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Climate change and automation: the emission effects of robot adoption

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Abstract

What are the environmental impacts of the increasing use of automation technologies? To answer this question, we propose a model of production in the age of automation that incorporates emission externalities. We derive a threshold condition subject to which the use of industrial robots affects emissions. This model leads to three testable predictions, i) the use of industrial robots causes higher emissions on average, ii) with increasing efficiency of industrial robots, the effect becomes weaker and could turn negative, and iii) in countries in which electricity is predominantly produced using (clean) renewable energy, industrial robot use has the potential of decreasing emissions. Empirically, we find support for the theoretical hypotheses implying that the effect of automation on emissions is non-linear or moderated by other variables.

JEL classification: O11, O33, O44, Q54, Q55, Q56

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1 Introduction

We are living in an era defined by rapid technological advancements and high pollution levels, which have raised environmental awareness towards sustainable development. One of the most noticeable technological advancements has been robotization, which has increased productivity to unprecedented levels (Autor, 2015; Baldwin, 2020). Existing data corroborate this evidence, as the International Federation of Robotics (2023) reported 553,052 new industrial robot installations around the world in 2022, with an annual growth rate of 5% compared to 2021. At the same time, energy-related carbon dioxide (CO_2) emissions reached a new peak of over 36.8 Gigatonnes and grew by 0.9% in 2022 (International Energy Agency, 2023). Automation, which can take different forms — from manufacturing robots to self-driving cars — promises increased efficiency but also higher electricity use. Thus, how automation shapes environmental sustainability can be considered as a complex and multifaceted issue, deserving a proper analysis.

As industries worldwide adopt automated processes, the potential for both positive and negative environmental impacts becomes apparent, giving rise to the aforementioned complexity. On the one hand, automation can lead to significant reductions in waste and energy consumption through an optimization of production processes. On the other hand, the production, operation, and disposal of automated systems may contribute to greenhouse gas emissions and greater energy consumption. Understanding these dynamics is crucial for developing strategies that maximize the environmental benefits of automation, while mitigating its adverse effects. Surprisingly, prior studies have mainly analyzed the impact of automation on economic growth, welfare, labor market outcomes, and inequality (Acemoglu and Restrepo, 2018; Blanas et al., 2019; Prettner and Bloom, 2020; Koch et al., 2021; Restrepo, 2023; Thuemmel, 2023), but did not focus on the environmental dimension.

The aim of this paper is to explore the relationship between automation and emissions, and also to examine whether their link hinges on specific factors. To this end, we provide a theoretical framework in which firms can produce either with robots or with human workers in combination with physical capital, and incorporate the emissions that are implied by the two different modes of production. The relationship between these factors of production along with the relative emissions generated by their respective production processes determines whether such processes are labor or capital-intensive. We then derive three hypotheses that we test empirically in the subsequent section. The first hypothesis states that robot adoption generates more emissions on average, while the second hypothesis states that the effect is non-linear. In later stages of robot adoption, improvements in energy efficiency weaken the link between automation and emissions. Our empirical findings support both of the theoretically implied hypotheses. For our third hypothesis — that the use of industrial robots in countries with a greater share of renewable electricity generation is associated with lower emissions than in countries with a lower renewable electricity share — we do not find statistically significant support.

The paper is structured as follows. In Section 2, we provide an overview of the literature on automation and the environment. In Section 3, we introduce the theoretical framework and the hypotheses that it implies. Section 4 is devoted to a description of the data, Section 5 outlines the empirical strategy, and Section 6 contains the results. Finally, we conclude in Section 7.

2 Literature Review

The rise of automation has been extensively investigated in recent years, but mostly focusing on its impact on economic growth, labor market outcomes, and inequality. While the first contributions focused on automation in the terms of computers or, more broadly, information and communication technologies (e.g., Autor et al., 1998, 2003), the more recent literature has evolved to focus on industrial robots (see, for example, Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020a; Dauth et al., 2021; Gregory et al., 2022; Cords and Prettner, 2022; Mann and Püttmann, 2023) and on artificial intelligence (see, for example, Webb, 2019; Acemoglu et al., 2022). Different approaches have been used based on country-, industry- or firm-level data. As a short glimpse, studies using more aggregate data tend to find — on average — negative effects of automation on employment, while those using more granular data tend to find the opposite effect. While the former contributions may suffer from aggregation bias, the latter fail to identify general equilibrium effects.

In our contribution, we do not focus on economic growth or labor market outcomes, but instead we aim at contributing to the literature investigating the relationship between the adoption of industrial robots and carbon dioxide (CO_2) emissions. Theoretical work by Gasteiger et al. (2023) has shown that robots require electricity inputs, which may be a source of emissions. So far, the empirical literature on automation and environmental outcomes in a broad sense has mostly found that robots are associated with better ecological outcomes. Using cross-country data, Lee et al. (2022) find that increased robot adoption fosters green technologies (measured in terms of "green R&D"-expenditure and personnel), Chen et al. (2022) conclude that robot usage reduces the ecological footprint through time saving, energy upgrading, and fostering green employment. Li et al. (2022) use data for 35 countries during the period from 1993 to 2017 and describe how industrial robots reduce carbon intensity. Also at the country level, Zhong et al. (2024) study the impact of automation on pollution for a sample of 66 countries during the period 1993-2019 and conclude that the negative relationship concentrates mainly on high-income countries. By contrast, Luan et al. (2022) find the opposite relationship with pollution because industrial robots are associated with air quality deterioration for a sample of 74 countries during the period 1993-2019.

The effect of automation on emissions has also been investigated at more disaggregated levels, but in this case only the Chinese economy has been examined. Yu et al. (2022, 2023), Wang et al. (2023), and Song et al. (2023) use city-level data and find that the use of robots is associated with a reduction in emissions and pollutants. Complementary evidence from Huang et al. (2022) suggests that more robot usage relates to lower energy intensity, while Gan et al. (2023) relate it to higher green innovation. Both of these studies use Chinese disaggregated data.

While most of the expanding empirical literature on the matter finds that automation, understood as the usage of industrial robots, leads to lower emissions, our aim is to contribute to the cross-country literature investigating this question further (i) by providing a theoretical framework that leads to the testable hypotheses and (ii) by improving the econometric approach through accounting for the non-linearity of the effect of robot use on emissions, treating zero entries appropriately in the dependent variable of interest, estimating the standard errors appropriately, and applying a wide range of robustness checks. Most of the reviewed contributions lack a theoretical foundation, do not analyze nonlinearities in the relationship between emissions and robot use, and do not account for the fact that robots can take the value of zero. The issue of zero entries in robot use is relevant to perform empirical analyses — the results can be altered by omitting such entries as has been frequently done. Thus, simply using the logarithmic transformation would deprive us from valuable information (Chen and Roth, 2024). In addition, we take care of the appropriate clustering of standard errors and provide a wide range of robustness checks that support our results. Overall, our approach is able to uncover a non-linear relationship between robot use and emissions. In early stages of robot adoption — when energy efficiency tends to be low, the increasing use of robots raises CO_2 emissions. By contrast, in later phases of adoption, the positive emission effect of automation weakens.

3 Robot adoption and CO_2 emissions: theory

Consider a situation in which firm i in country j produces output at time t according to the production technology

$$y_{i,j,t} = {k_{i,j,t}}^{\alpha} \left(a_{i,j,t} \cdot l_{i,j,t} + b_{i,j,t} \cdot z_{i,j,t}\right)^{1-\alpha}, \tag{1}$$

where $y_{i,j,t}$ is the output of one firm, $k_{i,j,t}$ is the input of traditional physical capital (machines, assembly lines, and production facilities) that is of fixed supply in the short run, $a_{i,j,t}$ refers to labor productivity in firm i, $l_{i,j,t}$ is the employment level of firm i, $b_{i,j,t}$ is the productivity of robots in firm i, $z_{i,j,t}$ is the number of robots used by this firm, and α is the elasticity of output with respect to the use of fixed installed capital (cf. Steigum, 2011). While robots and workers are perfect substitutes, the relative productivity of the two production factors depends on the relationship between $a_{i,j,t}$ and $b_{i,j,t}$ (cf. Prettner, 2023). Firms maximize their profits as given by

$$p_{y,j,t} \cdot {k_{i,j,t}}^{\alpha} \left(a_{i,j,t} \cdot l_{i,j,t} + b_{i,j,t} \cdot z_{i,j,t}\right)^{1-\alpha} - w_{j,t} \cdot l_{i,j,t} - p_{z,j,t} \cdot z_{i,j,t}, \tag{2}$$

where $p_{y,j,t}$ is the price that firms can charge for their product in market j at time t, $w_{j,t}$ is the wage rate in the economy, and $p_{z,j,t}$ is the going rental price of robots. We assume that the firm is a price taker on the goods and factor markets, which implies that $p_{y,j,t}$, $w_{j,t}$, and $p_{z,j,t}$ are given to the firm. As a consequence, the choice of which production technology to use in the firm depends only on $a_{i,j,t}$ and $b_{i,j,t}$. Assuming that neither $w_{j,t}$, nor $p_{z,j,t}$ are prohibitively high (such that no firm would ever want to employ the corresponding production factor), we would have the following sorting of firms: If $a_{i,j,t}$ is comparatively high in a firm, this firm would want to produce using labor, but would stay un-automated. If, by contrast, $b_{i,j,t}$ is comparatively high in a firm, this firm would choose to automate its production. Examples of the latter may include semi-conductor factories, car factories in which the use of industrial robots is already comparatively high, or the speed factory of Adidas as it was established a few years ago in Nuremberg in Germany.[1]

Sorting firms in descending order of $a_{i,j,t}/b_{i,j,t}$, we get that firms with a high level of $a_{i,j,t}/b_{i,j,t}$ produce with labor and firms with a low level of $a_{i,j,t}/b_{i,j,t}$ produce with robots. Accordingly, there is a threshold level of relative productivity $a_{i,j,t}/b_{i,j,t}$ at which a firm is indifferent between producing with workers or producing with robots (Krenz et al., 2021). If such a firm switches the mode of production from human labor to robots

[1] However, in 2019, the speed factory was closed.

and assuming that $y_{i,j,t}$ and $k_{i,j,t}$ are fixed in the short run, the firm would require

$$z_{i,j,t} = l_{i,j,t} \frac{a_{i,j,t}}{b_{i,j,t}} \tag{3}$$

robots. The main question of interest in our context is then whether or not this switch in the production mode, (i.e., robot adoption) is creating more emissions.

To analyze the effects of switching the production mode on emissions, let $e_{i,j,l,t}$ denote the emissions that are caused by one worker and $e_{i,j,z,t}$ the emissions that are caused by one robot. Reasonably, it would hold true that these emissions are externalities for the firm and that $e_{i,j,l,t} < e_{i,j,z,t}$ because robots require electricity to run, plenty of resources to build, etc., whereas a human needs a coffee in the morning and then a drive to work, which is associated with much lower but arguably still strictly positive emissions. In such a situation, emissions before the switch to robots are

$$l_{i,j,t} e_{i,j,l,t}$$

and emissions after the switch to robots are

$$l_{i,j,t} \frac{a_{i,j,t}}{b_{i,j,t}} e_{i,j,z,t}.$$

Thus, we need to assess

$$l_{i,j,t} e_{i,j,l,t} \lesseqgtr l_{i,j,t} \frac{a_{i,j,t}}{b_{i,j,t}} e_{i,j,z,t}, \tag{4}$$

which boils down to

$$\frac{e_{i,j,l,t}}{e_{i,j,z,t}} \lesseqgtr \frac{a_{i,j,t}}{b_{i,j,t}}. \tag{5}$$

This equation has a very intuitive interpretation. If the ratio of emissions of human workers to robots is large in comparison to the ratio of the productivity of human workers to the productivity of robots, then emissions should fall with the switch to automated production. If the reverse holds true, emissions should rise. Thus, whether or not robots raise emissions is generally an empirical question, which leads us to the first hypothesis that we test in the empirical part of our paper.

Hypothesis 1. *Robot adoption and emissions*

Robot adoption is associated with a rise in emissions on average.

However, given the likely evolution of relative robot efficiency, i.e., that the ratio $a_{i,j,t}/b_{i,j,t}$ has been falling in the past and is expected to fall further, we can formulate the following additional hypothesis on the timing of robot adoption and its effects on emissions.

Hypothesis 2. *Timing of the switch to robots and emissions*

H2a: In earlier phases of the switch of production from human workers to robots, robots will not be very efficient yet. This implies that the left-hand side of Equation (5) will be comparatively low and the right-hand side will be comparatively high. Thus, robot adoption should generate more emissions in earlier stages.

H2b: In later stages of robot adoption, robots will be more efficient so that the left-hand side of Equation (5) will be comparatively high and the right-hand side will be comparatively low. Thus, robot adoption should generate less emissions in later stages.

Finally, considering that $e_{i,j,l,t}/e_{i,j,z,t}$ will be lower in an economy in which electricity generation is mainly based on non-renewable and dirty energy sources such as coal and gas, we can formulate the following additional hypothesis on the spacing of robot adoption and its effects on emissions.

Hypothesis 3. *Spacing of the switch to robots and emissions*

H3a: In countries with a large share of non-renewable electricity generation, the left-hand side of Equation (5) will be comparatively low. Thus, robot adoption should generate more emissions in these countries.

H3b: In countries with a large share of renewable electricity generation, the left-hand side of Equation (5) will be comparatively high. Thus, robot adoption should generate less emissions in these countries.

In the following sections, we aim to test empirically these hypotheses using cross-country data on robot adoption and emissions. The next section is devoted to a description of the data, afterwards, we describe our empirical approach, and then we present the results.

4 The data

To test the predictions of the model, we use the dataset of the International Federation of Robotics (2022). It provides information on the stock of industrial robots for each country starting from 1993. Due to data availability, we are only able to use the data starting from 1993 up to 2019.[2] We then merge to this dataset our dependent and control variables (described below) from the World Development Indicators compiled by the World Bank.

Table 1 shows the summary statistics of our main variables. Our main dependent variable is CO_2 emissions per capita. We follow the prior literature and apply the logarithmic transformation to this variable. Our main variable of interest, the stock of robots in terms of employment, appears to have more variation than the former if we observe the ratio between the mean and the standard deviation.

We also consider an alternative way to measure robots per worker. Rather than using the logarithm as in the original variable, we follow Bellemare and Wichman (2020) and use the inverse hyperbolic sine transformation because doing so allows us to use the valuable information contained in the entries in which the stock of robots is zero. When we compare the amount of observations, we see that there is a sizeable amount of zeroes in this variable. Along the lines of Aller et al. (2021), who investigate the determinants of emissions, we also include gross domestic product in per capita terms to control for income effects. In addition, we add the share of the population living in urban areas and a variable that accounts for industrial value added, which we compute as the ratio between industrial value added as a percentage of Gross Domestic Product. Finally, we add the (logarithm of the) patent applications from residents (in per capita terms). These variables are also gathered from the World Development Indicators database.

Finally, we consider some additional variables to perform robustness checks. To account for institutional quality, we rely on democracy variables available at the Varieties of Democracy Project developed by Coppedge et al. (2024).[3] These variables range between 0 and 1, where 0 denotes the lowest quality of democracy and 1 the highest quality. More specifically, we use two variables: the index of democratization (Dem) and the index of institutionalized democracy (Instdem). In addition, we use two variables to measure the impact exerted by globalization: trade and financial openness. While trade openness is measured as the sum of total exports and imports over GDP, financial openness is the share of Foreign Direct Investment inflows and outflows over GDP. Lastly, we include the renewable energy consumption as a share of total final energy consumption. The last three variables are obtained from the World Development Indicators database.

Table 2 shows the bivariate correlation matrix. None of the bivariate correlations seem to be causing a threat in terms of multicollinearity. We see a positive correlation between

[2] In addition, 2020, which was the start of the COVID-19 pandemic, cannot be considered a "standard" year (e.g., there was a strong decline of economic activity due to lockdowns and social distancing measures) so this data limitation should not be restrictive.

[3] For more information, see `https://www.v-dem.net/`.

Table 1: Summary Statistics

Variable	Observations	Mean	Std. dev.	Min	Max
Ln(CO_2_emissions)	1,564	8.5200	0.7672	5.8151	10.4442
Ln(robots IHS)	1,564	4.3183	3.1365	0	10.0935
Ln(robots)	1,229	4.7532	2.5698	-3.4358	9.4003
Ln(GDPpc)	1,564	9.9189	0.8194	7.5541	11.6167
UrbanPop	1,564	69.030	17.4628	21.387	100
IndustVApercGDP	1,564	28.6586	8.1012	11.7418	73.4692
Ln(patentspc)	1,564	3.7453	1.8652	-2.0743	8.1167
Openness	1,429	86.33658	57.4553	15.6356	437.3267
Fin_openness	1,429	6.765785	23.27985	-82.3722	633.7993
Democ	1,429	24.6043	12.7409	0	49
Instdem	1,376	7.2057	3.6383	0	10
Ln(renew)	1,418	2.2731	1.5750	-4.6052	4.3977

automation and emissions (as predicted by the theory). Of note, the correlation between the logarithm of robots and the inverse hyperbolic sine transformation is rather high (almost one), showing that this transformation is barely changing the distribution of our main variable of interest. In addition, we see a positive sign as well between the dependent variable and GDP per capita, which is in line with early stages in the Environmental Kuznets Curve, where more income leads to more production and therefore to increased emissions. A greater urban population share is also expected to be related positively to GDP per capita. Patents exhibit a positive correlation showing that technological efforts do not seem to decrease pollution. As for trade and financial openness, both of them show a positive correlation suggesting that the impact of international economic relations seems to be detrimental for environmental quality. Finally, in relation to the democracy-related variables, we observe an unexpected positive correlation with emissions.

Table 2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(CO_2_emissions)	1.0000											
Ln(robots IHS)	0.4913	1.0000										
Ln(robots)	0.4974	0.9967	1.0000									
Ln(GDPpc)	0.7364	0.6958	0.6975	1.0000								
UrbanPop	0.5685	0.4080	0.4079	0.7083	1.0000							
IndustVApercGDP	0.0389	-0.3042	-0.2991	-0.2114	-0.1937	1.0000						
Ln(patentspc)	0.6185	0.7354	0.7348	0.6321	0.4660	-0.2597	1.0000					
Openness	0.1704	0.2033	0.2046	0.2798	0.1493	0.0707	-0.0098	1.0000				
Fin_openness	0.1448	0.1543	0.1534	0.2358	0.2199	-0.1085	0.0783	0.3475	1.0000			
Democ	0.2383	0.5256	0.5224	0.4981	0.3345	-0.5808	0.4507	-0.1363	0.1231	1.0000		
Instdem	0.1100	0.4294	0.4263	0.3731	0.1560	-0.5561	0.3266	-0.2489	0.0503	0.7973	1.0000	
Ln(renew)	-0.5205	0.0257	0.0267	-0.2178	-0.3448	-0.3906	-0.0909	-0.2493	-0.1210	0.3537	0.4618	1.0000

In Table A.1 in the Appendix, we display the list of countries included in our analysis. This list includes both high and low-and middle-income countries to account for different levels of automation derived from asymmetric technology diffusion trajectories. To avoid issues arising from the fact that the stock of robots of countries belonging to the former North American Free Trade Agreement (signed by Mexico, the United States, and Canada) has been reported under the United States until 2010, we have refrained from including these countries in the main analysis. As a robustness check, we have included them in the sensitivity analysis providing similar results.[4] Finally, Table A.2 in the Appendix also reports the sources of the variables used in the main analysis.

5 Empirical model and estimation strategy

The econometric model that we use to test the predictions of the theoretical model is given by

$$\begin{aligned} ln(emissions_{i,t}) \quad = \quad & \beta_0 + \beta_1 \cdot ln(robots_{i,j}) + \beta_2 \cdot ln(gdppc_{i,t}) + \beta_3 \cdot UrbanPop_{i,t} + \\ & + \beta_4 \cdot IndustVApercGDP + \beta_5 \cdot ln(patentspc_{i,t}) + \\ & + \sum_{t=1994}^{2018} \gamma_t \cdot year_t + \sum_{i=1}^{64} \delta_i \cdot country_i + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where subscripts i and t refer to country and year, respectively, and ln to the natural logarithm; β_0 is the constant term, β_1 is the coefficient that we are interested in, β_2, β_3, β_4, and β_5 are the coefficient estimates for the control variables, and $\epsilon_{i,t}$ is the error term. We include country fixed effects and either year fixed effects or the trend in the regressions.[5]

Our variable of interest, industrial robots, is included linearly, following previous studies analyzing the economic effects of automation (e.g., Acemoglu and Restrepo, 2020b; Gan et al., 2023). However, as noted above, the relationship between automation and pollution drawn from previous studies seems to be inconclusive because it may depend on the technology diffusion stages. Differences in such stages can reveal differences

[4]We have not considered any allocation of robots to Canada and Mexico from the stock reported to the United States in the years from which data appears as 0 for these two countries. Most of the available studies neglect this fact and given that there is no perfect way to account for this problem, we have decided not to include these countries in the main analysis.

[5]While here we have a least squares dummy variable estimator augmented with country and year fixed effects, when we do the empirical analysis, we use the commands in Stata for a fixed effects regression. These two methods deliver the same results under the given circumstances. For clarity in exhibition, we have explicitly included in the formula the fixed effects.

between countries. Income per capita is included following the environmental Kuznets curve argument (Li et al., 2022), which suggests the existence of a non-linear relationship between economic development and environmental degradation. This relationship depends on income per capita because low income levels are associated with environmental worsening, while high income levels with improvements. Regarding urbanization, it has been argued to raise economic growth, but constituting a threat to sustainability and hence increasing pollution levels (Song et al., 2023). Industrial value added is included because industrial production is highly pollutant. Patents capture the agents' absorptive capacity, which consists of identifying, absorbing, and applying external knowledge (Hashai and Almor, 2008). In this context, greater absorptive capacity by firms could promote the adoption of clean energy and thus reduce the overall country-level pollution. Finally, year and country fixed effects are included to account for unobservable characteristics stemming from the business cycle and country-specific heterogeneities.

We consider an additional set of variables empirically related to emissions to assess the robustness of our results.[6] The quality of institutions is proxied by two "democracy" variables. Such institutional quality is expected to shape environmental outcomes. As argued by Aller et al. (2021), better political institutions should result in more stringent environmental regulations in line with the recommendations suggested by international organizations. Regarding trade openness, the evidence is ambivalent. While greater trade openness can be related to industrial expansion and increased emissions, it can be also associated with the transfer of cleaner energy that could reduce emissions (Li et al., 2022). As for the case of foreign direct investment (henceforth, FDI), a lack of consensus seems to prevail because it could raise pollution in developing countries due to the transfer of energy-intensive businesses from developed nations but, at the same time, such inflows could promote the adoption of cleaner energy (Wang et al., 2023).

6 Empirical results

In this section, we show the results from testing the three different hypotheses outlined in Section 3.

6.1 Baseline results: Hypothesis 1

Table 3 shows the results of investigating whether Hypothesis 1 is supported by the data. To do so we estimate Equation (6). Since the stock of robots can be zero, we

[6]We report them as a robustness check only because including them all reduces our sample size significantly.

provide alternative results using the inverse hyperbolic sine (IHS) transformation of our main independent variable.[7] Column (1) shows that with higher robot adoption, more emissions will be produced — on average. A one percent increase in robot adoption is associated with a 0.02% increase in emissions. While this association is modest in size, one has to bear in mind that — as highlighted in Section 1 — the stock of robots increased by 5% between 2021 and 2022 in a context of rising emissions. The next column shows the results using the IHS transformation, where the coefficient is similar in size as that of column (1). As robustness checks, in columns (3) and (4), we replace the year dummies for a year-trend and the results remain qualitatively the same as those from columns (1) and (2).[8]

Regarding the other explanatory variables in Table 3, income per capita has a positive sign and is statistically significant in all columns, showing that more economic activity (in per capita terms) is associated with more emissions. The positive coefficient of urban population reflects that greater human concentration may be expected to increase pollution. Industrial value added seems to be only positive and significant in columns (2) and (4), suggesting that industries without robot penetration are highly pollutant. Patents are also positive and significant for all the scenarios, suggesting that research and development does not seem to reach patents associated with "greener" production processes or products in general.

We include in Table 4 an alternative source for our dependent variable (columns (1) and (2)) in our baseline specification and we also include in further columns additional explanatory variables to test the robustness of our results. Both the size and the significance of the main explanatory variables seem to hold. However, regarding industrial value added, it becomes significant in columns (2), (4), (6), and (8), where the robotization variable is computed by means of the IHS (the same pattern as in Table 3). Columns (5) to (8) include trade openness and financial openness. While trade openness seems to decrease pollution, which could be associated with the import of cleaner production technologies from foreign countries or from offshoring dirty production, financial openness seems to be related to increasing pollution derived from the greater presence of multinational firms from foreign countries (this result only holds for columns (5) and (6)). Third, in relation to the democracy-related variables, we find that only institutionalized democracy, unexpectedly, turns out to be significant in column (8).

In addition, in Table A.3 in the Appendix, we assess the robustness of the results of

[7] The transformation is: $\ln(x + \sqrt{1 + x^2})$, where x is the operational stock of robots.

[8] In auxiliary regressions using a zero-skewness log transformation to deal with the zero values in the robot stock, we obtain similar coefficients: 0.0189** for specification from column (2) and 0.0154* from column (4).

Table 3: Baseline Results

	(1)	(2)	(3)	(4)
Ln(robots)	0.0201*		0.0175	
	(0.0120)		(0.0114)	
Ln(robots_IHS)		0.0191**		0.0157*
		(0.00909)		(0.00893)
Ln(GDPpc)	0.574***	0.431***	0.575***	0.435***
	(0.111)	(0.109)	(0.105)	(0.106)
UrbanPop	0.0157***	0.0137***	0.0157***	0.0146***
	(0.00533)	(0.00465)	(0.00525)	(0.00475)
IndustVApercGDP	0.000654	0.0107***	0.00117	0.0103***
	(0.00301)	(0.00360)	(0.00308)	(0.00344)
Ln(patentspc)	0.0820***	0.127***	0.0824***	0.128***
	(0.0262)	(0.0216)	(0.0262)	(0.0218)
Year			-0.0230***	-0.0159***
			(0.00341)	(0.00310)
Constant	1.594	2.557**	47.56***	34.17***
	(1.065)	(1.196)	(6.136)	(5.479)
Observations	1,229	1,564	1,229	1,564
Number of countries	65	65	65	65
Source	WB	WB	WB	WB
Robots	Ln	IHS	Ln	IHS
Year	FE	FE	Trend	Trend

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses clustered at the country-level.

Table 4: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(robots)	0.0217		0.0206*		0.0232*		0.0282**	
	(0.0136)		(0.0118)		(0.0127)		(0.0118)	
ln(robots_IHS)		0.0213**		0.0181**		0.0191**		0.0254***
		(0.00919)		(0.00767)		(0.00865)		(0.00860)
Ln(GDPpc)	0.574***	0.425***	0.580***	0.435***	0.561***	0.415***	0.587***	0.407***
	(0.119)	(0.113)	(0.110)	(0.105)	(0.106)	(0.0947)	(0.102)	(0.0953)
UrbanPop	0.0159**	0.0129**	0.0158***	0.0140***	0.0128**	0.0120***	0.0129**	0.0120***
	(0.00611)	(0.00496)	(0.00532)	(0.00460)	(0.00525)	(0.00442)	(0.00525)	(0.00446)
IndustVApercGDP	0.00216	0.0126***	0.000564	0.0107***	0.00239	0.00979***	0.00170	0.00922***
	(0.00346)	(0.00400)	(0.00300)	(0.00358)	(0.00261)	(0.00287)	(0.00241)	(0.00335)
Ln(patentspc)	0.0707**	0.124***	0.0803***	0.126***	0.0795***	0.119***	0.0649**	0.118***
	(0.0281)	(0.0227)	(0.0258)	(0.0215)	(0.0278)	(0.0225)	(0.0247)	(0.0232)
Openness					-0.00111**	-0.00103*	-0.00129**	-0.00103
					(0.000486)	(0.000574)	(0.000521)	(0.000664)
Fin_openness					0.000410***	0.000289***	0.000156	2.67e-05
					(0.000102)	(9.36e-05)	(0.000309)	(0.000332)
Democ					0.00131	0.00253		
					(0.00178)	(0.00159)		
Instdem							-0.000155	0.0118**
							(0.00706)	(0.00586)
Constant	-12.17***	-11.12***	1.541	2.518**	1.888*	2.886***	1.753*	2.957***
	(1.122)	(1.254)	(1.055)	(1.158)	(0.988)	(1.012)	(0.981)	(0.994)
Observations	1,229	1,564	1,270	1,637	1,117	1,429	1,088	1,378
R-squared	0.522	0.561	0.560	0.584	0.564	0.586	0.578	0.602
Number of countries	65	65	68	68	63	63	61	61
Source	Science	Science	WB	WB	WB	WB	WB	WB
Robots	Ln	IHS	Ln	IHS	Ln	IHS	Ln	IHS
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Nafta			✓	✓				

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Standard errors in parentheses clustered at the country-level.

the fixed effects estimator (henceforth, FE) by estimating the bias-corrected fixed effects in line with Bruno (2005). This estimator includes the lagged values of the dependent variable, allowing to capture the dynamics of this variable. While in columns (1) to (6) the coefficient of robots (either in logarithm or with the IHS transformation) is not statistically significant, it is in columns (7) to (12), where we take into account the non-linearity by testing for Hypothesis 2 as described in the next section.

6.2 Additional Results: Hypothesis 2

To test Hypothesis 2, we first include the interaction terms between robots and a dummy variable for upper middle income countries and another interaction with another dummy variable for lower-middle income countries.[9] The results can be seen in Table 5, columns (1) and (2). The relationship between robots and emissions loses statistical significance, but it re-appears in the interaction terms. In line with Hypothesis 2, we observe that the positive effect of robot use on emissions is present for countries in early stages of the development process (column (1)). One arrives at the same conclusion when investigating column (2), which displays the results using the IHS transformation for the robot stock. In columns (3) and (4), we use a broader classification of countries, and we group them as upper- or lower-middle income (named $MidIncome$), while the baseline category is high income. The interaction with the new middle income dummy has a positive sign and is statistically significant. This means that compared to a high-income country, countries in earlier development stages generate more emissions with their robots. Therefore, we find supportive evidence for Hypothesis *H2a*.

An alternative way to test Hypothesis 2 is to investigate the presence of non-linear effects associated with robot adoption. This means that at the beginning of the robot adoption process, robot use is associated with higher emissions, but these emissions are then reduced with higher robot adoption over time. A more intense robot use is expected to be related to more efficient production processes and also a better quality of robots. Columns (5) and (6) confirm this finding. While robot adoption generates more emissions, this outcome becomes smaller with more intense robot adoption. Indeed, we find that the parent coefficient is positive but the squared term becomes negative.

Finally, Hypothesis *H2a* could be explained in a third way. Related to the point above, it has been argued that the quality and efficiency of robots has improved over time (Graetz and Michaels, 2018; Kromann et al., 2019; Jurkat et al., 2021, 2022)[10] and

[9]There was no data to include lower income countries in the study. We believe that the inclusion of these countries would only strengthen our results.

[10]As Kromann et al. (2019) notes: "There are many indications of quality increases over vintages of

therefore we could investigate whether this is the case by simply interacting the logarithm of robots (or the IHS transformation) with a year trend.[11] If this interaction is negative, then it means that a robot bought in, for example 2010, would be associated with lower emissions than one bought in 1993. This fact could be explained by the improvement of technology (in addition, diffusion also likely increases because the the costs of adoption decrease over time). Columns (7) and (8) show that this could be indeed the case. While in broad terms more robots do generate more emissions, at the same time the robots of newer vintages have less emissions, as shown by the negative coefficient of the interaction term between robots and the year trend.

6.3 Additional Results: Hypothesis 3

We now move on to test Hypothesis 3 in Table 6. We continue from the specifications used to test Hypothesis 2 and we consider a new variable, the share of renewable energy, which we will then interact with robot adoption. As shown in columns (1), (3), and (5), the interaction term between robot adoption and the share of renewables is positive (also when we include the IHS transformation instead in columns (4) and (6)), but not statistically significant. The robot coefficient is positive and only statistically significant when we include the zeroes in the regression, while the share of renewables is negative and statistically significant. Reassuringly, when a country uses cleaner energy, emissions go down.

Overall, our past results hold when we include the renewables in the analysis. This variable is statistically significant and has the expected sign. When we aim to test Hypothesis 3, however, we do not find support in terms of statistical significance, although the coefficients have the expected sign. With the availability of better data in the future on the use of renewable energies, we may find additional support for this hypothesis.

robots: In 1975, an average robot had five axes, a capacity of 6 kg and a reach of 1 m. These numbers had increased to 21 axes, a capacity of more than 120 kg and a reach of 2 m in 1995 and to 32 axes, a capacity of more than 1000 kg and a reach of at least 3 m in 2015" (Tilley, 2017).

[11] In this specification, we change the year dummies for the trend since using both would be doubling the efforts to control for time.

Table 5: Hypothesis 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(robots)	-0.0137		-0.0145		0.0401***		3.096	
	(0.0161)		(0.0163)		(0.0149)		(2.382)	
UpMidInc#ln(robots)	0.0446**							
	(0.0184)							
LowMidInc#ln(robots)	0.0730***							
	(0.0242)							
Ln(robots_IHS)		0.00633		-0.00119		0.0538***		3.222***
		(0.0114)		(0.0114)		(0.0139)		(1.087)
UpMidInc#ln(robots_IHS)		0.0177						
		(0.0176)						
LowMidInc#ln(robots_IHS)		0.0886***						
		(0.0265)						
MidIncome#ln(robots)			0.0568***					
			(0.0174)					
MidIncome#ln(robots_IHS)				0.0427***				
				(0.0141)				
Ln(robots)#ln(robots)					-0.00453**			
					(0.00195)			
Ln(robots_IHS)#ln(robots_IHS)						-0.00658***		
						(0.00204)		
Year							-0.0122	-0.00572
							(0.00869)	(0.00441)
Ln(robots)#Year Trend							-0.00154	
							(0.00119)	
Ln(robots_IHS)#Year Trend								-0.00160***
								(0.000544)
Ln(GDPpc)	0.546***	0.374***	0.541***	0.408***	0.593***	0.416***	0.553***	0.377***
	(0.101)	(0.0856)	(0.104)	(0.102)	(0.105)	(0.104)	(0.107)	(0.104)
UrbanPop	0.0116**	0.0125**	0.0100**	0.00622	0.0161***	0.0145***	0.0160***	0.0150***
	(0.00525)	(0.00517)	(0.00496)	(0.00436)	(0.00490)	(0.00414)	(0.00530)	(0.00442)
IndustVApercGDP	-0.000399	0.00837**	-0.000365	0.00881**	0.00213	0.0105***	0.00194	0.00882**
	(0.00328)	(0.00329)	(0.00326)	(0.00340)	(0.00284)	(0.00353)	(0.00275)	(0.00335)
Ln(patentspc)	0.0758***	0.117***	0.0760***	0.123***	0.0771***	0.124***	0.0776***	0.123***
	(0.0234)	(0.0180)	(0.0229)	(0.0212)	(0.0247)	(0.0208)	(0.0256)	(0.0230)
Constant	2.287**	3.336***	2.438**	3.405***	1.356	2.700**	26.13	14.52*
	(1.022)	(0.995)	(1.046)	(1.115)	(1.009)	(1.151)	(17.09)	(8.383)
Observations	1,229	1,564	1,229	1,564	1,229	1,564	1,229	1,564
Number of countries	65	65	65	65	65	65	65	65
Robots	Ln	IHS	Ln	IHS	Ln	IHS	Ln	IHS
Year	FE	FE	FE	FE	FE	FE	Trend	Trend

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Standard errors in parentheses clustered at the country-level.

Table 6: Hypothesis 3

	(1)	(2)	(3)	(4)	(5)	(6)
Ln(robots)	-0.00543		0.0228		1.165	
	(0.0158)		(0.0144)		(2.254)	
Ln(renew)	-0.141***	-0.159***	-0.151***	-0.158***	-0.155***	-0.162***
	(0.0328)	(0.0364)	(0.0307)	(0.0357)	(0.0317)	(0.0364)
Ln(robots)#ln(renew)	0.00177		0.00250		0.00288	
	(0.00452)		(0.00417)		(0.00428)	
MidIncome#ln(robots)	0.0337**					
	(0.0143)					
Ln(GDPpc)	0.471***	0.397***	0.493***	0.407***	0.479***	0.382***
	(0.101)	(0.0960)	(0.103)	(0.100)	(0.104)	(0.0974)
PercUrbanPop	0.00985**	0.00493	0.0132***	0.0109***	0.0130***	0.0113***
	(0.00408)	(0.00409)	(0.00379)	(0.00367)	(0.00399)	(0.00386)
IndustVApercGDP	-0.00101	0.00602*	0.000117	0.00692**	0.000459	0.00601**
	(0.00270)	(0.00325)	(0.00227)	(0.00327)	(0.00226)	(0.00293)
Ln(patentspc)	0.0653***	0.0954***	0.0662***	0.0961***	0.0675***	0.0958***
	(0.0231)	(0.0225)	(0.0241)	(0.0227)	(0.0242)	(0.0236)
Ln(robots_IHS)		-0.000664		0.0358**		1.906*
		(0.0169)		(0.0176)		(1.108)
Ln(robots_IHS)#ln(renew)		-8.22e-05		0.000210		0.00102
		(0.00536)		(0.00504)		(0.00497)
MidIncome#ln(robots_IHS)		0.0314**				
		(0.0121)				
Ln(robots)#ln(robots)			-0.00211			
			(0.00171)			
Ln(robots_IHS)#ln(robots_IHS)				-0.00409**		
				(0.00204)		
Year					-0.0121	-0.00449
					(0.00773)	(0.00399)
Ln(robots)#Year Trend					-0.000578	
					(0.00113)	
Ln(robots_IHS)#Year Trend						-0.000948*
						(0.000555)
Constant	3.432***	4.107***	2.917***	3.559***	27.21*	12.78
	(1.016)	(1.043)	(1.011)	(1.104)	(15.02)	(7.668)
Observations	1,227	1,553	1,227	1,553	1,227	1,553
Number of countries	65	65	65	65	65	65
Robots	Ln	IHS	Ln	IHS	Ln	IHS
Year	FE	FE	FE	FE	Trend	Trend

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Standard errors in parentheses clustered at the country-level.

7 Conclusions

We analyze the effects of automation on emissions from a theoretical and an empirical perspective. To this end, we propose a theoretical model of production in the age of automation that incorporates emission externalities and allows us to derive a threshold condition. If this condition is fulfilled, the switch to industrial robots raises emissions. The model leads to three testable predictions, i) the use of industrial robots causes higher emissions on average; ii) with an increasing efficiency of industrial robots, the effect becomes weaker and could turn negative; iii) in countries with a higher share of renewable electricity generation, industrial robot use should be associated with lower emissions than in countries with lower renewable electricity generation.

We test the theoretical predictions empirically and find support for two of the three predictions. Initially, when we explain emissions by the use of industrial robots (and other related variables), we find a positive relationship between CO_2 emissions and automation. However, when we include proxies for early versus late robot adoption, the emission effect of robots becomes relevant for countries with lower levels of economic development. Moreover, the impact of robots on pollution is significantly reduced over time, showing a substantial reduction compared to the initial production stages. Therefore, our results support Hypotheses *H1* and *H2*. By contrast, we do not find statistically significant support for Hypothesis *H3*.

From a policy perspective, attention needs to be paid to the emissions and the energy requirements that come with the deployment of industrial robots. While the policy discussions so far focus on the labor market effects of automation and the associated repercussions on inequality, emissions and their effects on climate change feature prominently on the agenda of most policymakers and international organizations. Recognizing the contribution of robots in this context is necessary to design policies that are aimed to reduce emissions (such as taxing carbon and emissions trading schemes) or to level the playing field in the competition between humans and robots (robot taxes, etc.). Acknowledging that there are externalities in both dimensions — on emissions and on labor markets — could lead to policies that are more efficient and effective in tackling both (Abeliansky et al., 2023; Gasteiger et al., 2023).

As far as future research is concerned, it would be interesting to get more disaggregated results, e.g., across regions, sectors, or even firms. In addition, the effects of artificial intelligence (AI) on emissions will be of particular interest in future research because AI-based applications such as large language models require vast amounts of electricity to be trained and in their use (Creutzig et al., 2022; Luccioni et al., 2022; Abeliansky et al., 2023). As a consequence, they are expected to be associated with a disproportionate increase in emissions. However, the crucial problem up to now is how to measure AI use. There is no comparable dataset on the presence of AI in production as there is with regards to the use of robots. Collecting accurate data on AI use would be a prerequisite for such analyses. Finally, assessing the overall welfare effects of automation and digitalization needs to take into account the impact of automation on emissions and the associated effects on global warming. While all these questions are beyond the scope of our contribution, they provide valuable areas for future research.

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A Appendix

Table A.1: Countries included

Argentina	Germany	Moldova	Slovak Republic
Australia	Greece	Morocco	Slovenia
Austria	Hungary	Netherlands	South Africa
Belarus	Iceland	New Zealand	Spain
Belgium	India	Norway	Sweden
Brazil	Indonesia	Oman	Switzerland
Bulgaria	Iran, Islamic Rep	Pakistan	Thailand
Chile	Ireland	Peru	Tunisia
China	Israel	Philippines	Turkey
Colombia	Italy	Poland	Ukraine
Croatia	Japan	Portugal	United Arab Emirates
Czech Republic	Korea, Rep	Qatar	United Kingdom
Denmark	Kuwait	Romania	Uzbekistan
Egypt, Arab Rep	Latvia	Russian Federation	Vietnam
Estonia	Lithuania	Saudi Arabia	
Finland	Malaysia	Serbia	
France	Malta	Singapore	

Table A.2: Data Sources

Variable	Description and units of measure	Source
Ln(CO_2)	Logarithm of CO_2 emissions (metric tons per capita)	World Development Indicators
Ln(robots)	Logarithm of stock of robots (per capita)	International Federation of Robotics and World Development Indicators
Ln(robots_IHS)	Logarithm of stock of robots transformed using Inverse Hyperbolic Syne (per capita)	International Federation of Robotics and World Development Indicators
Ln(gdppc)	Logarithm of GDP per capita, PPP (constant 2021 international USD)	World Development Indicators
UrbanPop	Urban population (percentage of total population)	World Development Indicators
Ln(patentspc)	Logarithm of patent applications from residents (per capita)	World Development Indicators
IndustVApercGDP	Industrial (including construction), value added (percentage of GDP)	World Development Indicators
Democ	Index of democracy	Varieties of Democracy Project (Coppedge et al. (2024))
Instdem	Index of institutionalized democracy	Varieties of Democracy Project (Coppedge et al. (2024))
Openness	Trade openness measured by the sum of total exports and imports (percentage of GDP)	World Development Indicators
Fin_Openness	Financial openness measured by the sum of total Foreign Direct Investment inflows and outflows (percentage of GDP)	World Development Indicators
ln(renew)	Renewable energy consumption (% of total final energy consumption)	World Development Indicators

Table A.3: Corrected Fixed Effects regressions for Hypothesis 1 and 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.ln(CO_2)	0.918***	0.920***	0.935***	0.916***	0.918***	0.926***	0.915***	0.905***	0.921***	0.900***	0.898***	0.906***
	(0.0231)	(0.0173)	(0.0152)	(0.0136)	(0.0121)	(0.0109)	(0.0262)	(0.0180)	(0.0159)	(0.0165)	(0.0127)	(0.0117)
Ln(robots)	-0.00434	-0.00381	-0.00452*				0.0537**	0.0507**	0.0420**			
	(0.00265)	(0.00237)	(0.00232)				(0.0227)	(0.0198)	(0.0194)			
Ln(robots_IHS)				-0.00181	-0.00138	-0.00122				0.0755***	0.0703***	0.0619***
				(0.00175)	(0.00162)	(0.00157)				(0.0167)	(0.0145)	(0.0144)
Ln(robots)#ln(gdppc)							-0.00614**	-0.00567***	-0.00486**			
							(0.00239)	(0.00206)	(0.00202)			
Ln(robots_IHS)#ln(gdppc)										-0.00783***	-0.00726***	-0.00641***
										(0.00167)	(0.00145)	(0.00144)
Ln(gdppc)	0.0815***	0.0867***	0.0951***	0.0853***	0.0882***	0.0972***	0.111***	0.101***	0.107***	0.0934***	0.0897***	0.0973***
	(0.0221)	(0.0195)	(0.0190)	(0.0135)	(0.0128)	(0.0122)	(0.0245)	(0.0206)	(0.0197)	(0.0145)	(0.0126)	(0.0122)
UrbanPop	0.000857	0.000683	0.000668	2.36e-05	-0.000241	-0.000273	0.000365	0.000346	0.000271	-0.000979	-0.00108	-0.00107
	(0.00115)	(0.00101)	(0.00100)	(0.000819)	(0.000774)	(0.000766)	(0.00123)	(0.000999)	(0.00101)	(0.000839)	(0.000745)	(0.000754)
IndustVApercGDP	0.00184*	0.00172**	0.00165*	0.00202***	0.00206***	0.00183***	0.00185*	0.00159*	0.00160*	0.00166**	0.00177***	0.00166***
	(0.000969)	(0.000861)	(0.000876)	(0.000653)	(0.000629)	(0.000602)	(0.000992)	(0.000860)	(0.000879)	(0.000675)	(0.000617)	(0.000601)
Ln(patentspc)	0.00611	0.00461	0.00379	0.00913**	0.00772**	0.00636*	0.00524	0.00494	0.00395	0.00959**	0.00918**	0.00781**
	(0.00522)	(0.00474)	(0.00465)	(0.00399)	(0.00377)	(0.00362)	(0.00566)	(0.00478)	(0.00471)	(0.00460)	(0.00371)	(0.00365)
Observations	1,227	1,227	1,227	1,562	1,562	1,562	1,227	1,227	1,227	1,562	1,562	1,562
Number of countries	65	65	65	65	65	65	65	65	65	65	65	65
Robots	Ln	Ln	Ln	IHS	IHS	IHS	Ln	Ln	Ln	IHS	IHS	IHS
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Initial estimator	ah	ab	bb	ah	ab	bb	ah	ab	bb	ah	ab	bb

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Standard errors are boostrapped with 250 repetitions. “ah” denotes the Anderson-Hsiao consistent estimator to initialize the bias correction, “ab” the Arellano-Bond and “bb” the Blundell-Bond (bb) one.

References

Abeliansky, A. L., Bloom, D. E., Bontadini, F., Gasteiger, E., Gil, P. M., Kuhn, M., Moraliyska, M., Peralta, C., and Prettner, K. (2023). Fostering a sustainable digital transformation. *VoxEU.*

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1):S293–S340.

Acemoglu, D. and Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6):1488–1542.

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

Acemoglu, D. and Restrepo, P. (2020b). Unpacking Skill Bias: Automation and New Tasks. NBER Working Paper No. 26681. National Bureau of Economic Research, Cambridge, MA.

Aller, C., Ductor, L., and Grechyna, D. (2021). Robust determinants of CO2 emissions. *Energy Economics*, 96:105154.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *The Journal of Economic Perspectives*, Vol. 29(No. 3):3–30.

Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing Inequality: Have Computers Changed the Labor Market? *The Quarterly Journal of Economics*, 113(4):1169–1213.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, Vol. 118(No. 4):1279–1333.

Baldwin, R. E. (2020). *The Globotics Upheaval: Globalization, Robotics, and the Future of Work*. Oxford University Press, New York.

Bellemare, M. F. and Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61.

Blanas, S., Gancia, G., and Lee, S. Y. (2019). Who is afraid of machines? *Economic Policy*, 34(100):627–690.

Bruno, G. S. (2005). Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Economics letters*, 87(3):361–366.

Chen, J. and Roth, J. (2024). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics*, 139(2):891–936.

Chen, Y., Cheng, L., and Lee, C.-C. (2022). How does the use of industrial robots affect the ecological footprint? International evidence. *Ecological Economics*, 198:107483.

Coppedge, M., Gerring, J., Knutsen, C. H., Lindberg, S. I., Teorell, J., Altman, D., Angiolillo, F., Bernhard, M., Borella, C., Cornell, A., et al. (2024). V-dem codebook v14.

Cords, D. and Prettner, K. (2022). Technological Unemployment Revisited: Automation in a Search and Matching Framework. *Oxford Economic Papers*, 74(1):115–135.

Creutzig, F., Acemoglu, D., Bai, X., Edwards, P. N., Hintz, M. J., Kaack, L. H., Kilkis, S., Kunkel, S., Luers, A., Milojevic-Dupont, N., Rejeski, D., Renn, J., Rolnick, D., Rosol, C., Russ, D., Turnbull, T., Verdolini, E., Wagner, F., Wilson, C., Zekar, A., and Zumwald, M. (2022). Digitalization and the Anthropocene. *Annual Review of Environment and Resources*, 47(1):479–509.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153.

Gan, J., Liu, L., Qiao, G., and Zhang, Q. (2023). The role of robot adoption in green innovation: Evidence from China. *Economic Modelling*, 119:106128.

Gasteiger, E., Kuhn, M, Mistlbacher, M, and Prettner, K. (2023). Electricity use of automation or how to tax robots? WU Department of Economics Working Paper 364 [accessed on July 20, 2024].

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

Gregory, T., Salomons, A., and Zierahn, U. (2022). Racing With or Against the Machine? Evidence on the Role of Trade in Europe. *Journal of the European Economic Association*, 20(2):869–906.

Hashai, N. and Almor, T. (2008). R&D intensity, value appropriation and integration patterns within organizational boundaries. *Research Policy*, 37(6-7):1022–1034.

Huang, G., He, L.-Y., and Lin, X. (2022). Robot adoption and energy performance: Evidence from Chinese industrial firms. *Energy Economics*, 107:105837.

International Energy Agency (2023). CO2 Emissions in 2023. A new record high, but is there light at the end of the tunnel? URL: https://www.iea.org/reports/co2-emissions-in-2023 [accessed on July 20, 2024].

International Federation of Robotics (2023). World Robotics. Industrial Robots and Service Robots. URL: https://ifr.org/ifr-press-releases/news/world-robotics-2023-report-asia-ahead-of-europe-and-the-americas [accessed on July 20, 2024].

Jurkat, A., Klump, R., and Schneider, F. (2021). Tracking the Rise of Robots: A Survey of the IFR Database and Its Applications. Munich Personal RePEc Archive. URL: https://mpra.ub.uni-muenchen.de/107909/ [accessed on April 19, 2024].

Jurkat, A., Klump, R., and Schneider, F. (2022). Tracking the Rise of Robots: The IFR Database. *Jahrbücher für Nationalökonomie und Statistik*, 242(5-6):669–689.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638):2553–2584.

Krenz, A., Prettner, K., and Strulik, H. (2021). Robots, Reshoring, and the Lot of Low-Skilled Workers. *European Economic Review*, 136:103744.

Kromann, L., Malchow-Møller, N., Skaksen, J. R., and Sørensen, A. (2019). Automation and productivity—a cross-country, cross-industry comparison. *Industrial and Corporate Change*, page dtz039.

Lee, C.-C., Qin, S., and Li, Y. (2022). Does industrial robot application promote green technology innovation in the manufacturing industry? *Technological Forecasting and Social Change*, 183:121893.

Li, Y., Zhang, Y., Pan, A., Han, M., and Veglianti, E. (2022). Carbon emission reduction effects of industrial robot applications: Heterogeneity characteristics and influencing mechanisms. *Technology in Society*, 70:102034.

Luan, F., Yang, X., Chen, Y., and Regis, P. J. (2022). Industrial robots and air environment: A moderated mediation model of population density and energy consumption. *Sustainable Production and Consumption*, 30:870–888.

Luccioni, A. S., Viguier, S., and Ligozat, A.-L. (2022). Estimating the Carbon Footprint of BLOOM, a 176B Parameter Language Model.

Mann, K. and Püttmann, L. (2023). Benign Effects of Automation: New Evidence from Patent Texts. *Review of Economics and Statistics*, 105(3):562–579.

Prettner, K. (2023). Stagnant Wages in the Face of Rising Labor Productivity: The Potential Role of Industrial Robots. *Finance Research Letters*, 58:104687.

Prettner, K. and Bloom, D. (2020). *Automation and Its Macroeconomic Consequences: Theory, Evidence, and Social Impacts.* Academic Press, Amsterdam, NL.

Restrepo, P. (2023). Automation: Theory, evidence, and outlook. *Annual Review of Economics*, 16.

Song, J., Chen, Y., and Luan, F. (2023). Air pollution, water pollution, and robots: Is technology the panacea. *Journal of Environmental Management*, 330:117170.

Steigum, E. (2011). Robotics and Growth. In de la Grandville, O., editor, *Frontiers of Economics and Globalization: Economic Growth and Development*, pages 543–557. Emerald Group. Bingley, UK.

Thuemmel, U. (2023). Optimal Taxation of Robots. *Journal of the European Economic Association*, 21(3):1154–1190.

Tilley, J. (2017). Automation, robotics, and the factory of the future. Report by McKinsey & Company. URL: https://www.mckinsey.com/capabilities/operations/our-insights/automation-robotics-and-the-factory-of-the-future [accessed on July 20, 2024].

Wang, J., Wang, W., Liu, Y., and Wu, H. (2023). Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China. *Technology in Society*, 72:102208.

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. *SSRN Electronic Journal.*

Yu, L., Wang, Y., Wei, X., and Zeng, C. (2023). Towards low-carbon development: The role of industrial robots in decarbonization in Chinese cities. *Journal of Environmental Management*, 330:117216.

Yu, L., Zeng, C., and Wei, X. (2022). The impact of industrial robots application on air pollution in China: Mechanisms of energy use efficiency and green technological innovation. *Science Progress*, 105(4):003685042211440.

Zhong, J., Zhong, Y., Han, M., Yang, T., and Zhang, Q. (2024). The impact of AI on carbon emissions: Evidence from 66 countries. *Applied Economics*, 56(25):2975–2989.