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RESEARCH ARTICLE

Social, economic, and technical factors affecting CO_2 emissions in Iran

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Abstract

Most scholars support the increase in carbon dioxide (CO2) emissions as one of the major causes of the increase in global climate change. Therefore, reducing CO2 emissions from the main emitter countries, including Iran as the sixth emitter, is important to deal with the harmful effects of global climate change. Accordingly, the main aim of this paper was to analyze the social, economic, and technical factors affecting CO2 emissions in Iran. Previous studies on diverse variables affecting emissions are not very accurate and reliable as they do not consider indirect effects. This study applied a structural equation model (SEM) to estimate the direct and indirect impacts of factors on the emissions by panel data for 28 provinces of Iran from 2003 to 2019. According to geographical location, three distinct regions, the north, center, and south of Iran were considered. The findings suggest that a 1% increase in social factor directly increased CO2 emissions by 2.23% (in the north) and 1.58% (in the center), but indirectly reduced emissions by 0.41% (in the north) and 0.92% (in the center). Hence, the total effects of the social factor on CO2 emissions were estimated at 1.82%, and 0.66% in the northern, and central regions, respectively. In addition, the total effects of the economic factor on CO2 emissions were estimated at 1.52%, and 0.73% in those regions. The results of this study showed that the direct effects of a technical factor on CO2 emissions were negative in the north and center. However, they were positive in the south of Iran. Based on the empirical results of this study, three policy implications are discussed in order to control CO2 emissions in regional distinctions of Iran as follows: First, policymakers should pay attention to the social factor, i.e., the growth of human capital in the southern region with the aim of increasing sustainable development. Second, Iranian policymakers must prevent unilaterally increasing gross domestic product (GDP) and financial development in the north and center. Third, policymakers should pay attention to the technical factor, i.e., improving energy efficiency, as well as upgrading information and communications technology (ICT) in the northern and central regions, and limiting the technical factor in the southern region.

Keywords CO_2 emissions · Direct and indirect effects · Regional distinctions · Structural equation model (SEM) · Social, economic, and technical factors

Introduction

Continuously rising temperatures are one of the most crucial themes that pose a drastic threat to human health and environmental conditions in the world (Liu et al. 2019; Aldieri and Vinci 2020). Mainly, increased emissions of carbon dioxide (CO2) from anthropogenic activities, for example, the burning of fossil fuels to generate electricity and provide urban transport services, lead to increased temperatures (Letcher 2019). Iran is the sixth-largest emitter of CO2 (Crippa et al. 2019). Therefore, it is obvious that reducing CO2 emissions from Iran is a very necessary task to deal with the harmful effects of global warming.

Figure 1 shows the average CO2 emissions per capita in different provinces of Iran from 2003 to 2019. In Iran, CO2 emissions per capita are higher in the southern and central provinces, although they are lower in the western

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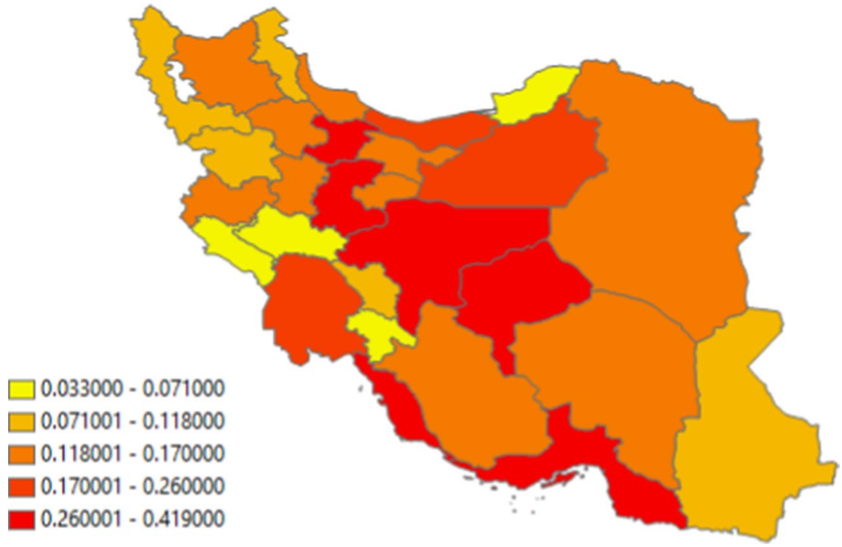

Fig. 1 Average CO_2 emissions per capita of Iranian provinces, 2003–2019. Source: Study findings

and northwest regions. So, investigating the factors causing CO2 emissions in Iran is important, in the light of variations in CO2 emissions across the provinces. To do that, the current paper considers the influence of social, economic, and technical drivers on emissions in Iran.

Numerous studies have probed into the social factors leading to increased CO2 emissions, mostly analyzing the influence of population (e.g., Li et al. 2019a; Wang and He 2019; Zhou and Wang 2018) and urbanization (i.e., Joshi and Beck 2018; Li et al. 2019a; Yang et al. 2019) on emissions. In addition, human capital can also effectively affect CO2 emissions, as reported in several studies (such as Khan et al. 2020; Mukhlis 2020; Sarkodie et al. 2020). Improving human capital can improve various aspects of social capital, such as encouraging regulatory compliance, reducing inequality, and reducing crime. As a result, economic growth can be enhanced. Human capital, then, represents an important factor in economic growth (Bano et al. 2018; Yao et al. 2020a). Meanwhile, economic growth affects CO2 emissions depending on production activities (Bano et al. 2018; Isiksal et al. 2022).

The economic factor is another factor that can affect CO2 emissions (Lv and Li 2021; Zafar et al. 2019; Zhao and Yang 2020). The economic aspect includes gross domestic product (GDP) and financial development. Some studies used the environmental Kuznets curve framework (e.g.,Salazar-Núñez et al. 2021; Kongkuah et al. 2021). Others, however, focused on the linear link between GDP and emissions (Apergis et al. 2018; Gierałtowska et al. 2022; McGee and York 2018; Nie et al. 2019; Wen and Li 2019). However, depending on the specifications of emissions, there may be positive or negative linear relationships between economic growth and emissions (Apergis et al. 2018; Aydin and Cetintas 2022; Inglesi-Lotz and Dogan 2018). When the relationship is positive, GDP requires more raw materials and thus increases emissions (Haputta et al. 2022; Wen and Li 2019). When the link between economic growth and emissions is negative, there is compatibility between economic growth and emission reduction. An increased GDP rate would raise the demand for environmental quality, which could lead to the adoption of environmental protection standards/criteria (Ahmad and Zhao 2018; Mohsin et al. 2022; Yang et al. 2019). In addition, financial development can also effectively affect CO2 emissions, as reported in some studies (such asLv and Li 2021; Zafar et al. 2019; Zakaria and Bibi 2019; Zhao and Yang 2020).

The technical factor is another factor that can affect CO2 emissions (Wang et al. 2018; Zhao and Yang 2020). Several studies explored energy intensity as the main driver of emissions (Liu et al. 2018; Wang and Zhao 2018a,b; Zhao and Yang 2020). Energy intensity refers to energy use per unit of GDP. Countries (or regions) with a high rate of energy intensity experience a high degree of energy consumption per unit of production. Energy consumption, especially in the case of fossil fuels, could directly destroy the environment by polluting it (Khan et al. 2022; Rahman et al. 2022). Reducing energy intensity leads to increased energy security, lower production costs, and more environmental protection (Lee et al. 2022). In addition, higher rates of energy intensity could reduce energy efficiency and negatively impact GDP and economic growth (Chen et al. 2022). Moreover, several scholars (e.g., Danish et al. 2018; Dehghan Shabani and Shahnazi 2018; Shahnazi and Dehghan Shabani 2019) investigated the effect of information and communications technology (ICT) on CO2 emissions.

Since socioeconomic development can affect technical factors (i.e., energy intensity, and ICT) that affect CO2 emissions, such indirect effects have not been investigated so far. Therefore, there is a research gap in the previous studies because they failed to investigate the indirect effects of social and economic factors on emissions through technical factors.

This paper investigates the social, economic, and technical factors influencing CO2 emissions in Iran. The current research contributes to the literature as it is distinct from previous research in two main respects. First, although the effect of diverse variables on CO2 emissions was investigated in previous studies, only the direct effects of influencing variables on emissions were estimated. Since socioeconomic factors can affect CO2 emissions through technical factors, indirect relationships have not been considered in previous studies. Due to not considering the indirect effects of affecting variables on CO2, there is a probability of underestimating or even opposite effects. Second, there is no study that examined the comprehensive set of variables on CO2 emissions in Iran at the regional and national levels. Regional analysis can help policymakers choose appropriate policies in each region to reduce emissions. To fulfill Iran's obligations under global environmental agreements, it is crucial to examine the effects of factors influencing the emissions in Iran. In fact, being among the top six CO2 emitting countries, along with an upward trend against the global average, has made Iran an important case study.

In the continuation of this article, a complete review of the literature has been reported in part 2. The third part has presented the methods applied in the paper. Part 4 has offered the effects and validation in detail eventually, and part 5 has discussed and concluded the study.

Theoretical background

Social factor and CO_2 emissions

Improving the social factor can be described by several measures, such as population growth, urban development, human capital progress, and expenditure increases on food and health. There are different perspectives on how each measure affects CO2 emissions.

There are two views of Malthus (1798) and Boserup (1965) on how population affects the quality of the environment including CO2 emissions. According to Malthus (1798), food supply does not increase in proportion to population growth caused by reducing the capacity of land resources and labor productivity (Naso et al. 2020). Boserup (1965) believed that population growth is a precondition for innovations (i.e., the green revolution in the agricultural sector) that increase crop yields. Thus, in the view of Malthus (1798), the increase in CO2 emissions was greater than population growth (Li et al. 2019a; Wang and He 2019; Zhang et al. 2018). However, in the view of Boserup (1965), there was no link between population growth and emissions, or it may even be negative (Yang et al. 2019; Zhao and Yang 2020).

There are also different views about the influence of urbanization on emissions. First, urbanization increases CO2 emissions based on several studies (i.e., Li et al. 2019a; Yang et al. 2019). In the opinion of the positive effect of urbanization on emissions, urban society often tries to consume high-energy products. Hence, modern city lifestyles lead to greater direct and indirect energy consumption, resulting in global rising temperatures and changing conditions (Rahmani et al. 2020; Wiedenhofer et al. 2013). In this regard, urban areas are responsible for 71% of global emissions (Gasimli et al. 2019). Thus, urbanization leads to increased use of energy and the burning of fossil fuels through rapid industrialization, mechanization of agricultural processes, and the transportation of food and supplies into cities (Benke and Tomkins 2017; Salim et al. 2019). Second, evidence suggests a negative link between urbanization and CO2 (i.e., Liu et al. 2018; Zhao and Yang 2020). In this case, urbanization with high resource efficiency improves environmental standards (Cui et al. 2019; Nathaniel et al. 2021). Thus, urbanization may reduce environmental degradation. Third, the various effects of urbanization on emissions depend on developed and underdeveloped countries. Numerous studies have shown a positive (Li et al. 2019a; Yang et al. 2019) and some negative (Liu et al. 2018; Zhao and Yang 2020) link between urbanization and CO2 emissions.

Human capital progress reduces CO2 emissions for two reasons. First, upgrading this capital will improve the understanding of the community about environmental pollution issues (Collins et al. 2017; Sarkodie et al. 2020), enabling individuals to efficiently operate the production process (Sima et al. 2020). Accordingly, energy consumption was efficient and CO2 emissions were decreased (Bano et al. 2018; Wang and Xu 2021). Second, raising human capital could be reflected in compliance with government laws, reducing inequality and decreasing crime, thus enhancing economic growth (Bano et al. 2018; Yao et al. 2020a). Ultimately, economic growth relying on human manufacturing activities affects CO2 emissions (Bano et al. 2018; Ganda 2021).

Some researchers, such as Apergis et al. (2018) and Wang and Zhao (2018a) argue that increasing health and nutrition expenditures have a significant effect on mitigating CO2 emissions. Increasing health and nutrition expenditures, which indicate an improvement in the living quality of society, can indicate economic development. Thus, people have more ability to allocate resources to protect the environment and reduce the harmful effects of emissions. Therefore, the first hypothesis of this study is as follows:

Hypothesis 1: Improving the social factor will reduce CO2 emissions.

Economic factor and CO_2 emissions

The economic factor can be enhanced by increasing GDP and rising financial development. Environmental quality during economic growth may change in three different ways: degradation, improvement, or both. In fact, economic growth relies on energy, and the expansion of the economic scale is related to increased energy consumption, including the consumption of polluting energy (e.g., coal, natural gas, and nuclear). Higher levels of productive and consuming activities require more energy and raw materials, resulting in producing more waste (Apergis et al. 2018; Li et al. 2019a; Zhao and Yang 2020). In this context, Apergis et al. (2018) explored economic development relying on energy consumption in 42 sub-Saharan African countries from 1995 to 2011; Li et al. (2019a) and Zhao and Yang (2020) evaluated GDP growth due to the consumption of polluting energy in China during 2001–2016. Researchers in Asian countries (i.e., Ahmad and Zhao 2018; Hajilary et al. 2018; Yang et al. 2019) believe that the fastest way to improve environmental quality is through improved economic growth. As increased income leads to higher demand for a better-quality environment and less use of raw materials, it indicates the acceptance of environmentally friendly standards and norms. Furthermore, using the Kuznets environmental curve, some scholars such as Dong et al. (2017) in BRICS countries from 1985 to 2016, Lv and Li (2021) in 97 countries from 2000 to 2014, and Wang and He (2019) in China from 1995 to 2013 showed that the level of environmental pollution increases with economic development. Then, when per capita income exceeds a certain level (explosion point), the environment also improves with economic growth.

There are two perspectives about the influence of financial development on environmental standards. According to the first perspective, a developed and efficient financial system can improve environmental standards (Acheampong 2019; Usman et al. 2022; Xu et al. 2021). Thus, financial development is useful for the environment for the following reasons. First, an efficient and developed financial system strengthens the level of research and development by attracting foreign investment, which is in the interest of environmental quality. Second, a number of researchers believe that financial development is an incentive to use cleaner technologies in industries. Third, an improved financial system provides low-cost loans for environmentally friendly plans, which reduce the environment's pollution. Fourth, financial development through technology innovation reduces CO2 emissions. Fifth, if the company complies with environmental regulations, then the developed financial system will lend. According to the second perspective, financial development has had harmful impacts on environmental quality (Zafar et al. 2019). A financial development program is both a facilitator of industrial activities and a means of strengthening economic development at the same time. As a result, pollution and CO2 emissions increase. The second hypothesis raised in this study is as follows:

> Hypothesis 2: Improving the economic factor will decrease CO_2 emissions

Technical factor and CO_2 emissions

The promotion of technical factors can be characterized by decreasing energy intensity, and increasing ICT. Based on different perspectives, each characteristic affects emissions differently.

Based on Liu et al. (2018), and Wang et al. (2018), energy intensity which is often used to evaluate the energy efficiency of a specific economy (Ang and Goh 2018) can be the main cause of global CO2 emissions. The energy intensity in Iran increases at an average rate of 3.4% per year, which is 50% and 100% higher than those in European and Middle Eastern countries (Mirzaei and Bekri 2017).

There are three views on the impact of ICT on emissions. The first view mentions the use effect which affects the production, installation, and commissioning of ICT equipment and increases energy consumption resulting in CO2 emissions (D'Ambra et al. 2021; Dehghan Shabani and Shahnazi 2018; Lee and Brahmasrene 2014). The second view refers to the establishment of production processes called the substitution effect. This view is based on Danish et al. (2018) includes the replacement of virtual goods with physical goods and the application of mobility services programs using ICT in emerging economies from 1990 to 2015. Therefore, it mainly reduces CO2 emissions. The third view relates to the costing effects as increasing demand for further goods and services as a result of falling prices (Dehghan Shabani and Shahnazi 2018; Lee and Brahmasrene 2014). Based on this view, CO2 emissions increase. The third hypothesis of this study is stated as follows:

> Hypothesis 3: Promoting the technical factor will increase CO_2 emissions

Empirical studies

From a general perspective, the factors influencing emissions can be grouped into three research classes social factors, economic factors, and technical factors.

Some studies in the first class are indicated in Table 1. Most of the studies investigated the influence of population and urbanization on CO_2 using spatial regression methods, including the spatial error model (such as Liu et al. 2018; Li et al. 2019a), the spatial autoregressive model (e.g., Wang and He 2019; Yang et al. 2019), the spatial lag regression (i.e., Li et al. 2019a), the spatial autocorrelation (e.g., Li et al. 2019a), the spatial panel data (i.e., You and Lv 2018), and the spatial Durbin panel model (i.e., Zhang et al. 2018). Although the results of most studies showed a positive

Table 1 Review of studies on influencing social factors on CO_2 emissions

Authors	Countries	Period	Methodology	Findings
Ahmad and Zhao (2018)	30 Chinese provinces	2000–2016	AMG, CCEMG	Urbanization $\xrightarrow{+}$ CO_2
Apergis et al. (2018)	42 sub-Saharan Africa countries	1995–2011	DOLS, FMOLS, VECM	Health expenditures $\xrightarrow{-}$ CO_2
Bano et al. (2018)	Pakistan	1971–2014	ARDL	Human capital $\xrightarrow{-}$ CO_2
Hajilary et al. (2018)	Iran	1976–2016	PLS	Urbanization $\xrightarrow{+}$ CO_2
Joshi and Beck (2018)	22 OECD and 87 non-OECD countries	1995–2010	GMM	Population $\xrightarrow{+}$ CO_2 ,Urbanization $\xrightarrow{+}$ CO_2
Lin and Xu (2018)	30 Chinese provinces	2001–2015	QRM	Population $\xrightarrow{+}$ CO_2 ,Urbanization $\xrightarrow{+}$ CO_2
Liu et al. (2018)	31 Chinese provinces	1996–2015	SEM	Population $\xrightarrow{+}$ EPI , Urbanization $\xrightarrow{-}$ EP
Wang and Zhao (2018a)	30 Chinese provinces	1998–2013	FE, FGLS, DK	Urbanization $\xrightarrow{+}$ CO_2, Engel′s coefficient $\xrightarrow{-}$ CO_2
Wang et al. (2018)	The Pearl River Delta in China	1991–2014	Stepwise regression	Economic urbanization $\xrightarrow{+}$ CO_2, Population urbanization $\xrightarrow{-}$ CO_2, Land urbanization $\xrightarrow{+}$ CO_2 ,Social urbanization $\xrightarrow{-}$ CO_2
You and Lv (2018)	83 countries	1985–2013	Spatial panel data	Direct effect: Urbanization $\xrightarrow{+}$ CO_2; Indirect effect: Urbanization $\xrightarrow{-}$ CO_2
Zhang et al. (2018)	30 Chinese provinces	2005–2014	SDPM	Population $\xrightarrow{+}$ CO_2, Population urbanization $\xrightarrow{-}$ CO_2, Land urbanization $\xrightarrow{+}$ CO_2
Zhou and Wang (2018)	China	1992–2013	DSM	Population $\xrightarrow{+}$ CO_2
Li et al. (2019a)	30 Chinese provinces	2002–2016	SLR, SEM, SAC	Population $\xrightarrow{+}$ CO_2, Urbanization $\xrightarrow{+}$ CO_2
Mahmood et al. (2019)	Pakistan	1980–2014	3SLS	Human capital $\xrightarrow{-}$ CO_2
			VECM Granger causality	Long run: Human capital $\xrightarrow{-}$ CO_2; Short run: Human capital $\xrightarrow{+}$ CO_2
Saleem et al. (2019)	BRICS countries	1991–2014	DSUR, FMOLS	Human capital $\xrightarrow{-}$ CO_2
Wang and He (2019)	Chinese provinces	1995–2013	SAR	Population $\xrightarrow{+}$ CO_2 ,Urbanization $\xrightarrow{NON}$ CO_2
Yang et al. (2019)	8 Chinese regions	1990–2014	SAR	Direct effect: Population $\xrightarrow{NON}$ CEI, Urbanization $\xrightarrow{+}$ CEI Indirect effect: Population $\xrightarrow{NON}$ CEI ,Urbanization $\xrightarrow{+}$ CEI
Khan et al. (2020)	7 OECD countries	1990–2018	Panel data	Human capital $\xrightarrow{-}$ CO_2
Mukhlis (2020)	Indonesia	1985–2017	VECM	Human capital $\xrightarrow{+}$ CO_2
Sarkodie et al. (2020)	China	1961–2016	AR(1), Dynamic ARDL simulations, Neural network algorithm	Human capital $\xrightarrow{+}$ CO_2
Yao et al. (2020a)	20 OECD countries	1870–2014	Fixed effects, AMG	Human capital $\xrightarrow{+}$ CO_2, $HC_{primary}$ $\xrightarrow{+}$ CO_2, $HC_{secondary}$ $\xrightarrow{-}$ CO_2 ,$HC_{tertiary}$ $\xrightarrow{-}$ CO_2

Table 1 (continued)

Authors	Countries	Period	Methodology	Findings
			PMG	Long run:$HC_{tertiary} \xrightarrow{-} CO_2$; Short run:$HC_{tertiary} \xrightarrow{+} CO_2$
Yao et al. (2020b)	China	1997–2016	Panel data	Human capital $\xrightarrow{-} CO_2$
Zhao and Yang (2020)	Chinese provinces	2001–2015	FMOLS, DOLS, PECM	Urban population $\xrightarrow{-} CO_2$
Haini (2021)	ASEAN countries	1996–2019	Panel data	Human capital $\xrightarrow{+} CO_2$
Hao et al. (2021)	G7 countries	1991–2017	Panel data	Human capital $\xrightarrow{-} CO_2$
Rahman et al. (2021)	Newly industrialized countries	1979 – 2017	DOLS, FMOLS, PMG	Human capital $\xrightarrow{+} CO_2$

Variables: CO_2=carbon dioxide emissions, CEI=carbon emission intensity measured as CO_2 per GDP, EPI=environmental pollution index

Methodology: SAC=spatial autocorrelation, SEM=spatial error model, GMM=generalized method of moments, FMOLS=fully modified ordinary least squares, AMG=augmented mean group, CCEMG=common correlated effects mean group, DOLS=dynamic ordinary least squares, VECM=vector error correction model, ARDL=autoregressive distributed lag, PLS=partial least square, QRM=quantile regression model, FE=fixed effects, FGLS=feasible generalized least squares, DK=Driscolle Kraay, SDPM=spatial Durbin panel model, DSM=dynamic spatial panel, SLR=spatial lag regression, 3SLS=three stage least square, DSUR=dynamic seemingly unrelated regression, SAR=spatial autoregressive model, AR(1)=first order autoregressive, PMG=pool mean grouped, PECM=panel error correction model

Source: Study findings

influence of population and urbanization on CO_2 emissions, negative and quadratic effects have also been discovered. In addition, several studies (e.g., Khan et al. 2020; Yao et al. 2020a, 2020b; Haini 2021; Hao et al. 2021) investigated the effect of human capital on emissions using the panel data method, and their results mostly showed a negative effect of human capital on CO_2.

Table 2 shows the second research class that incorporated the impact of economic factors on emissions. GDP is the most important economic factor affecting CO_2 emissions, which has been considered in various studies by using spatial regression methods, such as the spatial error model (e.g., Liu et al. 2018; Li et al. 2019a, 2019b; Lv and Li 2021), the spatial autoregressive model (i.e., Wang and He 2019; Yang et al. 2019), the spatial panel data (e.g., You and Lv 2018), the spatial Durbin Panel model (i.e., Zhang et al. 2018), the spatial lag regression (e.g., Li et al. 2019a), the spatial autocorrelation model (i.e., Li et al. 2019a), the spatial lag model (e.g., Li et al. 2019b; Lv and Li 2021), and the spatial Durbin model (i.e., Li et al. 2019b; Lv and Li 2021). The results of those studies showed a linear, quadratic, or cubic relationship. In addition, the effects of private sector growth as financial development on CO_2 emissions were investigated by some scholars, such as Lv and Li (2021) by applying the spatial lag model, the spatial error model, and the spatial Durbin model, Zafar et al. (2019) by using the panel Granger causality, and Zhao and Yang (2020) by using the dynamic ordinary least squares, and the fully modified ordinary least squares.

Previous studies (e.g., Li et al. 2019a; Lin and Xu 2018; Zhao and Yang 2020) have focused on the influence of socioeconomic factors on CO2 and provided notable intuitions. However, all of these discoveries directly investigated the link between the factors influencing emissions. You and Lv (2018) used spatial panel data, and Yang et al. (2019) applying spatial autoregressive models to investigate the direct and indirect effects of some variables on emissions, but they did not explore the technical variables. Even if some alternative methods are able to perform direct and indirect effects analysis, SEM is able to provide more significant and reliable results (Werner and Schermelleh-Engel 2009). Socioeconomic factors, however, indirectly affect CO2 emissions. Although Wen and Li (2019) have investigated the influences of some social and economic factors on emissions using a structural equation model (SEM) in China, the technical factor and indirect effects of socioeconomic factors on emissions through the technical factor have not been considered.

The third class of studies on technical factors is presented in Table 3. These studies focused on CO2 or other emissions due to two variables, ICT by using panel data method (i.e., Danish et al. 2018), and dynamic methods (e.g., Dehghan Shabani and Shahnazi 2018; Shahnazi and Dehghan Shabani 2019), and energy intensity by mostly using panel data method (such as Wang and Zhao 2018a, b). The impact of ICT on emissions could be positive, negative, and sometimes quadratic.

However, previous studies did not consider the relationships between socioeconomic and technical factors. Ignoring such relationships cannot show the exact effect of factors on emissions and leads to underestimation. Accordingly, this study differs from previous papers in three respects. First, three social, economic, and technical classes were considered for factors affecting CO2 emissions. Second, the indirect effect of socioeconomic factors on the emissions was examined through technical factor using the SEM approach. Third, the impacts of social, economic, and technical factors on emissions were analyzed in Iran. Although some studies (e.g., Dehghan Shabani and Shahnazi 2018; Hajilary et al.

Table 2 Review of studies on influencing economic factors on CO_2 emissions

Authors	Countries	Period	Methodology	Findings
Ahmad and Zhao (2018)	30 Chinese provinces	2000–2016	AMG, CCEMG	$GRP \overset{-}{\rightarrow} CO_2$
Apergis et al. (2018)	42 sub-Saharan Africa countries	1995–2011	DOLS, FMOLS, VECM granger causality	Real $GDP \overset{+}{\rightarrow} CO_2$
Hajilary et al. (2018)	Iran	1976–2016	PLS	Non oil $GDP \overset{-}{\rightarrow} CO_2$
Joshi and Beck (2018)	22 OECD and 87 non-OECD countries	1995–2010	GMM	$GDP \overset{+}{\rightarrow} CO_2, GDP^2 \overset{+}{\rightarrow} CO_2$
Lin and Xu (2018)	30 Chinese provinces	2001–2015	QRM	$GDP \overset{+}{\rightarrow} CO_2$
Liu et al. (2018)	31 Chinese provinces	1996–2015	SEM	$GDP \overset{+}{\rightarrow} EPI, GDP^2 \overset{-}{\rightarrow} EPI$
Sinha and Shahbaz (2018)	India	1971–2015	ARDL	$GDP \overset{NON}{\rightarrow} CO_{22}$
You and Lv (2018)	83 countries	1985–2013	Spatial panel data	Direct effect: $GDP \overset{+}{\rightarrow} CO_2$, $GDP^2 \overset{-}{\rightarrow} CO_2$ Indirect effect: $GDP \overset{+}{\rightarrow} CO_2$,$GDP^2 \overset{-}{\rightarrow} CO_2$
Zhang et al. (2018)	30 Chinese provinces	2005–2014	SDPM	$GDP \overset{+}{\rightarrow} CO_2$
Zhou and Wang (2018)	China	1992–2013	DSM	$GDP \overset{+}{\rightarrow} CO_2, GDP^2 \overset{NON}{\rightarrow} CO_2$
Li et al. (2019a)	30 Chinese provinces	2002–2016	SLR, SEM, SAC	$GDP \overset{+}{\rightarrow} CO_2$
Li et al. (2019b)	30 Chinese provinces	1995–2016	Panel data	$GDP \overset{-}{\rightarrow} CIWB, GDP^2 \overset{+}{\rightarrow} CIWB$,$GDP^3 \overset{-}{\rightarrow} CIWB$
			SLM	$GDP \overset{NON}{\rightarrow} CIWB, GDP^2 \overset{+}{\rightarrow} CIWB$,$GDP^3 \overset{-}{\rightarrow} CIWB$
			SEM	$GDP \overset{-}{\rightarrow} CIWB, GDP^2 \overset{+}{\rightarrow} CIWB$,$GDP^3 \overset{-}{\rightarrow} CIWB$
			SDM	$GDP \overset{-}{\rightarrow} CIWB, GDP^2 \overset{+}{\rightarrow} CIWB$,$GDP^3 \overset{-}{\rightarrow} CIWB$
Wang and He (2019)	Chinese provinces	1995–2013	SAR	$GDP \overset{-}{\rightarrow} CO_2, GDP^2 \overset{+}{\rightarrow} CO_2$,$GDP^3 \overset{-}{\rightarrow} CO_2$
Yang et al. (2019)	8 Chinese regions	1990–2014	SAR	Direct effect: $GDP \overset{-}{\rightarrow} CEI$ Indirect effect: $GDP \overset{NON}{\rightarrow} CEI$
Zafar et al. (2019)	27 OECD countries	1990–2014	CUP-BC, CUP-FM	Long run: $GDP \overset{+}{\rightarrow} CO_2, GDP^2 \overset{-}{\rightarrow} CO_2$,Financial development $\overset{-}{\rightarrow} CO_2$
			Panel Granger causality	Short run: $GDP \overset{+}{\rightarrow} CO_2, GDP^2 \overset{+}{\rightarrow} CO_2$, Financial development $\overset{+}{\rightarrow} CO_2$
Zakaria and Bibi (2019)	South Asia	1984–2015	Panel data	Financial development $\overset{+}{\rightarrow} CO_2$
Jebli et al. (2020)	102 countries	1990–2015	GMM	Low and high-income countries: $GDP \overset{+}{\rightarrow} CO_2$ Middle-income countries: $GDP \overset{-}{\rightarrow} CO_{2\ 2}$
			VECM Granger causality	$GDP \overset{+}{\rightarrow} CO_2, GDP^2 \overset{+}{\rightarrow} CO_2$
Zhao and Yang (2020)	Chinese provinces	2001–2015	FMOLS, DOLS	$GDP \overset{+}{\rightarrow} CO_2$, Financial development $\overset{-}{\rightarrow} CO_2$
Lv and Li (2021)	97 countries	2000–2014	SLM, SEM, SDM	$GDP \overset{+}{\rightarrow} CO_2, GDP^2 \overset{-}{\rightarrow} CO_2$,Financial development $\overset{+}{\rightarrow} CO_2$

Variables: CO_2 = carbon dioxide emissions, EPI = environmental pollution index, CIWB = carbon stress placed on the human well-being, which can be expressed as $\frac{\text{Carbon emission}}{\text{Well bing}}$, CEI = carbon emission intensity measured as CO_2 per GDP, GDP = gross domestic product, GRP = gross regional product

Methodology: DOLS = dynamic ordinary least squares, FMOLS = fully modified ordinary least squares, AMG = augmented mean group, CCEMG = common correlated effects mean group, ARDL = autoregressive distributed lag, PLS = partial least square, GMM = generalized method of moments, QRM = quantile regression model, SLR = spatial lag regression, SAC = spatial autocorrelation model, SLM = spatial lag model, SEM = spatial error model, SDM = spatial Durbin model, SAR = spatial autoregressive model, VECM = vector error correction model, SDPM = spatial Durbin Panel model, DSM = dynamic spatial panel, CUP-BC = continuously updated bias-corrected, CUP-FM = continuously updated fully modified ordinary least square

Source: Study findings

Table 3 Review of studies on influencing technical factors on CO_2 emissions

Authors	Countries	Period	Methodology	Findings
Amri (2018)	Tunisia	1975–2014	ARDL	$ICT \overset{NON}{\rightarrow} CO_2$
Danish et al. (2018)	Emerging economies	1990–2015	Panel data	$ICT \overset{-}{\rightarrow} CO_2$
Dehghan Shabani and Shahnazi (2018)	Iran	2002–2013	DOLS	Industry: $ICT \overset{+}{\rightarrow} CO_2$; Transportation: $ICT \overset{-}{\rightarrow} CO_2$; Services:$ICT \overset{-}{\rightarrow} CO_2$
Liu et al. (2018)	31 Chinese provinces	1996–2015	SEM	Energy intensity $\overset{+}{\rightarrow}$ EPI
Wang and Zhao (2018a)	Three parts of China based on urbanization level	1997–2012	FE, FGLS, DK	Energy intensity $\overset{+}{\rightarrow} CO_2$
Wang and Zhao (2018b)	Three regions in China	1997–2014	FE	National:Energy intensity $\overset{+}{\rightarrow} CO_2$
Wang et al. (2018)	The Pearl River Delta in China	1991–2014	Stepwise regression	Energy intensity $\overset{+}{\rightarrow} CO_2$
Shahnazi and Dehghan Shabani (2019)	The provinces of Iran	2001–2015	Dynamic SDM	$ICT \overset{+}{\rightarrow} CO_2$, $ICT^2 \overset{-}{\rightarrow} CO_2$
Zhao and Yang (2020)	The provinces of China	2001–2015	FMOLS, DOLS	Energy intensity $\overset{+}{\rightarrow} CO_2$
			PECM	Energy intensity $\overset{-}{\rightarrow} CO_2$

Variables: CO_2 = carbon dioxide emissions, EPI = environmental pollution index, ICT = information and communications technology

Methodology: FE = fixed effects, FGLS = feasible generalized least squares, DK = Regression with Driscoll-Kraay standard errors, DOLS = dynamic ordinary least squares, FMOLS = fully modified ordinary least squares, ARDL = autoregressive distributed lag, SEM = spatial error model, SDM = spatial Durbin model, PECM = panel error correction model

Source: Study findings

2018; Rahmani et al. 2020; Shahnazi and Dehghan Shabani 2019) have examined the effect of some variables on CO2 emissions in Iran, the difference between this study with them is that the effects of socioeconomic and technical factors on emissions were estimated by considering direct and indirect effects and also at the regional and national level in Iran.

Methodology

Conceptual framework

To consider the influential factors on CO2 emissions, this study relied on the conceptual framework of stochastic impact by regression on population, affluence, and technology (STIRPAT) model. The first time, the impact, population, affluence, and technology (IPAT) were offered by Ehrlich and Holdren (1971) to explain the environmental impact of anthropogenic interventions. Thus, the environmental impacts of anthropogenic interventions are represented through pollution emissions (e.g., CO2 emissions), which are affected by three factors, including population size, affluence, and technology. The IPAT framework, which attracted the attention of several researchers, does not have the ability to test the hypothesis (Li and Lin 2015; Zhang and Lin 2012). In addition, the conceptual framework considers only a limited number of variables, namely energy, affluence, and population (Wang et al. 2017). Therefore, Dietz and Rosa (1997) improved the IPAT framework to the STIRPAT that stochastic impact allows for non-monotonic or non-proportional effects from the socioeconomic and technical factors.

Some variables considered in this framework include population (i.e., Kang et al. 2016; Liu et al. 2018; Zhao and Yang 2020), urbanization (e.g., Ahmad and Zhao 2018; Li et al. 2019a; Yang et al. 2019), human capital (such as Hao et al. 2021; Rahman et al. 2021; Sarkodie et al. 2020; Yao et al. 2020b), health expenditure (i.e., Apergis et al. 2018), Engel's coefficient (Wang and Zhao 2018a), GDP per capita (e.g., Dong et al. 2017; Lin and Xu 2018; Zhou and Wang 2018), financial development (i.e., Lv and Li 2021; Zakaria and Bibi 2019; Zhao and Yang 2020), energy intensity (i.e., Wang and Zhao 2018a, 2018b; Wang et al. 2018), and ICT (Danish et al. 2018; Dehghan Shabani and Shahnazi 2018; Lee and Brahmasrene 2014).

In summary, a complete set of variables affecting CO2 emissions were considered based on the review of previous studies. Given the large number of affecting variables, they were classified into three classes according to their nature: social, economic, and technical. Social (e.g., population, urbanization, human capital, health expenditure, and Engel's coefficient), economic (such as GDP per capita, and financial development), and technical (i.e., energy intensity, and ICT) variables are measurements that assess the social, economic, and technological aspects of regions. Although the variables of R&D expenditures or patents can describe the technical aspect or the variable of trade between provinces can define the economic aspect. However, there is no information on these variables separately for the provinces of Iran, and this is a research limitation. The socioeconomic factors in addition to the direct effect on emissions indirectly affect CO2 emissions through the technical factor (Luo et al. 2018; Tambotoh et al. 2015) (Fig. 2).

Data

Based on the availability of data, this study selected panel data for 28 provinces of Iran from 2003 to 2019. The data used in the study are from the energy balance sheet of Iran, the economic and financial databank of Iran (databank.mefa.ir), and the statistical annals of provinces in Iran (www.amar.org.ir). In order to consider regional distinctions in the factors affecting CO_2 emissions, 28 provinces of Iran were divided into three regions in terms of geographical location: north, center, and south (Table 4).

CO_2 emission coefficients of each energy carrier and energy use of various carriers in every sector were used to calculate CO_2 emission data. Table 5 indicates the descriptive statistics of the variables under study. The social factor evaluates social determinants through five variables, including population, urbanization, human capital, health expenditure, and Engel's coefficient. The human capital variable is the average number of years of schooling, which can be calculated in Eq. (1):

$$AYS_{it} = \sum_{j} YR_{j.}HS_{jit} \tag{1}$$

where AYS_t is average of years of schooling for province i in year t, YR_j indicates number of years required to complete the degree j, and HS_{jt} is the percentage of the population for whom j is the highest level of education obtained for province i in year t. Health expenditure includes healthcare expenses. Engel's coefficient has been calculated as the proportion of money spent on food to total household expenses for both urban and rural regions. In addition, the economic factor assesses the two influential components of economic growth and financial development. For economic development, GDP per capita variable is considered that GDP data was deflated by the consumer price index in the year 2011. For financial development, two variables of debt to GDP ratio and ratio of domestic credit to private sector are taken into account. Finally, two variables of energy intensity, and ICT are evaluated by the technical factor. Accordingly, energy intensity is whole energy use distributed by real GDP. The energy consumption of each carrier was considered. In addition, real ICT capital stock was used per capita. Following Berlemann and Wesselhöft (2014), the initial capital stock was calculated as Eq. (2):

$$K_0 = \frac{IN_0}{\lambda} \tag{2}$$

where IN_0 and λ indicate respectively investment and long-run growth rate of investment which was estimated by the temporal effects of the investment. After calculating the initial capital stock, the capital stock was calculated applying the perpetual inventory procedure and considering the rate of capital depreciation ($\delta = 0.05$) in Eq. (3):

$$K_t = \frac{K_{t-1} + I_t}{1 + \delta} \tag{3}$$

All variables are first normalized based on Eq. (4):

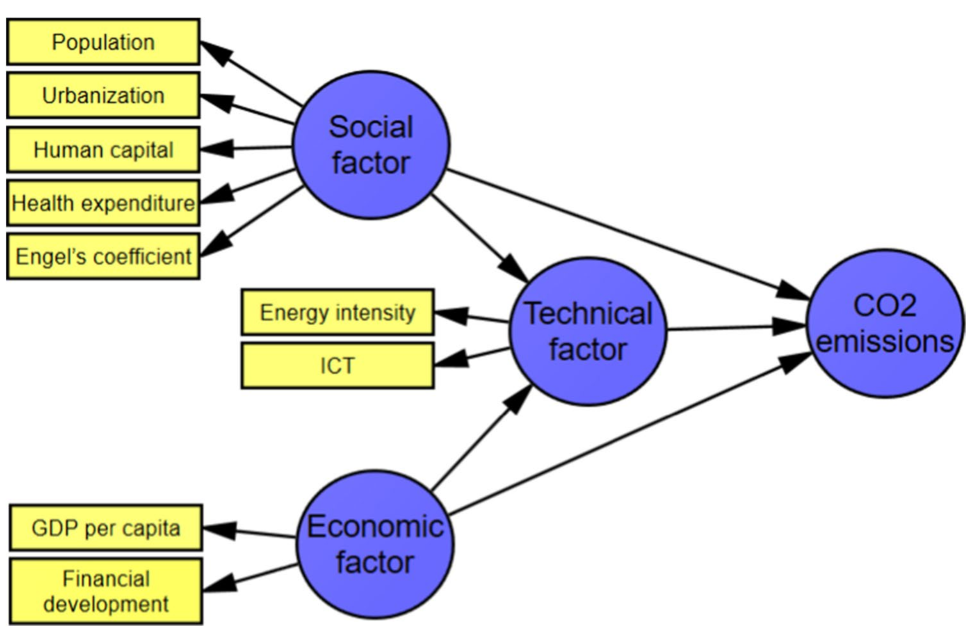

Fig. 2 The structural conceptual framework of factors affecting emissions. Source: Study findings

Table 4 Regional distinctions

Region	Provinces
North	Ardebil, Azarbayjan Qarbi, Azarbayjan Sharqi, Gilan, Golestsan, Khorasan, Mazandaran, Qazvin, Semnan, Tehran, Zanjan
Center	Chaharmahal and Bakhtyari, Esfahan, Hamedan, Ilam, Kermanshah, Kordestan, Lorestan, Markazi, Qom, Yazd
South	Boushehr, Fars, Hormozgan, Kerman, Khouzestan, Kohgiluyeh and Boyerahmad, Sistan and Baluchestan

Source: Study findings

$$\begin{cases} \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100, for\ CE1, SF1, SF2, SF3, SF4, SF5, SF6, EF1, TF2 \\ 100 - \left(\frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100 \right), for\ EF2, EF3, TF1 \end{cases} \quad (4)$$

where X_i represents the variable under investigation, X_{max} and X_{min} show the maximum and the minimum of X. The larger value of the normalized variables shows the worse CO_2 emissions but the better social, economic, and technical factors.

Figure 3 displays the average social variables of Iranian provinces. In the period 2003–2019, Tehran was the most populated province and the three provinces of Ilam, Semnan, and Kohgiluyeh and Boyerahmad were the least populated. The level of urbanization was the highest in Tehran, and Qom and the lowest in Golestsan, Hormozgan, Sistan and Baluchestan, and Kohgiluyeh and Boyerahmad. The province with the highest human capital was Azarbayjan Sharqi and the province with the lowest human capital was Azarbayjan Qarbi. In addition, health expenditure was the highest in Boushehr, Fars, and Sistan and Baluchestan and the lowest in Ilam. Finally, the most share of food expenditure in urban and rural regions was in Sistan and Baluchestan, and Kordestan, and the least share was in Tehran due to Engel's coefficients. The regional comparison of social factors showed that the southern region is better than the north and center of Iran (Fig. 6). Thus, the southern provinces have the highest expenditures on health and nutrition in comparison to other provinces (Fig. 3).

Figure 4 shows the economic factor variables in various provinces during 2003–2019. The highest GDP per capita belongs to Kohgiluyeh and Boyerahmad, Boushehr, and Khouzestan and the lowest belongs to Khorasan, Sistan and Baluchestan, and Kordestan. Kohgiluyeh and Boyerahmad, Khouzestan, and Ilam had the highest debt to GDP ratio and Tehran, Qom, and Chaharmahal and Bakhtyari had the lowest. Boushehr, Khouzestan, and Kohgiluyeh and Boyerahmad represented the greatest ratio of domestic credit to the private sector and Kermanshah, Tehran, and Hamedan represented the

Table 5 Mean and standard deviation of studied variables

Factor	Variable	Symbol	Mean (Standard deviation)				Normalization
			Nation	Northern region	Central region	Southern region	
CO_2 emissions		CE					Less is better
	CO_2	CE1	0.180 (0.125)	0.168 (0.090)	0.178 (0.122)	0.201 (0.167)	Less is better
Social		SF					More is better
	Population	SF1	0.142 (0.183)	0.206 (0.257)	0.077 (0.075)	0.133 (0.098)	More is better
	Urbanization	SF2	0.415 (0.243)	0.405 (0.229)	0.520 (0.241)	0.280 (0.192)	More is better
	Human capital	SF3	0.039 (0.047)	0.043 (0.073)	0.037 (0.104)	0.038 (0.017)	More is better
	Health expenditure	SF4	0.088 (0.138)	0.079 (0.117)	0.058 (0.106)	0.146 (0.186)	More is better
	Engel's coefficient in urban areas	SF5	0.271 (0.051)	0.256 (0.043)	0.280 (0.056)	0.282 (0.051)	More is better
	Engel's coefficient in rural areas	SF6	0.390 (0.058)	0.379 (0.058)	0.394 (0.051)	0.403 (0.065)	More is better
Economic		EF					More is better
	GDP per capita	EF1	0.139 (0.125)	0.098 (0.049)	0.114 (0.064)	0.238 (0.199)	More is better
	Debt to GDP ratio	EF2	0.896 (0.069)	0.887 (0.069)	0.892 (0.044)	0.914 (0.093)	More is better
	Ratio of domestic credit to private sector	EF3	0.990 (0.045)	0.990 (0.006)	0.985 (0.075)	0.996 (0.003)	More is better
Technical		TF					More is better
	Energy intensity	TF1	0.593 (0.152)	0.599 (0.114)	0.573 (0.142)	0.614 (0.206)	More is better
	ICT	TF2	0.015 (0.66)	0.013 (0.046)	0.021 (0.098)	0.010 (0.024)	More is better
Observation			476	187	170	119	

Source: Study findings

Fig. 3 Average social variables of Iranian provinces, 2003–2019. Source: Study findings

lowest. Regarding the economic factor, the southern region has a significantly more favorable situation than the two northern and central regions (Fig. 6). In this context, the southern provinces have the highest per capita economic growth and the most financial development (Fig. 4).

The average of technical variables is presented in Fig. 5. In the period 2003–2019, Kohgiluyeh and Boyerahmad, Ilam, and Tehran had the highest energy intensity and Qazvin, Hormozgan, and Esfahan had the lowest. Furthermore, Esfahan, and Ardebil had the highest ICT and Azarbayjan Qarbi, Azarbayjan Sharqi, Golestsn, Hamedan, Hormozgan, Kerman, Kermanshah, Sistan and Baluchestan, and Tehran had the least. Finally, the findings indicate that the central region of Iran is the leader in the technical factor compared to other regions (Fig. 6). It is because the central region has the most ICT components, especially in the Isfahan province (Fig. 5).

In addition, three social, economic, and technical factors indicate the gap among the studied regions (Fig. 6).

Econometrics methodology

SEM is one of the most complex methods of data analysis, which is not possible with other methods. This model has several practical advantages for data analysis: First, SEM allows the use of multiple observed variables in each latent construct simultaneously to achieve more valid results. Second, the model evaluates measurement error explicitly by including measurement error variables that correspond to the measurement error portions of the observed variables. A third advantage of the SEM is that it allows for complex patterns of relationships to be modelled and tested simultaneously across several hypotheses. Fourth, it is possible to test specific hypotheses on parameters by testing data consistency in intricate models (Werner and Schermelleh-Engel 2009).

Two sub-models have been used as the measurement and structural models as the SEM. Links between observed variables and latent constructs are specified by the measurement model and links among latent constructs are specified by the structural model.

In the measurement model, the column vector $X_j = \left(x_{j1}, x_{j2}, \cdots, x_{jP_j}\right)$, j = 1, 2, …, J of the observable variables link to the latent construct ξ_j, (j = 1, 2, …, J), which is noted as follows (Mueller 1996):

$$x_{jh} = \lambda_{jh}\xi_j + \varepsilon_{jh} \tag{5}$$

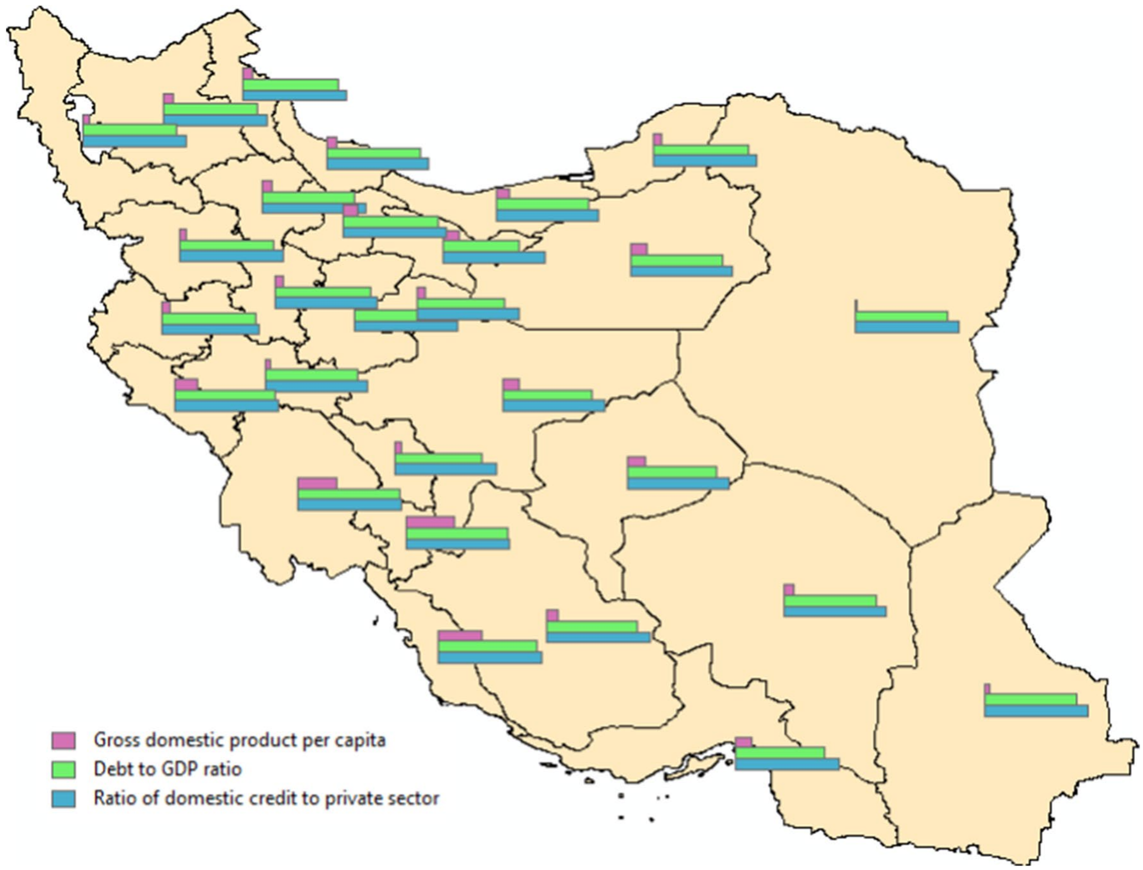

Fig. 4 Average economic variables of Iranian provinces, 2003–2019. Source: Study findings

And is a function of predictive specifications:

$$E\left(x_{ih}|\xi_j = \lambda_{ih}\xi_j\right) \tag{6}$$

where ε_{jh} indicates random error and $E(\varepsilon_{jh})=0$ (Mueller 1996). Equations 5 and 6 reveals $E(\xi_j)=0$ and $r(\varepsilon_{jh}, \xi_j)=0$. The linear relations among the latent constructs in the structural model is considered in Eq. 7:

$$\xi_j = \sum_{i\neq j} \beta_{ji}\xi_j + \zeta_j \tag{7}$$

where ζ_j represents random error, $E(\zeta_j)=0$, $r(\xi_j,\zeta_j)=0$ (Mueller 1996). If three latent constructs are considered as ξ_1, ξ_2, and ξ_3. ξ_1 directly affects ξ_3 based on Eq. 8 and ξ_1 and ξ_3 directly affects ξ_2 based on Eq. 9:

$$\xi_3 = \beta_3 + \beta_{13}\xi_1 + \zeta_3 \tag{8}$$

$$\xi_2 = \beta_2 + \beta_{32}\xi_3 + \beta_{12}\xi_1 + \zeta_2 \tag{9}$$

The indirect effect of ξ_1 on ξ_2 is calculated by Eq. 10:

$$\begin{aligned}\xi_2 &= \beta_2 + \beta_{32}\left(\beta_3 + \beta_{13}\xi_1 + \zeta_3\right) + \beta_{12}\xi_1 + \zeta_2 \\ &= \left(\beta_2 + \beta_{32}\beta_3\right) + \beta_{32}\beta_{13}\xi_1 + \beta_{12}\xi_1 + (\beta_{32}\zeta_3 + \zeta_2)\end{aligned} \tag{10}$$

Which $\beta_{32}\beta_{13}$ indicates the indirect effect of ξ_1 on ξ_2 and β_{12} indicates the direct effect of ξ_1 on ξ_2 (Gunzler et al. 2013). All procedure was operated with by the IBM SPSS Amos 20 package.

The estimated models are evaluated by several statistical criteria. Those criteria include the evaluation of a single parameter (t-test) and the whole model (Chi Square). Non-standard and standard regressions are also obtained by model estimation. The percentage of variance of the dependent variable that is explained by the independent variables is reported by R squared. In addition, the comparative fit index (CFI) compares the fit of a null model. And finally, the difference between the observed covariance matrix per degree of freedom and the hypothesized covariance matrix is calculated by the root mean square error of approximation (RMSEA). It is suggested that RMSEA values less than 0.05 are good, values between 0.05 and 0.08 are acceptable, values between 0.08 and 0.1

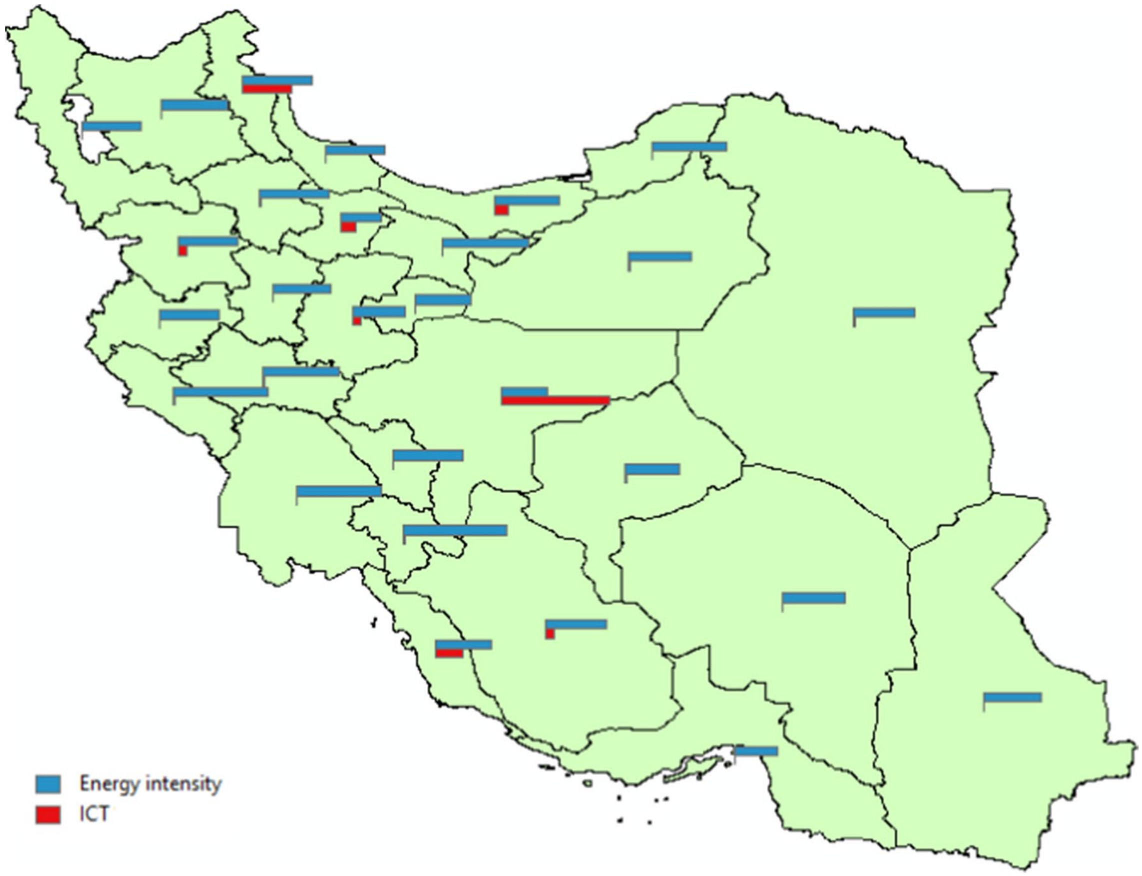

Fig. 5 Average technical variables of Iranian provinces, 2003–2019. Source: Study findings

are marginal, and values greater than 0.1 are poor (Xia and Yang 2018). In addition, two endogenous latent constructs (i.e., technical factors, and CO2 emissions) were affected by other latent constructs both directly and indirectly, hence the Hausman test suggested that there is no endogeneity problem with respect to the current model (Kock 2023).

Results

Table 6 shows the results of factor loading according to the measurement model of the SEM process. Factor analysis based on principal component analysis was used to load latent constructs from individual variables. For example, principal component analysis of the SF at the nation level showed that SF1, SF2, SF3, SF4, SF5, and SF6 loaded together on the factor (Table 6). The average variance extracted (AVE) was noted as a convergent accuracy index. As AVE is greater than half (Hair et al. 2010), proper convergence is guaranteed. As Table 6 shows, all standardized factor loadings were greater than half, indicating sufficient convergence and high reliability. Hence, the individual variables are significantly related to their latent constructs. Additionally, this study also formed hypotheses to identify variables in social, economic, and technical classes; therefore, the results were acceptable.

A correlation matrix is suggested for structural model estimation in the SEM process (Markus 2012). Accordingly, Table 7 shows the results of Spearman's correlation coefficients between latent constructs. The results of the analysis indicated a positive association between CE and SF and a positive association between CE and EF at the national level. In addition, there was a positive correlation between CE and TF. The reason for such a positive correlation is the unilateral focus on social, economic, and technological growth at the national level. TF were significantly and negatively correlated with SF but positively correlated with EF in nation. Although improving social status modulates technology growth, technology and economic growth are aligned. Moreover, there were positive correlations between CE and SF, and EF in the northern region. While CE was significantly and negatively correlated with TF in the north. In central region, CE were significantly and positively correlated with SF, and EF but negatively correlated with TF. Also, there were positive correlations between CE and SF, EF, and TF in the south. In the south compared to other regions, high energy intensity and low ICT have driven technology growth with CO2 emissions.

Table 6 Factor loadings by principal component analysis

Regional distinctions	Variable	SF	EF	TF	CE
Nation					
	SF1	0.799***			
	SF2	0.553***			
	SF3	0.727***			
	SF4	0.999***			
	SF5	0.747***			
	SF6	0.746***			
	EF1		0.774***		
	EF2		0.790***		
	EF3		0.507***		
	TF1			0.677***	
	TF2			0.677***	
	CE1				1
	AVE	0.955	0.764	0.542	1
Northern region					
	SF1	0.891***			
	SF2	0.894***			
	SF3	0.516***			
	EF1		0.772***		
	EF2		0.772***		
	TF1			0.717***	
	TF2			0.717***	
	CE1				1
	AVE	0.883	0.596	0.515	1
Central region					
	SF1	0.710***			
	SF2	0.780***			
	SF3	0.600***			
	EF1		0.706***		
	EF3		0.706***		
	TF1			0.646***	
	TF2			0.646***	
	CE1				1
	AVE	0.780	0.501	0.583	1
Southern region					
	SF1	0.721***			
	SF2	0.830***			
	SF3	0.962***			
	SF5	0.856***			
	SF6	0.828***			
	EF1		0.894***		
	EF3		0.894***		
	TF1			0.706***	
	TF2			0.706***	
	CE1				1
	AVE	0.981	0.798	0.509	1

*** significant at 1%

Source: Study findings

Table 7 Construct correlation matrix

Regional distinctions	Variable	SF	EF	TF	CE
Nation					
	SF	1			
	EF	-0.974*	1		
	TF	-0.682*	0.823***	1	
	CE	0.731*	0.868**	0.841***	1
Northern region					
	SF	1			
	EF	0.845***	1		
	TF	0.742**	0.867***	1	
	CE	0.516*	0.625*	-0.751***	1
Central region					
	SF	1			
	EF	-0.767*	1		
	TF	-0.625*	-0.754*	1	
	CE	0.873**	0.735**	-0.849***	1
Southern region					
	SF	1			
	EF	0.728***	1		
	TF	-0.614*	0.894***	1	
	CE	0.745**	0.721**	0.743***	1

*, **, *** significant at 10%, 5%, and 1%

Source: Study findings

Table 8 displays the findings of SEM. There was no significant relationship between SF and TF in the southern region. In the southern region, technology growth has originated from the attention to economic growth, especially in industrial sector, and the social factor (such as population, urbanization, and human capital) in this region is at a moderate level (Table 5). The relationship between EF and TF in the central region was also not significant. In this region, the dramatic growth of technology (i.e., ICT) is due to increasing urbanization but economic variables are at a moderate level (Table 5). Other constructs were statistically significant in all the study regions. The SF and EF had significant and negative effects on the TF in the nation (β = -0.009 and -0.269, respectively). The CE was positively affected by the TF in the national region (β = 0.763). In addition, the SF (β = -0.149) was detected to have a negative effect on the CE in the nation, while the EF (β = 0.477) had a positive effect on the CE. In the north, the CE was negatively affected by the TF (β = -0.637). In addition, the SF (β = 2.228) was detected to have a positive effect on the CE, and also the EF (β = 1.573) had a positive effect on the CE. In the central region, the TF (β = -0.826) was detected to have a negative effect on the CE, but the SF and the EF had significant and positive effects on the CE (β = 1.582 and 0.555, respectively). Finally, the CE was positively affected by the TF in the south (β = 0.596). In addition, the SF (β = 1.526) was detected to have

Table 8 The results of the structural model

	Nation		Northern region		Central region		Southern region	
	TF	CE	TF	CE	TF	CE	TF	CE
Exogenous variable								
SF	-0.009*	-0.149***	0.642**	2.228**	1.119**	1.582*	6.749	1.526*
EF	-0.269*	0.477***	0.087*	1.573**	-0.213	0.555*	6.289**	-0.970**
Endogenous variable								
TF		0.763*		-0.637**		-0.826***		0.596*
Overall R^2	0.834		0.830		0.907		0.748	
Chi-square	947.940***		327.372***		114.235***		445.952***	
Degrees of freedom	54		16		16		33	
CFI	0.939		0.938		0.984		0.989	
RMSEA	0.018		0.023		0.019		0.026	

*, **, *** significant at 10%, 5%, and 1%

Source: Study findings

a positive effect on the CE in the southern region, while the EF (β=-0.970) had a negative effect on the CE.

The SEM findings quite confirm the conceptual framework designed for STIRPAT because almost all coefficients from the three latent constructs were significant in the studied models (Table 8). The statistical criteria obtained from the results of the structural model show the good-ness of fit of the model. Chi-square statistics in four models of nation, north, center, and south were calculated to be 947.940 (with 54 degrees of freedom), 327.372 (with 16 degrees of freedom), 114.235 (with 16 degrees of freedom), and 445.952 (with 33 degrees of freedom), respectively that were statistically significant (probability level=0.000). The overall R^2 was 83% for the targeted construct, i.e., CE in the nation. This means that the 83% variation in CE was explained by latent constructs in the SEM. For the three regions of north, central, and south, the statistics were 83%, 91%, and 75%, respectively. The CFI that is not very sensitive to sample size was evaluated to be 0.939, 0.938, 0.984, and 0.989 in national, northern, central, and southern regions, respectively. Finally, the RMSEA was captured to be 0.018, 0.023, 0.019, and 0.026 in nation, north, center, and south, respectively.

According to the results of Table 9, the SF, and EF directly affected the CE in the nation (β= -0.149, and 0.477, respectively). In addition, the CE was indirectly influenced by the SF (β= -0.007), and the EF (β= -0.205). The indirect effects were from the TF path (Fig. 1). Therefore, the total effects of those factors on CE were -0.156, and 0.272, respectively. Thus, the SF which improved by population growth, urban development, improved human capital, and increased health and nutrition costs, reduced CO_2 emissions. Also, to justify the positive influence of the EF on the CE, per capita GDP and financial development are at low levels. In addition, the TF was directly affected by the SF (β= -0.009), and the EF (β= -0.269). Based on the positive coefficient of the TF (β= 0.763) on the CE, energy intensity is at the level of inefficiency and the ICT is still at the early stages.

In the north, the CE was directly affected by the SF, and EF (β= 2.228, and 1.573, respectively). Moreover, the CE was indirectly influenced by the SF (β= -0.409), and the EF (β= -0.056). Therefore, the total effects of those factors on the CE were 1.819, and 1.517, respectively. The improvement of the SF has taken the form of population growth, urbanization, human capital, and an increase in health and nutrition expenditures at the cost of increasing CO_2 emissions. Improving the EF through increasing GDP per capita and promoting financial development is accompanied by increased emissions. Also, the SF (β= 0.642), and the EF (β= 0.087) directly affect the TF. Based on the negative impact of the TF (β= -0.637) on the CE, energy consumption is efficient and the ICT is at a high level.

In the central region, SF, and EF directly affected the CE (β= 1.582, and 0.555, respectively). In addition, the SF indirectly influenced the CE (β= -0.924) and the EF indirectly influenced the CE (β= 0.176). Therefore, the total effects of those factors on the CE were 0.658, and 0.731, respectively. The positive coefficients of the impact of social and economic factors on CE indicate that the improvement of those factors has increased CO_2 emissions. In addition, the TF was directly affected by the SF (β= 1.119), and the EF (β= -0.213). According to the negative effect of the TF (β= -0.826) on the CE, improving this factor by reducing energy intensity and increasing the ICT can reduce CO_2.

SF and EF directly affected the CE in the south (β= 1.526, and -0.970, respectively). Moreover, the CE was indirectly influenced by the SF (β= -4.023), and the EF (β= 3.749). Therefore, the total effects of those factors on CE were -2.497, and 2.779, respectively. While improving the SF has an effect on reducing CO_2, improving the EF has no significant effect on emissions. Also, the SF (β= 6.749), and the EF (β= 6.289) directly affect the TF. Based on the positive effect of the TF (β=0.596) on the CE, energy intensity is at an inefficient level and the ICT is at an inappropriate level.

Table 9 The results of direct, indirect, and total effects

Regional distinction		TF			CE		
		Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Nation							
	Exogenous variable						
	SF	-0.009*	no path	-0.009*	-0.149***	-0.007*	-0.156***
	EF	-0.269*	no path	-0.269*	0.477***	-0.205**	0.272**
	Endogenous variable						
	TF				0.763*	no path	0.763*
Northern region							
	Exogenous variable						
	SF	0.642**	no path	0.642**	2.228**	-0.409***	1.819*
	EF	0.087*	no path	0.087*	1.573**	-0.056**	1.517*
	Endogenous variable						
	TF				-0.637**	no path	-0.637**
Central region							
	Exogenous variable						
	SF	1.119**	no path	1.119**	1.582*	-0.924**	0.658*
	EF	-0.213	no path	-0.213	0.555*	0.176	0.731*
	Endogenous variable						
	TF				-0.826***	no path	-0.826***
Southern region							
	Exogenous variable						
	SF	-6.749	no path	6.749	1.526*	-4.023***	-2.497***
	EF	6.289**	no path	6.289**	-0.970**	3.749	2.779
	Endogenous variable						
	TF				0.596*	no path	0.596*

*, **, *** significant at 10%, 5%, and 1%

Source: Study findings

According to Table 5, high urbanization increases emissions in northern and central regions, while high health and nutrition expenditures can reduce them in the southern areas.. However the social factor (β= 1.819, and -2.497) has the highest impact on reducing the CE in northern, and southern region, the technical factor (β= -0.826) has the most impact in the central region. In addition, the technical factor (β= 0.763) has the highest impact in the nation. According to the theoretical framework, urbanization leads to increasing use of energy and the burning of fossil fuels through rapid industrialization, mechanization, and transportation. In addition, health and nutrition expenditures, which can improve the living standards of the community, bring economic development. In all regions, the economic factor contributes to rising emissions as economic growth relies on energy use, including the consumption of polluting energy. Financial development is the financier of industrial activities and the motivator of economic growth. Moreover, the technical factor caused by severe energy intensity (Table 5) contributes to increased CO2 emissions in the southern region as well. The northern and central regions, however, can reduce emissions due to high ICT (Table 5) by applying resources more environmentally efficiently.

Discussion

The comparison of the empirical outcomes of this study and other studies as well as the mechanism of impact of social, economic, and technical variables on CO2 emissions is shown in Table 10. The results of this study indicate that the link between social factor and emissions was negative in the nation and the south of Iran. Accordingly, previous studies confirm that population growth (such as Kang et al. 2016; Yang et al. 2019; Zhao and Yang 2020), urbanization (i.e., Liu et al. 2018; Zhao and Yang 2020), promotion of human capital (e.g.,Hao et al. 2021; Khan et al. 2020; Yao et al. 2020b; Zhao and Yang 2020), and increased health (Apergis et al. 2018) and nutrition (Wang and Zhao 2018a) expenditures were reducing emissions. While the link between social factors and emissions was positive in the northern and central regions, there are several studies that confirmed the positive effects of population (e.g., Li et al. 2019a; Lin and Xu 2018; Liu et al. 2018; Wang and He 2019; Wen and Li 2019; Zhang et al. 2018; Zhou and Wang 2018), urbanization (i.e.,Hajilary et al. 2018; Li et al. 2019a; Wen and Li 2019; Yang et al. 2019), and human capital (such as Haini 2021; Mukhlis 2020; Rahman et al. 2021; Sarkodie et al. 2020) on CO2 emissions.

The negative effect of the social factor on CO2 emissions in the south of Iran compared to the positive effect of this factor on emissions in the center and north is justified based on three causes: first, the lowest mean of urbanization, second, the highest mean of health expenditure, and third, the greatest mean of nutrition in the south (Table 5). Therefore, despite the fact that there is a capacity for urbanization in the south, the living quality based on the two indicators of health and nutrition expenditures is the highest compared to other regions. The reason for the positive impact of social factors on emissions in the northern and central regions is widespread urbanization (Table 5) in those areas regardless of standard of living indicators such as health and nutrition expenditures (Table 5). In the northern and central regions, increasing 1% social factor directly increased the emissions by 2.23%, and 1.58%, respectively, but indirectly decreased the emissions by 0.41%, and 0.92%, respectively (Table 9). In other words, improving 1% social factor had directly positive effects on technical factor by 0.64% (in the north), and 1.12% (in the center). Hence, increasing technical factor resulted by improving social factor has reduced the effect size of social factor on CO2 emissions in the north (total effect: 1.819), and the center (total effect: 0.658) (Table 9). In this regard, the results of Hajilary et al. (2018) showed that the increase in urbanization rate considered a social factor causes a raise in CO2 in Iran. Regarding the developed nation, the results of Wen and Li (2019) showed that the two variables, population and urbanization rate had positive effects on CO2 emissions in China. They did not examine variables such as human capital, and health and nutrition expenditures. In addition, they limited themselves to the direct impacts of population and urbanization rates on emissions. Thus, not taking into account the indirect impacts of variables on the emissions or relationships between variables causes underestimation or even opposite effects in their study.

As shown in Table 10, economic factor was a positive driver for the emissions in the nation, the north, and the center of Iran. Accordingly, several scholars confirmed that GDP per capita (such as Li et al. 2019a; Wen and Li 2019; Zhao and Yang 2020), and financial development (i.e., Lv and Li 2021; Zakaria and Bibi 2019) were increasing emissions. In the southern region, however, there was no significant link between economic factors and CO2 emissions. The reason for the insignificance of the economic factor on emissions in the south area is the high standard deviation for variables of per capita economic growth and financial development index (Table 5). In addition, the economic variables, i.e., GDP per capita, debt to GDP ratio, and the ratio of domestic credit to the private sector are at the highest mean in the south of Iran compared to the center and the north, hence the capacity to increase the economic factor is limited in the southern regions. In Iran, improving 1% economic factor directly increased the emissions by 0.48% but indirectly decreased the emissions by 0.20% (Table 9). In other words, improving 1% economic factor had directly negative effects on technical factor by 0.27%. Hence, decreasing technical factor resulted by improving economic factors has reduced the effect size of economic factors on CO2 emissions (total effect: 0.272) (Table 9). In addition, the results of a study in Iran (i.e., Hajilary et al. 2018) showed that the impact of economic variables such as GDP, foreign investment, and energy expenditure on CO2 emissions is negligible. The results of a study in China (i.e., Wen and Li 2019) showed that economic growth was a positive driver for emissions. Despite the fact that a diverse set of variables were included in their study, they did not pay attention to the economic variable financial development. Moreover, only the direct impact of GDP growth on CO2 emissions was examined. Therefore, their results may be inaccurate and unreliable due to not considering the indirect impact of economic growth on pollution or the relationships between economic variables and social or technical variables.

Finally, the relation between technical factors and emissions was positive in Iran, as well as in the south of Iran. Accordingly, previous studies confirm that severe energy intensity (such as Liu et al. 2018; Wang and Zhao 2018a, 2018b; Wang et al. 2018; Wen and Li 2019), and increased ICT (i.e., Lee and Brahmasrene 2014) were raising the emissions. While the link between technical factor and the emissions was negative in the northern and central regions, Danish et al. (2018) confirmed the negative influence of ICT on pollution. The positive effect of the technical factor on emissions in the south of Iran compared to the negative effect of this factor on emissions in the center and north is justified based on the lowest mean of ICT in the south (Table 5). The effect of ICT on emissions is positive at low levels of ICT. The reason for the negative impact of technical factors on emissions in the northern and central regions is the reduction of energy intensity (Table 5) and the promotion of information technology (Table 5) in those regions. Technical factor decreases the emissions through applying of information technology and computer resources in a more environmentally efficient style and consuming more energy efficiently. Despite the importance of the role of ICT on CO2 emissions, foreign studies such as Wen and Li (2019), did not investigate the impact of this variable on emissions and only focused on the direct impact of energy intensity on emissions. Therefore, the contribution of this paper is that it considers a complete and diverse set of social, economic, and technical variables according to the availability of data, and in addition to the direct effects of the social factor and the economic factor on CO2 emissions, the indirect effect of those factors has been estimated through the technical factor on emissions.

Table 10 The empirical outcomes and the mechanism of impact of social, economic, and technical variables on CO_2 emissions

Factor	Variables	Studies	Mechanism of impact	Empirical outcomes	
				The current study	Other studies
Social				Nation: SF $\xrightarrow{-}$ CO_2 North: SF $\xrightarrow{+}$ CO_2 Center: SF $\xrightarrow{+}$ CO_2 South:SF $\xrightarrow{-}$ CO_2	
	Population	Li et al. (2019a), Lin and Xu (2018), Liu et al. (2018), Wang and He (2019), Zhang et al. (2018), Zhou and Wang (2018)	Natural resources are widely used to feed the growing population		Population $\xrightarrow{+}$ CO_2
		Kang et al. (2016), Yang et al. (2019), Zhao and Yang (2020)	High population density is a precondition for technological innovations i.e., the green revolution in agriculture, which increases the efficiency of production		Population $\xrightarrow{-}$ CO_2
	Urbanization	Ahmad and Zhao (2018), Hajilary et al. (2018), Kang et al. (2016), Li et al. (2019a), Lin and Xu (2018), Wang and Zhao (2018a), Yang et al. (2019)	Urbanization leads to greater use of energy and the burning of fossil fuels through rapid industrialization, mechanization, and transportation		Urbanization $\xrightarrow{+}$ CO_2
		Liu et al. (2018), Zhao and Yang (2020)	Urbanization improves resource efficiency		Urbanization $\xrightarrow{-}$ CO_2
	Human capital	Haini (2021), Mukhlis (2020), Rahman et al. (2021), Sarkodie et al. (2020)	Improving the level of human training with the unilateral goal of economic growth regardless of environmental issues		Human capital $\xrightarrow{+}$ CO_2
		Bano et al. (2018), Hao et al. (2021), Khan et al. (2020), Mahmood et al. (2019), Saleem et al. (2019), Yao et al. (2020b), Zhao and Yang (2020)	Upgrading human capital improves community understanding about environmental pollution issues and controls energy consumption		Human capital $\xrightarrow{-}$ CO_2
	Health expenditure	Apergis et al. (2018)	Improvement in the living quality of the society, and economic development		Health expenditures $\xrightarrow{-}$ CO_2
	Engel's coefficient	Wang and Zhao (2018a)	Improvement in the living quality of the society, and economic development		Engel′s coefficient $\xrightarrow{-}$ CO_2
Economic				Nation: EF $\xrightarrow{+}$ CO_2 North: EF $\xrightarrow{+}$ CO_2 Center: EF $\xrightarrow[NON]{+}$ CO_2 South:EF $\rightarrow$ CO_2	
	GDP per capita	Apergis et al. (2018), Joshi and Beck (2018), Li et al. (2019a), Lin and Xu (2018), Zhang et al. (2018), Zhao and Yang (2020), Zhou and Wang (2018)	Economic growth relies on energy consumption, including the consumption of polluting energy		GDP $\xrightarrow{+}$ CO_2
		Ahmad and Zhao (2018), Hajilary et al. (2018), Yang et al. (2019)	Higher levels of income increase demand for goods that use fewer raw materials		GDP $\xrightarrow{-}$ CO_2

Table 10 (continued)

Factor	Variables	Studies	Mechanism of impact	Empirical outcomes	
				The current study	Other studies
		Dong et al. (2017), Hosseini and Kaneko (2013), Kang et al. (2016), Li et al. (2019b), Liu et al. (2018), Lv and Li (2021), Wang and He (2019), You and Lv (2018)	The level of environmental pollution increases with economic growth. Then, when per capita income exceeds a certain level (explosion point), the environment also improves with economic growth		$GDP \xrightarrow{+} CO_2, GDP^2 \xrightarrow{-} CO_2$
	Financial development	Lv and Li (2021), Zakaria and Bibi (2019)	Financial development is the financier of industrial activities and the driver of economic growth		Financial development $\xrightarrow{+} CO_2$
		Zhao and Yang (2020)	Strengthening the level of research and development which is in the interest of environmental quality, incenting to use cleaner technologies in industries, providing low-cost loans for environmentally friendly plans, and causing company complies with environmental regulations		Financial development $\xrightarrow{-} CO_2$
Technical				Nation: $TF \xrightarrow{+} CO_2$ North: $TF \xrightarrow{-} CO_2$ Center: $TF \xrightarrow{-} CO_2$ South: $TF \xrightarrow{+} CO_2$	
	Energy intensity	Liu et al. (2018), Wang and Zhao (2018a), Wang and Zhao (2018b), Wang et al. (2018)	Burning of fossil fuels		Energy intensity $\xrightarrow{+} CO_2$
	ICT	Lee and Brahmasrene (2014)	The production, installation, and commission of ICT equipment and increasing demand for further goods and services as a result of falling prices		$ICT \xrightarrow{+} CO_2$
		Danish et al. (2018)	The application of information technology and computer resources in a more environmentally efficient style and consuming more energy efficiently		$ICT \xrightarrow{-} CO_2$

Variables: CO_2 = carbon dioxide emissions, SF = social factor, EF = economic factor, TF = technical factor, GDP = gross domestic product, ICT = information and communications technology

Source: Study findings

Conclusion

Confirming/rejecting the hypothesizes on the factors influencing CO_2 emissions

The current study investigated factors affecting CO2 emissions in Iran from 2003 to 2019. The STIRPAT conceptual framework was considered as a basic frame and factors affecting emissions were structured into three social, economic, and technical classes. The results of this study indicate that improving the social factor reduces emissions at the national level. The southern region also recognized a negative correlation between social factors and emissions. Thus, the first hypothesis has been confirmed in the south of Iran and at the national level. At the national level, the economic factor also increases emissions. The economic factor also had a positive impact on emissions in the northern and central regions. As a result, the second hypothesis has been rejected in the north, the center, and the nation. Ultimately, the advancement of the technical factor will increase CO2 emissions at the national level. The southern region also recognized such a positive relationship between technical factors and emissions. The third hypothesis has been confirmed in the south of Iran and at the national level.

CO2 emissions trap heat in the atmosphere and raises the global temperature of the earth since the emissions act like a cover in the atmosphere. As a result, global rising temperatures are affecting environmental conditions, food and water resources, climate patterns, and sea levels. This study proposes a new structure that offers appropriate solutions to reduce emissions that has originality in terms of contribution to the international literature.

Policy implications and recommendation

Based on empirical results, several policy implications and recommendations can be presented to Iran:

1. As mentioned above, the social factor in the southern region is in the highest level situation. However, this factor in the northern and central regions has led to a decrease in environmental quality as a result of increasing CO2 emissions. Thus, it is necessary to adjust the social conditions in the northern and central regions through population growth control policies. This includes reforming the current style of urbanization, and stopping rural migration and excessive population density in urban areas. In addition, the social factor in the south of Iran has a negative effect on CO2 emissions. Hence, policymakers should pay attention to the social factor if they are looking to reduce emissions in the southern region. In this regard, the growth of human capital in the south of Iran should be done with the aim of increasing sustainable development. Thus, it is recommended that environmental organization officials provide environmental awareness to skilled and educated people in the south of Iran.
2. Economic factor has a crucial impact on raising the pollution in the north and center compared to the south of Iran. Thus, Iranian policymakers should prevent a unilateral increase in GDP and financial development in those regions. Economic growth is the goal of all policymakers. However, if the policymaker seeks to reduce emissions, policies to improve the environment, especially CO2 emissions, must be considered along with growth. There are two recommendations to improve the environment. First, mandatory policies have been adjusted in Iran by the environmental protection organization and care for the environment is in Iran's development plans and prospects. Second, market-based policies encourage the private sector to reduce emissions. In the second recommendation of intervention, nations use tax and subsidy tools to influence market performance and the increase in pollution. However, in Iran, the second one is not taken solemnly. So far, no specific action has been taken on green taxation although the taxation was included in Iran's general environmental policies in 1995. Despite the development plans of environmental control and protection in Iran, their effectiveness has been very low according to the main goals of the economy, i.e., suitable economic growth. In other words, state development plans did not provide a good context for environmental protection. Thus, policies need to be market-based to increase efficiency in the economy of Iran.
3. The findings of this paper show that the technical factor is the most in the center of Iran. The direct impact of technical factors on the emissions in the north and central areas is negative, while positive in the south. If policymakers are looking to decrease emissions, it is better to pay attention to technical factors, i.e., improving energy efficiency as well as upgrading ICT in the northern and central regions. Policymakers should limit technical factors to reduce CO2 emissions in the southern area.

To guide future studies, it is recommended to extend the study approach to several major CO2-emitting countries. In this regard, a number of major CO2-emitting countries are selected and the factors affecting environmental pollution in three social, economic, and technical classes are examined. Also, the inter-regional spillover effects of economic, social and technical factors on CO2 emissions should be investigated using spatial models.

The limitation of the current study is that territorial differences for Iran have been provincial not based on three regions of north, center, and south. Thus, this study considered the northern, northwestern, and northeastern provinces as northern region; specified the central, western, and eastern provinces as central region; assigned the southern, southwestern, and southeastern provinces as southern region.

Appendix

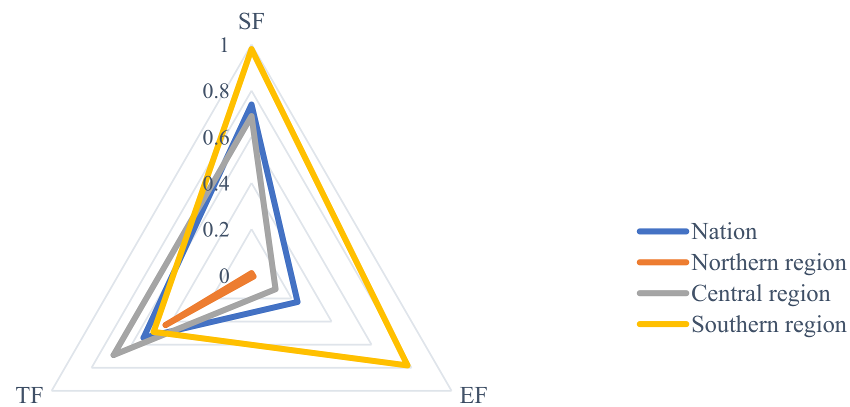

Fig. 6 The gap for social, economic, and technical factors among three studied regions

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Data availability The datasets generated and/or analyzed during the current study are available in the https://pep.moe.gov.ir/

Declarations

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