**ORIGINAL PAPER** 



# Revisiting the nexus between migration, energy consumption, innovation, and CO<sub>2</sub> emissions in Germany

I. Ullah<sup>1</sup> · R. Magdalena<sup>2,3,4,5</sup>

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#### Abstract

The study investigates the nexus between innovation, labor migrations, energy consumption and  $CO_2$  emissions in Germany for the period 1990–2020. This study applied a dynamic simulated ARDL (DS-ARDL) model for estimation, which can observe the negative and positive variations in variables both in long run and short run. The dependent variable in DS-ARD provides a more intuitive picture of dynamic effects than coefficients alone. In Addition, DS-ARDL may provide reliable estimations even if sample size is smaller. The results of this study suggest a long-term relationship among innovation, migration, energy consumption, and CO2 emissions. The results also confirm that migration has a positive relationship with  $CO_2$  emissions, while innovation has an adverse effect on CO2 emissions in long run. Policymakers can take action on both ends of the supply and demand spectrum to lessen the impact of migration on Germany's  $CO_2$  emissions. Human capital accumulation provided by international migration; therefore, receiving countries should encourage rapid technological advancement and improve their citizens' spending habits.

Keywords Migration · Energy consumption · Innovation · CO<sub>2</sub> emissions · Germany

# Introduction

Climate change, which is triggered by human activities, has far-reaching, negative consequences for businesses, regions, and the environment in general. (IPCC 2022). Carbon dioxide (C02) in the atmosphere has risen due to human economic

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 R. Magdalena Magdalena.radulescu@upit.ro; Magdalena.radulescu@upb.ro
 I. Ullah irfanecon@nuist.edu.cn

- <sup>1</sup> Nanjing University of Information Sciences and Technology, Nanjing, China
- <sup>2</sup> National University of Science and Technology Politehnica Bucharest, Pitesti University Centre, Pitesti, Romania
- <sup>3</sup> Institute of Doctoral and Post-Doctoral Studies, Lucian Blaga University of Sibiu, Sibiu, Romania
- <sup>4</sup> BEU-Scientific Research Center, Baku Engineering University, Baku, Azerbaijan
- <sup>5</sup> UNEC Research Methods Application Center, Azerbaijan State University of Economics (UNEC), Istiqlaliyyat Str. 6, 1001 Baku, Azerbaijan

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activity, specifically the burning of fossil fuels. The effects of global warming are widespread and devastating, caused by high temperatures and repeated catastrophic events. Initiatives to diminish greenhouse gas emissions undoubtedly expedited the implementation of international agreements. International environmental agreements have helped define the global environmental system, even if just a few countries are involved. Increasing production and decreasing carbon dioxide emissions while maintaining environmental quality remains challenging in the current era. Innovations are considered an engine of growth, and can occur at different levels, such as organizational innovation, service innovation, or product innovation (Serrat 2009). Innovation boosts productivity and reduces energy consumption and CO<sub>2</sub> emissions. A significant benefit of innovation is that it reduces CO<sub>2</sub> emissions without slowing economic growth. Besides reducing energy costs, it has also led to developing of novel solutions to conserve energy. Energy efficiency can be measured in terms of the energy density indicator. Energy density is the energy input ratio to economic output. When this ratio is considered, it might be helpful to determine the innovation effects on energy efficiency. (Pan et al. 2019). Rapid economic expansion has been linked to rising carbon dioxide emissions despite improvements in energy efficiency. Global



climate change, exacerbated by rising emissions of greenhouse gases, has emerged as a significant threat to human survival and development. Several studies have revealed the positive association between energy consumption and carbon emissions (e.g. Ang 2008, Zhang and Cheng 2009, Soytas and Sari 2009, Alkhathlan and Javid 2015, Ahmad et al. 2016). Environmental degradation, economic growth and energy consumption have received considerable attention in the literature (Stern 2004). For example, increased economic growth and energy consumption have contributed to rising carbon dioxide emissions and environmental degradation (Das and Paul 2014).

Germany has opened its doors for migration over the last few decades, significantly contributing to economic development and environmental quality. Migration increases host countries' carbon emissions and energy consumption (Hoesly et al. 2018; Turton and Hamilton 1999; Qi & Li 2020). For example immigrants entering the United States are responsible for producing an additional 482 million metric tonnes of carbon dioxide equivalent annually. Greenhouse gas emissions in Australia are forecast to rise during the next 20 years due to the nation's rising immigration and population (Turton and Hamilton 1999, Hoesly et al. 2018).

This study aims to fill a gap in the existing literature by using innovation as a significant variable and its implications on CO<sub>2</sub> emissions. This study contributes to the literature in the following aspects: First, although the relationship between energy use, innovation, and CO<sub>2</sub> emissions has been extensively investigated, little has been explored about the role of migration as a key explanatory factor, especially in the context of a developed economy such as Germany. This study provides new insights on how demographic changes impact energy consumption and environmental consequences by incorporating migration into the environmental-economic framework. Second, in order to evaluate both short-run and long-run dynamics, this study reexamines the relationship using updated data and sophisticated econometric techniques, such as nonlinear ARDL and causality testing. Potential asymmetries and involved feedback mechanisms that previous linear models might have missed are addressed by this methodological improvement. Third, Germany represents a special case for studying how technological innovation, driven in part by skilled migration, interacts with environmental sustainability objectives since it is a leading industrial economy and a major recipient of migrants in Europe. This work empirically investigates whether innovation acts as a mitigating or amplifying agent in the energy-emissions path. The remaining paper is organized as; Sect. "Literature review" consists of review of literature, Sect. "Materials and methods" and "Results and discussion" contain the research methodology and results & discussion. While Sect. "Conclusion" is based on the conclusion of the study.

#### Literature review

Literature has examined the migration, energy consumption, innovation and CO<sub>2</sub> emission in different regions. Isik et al. (2019) examined GDP, population, and energy in eleven US states from 1989 to 2915. The results suggest that Florida, Illinois, Michigan, New York, and Ohio are among the states for which the EKC hypothesis is true. The energy from the fossile fuels has a negative impact on CO2 emissions in Texas and has a positive effect on CO2 emissions in Florida. However, this effect is less pronounced than in other US states. Hanif (2018) applied the GMM model to analyze the relationships between urbanization, the consumption of fossil fuels, economic growth and renewable energy on CO<sub>2</sub> emissions in Sub-Saharan African economies during 1995-2015. Their findings suggest that fossil fuels positively affected CO<sub>2</sub> emissions. Saboori and Sulaiman (2013) studied long run relationship between oil consumption and environmental degradation in three Asian nations between 1980 and 2013. They applied Johansen cointegration and found that South Korea's energy consumption and CO<sub>2</sub> emissions are causally related in a single direction. Bhat (2018) examines the relationships between the effects of energy consumption and economic growth on carbon dioxide during 1992-2016. They found that energy consumption has a favorable impact on CO<sub>2</sub> emissions. Sulaiman and Abdul-Rahim (2017) examine nexus between energy consumption, CO<sub>2</sub> emissions, and economic activity in Malaysia and suggest that energy consumption positively affects the CO<sub>2</sub> emissions. Past studies on innovation and CO<sub>2</sub> have produced mixed results using various samples, methods, and procedures. Various reforms have been adopted to promote renewable energy and reduce CO2 emissions. By encouraging renewable power sources, innovation helps reduce greenhouse gas production. Dauda et al. (2021a, b) discovered, using panel data from 1990 to 2016, that innovation and CO2 emissions were inversely associated in various African countries, lending credence to EKC's hypothesis. Using panel data, Dauda et al. (2021a, b) found a negative nexus between innovation and CO<sub>2</sub> emissions in different African countries. Similarly, Toblemann and Wendler (2020) have also investigated the impact of environmental innovation on CO<sub>2</sub> emissions. The authors compare nations' responses to innovation and find that the less developed countries are more likely to show significant variability. They also discovered that environmental innovation is significantly related to lower carbon dioxide emissions, and innovation has no effect.

According to Du et al. (2019), green technologies have a limited impact on  $CO_2$  reduction in poor economies, while there is high effect in developed economies. Fernández et al. (2018) analyzed technological advancement affected  $CO_2$  emissions in China for the period 1990–2013, the United



States, and the European Union. They found that industrialized countries' CO<sub>2</sub> emissions have decreased dramatically due to their investment in R&D but that this effect has not been seen in developing nations. Similarly, another study shows that different types of innovation will have a varying impact on  $CO_2$  emissions. According to Yan et al. (2017), green innovations cut carbon dioxide emissions significantly, but grey innovations has a negligible effect. Since empirical studies suggest a negative correlation between CO<sub>2</sub> emissions and technological innovation, government stakeholders may need to finance the R&D activities to promote economic growth and environmental sustainability. According to Long et al. (2018), Innovation helps lower China's CO2 emission intensity. Samargandi's (2017) findings suggest that cutting-edge production-side technical innovation is the key to mitigating the effects of emissions. They found that technological advancements improve production and consumption choices, reducing the negative impact of emissions from all sources (Apergis et al. 2013). Kahouli (2018) analyzed the relationships between R&D activities, CO<sub>2</sub> emissions, and economic growth in Mediterranean Countries (MCs) for the period 1990–2016.

Mensah et al. (2018) analyzed relationships between GDP, renewable and non-renewable resources, R&D, and CO<sub>2</sub> emissions in 28 OECD countries. The findings indicate that R&D helps reduce emissions and maintain ecosystem, while both GDP and non-renewable energy sources increase CO<sub>2</sub> emissions.

Population migration literature we have been analyzed in the literature such as Birdsall (1994), which suggests that a growing population may raise emissions of greenhouse gases. First, increased transportation, industry, and power demand could increase fossil fuel emissions due to a growing population. Second, a growing human population means more trees are cut down, new land uses are developed, and more firewood is used. Komatsu et al. (2013) used data from Hanoi, Vietnam, to conclude that population movement had a negative impact on both energy usage and carbon emissions. This may have occurred because of the increased population density due to rural residents migrating to Hanoi. A recent study employing an input-output and network approach discovered that interprovincial mobility at the national level influenced China's trade-induced carbon emissions (Gao et al. 2021).

# **Materials and methods**

#### Data

This study analyses annual frequency time series data for Germany between 1990 and 2021. The study contains variables such as population migration, innovation, and energy consumption on the country's carbon dioxide  $(CO_2)$  emissions. This study analyzes the effects of energy consumption, innovation, and population on Germany's CO<sub>2</sub> output. The country was chosen because of the rapid expansion of its Biofuel industries (Xu et al. 2020). The data is obtained from World Bank and Federal Reserve websites. CO2 emissions are the dependent variable, measured in metric tons per capita; the explanatory factors include energy consumption, measured as a fraction of final energy consumption; the percentage of land used for agriculture; and the percentage of land used for crop production. While the number of newcomers measures international migration, research and development (R&D) efforts provide a measure of innovation (Table 1).

# Specifications of the model and methodology

Conventionally, researchers have investigated the relationship between innovation and CO<sub>2</sub> emissions using timeseries methods, including cointegration analysis with ARDL, Granger causality, and error correction modeling. However, only the long- and short-term correlations can be assessed using the auto-regressive distributed lags model described by (Pesaran et al. 2001). These methods cannot adequately address the problems that arise from contrasting model specifications over long and short periods. The current approach allows for the automated stimulation, estimation, and plotting of counterfactual predictions of variations in one independent variable and its effects on variable which is dependent by maintaining the other independent variable as constant. The dynamically simulated ARDL model was expanded to investigate further for analysis. It is a novel technique developed by Jordan and Philips (2018). Stationarity and sequential integration of the variables were tested with unit root tests. While most ARDL models integrate all of their variables at the I(0)

 Table 1
 Variable Description

Variables operationalization					
Variable		Туре	Measurement Technique & Proxy		
CO <sub>2</sub>	Carbon Dioxide emissions	Dependent variable	CO <sub>2</sub> metric tons per capita		
MIG	Migration	Independent variable	Migration (Arrivals)		
INNV	Innovation	Independent variable	R&D spending		
EC	Energy Consumption	Independent variable	% of total final energy consumption		



level, this one merely integrates a subset of them at that level. Before using a dynamically simulated ARDL, we conducted ADF (Dickey & Fuller 1979) tests to ensure that the stationarity of the variables, a prerequisite for the ARDL, was maintained throughout simulations. The estimation can be performed using the following equation.

$$CO_2 = f(INNV, MG, EC)$$
 (1)

In regression form,

$$Y(CO_2) = \alpha + \vartheta_1(INNV) + \vartheta_2(MG) + \vartheta_3(EC) + \varepsilon_t$$
(2)

where CO2 stands for carbon dioxide,  $\vartheta_1$ ,  $\vartheta_2$ ,  $\vartheta_3$ ,  $\vartheta_4$  all indicate the coefficients of the corresponding explanatory variables, including innovation (INNV), population migration (MG), and energy consumption (EC). Before running cointegration tests, it is crucial to ensure that all time series are stationary because spurious regression may occur if nonstationary variables are discovered. ADF testing is done as a result. Following are the general equations for the ADF test:

$$x_t = r_t + \beta t + \varepsilon_1$$

The regression equation decomposes this into a random walk (represented by rt), a deterministic trend (represented by  $\beta$ t), and a stationary error (represented by  $\epsilon$ 1).

$$\Delta x_t = \varphi x_{t-1} + \sum_{i=1}^m \delta \Delta x_{t-i} + \varepsilon_t$$

In this expression,  $\Delta$  means the difference operator,  $\alpha$  means the intercept, t means the time index,  $\varphi$  means Y denotes the coefficient, the coefficient of the time trend, m means the number of lags in the autoregressive model and  $\varepsilon_t$  means random error.

The dynamic simulated ARDL approach performs the limits test in order to investigate the long-run nexus between variables. The model's equation is written as follows:

$$\begin{split} \Delta CO_2 = & \beta_0 + \sum_{i=0}^u \beta_1 \Delta \big( CO_2 \big)_{t-1} + \sum_{i=1}^t \beta_2 \Delta (MG)_{t-1} + \sum_{i=0}^u \beta_3 \Delta (EC)_{t-1} \\ & + \sum_{i=0}^v \beta_4 \Delta (INNV)_{t-1} + \beta_1 \big( CO_2 \big)_{t-1} + \beta_1 (MG)_{t-1} \\ & + \beta_2 (EC)_{t-1} + \beta_3 (INNV)_{t-1} + \epsilon_t \end{split}$$

where it denotes the first dissimilarity term, EC stands for electrical consumption, MG stands for international movement, INNV denotes technological advancement, and  $CO_2$  denotes carbon dioxide. When t I, the first lag is taken into account. The long-run nexus is estimated using the equation mentioned above. Alternative and null hypotheses for the ARDL limits test are presented as follows.

$$H_0 = \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = \varphi_6 = 0$$



$$H_1 \neq \varphi_1 \neq \varphi_2 \neq \varphi_3 \neq \varphi_4 \neq \varphi_5 \neq \varphi_6 \neq 0$$

Both accepting and rejecting the null hypothesis are supported by the calculated F-statistics. There will be a longterm association between the study's variables if the F-statistic values are higher than the upper bounds; otherwise, there will be no such relationship (Pesaran et al. 2001). If, however, F-statistic value reaches both extremes, the result is inconclusive. CUSUM and CUSUMS-Q are used to evaluate the model's reliability of the estimations (Brown et al. 1975). Both the cumulative sum control chart (CUSUM) and the cumulative sum control chart assess the model's consistency (CUSUMS-Q).

### The ARDL model

Compared to other time series models, the ARDL approach has significant advantages (Pesaran et al. 2001). Longitudinal data are not a good fit for the traditional ARDL approach (Haug 2002). The approach intends to unearth temporal patterns in otherwise unrelated data sets. Researchers in the past and present have used a variety of cointegration techniques. The cointegration technique has been developed by many researchers (Engle & Granger 1987; Johansen & Juselius 1990; Philips and Hanson 1990), and all have their drawbacks, such as an illegible order of integration for variables and an inability to estimate structural breaks. As an alternative to the other choices, ARDL is comparatively better estimation tool.

#### **Dynamic simulated ARDL model**

A dynamic simulated ARDL model is applied in this study; the conventional ARDL model has some shortcomings, which made it unusable for evaluating different model specifications over long and short run parameters, which the dynamic simulated ARDL model aims to rectify. Dynamic simulated ARDL model's potential is emphasized by its ability to promote, estimate, and forecast the counterfactual variations in a single independent variable and its effect on the regression by keeping the other independent variable constant (Jordon and Philips 2018; Sarkodie & Strezov 2019). This approach facilitates the estimation, stimulation, and tracking of charts, as well as the identification of both immediate and long-term relationships between negative and positive elements. While ARDL model of Pesaran et al., (2001) can only estimate the long-term relationships between variables. The technique can be applied to the combined/mixed integration order of I(0) and I(I), which takes all the other parameters constant. This research explores the types of regressors affected by spurious adjustments and the specific ways in which these effects manifest themselves. In order to fix ARDL shortcomings, DS-ARDL modifies the equation of (E.g., Jordon & Philips, 2018; Sarkodie & Strezov 2019) as follows

Descriptive Statistics					
	CO <sub>2</sub>	EC	INNV	MG	
Mean	0.221421	8.401612	2.54384	270,301.3	
Median	0.218908	7.935	2.4664	302,893	
Maximum	0.327705	17.17	3.19114	482,849	
Minimum	0.146703	1.988633	1.88235	45,985	
Std. Dev	0.048347	5.429243	0.39721	143,768.4	
Skewness	0.312853	0.153603	0.034193	-0.19857	
Kurtosis	2.190451	1.421534	1.853271	1.717463	
Jarque–Bera	1.395838	3.447907	1.759551	2.403485	
Probability	0.49762	0.17836	0.414876	0.30067	

Table 3 ADF Unit root test

Stationarity Tests (ADF)					
	At level	At first difference			
Variables	constant	constant	Conclusion		
CO <sub>2</sub>	-2.460648 (0.1345)	-5.607024 (0.0001)	I (1)		
REC	-1.275578 (0.6276)	-5.518533 (0.0001)	I (1)		
MG	-5.132299 (0.0002)		I (0)		
INNV	-0.423123 (0.8930)	-5.554054 (0.0001)	I (1)		

 $\Delta CO_{2t} = \beta_0 + \theta_0 CO_{2t-1} + \beta_1 \Delta INNV_t + \theta_1 INNV_{t-1}$ 

+  $\beta_2 \Delta EC_t + \theta_2 EC_{t-1}$ +  $\beta_3 \Delta MG_t + \theta_3 MG_{-1} + \gamma_1 ECT + \varepsilon_t$ 

## **Results and discussion**

Before analyzing the data, a detailed statistical analysis is conducted for the study variables. Table 2 contains the descriptive statistics results, which reveal that the mean value of  $CO_2$  is 0.221421 with a standard deviation of 0.048347. The average value for EC is 8.401612 along with a standard deviation of 5.429243, the mean value for INNV is 2.54384 with a standard deviation of 0.39721, and the mean value for MG is 270,301.3 with a standard deviation of 143,768.4.

The ADF test was utilized to examine the stationarity properties of the variables. Table 3 shows ADF findings; all the variables are not stationary at level except for one series, i.e., the migrations. When converting to the first difference, all series with a unit root become stationary. In other words, all variables except for migration, which is stationary at level,  $CO_2$ , EC, and INNV become stationary at first difference. Given that the variables are stationary, the ARDL Bounds test can be used to identify cointegration. The inconsistencies in the results have led us to consider using dynamic simulated ARDL to estimate and analyze the variables in our study. All of the variables in this work have mixed findings when considered stationary and integrated at mixed orders of I(0) and I(1), which suggests applying the ARDL model for long-term estimations.

Values in parentheses are Asymptotic critical values\*

#### **KPSS unit test result**

Table 4 presents the unit root results; The KPSS unit root test estimates the unit root with constant time trend functions. The estimated t-statistics values of CO<sub>2</sub> emissions, EC, and INNV are greater than critical values, this implies that at level the series are not stationary. The test is performed at first difference of the variables and at first difference CO<sub>2</sub> emissions, EC and INNV become stationary as their estimated coefficients are less than critical values. MG unit root test shows that it is stationary at the level since their t-statistics values are below the threshold value. In addition, Except MG, the results suggest that at level all the variables are non-stationary. This indicates that most of the series contains a unit root which can be fixed by converting them into first difference. To summarize the unit root test results MG is only stationary variables at the level while CO<sub>2</sub>, EC, and INNV are all non-stationary variables.

Wald F-test results are presented in Table 5, which was estimated by using the Narayan (2004) critical values. The results suggest that estimated F-statistic exceeds the upper bound critical value at 5% level of significance. This indicates the existence of the long-term relationship between the study variables.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS)						
	At level		At first difference			
Variables	Constant	Constant with trend	Constant	Constant with trend	Conclusion	
CO <sub>2</sub>	0.754087 (0.463000)	0.194489 (0.146000)	0.309104 (0.463000)	0.070591 (0.146000)	I (1)	
REC	0.613569 (0.463000)	0.119810 (0.106000)	0.201076 (0.463000)	0.202709 0.146000	I (1)	
MG	0.176215 (0.463000)	0.163167 (0.216000)			I (0)	
INNV	0.746690 (0.463000)	0.161254 (0.146000)	0.049955 (0.463000)	0.049855 (0.146000)	I (1)	



Table 5	ARDL	Bounds	cointegrat	tion test
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Significance level	critical values	f statistics	
	lower bound	upper bound	
1%	3.37	3.81	
5%	2.67	3.93	4.66
10%	2.49	4.58	

Bounds test values are based on Narayan (20,040; case D: restricted constant & no time trend

Table 6 The Dynamic Simulated ARDL long and short-term results

Variables	Coefficients	SE	T-ratio	P-value
Intercept	-0.088	0.036	-2.444	0.033
MG	0.0466	0.0146	3.193	0.003
EC	0.0431	0.0123	3.583	0.001
INNV	-0.0168	0.0069	-2.434	0.015
$\Delta$ MG	0.0048	0.0037	1.297	0.198

Table 6 shows variables' short- and long-term effects on carbon emissions, with conflicting results for Germany. A negative and significant association between innovation (INNOV) and CO<sub>2</sub> emissions has been found. Recently, a new research stream suggested that technological innovation helps to lower CO<sub>2</sub> emissions (Erdoğan et al. 2020; Nguyen et al. 2020; Chen and Lei 2018). This argument is supported by our results since innovations (INNOV) has negative and significant effect on Co2 emissions. This indicates that 1% increase in INNOV contributes to a 1.68% decrease in CO2 emissions in long run. The results of this study are in line with the findings of Du et al. (2019) and Braungardt et al. (2016) suggesting a negative relationship between innovations and CO<sub>2</sub> emissions.

Further, Mensah et al. (2018) studied the linkages between innovation and CO<sub>2</sub> emissions for the OECD countries and reported that innovation is essential factor in reducing  $CO_2$ emissions. Innovation improves environmental quality, provides sustainable economic growth. It has been found that there is a long-term, very significant positive correlation between migration (MG) and CO<sub>2</sub> emissions in Germany, with a 5% level of significance. The model finds that migration has a positive and considerable impact on CO<sub>2</sub> emissions, with a 1% increase in migration leading to a 4.66% increase in CO<sub>2</sub> emissions in the long run. Our results provide conclusive evidence for the hypothesis that carbon flows will grow if migrations increase due to transport and communication technology developments and, more generally, globalization processes. However, Menyah and Wolde-(2010) Rufael's research found the opposite. This research lends credence to the idea that migration raises carbon emissions

outside of the Northwest's borders, comparing it to the other four subregions (Gao et al. 2021). This finding credences to concerns that human migration increases atmospheric carbon dioxide concentrations (Price and Feldmeyer 2012; Migration Watch 2010). Thus, migration patterns may contribute to rising levels of carbon dioxide emission in Germany due to factors like population expansion, rapid urbanization, rising consumption, and rising transportation needs (Migration Watch 2010). However, migration is a key factor in the expansion of international aviation. Immigrants also need reliable means of transportation. Many immigrants fly to different nations. Over the next few decades, aviation is projected to significantly expand its emissions of greenhouse gases (Migration Watch 2010). Furthermore, obtaining work is the most pressing issue for immigrants. Due to their employment search, immigrants flock to metropolitan regions, contributing to the aforementioned trends of urban population expansion and increased transit usage (Kim 2009). This means that an increase in the urban population and the demand for transportation services directly impact the amount of greenhouse gases released into the atmosphere.

Furthermore, there is a long-term, substantial positive link between energy consumption and CO<sub>2</sub> emissions, and this relationship is significant at the 5% level in Germany. According to Zhang and Cheng (2009), we used data from 1960–2007 to look at China's energy consumption and carbon dioxide emissions to determine whether or not there was a Granger causality relationship between the two. Indications are that long-term CO<sub>2</sub> emissions are rising due to increased energy use. The co-integration between energy use and CO<sub>2</sub> emissions is demonstrated by Bekun et al. (2019). Our findings are supported by theirs, which show that increasing energy use raises CO<sub>2</sub> emissions. Compare and contrast (Salim 2012) with (Salim et al. 2017) to see how the two sets of results compare to the ones presented here (Sapkota & Bastola 2017; Nequaye & Oladi, 2015; Zhu et al. 2016). There is a positive correlation between  $CO_2$ emissions and energy usage, as demonstrated by our findings and corroborated by those of Menyah and Wolde-Rufael (2010) for the United States and Apergis and Payne (2010) for a group of 19 industrialized and developing nations.

The relationships between MG and  $CO_2$  in Germany are shown in Fig. 1. The graph shows how the fluctuation in population migration has affected carbon dioxide levels in the real world. When MG levels rise by just 5%,  $CO_2$  levels in Germany begin to decline. A drop of just 5% in MG has positive long-term and short-term effects on Germany's  $CO_2$ emissions.

The correlations between Germany's EC and  $CO_2$  emissions are shown in Fig. 2. Changes in EC and their effect on carbon dioxide emissions are shown graphically. If Germany's EC were to grow by 5%, the country's  $CO_2$  emissions

would decrease. However, a drop of 5% in Germany's EC has beneficial effects on  $CO_2$  in both the long and short term.

The relationships between INNV and  $CO_2$  in Germany are shown in Fig. 3. The graph shows how the fluctuation in innovation has affected carbon dioxide levels in the real world. When INNV levels rise by just 5%,  $CO_2$  levels in Germany begin to decline. A drop of just 5% in INNV has positive long-term and short-term effects on Germany's  $CO_2$ emissions.

Several statistical diagnostic tests are summarized in Table 7. The purpose of these tests was to determine how accurate the model was. Serial correlations are absent in the model, as demonstrated by the "Breusch Godfrey LM" test. The normality of the generated residual models is confirmed by the Shapiro–Wilk test, while the "Ramsey RESET" test validates correct model usage and specification.

# Stability tests

This analysis, depicted in Fig. 4, employs the cumulative sum of resources (CUSUM) for evaluating stability of parameters in the models. The coefficients in the following graphs show stability at the 5% significance level, indicating that the models used in this study are accurate. In the middle of the red lines, there are blue lines located. All sampling periods in China use the same parameters.

# Conclusion

In this state-of-the-art model for 1990–2021, we study the link between Germany's  $CO_2$  emissions, energy consumption, migration, and innovations. This study investigates how variations in innovation, energy consumption, and



Fig. 1 Impulse response plot for Migration and CO<sub>2</sub>



Fig. 2 The "Impulse Response Plot" for Energy Consumption and CO<sub>2</sub>









Fig. 3 Impulse response plot for Innovations and CO<sub>2</sub>

 Table 7
 The diagnostic tests

Serial cor- relation Breusch- Godfrey LM test	Shapiro– Wilk Test for Normality	Ramsey RESET test	R-squared	Adj. R-squared
0.023 (0.879)	0.943 (0.103)	0.053 (0.265)	0.9872	0.9847

migration have affected  $CO_2$  emissions in Germany by using simulated ARDL model. This study uses novel technique of dynamically simulated ARDL model to analyze the impact of innovation, migration, and energy consumption on  $CO_2$ emissions in Germany. The augmented Dickey-Fuller (ADF) and KPSS tests are applied for the unit root test. The results of the ARDL bounds test confirm long-term interdependence between variables. Results over time show that Germany's energy usage has a significant positive effect on the country's  $CO_2$  output. In addition, the novel Dynamic simulated ARDL model discovered a positive and significant correlation between migration (MG) and  $CO_2$  emissions.



Increases in long-term migration in Germany lead to a substantial increase in greenhouse gas emissions. The result of this study provides conclusive evidence for the hypothesis that carbon flows will grow if migrations increase due to transport and communication technology developments and, more generally, globalization processes. The impact of innovations on carbon dioxide emissions is large and detrimental. To be more explicit, reducing CO<sub>2</sub> emissions by 1.68% results from a 1% rise in INNOV over the long run. Numerous people enter Germany for employment. The current trend is expected to persist. Policymakers can take action on both ends of the supply and demand spectrum to lessen the impact of migration on Germany's CO<sub>2</sub> emissions. Human capital accumulation is aided by international migration; therefore, receiving countries should encourage rapid technological advancement and improve their citizens' spending habits. Carbon taxes on final goods and services are one tool governments can use to influence consumer behavior.

First and foremost, Germany's federal and state governments need to pay attention to these unfavorable effects of



Fig. 4 CUSUM and CUSUMSQ tests for Parameter Stability

¥ 4

migration. Regarding population migration, the government has historically focused on economic development issues and ignored migration's impact on carbon emissions. Additionally, this paper's findings have substantial policy implications for the federal and state governments of Germany. To begin, increasing energy usage always has a negative impact on the environment. However, energy consumption is fundamental to economic expansion and output generation. Therefore, policymakers should weigh the costs and benefits of various energy consumption scenarios to determine the sweet spot. From a policy standpoint, the study emphasizes the significance of allocating resources to environmentally friendly and innovative activities to reduce pollution. Finding the right amount of money and the right direction for it is crucial for maximum pollution reduction in response to new ideas. Germany should promote innovations especially to efficient energy consumption technologies, in order to meet the migration demand for energy consumption. In addition, migration will put pressure on the transportation sector, and the government may provide incentives to move to electric vehicles which could significantly reduce the CO<sub>2</sub> emissions in the country. In addition, government policy should be directed toward skilled worker migration (scientist researchers), which may support the innovation activities and lead to sustainable development.

# Future direction of the study

This suggests some future direction, since we use DS-ARDL, future research may use more advanced techniques such as "Machine learning", which could be applied in future studies. These advanced techniques could provide more robust estimations. Secondly the study is only related to Germany, and it focuses on one country, which could be further expand to some regions, and multiple countries can be tested simultaneously. Furthermore, future studies may add some variables to better understand the relationship between migration, emissions, and climate change.

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Data availability Data has been provided by the authors.

# Declarations

Conflict of interests Authors declare no conflict of interests.

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