Innovation at country-level:

Does air pollution drive green-tech innovation?

Erasmus University Rotterdam

Erasmus School of Economics

Master Thesis [Strategy Economics]

Supervisor: Jolanda Hessels

Second assessor: Ajay Bhaskarabhatla

Date Final version: December 8, 2022

Name student: Olivier Koster

Student ID number: 461861

Abstract

In this master's thesis, A one-way system GMM model is employed to examine the causal effect of ambient air quality on green-tech innovation activity on a country level, using a cross-sectional time-series dataset on major OECD countries worldwide over a period between 2015-2021. Additionally, we examine if this effect is greater in higher GDP countries, and (non-)democratic countries, respectively. By doing this, the paper contributes to a growing body of existing literature by trying to shed new perspective on the relationship between environmental-related technological innovation and air quality. The findings suggest that there is positive and significant relationship between air pollution and green-tech innovation on a country level. Furthermore, our findings suggest that this effect is more pronounced for low-income countries, compared to high-income countries. Finally, our findings also suggest that the aforementioned effect is more pronounced for democratic countries, compared to autocratic countries. Robustness analysis provides support for these findings.

Contents

1 Introduction

One of the hallmarks of our generation, as well as one of the biggest challenges of the twenty-first century, is illustrated by how our species faces the problems of pollution and climate change. Today, much is being done to combat the adverse effects of man-made pollution, to try and stop or reverse the effects of climate change, and raise global health in the process.

The ever-increasing struggle for humankind to achieve sustainability in its pursuits has spawned the concept of *green innovation*. Urbaniec et al. [2021] defines green innovation as a reduction in negative environmental impacts and more efficient use of resources. This includes technological innovations in pollution prevention, environmental management, energy conservation, waste recycling, and green product design. This type of innovation is typically identified by having a benefit for businesses and consumers alike, as opposed to solely businesses, by significantly reducing the negative impact it places on its environment [Karimi Takalo et al., 2021].

However, despite our best efforts, thus far, Particulate Matter (PM) and Green House Gas (GHG) emission targets are not being met globally [Den Elzen et al., 2019]. Evidently, the current rate of air pollution mitigation is not enough. Solomon et al. [2009]; Collins et al. [2013] indicate the potential irreversibility of rising temperatures and, therefore, rising sea levels. Moreover, according to World Health Organisation (WHO) [2014] in 2012 alone, poor air quality has contributed to the deaths of approximately 7 million people worldwide.

Historically, to governments and companies around the world, short-term financial and economic gains have long outweighed environmental concerns, and for years, they have prioritized their strategies accordingly. Only recently has this picture started to change. It seems that, in today's economy, prioritizing corporate social responsibility has started to reap its own economic benefits, through increased profits and lower costs of compliance [Fraj-Andrés et al., 2009; Brammer and Millington, 2008]. Still, despite this recent turnaround, it seems the road ahead of us is long.

In 1956, The UK successfully passed the world's first Clean Air act due to a tragic incident in London, where a fog of black smoke killed an estimated 4,000-12,000 people and burdened an estimated 100,000 with serious chronic illnesses [Bell and Davis, 2001]. In 2017, according to Ebenstein et al. [2017] an estimated 4.5 billion people were exposed to particulate matter (PM) levels at least twice the concentration that the World Health Organisation (WHO) considers safe. Ambient air pollution is now fully acknowledged to be a significant public health problem, responsible for a growing range of health effects and premature deaths that are well documented as a result of extensive research efforts conducted in many regions of the world.

These severe health concerns and effects, may trigger a more immediate response for adequate technological innovation, than the effects of climate change do. The reasoning being that chronic illnesses and fatalities related to ambient air pollution are arguably more pressing and more visible to the greater population than the gradual effects of climate change. This in turn could put firms under more pressure to reduce PM-emmissions than GHG-emissions. As we have previously mentioned, a great deal of research has been carried out to study the effect that novel green-tech innovation has on mitigating the ever-deteriorating state of the environment [Shan et al., 2021; Alvarez-Herranz et al., 2017]. However, to this day, very little research has focused on studying how low air quality and other environmental hazards, in association with macroeconomic and political factors, drive the rate at which green-tech innovation is being carried out. One such study is Brunnermeier and Cohen [2003]. It researches the relationship between pollution abatement expenditures and regulatory enforcement and environmental innovation by US manufacturing industries, during the period 1983 through 1992. The authors focus on mechanisms that are purely socio-economic in nature. No direct effect of air pollution was taken into account. While Su and Moaniba [2017] have found a positive relationship between GHG-emissions and environmental innovation, insufficient research has been carried out on the relationship between ambient PM-concentrations and environmental innovation.

1.1 Thesis outline

In this master's thesis, we examine the causal effect of yearly average air quality on the rate of green-tech innovation on a country-level. We employ the current industry standard of regression techniques for cross-sectional time-series data, otherwise known as panel data. Specifically, we use a one-way system Generalised Method of Moments (GMM) estimator. Additionally, we examine if the observed effect is greater in higher GDP countries and in (non-)democratic countries. Green-tech innovation is a type of technological innovation that can benefit both consumers and businesses alike, by significantly reducing negative environmental impact. These include technological innovations in energy conservation, (air) pollution prevention and removal, waste recycling, green product design and environmental management. We understand low air quality to be polluted air with higher concentrations of ground-level ozone, particle pollution (also known as particulate matter, including $PM_{2.5}$ and PM_{10}), carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). A consistent overall metric for air quality pollution is the U.S. Air Quality Index (AQI). Our panel dataset includes annual-mean Air Quality Indices of these particles over a period between 2015-2021, on major OECD countries worldwide (the full list can be found in the Appendix A). We use the annual number of environmental-related patents per country, as a proxy for the rate of green-tech innovation. Furthermore, we provide robustness analysis substituting the dependent and independent variables. To our knowledge, this is the first study that analysis these relationships.

The remainder of the master's thesis is organized as follows. Section 2 presents a brief review of the literature on the characteristics of green-tech innovation and factors that potentially influence its innovation activity, including air pollution and socio-economic factors. In Section 3, we present our theoretical framework and define the variables and sample to be used in our empirical analysis. Next, the results and robustness analysis are presented in Section 4. Our empirical findings and the limitations of our research are discussed in Section 5. Finally, Section 6 highlights the main conclusions, implications and contributions of this thesis.

2 Literature review

Innovation in green technologies is a key factor in confronting man-made environmental deterioration and maintaining the right balance within the fragile eco-system we live in. In recent years, growing global environmental awareness is driving demand for policymakers and companies to meet ever-higher standards in sustainability. This phenomenon is paving the way for a new definition of success, where economic profitability and prosperity do not come at the expense of, but rather, is partially driven by sustainability. As such, achieving sufficient green innovation is becoming a major source of keeping a competitive advantage[Biswas and Roy, 2016]. Accordingly, it is no surprise that the importance of green innovation is ever-growing in today's literature [Urbaniec et al., 2021; Karimi Takalo et al., 2021; Díaz-García et al., 2015].

Green, eco/ecological, sustainable, and environmental innovation in technologies are terms that are generally used synonymously [Takalo et al., 2021]. Henceforth, we will refer to this innovation type as *Green-tech innovation*. Its general definition boils down to technological innovation in products or processes, that can benefit both consumers and business alike by significantly reducing negative environmental impact. These innovations include technological innovations in energy conservation, (air) pollution prevention and removal, waste recycling, green product design and environmental management. As such, green-tech innovation yields double dividend. It reduces the burden on the environment while contributing to the technological modernisation of the economy.

The main analysis in this thesis is aimed at examining whether green-tech innovation activity is driven by air pollution, and related socio-economic factors. However, to understand the potential influence of air pollution on environmental innovation, we must elaborate on other core drivers of environmental innovation in general. These three core drivers of green innovation activity are considered to be government support and policy, and Corporate Social Responsibility. Their respective effectiveness, however, is widely debated.

Because benefits from green-tech innovation are public, rather than private, customers' willingness to pay for these innovations has historically been quite low Biswas and Roy [2016]. As consequence, until recently, a large part of environmental responsibility has always been pushed into the hands of governments and international institutions. Government environmental support policies are aimed at reducing the negative environmental impact of a country's economic activity. These government policies mostly exist as grants, subsidies, regulations, taxes, voluntary agreements, public funding, and other financial help and restrictions. According to Díaz-García et al. [2015], there is general agreement in literature that regulation drives green innovation and helps its diffusion. The authors propose that policies are more effective when there is a consistent long-term mix of several combined policies. However, the authors find that policies are not universally effective. Environmental regulations affect firms with varying innovation activity differently and affect some types of green innovation more than others. Furthermore, the effectiveness of these regulations may also be affected by many socioeconomic factors, such as the level of urbanisation and economic development. Thus they propose that findings in this context are inconclusive or incomplete, and require future research. Bernauer et al. [2007] summarised it best by arguing "the jury is still out", other words, statistical evidence of a positive relationship is still inconclusive, and that "win-win outcomes" are very rare. Conclusive evidence requires analysis of a combination of the effects of many particular regulations and producer/consumer benefits of particular environmental innovations alongside firm- internal and market conditions. In China, a unique approach is taken in the form of green credit guidelines. Green credit and similar policies are aimed at reducing the scale of debt financing, increasing the cost of debt, and affecting the production and operation activities of enterprises. Using a DiD model with data from Chinese listed companies between 2008 and 2019, Wang et al. [2022]'s findings show that Green Credit Guidelines significantly improve the quality of enterprises' green innovation. However, they do not shed light on the rate of green innovation. Finally, effective government policies in turn may lead firms to imitate peer enterprises' green innovation decisions, so that they may avoid risks by learning from their success and mistakes.

Fan et al. [2022] focus on the relationship between peer effect and government policies and find that based on a peer effect, green innovation incentives, protection tax and innovation subsidies are effective tools to promote green innovation diffusion. Nevertheless, although the relationship between government policy and environmental innovation is very important to the discussion within this thesis, they are not the main topic of analysis, but merely an extension in discussing the larger mechanism. We are not interested in the relationship between the effectiveness of a country's environmental policy and its innovation activity. Rather, we are interested in how low air quality can drive a country to put regulations in place that in turn can induce environmental innovation. In this context, governmental policy is a tool for inducing innovation and is one part of the mechanism we are interested in.

As mentioned earlier, customers' willingness to pay for green innovations has historically been quite low, because its benefits are public, rather than private. However, in the recent decade, public awareness of sustainability has increased substantially, and as a result, a firm's focus on sustainability has become a key factor in keeping a competitive advantage and sustaining profits [Biswas and Roy, 2016]. This phenomenon is best captured by a firm's Corporate Social Responsibility (CSR). CSR engagement requires firms to consider the interests of stakeholders such as the environment, society and consumers during their operations. This can be done through mandatory disclosure of CSR reports, or can be visible through internal and external marketing of sustainability in firms products or processes. Kraus et al. [2020]; Shahzad et al. [2020]; Hao and He [2022] find that CSR is positively correlated with green innovation. In China since 2008, there has been a regulatory requirement for publicly listed firms to disclose CSR reports. This has in turn has led listed and unlisted companies to focus on CSR issues to gain a unique competitive advantage. Using a DiD estimation approach that exploits this regulation change, Ren et al. [2022] find that mandatory CSR reporting firms show substantially higher green innovation performance than non-CSR reporting firms. Moreover, they find that the effect is stronger for firms with higher media coverage. They find this to be the case for both positive and negative media coverage. Similarly, increased customer awareness towards environmental improvement and green consumption push firms to deliver environmentally friendly products or services and strengthen green market demand [Flores and Jansson, 2022]. Such improvements directly impact business performance of the firm [Pujari, 2006; Dangelico and Pujari, 2010]. However as Lin et al. [2014] point out, while consumers are positively related to green product innovation, they are negatively related to green process innovation. Additionally, they find that political capital plays a significant but negative role in firm's green product and process innovation performance. Finally, they propose that competition effects do not have any significant effects on both green product and green process innovation.

2.1 *Air quality & health hazards*

Health hazards stemming from man-made pollution are by no means a novel global issue, although they have become more publicly widespread, due to relatively recent discoveries in science. Paleopathological discoveries dating from as far back as the ancient mummies show cases of pneumonia, emphysema, pulmonary oedema, and atherosclerosis, likely caused by daily inhalation of smoke from fuels used for warmth cooking, and lighting. [Zweifel et al., 2009] Much later in the 19th century, the mystical chromatic fogs in industrialized cities, created by at-the-time-unknown deadly toxins, gave an allure of the contemporary developed cosmopolitan world, inspiring writers and painters alike. However, the perspective, quickly shifted to something more sinister, when in December 1952, a smog resulted in the deaths of an estimated 4,000-12,000+ people, as well as a sizable increase in respiratory and cardiovascular complications Bell and Davis [2001]. This disaster resulted in the passing of the Clean Air Act of 1956 (UK), the rest of the developed world followed suit. In the last few years, both individual persons and policy-makers have been showing an increasing interest in assessing air quality and in indices devoted to quantifying it. Clean air is an important requirement for human health, which is why the World Health Organization (WHO) has been concerned with air pollution and its impact on human health for more than 50 years, publishing guidelines which aim to protect public health from the adverse effects of air pollutants. The effects of inhaling PM on human health have been studied extensively and have been found to be robustly associated with an elevated risk of heart disease, stroke and lung cancer, and consequently premature death [Pope et al., 2011]. According to (OECD) Organisation for economic Co-operation and development [2014], ambient air pollution has become the main environmental cause of premature death, succeeding poor sanitation and a lack of drinking water, contributing to the deaths of approximately 7 million people worldwide in 2012 World Health Organisation (WHO) [2014]. Geng et al. [2017] have found evidence that current local air quality levels in China may shorten life expectancy by five life years, and their estimates imply that bringing all of China into compliance with its Class I standards for PM_{10} would save 3.7 billion life-years. Furthermore, Yu et al. [2020] show long-term exposure of $PM_{2.5}$ concentrations, much lower than current WHO standards, is consistently associated with cardiovascular, respiratory, and non-accidental mortality. Sad to say, most areas around the world do not comply to those same WHO air quality guidelines. With that in mind, it is particularly disheartening that in recent years, improvements in air quality in many urban areas around the world have miserably stalled. It is apparent that the existing evidence has not convinced countries sufficiently to adopt and enforce tough enough emission standards. Current policies regarding PM also influence the probability that the world will face disruptive climate change, because the combustion of fossil fuels that causes PM also causes greenhouse gas emissions.

Air pollution measurement data is complex, however, environmental synthetic indices are able to summarize complex situations in a single figure, allowing for comparisons in time and space [Bruno and Cocchi, 2002]. Today, six primary air (quality) pollutants are recognised and monitored by stations around the world. These include fine particulate matter ($PM_{2.5}$, 2.5 μm), respirable particulate matter (PM_{10}, 10 μm), ground-level ozone (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen (di)oxide(s) (NO_x). Often these pollutants are measured in $\mu g/m_3$ within a 8 to 24 hours time span. Alternatively, for some pollutants, a 24-hour average is measured. A better metric that conveys health-specific relevant pollution thresholds is known as the Air Quality Index (AQI). Several of these indexes fabricated by different agencies worldwide exist. However, the most commonly adopted is the AQI developed by the United States Environmental Protection Agency (EPA). The U.S. Air Quality Index (AQI) encompasses all six major pollutants that are regulated under the U.S. Clean Air Act (1990) into one metric IQAir [2021]. This index is divided into six categories indicating increasing levels of health concern (0-50 $\rightarrow$ Green $\rightarrow$ Good, 51-100 $\rightarrow$ Yellow $\rightarrow$ Moderate, 101-150 $\rightarrow$ Orange $\rightarrow$ Unhealthy for Sensitive Groups, 151-200 $\rightarrow$ Red $\rightarrow$ Unhealthy, 201-300 $\rightarrow$ Purple $\rightarrow$ Very Unhealthy, 301-500 $\rightarrow$ maroon $\rightarrow$ Hazardous).

Su and Moaniba [2017] show that GHG-emissions can have a significant positive influence on the development of climate-related technologies. Similarly, we expect PM-emissions, and consequently, low air quality to also positively influence air pollution-related technological innovation. As mentioned earlier, we expect this positive effect to be more pronounced than the effect of GHG-emissions, because we think it likely that chronic illnesses and fatalities related to ambient air pollution are more pressing, as well as, more visible to the greater population than the gradual effects of climate change. The resulting CSR would put firms under more pressure to reduce PM-emmissions, than GHG-emissions. Similarly, it would put government under more pressure to act in the form of environmental policies, which in turn would stimulate firms to innovate further. Of course, this can only be the case when the public is fully aware of the dangers imposed on them by air pollution. This means that government and air quality measurement stations need to be transparent about local air pollution levels. Zhang et al. [2022] used DiD estimation to show that air quality information programs in China, significantly increased green innovation of domestic firms. Similarly, Du et al. [2022] show that establishing additional local monitoring station positively affects green innovation, displaying a crowding-out effect. In trying to examine these relationship, we formulate the following hypothesis:

- **H_1:** Countries with higher levels of air pollution have a higher output in environment-related patents per capita, compared to countries with lower levels of air pollution.

2.2 Politics & socioeconomics

The association between economic growth and innovation has been extensively documented. As such, GDP per capita is generally positively associated with innovation [Ulku, 2004]. However, the relationship between economic development and green-tech innovation is less clear-cut. Tudor and Sova [2021] indicate that GDP per capita promotes the use of energy consumption generated by green technologies, or renewable energy consumption, when it surpasses the 5,000 USD threshold. Studies similar in nature to ours, like Su and Moaniba [2017], use GDP per capita as a control variable to isolate the effect of (GHG-)emissions on innovation. However, we want to study the joint effect of GDP per capita and PM pollution on innovation. A sufficient GDP per capita is potentially a major indicator that a country and its citizens have the financial and knowledge capital required to fund green-tech innovation. We assume that lower-income countries with low air quality overall, will have fewer resources required to combat pollution, and more importantly, will favour easier & more immediate economic growth over sustainable economic growth. In contrast, higher-income countries with low air quality might prioritise sustainability to a greater extent, than lower-income countries would. In trying to examine this relationship, we formulate the following hypothesis:

- **H_2:** For higher-income per capita countries, lower levels of air pollution have a larger positive effect on the output of environment-related patents, compared to lower-income countries with similar levels of air pollution.

Wang et al. [2021] investigate Popper's Hypothesis. This hypothesis reads "democratic countries have advantages in fostering innovation performance". They find evidence in support of the hypothesis and show that democracies exert a significant positive influence on innovation in general, whereas an autocratic political regime inhibits innovation. Of course, we are interested in green-tech innovation specifically. Zakari et al. [2022] find statistical evidence that corruption has a significant and negative effect on green innovation in OECD countries. Since, corruption is widely thought to be linked to autocratic regimes [Méndez and Sepúlveda, 2006; Nur-Tegin and Czap, 2012; Chang and Golden, 2010], it is not hard to suggest that a country's political regime may affect its propensity to eco-innovate. In a similar way, an autocratic regime could potentially motivate opaqueness of public information concerning air quality (evidence and possible consequences of this phenomenon are expanded upon in section 5.2). As mentioned in Section 2.1, non-transparent reporting of air quality information could be detrimental to the rate of development of green-tech innovation. In contrast, an argument could be made that in a stable autocratic regime, knowledge & resources can be directed towards a singular problem more efficiently. Nonetheless, we expect that the potential negative effects of autocratic regimes outweighs the potential positives, overall. In trying to examine this relationship, we formulate the final hypothesis:

- $\mathbf{H_3}$**:** A lower quality of air has a larger positive effect on the output of environment-related patents over time for autocratic countries, compared to democratic countries with similar levels of air quality pollution.

3 Model & data

Our objective is to study the nature of the relationship, if any, between air quality and environmental innovation. Additionally, we would like to study the joint effect of national GDP and air quality, as well as the joint effect of political regime and air quality, respectively, on innovation. In particular, we estimate the following main reduced-form equation:

$$
\begin{aligned}
(PATENTS_{i,t}) = \gamma_t &+ \beta_1(AQI_{i,t}) \\
&+ \beta_2(ln(GDP_{i,t})) \\
&+ \beta_3(DEMOCRATIC_{i,t}) \\
&+ \beta_4(AQI_{i,t}) \cdot (ln(GDP_{i,t})) \\
&+ \beta_5(AQI_{i,t}) \cdot (DEMOCRATIC_{i,t}) \\
&+ \beta_6(CONTROLS_{i,t}) \\
&+ \alpha_i + \epsilon_{i,t}
\end{aligned} \tag{1}
$$

where i indexes country, t indexes time (in years), PATENTS is the number of patents, AQI is the EPA air quality index, GDP is the Gross Domestic Product per capita, DEMOCRATIC is the dummy variable indicating political regime, CONTROLS is a vector of relevant control variables, α_i captures unobservable country heterogeneity, γ_t represents time effects, and $\epsilon_{i,t}$ is a residual error term capturing all other effects. More elaboration on the variables and data can be found in Section 3.1 through 3.5 The one-way system GMM regression results for this model specification can be found in Section 4.2 in Table 2 under model (3). Results for variations of this model, substituting the main dependent and independent variables, can be found in 4.3 in Table 3. We perform these additional analysis to make sure our findings are robust.

3.1 Innovation

Conform to preceding research on the topic of innovation, we use successful environmentally related patent applications per capita (PATENTS) as a proxy for environmental innovation. As such, this is the main dependent variable in our model. This data was compiled from a database maintained by The Organisation for Economic Co-operation and Development (OECD) [OECD, 2017]. The database is called 'Technology indicators', and includes patent applications filed in one or more jurisdictions. The database distinguishes several characteristics related to the patent's; date specification, country of residence and to or by which patent office the patent was filed/granted. In our model we have selected 'Priority date', 'inventor(s) country(ies) of residence', and filed under 'Patent Cooperation Treaty (PCT)'. The dataset includes patents ranging from 'environmental-related technologies' to, 'environmental management technologies', 'climate change mitigation technologies', and 'technologies related to the capture, storage, sequestration or disposal of GHGs'. However, since we intend on capturing an effect (if any) of air quality on environmental innovation, we will be focusing solely on those patents in the dataset that include air quality innovation. Therefore we exclude all climate change mitigation technologies and Capture, storage, sequestration or disposal of GHGs technologies from our model. Furthermore, another variable present in this dataset is environmental patents as a percentage of all technologies (PATENTS%ALL). This variable will be used as second dependent variable in the robustness analysis (Section 4.3). Additionally, the control variables (CONTROLS) include four variables, captured from an adjacent OECD database called 'Research & Development Statistics', namely, Gross Domestic Spending on R&D (R&D INTENSITY) [(OECD) Organisation for economic Co-operation and development, 2017b], measured as a percentage of GDP, the total number of triadic patent families (TRIADIC) [(OECD) Organisation for economic Co-operation and development, 2017c], Foreign Direct Investment inflow in millions of US$ (FDI INFLOW) [(OECD) Organisation for economic Co-operation and development, 2017a], and environmentally related taxes as a percentage of total domestic taxes (ENV TAX) [(OECD) Organisation for economic Co-operation and development, 2019].

3.2 Air pollution

Included in the model is data from the World Air Quality Index Project (WAQI), a database from the Air Quality Open Data Platform IQAir [2021]. This dataset provides Air Quality Data covering about 380 major cities from many countries worldwide, from between 2015-2021, updated 3 times a day. The data for each major cities is based on the average (median) of several stations, but also includes the minimum, maximum U.S. EPA AQI standard values (i.e. no raw concentrations), and standard deviation for each of the air pollutants. Additionally, this database includes some meteorological indicators (Wind, Temperature, etc.). Since the dataset suffers from heavy, unbalanced attrition, we have opted to include in the model only a single ordinal normalised Maximum AQI score (AQI) taken over all pollutants. The consequences of this decision are elaborated upon in Section 5.1. This Maximum AQI score (AQI) ranging from 0 to 5 (where 0 denotes 'good' and 5 denotes 'hazardous') is derived from the U.S. EPA AQI values found in the WAQI Database.

3.3 Gross Domestic Product per capita

The World Bank offers an extensive database of many economic growth indicators [The World Bank, 2021b]. In this case, the indicator best suited for this study is Gross Domestic Product per capita constant 2015 US$ or (GDP). Since we are comparing many countries worldwide over a time-span of several years, it is best to take into account population size, and factor out any difference between currencies and account for inflation. Additionally, for robustness analysis we include another indicators. Namely, GDP per capita constant 2017 US$ accounting for Purchasing Power Parity (2017PPP). The variables includes cross-sectional time-series data of all 249 ISO recognised countries, between 1960-2021 with minor attrition. To normalise we have taken the log of the variables.

3.4 Political regime

Classifying countries under types of political regimes is a reasonably complicated, and somewhat subjective, undertaking. Thankfully, databases exist that aim to make this practice less ambiguous. One such initiative is the Varieties of Democracy (V-Dem) Research Project [von Römer et al., 2022], created by the Department of Political Science, University of Gothenburg, Sweden. The project takes a data-driven comprehensive approach to understanding democratization, encompassing core principles such as electoral, Liberal, majoritarian, consensual, participatory, deliberative, and egalitarian. An analysis of the broader set of variables together combine to create a single ordinal variable that takes 0 for countries that can be considered a closed autocracy, 1 for electoral autocracy, 2 for electoral democracy, and 3 for liberal democracy. We have used this variable to generate a dummy variable (DEM) that takes takes value 1 if the country is characterised by a mainly democratic political system, and 0 mainly autocratic political system.

3.5 Health hazards

The World Health Organization (WHO) provides several datasets on the impact of low air quality and the adverse effects on health worldwide [World Health Organisation (WHO), 2018]. One of the metrics included is annual mortality rates attributed to respiratory risk from ambient air pollution (DEATHS). This variable are used in the robustness analysis (section 4.3) as proxies of more tangible effect of poor air quality.

Table 1: Descriptive Statistics of most important variables

Variable	N	$mean$	σ	min	max
PATENTS	127	16.36	19.98	0.100	76.26
AQI	113	1.460	0.846	0	4
GDP	127	31,304	21,064	6,126	108,570
ln(GDP)	127	10.12	0.707	8.720	11.60
DEM	127	0.921	0.270	0	1
R&D INTENSITY	127	1.737	1.017	0.261	4.797
TRIADIC	127	1,534	3,810	3.009	17,702
ln(TRAIDIC)	127	4.935	2.351	1.102	9.781
FDI IN	127	35,814	70,073	225.8	480,016
ln(FDI IN)	127	9.343	1.551	5.420	13.08
ENV TAX	127	2.275	0.932	0.610	4.640
DEATHS	127	4.338	3.181	0.616	17.95
GDP2017PPP	127	39,899	17,589	13,399	116,518
ln(GDP2017PPP)	127	10.50	0.448	9.503	11.67

4 Empirical results

Table 1 represents the summary statistics for all variables of interest. These statistics include the number of observations, mean, standard deviation, minimum and maximum values across the countries-year observations in the sample.

4.1 Model testing

To assess which estimator will be unbiased, and therefore, the most suitable for our model, we should first test for the presence of fixed or random effects in the panel dataset. We can test if the data contains fixed effects by performing an F-test, which is based on loss of goodness-of-fit. If H_0 is rejected, it is possible to conclude that there is a significant fixed effect or significant increase in goodness-of-fit in the fixed effect model; therefore, the fixed effect model is better than pooled OLS. Performing the F-test results in a p-value of 0.000. This means that we can reject the null hypothesis that all dummy parameters are zero and that a significant fixed effect is present. Breusch and Pagan [1980] Lagrange Multiplier (B-P LM) test examines if individual (or time) specific variance components are zero. If H_0 is rejected, it is possible to conclude that a significant random effect is present in the panel data and that the random effect model is able to deal with heterogeneity better than the pooled OLS model. Performing the B-P LM results in a p-value of 0.000. This means we can reject the null hypothesis, indicating that a significant random effect is present.

The Hausman test [Hausman, 1978] tests whether group- or time-specific effects are correlated with any regressors. In this case, the Hausman test evaluates whether the random effects estimate is insignificantly different from the unbiased fixed effect estimate and can, therefore, be used to choose between fixed effects and random effects model. H_0 indicates that the random effects is the more efficient model. Alternatively, H_1 indicates that fixed effects model is the more consistent model. Performing the Hausman test results in a p-value of 0.0000. This means that we reject the null hypothesis, that the errors are systematically different on a 1% level, indicating that the Hausman test results support the random effects model will be biased and inconsistent.

However, given our dataset is relatively small and unbalanced, possible concerns of endogeneity must be addressed. Several characteristics in datasets point to one-way system Generalised Method of Moments (GMM) being a more suitable estimator. The GMM [Hansen, 1982] estimators are generic methods for estimating parameters in statistical models, designed to handle important modeling concerns, while avoiding dynamic panel bias. The estimators are especially suitable for models with relatively short time dimensions (T) and arbitrarily distributed fixed effects. GMM estimators flexibly accommodate unbalanced panels and multiple independent variables that are not strictly exogenous (meaning they are correlated with past and possibly current realisations of the error term). It does this by uses moment conditions that are functions of the model parameters and the data, so that their expectation is zero at the parameters' true values. In doing so, the estimator controls for endogeneity of the lagged dependent variable in a dynamic panel model, omitted variable bias, unobserved panel heterogeneity and measurement errors. All of these properties make a strong argument for the use of one-way system GMM in our study.

4.2 Main analysis

A summary of the parameter estimate estimates and associated standard errors for all models is presented in Table 2. Model (1) shows a model with only the controls, while model (2) and (3) include the independent variables, with and without joint effects, respectively.

The inclusion of the joint effects influences the significance of most variables. In model (2) we see that all parameter estimates of the main independent variables are positive, but only DEM is significant. Model (2) suggests that having a mainly democratic political system is associated with a 3.824 increase in PATENTS in the short-run, ceteris paribus. This effect is statistically significant on a 10% level.

In model (3), the parameter estimate for AQI is positive and significant on a 5% level. This suggests that a 1-point increase in AQI is associated with a 40.28 increase in PATENTS. The parameter estimate for GDP is also positive and significant on a 5% level. This suggests that a percentage change in GDP is associated with a 7.368 increase in PATENTS in the short-run, ceteris paribus. However, the joint effect of GDP and AQI is negative and significant. This result suggests that the effect of AQI on PATENTS is dependent on GDP, and vice versa. In model (3), the parameter estimate for DEM is not significant on a 10% level. Interestingly, however, the parameter estimate of the interaction term of DEM and AQI is positive and significant on a 10% level. This suggests that the effect of DEM is dependent on AQI, and vice versa.

All parameter estimates for the lagged dependent variables are positive and significant on a 1% level. The signs and significance levels of the control variables in model (1) are as expected. These parameter estimates stay mostly consistent in subsequent models. R&D INTENSITY has a positive and significant effect on PATENTS (but is not significant on a 10% level in model (2)). Equally, TRIADIC has a positive and significant effect on PATENTS. FDI IN has a negative and significant effect on PATENTS. While, the parameter estimates of ENV TAX are positive in model (1) and (2), but negative in model (3), all three parameter estimates are not significant on a 10% level. In the next section we will analyse the robustness of our model.

Table 2: Main regression results of GMM estimation

Variable	Model (1)	Model (2)	Model (3)
AQI		1.153	40.28**
		(1.132)	(18.63)
ln(GDP)		2.401	7.368**
		(1.890)	(3.514)
ln(GDP)*AQI			-4.281**
			(1.933)
DEM		3.824*	-1.495
		(2.085)	(2.063)
DEM*AQI			3.030*
			(1.502)
R&D INTENSITY	2.946**	2.717	3.254*
	(1.333)	(1.907)	(1.603)
ln(TRAIDIC)	1.523**	1.968***	2.360***
	(0.709)	(0.711)	(0.781)
ln(FDI IN)	-2.014**	-2.561**	-3.110***
	(0.905)	(0.943)	(1.070)
ENV TAX	-0.564	-0.238	0.506
	(0.534)	(0.969)	(1.064)
L.PATENTS	0.680***	0.599***	0.585***
	(0.0684)	(0.0782)	(0.0971)
Constant	12.52**	-12.94	-56.75*
	(5.954)	(14.74)	(30.36)
Year dummies	Yes	Yes	Yes
Hansen-stat (chi2)	0.135	0.103	0.171
AR(2) (z)	0.794	0.861	0.911
F-stat	179.73	83.79	88.75
Number of instruments	9	12	14
Number of countries	37	34	34
Number of observations	127	113	113

***p<0.01, **p<0.05, *p<0.1 denote the statistical confidence levels. P-values are reported for AR(2) and Hansen statistic. Models are estimated using the generalised methods of moments regression method. The dependent variable is PATENTS. The regression coefficients are in the upper rows. t-statistics (in parentheses) are calculated using robust standard errors that are heteroskedasticity-consistent.

4.3 Robustness analysis

In this section we the robustness of our model by providing additional analysis and results. Model (1), (3) and (5) use our main dependent variable PATENTS as the dependent variable, while model (2), (4) and (6) use PATENTS%ALL as the dependent variable. Models (1), (2), (5) and (6) use AQI as the main independent variable, while model (3) and (4) use DEATHS as the main independent variable. Models (1), (2), (3) and (4) use GDP as the second independent variable, while model (5) and (6) use GDP2017PPP as the second independent variable.

The sign and significance levels of the parameter coefficients across the these models are fairly consistent. AQI and DEATHS seem to have a similar effect on the dependent variables, while the same can be said both GDP per capita indicators. However, R&D intensity behaves somewhat differently across the 2 dependent variables.

Table 3: Robustness analyses of GMM estimation

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	AQI		DEATHS		GDP2017PPP	
AQI/DEATHS	40.28**	1.330*	34.82**	0.952**	62.82**	1.963
	(18.63)	(0.706)	(16.76)	(0.451)	(29.81)	(1.242)
ln(GDP)	7.368**	0.362**	19.36	0.906***	11.80**	0.527**
	(3.514)	(0.140)	(13.21)	(0.320)	(5.513)	(0.244)
DEM	-1.495	0.258	-22.68	-0.535	-0.680	0.345**
	(2.063)	(0.161)	(14.17)	(0.385)	(2.838)	(0.152)
$\times_{GDP}$	-4.281**	-0.121	-3.818**	-0.0972*	-6.249**	-0.174
	(1.933)	(0.0734)	(1.813)	(0.0495)	(2.909)	(0.121)
$\times_{DEM}$	3.030*	0.00194	4.338*	0.160***	3.015	-0.0243
	(1.502)	(0.0702)	(2.449)	(0.0581)	(2.059)	(0.0674)
R&D INTENSITY	3.254*	-0.0790	3.860	-0.0930*	3.124*	-0.0747
	(1.603)	(0.0532)	(2.426)	(0.0524)	(1.656)	(0.0514)
ln(TRAIDIC)	2.360***	0.0492	2.262*	0.00968	2.589***	0.0555*
	(0.781)	(0.0323)	(1.261)	(0.0301)	(0.837)	(0.0327)
ln(FDI IN)	-3.110***	-0.0948**	-3.059*	-0.0811**	-3.278***	-0.0926**
	(1.070)	(0.0376)	(1.508)	(0.0345)	(1.053)	(0.0366)
ENV TAX	0.506	-0.0168	1.071	-0.0290	0.535	-0.0223
	(1.064)	(0.0454)	(1.830)	(0.0449)	(1.219)	(0.0491)
L.Y	0.585***	0.236	0.501***	0.451***	0.560***	0.276
	(0.0971)	(0.188)	(0.170)	(0.161)	(0.0919)	(0.184)
Constant	-56.75*	-1.450	-162.4	-6.968**	-106.1*	-3.545
	(30.36)	(1.204)	(117.5)	(3.038)	(53.43)	(2.340)
Hansen-stat (chi2)	0.171	0.107	0.159	0.139	0.175	0.095
AR(2) (z)	0.911	0.326	0.624	0.194	0.807	0.277
F-stat	88.75	4.38	29.70	15.32	74.61	5.03
Instruments	14	14	14	14	14	14
Observations	113	113	113	113	113	113
Countries	34	34	34	34	34	34

Models are estimated using the generalised methods of moments regression method. ***p<0.01, **p<0.05, *p<0.1 denote the statistical confidence levels. × denotes the interaction term with AQI/DEATHS. P-values are reported for AR(2) and Hansen statistic. The dependent variable is PATENTS in models (1), (3) and (5), while it is PATENTS%ALL in model (2), (4) and (6). The regression coefficients are in the upper rows. Year dummies used. t-statistics (in parentheses) are calculated using heteroskedasticity-consistent robust standard errors.

5 Discussion

Concerning the findings from table 2 in Section 4.2, model (2), on its own, does not provide support for H_1 (countries with higher levels of air pollution have a higher output in environment-related patents per capita, compared to countries with lower levels of air pollution), since the parameter estimate of AQI in model (2) is not significant on a 10% level. However, the results of model (3) do provide support for H_1, since the parameter estimate of AQI in model (3) is positive and significant on a 5% level. Model (3) suggests that there is a positive and significant relationship between air pollution and green-tech innovation on a country level. These findings are similar to those of Su and Moaniba [2017], in that they find a positive and significant relationship between air pollution (GHG instead of PM) and environmental innovation. However, this finding should not be taken at face value, given the parameter estimate of model (2) is not significant.

Model (3) does not provide support for H_2 (For higher-income per capita countries, lower levels of air pollution have a larger positive effect on the output of environment-related patents, compared to lower-income countries with similar levels of air pollution), since the parameter estimate for the joint effect ln(GDP)*AQI is negative and significant on a 5% level. Rather, it provides support for the opposite. It seems that the positive relationship between air pollution and green-tech innovation is more pronounced for low-income countries, compared to high-income countries. At first glance, one would assume that high-income countries possess more financial and intellectual resources to innovate in general and would, thus, have a higher green innovation activity when confronted with low air quality, compared with low-income countries. However, there might be some logic to our findings yet. It could be the case, that health risks from air pollution in developing countries are even more apparent to the greater population, while at the same time healthcare might be less able to ease this burden, and thus, drive its propensity to eco-innovate even more. This idea is further supported by the robustness analysis (Table 3 Section 4.3), where the main independent AQI is substituted for DEATHS.

Model (3) provides some support for H_3 (A lower quality of air has a larger positive effect on the output of environment-related patents over time for autocratic countries, compared to democratic countries with similar levels of air quality pollution), since the parameter estimate for the joint effect DEM*AQI is positive and significant on a 10% level. These findings align well with Popper's Hypothesis (democratic countries have advantages in fostering innovation performance).

5.1 Limitations

By all accounts there are several limitations to our model and the findings it suggests. For one, GMM estimation, while good at dealing with omitted variable bias and reverse causality, is highly sensitive to model specification.

Furthermore, unfortunately, there is no patent data available exclusively for air pollutant mitigation technologies innovation within the OECD database. Although we exclude all patents that are classified under 'technologies related to the capture, storage, sequestration or disposal of GHGs' and 'climate change mitigation technologies', much of the remaining patents fall under considerably broad categories, namely 'environmental-related technologies' and 'environmental management technologies'. Given a patent specifying for solely air quality related technologies, it would be much easier to isolate and reliably estimate the specific effect of air quality on the innovation activity related to air pollution mitigation technologies. However, from the data available, the currently employed innovation indicator is that which resembles this hypothetically ideal dataset most closely.

Finally, the sample size of the time component in the main analysis is arguably too small to consider the regression predictions accurate. Although the unbalanced dataset overall is quite large, when all variables of interest are included in the model, the sample only includes $nT = 127$ observations, $n = 37$ countries, measured over an average $t = 3.4$ years, between 2015-2021. These numbers can also be found in Table 2, Section 4.2. Additionally, the limited number of year observations inhibits imposing a lag-structure in the model any further than 1 year. Naturally, this is an all too common problem within the scientific community that work with yearly country-level data. Naturally, there are only 249 countries (193 recognised by the U.N.) in the world today according to the International Organization for Standardization (ISO) [International Organization for Standardization, 2022]. Only 81 of which can be considered industrialised or developed, according to The World Bank [2021a]. Digital measurement of air pollution wasn't pioneered until 1987, and consistent measurement of local ambient air pollution hasn't started to gain traction internationally until 2015. Technically, however, this issue is exacerbated as a consequence of a different problem, namely, attrition. Since the AQI database takes averages from independent weather stations all over the world, attrition is quite large. However, potential concerns for attrition bias seem quite unlikely. Once a connection to the WAQI platform is made, data-reporting happens autonomously. In that sense, human error can be largely excluded. As such, there is no serious concern of attrition bias. That is to say, there would be no concern for attrition bias, except for one condition. Intentional omission of data or misreporting.

5.2 Evidence of misreporting in China

By all accounts, sample size and attrition are only minor concerns in the face of serious misreporting bias. In 2012, Chen et al. [2012] presented statistical verification of significant air quality misreporting by government official-owned monitoring stations. The authors report a much higher-than-expected frequency of API values just below 100 AQI (and a correspondingly lower-than-expected frequency just above 100 AQI). This and other accusations prompted the government to restructure China's air quality monitoring system, to discourage local officials from misreporting data. Post-2012, Turiel and Kaufmann [2021] have provided statistical evidence of significant misreporting once more, albeit to a different extent. The authors state that statistically significant divergences exist between $PM_{2.5}$ levels reported by government-owned monitoring stations, and neighbouring U.S. embassy monitoring stations, respectively. specifically, they observe that these divergences are more likely to occur during hours when air pollution concentration is high, and are more frequent, as well as more positive, than can be expected by random chance. In other words, relative to U.S.-controlled monitoring stations, government-controlled stations systematically underreport pollution levels when local air quality is poor. While this is a grave accusation, it should not be taken lightly. One can only wonder about the validity of air quality data from other stations in the world. Crucially, despite this genuine concern, excluding the People's Republic of China (PRC), from the model, does not yield remarkably different results.

6 Conclusion

This master thesis investigates the relationship between air quality and the rate of green-tech innovation, on a country-level. Additionally, it examines the added effect of a country's GDP per capita and political regime. By doing this, the paper contributes to a growing body of existing literature by trying to shed new perspective on the relationship between green technological innovation and air quality.

A one-way system GMM model was estimated using a cross-sectional time-series dataset. The findings suggest that there is a positive and significant relationship between air pollution and green-tech innovation on a country level. However, this finding is only supported in our models that introduce a joint effect of air pollution and GDP per capita, as well as the joint effect of air pollution and political regime. Furthermore, our findings suggest that this effect is more pronounced for low-income countries, compared to high-income countries. This is the opposite of what we expected. Finally, our findings also suggest that the aforementioned effect is more pronounced for democratic countries, compared autocratic countries.

Robustness analysis provides support for these findings.

The findings presented in this thesis could help policy-makers from international and domestic institutions understand how to tackle air pollution globally, for countries with varying environmental and socioeconomic characteristics. For example, policy-makers and international institutions should aim to be transparent about ambient air quality levels and inform the public on consequent health-related issues. This seems to be especially vital in low-income countries and democratic regimes. This in turn could drive domestic firm's Corporate Social Responsibility, which in turn should drive green-tech innovation.

In conducting our research we have contributed to existing literature on the determinants of green-tech innovation activity. Moreover, this thesis adds to prior research that investigates the relationship between air pollution and environmental innovation. To our knowledge, this is the first body of scientific work that empirically analyses the relationship between ambient particle matter and green-tech innovation activity.

Future research could expand on this topic by using new datasets with more data points with, specifically, a longer time component. Furthermore, we would suggest using datasets that use patents or other innovation indicators that relate to PM specifically, and, thus, exclude GHG.

References

Alvarez-Herranz, A., Balsalobre-Lorente, D., Shahbaz, M., and Cantos, J. M. (2017). Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy*, 105:386–397.

Bell, M. L. and Davis, D. L. (2001). Reassessment of the lethal london fog of 1952: novel indicators of acute and chronic consequences of acute exposure to air pollution. *Environmental Health Perspectives*, 109(suppl 3):389–394.

Bernauer, T., Engel, S., Kammerer, D., and Sejas Nogareda, J. (2007). Explaining green innovation: ten years after porter's win-win proposition: how to study the effects of regulation on corporate environmental innovation? *Politische Vierteljahresschrift*, 39:323–341.

Biswas, A. and Roy, M. (2016). A study of consumers' willingness to pay for green products. *Journal of Advanced Management Science*, 4(3).

Brammer, S. and Millington, A. (2008). Does it pay to be different? an analysis of the relationship between corporate social and financial performance. *Strategic Manage. J.*, 29(12):1325–1343.

Breusch, T. S. and Pagan, A. R. (1980). The lagrange multiplier test and its applications to model specification in econometrics. *The review of economic studies*, 47(1):239–253.

Brunnermeier, S. B. and Cohen, M. A. (2003). Determinants of environmental innovation in us manufacturing industries. *Journal of Environmental Economics and Management*, 45(2):278–293.

Bruno, F. and Cocchi, D. (2002). A unified strategy for building simple air quality indices. *Environmetrics*, 13(3):243–261.

Chang, E. and Golden, M. A. (2010). Sources of corruption in authoritarian regimes. *Social Science Quarterly*, 91(1):1–20.

Chen, Y., Jin, G. Z., Kumar, N., and Shi, G. (2012). Gaming in air pollution data? lessons from china. *B. E. J. Econom. Anal. Policy*, 12(3).

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W., Johns, T., Krinner, G., Shongwe, M., Tebaldi, C., Weaver, A., Wehner, M., Allen, M., Andrews, T., Beyerle, U., Bitz, C., Bony, S., and Booth, B. (2013). *Long-term Climate Change: Projections, Commitments and Irreversibility*, pages 1029–1136. Intergovernmental Panel on Climate Change. Cambridge University Press, United Kingdom.

Dangelico, R. M. and Pujari, D. (2010). Mainstreaming green product innovation: Why and how companies integrate environmental sustainability. *Journal of business ethics*, 95(3):471–486.

Den Elzen, M., Kuramochi, T., Höhne, N., Cantzler, J., Esmeijer, K., Fekete, H., Fransen, T., Keramidas, K., Roelfsema, M., Sha, F., et al. (2019). Are the g20 economies making enough progress to meet their ndc targets? *Energy policy*, 126:238–250.

Díaz-García, C., González-Moreno, Á., and Sáez-Martínez, F. J. (2015). Eco-innovation: insights from a literature review. *Innovation*, 17(1):6–23.

Du, L., Lin, W., Du, J., Jin, M., and Fan, M. (2022). Can vertical environmental regulation induce enterprise green innovation? a new perspective from automatic air quality monitoring station in china. *Journal of Environmental Management*, 317:115349.

Ebenstein, A., Fan, M., Greenstone, M., He, G., and Zhou, M. (2017). New evidence on the impact of sustained exposure to air pollution on life expectancy from china’s huai river policy. *Proceedings of the National Academy of Sciences*, 114(39):10384–10389.

Fan, R., Wang, Y., Chen, F., Du, K., and Wang, Y. (2022). How do government policies affect the diffusion of green innovation among peer enterprises?-an evolutionary-game model in complex networks. *Journal of Cleaner Production*, 364:132711.

Flores, P. J. and Jansson, J. (2022). Spice—determinants of consumer green innovation adoption across domains: A systematic review of marketing journals and suggestions for a research agenda. *International Journal of Consumer Studies*.

Fraj-Andrés, E., Martinez-Salinas, E., and Matute-Vallejo, J. (2009). A multidimensional approach to the influence of environmental marketing and orientation on the firm's organizational performance. *J. Bus. Ethics*, 88(2):263–286.

Geng, Z., Chen, Q., Xia, Q., Kirschen, D. S., and Kang, C. (2017). Environmental generation scheduling considering air pollution control technologies and weather effects. *IEEE Transactions on Power Systems*, 32(1):127–136.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the econometric society*, pages 1029–1054.

Hao, J. and He, F. (2022). Corporate social responsibility (csr) performance and green innovation: Evidence from china. *Finance Research Letters*, 48:102889.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, pages 1251–1271.

International Organization for Standardization (2022). ISO 3166: Country Codes. `https://www.iso.org/obp/ui/#search`. Accessed: 2022-10-12.

IQAir (2021). Air quality historical data platform. data retrieved from Air Quality Historical Data Platform, `https://aqicn.org/data-platform/register/`.

Karimi Takalo, S., Sayyadi Tooranloo, H., and Shahabaldini parizi, Z. (2021). Green innovation: A systematic literature review. *Journal of Cleaner Production*, 279:122474.

Kraus, S., Rehman, S. U., and García, F. J. S. (2020). Corporate social responsibility and environmental performance: The mediating role of environmental strategy and green innovation. *Technological Forecasting and Social Change*, 160:120262.

Lin, H., Zeng, S., Ma, H., Qi, G., and Tam, V. W. (2014). Can political capital drive corporate green innovation? lessons from china. *Journal of cleaner production*, 64:63–72.

Méndez, F. and Sepúlveda, F. (2006). Corruption, growth and political regimes: Cross country evidence. *European Journal of political economy*, 22(1):82–98.

Nur-Tegin, K. and Czap, H. J. (2012). Corruption: Democracy, autocracy, and political stability. *Economic Analysis and Policy*, 42(1):51–66.

OECD (2017). Technology indicators.

(OECD) Organisation for economic Co-operation and development (2014). The cost of air pollution. health impacts of road transport. `http://www.keepeek.com/Digital-Asset-Management/oecd/environment/the-cost-of-air-pollution_9789264210448-en#page1`. Retrieved on 12.10.2022.

(OECD) Organisation for economic Co-operation and development (2017a). FDI flows. Title of the publication associated with this dataset: Foreign direct investment (FDI).

(OECD) Organisation for economic Co-operation and development (2017b). Gross domestic spending on R&D. Title of the publication associated with this dataset: Research and development (R&D).

(OECD) Organisation for economic Co-operation and development (2017c). Triadic patent families. Title of the publication associated with this dataset: Research and development (R&D).

(OECD) Organisation for economic Co-operation and development (2019). Environmental tax. Title of the publication associated with this dataset: Environmental policy.

Pope, C. A., Burnett, R. T., Turner, M. C., Cohen, A., Krewski, D., Jerrett, M., Gapstur, S. M., and Thun, M. J. (2011). Lung cancer and cardiovascular disease mortality associated with ambient air pollution and cigarette smoke: Shape of the exposure–response relationships. *Environmental Health Perspectives*, 119(11):1616–1621.

Pujari, D. (2006). Eco-innovation and new product development: understanding the influences on market performance. *Technovation*, 26(1):76–85.

Ren, S., Huang, M., Liu, D., and Yan, J. (2022). Understanding the impact of mandatory csr disclosure on green innovation: Evidence from chinese listed firms. *British Journal of Management*.

Shahzad, M., Qu, Y., Javed, S. A., Zafar, A. U., and Rehman, S. U. (2020). Relation of environment sustainability to csr and green innovation: A case of pakistani manufacturing industry. *Journal of Cleaner Production*, 253:119938.

Shan, S., Genç, S. Y., Kamran, H. W., and Dinca, G. (2021). Role of green technology innovation and renewable energy in carbon neutrality: A sustainable investigation from turkey. *Journal of Environmental Management*, 294:113004.

Solomon, S., Plattner, G.-K., Knutti, R., and Friedlingstein, P. (2009). Irreversible climate change due to carbon dioxide emissions. *Proceedings of the National Academy of Sciences*, 106(6):1704–1709.

Su, H.-N. and Moaniba, I. M. (2017). Does innovation respond to climate change? empirical evidence from patents and greenhouse gas emissions. *Technological Forecasting and Social Change*, 122:49–62.

Takalo, S. K., Tooranloo, H. S., et al. (2021). Green innovation: A systematic literature review. *Journal of Cleaner Production*, 279:122474.

The World Bank (2021a). Developed countries. `https://data.worldbank.org/country`. Accessed: 2022-10-12.

The World Bank (2021b). GDP per capita (constant 2015 US$). `https://data.worldbank.org/indicator/NY.GDP.PCAP.KD`. Accessed: 2022-10-12.

Tudor, C. and Sova, R. (2021). On the impact of gdp per capita, carbon intensity and innovation for renewable energy consumption: Worldwide evidence. *Energies*, 14(19):6254.

Turiel, J. S. and Kaufmann, R. K. (2021). Evidence of air quality data misreporting in china: An impulse indicator saturation model comparison of local government-reported and u.s. embassy-reported pm2.5 concentrations (2015–2017). *PLOS ONE*, 16(4):1–18.

Ulku, H. (2004). R&D, innovation, and economic growth: An empirical analysis. *IMF Working paper*.

Urbaniec, M., Tomala, J., and Martinez, S. (2021). Measurements and trends in technological eco-innovation: Evidence from environment-related patents. *Resources*, 10(7):68.

von Römer, Hindle, G., Seim, B., Sigman, R., Staton, J., Alizada, N., Tzelgov, E., ting Wang, Y., Wig, T., Wilson, S., Ziblatt, D., Ilchenko, N., Grahn, S., Kinzelbach, K., Rydén, O., Coppedge, M., Gerring, J., Knutsen, C. H., Lindberg, S. I., Skaaning, S.-E., Teorell, J., Altman, D., Bernhard, M., Fish, M. S., Cornell, A., Gjerløw, H., Glynn, A., Hicken, A., Krusell, J., Marquardt, K. L., Mcmann, K., Mechkova, V., Medzihorsky, J., Gastaldi, L., Paxton, P., Pemstein, D., and Johannes (2022). Varieties of democracy (v-dem) project; V-Dem dataset 2022.

Wang, H., Qi, S., Zhou, C., Zhou, J., and Huang, X. (2022). Green credit policy, government behavior and green innovation quality of enterprises. *Journal of Cleaner Production*, 331:129834.

Wang, Q.-J., Feng, G.-F., Wang, H.-J., and Chang, C.-P. (2021). The impacts of democracy on innovation: Revisited evidence. *Technovation*, 108:102333.

World Health Organisation (WHO) (2014). Burden of disease from the joint effects of household and ambient air pollution for 2012. `https://www.ccacoalition.org/en/resources/world-health-organization-\OT1\textendash-burden-disease-joint-effects-household-and-ambient-air`. Retrieved on 12.10.2022.

World Health Organisation (WHO) (2018). Air pollution data portal. data retrieved from Air Quality Database, `https://www.who.int/data/gho/data/themes/air-pollution/who-air-quality-database`.

Yu, W., Guo, Y., Shi, L., and Li, S. (2020). The association between long-term exposure to low-level pm2. 5 and mortality in the state of queensland, australia: a modelling study with the difference-in-differences approach. *PLoS medicine*, 17(6):e1003141.

Zakari, A., Tawiah, V., Oyewo, B., and Alvarado, R. (2022). The impact of corruption on green innovation: The case of oecd and non-oecd countries. *Journal of Environmental Planning and Management*, pages 1–33.

Zhang, S., Zhang, M.-a., Qiao, Y., Li, X., and Li, S. (2022). Does improvement of environmental information transparency boost firms' green innovation? evidence from the air quality monitoring and disclosure program in china. *Journal of Cleaner Production*, 357:131921.

Zweifel, L., Büni, T., and Rühli, F. J. (2009). Evidence-based palaeopathology: meta-analysis of pubmed-listed scientific studies on ancient egyptian mummies. *Homo*, 60(5):405–427.

A Appendix

Country	observations	percentage
Argentina	4	3.15
Australia	2	1.57
Austria	3	7.09
Belgium	2	1.57
Chile	4	3.15
China	4	3.15
Colombia	4	3.15
Czech Republic	4	3.15
Denmark	4	3.15
Estonia	4	3.15
Finland	3	2.36
France	4	3.15
Germany	4	3.15
Greece	4	3.15
Hungary	3	2.36
Ireland	3	2.36
Israel	3	2.36
Italy	4	3.15
Japan	4	3.15
Latvia	2	1.57
Lithuania	4	3.15
Luxembourg	2	1.57
Mexico	4	3.15
Netherlands	3	2.36
New Zealand	2	1.57
Norway	2	1.57
Poland	4	3.15
Portugal	4	3.15
Slovakia	4	3.15
Slovenia	4	3.15
South Africa	4	3.15
Spain	4	3.15
Sweden	4	3.15
Switzerland	1	0.79
Turkey	4	3.15
United Kingdom	4	3.15
United States Of America	4	3.15