Industrial robots and air environment: A moderated mediation model of population density and energy consumption

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Abstract

The relationship between new digital manufacturing technologies (also known as Industry 4.0) and environmental performance has become a subject of interest for both academia and policymakers. An analysis of the impact of robot usage on air environment mediated by energy consumption and moderated by population density is developed and tested using a longitudinal dataset from 74 countries and regions worldwide during 1993-2019. We find the use of robots exacerbates air pollution and climate warming because enhanced productivity and energy efficiency in light of robot usage offer an incentive to expand production and consumption, and thus increase total energy consumption that finally leads to air deterioration. By decomposing the total effect into the direct and the indirect effect, we find that, though industrial robots weakly contribute to reduction in greenhouse gas emission, the indirect adverse impact dominates the direct benefit. In addition, the nexus between robot usage and air environment is conditional on population density which, at large, mitigates the direct effect while amplifies the indirect effect of the adoption of robots on air environment. This study emphasizes the importance of energy consumption and population density in understanding the mechanisms underlying the relationship between robot usage and air environment, which provides both theoretical and practical implications for the balance of industrial intelligentization and ecological environment.

Keywords: industrial robots, air environment, energy consumption, population density, rebound effect

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1. Introduction

Air pollution and climate change have become principle threats to ecosystem, human health and sustainable development. The World Health Organization (WHO)'s 2014 urban air quality database indicated the air quality continues to deteriorate in most cities and 88% of the people is exposed to air pollution. In light of carbon dioxide (CO_2), methane (CH_4), and greenhouse gas (GHG) emissions, the climate change has also been an increasing important matter that continuously trigger alarms when the global elevation in temperature is more likely to occur. Considering that air quality and climate change account for 50% and 40% of environmental health and ecosystem vitality, as reported in the 2020 Environmental Performance Index (Wendling et al., 2020), the analysis of the determining factors of air environment measured by both indicators is important not only for academia, but also imperative for industry organizations, government agencies, and puts the public in a better position to achieve sustainable development.

Existing literature in the field of environmental studies has identified some factors. They were economic, policy, demographic, external shock, and technology factors. Economic factors cover a wide range of variables such as economic growth (Zhu et al., 2019), financial development (Nasir et al., 2019), foreign direct investment (FDI) and trade (Yasmeen et al., 2019), energy (Chien et al., 2021), and infrastructure investment (Huang et al., 2020). Policy factors mainly refer to environmental taxes and regulations (Neves et al., 2020; Wu et al., 2021). Population level and urbanization were viewed as two main demographic variables that impact on CO_2 emission (Sadorsky, 2014).

Recent studies shifted their attention to the impact of external shocks such as financial crisis and the breakout of the Coronavirus disease 2019 (COVID-19) on energy intensity and carbon emission (Wang and Zhang, 2021; Wang et al., 2021; Wang et al., 2022b; Wang et al., 2022c). With fast development in technology from the start of fourth Industrial Revolution, researchers have been paying renewed attention to the impact of technology progress on air pollution, though the debate has never ceased since the pioneering studies by Ehrlich and Holdren (1971) and Simon (1973). The subsequent studies also suggested that technology provides a solution to mitigate pollution (Ausubel and Sladovich, 1989, Grossman and Krueger, 1991; Shi and Lai, 2013), while the following studies provided mixed results (Afonso et al., 2021; Shao et al., 2021; Yi et al., 2020). In spite of the above extensive research carried out on factors thought to influence air environment, no study has thoroughly analyzed the link between industrial robots and air environment.

The International Federation of Robotics (IFR) defines an industrial robot as an automatically controlled, multipurpose, and reprogrammable machine. An analysis by McKinsey Global Institute (MGI, 2017) reported that, by 2030, 400 million (15%) of the global labor force could be displaced by automation under a midpoint adoption scenario. This suggested that as a symbol of artificial intelligence under Industry 4.0 (Dantas et al., 2020; Elpidio et al., 2020; Wang et al., 2022a), industrial robots have increasingly penetrated into the production process and would bring significant economic and social consequences (Acemoglu and Restrepo, 2019, 2021; Acemoglu and Autor, 2011; Lei, 2021). In addition to the literature that focused on discussing labor market implications of the robot usage (Acemoglu and Restrepo, 2018a; Acemoglu and Restrepo, 2020), the mounting literature also concerned the impact of robots adoption on economic growth (Aghion et al., 2019), energy consumption (An et al., 2020; Wang et al., 2022a), productivity (Kromann et al., 2020; Ballestar et al., 2020), innovation (Liu et al., 2020), and the social implication on equity (Lei, 2021).

However, the profound implications of robot usage on environment, air quality and climate change in particular, was almost neglected, and policy support to promote the adoption of robots in many countries was generally lack of formal environmental assessments (Dusik et al., 2018). Even less clear was through which channels and under what conditions the automation technology affects air environment. These considerations motivate us to answer three main questions: 1) do industrial robots reduce air pollution or combat climate change; 2) through which channels robotics influence the air environment; and 3) does the nexus between industrial robots and air environmental performance vary with some other factors? The answers to these questions have important and rich implications not only to policy makers, academics, business practitioners but to the public as a whole.

How do industrial robots affect air environment? Inspired by Simon (1973) who argued that the advance of technology produces unintended side effects that are typically proportional to its intended effects in size, we developed a theoretical framework, dissembling the complex change to air environment the new-generation technology is likely to bring into the direct and the indirect effect, and hypothesized the total effect depends on the relative size of the two. Intuitively, the expected benefits robots bring to environment may include reduced material losses in manufacturing and supply chain operations, opportunities for digitized environmental monitoring and environmental accounting systems, and the smart circulation system that transforms the waste into high-quality secondary raw material (Dusik et al., 2018; Wilts, et al., 2021).

However, the negative environmental externality may arise, attributed to increased energy intensity, more electronic waste from proliferated production in electronics that heavily use industrial robots, higher consumption of energy-saving products, and rising demand for upstream material and energy inputs. Thus, we hypothesized that the indirect effect of industrial robots on air environment depends on the impact of robots on energy consumption, and the impact of energy consumption on air environment. With regard to the nexus between robots and energy, we argued that three countervailing forces work systematically and co-determine the impact, among which the energy-efficiency or energy-saving effect leads to the opposite directional change in robot use and energy consumption (Yi et al., 2013: Xu and Lin, 2018, amongst others), while the rebound effect (take-back effect) and scale effect move the variation of robot use and energy demand in the same direction (Ertel, 2019; Vivanco et al., 2016, amongst others). The relation between energy consumption and air environment is less complex. Many studies and research reports have shown energy consumption is the main cause of air pollution (Afonso et al., 2021) and increased carbon dioxide emissions (Rafindadi, 2016; Rahman and Kashem, 2017).

Our contribution not only lies in identifying the direct effect of robots from its indirect effect on air environment. We also extended the mediated modelling to identify the role of one demographic factor—population density—in moderating the direct, the indirect, and the total effect of technology advance on environmental performance. On one hand, countries or regions with denser population have more environmental concerns that affect their choices in robotics technology. In addition, the productivity gains by replacing labor with robots in denser areas are smaller since sufficient labor supply reduces the gap between labor cost and capital cost. This leads to a lower level of robot adoption. In both cases, the direct impact of robot usage on air environment could be mitigated. However, this moderation effect of population density may vary depending on the country's environmental performance, innovation capacity and its industry characteristics.

We also analyzed how population density moderates the robots-air environment nexus through its influence on the indirect effect. First, the energy-saving effect is stronger in countries or regions with higher density of population because of the economics of scale resulting from better infrastructure, such as denser road networks and electoral grids. Second, the scale effect is stronger since countries with a higher level of population density usually have higher economic growth driven by productivity boom in light of the use of robots. Third, the rebound effect is also shaped by population density. Even though the energy efficiency was improved, the lower price for more energy-saving products may lead to higher energy consumption in denser countries or regions. Due to the heterogeneous effects on the countervailing forces, we hypothesized the relation between the use of industrial robots and energy consumption would be conditional on the density of population.

To achieve the goals, we constructed a cross-country panel data covering 74 countries during 1993-2019 and applied a structural equation model (SEM) to estimate a system of two important equations with bootstrapping approach to determine the statistical significance of the indirect effect. Our results disclosed that the use of robots significantly increases nitrous oxide (NO_x), CO_2, CH_4, and GHG emissions, while has a minimum impact on PM2.5 concentration. More specifically, the direct contribution of industrial robots to improve air environment is, at large, not as strong as we expected. The use of robots in production is conductive to combat global warming by reduction of CO_2, CH_4, and GHG emissions, but this effect is occasionally insignificant. In terms of air quality, the use of robots has negligible impact on $PM_{2.5}$ concentration and induces more NO_x emission.

However, we found significant and larger adverse impact of robots on air environment transmitted through energy consumption. Comparing the size of the direct and the indirect effect, we find the latter has a strong dominant power over the former. The moderated mediation analysis suggests that the direct effect of robot usage is mitigated while the indirect effect is amplified in denser regions or areas at country level. Interestingly, when we focus on the use of robots at manufacturing industry, the indirect effect gets smaller as population density rises. These results imply that we have to abate the scale and the rebound effect or to further enhance the energy efficiency in the use of robots to reduce its adverse impact on the air environment.

Our paper is closest to Yi et al. (2020) which investigated the impacts of three types of technical progress on haze pollution—the neutral, the labor-saving, the capital-saving and the energy-saving technologies. They used the counts of invention patents as a measure for neutral technology, the years of education for labor-saving technology, the ratio of GDP to capital stock for capital-saving technology, and energy consumption per unit of GDP for energy-saving technology. We are different from them not only in the measure of technology progress but also in the theoretical modelling and econometric estimations. Existing studies including Yi et al. (2020) explored the total impact of technology advance on air environment, while few decomposed the total into the direct and indirect effects; many of them studied the general-purpose technology advance on air environment, though few analyzed the specific automation technology, robotics in particular, on heterogeneous air environmental indicators including both air quality and climate change; the technology-environment nexus could also be varying with local market conditions, while this conditional effect was rarely looked into in current research.

We filled in these research gaps and contributed in multiple aspects. First, we provided a systemic theoretical perspective that answers the question of why the use of industrial robots has significant influence on air environment; Second, following the theoretical analyses, we constructed a structural equation model that estimates the size of the direct and the indirect effect, respectively, of robotics on air environment, and furthermore, we adopted the bootstrap method to test whether the indirect effect is statistically significant. Third, we investigated the role of population density in moderating the relation between use of robots and air environment. This moderated mediation effect was first identified in our paper. Fourth, we conducted analysis not only at the country level but also at the industry level, and presented heterogeneous findings taking a country's innovation capacity and environmental performance into account.

The next Section reviewed the literature on the determinants of air environment and the literature on the influence of industrial robots. Section 3 presented theories and illustrated how we developed hypotheses, followed by data descriptions, variable definitions and the econometric specifications. The main results with supplementary analysis were presented in Sections 5 and 6. The final section concluded with policy implications.

2. Literature review

2.1 Literature on the determining factors of air environment

Our paper is closely related to the literature that study the determining factors of air environment. We classified them into five main strands, focusing on the impacts of economic, policy, demographic, external shocks, and technological indicators, respectively.

Amongst the five types of determinants, economic variables play the most important role with a long and extensive academic debate, such as economic growth (Zhu et al., 2019, amongst others), financial development (Nasir et al., 2019, amongst others), trade and FDI (Yasmeen et al., 2019; Omri, 2018, amongst others), energy (Chien et al., 2021, amongst others), and infrastructure investment (Huang et al., 2020; Rasool et al., 2019, amongst others). In terms of economic growth, Nasir et al. (2019)

found financial and economic development have significant long-run relationships with environmental degradation. In terms of FDI and trade, there were two competing arguments: the pollution-haven and the pollution-halo hypothesis. The first stated the FDI leads to environmental degradation because host countries intend to attract FDI by relaxing their environmental regulations; the second stated FDI and trading bring high technologies and good management practices that help reducing carbon emissions. Along these two lines of arguments, there were mixed and inconclusive empirical findings. Some confirmed the pollution-haven hypothesis (Hanif et al., 2019; Shahbaz et al., 2018; Zhang and Zhou, 2016), while others found FDI either exerts positive environmental externality (Tang and Tan, 2015; Paramati et al., 2017; Zhu et al., 2016) or has a nonlinear relation with carbon emissions (Alshubiri and Elheddad, 2019; Omri, 2018; Yasmeen et al., 2019). Though the transformation of energy structure from non-renewable to renewable and the abatement of solid fuels help reducing air pollution (Chien et al., 2021; Meng et al., 2019), the increase in total energy use results in higher emissions (Narayanan and Sahu, 2014, amongst others) and energy intensity plays a similar role (Sadorsky, 2014). In terms of infrastructure investment, Huang et al. (2020) showed the investment in infrastructure leads to increase in air pollution. And Rasool et al. (2019) stated the transport infrastructure plays an imperative role.

The second strand of literature explored the impact of policy factors such as taxes (Chien et al., 2021) and regulations (Neves et al., 2020; Wu et al., 2021). For example, Chien et al. (2021) found environment tax works in reducing carbon emission. Both Neves et al. (2020) and Wu et al. (2021) found environmental regulation is effective in cutting CO_2 emissions in the long-run as well.

The third line of research focused on demographic factors (Cole and Neumayer, 2004; Sadorsky, 2014). Cole and Neumayer (2004) presented the first study examining the impact of demographic factors on sulfur dioxide. They found a U-shaped relation between population level with the pollutant, while urbanization and average house size playing insignificant role. Sadorsky (2014) also found an insignificant effect of urbanization on CO_2 emissions, while the opposite results were obtained by Zhang and Lin (2012).

The fourth strand of literature analyzed the external shocks such as the financial crisis and the breakout of the Coronavirus disease 2019 (COVID-19) on carbon emission (Wang et al., 2021; Wang et al., 2022b). Wang et al. (2021), using data from 55 industries, investigated the driving factors for the change in carbon intensity before and after financial crisis, by decomposing the change at sector-level. Wang et al. (2022b) used two new method to simulate the carbon emissions of China, India, U.S., and E.U. under the pandemic-free scenario and facilitated our understanding of the impact of the pandemic on carbon emissions in 2020.

The fifth strand of literature was closest to our study that investigates the impact of technology progress on air pollution (Ehrlich and Holdren, 1971; Grossman and Krueger, 1991; Yi et al., 2020; amongst others). Ehrlich and Holdren (1971) and Grossman and Krueger (1991) were among the first to build the theoretical framework linking environmental impact with technology, suggesting that technology provides a solution to mitigate pollution due to growth of population. However, the empirical evidence with regard to such impacts is quite mixed. Some scholars identified the reduction of CO_2 emission has strong dependence on technological knowledge (Afonso et al., 2021). A few others argued that the advance of technology is not sufficient to avoid the massive climate change induced by greenhouse gas emissions (Shao et al., 2021; Stokey,1998). The inconsistent findings mainly resulted from two reasons, one of which is the lack of a clear analysis into the transmission mechanism and the other is neglecting the context that moderates the relation between technical progress and air pollution.

We identify a few research gaps based on the above literature review: First, existing studies explore the total impact of technology advance on air environment, while few decompose the total into the direct and the indirect effect; Second, though the general-purpose technology advance has been studied on air quality, few investigate the impact of the specific automation technology, robotics in particular, on heterogeneous air environmental indicators of air pollution and climate change. Third, the impact of technology on air environment could be changing with the variation in local market conditions. This conditional impact that shapes the relation between adoption of new technology and air environment is largely overlooked.

2.2 Literature on the influence of industrial robots

The fast development and adoption of automation technologies exemplified by automatic vehicles, industrial robots, and artificial intelligence in the past few decades generate significant social and economic implications (Acemoglu and Restrepo, 2019; Lei, 2021). Many existing studies focus on the influence of industrial robots on labor market out of the concern that machines are competing with human beings (Acemoglu and Restrepo, 2021; Acemoglu and Autor, 2011).

Some scholars saw the adoption of industrial robots as the harbinger of joblessness. Workers, especially those of low-skill, are increasingly replaced by robotics with lower payment (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Others viewed robots used in the new industrial revolution, like previous technologies, will ultimately boost demand for labor and increase their income share (Acemoglu and Restrepo, 2018b).

The opposite conclusions were reached because of three different working mechanisms—productivity effect, displacement effect, and reinstatement effect (Acemoglu and Restrepo, 2019). The productivity effect arises, when more expensive labors were replaced with cheaper machines, there would be a reduction in production costs and a rise in production. Thus, the productivity enhances the demand of labor. The displacement effect results when more tasks that were previously taken by labor were transferred to industrial robots. It reduces job availability and lowers labor demand and wages. The reinstatement effect was due to the comparative advantage of labor in doing more complex and innovative tasks. Automation standardizes the production process with a great portion of high-skill workers to be shifted out of routine tasks to create new production contents or to engage in new labor-intensive tasks. The balance between the three effects leads to various labor market implications.

In addition to the debates relating robots use with employment, wage and income share, the literature also touches upon the economic influence of industrial robots in economic growth (Aghion et al., 2019; Berg et al., 2018), energy consumption (Wang et al., 2022a), productivity (Kromann et al., 2020; Ballestar et al., 2020), technology advance (Liu et al., 2020), and the social impact (Lei, 2021).

3. Hypothesis development: how do industrial robots affect air environment?

3.1 The impact of robots on air environment mediated by energy consumption

The advance of technology often produces unintended side effects, typically proportional in size to its intended ones (Simon, 1973). The invent and adoption of industrial robots greatly enhances the productivity and saves labor from taking dirty, dangerous, and routine works, though its environmental impact is ambiguous and lack of a formal assessment. When discussing the link between technology and environment, existing literature often mixed two effects—the direct and the indirect effect, and neglects the context when the new technology was deployed. We herein developed a theoretical framework arguing that the total effect actually depends on the relative size of the two. This was summarized into the first hypothesis:

H1: *The total mediated effect depends on the relative size of the direct and indirect effect.*

In terms of the direct effect, Dusik et al. (2018) pointed out the benefits that robots directly bring to environment include reduced material losses in manufacturing and supply chain operations, and opportunities for digitized environmental monitoring and environmental accounting systems. In addition, Wilts et al. (2021) emphasized the use of industrial robots (based on optical recognition and intelligent evaluation algorithms) enables a circular economy that could transform the organic waste or solid waste into high-quality secondary raw material, and achieve the sustainability goals. Therefore, we proposed the second hypothesis with regard to the direct effect of robot usage on air environment:

H2: *The use of industrial robots is expected to bring direct benefits to air environment.*

However, the increasing use of industrial robots may exert unexpected responses, that is, negative environmental externality through the other channel. The adverse impacts of robot adoption on environment are mainly attributed to increased total energy intensity of operations, more electronic waste from proliferated production in electronic appliances and equipment that heavily rely on industrial robots, higher consumption of energy-saving products, and more demand for upstream material and energy inputs.

Some researchers believe air pollution was reduced due to technology innovation since it demands less energy (Grossman and Krueger, 1991; Shi and Lai, 2013; Yi et al., 2020; Xu et al., 2021), while others suggested the technology development aggravates air pollution driven by more energy consumption (Simon, 1973; Ausubel and Sladovich, 1989). Both strands of literature underscore the importance of energy, but they did not distinguish its indirect effect from the direct effect, neither modelling nor testing the relative size of each. Based on such a debate, we proposed the second hypothesis regarding the indirect effect of robot usage on air environment:

H3: *The indirect effect of robot usage on air environment depends on, (a) the impact of* *robots on energy consumption, and (b) the impact of energy consumption on air environment.*

In the last decades, the adoption of industrial robots, as an important component of technology advance, has experienced a steady growth and become prevalent in many industries (Pires, 2007; IFR, 2020). Past researches pointed out that technological progress is often associated with energy consumption (e.g. Acemoglu et al., 2016; Ertel, 2019). In particular, Uhlmann et al. (2016) and Dusik et al. (2018) claimed that the large-scale applications of industrial robots are more likely to give rise to more energy consumption. However, they did not provide solid statistical and econometric analysis.

Theoretically, there are three effects that work systematically and co-determine the impact of robots use on energy consumption. One of them is the pushing force that leads to the opposite directional change in robots use and energy consumption; the other two are pulling forces that move the variation of robot use and energy demand along the same direction. The pushing force includes the energy-efficiency or energy-saving effect (Yi et al., 2013; Shi and Lai, 2013; Sohag et al., 2015; Xu and Lin, 2018), and the pulling force consists of scale and rebound effect (Ertel, 2019; Vivanco et al., 2016).

Some researchers believe technology decreases energy consumption by improving energy efficiency (Yin et al., 2018; Yi et al., 2020). First, when production activities were automated by application of industrial robots, the total outputs would be increased given the same amount of energy, and this reduces the per-unit energy cost. Second, the design and the use of robots itself could be biased towards energy-saving, when the performance of robotics is usually characterized by the ratio of locomotion kinetic energy to the input mechanical energy. The energy efficiency of locomotion is the key to determine the overall energy efficiency that depends on the robots' material properties, geometric sizes, actuation states, and the optimization of operation (Carabin et al., 2017; Shui et al., 2017). The design, selection and adoption of these energy-saving robots leave some leeway for energy saving.

However, the effectiveness of energy-saving effect may be undermined in some situations. Metcalf and Hassett (1999) showed that even though developed technology produces energy-saving of input significantly, the actual savings are much less than those supporters of energy-saving effect claimed. In addition, robots can play roles in impacting energy consumption through the "rebound effect" (or "takeback effect"), which describes that as energy price lowers due to lower costs saved from improved energy efficiency, this tends to motivate manufacturers to substitute energy factor for other more expensive factors such as labor and capital (Lin and Zhao, 2016). Thus, even though energy efficiency has been improved, it is unlikely to lessen total energy consumption (Herring, 2004; Alcott, 2005; Herring, 2006; Ertel, 2019). Besides the rebound effect, there was another pushing force termed as "scale effect" (Yi et al., 2020). The application of robots increases the total factor productivity and boosts economic growth as well as the total demand for products and services. Higher consumption in the general equilibrium may lead to more demand for energy.

We summarized these theoretical arguments into the hypothesis below:

H3(a): *The impact of robots on energy consumption depends on the countervailing forces of energy-saving, rebound and scale effect.*

Compared with the complex impacts of industrial robots on energy consumption, the relationship between energy consumption and environment is monotonic (An et al., 2020; Jin and Hu, 2021). As the role of air environment is vital as discussed in Section 1, we mainly focus on the air environmental performance including air quality and climate change indicators defined by Environmental Performance Index (Wendling et al., 2020).

According to the International Energy Agency (IEA 2015), energy is responsible for 80% of CO_2 emission and for 2/3 of total greenhouse gas emissions. Similarly, European Environment Agency (2004) indicated "the environmental problems directly related to energy production and consumption include air pollution, climate change……The emission of air pollutants from fossil fuel combustion is the major cause of urban air pollution. Burning fossil fuels is also the main contributor to the emission of greenhouse gases." In addition to the data evidence provided by these energy and environmental research agencies, many studies have shown energy consumption is the main cause of air pollution (e.g. Afonso et al., 2021) and increased carbon dioxide emissions (Soytas et al., 2007; Rafindadi, 2016; Rahman and Kashem, 2017). Based on the data and empirical evidence, we summarized the relation between energy consumption and air environment in H3(b).

H3(b): *The rising energy consumption leads to deterioration of air environment.*

3.2 The moderated mediating effect of robots on air environment

Previous research suggested that the population plays an ineligible role in shaping the natural environment and affecting energy demand (Ehrlich and Holdren, 1971;

O'Neill et al., 2005; Mamun, et al., 2014; Ohlan, 2015; Rahman, 2020; Rahman and Alam, 2021). As early as 1971, Ehrlich and Holdren stated “population growth causes a disproportionate negative impact on the environment” and the smog problem is related to population distribution. Rahman (2020) noted that the population density is positively related to the energy consumption and CO_2 emissions, and the similar results were found in Bangladesh by Rahman and Alam (2021), in European Union nations by York (2007), and in China by Wang et al. (2014).

These studies either analyzed the population-environment nexus or the population-energy association, while none of them viewed population as a key condition that moderates the relation between technology and environment. As far as we know, we are the first to analyze the role of the distribution of population in moderating the total effect of technology advance on environment performance. Hereby, we offered a theoretical rationale to explore how population density moderates the direct and indirect effect, respectively.

In countries with higher population density, on one hand, the environmental risks that accompany the adoption of robots, if any, could be weaker, since people in denser areas have more environmental concerns and are more demanding in the selection of robotics that were biased towards energy-saving and environmental-friendly technologies. On the other hand, the labor costs relative to the capital costs were usually lower in countries with sufficient labor supply. Thus, the productivity gains from replacing labor with robots were smaller in densely populated countries, and this leads to less applications of robots at the country level, also mitigating their direct impacts of robot usage on air environment.

However, a few exceptions should be noted. The conditional effect of population density may vary due to country heterogeneity or industry characteristics. For example, in countries with worse environment performance or slower technical progress, the population growth is more likely driven by the fast expansion of secondary industry that has a higher penetration of automation technology. In these scenarios, the direct impacts of robots are more likely to be stronger. These considerations lead us to propose the fourth hypothesis which is an extension of H1:

H4: *The direct impact of robot usage on air environment is conditional on population density.*

Next, we analyze how population density affects the technology-environment nexus through its impact on the indirect effect. That is, the energy response to the use of robots may vary with the density of population. We argued that, in countries with higher population density, infrastructures such as road networks and electoral grids are usually better developed. Higher density of population helps to facilitate economies of scale and this enhances the energy-saving effect, leading to lower environmental damages (Sadorsky, 2014). However, countries with denser population distributed across limited urban area have higher demand for industrial clusters and multi-story high buildings (Resch et al., 2016; Lariviere and Lafrance, 1999). This induces more economic activities and leads to higher energy demand (scale effect). The rebound effect can also be shaped by population density. People who live in more urbanized and denser areas tend to consumer more energy-intensive products such as motor vehicles, air conditioners, microwave ovens, which require more energy (Bilgili, et al., 2017). Even though the energy efficiency was improved, the lower price for energy-saving products may lead to higher aggregate spending on these products due to both substitution effect and income effect in more dense areas. Based on the heterogeneous effects on the countervailing forces, the relation between robots use and energy consumption may as well depend on the density of population. This argument was summarized into the fifth hypothesis:

H5: *The indirect impact of robot usage on air environment is also conditional on population density, through its moderation on the relation between robot usage and energy consumption.*

Figure 1 summarizes the above hypothesis conceptual model and presents the moderated mediation mechanisms that is put forward in this study.

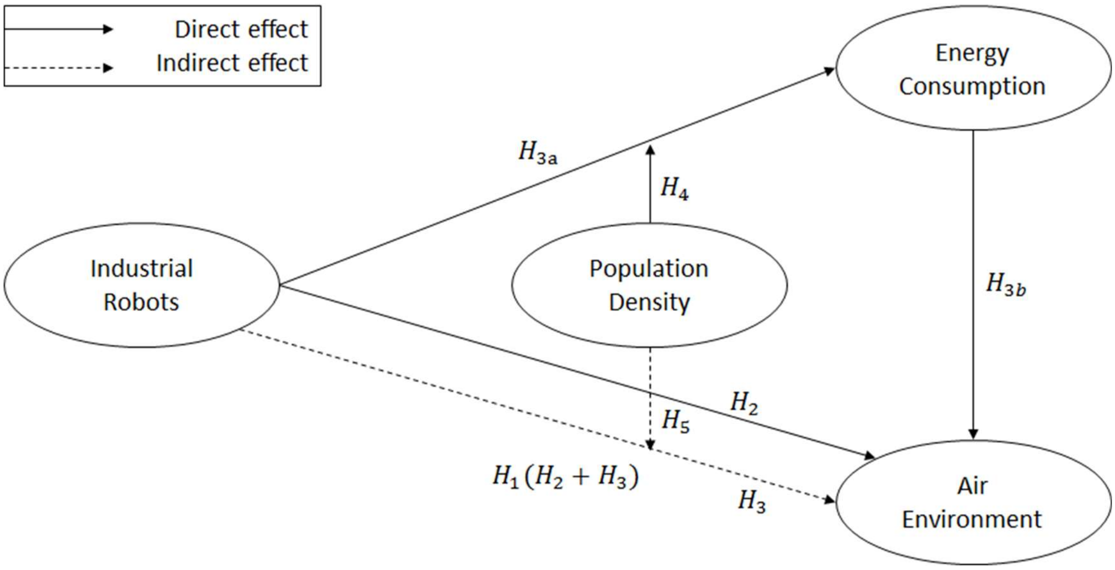


Figure 1. Proposed Research Model

4. Data, variables and methodology

4.1 The sample and data sources

To test the hypotheses, we constructed a national-level dataset from a combination of various sources. The two major data sources for this study were the World Development Indicators (WDI) and Worldwide Governance Indicators (WGI) database provided by the World Bank[1]and the International Federation of Robotics (IFR)[2]. The former contained the segmented information on a variety of topics, such as economic-related indictors, environment-related indicators, governance-related indicators, etc.; and the latter provided data on the stock of robots and new robot installations by type, country, industry and application, which has been used in several previous studies (such as Acemoglu and Restrepo, 2021). We also collected and used two indices: the Global Innovation Index (GII)[3] from the World Intellectual Property Organization and the Environmental Performance Index (EPI)[4] from the Yale Center for Environmental Law & Policy (Wendling et al., 2020) to identify countries into high-innovation performance, low-innovation performance, high-environmental performance and low-environmental performance, respectively.

The IFR covered data on the use of robots around the world since 1993 but the breakdown by customer industry starts in different years. Our sample includes 75 countries and regions with tracked record for robot usage. After merging various datasets and omitting the missing statistics, our final sample consists of 74 countries and regions in the world from 1993 to 2019, leading to an unbalanced panel of 702

[1] The data is available from https://databank.worldbank.org/home.aspx.
[2] The data is collected from https://ifr.org/.
[3] The GII was collected from the World Intellectual Property Organization. https://www.wipo.int/global_innovation_index/en/.
[4] The EPI data were collected from https://epi.yale.edu/downloads.

country-year observations.

4.2 Variables

All variables and their definitions used to assemble the country-year database were summarized in Table 1.

Table 1. Variables and definitions

Variables	Definition
Dependent variables:	
NO_x	Total nitrous oxide emissions (logs), in units of thousand metric tons.
$PM_{2.5}$	$PM_{2.5}$ air pollution, mean annual exposure (logs), in units of micrograms per cubic meter.
CO_2	CO_2 emissions (logs), in units of kilotons.
CH_4	Methane emissions (logs), in units of kilotons.
GHG	Greenhouse gas emissions (logs), in units of kilotons.
Independent variable:	
Robot usage	The number of the stock of robots in use (logs).
Mediator:	
Energy consumption	Total final energy consumption (logs), in units of kilojoules.
Moderator:	
Population density	Population divided by land area in square kilometers (logs).
Control variables:	
GDP	GDP per capita (logs).
FDI	Share of inward and outward FDI in GDP.
Openness	Share of exports of goods and services in GDP.
Innovation capacity	Per capita patent applications (logs).
Physical capital	Gross capital formation to GDP ratio.
Human capital	Share of total working-age population with advanced education.
Industrial structure	Share of industrial output in GDP.
Population structure	Share of population ages 65 and above (logs).
Regulatory quality	The country's score on the aggregate indicator, collected directly from DataBank database.

Dependent variables

We measured environmental performance from two dimensions: air quality and climate change. We employed NO_x emissions and annual average $PM_{2.5}$ concentration as the measure of air quality, and emissions of CO_2, CH_4 and GHG to measure climate change. Compared with existing studies that use either PM2.5 concentration for haze pollution (Xu and Lin, 2018; Xu et al., 2021; Yi et al., 2020) or CO_2 emission for air quality (Rahman, 2020; Rahman and Alam, 2021; Simon, 1973; Wang and Zhu, 2020), we considered impacts of automation technology on different aspects of environmental performance.

Independent variable

We use the logarithm of industry-level stocks of industrial robots as the independent variable, similar to Fan et al. (2021) and Yang and Hou (2020). The IFR data on the stock of robot usage covers a wide range of industrial sectors such as agriculture, forestry and fishing, mining and quarrying, construction, manufacturing, education, utilities, and the unspecified, and etc. The database also provides more detailed information based on subsector classification. For example, the industrial robot data were available for manufacturing subsectors, such as automotive, metals, electronics, food and beverages, glass, paper, pharmaceuticals cosmetics, rubber and plastic, semiconductors, textiles, wood and furniture, and etc. To make the classification consistent, we dropped the robot data with unspecified industry category. We also conducted a sub-sample supplementary analysis focusing on the manufacturing industry.

Mediation and moderation variables

To understand why and under what conditions robot usage influences air environment would deepen our understanding of how to achieve environmental goals of reducing pollution and combating climate change. For this reason, we considered the logarithm of total final energy consumption as a mediator in explaining how robots use associates with different aspects of environmental performance. Suggested by Borck and Schrauth (2021), Chen et al. (2020) and Erdogan (2021), we employed population density, measured by the logarithm of population divided by land area in square kilometers, as the moderator. It captured whether and how the effect of robot use is conditional on the population density.

Control variables

We controlled for a series of factors that affect a country's environmental performance: GDP per capita, FDI, openness, innovation capacity, physical capital, human capital, industrial structure, population structure and governance efficiency.

First, the impact robot use on environmental performance could be confounded by a country's economic size or economic growth (Grossman and Krueger, 1991), we thus control for this impact using the logarithm of GDP per capita. FDI is also an important confounder that may produce entirely different outcomes for local environment (Cole et al., 2011; Golub et al., 2011). For instance, foreign investment sourced from countries with higher environment standards may bring green technologies and has positive impact on host country's environmental performance (Eskeland and Harrison, 2003). It is equally possible foreign investors treat the FDI destinations as the "pollution haven" and generate negative environmental externality (Sapkota and Bastola, 2017). We thus controlled for FDI, measured as a nation's inward and outward FDI scaled by its GDP. Similarly, following Ma and Wang (2021), we controlled for the impact of trade openness measured by exports of goods and services divided by GDP.

We also considered heterogeneous technological progress such as neutral technological progress, capital-saving technological progress and labor-saving technological progress that were frequently overlooked in the literature as further controls (Yi et al., 2020). We log-linearized the number of patent applications over total population to proxy neutral technological progress. Capital-saving technological progress was captured by gross capital formation over local GDP and labor-saving technological progress was measured using the ratio of labors having advanced education to total working-age population.

The degree of industrialization is also closely associated with national environmental performance which was measured by the proportion of the industrial output value to GDP. Moreover, we controlled for the impact of demographics on environment. For example, aging could induce either industrial adaptation or new technology adoption, both of which may have influential impact on environment (Wang and Li, 2021). We used the population aged sixty-five and above relative to the total population to measure the change of this demographic trend. Finally, as suggested by Ibrahim and Ajide (2021), we included an institutional factor, measured by regulatory quality, to control the effect of government intervention on environmental performance.

4.3 Models and estimation methods

Based on the above hypotheses (see Figure 1), the impact of robot usage on air environment through energy consumption and the moderating role of population density were tested with a two-equation model. The conceptual framework can be formulated into a system of energy and environment equations:

$$Energy_{it} = \alpha_0 + \alpha_1 Robot_{it} + \alpha_2 Popden_{it} + \alpha_3 Robot_{it} \times Popden_{it} + X'_{it}\Theta + \varepsilon_{it} \qquad (1)$$

$$Envrmt_{it} = \beta_0 + \beta_1 Energy_{it} + \beta_2 Robot_{it} + \beta_3 Popden_{it} + \beta_4 Robot_{it} \times Popden_{it} + X'_{it}\Gamma + u_{it} \qquad (2)$$

where $Envrmt_{it}$ denotes the air environment in country i and year t (the dependent variable); $Robot_{it}$ is the industrial robot usage (the independent variable); $Energy_{it}$ denotes the total energy consumption (the mediator); $Popden_{it}$ refers to population density (the moderator); X_{it} is the vector of control variables and ε_{it} and u_{it} are the error terms of the energy and environment equations, respectively. This framework fits into the procedures suggested by Baron and Kenny (1986) and Muller et al. (2005).

Table 2 describes the total effect, indirect effect, and direct effect in the constrained and the full model based on our two-equation framework. First, we consider a constrained model where only the mediator is included. When the moderation effect is excluded the model, it captures the indirect effect of robots on the environment through energy consumption. Next, we consider the role of population density in moderating the relation between robot and energy consumption and between robot and air environment. In the full model, the mediating and moderating effects together determine the impact of robots on environmental performance. When the moderator variable is included, the direct and indirect effects depend on the level of population density.

Table 2. Total, direct, and indirect effects of a 1% increase in robots

	Constraints	Total effect	Direct effect	Indirect effect
Model without moderation effect	$\beta_3 = 0, \beta_4 = 0$ $\alpha_2 = 0, \alpha_3 = 0$	$\beta_2 + \beta_1\alpha_1$ (***H1***)	β_2 (***H2***)	$\beta_1\alpha_1$ (***H3***)
Full model	None	$\beta_2 + \beta_1\alpha_1$ $+ (\beta_4 + \beta_1\alpha_3)$ $* Popden_{it}$	$\beta_2 + \beta_4$ $* Popden_{it}$ (***H4***)	$\beta_1(\alpha_1 + \alpha_3$ $* Popden_{it})$ (***H5***)

Notes: the total effect is the summation of direct and indirect effects obtained from equations (1) and (2). The model with no moderation effect is a simplification of the framework where four constraints are imposed to exclude population density. H1 to H5 in the bracket correspond to each hypothesis in the section 3.

To analyse the direct and indirect effects of robot usage on air environment, we first constructed a Structural Equation Model (SEM) in Stata 16.0 based on equations (1) and (2) excluding the moderator. We implemented a bootstrapping method to determine the statistical significance of the indirect effects. It performs better than the traditional causal steps approach in terms of its statistical power as well as Type I error (MacKinnon et al., 2002). The 95% bias-corrected confidence interval and 5000 bootstrap resamples were applied. We further explore how the direct and indirect effect of robot usage on environment through energy consumption was moderated by population density (Baron and Kenny, 1986; MacKinnon, 2008). The moderated mediation analysis was also performed in Stata 16.0. All controls were included across the models.

5. Main empirical results

Table 3 presents the means, standard deviations, and pairwise correlations across all variables of interests. There is no multicollinearity issue since the mean VIF is 2.04 and the VIF for each repressor is less than 4.06.

Table 3. Descriptive statistics and correlation coefficients

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1 Robot usage	5.34	4.39	1.00											
2 Energy consumption	13.85	1.57	0.39	1.00										
3 Population density	4.47	1.55	0.17	-0.20	1.00									
4 GDP	9.23	1.31	0.40	-0.04	0.05	1.00								
5 FDI	7.89	28.75	0.01	-0.18	0.20	0.13	1.00							
6 Openness	46.02	33.13	0.02	-0.44	0.53	0.29	0.29	1.00						
7 Innovation capacity	-8.91	1.45	0.29	0.11	0.02	0.65	0.11	0.19	1.00					
8 Physical capital	23.84	6.01	-0.01	0.16	0.05	-0.14	0.02	0.05	0.03	1.00				
9 Human capital	79.56	5.88	-0.15	-0.10	-0.13	0.23	0.00	0.04	0.13	0.01	1.00			
10 Industrial structure	29.09	9.70	-0.15	0.18	-0.25	-0.19	-0.11	-0.06	0.15	0.26	0.01	1.00		
11 Population structure	-2.32	0.64	0.38	-0.05	0.04	0.42	0.08	0.06	0.39	-0.09	0.02	-0.56	1.00	
12 Regulatory quality	0.60	0.96	0.34	-0.12	0.10	0.79	0.16	0.35	0.56	-0.17	0.33	-0.34	0.46	1.00

To examine whether energy consumption mediates the relation between robot usage and environmental performance, we first conducted mediation analysis through 5000 bootstrap resampling. Table 4 presents the estimation results of the total effect, direct effect and indirect effect of robot usage on air environment. The total effects related to Hypothesis 1 in Models 2 to 6 indicate that the environmental performance deteriorates as more robots were adopted. Specifically, a one standard deviation increase in robot usage is associated with an increase of emission in CO_2 and GHG equivalent to 0.9%, followed by the emissions of NO_x and CH_4 equivalent to 0.85%, and a rise of $PM_{2.5}$ concentration equivalent to 0.06%.

The direct effects are presented in Models 2 to 6, in which robot usage is only significantly and positively associated with NO_x emissions ($b = 0.010, p < 0.1$ in Model 2) while plays insignificant role in the rest of four environmental indicators. It indicates that the environmental risks induced by the use of industrial robots do not seem to be offset by the benefits they bring to the environment including reduction in material losses, smart recycling systems, digitized environmental monitoring, etc. This might be because factors such as environmental awareness or technology levels differ across countries, limiting the positive role of robot usage in optimizing climate change. Therefore, Hypothesis 2 was weakly supported. In addition, the significantly positive effect of energy consumption on NO_x suggests a partial mediating effect ($b = 0.942, p < 0.01$ in Model 2), and this raises our concerns of indirect effects.

Model 1 of Table 4 shows the impact of the use of robots on energy consumption, and finds that robot usage significantly increases total energy consumption ($b = 0.196, p < 0.01$ in Model 1). It implies that the energy-saving effect was dominated by the rebound and scale effects, and thus the use of robots fails to reduce total energy consumption. This result echoes arguments in Wei et al. (2019) and Yi et al. (2020). Therefore, Hypothesis 3(a) was supported. We also find that the coefficients of energy consumption for all environmental indicators are positive and significant across Models 2 to 6, consistent with the findings in An et al. (2020). This result supports Hypothesis 3(b), suggesting that less energy consumption helps reducing air pollution and combating climate change.

We find that robot usage has positive and significant indirect effects on all kinds of air indicators through the mediation of energy consumption. The ratio of indirect effect on NO_x relative to total effect is 94.8% and the ratio of indirect effect on $PM_{2.5}$ is 76.9% ($b = 0.184, p < 0.01, 95\%\ CI = [0.159, 0.209]$ in Model 2; $b = 0.010, p < 0.05$, $95\%\ CI = [0.0004, 0.020]$ in Model 3). Given that the indirect effect and direct effects on climate change have opposite signs, suppressing effects arise (MacKinnon, 2008; Shrout and Bolger, 2002). The impact of robot use on climate change is dominated by the indirect effect mediated by energy consumption. Our findings provide a fresh perspective to explain for the seemingly contradictory relationship between technology advance and environmental deterioration. The rebound and scale effects caused by robot expansion assumes the major responsibility, making the robots' energy-saving effect become less effective in ameliorating air quality. Therefore, Hypothesis 3 was supported.

Table 4. Mediation effects: energy consumption as a mediator between robot usage and air environment

	(1) EC	(2) NO_x	(3) $PM_{2.5}$	(4) CO_2	(5) CH_4	(6) GHG
EC		0.942***	0.047**	1.064***	1.025***	1.047***
		(0.017)	(0.019)	(0.015)	(0.017)	(0.012)
Robot usage						
Total effect	0.196***	0.194***	0.013**	0.205***	0.196***	0.203***
	(0.010)	(0.011)	(0.006)	(0.012)	(0.011)	(0.011)
Direct effect		0.010*	0.003	-0.003	-0.004	-0.002
		(0.006)	(0.007)	(0.005)	(0.006)	(0.004)
Indirect effect		0.184***	0.010**	0.208***	0.200***	0.205***
		(0.013)	(0.005)	(0.015)	(0.014)	(0.014)
LL 95% CI		0.159	0.0004	0.179	0.173	0.177
UL 95% CI		0.209	0.020	0.237	0.227	0.233
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	702	702	381	702	702	702

Notes: * (**, ***) denotes significance at the 10% (5%, 1%) level with bootstrap standard errors in parentheses. CI is the 95% bootstrap confidence interval calculated based on 5000 bootstrap resampling. LU is the lower limit, UL is the upper limit, and EC is energy consumption.

We presented the moderation analysis with the inclusion of population density and its interaction with robot use in Table 5. When the interaction term was added, we find a significantly positive impact of robot use on energy consumption ($b = 0.130, p < 0.01$ in Model 1). The coefficients of robot usage for climate change indicators in Models 4-6 are still significant and positive ($b = 0.048, p < 0.01$ in Model 4; $b = 0.038, p < 0.01$ in Model 5; $b = 0.046, p < 0.01$ in Model 6), consistent with the total effects in Models 3-5 of Table 4.

However, the impacts of robot use on two air quality indicators become insignificant ($b = 0.010, p > 0.1$ in Model 2; $b = -0.018, p > 0.1$ in Model 3). Population density is positively associated with both energy consumption and air environment, except for NO_x in Model 2. Our result, consistent with findings of Mamun, et al. (2014), Pham et al. (2020) and Rahman (2020), implies that the denser the population, the greater the energy consumption, and the worse the air quality would be.

The moderating effect of population density on the relation between robot use and energy consumption is positive but insignificant ($b = 0.010, p > 0.1$ in Model 1). Similarly, the relation between robot use and NO_x or $PM_{2.5}$ is not conditional on population density ($b = 0.003, p > 0.1$ in Model 2; $b = 0.001, p > 0.1$ in Model 3). As a comparison, estimations in Models 4-6 suggest that the increasing emissions of CO_2, CH_4, and GHG in light of robot use are mitigated in countries with denser population ($b = -0.016, p < 0.01$ in Model 4; $b = -0.010, p < 0.01$ in Model 5; $b = -0.014, p < 0.01$ in Model 6). This is possibly because, on one hand, the adoption of robots in denser countries or regions has more environmental concerns. On the other hand, relatively sufficient labor supply in densely populated countries indicates the smaller productivity gains from replacing labor with robots, which leads to less applications of robots that may mitigate their direct impacts of robot usage on air environment.

When population density is at its mean, a 1% increase of robot usage reduces emissions of CO_2, CH_4 and GHG by 0.024%, 0.007% and 0.017%, respectively. In particular, when population density is one standard deviation below the mean, a 1% increase of the number of robots decreases emissions of CO_2, CH_4 and GHG by 0.001%, 0.001% and 0.005%, respectively. As population density increases from the mean to one standard deviation above the mean, the growth of robots decreases emissions of CO_2, CH_4 and GHG by an additional 0.024%, 0.008% and 0.021%, respectively. Therefore, Hypothesis 4 is supported.

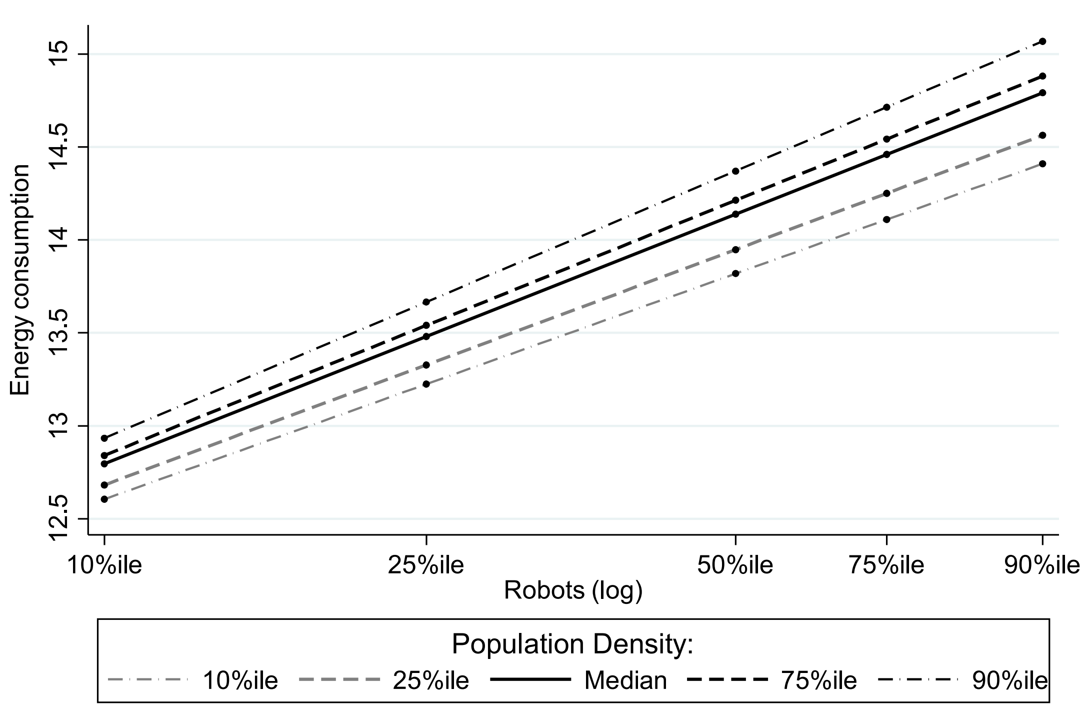
In addition to focusing on the interaction terms of robot and population density, we further explore exactly how population density moderates the direct robot-environment nexus. We find the heterogeneous conditional effect of population density on air quality and climate change. In detail, population density positively moderates the relation between robots and NO_x emissions ($b = 0.024, p < 0.01$), while produces negative moderating effects on the direct impacts of robots on CO_2 and GHG emissions ($b = -0.024, p < 0.01; b = -0.017, p < 0.01$). Such a relationship is also illustrated on the left of Figure 3 below.

Table 5. Moderation effects: Population density as a moderator between robot usage, energy consumption and air environment

Variables	(1) EC	(2) NO_x	(3) $PM_{2.5}$	(4) CO_2	(5) CH_4	(6) GHG
Robot usage	0.130***	0.010	-0.018	0.048***	0.038***	0.046***
	(0.030)	(0.013)	(0.016)	(0.011)	(0.013)	(0.009)
Popden	0.115*	-0.145***	0.141***	0.229***	0.046*	0.173***
	(0.060)	(0.026)	(0.030)	(0.022)	(0.027)	(0.019)
Robot* Popden	0.010	0.003	0.001	-0.016***	-0.010***	-0.014***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
EC		0.965***	0.022	1.046***	1.032***	1.037***
		(0.016)	(0.017)	(0.014)	(0.017)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	702	702	381	702	702	702

Notes: * (**, ***) denotes significance at the 10% (5%, 1%) level with bootstrap standard errors in parentheses. EC is energy consumption and Popden is population density.

After showing the moderation effects in Table 5, we attempt to visualize the size of moderation effects of population density on energy consumption (Figure 2) and on environmental performance (Figure 3). In Figure 2 we plot the effect of robots on energy consumption based on equation (1). The function is evaluated at the 10, 25, 50, 75 and 90 percentiles of the distributions of robots and population density. Both the position and the slope of the curve depend on the moderator (population density). In the plot, the slope is positive and turns slightly larger with the increase of population density. There is an upward shift of the curve as well, indicating that given the same distribution of robots use, the initial energy consumption is higher in countries with denser population.



Notes: The plots show relationship between energy consumption (y axis) and robots (x axis) based on equation (1). The function is evaluated at the 10, 25, 50, 75 and 90 percentiles (%iles) of the distributions of both robots (movement from one point to the next in the line) and population density (a shift of the line upwards). The control variables from equation (1) are evaluated at their sample mean.

Figure 2. Moderation impact of population density on the relation between robot usage and energy consumption

We also used bootstrapping with 5000 iterations to establish the 95% confidence interval for the conditional indirect effect of population density on the relationship between robots use and environmental performance via energy consumption. Results were reported in Table 6.[5] The conditional indirect effect of robot usage on NO_x emissions via energy consumption is stronger with higher population density ($b = 0.184, p < 0.01, 95\%\ CI = [0.142, 0.228]$ in Model 1), while it is weaker with lower population density ($b = 0.154, p < 0.01, 95\%\ CI = [0.118, 0.192]$ in Model 1). Similar results were found for emissions of CO_2, CH_4, and GHG in Models 3-5. Thus, Hypothesis 5 was supported. Notably, the conditional indirect effect of robot usage on $PM_{2.5}$ is insignificant with both low and high population density ($b = 0.005, p > 0.1, 95\%\ CI = [-0.004, 0.013]; b = 0.004, p > 0.1, 95\%\ CI = [-0.003, 0.011]$ in Model 2).

Table 6. Conditional indirect effects of population density

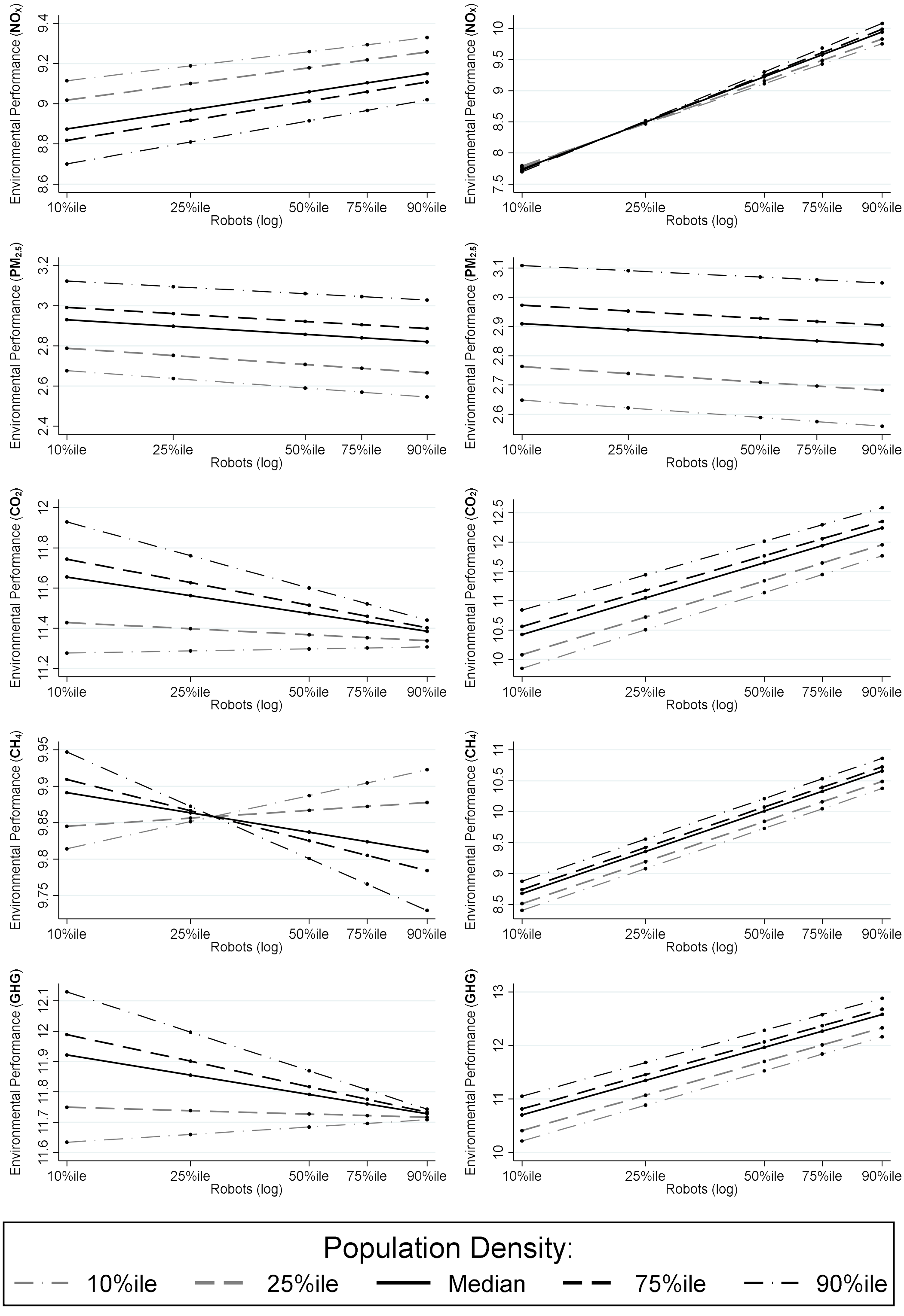
	(1) NO_x	**(2) $PM_{2.5}$**	**(3) CO_2**	**(4) CH_4**	**(5) GHG**
−1 SD	0.154***	0.005	0.167***	0.164***	0.165***
	(0.019)	(0.004)	(0.021)	(0.020)	(0.020)
LL 95% CI	0.118	-0.004	0.127	0.125	0.126
UL 95% CI	0.192	0.013	0.207	0.206	0.206
M	0.169***	0.004	0.183***	0.181***	0.182***
	(0.012)	(0.004)	(0.013)	(0.154)	(0.013)
LL 95% CI	0.145	-0.004	0.157	0.154	0.156
UL 95% CI	0.194	0.011	0.209	0.207	0.207
+1 SD	0.184***	0.004	0.200***	0.197***	0.198***
	(0.022)	(0.003)	(0.024)	(0.024)	(0.024)
LL 95% CI	0.142	-0.003	0.152	0.149	0.151
UL 95% CI	0.228	0.011	0.246	0.244	0.244
Controls	Yes	Yes	Yes	Yes	Yes
Observations	702	381	702	702	702

Notes: * (**, ***) significance at the 10% (5%, 1%) level, bootstrap standard errors in parentheses. Confidence Intervals (CI) is 95% bootstrap confidence interval, bootstrap based on 5000 bootstrap samples. LU is lower limit and UL is upper limit.

Figure 3 shows the conditional direct and total effects of the use of robots on air environment. Only in one case these two effects are both statistically insignificant, which is $PM_{2.5}$. In the case of NO_x, the moderator effect of population density is significant in the indirect effect, while plays no significant role in the direct effect. The

[5] Due to the space constraint, we only reported the condition indirect effect. The conditional total and direct effects are available upon requests.

total effect of robots use on air NO_x is significantly positive. The total effects of robots use on the three climate-change related variables are positive and statistically significant, implying a negative environmental externality. Though the direct effect implies that robots' adoption leads to less emissions in CO_2, CH_4, and GHG in denser areas, the indirect effect implies that robot adoption causes more emissions via increasing consumption of energy in countries with higher population density. Overall, the total effect remains positive because it is dominated by the indirect effect.



Notes: The relationship between air environment (y axis) and robots (x axis) based on equations (1) and (2). The plots on the left are the direct effect, based on columns (2) to (6) of Table 5. The plots of the total effect on the right adds both the direct and indirect effects (see Table 2). The function is evaluated at the 10, 25, 50, 75 and 90 percentiles (%ile) of the distributions of both robots and population density (the moderator). The control variables are evaluated at their sample mean.

Figure 3. Moderation impact of population density on the direct and total relations between robots and air environment

6. Supplementary analyses

In this section, we conducted supplementary analyses dividing the full sample into sub-samples based on EPI, GII and industry. The sub-sample results based on EPI and GII were reported in Table 7 and Table 8, respectively, and the sub-sample results based on industry were presented in Table 9.

6.1 Classification of countries into high/low EPI

In Table 7, we distinguished high- from low-EPI countries and examined the heterogeneous impacts of robot usage on air environmental indicators through the analysis of mediation effect, moderation effect, and moderated mediation effect. The total effect of robot use on air environment is most of time positive and significant for both high- and low-EPI countries, except for the impact on $PM_{2.5}$ concentration in low-EPI countries. Comparing the total effect in Panel a and b, we find the total effect is greater in low-EPI countries than in high-EPI countries.

However, the direct and indirect effects of the use of robots on environment indicate possibly different transmission mechanisms for high- and low-EPI countries. In terms of the direct effect, robot usage significantly increases NO_x emission and $PM_{2.5}$ concentration for both types of countries (Models 1a, 2a, 1b and 2b), while it reduces emission of CO_2 and GHG more significantly in high-EPI countries (Models 3a & 5a). In terms of the indirect effect, the coefficients for emissions of NO_x, CO_2, CH_4 and GHG are positive and significant, while being insignificant for $PM_{2.5}$ concentration for both panels (Models 1, 3, 4 & 5). These finding show that energy consumption partially mediates the association between the use of robots and air environment.

Looking at the moderating effect (without inclusion of the mediator), we find population density does not have significant moderation impact on the relation between robot use and NO_x and $PM_{2.5}$ concentration. However, it significantly reduces the impact of robot use on climate change in high-EPI countries, and similarly reduces the impact on CH_4 emission in low-EPI countries. However, the impact on CO_2 emission is stronger as population density rises in low-EPI countries.

Through moderated mediation analysis, our results on the conditional indirect effect are similar to those in Table 6. The difference is the indirect effect of robot usage on air environment via the change of energy consumption is larger and more significant in high-EPI countries as population density rises.

Table 7. Mediation effect of energy consumption and moderation effect of population density: high EPI countries vs. low EPI countries

	(1a) NO_x	(2a) $PM_{2.5}$	(3a) CO_2	(4a) CH_4	(5a) GHG	(1b) NO_x	(2b) $PM_{2.5}$	(3b) CO_2	(4b) CH_4	(5b) GHG
Mediation effect	*Panel a: high EPI countries*					*Panel b: low EPI countries*				
Total effect	0.184***	0.022***	0.191***	0.184***	0.191***	0.234***	-0.055	0.200***	0.226***	0.211***
	(0.011)	(0.006)	(0.013)	(0.012)	(0.012)	(0.021)	(0.068)	(0.028)	(0.027)	(0.023)
Direct effect	0.011*	0.015**	-0.011**	-0.007	-0.007*	0.074***	0.212*	0.005	0.013	0.010
	(0.006)	(0.007)	(0.005)	(0.006)	(0.004)	(0.026)	(0.118)	(0.036)	(0.031)	(0.022)
Indirect effect	0.173***	0.007	0.202***	0.191***	0.198***	0.160***	-0.267	0.195***	0.213***	0.201***
	(0.014)	(0.005)	(0.016)	(0.015)	(0.016)	(0.062)	(0.177)	(0.070)	(0.054)	(0.054)
[LL 95% CI, UL 95% CI]	[0.146, 0.201]	[-0.004, 0.017]	[0.170, 0.234]	[0.161, 0.221]	[0.166, 0.229]	[0.038, 0.282]	[-0.615, 0.081]	[0.057, 0.332]	[0.107, 0.319]	[0.096, 0.306]
Moderation effect										
Robot usage	0.013	-0.007	0.037***	0.042***	0.040***	0.005	0.180	-0.130	0.174***	0.014
	(0.013)	(0.015)	(0.010)	(0.013)	(0.009)	(0.057)	(0.223)	(0.080)	(0.061)	(0.051)
PD	-0.145***	0.152***	0.244***	0.065**	0.187***	0.150	0.566	-0.499***	0.670***	-0.148
	(0.027)	(0.028)	(0.019)	(0.026)	(0.018)	(0.137)	(0.396)	(0.191)	(0.145)	(0.123)
Robot x PD	0.003	0.001	-0.016***	-0.012***	-0.014***	0.014	-0.001	0.032**	-0.039***	-0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.012)	(0.039)	(0.016)	(0.012)	(0.011)
Moderated mediation effect										
−1 SD	0.151***	0.003	0.169***	0.164***	0.167***	0.120**	-0.286	0.177**	0.159***	0.177***
	(0. 020)	(0.005)	(0.022)	(0.021)	(0.022)	(0.056)	(0.261)	(0.074)	(0.058)	(0.062)
[LL 95% CI, UL 95% CI]	[0.113, 0.191]	[-0.006, 0.012]	[0. 126, 0.211]	[0.122, 0.205]	[0.125, 0.209]	[0.049, 0.253]	[-1.354, 0.222]	[0.052, 0.356]	[0.068, 0.295]	[0.071, 0.315]
M	0.160***	0.003	0.179***	0.173***	0.177***	0.123**	-0.270	0.181**	0.163**	0.181***
	(0.013)	(0.004)	(0.014)	(0.014)	(0.014)	(0.062)	(0.214)	(0.075)	(0.066)	(0.067)
[LL 95% CI, UL 95% CI]	[0.135, 0.186]	[-0.005, 0.010]	[0.152, 0.207]	[0.146, 0.201]	[0.150, 0.204]	[0.041, 0.279]	[-1.298., -0.026]	[0.062, 0.390]	[0.065, 0.336]	[0.074, 0.346]
+1 SD	0.169***	0.002	0.189***	0.183***	0.186***	0.126	-0.254	0.185*	0.167*	0.185*
	(0.019)	(0.004)	(0.021)	(0.021)	(0.021)	(0.087)	(0.272)	(0.104)	(0.099)	(0.100)
[LL 95% CI, UL 95% CI]	[0.134, 0.207]	[-0.005, 0.010]	[0.149, 0.232]	[0.144, 0.225]	[0.147, 0.228]	[-0.011, 0.332]	[-1.568., 0.006]	[0.014, 0.436]	[-0.002, 0.391]	[0.007, 0.398]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	347	650	650	650	52	34	52	52	52

Notes: * (**, ***) significance at the 10% (5%, 1%) level, bootstrap standard errors in parentheses. Confidence Intervals (CI) is 95% bootstrap confidence interval, bootstrap based on 5000 bootstrap samples. LU is lower limit, UL is upper limit, five indicators of air environment are the dependent variables, energy consumption is a mediation variable, and population density is a moderation variable.

6.2 Classification of countries into high/low GII

Table 8 reports the results for high- and low-GII countries, respectively. The total effects of robot usage on air environment are still found to be positive and statistically significant across all models for high-GII countries. Similar results were observed for low-GII countries, except for the impact on $PM_{2.5}$ concentration. The use of robots produces larger impacts on air environmental indicators in high-GII countries than in low-GII countries.

In addition, for both the high- and low-GII countries, the positive indirect effect dominates the negative direct effect, with both effects more significantly embodied in high-GII countries. It indicates that the climate warming is mitigated due to the direction contribution of robot usage, however, it is worsened due to the indirect effect because of more energy consumption induced by a higher penetration of robots.

The moderation effects of population density on the relation between robot usage and air environment are distinct for high- and low-GII countries. Specifically, for high-GII countries, the positive impact of robot on CO_2, CH_4, and GHG emissions, key indicators of climate warming, was weakened as population is more densely distributed. Interestingly, population density does not have significant moderating effect on robot usage and $PM_{2.5}$ concentration. In contrast, in low-GII countries, robot usage significantly reduces emissions of NO_x, CH_4 and GHG and increases $PM_{2.5}$ concentration but such negative impacts are offset as population density rises.

We further conducted the moderated mediation analysis and presented the conditional indirect effects as a focus for discussion. We find a striking distinction of the indirect effect in the high- and low- GII countries. In countries with better innovation performance, the indirect effects of robot usage on NO_x and climate change related indicators are positive when population density is at its mean, and become stronger in countries with denser population. In less innovative countries, the indirect effects of robot usage on NO_x, CO_2, and CH_4 are insignificant when population density is at its mean, and turns negative when population density rises. The heterogeneity in the indirect effect suggests that, density could be a solution as a crucial climate mitigation measure through energy saving in countries with lower level of innovation, but not so in more innovative countries.

Table 8. Mediation effect of energy consumption and moderation effect of population density: high GII countries vs. low GII countries

	(1a) NO_x	(2a) $PM_{2.5}$	(3a) CO_2	(4a) CH_4	(5a) GHG	(1b) NO_x	(2b) $PM_{2.5}$	(3b) CO_2	(4b) CH_4	(5b) GHG
Mediation effect	***Panel a: high GII countries***					***Panel b: low GII countries***				
Total effect	0.226***	0.015**	0.239***	0.225***	0.236***	0.094**	-0.060**	0.094**	0.099***	0.090**
	(0.016)	(0.007)	(0.017)	(0.017)	(0.016)	(0.042)	(0.030)	(0.041)	(0.038)	(0.038)
Direct effect	0.006	0.003	-0.019**	-0.018*	-0.014**	0.005	-0.052*	0.005	0.026	0.006
	(0.010)	(0.009)	(0.008)	(0.010)	(0.007)	(0.016)	(0.029)	(0.013)	(0.022)	(0.008)
Indirect effect	0.220***	0.012	0.258***	0.243***	0.250***	0.089*	-0.008	0.089*	0.073*	0.084*
	(0.020)	(0.008)	(0.024)	(0.021)	(0.023)	(0.052)	(0.014)	(0.050)	(0.054)	(0.048)
[LL 95% CI, UL 95% CI]	[0.181, 0.259]	[-0.003, 0.027]	[0.211, 0.305]	[0.201, 0.285]	[0.205, 0.295]	[-0.013, 0.190]	[-0.035, 0.019]	[-0.009, 0.187]	[-0.011, 0.158]	[-0.010, 0.179]
Moderation effect										
Robot usage	0.035*	-0.027	0.052***	0.078***	0.061***	-0.380***	1.118***	-0.147	-0.837***	-0.414***
	(0.021)	(0.017)	(0.015)	(0.021)	(0.014)	(0.106)	(0.272)	(0.097)	(0.151)	(0.046)
PD	-0.102**	0.179***	0.294***	0.134***	0.251***	-1.176***	2.418***	0.080	-1.894***	-0.663***
	(0.041)	(0.032)	(0.030)	(0.041)	(0.027)	(0.213)	(0.585)	(0.194)	(0.302)	(0.092)
Robot x PD	-0.003	0.001	-0.022***	-0.022***	-0.021***	0.093***	-0.259***	0.028	0.196***	0.091***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.023)	(0.060)	(0.021)	(0.033)	(0.010)
Moderated mediation effect										
−1 SD	0.202***	0.008	0.228***	0.220***	0.222***	0.402***	-0.099	0.290***	0.390***	0.332***
	(0. 031)	(0.006)	(0.034)	(0.032)	(0.033)	(0.099)	(0.084)	(0.071)	(0.094)	(0.078)
[LL 95% CI, UL 95% CI]	[0.148, 0.271]	[-0.003, 0.20]	[0.169, 0.300]	[0.164, 0.291]	[0.165, 0.292]	[0.205, 0.561]	[-0.565, - 0.003]	[0.167, 0.452]	[0.212, 0.572]	[0.186, 0.484]
M	0.210***	0.007	0.237***	0.228***	0.231***	0.079	-0.005	0.057	0.077	0.066
	(0. 018)	(0.005)	(0.019)	(0.018)	(0.019)	(0.060)	(0.026)	(0.045)	(0.058)	(0.050)
[LL 95% CI, UL 95% CI]	[0.175, 0.247]	[-0.003, 0.016]	[0.199, 0.274]	[0.193, 0.266]	[0.195, 0.267]	[-0.049, 0.181]	[-0.116, 0.022]	[-0.033, 0.141]	[-0.042, 0.181]	[-0.039, 0.155]
+1 SD	0. 217***	0.006	0.246***	0.237***	0.240***	-0.243***	0.088	-0.176***	-0.236***	-0.201
	(0.025)	(0.004)	(0.027)	(0.027)	(0.027)	(0.062)	(0.078)	(0.042)	(0.054)	(0.045)
[LL 95% CI, UL 95% CI]	[0.173, 0.271]	[-0.002, 0.014]	[0.195, 0.306]	[0.186, 0.296]	[0.190, 0.298]	[-0.370, - 0.122]	[-0.032, 0.299]	[-0.260, - 0.088]	[-0.341, - 0.119]	[-0.287, - 0.099]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	366	261	366	366	366	72	46	72	72	72

Notes: * (**, ***) significance at the 10% (5%, 1%) level, bootstrap standard errors in parentheses. Confidence Intervals (CI) is 95% bootstrap confidence interval, bootstrap based on 5000 bootstrap samples. LU is lower limit, UL is upper limit, five indicators of air environment are the dependent variables, energy consumption is a mediation variable, and population density is a moderation variable.

6.3 Classification of different industries

Table 9 presents the impact of robot usage on air environment in manufacturing industry (Panel a) and five more segmented sub-industries (Panels b-f), namely, automotive, electrical and electronics, metal, motor vehicles engines and bodies, and plastic and chemical products. The total, direct and indirect effects are similar to those presented in Table 4. The total effects of robot usage on all air environment indicators are positive, though being less significant in $PM_{2.5}$. Compared with other four sub-industries, only in the industry of plastic and chemical, the adoption of more industrial robots leads to heavier air pollution indicated by a higher level of $PM_{2.5}$ concentration ($b = 0.012, p < 0.05$ in Model 2f).

Though the direct effect varies across sub-industries, the pattern remains that the direct effect was still dominated by the indirect effect. In terms of the direct effect, for manufacturing industry as a whole, robot adoption predicts a significant rise in NO_x emission, while plays no role in affecting other air environment indicators. Similar direct effect on NO_x emission was identified in the sub-industry producing plastic and chemical products ($b = 0.013, p < 0.05$ in Model 1f). Notably, a higher penetration of robots in production activities reduces CO_2 emission, directly contributing to ameliorate climate warming, in three sub-industries electrical and electronics, metal, and plastic and chemical products. $PM_{2.5}$ concentration was also lower in the motor vehicles engines and bodies sub-industry as the robot use rises ($b = -0.018, p < 0.01$ in Model 2e). The indirect effects are consistent across all sub-industries and confirms the important role for energy consumption that significantly mediate the relation between robot usage and air environment.

In terms of the moderation effect, we find that the response of climate-change indicators to robot usage is more responsive to the variation in population density than the air quality indicators, except for the electrical and electronics sub-industry. In the sub-industry of electrical and electronics, the relationship between robot usage and air pollution is stronger in denser areas.

Last but not the least, we find that for manufacturing as a whole and its five sub-industries, the mediation effects of energy consumption are significantly moderated by population density. That is to say, robot usage in manufacturing industry worsens air quality and exacerbates climate change due to higher demand in energy, and this negative environmental externality was significantly enhanced in countries or regions with more dense population.

Table 9. Mediation effect of energy consumption and moderation effect of population density in different industries

	(1a) NO_x	(2a) $PM_{2.5}$	(3a) CO_2	(4a) CH_4	(5a) GHG	(1b) NO_x	(2b) $PM_{2.5}$	(3b) CO_2	(4b) CH_4	(5b) GHG
Mediation effect	***Panel a: Manufacturing***					***Panel b: Automotive***				
Total effect	0.167***	0.010*	0.170***	0.166***	0.169***	0.186***	-0.060	0.201***	0.192***	0.199***
	(0.011)	(0.005)	(0.012)	(0.012)	(0.012)	(0.011)	(0.005)	(0.012)	(0.011)	(0.011)
Direct effect	0.014***	0.000	-0.004	0.000	-0.002	0.003	-0.008	-0.004	-0.006	-0.003
	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.006)	(0.007)	(0.005)	(0.005)	(0.004)
Indirect effect	0.153***	0.010**	0.174***	0.166***	0.171***	0.183***	0.014***	0.205***	0.198***	0.202***
	(0.012)	(0.004)	(0.014)	(0.013)	(0.014)	(0.011)	(0.005)	(0.013)	(0.012)	(0.012)
[LL 95% CI, UL 95% CI]	[0.130, 0.177]	[0.002, 0.019]	[0.147, 0.201]	[0.140, 0.193]	[0.144, 0.198]	[0.161, 0.206]	[0.005, 0.023]	[0.180, 0.229]	[0.173, 0.222]	[0.177, 0.226]
Moderation effect										
Robot usage	0.012	-0.024	0.037***	0.036**	0.037***	0.026	-0.043**	0.041***	0.044***	0.042***
	(0.015)	(0.017)	(0.012)	(0.015)	(0.011)	(0.016)	(0.017)	(0.014)	(0.016)	(0.012)
PD	-0.122***	0.131***	0.165***	0.015	0.119***	-0.094***	0.128***	0.154***	0.020	0.113***
	(0.022)	(0.026)	(0.019)	(0.022)	(0.016)	(0.020)	(0.023)	(0.017)	(0.021)	(0.015)
Robot x PD	0.002	0.003	-0.011***	-0.008**	-0.010***	-0.004	0.005	-0.011***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Moderated mediation effect										
−1 SD	0.152***	0.004	0.160***	0.159***	0.160***	0.206***	0.010**	0.216***	0.216***	0.215***
	(0.021)	(0.004)	(0.022)	(0.021)	(0.021)	(0.020)	(0.005)	(0.020)	(0.020)	(0.020)
[LL 95% CI, UL 95% CI]	[0.112, 0.193]	[-0.003, 0.013]	[0.118, 0.203]	[0.117, 0.201]	[0.118, 0.202]	[0.169, 0.245]	[0.0002, 0.020]	[0.175, 0.252]	[0.175, 0.254]	[0.175, 0.252]
M	0.130***	0.003	0.138***	0.137***	0.137***	0.162***	0.007**	0.169***	0.169***	0.168***
	(0.012)	(0.003)	(0.113)	(0.013)	(0.13)	(0.011)	(0.004)	(0.012)	(0.012)	(0.011)
[LL 95% CI, UL 95% CI]	[0.107, 0.155]	[-0.003, 0.009]	[0.163, 0.192]	[0.112, 0.163]	[0.113, 0.162]	[0.140, 0.186]	[0.0003, 0.014]	[0.147, 0.192]	[0.146, 0.193]	[0.146, 0.191]
+1 SD	0.109***	0.002	0.115***	0.114***	0.114***	0.117***	0.005**	0.123***	0.123***	0.122***
	(0.021)	(0.002)	(0.022)	(0.022)	(0.021)	(0.019)	(0.002)	(0.020)	(0.020)	(0.019)
[LL 95% CI, UL 95% CI]	[0.071, 0.151]	[-0.001, 0.007]	[0.075, 0.158]	[0.074, 0.158]	[0.074, 0.157]	[0.081, 0.156]	[0.001, 0.011]	[0.085, 0.162]	[0.085, 0.163]	[0.085, 0.161]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	702	381	702	702	702	702	381	702	702	702
	(1c) NO_x	**(2c) $PM_{2.5}$**	**(3c) CO_2**	**(4c) CH_4**	**(5c) GHG**	**(1d) NO_x**	**(2d) $PM_{2.5}$**	**(3d) CO_2**	**(4d) CH_4**	**(5d) GHG**
Mediation effect	***Panel c: Electrical/electronics***					***Panel d: Metal***				
Total effect	0.228***	0.007	0.227***	0.226***	0.230***	0.197***	0.011	0.199***	0.197***	0.200***

	(0.015)	(0.007)	(0.017)	(0.016)	(0.016)	(0.014)	(0.06)	(0.015)	(0.015)	(0.015)
Direct effect	0.010	-0.008	-0.021***	-0.010	-0.013**	0.011*	-0.001	-0.011**	-0.004	-0.006
	(0.007)	(0.008)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)
Indirect effect	0.218***	0.015***	0.248***	0.236***	0.243***	0.186***	0.012***	0.210***	0.201***	0.206***
	(0.018)	(0.005)	(0.020)	(0.019)	(0.020)	(0.016)	(0.004)	(0.018)	(0.017)	(0.017)
[LL 95% CI, UL 95% CI]	[0.183, 0.252]	[0.005, 0.025]	[0.208, 0.288]	[0.198, 0.274]	[0.204, 0.282]	[0.155, 0.216]	[0.003, 0.020]	[0.175, 0.245]	[0.167, 0.234]	[0.172, 0.240]
Moderation effect										
Robot usage	-0.013	-0.086***	-0.009	-0.002	-0.006	0.014	-0.041**	0.025	0.027	0.026**
	(0.020)	(0.022)	(0.017)	(0.021)	(0.015)	(0.018)	(0.020)	(0.015)	(0.018)	(0.013)
PD	-0.137***	0.113***	0.138***	-0.016	0.089***	-0.116***	0.122***	0.150***	0.003	0.104***
	(0.020)	(0.022)	(0.017)	(0.020)	(0.014)	(0.021)	(0.024)	(0.018)	(0.022)	(0.015)
Robot x PD	0.008*	0.013***	-0.005	-0.001	-0.003	0.001	0.006	-0.010***	-0.007*	-0.009***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Moderated mediation effect										
−1 SD	0.228***	0.011**	0.243***	0.240***	0.240***	0.197***	0.006	0.207***	0.206***	0.206***
	(0.028)	(0.005)	(0.030)	(0.029)	(0.029)	(0.024)	(0.004)	(0.025)	(0.025)	(0.025)
[LL 95% CI, UL 95% CI]	[0.173, 0.283]	[0.001, 0.023]	[0.182, 0.301]	[0.181, 0.297]	[0.181, 0.297]	[0.149, 0.245]	[-0.002, 0.015]	[0.156, 0.257]	[0.155, 0.255]	[0.155, 0.255]
M	0.185***	0.008**	0.197***	0.195***	0.195***	0.153***	0.004	0.161***	0.160***	0.160***
	(0.019)	(0.004)	(0.020)	(0.020)	(0.019)	(0.016)	(0.003)	(0.016)	(0.017)	(0.016)
[LL 95% CI, UL 95% CI]	[0.151, 0.223]	[0.001, 0.016]	[0.161, 0.237]	[0.158, 0.234]	[0.159, 0.234]	[0.122, 0.184]	[-0.002, 0.010]	[0.129, 0.193]	[0.128, 0.192]	[0.128, 0.191]
+1 SD	0.142***	0.005**	0.152***	0.150***	0.150***	0.108***	0.002	0.114***	0.114***	0.114***
	(0.026)	(0.002)	(0.027)	(0.027)	(0.027)	(0.026)	(0.002)	(0.027)	(0.027)	(0.027)
[LL 95% CI, UL 95% CI]	[0.094, 0.194]	[0.002, 0.012]	[0.101, 0.208]	[0.100, 0.205]	[0.100, 0.205]	[0.060, 0.160]	[-0.0002, 0.008]	[0.062, 0.168]	[0.062, 0.168]	[0.062, 0.167]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	702	381	702	702	702	702	381	702	702	702
	(1e) NO_x	**(2e) $PM_{2.5}$**	**(3e) CO_2**	**(4e) CH_4**	**(5e) GHG**	**(1f) NO_x**	**(2f) $PM_{2.5}$**	**(3f) CO_2**	**(4f) CH_4**	**(5f) GHG**
Mediation effect	***Panel e: Motor vehicles engines and bodies***					***Panel f: Plastic and chemical products***				
Total effect	0.189***	-0.001	0.203***	0.193***	0.202***	0.191***	0.012**	0.193***	0.193***	0.194***
	(0.011)	(0.005)	(0.012)	(0.012)	(0.012)	(0.013)	(0.006)	(0.014)	(0.014)	(0.014)
Direct effect	0.001	-0.018***	-0.006	-0.009	-0.004	0.013**	0.002	-0.011**	0.000	-0.006
	(0.006)	(0.007)	(0.005)	(0.006)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)	(0.004)
Indirect effect	0.188***	0.017***	0.209***	0.202***	0.206***	0.179***	0.10**	0.204***	0.193***	0.200***
	(0.011)	(0.004)	(0.012)	(0.011)	(0.011)	(0.014)	(0.004)	(0.016)	(0.015)	(0.015)

[LL 95% CI, UL 95% CI]	[0.167, 0.208]	[0.009, 0.026]	[0.186, 0.232]	[0.180, 0.225]	[0.183, 0.228]	[0.153, 0.206]	[0.002, 0.019]	[0.173, 0.234]	[0.164, 0.222]	[0.170, 0.230]
Moderation effect										
Robot usage	0.018	-0.051***	0.048***	0.064***	0.050***	0.014	-0.025	0.042***	0.043**	0.041***
	(0.018)	(0.019)	(0.015)	(0.018)	(0.013)	(0.018)	(0.020)	(0.015)	(0.018)	(0.013)
PD	-0.096***	0.125***	0.144***	0.023	0.105***	-0.124***	0.143***	0.169***	0.009	0.119***
	(0.019)	(0.021)	(0.016)	(0.019)	(0.014)	(0.021)	(0.024)	(0.018)	(0.021)	(0.015)
Robot x PD	-0.003	0.006	-0.012***	-0.015***	-0.012***	0.002	0.002	-0.014***	-0.009**	-0.012***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Moderated mediation effect										
−1 SD	0.233***	0.013**	0.240***	0.242***	0.240***	0.179***	0.005	0.191***	0.188***	0.189***
	(0.020)	(0.005)	(0.021)	(0.021)	(0.021)	(0.023)	(0.004)	(0.025)	(0.024)	(0.025)
[LL 95% CI, UL 95% CI]	[0.194, 0.273]	[0.003, 0.025]	[0.199, 0.280]	[0.200, 0.281]	[0.198, 0.279]	[0.134, 0.225]	[-0.003, 0.014]	[0.141, 0.239]	[0.139, 0.236]	[0.140, 0.238]
M	0.172***	0.009**	0.177***	0.178***	0.177***	0.150***	0.004	0.160***	0.157***	0.159***
	(0.011)	(0.004)	(0.010)	(0.011)	(0.010)	(0.014)	(0.003)	(0.015)	(0.015)	(0.015)
[LL 95% CI, UL 95% CI]	[0.152, 0.194]	[0.002, 0.016]	[0.157, 0.198]	[0.158, 0.200]	[0.157, 0.197]	[0.123, 0.176]	[-0.002, 0.010]	[0.131, 0.189]	[0.129, 0.187]	[0.130, 0.187]
+1 SD	0.111***	0.005**	0.114***	0.115***	0.114***	0.121***	0.002	0.129***	0.127***	0.128***
	(0.018)	(0.002)	(0.018)	(0.018)	(0.018)	(0.024)	(0.002)	(0.025)	(0.025)	(0.025)
[LL 95% CI, UL 95% CI]	[0.078, 0.147]	[0.002, 0.011]	[0.080, 0.149]	[0.081, 0.151]	[0.080, 0.149]	[0.077, 0.170]	[-0.001, 0.008]	[0.082, 0.181]	[0.082, 0.178]	[0.081, 0.179]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	702	381	702	702	702	702	381	702	702	702

Notes: * (**, ***) significance at the 10% (5%, 1%) level, bootstrap standard errors in parentheses. Confidence Intervals (CI) is 95% bootstrap confidence interval, bootstrap based on 5000 bootstrap samples. LU is lower limit, UL is upper limit, five indicators of air environment are the dependent variables, energy consumption is a mediation variable, and population density is a moderation variable.

7. Discussion and conclusion

With an increasing pace and complexity of the ongoing innovation in automation technology and artificial intelligence, a deep understanding of their implications on air environment is important and imperative to identify measures that can be taken to avoid, minimize or offset potential adverse impacts, if any. Against this backdrop, we explored whether, to what extent, and how the use of industrial robots influences both air quality and climate change. Regulations of the new automation technology would be based on our anticipatory foresight study that provokes thinking on where the robotics should be applied, are there any fields that should promote the use or restrict the use of such innovations, and, why so is.

We contributed to the technology-environment literature that has thus far provided very inconsistent results. Using a cross-country panel dataset during 1993-2019, several interesting conclusions were drawn, among which the main take-away is that technology is a solution to overcome environmental challenge, however, we cannot neglect its adverse impact, or, the unintended side effect. Due to the dominant adverse impact, the total effect of the use of robots is against our expectation. This finding echoes the perspective in Simon (1973). Our analyses not only decomposed the direct, and the indirect effect from the total effect. But also, we highlighted and identified that population distribution plays a role in moderating the relation between machines and air environment. This is the first study, as far as we know, that systemically provided a theoretical framework and statistical modeling to examine the complex nexus among industrial robots, energy consumption, population density, and air environment.

Our findings yielded three broad implications for policymakers. First, our results suggested that, it is through inducing more energy demand, that industrial robots produced negative environmental externality, especially in the low-EPI and high-GII countries, and the electrical and electronics industry. Considering such implications, policymakers might need to consider how to minimize, reduce, and offset the rebound effect and the scale effect when energy efficiency has been significantly improved in light of robot adoption. For countries with low environmental performance index or high innovation capacity, they were faced with more serious challenges to balance the industrial policy in robot adoption and environmental protection. When more industrial robots penetrated into production process, a caution has to be made against the old wisdom "the more the better." Second, when deciding upon where robotics was applied and in which industries we should promote the use or restrict the use of robotics, population density is the key element that could be incorporated into such decision-making. And third, in countries with denser population, more heed should be paid to the adverse impact of robot adoption on air environment.

This study naturally has its limitations that may encourage several directions of future research. First, it is interesting to explore what are the alternative mechanisms that mediate the relation between robots and air environment, and what are the institutional factors that moderate this relation. Second, a more rigorous theory could be developed to improve our current understanding of robots-environment nexus. Third, since our empirical results suggested heterogeneous findings due to different country features. An extension of study to sub-country level could be a future research direction when detailed robot data are more available at regional level.

Reference

Acemoglu, D., Autor, D. 2011. Skills, tasks and technologies: Implications for employment and earnings. In Handbook of labor economics (Vol. 4, pp. 1043-1171). Elsevier.

Acemoglu, D., Restrepo, P. 2018a. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488-1542.

Acemoglu, D., Restrepo, P. 2018b. Low-skill and high-skill automation. *Journal of Human Capital*, 12(2), 204-232.

Acemoglu, D., Restrepo, P. 2019. Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2): 3-30.

Acemoglu, D., Restrepo, P. 2020. Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6), 2188—2244.

Acemoglu, D., Restrepo, P. 2021. Demographics and automation. *The Review of Economic Studies*, 89, 1, 1–44.

Acemoglu, D., Akcigit, T., Hanley, U. 2016. Transition to clean technology. *Journal of Political Economy*, 124(1), 52–104.

Afonso, S., Fonseca, L., Magalhaes, M., Vasconcelos, P. B. 2021. Directed technical change and environmental quality. *Portuguese Economic Journal*, 20, 71-97.

Aghion, P., Jones, B. F., Jones, C. I. 2019. 9. Artificial Intelligence and Economic Growth (pp. 237-290). University of Chicago Press.

Alcott, B. 2005. Jevons' paradox. *Ecological Economics*, 441, 9-21.

Alshubiri, F., Elheddad, M. 2019. Foreign finance, economic growth and CO2 emissions nexus in OECD countries. *International Journal of Climate Change Strategies and Management*.

An, H., Xu, J., Ma, X. 2020. Does technological progress and industrial structure reduce electricity consumption? evidence from spatial and heterogeneity analysis. *Structural Change and Economic Dynamics*, 52, 206-220.

Ausubel, J. H., Sladovich, H. E. 1989. Technology and environment (No. PB-96-189451/XAB). National Academy of Engineering, Washington, DC United States.

Ballestar, M. T., Díaz-Chao, Á., Sainz, J., Torrent-Sellens, J. 2020. Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research*, 108, 119-131.

Baron, R. M., Kenny, D. A. 1986. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 5, 1173-1182.

Berg, A., Buffie, E., Zanna, L. F. 2018. Should we fear the robot revolution? (the correct answer is yes). *Journal of Monetary Economics*, 97, 117–148.

Bilgili, F., Koçak, E., Bulut, Ü., Kuloğlu, A. 2017. The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity. *Energy*, 133, 242-256.

Borck, R., Schrauth, P. 2021. Population density and urban air quality. *Regional Science and Urban Economics*, 86, 103596.

Carabin, G., Wehrle, E., Vidoni, R. 2017. A review on energy-saving optimization methods for robotic and automatic systems. *Robotics*, 6(4), 39.

Chen, J., Wang, B., Huang, S., Song, M. 2020. The influence of increased population density in China on air pollution. *Science of The Total Environment*, 735, 139456.

Chien, F., Sadiq, M., Nawaz, M. A., Hussain, M. S., Tran, T. D., Le Thanh, T. 2021. A step toward reducing air pollution in top Asian economies: The role of green energy, eco-innovation, and environmental taxes. *Journal of Environmental Management*, 297, 113420.

Cole, M. A., Neumayer, E. 2004. Examining the impact of demographic factors on air pollution. *Population and Environment*, 26(1), 5-21.

Cole, M. A., Elliott, R. J., Zhang, J. 2011. Growth, foreign direct investment, and the environment: evidence from Chinese cities. *Journal of Regional Science*, 51(1), 121-138.

Dantas, TET., de-Souza, ED., Destro, IR., Hammes, G., Rodriguez, CMT., Soares SR. 2020. How the combination of circular economy and industry 4.0 can contribute towards achieving the Sustainable Development Goals, *Sustainable Production and Consumption*, 26(4), 213-227.

Dusik, J., Fischer, T. B., Sadler, B., Therivel, R., Saric, I. 2018. Strategic environmental and social assessment of automation: scoping working paper. ResearchGate, Berlin.

Ehrlich, P. R, Holdren, J. P. 1971. Impact of population growth. *Science*, 171(3977), 1212-1217.

Elpidio, O. B. N., Matheus, B., Ismael, C. B., Jones, L. S., Guilherme, B. B., Leonardo, M. A. L., Lisianne, B. B. 2020. Expected Impact of Industry 4.0 Technologies on Sustainable Development: A study in the context of Brazil's Plastic Industry, *Sustainable Production and Consumption*, 25, 102-122.

Erdogan, S. 2021. Dynamic nexus between technological innovation and buildings Sector's carbon emission in BRICS countries. *Journal of Environmental Management*, 293, 112780.

Ertel, W. 2019. Artificial Intelligence, the spare time rebound effect and how the ECG would avoid it. In: International Conference: Economy for the Common Good (ECGPW-2019), Bremen.

Eskeland, G. S., Harrison, A. E. 2003. Moving to greener pastures? Multinationals and the pollution haven hypothesis. *Journal of Development Economics*, 70(1), 1-23.

European Environment Agency, 2004. Environmental Impact of Energy. https://www.eea.europa.eu/help/glossary/eea-glossary/environmental-impact-of-energy.

Fan, H., Hu, Y., Tang, L. 2021. Labor costs and the adoption of robots in China. *Journal of Economic Behavior Organization*, 186, 608-631.

Golub, S.S., Kauffmann, C., Yeres, P., 2011. Defining and Measuring Green FDI. Organization for Economic Development and Cooperation Working paper 2011/102.

Graetz, G., Michaels, G. 2018. Robots at Work. *The Review of Economics and Statistics*, 100(5), 753-768.

Grossman, G. M., Krueger, A. B. 1991. Environmental impacts of a North American free trade agreement. CEPR Discussion Papers, 8(2), 223-250.

Hanif, I., Faraz Raza, S. M., Gago-de-Santos, P., Abbas, Q. 2019. Fossil fuels, foreign direct investment, and economic growth have triggered CO2 emissions in emerging Asian economies: Some empirical evidence. *Energy*, 171, 493-501.

Herring, H. 2004. The rebound effect and energy conservation. In: Cleveland, C. (Ed.), The Encyclopaedia of Energy. Academic Press, Elsevier Science, New York, Amsterdam.

Herring, H. 2006. Energy efficiency: a critical view, Special issue dedicated to the international workshop on advances in energy studies, Porto Venere, Italy, May 2000, 31(1), pp. 10–20.

Huang, G., Zhang, J., Yu, J., Shi, X. 2020. Impact of transportation infrastructure on industrial pollution in Chinese cities: A spatial econometric analysis. *Energy Economics*, 92, 104973.

Ibrahim, R. L., Ajide, K. B. 2021. The dynamic heterogeneous impacts of nonrenewable energy, trade openness, total natural resource rents, financial development and regulatory quality on environmental quality: Evidence from BRICS economies. *Resources Policy*, 74, 102251.

IFR, 2020. World Robotics 2020, International Federation of Robotics and the United Nations.

International Energy Agency (IEA), 2015 World Energy Outlook 2015. Paris, France.

Jin, C., Hu, H. 2021. The non-linear effect of china's energy consumption on eco-environment pollution. *Energy Engineering*, 118(3), 655-665.

Kromann, L., Malchow-Møller, N., Skaksen, J. R., Sørensen, A. 2020. Automation and productivity—a cross-country, cross-industry comparison. *Industrial and Corporate Change*, 29(2), 265-287.

Lariviere, I., Lafrance, G. 1999. Modelling the electricity consumption of cities: effect of urban density. *Energy economics*, 21(1), 53-66.

Lei, Y. W. 2021. Upgrading China through Automation: Manufacturers, Workers and the Techno-Developmental State. *Work, Employment and Society*, 0950017021999198.

Lin, B., Zhao, H. 2016. Technological progress and energy rebound effect in China′ s textile industry: Evidence and policy implications. *Renewable and sustainable energy reviews*, 60, 173-181.

Liu, J., Chang, H., Forrest, Y. L., Yang, B. 2020. Influence of artificial intelligence on technological innovation: evidence from the panel data of China's manufacturing sectors. *Technological Forecasting and Social Change*, 158, 120142.

Ma, T., Wang, Y. 2021. Globalization and environment: Effects of international trade on emission intensity reduction of pollutants causing global and local concerns. *Journal of Environmental Management*, 297, 113249.

MacKinnon, D. P. 2008. Introduction to statistical mediation analysis. Mahwah, NJ: Erlbaum.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., Sheets, V. 2002. A comparison of methods to test mediation and other intervening variable effects. *Psychological methods*, 7(1), 83.

Mamun, A., Sohag, K., Mia, A. H., Uddin, G. S., Ozturk, I. 2014. Regional differences in the dynamic linkage between CO2 emissions, sectoral output and economic growth. *Renewable Sustainable Energy Reviews*, 38(oct.), 1-11.

McKinsey Global Institute MGI 2017. Jobs lost, jobs gained: Workforce transitions in a time of automation, 150.

Meng, W., Zhong, Q., Chen, Y., Shen, H., Yun, X., Smith, K. R., et al. 2019. Energy and air pollution benefits of household fuel policies in northern China. *Proceedings of the National Academy of Sciences*, 116(34), 201904182.

Metcalf, G. E., Hassett, K. A. 1999. Measuring the Energy Savings from Home Improvement Investments: Evidence from Monthly Billing Data. *Review of Economics Statistics*, 81(3), 516-528.

Muller, D., Judd, C. M., Yzerbyt, V. Y. 2005. When moderation is mediated and mediation is moderated. *Journal of Personality and Social Psychology*, 89(6), 852–863.

Narayanan, K., Sahu, S. K. 2014. Energy Consumption Response to Climate Change: Policy Options for India. *IIM Kozhikode Society Management Review*, 3(2), 123–133.

Nasir, M. A., Huynh, T., Tram, H. 2019. Role of financial development, economic growth foreign direct investment in driving climate change: a case of emerging ASEAN. *Journal of Environmental Management*, 242(JUL.15), 131-141.

Neves, S. A., Marques, A. C., M Patrício. 2020. Determinants of CO2 emissions in European union countries: does environmental regulation reduce environmental pollution? *Economic Analysis and Policy*, 68, 114-125.

Ohlan, R. 2015. The impact of population density, energy consumption, economic growth and trade openness on CO2 emissions in India. *Natural Hazards*, 79(2), 1409-1428.

Omri, A. 2018. Entrepreneurship, sectoral outputs and environmental improvement: International evidence. *Technological Forecasting and Social Change*, 128, 46-55.

O'Neill, B.C., Mackellar, F.L., Lutz, W. 2005. Population and climate change. Cambridge University Press.

Paramati, S. R., Alam, M. S., Chen, C. F. 2017. The effects of tourism on economic growth and CO2 emissions. *Journal of Travel Research*, 56(6), 712-724.

Pham, N. M., Huynh, T. L. D., Nasir, M. A. 2020. Environmental consequences of population, affluence and technological progress for European countries: A Malthusian view. *Journal of environmental management*, 260, 110143.

Pires, N. J. 2007. Introduction to the Industrial Robotics World. Springer US.

Rafindadi, A. A. 2016. Does the need for economic growth influence energy consumption and CO2 emissions in Nigeria? Evidence from the innovation accounting test. *Renewable and Sustainable Energy Reviews*, 62, 1209-1225.

Rahman, M. M. 2020. Exploring the effects of economic growth, population density and international trade on energy consumption and environmental quality in India, *International Journal of Energy Sector Management*, 14(6), 1177–1203.

Rahman, M. M., Alam, K. 2021. Clean energy, population density, urbanization and environmental pollution nexus: evidence from Bangladesh. *Renewable Energy*, 172(7), 1063-1072.

Rahman, M. M., Kashem, M. A. 2017. Carbon emissions, energy consumption and industrial growth in Bangladesh: Empirical evidence from ARDL cointegration and Granger causality analysis. *Energy Policy*, 110, 600-608.

Rasool, Y., Zaidi, S. A. H., Zafar, M. W. 2019. Determinants of carbon emissions in Pakistan's transport sector. *Environmental Science and Pollution Research*, 26(22), 1-15.

Resch, E., Bohne, R. A., Kvamsdal, T., Lohne, J. 2016. Impact of urban density and building height on energy use in cities. *Energy Procedia*, 96, 800-814.

Sadorsky, P. 2014. The effect of urbanization on CO2 emissions in emerging economies. *Energy Economics*, 41(Jan.), 147-153.

Sapkota, P., Bastola, U. 2017. Foreign direct investment, income, and environmental pollution in developing countries: Panel data analysis of Latin America. *Energy*

Economics, 64, 206-212.

Shahbaz, M., Nasir, M. A., Roubaud, D. 2018. Environmental degradation in France: the effects of FDI, financial development, and energy innovations. *Energy Economics*, 74, 843-857.

Shao, X., Zhong, Y., Liu, W., Li, R. Y. M. 2021. Modeling the effect of green technology innovation and renewable energy on carbon neutrality in N-11 countries? Evidence from advance panel estimations. *Journal of Environmental Management*, 296, 113189.

Shi, Q., Lai, X. 2013. Identifying the underpin of green and low carbon technology innovation research: a literature review from 1994 to 2010. *Technological Forecasting and Social Change*, 80, 839–864.

Shrout, P. E., Bolger, N. 2002. Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, 7, 422–445.

Shui, L., Zhu, L., Yang, Z., Liu, Y., Chen, X. 2017. Energy efficiency of mobile soft robots. *Soft Matter*, 13(44), 8223-8233.

Simon, H. A. 1973. Technology and Environment. *Management Science*, 19(10), 1110–1121.

Sohag, K., Begum, R.A., Abdullah, S.M.S., Jaafar M. 2015. Dynamics of energy use, technological innovation, economic growth and trade openness in Malaysia. *Energy*, 90, 1497–1507.

Soytas, U., Sari, R., Ewing, B. T. 2007. Energy consumption, income, and carbon emissions in the United States. *Ecological Economics*, 62(3-4), 482-489.

Stokey, N. L. 1998. Are There Limits to Growth? *International Economic Review*, 39(1), 1-31.

Tang, C. F., Tan, B. W. 2015. The impact of energy consumption, income and foreign direct investment on carbon dioxide emissions in Vietnam. *Energy*, 79, 447-454.

Uhlmann, E., Reinkober, S., Hollerbach, T. 2016. Energy efficient usage of industrial robots for machining processes. *Procedia CIRP*, 48, 206-211.

Vivanco, D. F., Kemp, R., Ester, V. 2016. How to deal with the rebound effect? A policy-oriented approach. *Energy Policy*, 94, 114-125.

Wang, E., Lee, C. Li, Y. 2022a. Assessing the impact of industrial robots on manufacturing energy intensity in 38 countries. *Energy Economics*, 105, p.105748.

Wang, Q., Li, L. 2021. The effects of population aging, life expectancy, unemployment rate, population density, per capita GDP, urbanization on per capita carbon emissions. *Sustainable Production and Consumption*, 28, 760-774.

Wang, Q., Li, S., Li, R., Jiang, F. 2022b. Underestimated impact of the COVID-19 on carbon emission reduction in developing countries – A novel assessment based on scenario analysis. *Environmental Research*, 204, 111990.

Wang, Q., Li., S., Zhang, M., Li R. 2022c. Impact of COVID-19 pandemic on oil consumption in the United States: A new estimation approach. *Energy*, 239, 122280.

Wang, Q., Wang, S., Jiang, X. T. 2021. Preventing a rebound in carbon intensity post-covid-19 at the global level – lessons learned from the change in carbon intensity before and after the 2008 financial crisis. *Sustainable Production and Consumption*, 27, 1841-1856.

Wang, Q., Zhang, F. 2021. What does the China's economic recovery after covid-19 pandemic mean for the economic growth and energy consumption of other countries? *Journal of Cleaner Production*, 295(6), 126265.

Wang, S., Fang, C., Guan, X., Pang, B., Ma, H. 2014. Urbanisation, energy consumption, and carbon dioxide emissions in China: A panel data analysis of China's provinces. *Applied Energy*, 136, 738-749.

Wang, Z., Zhu, Y. 2020. Do energy technology innovations contribute to CO2 emissions abatement? a spatial perspective. *Science of The Total Environment*, 726(6), 138574.

Wei, T., Zhou, J., Zhang, H. 2019. Rebound effect of energy intensity reduction on energy consumption. *Resources, Conservation and Recycling*, 144, 233-239.

Wendling, Z. A., Emerson, J. W., de Sherbinin, A., Esty, D. C., et al. 2020. 2020 Environmental Performance Index. New Haven, CT: Yale Center for Environmental

Wilts, H., Garcia, B. R., Garlito, R. G., Gómez, L. S., Prieto, E. G. 2021. Artificial intelligence in the sorting of municipal waste as an enabler of the circular economy. *Resources*, 10(4), 28.

World Health Organization (WHO), 2014. Air quality deteriorating in many of the world's cities. https://www.who.int/news/item/07-05-2014-air-quality-deteriorating-in-many-of-the-world-s-cities.

Wu, X., Deng, H., Li, H. Guo, Y. 2021. Impact of Energy Structure Adjustment and Environmental Regulation on Air Pollution in China: Simulation and Measurement Research by the Dynamic General Equilibrium Model. *Technological Forecasting and Social Change*, 172, 121010.

Xu, B., Lin, B. 2018. What cause large regional differences in pm 2.5 pollutions in China? Evidence from quantile regression model. *Journal of Cleaner Production*, 174(FEB.10), 447-461.

Xu, N., Zhang, F., Xuan, X. 2021. Impacts of Industrial Restructuring and Technological Progress on PM2.5 Pollution: Evidence from Prefecture-Level Cities in China. *International Journal of Environmental Research and Public Health*, 18, 5283.

Yang, G. Hou, Y. 2020. The usage of industry robots, technology upgrade and economic growth in Chinese. *China Industrial Economics*, 10, 138-156.

Yasmeen, R., Li, Y., Hafeez, M. 2019. Tracing the trade–pollution nexus in global value chains: evidence from air pollution indicators. *Environmental Science and Pollution Research*, 26(5), 5221-5233.

Yi, L., Sun, L., Feng, T., Zhu, C. 2013. How to reduce energy intensity in China: a regional comparison perspective. *Energy Policy*, 61(oct.), 513-522.

Yi, M., Wang, Y., Sheng, M., Sharp, B., Zhang, Y. 2020. Effects of heterogeneous technological progress on haze pollution: evidence from China. *Ecological Economics*, 169.

Yin, J., Wang, S., Gong, L. 2018. The effects of factor market distortion and technical innovation on China's electricity consumption. *Journal of Cleaner Production*, 188, 195-202.

York, R. 2007. Demographic trends and energy consumption in European Union Nations, 1960–2025. *Social science research*, 36(3), 855-872.

Zhang, C., Lin, Y. 2012. Panel estimation for urbanization, energy consumption and CO2 emissions: A regional analysis in China, *Energy Policy*, 49, 488-498.

Zhang, C., Zhou, X. 2016. Does foreign direct investment lead to lower CO2 emissions? evidence from a regional analysis in China. *Renewable Sustainable Energy Reviews*, 58(May), 943-951.

Zhu, H., Duan, L., Guo, Y., Yu, K. 2016. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: evidence from panel quantile regression. *Economic Modelling*, 58, 237-248.

Zhu, L., Hao, Y., Lu, Z. N., Wu, H., Ran, Q. 2019. Do economic activities cause air pollution? Evidence from China's major cities. *Sustainable Cities and Society*, 49, 101593.