economic growth. Unlike the previous correlations, the figure indicates a low negative correlation at the initial frequency with economic growth

TABLE 9 | Recursive long-run impulse response (F triangular).

Model: e = Phi*Fu where E [uu'] = I

F =					
C (1)	0	0	0	0	0
C (2)	C (7)	0	0	0	0
C (3)	C (8)	C (12)	0	0	0
C (4)	C (9)	C (13)	C (16)	0	0
C (5)	C (10)	C (14)	C (17)	C (19)	0
C (6)	C (11)	C (15)	C (18)	C (20)	C (21)

	Coefficient	Std. Error	z-Statistic	Prob
C (1)	0.471282	0.034191	13.78388	0.0000
C (2)	0.334142	0.028187	11.85439	0.0000
C (3)	1.482267	0.116316	12.74343	0.0000
C (4)	−0.470650	0.036640	−12.84517	0.0000
C (5)	0.301446	0.043265	6.967367	0.0000
C (6)	−0.106691	0.030385	−3.511298	0.0004
C (7)	0.140186	0.010170	13.78403	0.0000
C (8)	0.411340	0.032785	12.54666	0.0000
C (9)	−0.081476	0.011903	−6.844827	0.0000
C (10)	−0.225054	0.033572	−6.703698	0.0000
C (11)	−0.232290	0.024070	−9.650743	0.0000
C (12)	0.132324	0.009600	13.78405	0.0000
C (13)	0.035146	0.010012	3.510192	0.0004
C (14)	0.154464	0.027109	5.697856	0.0000
C (15)	0.071951	0.016374	4.394237	0.0000
C (16)	0.094372	0.006846	13.78405	0.0000
C (17)	0.063020	0.024258	2.597939	0.0094
C (18)	−0.015835	0.015477	1.023110	0.3063
C (19)	0.232196	0.016845	13.78405	0.0000
C (20)	0.018387	0.015377	1.195749	0.2318
C (21)	0.149308	0.010832	13.78405	0.0000

Notes: the estimation method: Maximum likelihood via Newton-Raphson (analytic derivatives). The SVAR, lag = 2 according to Schwarz information criterion (SC). Log likelihood = 2194.485. Convergence achieved after 18 iterations.

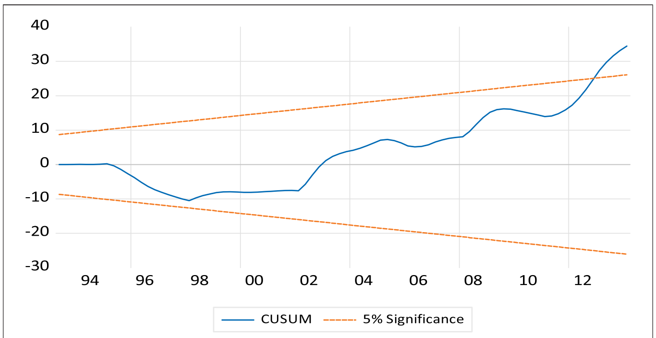

FIGURE 3 | CUSUM test.

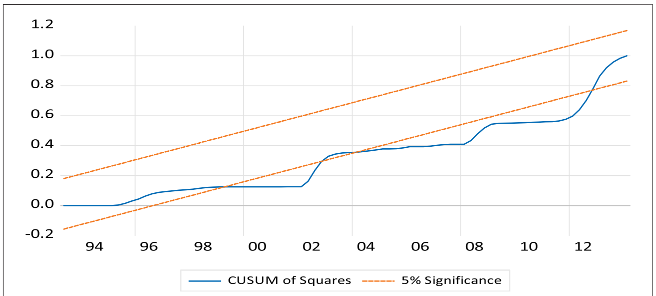

FIGURE 4 | CUSUMQ test.

TABLE 10 | Variance Decomposition of transport-based carbon emissions.

Period	S.E	GDP	URB	WIS	BIW	ERT	TCO_2
1	0.010608	4.698133	0.008346	0.405883	14.93351	0.334971	79.61915
2	0.020462	4.749418	0.171588	0.212658	14.15488	0.371836	80.33962
3	0.029496	4.868806	0.586820	0.144646	12.41426	0.302070	81.68340
4	0.037124	4.978211	1.124604	0.134986	10.25146	0.201865	83.30888
5	0.043239	4.995660	1.690747	0.176946	8.176828	0.174042	84.78578
6	0.048007	4.861367	2.213822	0.288539	6.642620	0.303946	85.68971
7	0.051710	4.570419	2.645932	0.494623	5.966900	0.616055	85.70607
8	0.054640	4.190355	2.964828	0.816678	6.265610	1.056947	84.70558
9	0.057044	3.844593	3.171450	1.268718	7.440729	1.518445	82.75606
10	0.059108	3.663271	3.282362	1.858098	9.236923	1.888672	80.07067

TABLE 11 | Diagnostic test results.

	Statistics	Probably
VAR Residual Serial Correlation LM Tests	0.660744	0.9340
VAR Residual Normality Tests (Skewness)	−0.104235	0.6799
VAR Residual Heteroskedasticity Tests (Joint test)	414.2482	0.9986
Ramsey Reset test (model specification)	1.644183	0.1036

leading. At the medium frequencies, the analysis shows a negative correlation but the TCO_2e still lagging in economic growth till period 50. On the 50 scale, the correlation started to reverse and TCO_2e was leading the economic growth with a positive correlation. Lastly, the wavelet coherence between economic growth and environment-related technological development is presented in panel (F). In the beginning, the analysis indicates almost no co-movement between the series till period 20. At a medium frequency, economic growth derives environmental technology negatively. As the arrows were pointed to the right and up, the correlation changed to the opposite direction but economic growth still leads the environment technology. Overall, the analysis reveals low time frequency dependence between economic growth and environmental technology.

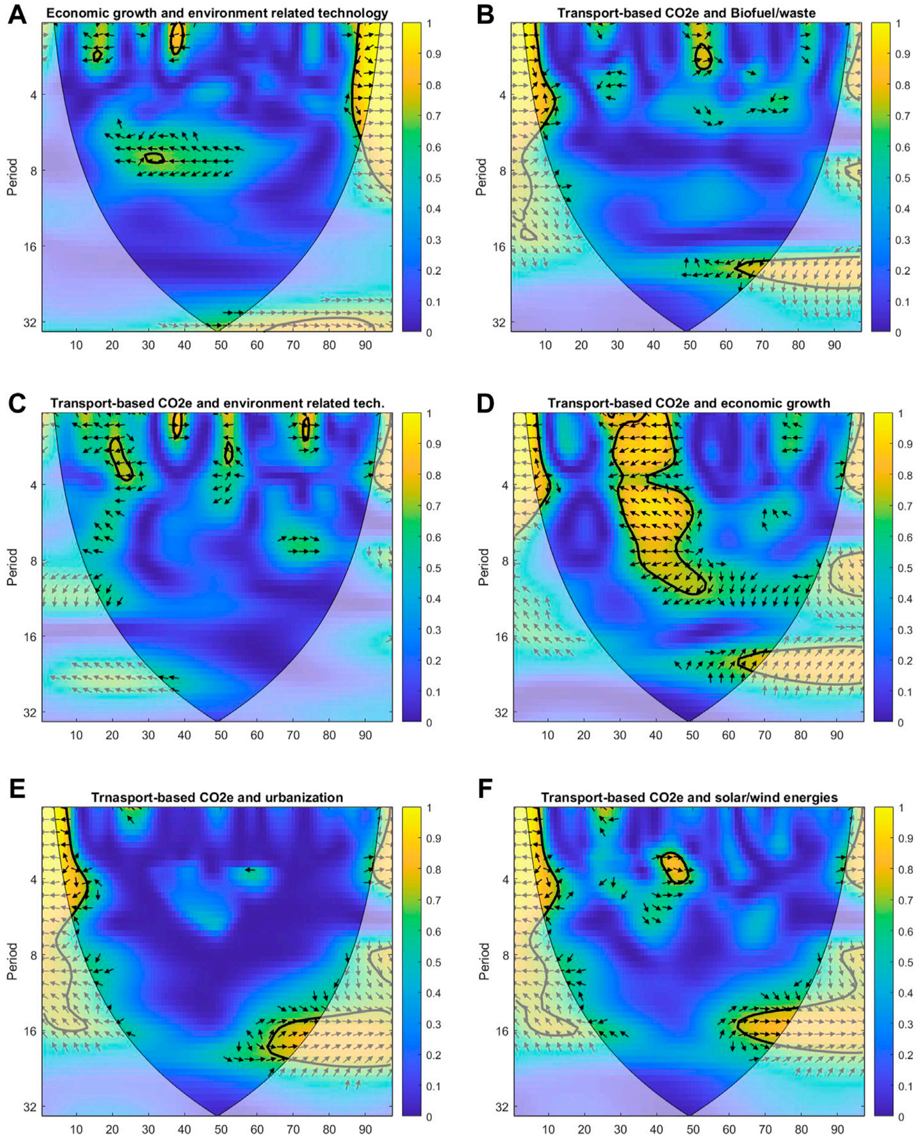

FIGURE 5 | (A–F). Wavelet coherence between TCO2, ERT, BIW, WIS, URB, and GDPPC.

While the SVAR estimates uncover insignificant interaction among the variables, there are some considerable outputs from the recursive short-run and long-run impulse response function on which we based our conclusions. Given the long-run impulse response function, an important emerging result is the high potential of economic growth in mitigating the carbon emissions from the transport sector (-0.106691). This finding is in line with those of (Lv et al., 2019; Ozkan, 2019; Ozkan et al., 2019; Rasool et al., 2019; Godil et al., 2020a; Amin et al., 2020). However, this finding challenges the outcome of (Godil et al., 2021) when using the quantile ARDL model, the authors reported a significant impact of GDP on transport-based carbon emissions for China at all quantiles. Given the overall carbon emissions-growth relation, this result is also compatible with (Jebli et al., 2016; Ganda, 2019a; Sharif et al., 2019). This result may reflect the role of a country's income level in the environmental effect of the transport system, which may indicate that the economic costs of sustainable investment planned in this sector are directly pertinent to income level. Moreover, this finding may implicitly promote the argument that the nations with the greatest emissions will pay more to cut emissions than those with lower emissions. As this result may partially answer the question about whether the impact of renewable and green technology on carbon emissions is subject to an income baseline, it necessitates further investigation to determine the threshold level of income. The second important result of our experiment is the negative impact of urbanization on carbon emissions from the transport sector in Turkey. This result agrees with that of others (Bekhet and Othman, 2017; Amin et al., 2020; Mehmood, 2021). The possible interpretation of this finding is twofold; first, it may reveal that the sustainable and green city projects that a country has launched over a few years are beneficial to the transportation sector. Over recent years, Turkey has launched the Sustainable Cities Program (SCP) which is meant to improve the economic, financial, environmental, and social sustainability of Turkish cities. Second, it may reflect the level of environmental awareness of the citizens in urban cities and their better use of transport infrastructures.

Deviating from the theoretical expectation, renewable energy sources demonstrate inconclusive outcomes. The recursive impulse response function reveals that biofuels tend to increase the TCO_2e in the short run but have an insignificant effect in long run, while solar/wind energy increases the transport-based CO_2e in long run. Given the overall renewable energy, these findings are partially consistent with those of Danish I Godil et al. (2021), who outlined that renewable energy has no significant impact on TCO2e in China at a low quantile (0.10), whereas, at higher quantiles (0.15–0.95) renewable energy significantly reduces the carbon emissions stemming from China's transport system. Similarly, other studies (Hasanov et al., 2021; Ulucak, 2021) have documented that renewable energy can mitigate pollution in BRICS countries, and the United States and China respectively. Although the positive implications of renewable energy on carbon emissions challenge our theoretical plausibility, there are some supportive empirical clues. For instance, Alnour and Atik (2021) claim that solar and wind energy systems do not produce air pollution or greenhouse gases and that using solar and wind energies can have a positive effect on the environment when these energies replace or reduce fossil fuels. However, some toxic materials and chemicals are used to make photovoltaic cells that convert sunlight into electricity. As a result, these materials can be harmful to the environment. Moreover (Xin et al., 2021), stress that wind energy can negatively affect the environment through the visual and noisy impact it produces. For Turkey, the insignificant impacts of renewables on transport-based CO_2e could also be attributed to the low share of renewable energy in the power system of the transport sector, which means it has no significant implications on the carbon emissions.

Shedding light on the other recursive impulse response results, one can observe the insignificant effect of green technology on carbon emissions from the transport sector. This result is compatible with (Ulucak, 2021) given the total carbon emissions in China. However, our result contradicts the findings of others (Danish I. Godil et al., 2021; Hasanov et al., 2021), which confirm the theoretical plausibility of the effectiveness of technology innovation in curbing pollution. While this outcome is not surprised in the relevant literature, there has been no consensus on a possible explanation. Some strands of literature refer to the innovation rebound effect and green paradox, which shows how the progress in environment-related technology may not significantly influence pollution or may result in higher carbon emissions (Wang and Wei, 2020). Based on the innovation reverse effect mechanism, technological progress could enable people to demand more goods and services due to resource efficiency, although it provides the production with less carbon emissions (Ulucak and Koçak, 2018). The green paradox also takes into account how the inappropriateness of environmental regulations can lead to the over-exploitation of natural resources, thereby increasing pollution (Ulucak and Kassouri, 2020). Some literature provides relatively different channels for green technology to influence carbon emissions. Chen et al. (2020) and Sharma et al. (2021) argue that environment-related technology can mitigate pollution only if it promotes the usage of a clean production process. Without upgrading the industrial and production sector, green technology innovation will not decrease carbon emissions. Zafar et al. (2020) outline that the pro-growth strategies implemented in many developing and emerging economies could be another reason for the negative impact of green technology. Achieving a high rate of growth with less attention to environmental issues and sustainability infrastructures may restrain the effectiveness of newly developed technology to mitigate pollution.

CONCLUSION AND POLICY RECOMMENDATIONS

Transportation is one of the leading sectors that plays an essential role in achieving socio-economic development in any community, as it improves the mobility of citizens and the traffic of goods and offers employment opportunities. It is also being identified as one of the main reasons for suburbanization among cities (Ševčenko-Kozlovska and Čižiūnienė, 2022). Given its major role, transportation becomes a yardstick for measuring development. Efficient transport systems provide economic and social opportunities and benefits that result in a positive multiplier effect such as better accessibility to markets, job creation, and additional investments. In terms of capacity and reliability, deficient transport systems can have economic costs such as reduced or missed opportunities and lower quality of life.

Despite its important contribution to economic development, the transport sector has been identified as the second-largest contributor to carbon emissions, which is a major obstacle that restrains the efforts toward attaining a green transportation system and environmental sustainability. This negative implication has caused a race to develop a more efficient transport system. Given the vibrant development of renewable energy resources and environment-related technology, the current research attempts to explore the role of biofuels and solar/wind energy and environment-related technological innovation in the reduction of TCO2e in Turkey during 1990Q1-2014Q1, selected according to data availability. In response to literature limitations and given the methodological weaknesses, this study applied the SVAR model and wavelet coherence technique. While the SVAR model is powerful in controlling structural shocks, the wavelet-based approach is preferable in detecting the time-frequency dependency and co-movement among the series. These vis-à-vis methods are thought to give a clearer view of the potential effect of renewables and green technology on TCO2e.

Apart from estimating the basic SVAR model (A and B matrices), the current study also experiments with a recursive short-run and long-run impulse response function through triangular (S and F) matrices. The important emerging results are 1) that environment-related technological progress has no significant impact on TCO_2e in Turkey, 2) biofuels only impact the TCO_2e in the short-run with positive signs, while solar and wind energy contribute to the increase of TCO_2e in the long-run, 3) urbanization negatively affect the TCO_2e in long run, 4) GDP per capita improves transport-based CO_2e in all periods. A wavelet analysis revealed that environment-related technology and renewable energy lead to transport-based CO_2e. The most dominant frequencies are the fourth and 16th periods. These outputs call for several important policy implications. First, since the green technologies have no significant impact, the study suggests that innovation in environment-related technologies is not enough to mitigate the pollution that stemming from the transport system in Turkey, it should be accompanied by strong and effective environmental policies and measures. These policies might include environmental taxations, carbon pricing and trading schemes, which aim not only to prevent the pollution and over-extraction of resources and increase the resources efficiency, but also promote the public revenues from different activities that related to environmental purposes and other applications such as energy product and vehicle fuels. Second, as biofuels mitigate the transport-based emissions, it is suggested to strengthening the transportation system through the deployment of renewables and high-tech eco-friendly modes of transportation. Third, since economic growth holds desirable effect on TCO_2e, policies that prevent the innovation exhaustion, technological obsolescence, and continuously promoting the utilization of cleaner products should be considered. Fourth, policies that emphasize the positive role of urbanization in mitigating the transport pollution should be placed. This can be done through effective and sustainable urban policies that enhance environmental awareness and better use of urban infrastructures.

LIMITATION AND SCOPE FOR FUTURE RESEARCH

Although the SVAR is a powerful method for monitoring structural shocks, its major limitation lies in treating negative and positive changes to have the same impacts in absolute terms, which may not be realistic under some regimes. While the wavelet technique may partially solve the asymmetricity problem, as it gives different results through time (time frequencies), it lacks the power to explore the reverse effects among the series. Therefore, future research on green transport should focus more on the asymmetric effects. Therefore, applying nonlinear regression models such as panel smooth transition regression, spatial spillover analysis, and quantile analysis would expand our understanding of this issue, because members of the public and other stakeholders may need to understand the mechanism of the effect rather than the effect itself or the channels of correlation rather than the correlation itself.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Author listed has made a substantial, and direct contribution to the study and approved it for publication.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.902562/full#supplementary-material

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GLOSSARY

ADF Augmented Dickey and Fuller, (1979)

AMG Augmented Mean Group

ARDL Autoregressive Distributed Lag model

A-S-I Avoid-Shift-Improve

CWT Continuous Wavelet Transformation

DARDL Dynamic Autoregressive Distributed Lag model

DOLS Dynamic ordinary least squares method

EKC Environmental Kuznets Curve hypothesis

EU European countries

FMOLS Fully modified least squares methods

GHG Greenhouse gas

GMM Generalized Method of Moments

GT Green transport

MEDC Mediterranean countries

NARDL Non-linear Autoregressive Distributed Lag model

OECD Organization of Economic Cooperation and Development

PMG Pooled Mean Group

PP Phillips and Perron, (1988)

QARDL Quantile Autoregressive Distributed Lag model

R&D Research and Development

R-M-I Reduce-Maintain-Improve

SC Schwarz information criterion

SCP Sustainable Cities Program

SVAR Structural Vector Autoregressive model

TCO_2e Transport-based carbon emissions

VECM Vector Error Correction Model

WPS Wavelet Power Spectrum

WTW Wheel to Wheel method