STIRPAT analysis revisited – new insights and applications on the relationship of anthropogenic impacts with the environment

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1. Zusammenfassung / Summary

Das Bewusstsein für die Auswirkungen menschlicher Aktivitäten auf die Umwelt stellt nicht nur ein Merkmal unserer Zeit dar. Die enge Beziehung zwischen Mensch und Umwelt ist jedoch aufgrund der Auswirkungen des Klimawandels heute und in naher Zukunft offensichtlicher als je zuvor. Mittlerweile stellt der Mensch die einflussreichste Spezies auf der Erde dar, sodass Wissenschaftler die aktuelle geologische Epoche bereits als Anthropozän (der Terminus technicus bringt den umweltprägenden Charakter menschlicher Aktivitäten, wie zum Beispiel Veränderungen der Erdoberfläche oder der Atmosphärenzusammensetzung, zum Ausdruck) bezeichnen (Crutzen and Stoermer, 2000; Lewis and Maslin, 2015). Ein genereller Zusammenhang zwischen Mensch und Umwelt wurde jedoch schon seit langer Zeit erkannt und beschrieben.

Bereits Seneca (4 v.C. – 65) macht auf diesen Zusammenhang aufmerksam. Er beschreibt beispielsweise die Korrelation zwischen Feuerstellen, Verkehr oder das Verbrennen von toten Körpern und der Luftverschmutzung in Rom (Seneca, 1971[62 A.D.]).

Viele Jahrhunderte später stellt sich Thomas Malthus (1766 - 1834) die Frage wie eine permanent schneller wachsende Bevölkerung die Verfügbarkeit von lebenswichtigen Ressourcen beeinflusst (Malthus, 1960 [1798]). Thomas Malthus äußert starke Zweifel daran, ob sich eine exponentiell wachsende Bevölkerung auf Dauer von begrenztem Land und Boden ernähren kann. Obwohl sich diese Bedenken zunächst nicht bewahrheiten (aufgrund sehr hoher Produktivitätswachstumsraten u.a. im Landwirtschaftsbereich) ist die Debatte bezüglich der Mensch-Umwelt Beziehung nie abgerissen (Galor and Weil, 2000).[1] Lediglich die Schwerpunkte der Diskussion haben sich verlagert wie z.B. auf die Erschöpfung von natürlichen Ressourcen (z.B. fossile Brennstoffe) oder auf den Abbau erneuerbarer Ressourcen (Panayotou, 2000).

Mit den Schriften der klassischen Ökonomen (wie beispielsweise Thomas Malthus) hat die Beziehung zwischen Mensch und Umwelt das erste Mal eine gewisse Systematik erhalten (Dietz and Rosa, 1994). Davon sind auch weitere Wissenschaftler anderer Fachrichtungen inspiriert worden. Charles Darwin (1809 - 1882) äußert ähnliche Gedanken als er darstellt, wie eine immer größer werdende Bevölkerung den Druck auf

[1] Heutzutage bekommen die Bedenken von Malthus wieder eine gewisse Relevanz. Während die Weltbevölkerung immer noch weiter wächst zeigen sich die Wachstumsraten an (landwirtschaftlicher) Produktivität immer unsicherer aufgrund Auswirkungen des Klimawandels sowie anderer globaler Bedrohungen (wie etwa kriegerische Auseinandersetzungen).

notwendige Ressourcen erhöht und somit auch die Evolution antreibt (Darwin, 1958 [1859]).

Im Laufe der Zeit haben so immer mehr öfters verschiedene Wissenschaftsdiziplinen versucht die Phänomene zwischen Mensch und Umwelt von ihrer Perspektive aus zu beschreiben und zu verstehen. Eine vollständig systematische Untersuchung des Gegenstandes gab es jedoch größtenteils nicht. Die im Verlauf des 20. Jahrhunderts sich langsam herausbildende Disziplin der Ökologie änderte diesen Sachverhalt (Dietz and Rosa, 1994).

Seitdem sind viele Versuche unternommen worden, um die Mechanismen zwischen menschlichen Aktivitäten und der Umwelt zu verstehen. Dafür sind unter anderem Erkenntnisse aus Biologie, Ökologie und Umweltwissenschaften kombiniert worden. Mittlerweile gibt es verschiedene Modelle, welche versuchen die Wirkungsweisen zwischen Mensch und Umwelt abzubilden. Solche Modelle können wichtige Instrumente sein, um anhand empirischer Schätzungen Handlungsempfehlungen abzuleiten (Schneider, 2022).

Vor circa 50 Jahren haben Ehrlich und Holdren (1971) die Beziehung zwischen menschlichen Aktivitäten und der Umwelt mithilfe des IPAT-Modells (*environmental Impacts of Population, Affluence and Technology*) formalisiert. Das IPAT-Modell basiert auf der offenkundigen Annahme, dass menschliche Auswirkungen auf die Umwelt anhand der drei Faktoren Bevölkerung, Wohlstand und Technologie zum Ausdruck gebracht werden können. Das IPAT-Modell stellt dabei eine mögliche Ausgangslage zur Strukturierung dieser Debatte dar (Dietz and Rosa, 1994). Kurze Zeit nach diesen mehr theoretischen Überlegungen von Ehrlich und Holdren (1971) formuliert Commoner et al. (1971) das IPAT-Modell als mathematische Identität aus. Das Diese IPAT-Identität drückt nun konkret aus, dass sich Auswirkungen auf die Umwelt aus dem multiplikativen Produkt von Bevölkerung, Wohlstand und Technologie zusammensetzen. Die IPAT-Identität kann somit für jeden Faktor gelöst werden und ist beispielsweise häufig zur Berechnung der Technologiekomponente verwendet worden (z.B. Raskin, 1996). In der Anwendung der IPAT-Identität ist Bevölkerung als Anzahl der Einwohner, Wohlstand als Konsum oder Produktion pro Kopf sowie Technologie als Umweltauswirkung pro Produktionseinheit konzeptualisiert worden.

Eine wesentliche Stärke dieses Modells ist die überschaubare und klare Spezifikation der menschlichen Faktoren, welche die Umwelt beeinflussen sowie die Implikation, dass diese treibenden Kräfte nicht unabhängig voneinander wirken (aufgrund der multiplikativen Verflechtung). Die Formalisierung eines funktionalen Zusammenhanges reicht jedoch nicht für eine Hypothesenprüfung oder einer kausalen Interpretation aus (York et al., 2003). Außerdem können zusätzliche funktionale Annahmen (z.B. Nicht-Linearitäten) notwendig oder weitere mögliche Treiber auf die Umwelt gegeben sein. Der etwas enge Rahmen des IPAT-Modells kann solche Fragestellungen nicht adressieren.

Daher haben Dietz und Rosa (1997) das IPAT-Modell zum STIRPAT-Modell (*STochastic Impacts on the environment by Regression on Population, Affluence and Technology*) transformiert. Das STIRPAT-Modell ermöglicht empirische Analysen und gibt somit eine flexible Grundlage für die Hypothesenprüfung (Liddle and Lung, 2010). Viele Studien verwenden das STIRPAT-Modell für unterschiedliche empirische Anwendungen wie beispielsweise globale oder regionale Analysen oder die Evaluierung verschiedenster menschlicher Umwelttreiber (z.B. Vélez-Henao et al., 2019 oder Schneider, 2022).

Die meisten STIRPAT-Studien befassen sich mit der Analyse von Auswirkungen auf die Umwelt im Hinblick auf CO_2-Emissionen. CO_2-Emissionen gelten als das wesentliche Treibhausgas und sind ein weltweit akzeptierter Maßstab zur Messung und Quantifizierung von Klimazielen. Zusätzlich gibt es eine umfängliche und solide Datenlage für CO_2-Emissionen weltweit. Darüber hinaus werden jedoch auch alternative Maßstäbe wie beispielsweise Varianten des ökologischen Fußabdruckes oder Luftverschmutzungsindikatoren wie NO_x- oder SO_2-Emissionen näher betrachtet (Vélez-Henao et al., 2019).

Das STIRPAT-Modell wird generell verwendet, um die sogenannten ökologischen Elastizitäten zu schätzen. Diese geben den prozentualen Anstieg des jeweiligen Umweltindikators bei einer einprozentigen Steigerung der jeweiligen erklärenden Variablen an (alle weiteren erklärenden Variablen werden dabei konstant gehalten; Knight et al., 2013). Viele Studien kommen dabei zu dem Ergebnis, dass ein Anstieg der Bevölkerung um ein Prozent die CO_2-Emissionen ebenfalls um ein Prozent ansteigen lässt. Die bisherigen Studien zeigen, dass Bevölkerung und Wohlstand (typischerweise operationalisiert als BIP pro Kopf) signifikante Treiber von CO_2-Emissionen darstellen. Die meisten Studien analysieren dagegen nicht explizit die Auswirkungen von Technologie auf die Umwelt. Hier gibt es keinen überzeugenden Konsens bezüglich valider Technologieindikatoren (Knight et al., 2013). Es wird daher häufig angenommen,

dass die technologische Komponente entweder im Fehlerterm oder in weiteren erklärenden Variablen der Schätzgleichung implizit berücksichtigt wird.
Die empirische Anwendung erlaubt es also neben den drei Hauptkomponenten (d.h. Bevölkerung, Wohlstand und Technologie) die Aufnahme weiterer potentieller Treiber in die Analyse mitaufzunehmen und bietet so ein großes empirisches Erweiterungspotential (Wu et al., 2021; Schneider, 2022). Der STIRPAT-Ansatz ermöglicht außerdem eine tiefere Untersuchung der drei Hauptkomponenten. Die Komponenten können beispielsweise in Variablen, welche umfassendere soziale Bedeutung haben, zerlegt werden (Rosa and Dietz, 1998).
Das STIPRAT-Modell stellt eine starke und robuste Grundlage für zahlreiche empirische Anwendungen dar. Es gibt jedoch trotz zahlreicher Studien oftmals inkonsistente Ergebnisse oder Wissenslücken (Vélez-Henao et al., 2019). Dieses Phänomen lässt sich größtenteils auf verschiedene Modellspezifikationen (z.B. der Umgang mit der Technologiekomponente), verschiedene Beobachtungsgrundlagen (z.B. regional oder global), verschiedene Schätztechniken oder verschiedene Zeiträume zurückführen.

Die hier vorliegende Dissertation (bestehend aus fünf zusammenhängenden aber in sich eigenständigen Beiträgen) trägt zur bestehenden STIRPAT-Literatur methodologisch sowie konzeptionell auf verschiedene Art und Weise bei. Die ersten beiden Beiträge (2. und 3. Kapitel) adressieren vor allem methodologische Herausforderungen, wohingegen die weiteren drei Beiträge (4., 5. und 6. Kapitel) vor allem konzeptionelle Fragestellungen behandeln und/oder neue Variationen in der Anwendung ausführen.
Der erste Beitrag (2. Kapitel) gibt eine komplementäre Sichtweise hinsichtlich der relativen Einschätzung menschlicher Auswirkungen auf die Umwelt.
Der zweite Beitrag (3. Kapitel) präsentiert eine alternative Möglichkeit der STIRPAT-Anwendung anhand umgekehrter Kausalitätsannahmen.
Der dritte Beitrag (4. Kapitel) beschäftigt sich mit den unterschiedlichen Rollen von Wohlstandsaspekten und deren Auswirkungen auf die Umwelt.
Der vierte Beitrag (5. Kapitel) differenziert bei der Analyse von menschlichen Treibern auf die Luftverschmutzung hinsichtlich der zugrundeliegenden Siedlungsstrukturen.
Der fünfte und letzte Beitrag (6. Kapitel) untersucht die Auswirkungen von technologischem Fortschritt auf die Umwelt.

Der **erste Beitrag** (The role of demographic and economic drivers on the environment in traditional and standardized STIRPAT analysis; siehe 2. Kapitel) zeigt, dass die STIRPAT-Analyse standardisierte Koeffizienten in die Untersuchung miteinbeziehen sollte, falls der Fokus auf einer Analyse der relativen Wirkungsweisen von Umwelttreibern liegt.
Die meisten Studien finden höhere ökologische Elastizitäten in Abhängigkeit von Bevölkerung als von BIP pro Kopf. Einige Autoren argumentieren daher, dass der trade-off zwischen Wirtschaftswachstum und Umweltzerstörung durch eine Priorisierung von Bevölkerungsabnahmestrategien gelöst werden kann. Die Frage nach der relativen Wirkungsweise zwischen Variablen kann jedoch mit den herkömmlichen ökologischen Elastizitäten nicht hinreichend beantwortet werden.
Daher ergänzt dieser Beitrag die traditionellen ökologischen Elastizitäten mit der Berechnung von β-Koeffizienten (die Untersuchungsgrundlage bilden 84 Länder für den Zeitraum zwischen 1980 bis 2014). Die Ergebnisse zeigen, dass das Wachstum von BIP pro Kopf zur Erklärung von negativen Umweltauswirkungen stärker ins Gewicht fällt als das für Bevölkerungswachstum der Fall ist. Zur Interpretation von standardisierten Koeffizienten muss jedoch folgendes beachtet werden. Erstens sind standardisierte Koeffizienten untersuchungsabhängig und können daher nicht über verschiedene Studien hinweg verglichen werden. Zweitens beeinflusst eine bestimmte Variable die Umwelt wahrscheinlich nicht für sich alleine. Der vorliegende Beitrag adressiert diese Problemstellungen und liefert eine umsichtige Interpretation von standardisierten β-Koeffizienten (gerade auch im Vergleich mit nicht-standardisierten Koeffizienten). Die Ergebnisse zeigen alles in allem, dass negative Umweltauswirkungen effektiver mit passenden Maßnahmen im Hinblick auf das Wirtschaftswachstum als auf das Bevölkerungswachstum vermindert werden können.

Der **zweite Beitrag** (Reversed STIRPAT modelling: the role of CO_2-emissions, population and technology for a growing affluence; siehe 3. Kapitel) beschäftigt sich mit der grundsätzlichen Kausalitätsannahme der STIRPAT-Modellierung. Es wird dabei generell eine einseitige kausale Auswirkung von menschlichen Faktoren auf die Umwelt angenommen. Ein Blick in die allgemeine (und nicht nur STIRPAT-) Literatur gibt jedoch keinen Anlass zu dieser einseitigen Annahme. Die Kausalitätsbeziehung zwischen Variablen hängt oftmals von betrachteten Zeiträumen, Entwicklungsstufen oder sektoralen Strukturen der betrachteten Länder ab (Costantini and Martini, 2010; Ozturk, 2010).

Dieser Beitrag stellt daher einen alternativen STIRPAT-Ansatz vor und zeigt ein stochastisches Modell, welches Wirtschaftswachstum mithilfe von Bevölkerung, CO_2-Emissionen (als Annäherungsvariable für Energieverbrauch oder Ökosystemdienstleistungen) und Technologie erklärt. Die Durchführung von Granger-Kausalitäts-Tests lassen ebenso auf eine solche umgekehrte Wirkungsweise zwischen den Variablen hin schließen. Darauf basierend wird der Zusammenhang zwischen Wirtschaftswachstum, demographischer Entwicklung und CO_2-Emissionen im Rahmen einer STIRPAT-Analyse für 30 Industrieländer zwischen 1982 bis 2014 analysiert.

Die Ergebnisse zeigen, dass sich Wachstumsraten von BIP pro Kopf in industrialisierten Ländern signifikant von CO_2-Emissionen, Bevölkerung und Energieintensität erklären lassen. Die Koeffizienten bleiben auch für verschiedenen Variationen (z.B. weitere Struktur- und Energievariablen, Schätzungen kurz- oder langfristiger Koeffizienten) konsistent. Die signifikanten und robusten Regressionsergebnisse für alle Modellvariationen demonstrieren die berechtigte Anwendung des STIRPAT-Modells in dieser Art und Weise. Die Ergebnisse zeigen außerdem die hohe Abhängigkeit von hochentwickelten Volkswirtschaften an Verfügbarkeit und Konsum von günstiger Energie.

Die meisten Ergebnisse basierend auf STIRPAT-Analysen untersuchen Auswirkungen auf die Umwelt durch Bevölkerung (typischerweise als Anzahl der Einwohner definiert) oder durch Wohlstand (typischerweise als BIP pro Kopf definiert). Diese Ergebnisse zeigen sich größtenteils unabhängig von Modellspezifikationen oder dem zugrundeliegenden Datenset.

Einige Studien untersuchen dabei die Auswirkungen von Bevölkerung anhand von Altersgruppen oder Bildungshintergrund auf die Umwelt detaillierter (z.B. Cole and Neumayer, 2004; Liddle and Lung, 2010).

Im Gegensatz zu dieser differenzierteren Untersuchung von Umweltauswirkungen der Bevölkerung (und Technologie), wird Wohlstand zumeist ausschließlich anhand BIP pro Kopf analysiert. Das BIP pro Kopf stellt einen sehr zweckmäßigen Maßstab für Wohlstand dar. Dieser alleinige Maßstab vernachlässigt jedoch die vielen (und teilweise gegensätzlich wirkenden) Facetten von Wohlstand (gerade im Hinblick auf Auswirkungen auf die Umwelt). Interessanterweise wurde bereits seit Beginn der IPAT-Theorie darauf hingewiesen, dass Wohlstand von der Produktions- sowie von der Konsumseite betrachtet werden sollte (Dietz and Rosa, 1994).

Daher analysiert der **dritte Beitrag** (The varying roles of the dimensions of affluence in air pollution: a regional STIRPAT analysis for Germany; siehe 4. Kapitel) die Rolle von Wohlstand hinsichtlich deren Auswirkungen auf NO_x-Emissionen in einer differenzierteren Art und Weise. Die Auswirkungen von Wohlstand werden mithilfe einer Betrachtung von drei Aspekten, nämlich Einkommen pro Steuerzahler, Motorisierungsrate und Anteil an Einfamilienhäusern, untersucht. Die Ergebnisse für 367 deutsche Landkreise (NUTS 3-Ebene) zwischen 1990 und 2020 zeigen, dass die Motorisierungs- sowie Einfamilienhäuserrate als wesentliche Treiber von NO_x-Emissionen gelten können. Dagegen wirkt sich das Einkommen pro Steuerzahler mildernd auf NO_x-Emissionen aus (falls für Motorisierungs- sowie Einfamilienhäuser kontrolliert wird). Während Motorisierung sowie Einfamilienhäuser eher als material- und energieintensive Aspekte von Wohlstand gesehen werden können, deckt das Einkommen pro Steuerzahler tendenziell Alltagsausgaben (z.B. Lebensmittel) oder Ausgaben für Konsum, welche typischerweise für Wohlhabendere gelten (z.B. kulturelle Aktivitäten oder Dienstleistungen) ab.

Der **vierte Beitrag** (Drivers of local air pollution: a regional STIRPAT analysis for Germany; siehe 5. Kapitel) knüpft am vorherigen Beitrag an und verwendet das STIRPAT-Modell auf Landkreisebene (NUTS 3 Ebene) zur Analyse von Bevölkerung, Wirtschaftswachstum und Technologie auf die lokale Luftverschmutzung. Es werden dafür Daten von 367 deutschen Landkreisen zwischen 1990 und 2020 verwendet. [2] Außerdem wird zwischen städtischen und ländlichen Regionen unterschieden. Zusätzlich werden anhand von Marginaleffekten mögliche nicht-lineare Wirkungsweisen der ökologischen Elastizitäten betrachtet. Die Ergebnisse zeigen, dass NO_x-Emissionen signifikant von der Motorisierungsrate, regionaler Bevölkerung und Anteile an industrieller Produktion getrieben werden. Dieses Ergebnis gilt für ländliche und städtische Regionen zugleich. Das ist jedoch nicht der Fall hinsichtlich der Umweltauswirkungen von BIP pro Kopf und Bevölkerungsdichte. Es zeigt sich beispielsweise nur im Fall von ländlichen Gebieten ein abnehmender Effekt von

[2] Der vierte Beitrag basiert auf derselben Datengrundlage wie der dritte Beitrag.

Bevölkerungsdichte auf die Umwelt. Die Marginaleffekte deuten zudem an, dass Auswirkungen der Bevölkerung auf die lokale Verschmutzung stark an dem jeweiligen Bevölkerungsniveau abhängen. Je höher die Perzentile der Bevölkerung, desto stärker wird der marginale Effekt auf die Luftverschmutzung.

Das STIRPAT-Modell wurde bisher selten angewendet um den (umweltbezogenen) Rebound-Effekt zu analysieren (Vélez-Henao et al., 2019). Der Rebound-Effekt beschreibt typischerweise die Veränderung von Konsum und Produktion bei einer Veränderung einer ökonomischen Variablen, welche wiederum anhand einer Veränderung der Energieeffizienz ausgelöst worden ist (Font Vivanco and Voet, 2014). Der umweltbezogene Rebound-Effekt gibt einen etwas umfassenderen Ansatz und drückt den Rebound-Effekt anhand verschiedener umweltbezogener Dimensionen (z.B. Emissionen) aus (Vélez-Henao et al., 2019).
Produktivitätssteigerungen, welche durch technologischen Fortschritt erreicht werden, gelten üblicherweise als vielversprechende Maßnahme, um die negativen Auswirkungen des Klimawandels abzumildern (IPCC, 2018).
Vor diesem Hintergrund beschäftigt sich der **fünfte Beitrag** (The effects of technological progress on CO_2 emissions: a macroeconomic analysis; siehe 6. Kapitel) mit Auswirkungen von (technologischen) Produktivitätssteigerungen auf die Umwelt and versucht zu klären, ob sich hierbei ein umweltbezogener Rebound-Effekt feststellen lässt. Es werden dabei konkret Auswirkungen der Steigerung von Karbonintensität (definiert als „Ressourcenproduktivität"; d.h. CO_2-Emissionen pro BIP) und genereller Produktivität (definiert als „Faktorproduktivität"; indirekt abgeleitet anhand einer Dekomposition der Produktionsfunktion) auf CO_2-Emissionen untersucht. Für diese Analyse liegen Daten von 118 Ländern zwischen 1962 bis 2014 zugrunde. Die Ergebnisse lassen darauf schließen, dass ein umweltbezogener Rebound-Effekt im Hinblick auf eine steigende Karbonintensität vorhanden ist. D.h. Steigerungen der Karbonintensität führen zu einer vergleichsweisen geringen Abnahme von CO_2-Emissionen. Steigerungen der generellen Produktivität führen sogar zu mehr CO_2-Emissionen (Backfire-Effekt, d.h. Rebound-Effekt > 100 Prozent). Zusammenfassend lässt sich schließen, dass technologischer Fortschritt im Sinne von Produktivitätssteigerungen die Spannungen zwischen Umwelt und Wirtschaftswachstum nicht lösen kann.

Diese Dissertation analysiert also unterschiedliche Forschungsfragen hinsichtlich der Mensch-Umwelt Beziehung mithilfe des STIRPAT-Modells. Alle Beiträge stellen dabei Handlungsempfehlungen, welche sich aus der Interaktion der Effekte von Bevölkerung, Wohlstand und Technologie auf die Umwelt ableiten, zur Verfügung.

Dabei bleiben weiterhin theoretische und empirische Fragestellungen, welche für eine vollumfängliche Durchdringung der Mensch-Umwelt Beziehung beantwortet werden müssen, bestehen. Vor diesem Hintergrund gibt es noch viele Möglichkeiten zukünftiger Erweiterungen und Anwendungen des STIRPAT-Modells aufgrund dessen empirischer Flexibilität (Kilbourne and Thyroff, 2020). STIRPAT-Analysen können so auch zukünftig wichtige Hilfestellungen geben, um mit Problematiken, welche aus der Mensch-Umwelt Beziehung resultieren, umzugehen und so weiterhin für ein umfassendes Verständnis von menschlichen Treibern auf die Umwelt sorgen.

The awareness that human behavior is affecting the environment is not a unique attribute of these days. Probably, the human-environment interrelationship is present as never before due to the tremendous adverse effects of climate change in the near future. Humans have become the single most influential species on earth so scientists are even discussing to assign the term "anthropocene" (stating that human activities are the dominant influence on climate and environment causing land surface transformation and changes in the composition of the atmosphere) to the current geological epoch (Crutzen and Stoermer, 2000; Lewis and Maslin, 2015). Basically, the general human-environment interrelationship has been recognized and described for a long time in history.

For example, Seneca the Younger (4 B.C. – 65 A.D.) already notes that there exists a relationship between human activities and environmental phenomena. Specifically, he argues that household cooking fires, traffic or burning of dead bodies is correlated with the pollution in Rome (Seneca, 1971[62 A.D.]).

Thomas Malthus (1766 - 1834) is another popular example being part of this tradition. He asks how population growth affects the availability of resources needed for human welfare (Malthus, 1960 [1798]). Though Malthus' concerns, which basically address the incapacity of fixed land feeding an exponentially growing population were considered to be wrong due to even higher growth rates of total production (Galor and Weil, 2000), the debate regarding the human-environment nexus does not disappear.[3] Rather, it shifts to topics like the depletion of natural resources (e.g. fossil fuels) or the degradation of renewable resources (Panayotou, 2000).

With the writings of classical economists like Malthus, "the population-resource link receives systematic attention" for the first time (Dietz and Rosa, 1994, p. 278). In addition, also scientists from other disciplines were inspired by Malthus. For example, Charles Darwin (1809 - 1882) is driven by the same basic thought when he argues that population pressure on critical environmental resources drives evolutionary changes (Darwin, 1958 [1859]).

So, various sciences (like social or biological ones) try to understand a similar phenomenon from their point of view throughout history. But, a systematic investigation of interrelations between human behavior and the environment is ignored for a long time.

[3] Nowadays, Malthus' thesis is again becoming more relevant. While population is still increasing, the usually related increase in (agricultural) productivity is getting more and more uncertain due to climate change impacts or other global threats.

The raising discipline of ecology in the 20th century investigating the relations between organisms and environment slowly changes this status (Dietz and Rosa, 1994).

Since then, many efforts are made in order to understand the mechanisms of human activities on the environment by combining the insights of biologists, ecologists and environmental scientists. Theoretical ideas are gradually transformed into models in order to determine and analyze the response of environmental change to a set of potential anthropogenic factors. One important objective of these models is to deliver policy recommendations based on robust (empirical) estimations (Schneider, 2022).

About fifty years ago, Ehrlich and Holdren (1971) propose the idea of IPAT (environmental Impacts of Population, Affluence and Technology) in order to formalize the relationship between human activities and the environment. The IPAT model is based on the simple but plausible assumption that population, affluence and technology must be part of any serious effort to understand human impacts on the environment. Thus, the IPAT model provides a useful starting point for structuring this debate (Dietz and Rosa 1994). Shortly after, Commoner at al. (1971) firstly formulated the IPAT model as algebraic equation. This mathematical accounting identity specifies that environmental impacts are the multiplicative product of population, affluence and technology that allows to solve for any variable of interest. For example, the IPAT identity has often been used to calculate the term of technology (given the remaining components; e.g. Raskin, 1996). Specifically, population is conceptualized as population size, affluence as per capita consumption or production and technology as environmental impact per unit of production.

The main strengths of the IPAT model are the parsimonious and clear specification of anthropogenic driving forces affecting the environment as well as the implication that these driving forces do not influence impacts independently due to their multiplicative interconnectedness. However, the pure formalization of a functional relationship between variables does not allow any hypothesis testing or causal interpretations (York et al., 2003). Further, there may be different underlying functional assumptions (e.g., non-linearities) or other potential driving forces affecting the environment. Obviously, the relative tight framework of the IPAT model cannot address these issues.

Consequently, Dietz and Rosa (1997) develop a stochastic version of the IPAT model by transforming it into the STIRPAT (STochastic Impacts on the environment by Regression on Population, Affluence and Technology) model. The STIRPAT model allows empirical analysis and thus builds a powerful and flexible framework for hypothesis testing (Liddle and Lung, 2010). Indeed, many studies use the STIRPAT framework for broad empirical applications, such as global and regional analyses or the assessment of various anthropogenic driving forces (e.g., see Vélez-Henao et al., 2019 or Schneider, 2022 for literature reviews regarding STIRPAT studies).

The major part of studies using the STIRPAT approach estimates environmental impacts with respect to the principal of greenhouse gas emissions, i.e. CO_2 emissions. CO_2 emissions are a globally accepted measure of environmental outcome in order to quantify climate policy goals. Moreover, there exist accurate and sound data for CO_2 emissions for almost all parts of the world. However, also alternative measures for the environmental outcome like (variants of) the ecological footprint or different air pollutants (e.g., NO_x or SO_2 emissions) are analyzed within STIRPAT applications (Vélez-Henao et al., 2019).

Traditionally, the STIRPAT approach is used to estimate the so-called ecological elasticities. The ecological elasticities indicate the percentage change in the environmental variable associated with a one percentage point increase in the respective explaining variable, holding the effects of the other explaining variables constant (Knight et al., 2013; for example, many studies found that a 1 percent increase in population increases CO_2 emissions by about 1 percent).

Generally, studies find that both population and affluence (typically operationalized as number of residentials and GDP per capita, respectively) are significant drivers of emissions. In contrast, most applications do not explicitly estimate the impacts of technology mainly due to the missing consensus on valid indicators for technology (Knight et al., 2013). So, technology is usually seen as included in the error term of the regression equation or (partly) captured by additional explanatory variables.

Therefore, the empirical application of the STIRPAT model allows for the inclusion of additional potential driving factors into the analysis beside the three core components (population, affluence and technology) and thus offers a high potential for extensions compared to the benchmark framework (Wu et al., 2021; Schneider, 2022). Additionally, the approach encourages the investigation of environmental impacts regarding the three core components in more detail. For example, the components can be disaggregated into forms that have more social meaning (Rosa and Dietz, 1998).

All in all, the STIRPAT model represents a strong tool for various applications. However, "[…] despite the multiple applications and the high potential of the STIRPAT model, inconclusive results and/or knowledge gaps remain […]" (Vélez-Henao et al., 2019, p. 1). The inconclusive results are mainly due to different model specifications (e.g. the treatment of technology), different underlying samples (regional or global data), different estimation techniques or different periods of time.

This dissertation (consisting of five related but individual contributions) contributes to the existing STIRPAT literature methodologically as well as conceptually in several ways. The first two contributions (sections 2. and 3.) principally address methodological challenges whereas the last three contributions (sections 4., 5. and 6.) mainly address conceptual issues of STIRPAT modelling and/or provide novel variations of application.
The first contribution (section 2.) gives a complementary perspective when dealing with the relative importance between environmental impacts.
The second contribution (section 3.) presents an alternative way of using the STIRPAT model with the focus on reversed causality.
The third contribution (section 4.) deals with the varying roles of the dimensions of affluence on the environment.
The fourth contribution (section 5.) differentiates between settlement structures when analyzing human impacts on air pollution.
The last and fifth contribution (section 6.) covers the effects of technological progress on the environment.

To begin with, the **first contribution** (The role of demographic and economic drivers on the environment in traditional and standardized STIRPAT analysis; see section 2.) shows that the STIRPAT analysis should at least be complemented with standardized coefficients if the research focus lies in the assessment of the relative importance between the driving forces.
Most studies find higher ecological elasticities related to population compared to GDP per capita growth. Hence, some authors suggest to mitigate the trade-off between economic growth and environmental pressure by giving priority to population policies and reducing population growth in first place. However, the question of the predictor variables' relative importance cannot be finally answered by this approach.

In response, the contribution complements the traditional ecological elasticities by the calculation of standardized β-coefficients (for a sample of 84 countries and the period between 1980 and 2014). Results indicate that GDP per capita rather than population growth matters more for explaining environmental impacts. Admittedly, interpretation of standardized coefficients is not without limitations. First, they are sample-specific and cannot be compared across different studies. Second, a predictor variable might not affect the environment only on its own, but joint impacts could be present. The contribution addresses these problems and provides a careful interpretation of and comparison between non-standardized and standardized β-coefficients. Overall, there is good reason to assume that environmental impacts can be reduced more readily by a policy giving priority to economic rather than population growth.

The **second contribution** (Reversed STIRPAT modelling: the role of CO_2 emissions, population and technology for a growing affluence; see section 3.) challenges the prevailing assumption of STIRPAT modelling, which in most cases proposes a one-way causality running from the anthropogenic factors to the environment. However, the rich portfolio of theoretical and empirical studies reveals no universal direction of causality between economic growth and the environment, findings rather depend on the considered time periods and countries' stage of development and sectoral structure (Costantini and Martini, 2010; Ozturk, 2010).

Consequently, the contribution proposes to add a new perspective to the IPAT/STIRPAT approach by setting up a stochastic model that explains impacts on economic growth (affluence) by regression on population, CO_2 emissions (as a proxy for energy use or ecosystem services) and technology. Indeed, the applied Granger-causality tests indicate a reversed causal relationship. Therefore, the relationship between economic growth, demographic development and CO_2 emissions for 30 industrialized countries using time-series data from 1982-2014 in the IPAT/STIRPAT setting is analyzed.

The results confirm that GDP per capita growth rates of highly industrialized economies are significantly driven by the development of CO_2 emissions, population and energy intensity. Coefficients remain robust with or without integrating structural and energy variables and for the short- and long-run perspective. Thus, the significant and robust regression results in all model variants demonstrate the reasonableness of applying this setup in addition and complementary to the traditional STIRPAT model. In addition, the findings confirm the ongoing high dependence of advanced economies on the availableness and consumption of cheap energy.

The empirical findings of most STIRPAT studies show positive impacts of both population (commonly measured as number of residentials) and affluence (commonly measured as GDP per capita) on the environment independent of the model setup or underlying dataset.

Furthermore, some studies are examining the effects of population on the environment in more detail. Thereby, authors differentiate population by region, economic status, settlement structure, age group or educational achievement (e.g., Cole and Neumayer, 2004; Liddle and Lung, 2010).

In contrast to the more differentiated investigations of the environmental effects of population (and technology), affluence is almost only analyzed by GDP per capita. Obviously, GDP per capita is a very convenient measure of affluence. But, this measure alone potentially neglects the possibility that increasing affluence affects the environment in varying - even opposing - ways.[4] Interestingly, already the initial concept of the IPAT model suggest to think about affluence as some measure of (national) production *and* consumption patterns (Dietz and Rosa, 1994).

Hence, the **third contribution** (The varying roles of the dimensions of affluence in air pollution: a regional STIRPAT analysis for Germany; see section 4.) analyzes the role of affluence for the production of local NO_x emissions in a more differentiated way. The study addresses this gap by decomposing affluence into three dimensions—income per taxpayer, private car ownership, and the share of single-family houses—and analyzing their roles in the production of local NO_x emissions. Results for 367 German districts and autonomous cities between 1990 and 2020 indicate that private car ownership per capita and single-family houses per capita can indeed be considered drivers of local pollutants. In contrast, income per taxpayer has a negative impact on NO_x emissions. While private car ownership and single-family houses could reflect the material- and energy-intensive part of affluence, taxable income per taxpayer might cover (if we control for car ownership and the housing situation) expenditures for material (e.g., food, consumables)

[4] For the sake of completeness, some studies investigate potential non-linear effects of population or affluence on emissions by adding squared terms of GDP per capita or population size into the STIRPAT equation (e.g., Cole and Neumayer, 2004 or Arshed et al., 2021).

as well as types of consumption more common among the financially affluent (e.g., services, cultural activities).

The **fourth contribution** (Drivers of local air pollution: a regional STIRPAT analysis for Germany; see section 5.) offers an assessment of the role played by population, economic growth and technology change in the evolution of local air pollution, using the STIRPAT approach at the district level (NUTS 3). The analysis covers the development of 367 German districts and autonomous cities between 1990 and 2020.[5] This procedure does not only allow for an analysis of the cities but also the rural districts. Further, the contribution analyzes the estimated environmental elasticities in detail by controlling for non-linear impacts. In this context, predicted margins of environmental elasticities are calculated.

Results indicate that the development of local pollutants (NO_x emissions) is clearly related to car ownership, regional population and industrial manufacturing. While the findings largely hold for urban and rural districts, they also indicate that environmental impacts depend on the types of regions for GDP per capita and urban density. For example, a negative environmental impact of urban density can be shown for rural but not for urban districts. Finally, the predicted margins analysis indicates that the effect of population on the environment strongly depends on its respective level. So, high percentiles of population reveal a (much) higher marginal impact compared to low percentiles.

Finally, the STIRPAT model "[…] offers a valuable yet underused platform to address the (environmental) rebound effect […]" (Vélez-Henao et al., 2019, p. 1378). Traditionally, the rebound effect describes the change in overall consumption and production as a consequence of a change in economic variables induced by a change in the energy efficiency (Font Vivanco and Voet, 2014). The environmental rebound effect provides a more holistic perspective and thus expresses the rebound effect through different environmental dimensions like emissions (Vélez-Henao et al., 2019).

Typically, improvements in productivity induced by technological progress are seen as promising measure in order to mitigate the adverse effects of climate change (IPCC, 2018). Against this background, the **fifth contribution** (The effects of technological progress on CO_2 emissions: a macroeconomic analysis; see section 6.) analyses the effects of

[5] This contribution exploits the same dataset as the third contribution.

(technological) productivity increases on the environment and thus tries to clarify whether an environmental rebound effect exists. Specifically, the effect of improvements in carbon intensity (defined as “resource productivity” and estimated directly by CO_2 emissions per GDP) and in overall productivity (defined as “factor productivity” and estimated indirectly by decomposition of a production function) on CO_2 emissions is investigated. Therefore, data from 118 countries between 1962 and 2014 are analyzed. Findings indicate that there exists an environmental rebound effect regarding an increasing carbon intensity. So, improvements in carbon intensity lead to comparable underproportional decreases of CO_2 emissions. Further, improvements of overall productivity could even lead to higher CO_2 emissions (backfire-effect, i.e. rebound effect > 100 percent). In summary, technological progress in terms of productivity improvements cannot solve the environment-growth trade-off per se.

All in all, the five contributions of this dissertation address several research questions regarding the human-environment nexus in the context of STIRPAT modelling. Moreover, all contributions provide environmental policy implications by taking the interaction between the effects of population, affluence and technology into account.

Obviously, theoretical and empirical questions still remain to be solved in order to fully understand the complex human-environment relationship. There is no doubt that there are “many avenues for future expansion of the STIRPAT model” due to its wide flexibility in application (Kilbourne and Thyroff, 2020, p. 360). So, future STIRPAT studies can play a crucial role in gaining a comprehensive understanding of anthropogenic impacts on the environment and thus can help to deal with prospective challenges related to the multifaceted human-environment nexus.

2. The role of demographic and economic drivers on the environment in traditional and standardized STIRPAT analysis[6]

2.1. Introduction

There is plenty of literature investigating the anthropogenic impacts on the environment. On a global level, many studies deal with climate change triggered by greenhouse gases (e.g., Auffhammer, 2018; Manabe, 2019). One common approach is to make use of Integrated Assessment Models (IAM) to identify optimal climate policy strategies, another to apply probabilistic models to capture uncertainty. Though empirical findings differ substantially, there is broad consensus that current mitigation efforts are not sufficient to limit global surface warming to 1.5°C (Masson-Delmotte et al., 2018). Policy implications mostly refer to technological solutions or some sort of economic degrowth. This is in contrast to population growth, which is indeed part of the models but either not made a major subject or considered to play a minor role in the optimal policy mix (e.g., Raftery et al., 2017).

This is different for the so-called STIRPAT (STochastic Impacts by Regression on Population, Affluence and Technology) approach that is in the focus of the presented paper. STIRPAT models explicitly investigate the impacts of population, GDP per capita and additional variables (often used as proxy for technology) on the environment (e.g., CO_2 emissions, ecological footprint, etc.). In doing so, most STIRPAT analyses focus on the calculation of "ecological elasticities" that calculate the percentage change of the environmental outcome in response to a 1 percent increase of a driving factor (York et al., 2003).

Whether these elasticities are robust for different countries or time periods is a matter of an ongoing discussion (see section 2.2. for details). Most empirical studies, however, find clearly higher ecological elasticities with regard to population compared to economic growth (measured as GDP/capita). This is why some authors suggest to mitigate the trade-off between economic growth and environmental pressure by giving priority to population policies and reducing population growth in first place (e.g., Casey and Galor, 2017). This shows that the interest of STIRPAT analysis lies not only in the calculation of generally valid elasticities, but also in the *relative importance* of the predictor variables.

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[6] The contribution is based on joint work together with Axel Schaffer (Bundeswehr University Munich) and Andreas Brieden (Bundeswehr University Munich) and is published in *Ecological Economics* (Lohwasser, J., Schaffer, A., & Brieden, A. (2020). The role of demographic and economic drivers on the environment in traditional and standardized STIRPAT analysis. Ecological Economics, 178).

More precisely, it might be interesting to know, how to rank the effect of one predictor on the response variable in comparison to the effects originating from the remaining variables.
Against this background, we suggest (to our knowledge for the first time in the STIRPAT setting) to complement the identification of ecological elasticities with the calculation of standardized coefficients. First results confirm the findings on unstandardized ecological elasticities from the literature (with elasticities for population exceeding these of economic growth). At the same time standardized coefficients of growing GDP per capita are clearly higher compared to growing population. This holds for different dependent variables (CO_2 emissions and ecological footprints), country samples and periods of observation.
Even though standardized coefficients cannot be compared directly with unstandardized elasticities (see section 2.4.1. for details), resulting policy implications clearly deviate from most STIRPAT analyses. In particular policies aiming at reducing economic growth rates seem to be more promising compared to strategies diminishing population growth, if environmental pressure should be reduced.
The remainder of the paper is organized as follows. Section 2.2. introduces the STIRPAT approach and provides an overview on relevant findings of empirical studies so far. This is followed by methodological considerations and the applicability of standardization within the STIRPAT context in section 2.3. and the model description as well as the discussion of results in section 2.4.. Finally, the paper closes with concluding remarks and policy implications.

2.2. The tradition of STIRPAT

2.2.1. General methodology

The STIRPAT approach is the stochastically extension of the so-called IPAT formula that considers environmental impacts being the product of population, affluence and technology (Ehrlich and Holdren, 1971). The following STIRPAT equation can be used as a non-linear regression equation in order to test hypotheses (York et al., 2002; Dietz et al., 2007).

$$I_{i,t} = c_t \cdot P_{i,t}^{\alpha} \cdot A_{i,t}^{\beta} \cdot T_{i,t}^{\gamma} \cdot e_{i,t}. \quad (1)$$

$I_{i,t}$ is the environmental impact of country i at time t. $P_{i,t}$ is population, $A_{i,t}$ is affluence (commonly defined as GDP per capita), $T_{i,t}$ is technology and $e_{i,t}$ is the residual error term. The constant c_t scales the model and accounts for the different dimensions and units of variables. α, β and γ are the environmental outcome elasticities with respect to population, affluence or technology, respectively. It is assumed that all observational units show the same elasticities. This seems a hard assumption since there are large differences across countries or regions. For exact policy implications based on a STIRPAT analysis one should account for regional differences (Singh and Mukherjee, 2019). However, the focus of this paper is to demonstrate the effects of standardization within a STIRPAT analysis and not to clarify differences across broader regions. Next, after taking natural logs equation (1) yields:

$$\ln I_{i,t} = \ln c_t + \alpha \cdot \ln P_{i,t} + \beta \cdot \ln A_{i,t} + \gamma \cdot \ln T_{i,t} + \ln e_{i,t}. \tag{2}$$

The logarithmic form of the STIRPAT equation gives not only a very tractable regression equation, but also dampens the skewed distribution of the variables (Jorgenson and Clark, 2010).

STIRPAT analysis is generally based on the assumption that the panel data are stationary. However, empirical studies reveal that panel data are often not stationary in their levels but their differences (e.g., Bilgili, 2017). Thus, in the attempt to address non-stationarity of variables and to avoid spurious results, most studies follow a first-differences structure of equation (2) (Jorgenson and Clark, 2010; Liddle, 2014; Casey and Galor, 2017). In addition, first-differences estimation considers time constant (and unobserved) unit-effects and mitigates cross-sectional dependences (Liddle, 2015; Wooldridge, 2015). The following equation is formed by taking first-differences of equation (2) and represents the most established way for estimating the STIRPAT equation.

$$\Delta \ln I_{i,t} = \Delta \ln c_t + \alpha \cdot \Delta \ln P_{i,t} + \beta \cdot \Delta \ln A_{i,t} + \gamma \cdot \Delta \ln T_{i,t} + \Delta \ln e_{i,t}. \tag{3}$$

$\Delta \ln I_{i,t}$ is the change of log environmental outcome in country i from time t−1 to t. $\Delta \ln P_{i,t}$ is the change of log population, $\Delta \ln A_{i,t}$ is the change of log GDP per capita, $\Delta \ln T_{i,t}$ is the change of log technology. $\Delta \ln c_t$ is the change of the log constant and $\Delta \ln e_{i,t}$ is the change of the log error term. In contrast to the other variables, technology is treated differently across studies. While some studies use a specific variable or a combination of variables representing technology (e.g., energy intensity or research and development), others consider technology to be included in the error term.[7]

2.2.2. Findings of empirical studies

The STIRPAT framework is frequently applied to estimate human impacts on environmental outcome. Although all studies are using the same theoretical model (i.e. STIRPAT) there are many possibilities regarding its application and the findings differ substantially across studies. Vélez-Henao et al. (2019) suggest that the different findings across studies are due to geographical imbalances, variations regarding the choice of data, different additional explanatory variables or different regression models. Another explanation is the above mentioned different treatment of technology.[8] However, despite the differences in application, most empirical findings indicate higher ecological elasticities of growing population compared to GDP per capita growth (see table (1) for an overview regarding the findings of recent literature using CO_2 emissions for the environmental outcome).

Table 1: Cross-national, inter-temporal STIRPAT studies estimating the drivers of CO_2 emissions (all studies address the non-stationarity of variables). Values indicate elasticities of CO_2 emissions with respect to changes in GDP per capita and population. The table is based on Liddle (2015).

Study	GDP per Capita	Population	Data Structure
Casey and Galor (2017)	0.22	1.44	156 countries, 1950-2010
Xu et al. (2016)	1.01	0.93	29 provinces, 1995-2011
Knight et al. (2013)	0.59	2.25	29 countries, 1971-2007
Zhu et al. (2012)	1.12	0.79	20 countries, 1992-2008
Liddle (2011)	1.06	2.35	22 countries, 1960-2007
Poumanyvong & Kaneko (2010)	1.08	1.12	99 countries, 1975-2005
Jorgenson & Clark (2010)	0.65	1.43	86 countries, 1960-2005
Jorgenson et al. (2010)	0.33	0.70	57 countries, 1990-2005
Cole & Neumayer (2004)	0.89	0.98	86 countries, 1975-1998

[7] Generally, this is a critical assumption since technology has different levels across countries and time and therefore the error term is probably no longer normally distributed.
[8] See Wei (2011) for more details regarding the role of technology on STIRPAT models.

Only few studies, generally focusing on specific country groups or regional entities, indicate that elasticities of CO_2 emissions with respect to GDP per capita growth are higher compared to growing population (e.g., Zhu et al. (2012) for a sample of 20 emerging countries or Xu et al. (2016) for 29 provinces of China). Given the broad consensus on the ecological elasticities of the key variables, the focus of STIRPAT studies has shifted from an in-depth analysis of the assessment of the main factors (i.e. population and GDP per capita) to the inclusion of alternative control variables or the application of the STIRPAT equation on specific country groups.

Based on the higher ecological elasticity with respect to population compared to GDP per capita, many studies see a higher importance of the first predictor with respect to policy design. Casey and Galor (2017), for example, argue that population plays an utmost important role regarding the reduction of CO_2 emissions. Due to a relatively higher population elasticity, Casey and Galor (2017) suggest that a 1 percent slower population growth would allow for increases of per capita income up to 7 percent with constant or even slightly decreasing CO_2 emissions.

Interestingly enough, the main results of the STIRPAT literature are in contrast to findings of other studies not using the STIRPAT approach. Usually, these attribute minor impacts of population growth on CO_2 emissions. For example, Raftery et al. (2017) develop a statistically based probabilistic forecast of CO_2 emissions. Findings indicate that population growth is not a major contributing factor but that sustainable development requires adjustments of the economic sphere (Rauf et al., 2018; Ahmed et al., 2019).[9]

2.3. Standardization in the context of STIRPAT

As mentioned already, the key interest of most STIRPAT models is the calculation of "ecological elasticities", which, in their unstandardized form, reflect the slope of the relationship between the response and the considered predictor variable. They are predictive in a sense that they approximately estimate the response variable's mean expected percentage change associated with a 1 percent change of the considered predictor variable. For example, the elasticity of CO_2 emissions with respect to population

[9] Studies applying the STIRPAT approach but using indirect measures of CO_2 emissions like energy demand come to similar conclusions (e.g. Shahbaz et al., 2017).

(GDP per capita) is the percentage change of CO_2 emissions when population (GDP per capita) increases by 1 percent.

For large enough samples and long enough periods of observation, the related coefficients remain rather stable for various subsamples and can easily be compared across different studies. Furthermore, the application of the logarithmic form of the STIRPAT equation reduces the skewness of the data by pulling outliers closer to the bulk of the sample and partly accounts for the predictor variables' different variances and raw units. However, in case the predictor variables are developing with quite different dynamics and the main interest lies in the relative importance of different predictor variables within one sample, it might be helpful to fully eliminate the problem of different units and variances and to complement the calculation of the traditional ecological elasticities with the standardization of the parameters (e.g., Bring, 1994; Grace and Bollen, 2005; German-Soto and Gutiérrez Flores, 2015, Gelman and Hill, 2007; Schielzeth, 2010).

More concrete, standardization weights the past variation of variables with the help of their respective standard deviations, for example according to equation (4) (e.g., Bring, 1994; Wooldridge, 2015):

$$\beta_x^S = \beta_x \cdot \frac{\sigma_x}{\sigma_z}, \tag{4}$$

where β_x^S is the standardized coefficient of the independent variable x, β_x is the estimated coefficient of x, σ_z is the standard deviation of x and σ_z is the standard deviation of the dependent variable z. This means they reflect the change of the response variable measured in units of standard deviations for a one standard deviation change in the chosen predictor variable, holding the remaining independent variables constant.

To illustrate the idea behind this standardization and to provide more insight for the following interpretation consider the standard linear equation from bivariate linear regression:

$$z = \alpha + \beta_x \cdot x + \beta_y \cdot y. \tag{5}$$

An implicit goal of regression is to explain how the dependent variable z varies depending on variation of the independent variable x and y. Under the (idealistic) standard assumption that x and y are independent the equation

$$var(z) = var(\beta_x \cdot x) + var(\beta_y \cdot y), \tag{6}$$

equivalent to

$$1 = 100\% = \frac{\mathrm{var}(\beta_x \cdot x)}{\mathrm{var}(z)} + \frac{\mathrm{var}(\beta_y \cdot y)}{\mathrm{var}(z)} = \frac{\beta_x^2 \cdot \mathrm{var}(x)}{\mathrm{var}(z)} + \frac{\beta_y^2 \cdot \mathrm{var}(y)}{\mathrm{var}(z)} = (\beta_x^S)^2 + (\beta_y^S)^2, \qquad (7)$$

holds for the overall variance $\mathrm{var}(z) = \sigma_z^2$ of z.

Straightforward, the squared standardized coefficient of an independent variable measures the relative contribution of this variable to the overall variance of the dependent variable and hence reflects the relative influence of the independent variable.[10]

Additional information on “context-free” interpretation of standardization can be found, e.g., in Bring, 1994, Grace and Bollen, 2005 or Wooldridge, 2015, an example for domain-specific application of standardization in German-Soto and Gutiérrez Flores, 2015.

While standardization is rather common for multiple regression models, it has (to our knowledge) not been applied within the STIRPAT tradition yet. However, the basic idea is that standardization improves the comparability of the predictors’ effect on the response variable, since it accounts for the fact that a one unit change of one predictor variable (e.g., economic growth) might be easy to accomplish, whereas a one unit change in another factor (e.g., population) may be profound. Indeed, the two main predictor variables of our (and most other STIRPAT) model exhibit quite different standard deviations (see appendix, table (A.2.)). Historically, a 1 percent change of GDP per capita growth represents a much smaller change within its range compared to a 1 percent change of population growth. Thinking in “standard deviation units” therefore means to account for the variable’s changeability. This is a different dimension of analysis compared to elasticities that could help to design more feasible policy measures.

The better comparability of the coefficients, however, does not automatically allow for an unconditional assessment of the independent variables’ relative contribution to the prediction of the response variable. Limitations addressed in the literature are basically twofold: To begin with, β-coefficients are sample specific and cannot be compared across different studies (King, 1986). Furthermore, a predictor variable might not affect the response variable on its own, but impacts could (partly) occur in combination with other predictor variables only. The higher the correlation of the predictor variables, the higher

[10] Note that in general the sum of the squared standardized coefficients is less than 100%, since above we omitted the error variable ϵ that contributes $\mathrm{var}(\epsilon)$ to $\mathrm{var}(z)$.

the joint contribution and the lower a variable's unique impact (e.g., Bring, 1994; Schielzeth, 2010).

The first issue is of minor importance for our study, since we are not interested in calculating concrete (or even generally valid) coefficients but primarily in the relative importance of the main predictors within this sample. The second issue, however, is exactly in the core of our research and it is addressed in two ways.

First, the full model which includes the two main predictor variables and several control variables is complemented by a two-predictor model based on the growth of population and GDP per capita only. This is due to the fact that the problem of interpretation particularly holds for three- or more predictor equations, when shared explanatory power can unfold in various (unobserved) ways but it seems less problematic for two-predictor equations. Even though both predictors might still unfold some of their impact only in the presence of the other factor, β-coefficients can be considered "a good measure of relative importance of each variable" (Thayer, 1991, p. 12).

Second, an alternative method of standardization, based on partial standard deviations rather than ordinary standard deviations, is applied. Following this idea, mentioned by Healy (1990) and further developed by Bring (1994), standardized coefficients could control for the shared explanatory power by taking into account the amount of multicollinearity for the predictor variables via the variance inflation factor (VIF) (Bring, 1994, p. 211):

$$VIF_x = \frac{1}{1-R_{k-1}^2}, \tag{8}$$

where k is the number of independent variables, R_{k-1}^2,is the coefficient of determination when a predictor variable x is regressed on the k-1 other predictor variables. Partial standard deviation $\sigma_x^{partial}$ is then defined as

$$\sigma_x^{partial} = \frac{\sigma_x}{\sqrt{VIF_x}} \cdot \sqrt{\frac{n-1}{n-k}}, \tag{9}$$

where n is the number of observations.

Finally, the estimated coefficients can be standardized by using partial standard deviations according to

$$\beta_x^S = b_x \cdot \frac{\sigma_x^{partial}}{\sigma_z}. \tag{10}$$

In contrast to ordinary β-coefficients, standardized coefficients based on partial standard deviations are directly related to a variable's *unique* contribution to the prediction of the response variable (Bring, 1994, p. 212). Thus β-coefficients based on partial standard deviation may be preferred over ordinary standardized coefficients, if relative importance is understood in this sense.

Admittedly, the whole process of standardization (based on ordinary or partial standard deviation) at least partially moves the analysis away from the original data and the straightforward impacts of a one-unit change. To be more explicit, while the unstandardized coefficients still can be interpreted as elasticities, the standardized coefficients are defined by means of standard deviations of logarithmized data or in case stationarity is not given even by means of standard deviations of differences of logarithmized data. Nevertheless, they provide complementary information and should be presented and discussed next to unstandardized coefficients. [11]

2.4. Empirical analysis

2.4.1. Method and data

Following a common approach within STIRPAT literature, we assume that part of technology is disaggregated and can be (partly) captured by including time fixed-effects and structural control variables (e.g., York et al., 2003; Casey and Galor, 2017). This means that in equation (3) the term $T_{i,t}$ for technology is replaced by $X_{i,t}$ (i.e. a set of control variables). [12]

Including these control variables, the empirical analysis starts with the setup of the STIRPAT equation in logarithmic form (equation (2)) and the Hadri Lagrange Multiplier (LM) test for panel stationarity. As shown by table (2), the null hypothesis (H_0: all panels are stationary) must be rejected at 0.01 significance level for all variables. Thus, the test results indicate non-stationarity in all cases.

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[11] As most STIRPAT analyses focus on first-differences of the variables, the interpretation of the coefficients moves away from original data anyway. In particular elasticities no longer reflect long-run but rather short-term relationships (Liddle, 2015). So, econometric refinements demand for a trade-off between the originality of data and statistical needs independent of the matter of standardization.

[12] Formally, it is assumed that technology is a multiplicative function of some structural variables (and a time trend):

$$\ln T_{i,t} = f(U_{i,t}, W_{i,t}, \varphi_t),$$

where $U_{i,t}$ is the fraction of urban population, $W_{i,t}$ is the fraction of working aged (15-64) and φ_t is the time fixed-effect.

In line with many STIRPAT literature, we therefore turn to the first-differences equation (see section 2.2.). This time findings of the Hadri LM test are inconclusive, so the Im-Pesaran-Shin (IPS) and Levin-Lin-Chu (LLC) test (both with the null hypothesis that panels are *not* stationary) are applied. It turns out that first-differences are indeed stationary (i.e. null hypothesis can be rejected at 0.01 significance level) for all variables (table (2)).

Table 2: Panel Unit Root Tests

	Hadri-LM-test	**IPS-test**	**LLC-test**
	Order of differences: 0	**Order of differences: 1**	**Order of differences: 1**
	H_0: All panels are stationary	***H_0: Panels contain unit roots***	***H_0: Panels contain unit roots***
	z-statistic	W-t-bar-statistic	Adjusted-t-statistic
CO_2-Emission	168.80***	-44.54***	-43.41***
Population	195.90***	-25.35***	-18.06***
GDP per capita	161.38***	-31.98***	-31.23***
Urban	125.36***	-3.34***	-5.45***
Working	185.13***	-2.45***	-3.08***

***p<0.01; LLC-test: Levin-Lin-Chu-test assumes common autoregressive (AR) parameters across panels, Akaike Information Criterion is minimized; IPS-test: Im-Pesaran-Shin-test assumes panel-specific AR parameters, Akaike Information Criterion is minimized; Hadri-LM-test: Hadri-Lagrange-Multiplier-test.

Thus, the applied regression equation generally follows equation (3) and includes the set of structural variables and time-fixed effects ($X_{i,t}$). For the estimation of equation (11) a random effects regression model is used.

$$\Delta \ln I_{i,t} = \Delta \ln c_t + \alpha \cdot \Delta \ln P_{i,t} + \beta \cdot \Delta \ln A_{i,t} + \gamma \cdot \Delta \ln X_{i,t} + \Delta \ln e_{i,t}. \qquad (11)$$

In line with a large body of the STIRPAT literature, we use CO_2 emissions as a measure of environmental impact. However, some highly-industrialized countries have successfully outsourced emission-intensive production branches but nevertheless show increasing trends in (imported) consumption-based emissions. Davis and Caldeira (2010), for example, find that in some highly developed countries more than 30 percent of consumption-based emissions are imported. The ecological footprint of consumption is applied as an alternative measure in order to catch this effect (see appendix, table (A.1.)).

Only few STIRPAT studies take care of this issue so far (e.g., Jia et al., 2009; Knight et al., 2013).

The main explanatory variables are population and GDP per capita. Further, two structural control variables are considered. First, the share of the working aged (15-64) population (% of total) controls for the assumption that this group consumes more energy compared to young and old people (e.g., Jorgenson et al., 2010; Casey and Galor, 2017). Second, the share of the urban population (% of total) accounts for the effects of urbanization and increasing population density (e.g., Jorgenson and Clark, 2009; Menz and Welsch, 2012). There is little doubt that urbanization has impacts on the environment but there is no consensus so far in which direction. On the one hand, urbanization could have negative effects due to a rising energy demand (e.g., Cole and Neumayer, 2004; York, 2007; Liddle and Lung, 2010). On the other hand, urbanization might well increase energy efficiency (e.g., through mass public transportation or dense housing (e.g., Liddle, 2004)).

Equation (11) is estimated by using cross-country panel data of 84 countries. The balanced yearly data are from 1980-2014. CO_2 emissions are measured in kilotons and the data stem from Oak Ridge National Laboratory (Boden et al., 2015). The ecological footprint is measured in global hectares and the data refer to the Global Footprint Network National Footprint Accounts (Global Footprint Network, 2018). The main independent variables, GDP per capita (measured in millions US$ 2011) and population (measured in millions), are taken from the Penn World Tables version 9.0 (Feenstra et al., 2015). The shares of the working aged (15-64) and the urban population (% of total) stem from the World Bank data base (The World Bank, 2018).

Complementing the full model, we also show the results for a two-predictor equation including only GDP per capita and population growth.

2.4.2. Results

Table (3) presents the results based on estimating equation (11) with CO_2 emissions as response variable. In order to provide as many information as possible and to allow for a better comparison with existing literature, columns (1) and (2) present the unstandardized coefficients for the two-predictor and the full model. Columns (3) and (4) show the respective standardized coefficients based on ordinary standard deviations. Finally, the standardized coefficients based on partial standard deviations are given by columns (5) and (6).

Looking at the unstandardized coefficients, the ecological elasticity with respect to population growth clearly exceeds the CO_2 emissions elasticity with respect to GDP per capita. Results of the two-predictor model imply that CO_2 emissions growth rises by 1.38 percent (0.28) when population (GDP per capita) growth is increased by 1 percent (column (1)).[13] This is qualitatively similar to the findings for the full model (column (2)) and in line with most empirical studies in this field.

Table 3: The Effects of Standardization on CO_2 Emissions

	Unstandardized		**Standardized**		**Standardized (Partial SD)**	
Ln CO_2	(1)	(2)	(3)	(4)	(5)	(6)
Ln Population	1.38*** (0.22)	1.37*** (0.23)	0.11*** (0.02)	0.11*** (0.02)	0.06*** (0.01)	0.06*** (0.01)
Ln GDP p.c.	0.28** (0.12)	0.28** (0.12)	0.16** (0.07)	0.16** (0.07)	0.15** (0.06)	0.15** (0.06)
Ln Urban		0.10 (0.23)		0.01 (0.02)		0.01 (0.02)
Ln Working		1.88*** (0.49)		0.06*** (0.02)		0.05*** (0.01)
Constant	- 0.05** (0.02)	-0.06** (0.02)	-0.32** (0.17)	-0.32** (0.15)	1.13*** (0.27)	1.11*** (0.28)
R^2 (*within*)	0.045	0.047	0.045	0.047	0.045	0.047
R^2 (*between*)	0.561	0.603	0.562	0.603	0.561	0.603
R^2 (*overall*)	0.058	0.061	0.058	0.061	0.058	0.061

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Year fixed-effects are included; Number of countries: 84; Number of observations: 2856; Partial SD: Partial Standard Deviation.

With regard to ordinary standardization, β-coefficients of population are smaller compared to the standardized coefficients of GDP per capita for both models (columns (3)-(4)). If, for example, GDP per capita (population) growth is increased by one standard deviation CO_2 emissions growth rises by 0.16 (0.11) standard deviations in the two-predictor model (column (3)). As expected standardized coefficients based on partial standard deviations are slightly smaller, but overall results strengthen the findings of the ordinary standardization. Again, coefficients are higher for GDP per capita compared to population growth (columns (5)-(6)).[14]

[13] Usually, first-differences of logarithmized variables can be interpreted as growth rates. This holds especially for small changes (Wooldridge, 2015).

[14] In order to estimate the standardized coefficients based on partial standard deviations, the VIFs are calculated (see appendix, table A.2.). The low values (with a maximum of 3.11) indicate that multicollinearity is not a critical issue here.

With regard to the control variables, the share of the working population positively and significantly affects environmental impacts for all regressions. The coefficients of urbanization are positive but (just) not significant.

Using ecological footprints instead of CO_2 emissions as response variable reveals a very similar picture (see appendix, table (A.1.))

2.4.3. Discussion of results

Our findings regarding the classical ecological elasticities (unstandardized coefficients) show that when investigating the development of CO_2 emissions or ecological footprints, which are of high relevance for a sustainable development, the impact of both main predictor variables (population and GDP per capita growth) is positive and significant. Furthermore, and in line with most empirical studies, elasticities for population growth are clearly higher compared to ecological elasticities related to economic growth. However, the question whether an input factor with high elasticity has indeed had large influence on an output factor cannot be finally answered.

Even though standardized coefficients cannot be directly compared to unstandardized coefficients, they offer complementary information and may allow for drawing different conclusions. For our sample, impacts are still positive and significant for both main predictor variables. The higher β-coefficients for GDP per capita, however, indicate that economic development rather than population growth matters more for the development of CO_2 emissions and ecological footprints. As this is true for the two-predictor and the full model economic growth can be considered to be of higher relative importance for this sample.

Clearly, the main variables of interest, GDP per capita and population, are related to each other, thus CO_2 emissions are likely to be driven partly by related trends. As mentioned already, standardized coefficients based on partial standard deviations can control for these joint effects and identify the predictor variables' unique impact on the response variable. So not surprisingly, coefficients are smaller for both variables compared to the ordinary standardized coefficients. Nevertheless, the qualitatively similar results for standardized coefficients based on partial standard deviations demonstrate the general robustness of our results.

Notably, we find very similar results for alternative measures of environmental impacts (e.g., ecological footprint), the inclusion of additional control variables (e.g., trade), different groups of countries (e.g., relatively rich and poor countries) and for different time periods.

Our approach is not without limitations. Aside from the more abstract interpretation of standardized parameters, applying first differences moves the analysis further away from original data and harbors the risk to neglect the variables' long-term relationship. This is why some authors suggest to complement the unit root test by checking for the variables' potential cointegration.

If variables are not stationary but their first differences are, a test on cointegration might shed light on their mutual short- and long-run relationship. In case variables are not cointegrated, the long-term relationship is only weakly defined and the short-term relationship can be calculated by the estimation of the first differences equation. If, however, variables are cointegrated, the estimation of first differences would overlook a potential long-term relationship of the key variables and an error correction model should be applied to account for both, short- and long-run relationships (Engle and Granger, 1987; Liddle, 2011).

For this reason, we apply two cointegration tests (namely the Kao and the Pedroni test) in a last step. In contrast to the unit root tests, results are inconclusive (see Table 4). In the case of Kao test two out of three test statistics cannot reject the null hypothesis assuming no cointegration (i.e. Modified Dickey-Fuller and Augmented Dickey-Fuller). For the Pedroni test, this holds for one out of three test statistics (i.e. Modified Phillips-Perron).

Table 4: Results of the Kao- and Pedroni Cointegration tests

Kao-test *H_0: No cointegration*			**Pedroni-test** *H_0: No cointegration*		
CO_2-Emission, Population, GDP per capita, Urban, Working (all variables logged)					
Modified Dickey-Fuller t	-0.88	(0.19)	Modified Phillips-Perron t	0.40	(0.35)
Dickey-Fuller t	-1.97**	(0.02)	Phillips-Perron t	-15.97***	(0.00)
Augmented Dickey-Fuller t	0.90	(0.19)	Augmented Dickey-Fuller t	-13.23***	(0.00)

***p<0.01, p-value in parantheses; Kao-test assumes a constant cointegration vector; Pedroni-test assumes panel-specific AR parameters and includes specific time trends and uses panel specific means.

In case of cointegration, which we cannot be sure about, equation (11) can be estimated by a pooled-mean-group estimator and augmented by an error correction model. Results (given in the appendix) indicate that the CO_2 emissions' long-run elasticity for GDP per capita (0.32) is higher compared to the elasticity related to population (0.21) (table (A.3.), column (1)). The coefficient representing the speed of adjustment is negative (-0.38) and suggests that the variables exhibit a return to long-run equilibrium. The short-run dynamics indicate a positive effect of GDP per capita on CO_2 emissions (0.20). The short-run dynamic of population is not significant. We are not going further into this direction as this is not the intention of this paper. However, the aspect of cointegration between variables and the estimation of error correction models is an interesting field for future research.

2.5. Concluding remarks and policy implications

The presented paper offers a complementary perspective regarding STIRPAT analysis that is commonly used to calculate ecological elasticities with respect to population and GDP per capita. Following this approach, elasticities show the percentage increase of environmental outcome (e.g., CO_2 emissions or ecological footprint) when the considered factor (e.g., population or GDP per capita) is increased by 1 percent.

Most empirical findings suggest that the ecological elasticity with respect to population growth exceeds the elasticity with respect to growing GDP per capita. Therefore, some studies conclude that the conflict between economic growth and environmental pressure can be successfully resolved by prioritizing degrowth strategies with regard to population rather than the economy (e.g., Casey and Galor, 2017).

In this paper we argue, that this conclusion should not be based on the calculation of unstandardized ecological elasticities only. Instead, if the interest lies in the relative importance of the independent variables to the prediction of the response variable, we suggest to complement the analysis by also considering standardized coefficients. Following this line of thought, we find strong support that – for the selected countries and over the chosen period of observation – the development of CO_2 emissions and ecological footprints was more affected by economic development than by population growth.

The seemingly conflicting result can be explained by the higher changeability of the economic development (in the past). Thus, while traditional ecological elasticities related to population might indeed be larger compared to elasticities related to GDP per capita – a result that can also be confirmed for our sample – it could be much more feasible to accomplish a 1 percent change of the economic drivers.

Admittedly, standardized variables are always sample-specific and should not be generalized. However, if similar findings could be found for other country samples and periods of observation, there is good reason to prioritize strategies that limit emissions coupled to economic growth over explicit population policies.

Of course, the practical implementation of appropriate policies is context- and region-specific and STIRPAT models, like any other model, cannot provide blueprints for policymakers. But in our view, they are helpful tools and give important insights regarding human impacts on the environment. This is particularly true for analysing impacts of population *and* economic dynamics on the environment, which both remain closely tied to growing demands of the environment (and STIRPAT models play a crucial role in communicating this point to politics). However, coefficients should be interpreted carefully depending on what aspect (e.g., general elasticities or a comprehensive relative assessment of variables) one is interested in. The suggested application of standardization processes is not without problems but it could provide a complementary tool to do so.

3. Reversed STIRPAT modelling: the role of CO_2 emissions, population and technology for a growing affluence[15]

3.1. Introduction

In the past decade (2010-2020) global mean surface temperature has, on average, increased by approximately 1°C compared to pre-industrial levels. According to leading climate scientists this can be attributed to increasing anthropogenic greenhouse gas emissions mostly related to economic and population growth (e.g., IPCC 2014 and 2018).

However, despite broad consensus that economic production has substantially altered the global environment, empirical findings on the causal relationship between economic growth and environmental impacts are (at least in some parts) inconclusive. While some authors identify a monocausal relationship running from economic growth to the production of anthropogenic greenhouse gases, others find strong evidence for a reversed causality running from environmental emissions to economic growth. Yet others observe bidirectional relationships or no causal link at all. In conclusion, the rich portfolio of empirical studies reveals no universal direction of causality, findings rather depend on the considered time periods and countries' stage of development and sectoral structure (Costantini and Martini, 2010; Ozturk, 2010).

Against this background the presented paper seeks to analyze the relationship between economic growth, demographic development and CO_2 emissions for 30 industrial countries in the well-known STIRPAT (STochastic Impacts by Regression on Population, Affluence and Technology) setting. However, in contrast to the general assumption of STIRPAT modelling, which proposes a one-way causality running from the anthropogenic factors to the environment, applied Granger-causality tests indicate a reversed causal relationship for the sample at hand. Thus, in contrast to existing applications of the STIRPAT model, this paper uses, to our best knowledge for the first time, the STIRPAT framework to estimate environmental impacts on economic growth. This means CO_2 emissions can be, for industrial countries and the time period between 1982 and 2014, considered a driver of economic growth rather than vice versa. Based on

[15] The contribution is based on joint work together with Axel Schaffer (Bundeswehr University Munich) and Tom Brökel (University of Stavanger Business School) and is published in *Theory and Applications of Time Series Analysis and Forecasting* (Lohwasser, J., Schaffer, A., & Brökel, T. (2023). Reversed STIRPAT modelling: the role of CO2 emissions, population and technology for a growing affluence. In: Valenzuela et al. (eds.): Theory and Applications of Time Series Analysis and Forecasting: Selected Contributions from ITISE 2021. Springer).

these results we suggest to complement the STIRPAT model family by a reversed version that explains stochastic impacts on affluence (rather than on the environment) by regression on population, technology and environmental impacts or inputs.

The remainder of the paper is organized as follows. Section 3.2. discusses the general issue of causality and offers a new perspective on the IPAT and STIRPAT modelling. Section 3.3. continues with methodological remarks followed by the empirical application of the revised model for 30 advanced economies and the discussion of results in sections 3.4. and 3.5. respectively. Finally, the paper closes with concluding remarks and some brief policy implications in section 3.6..

3.2. Perspectives of causality in the IPAT /STIRPAT model approach

One way to analyze the relationship of anthropogenic factors and the environment is the so-called *IPAT* approach, which presumes that environmental impacts (I) are the multiplicative product of population (P), affluence (A) and technology (T) (Ehrlich and Holdren, 1971; Commoner et al., 1971):

$$I = P \cdot A \cdot T. \quad (1)$$

Notably the formula proposes a functional relation between anthropogenic factors and the environment but does not tell us much about the causality of this relationship (e.g., York et al., 2003). As a mathematical identity, the equation can be solved for any variable, e.g., for technology T, defined as environmental impact per unit output (e.g CO_2 emissions per unit of GDP; Commoner, 1971; Ehrlich and Holdren, 1972; Raskin, 1996) or affluence A (2):

$$A = \frac{I}{P \cdot T} \quad (2)$$

Accordingly, affluence (typically given as GDP per capita) rises with environmental impacts or inputs (operationalized by CO_2 emissions) and technical progress T (if defined as *decreasing* fossil fuel consumption per unit of GDP).[16] At the same time it decreases with an increasing population P. Or, the other way around, a shrinking population pushes GDP per capita.

[16] For a better traceability the environmental/energetic input is still denoted as I.

While clarity and simplicity certainly add to the popularity of the *IPAT* approach, the pure identity undermines hypothesis testing and causal interpretation (e.g., York et al., 2003). This is why Dietz and Rosa (1994) suggest to transfer the IPAT equation into the so-called STIRPAT model that explains *St*ochastic *I*mpacts on the environment by *R*egression on *P*opulation, *A*ffluence and *T*echnology and provides the framework for empirical analysis (3).

$$I_{i,t} = c_t \cdot P_{i,t}^{\alpha} \cdot A_{i,t}^{\beta} \cdot T_{i,t}^{\gamma} \cdot e_{i,t}, \tag{3}$$

where $I_{i,t}$ is the environmental impact of country i at time t, $P_{i,t}$ is population, $A_{i,t}$ is affluence, $T_{i,t}$ is technology, c_t is the constant and $e_{i,t}$ is the residual error term.

In order to address the skewness and non-stationarity of variables, STIRPAT models generally take logs and use first-differences (4) (e.g., Liddle, 2014; Casey and Galor, 2017):

$$\Delta \ln I_{i,t} = \Delta \ln c_t + \alpha \cdot \Delta \ln P_{i,t} + \beta \cdot \Delta \ln A_{i,t} + \gamma \cdot \Delta \ln T_{i,t} + \Delta \ln e_{i,t}. \tag{4}$$

where $\Delta \ln I_{i,t}$ is the change of log CO_2 emissions in country i from time t−1 to t. $\Delta \ln P_{i,t}$ is the change of log population, $\Delta \ln A_{i,t}$ is the change of GDP per capita, $\Delta \ln T_{i,t}$ is the change of log technology, $\Delta \ln c_t$ is the change of the log constant and $\Delta \ln e_{i,t}$ is the change of the log error term.

In contrast to the simple IPAT identity, the very thought of setting up the main *STIRPAT* equation already implies the assumption of causality. Considering affluence, population and technology as *key driving forces*, *contributing factors, predictive or explanatory variables* that *explain, determine* or *lead to* environmental impacts further strengthens the underlying assumption of causality (Rosa and Dietz, 1998; York et al., 2003; Liddle, 2014; Casey and Galor, 2017; Singh and Mukherjee, 2019). After all, it is probably fair to say that the large majority of STIRPAT models assume a one-way causal impact through affluence (typically GDP per capita), population and technological progress (measured as environmental impact per output) on the environment (typically CO_2 emissions).

However, this monocausal perspective is not undisputable. *First*, many studies analysing the relationship between economic growth and the environment propose a bidirectional causality running from economic growth to the environment but also – e.g., through the provision of ecosystem services – from the environment to economic growth (e.g., Guo et al., 2010). This can easily be shown for CO_2 emissions, which are frequently used to illustrate and measure regulative services of the terrestrial ecosystem. Increasing carbon concentration, possibly exceeding the ecosystem's regulative capacity, is not only the result of industrial production but might as well affect production factors and outputs and hamper economic growth (and affluence) in the long-run. In accordance with leading climate economists, impacts could be severe and equal up to 20 percent of GDP and more (Stern, 2007; Weitzman, 2007). Following this line of thought a bidirectional relationship between economic growth and the ecosystem services could be assumed in the long-run.

Second, the estimates of CO_2 emissions, probably the most common indicator for measuring environmental impacts within the STIRPAT analysis, generally derive from (fossil) energy consumption. This means they are not only a proxy for environmental impacts but equally reflect the use of (cheap) fossil fuels, which, until now, clearly dominates global energy use. Per se, this says nothing about the causal relation between economic growth and CO_2 emissions, but it draws the attention to the broad literature on the relationship between the energy and the economic sphere.

Empirical findings in this field reveal a strong and positive relationship between economic growth and energy consumption. However, the question of causality cannot be answered unequivocally. Following the "conservation hypothesis", mainstream economics literature seem to focus on how a growing economy affects energy consumption rather than the other way around.[17] Significant results indicating a causality in this direction can particularly be found for developing countries (Toman and Jemelkova, 2003; Wolde-Rufael, 2005 and 2006, Akinloo, 2008), but in some settings also for advanced industries (Kraft and Kraft, 1978; Yu and Choi, 1985; Soytas and Sari, 2003; Narayan and Smyth, 2005; Bowden and Payne, 2008).

In comparison with this and deeply rooted in Georgescu-Roegen's (e.g., 1971 or 1984) work on the physical basis of economic production, biophysical economists argue that any production process relies on material and energy inputs (flows), which are transformed by use of human labor, physical capital and Ricardian land (funds) into production outputs. Thus, the availableness of (cheap) energy can be considered a key prerequisite for economic growth and the constitution of the "age of affluence" (Hall and

[17] The "conservation hypothesis" (or "conservative hypothesis") assumes that economic growth affects the production of emissions but that energy policies have no or negligible impact on growth (in the long-run). This is in contrast to the "growth hypothesis", according to which (cheap) access to energy constitutes a key driver of economic growth. Finally, some authors argue in favor of a bidirectional causality ("feedback hypothesis") or presume no causal relationship at all ("neutrality hypothesis") (e.g. Behmiri and Manso, 2012).

Klitgaard, 2018, p. 155; Georgescu-Roegen, 1971 and 1984; Stern and Cleveland, 2004).

This so-called "growth hypothesis" played a minor role in economics for a long time, but gained in importance when some economists could convincingly explain the economic recession in the aftermath of the major oil crises by the declining availableness of cheap fossil fuels (e.g., Cleveland et al., 1984). Since then many empirical studies in this field confirm the idea that energy use drives economic growth. Notably, the causal relation running from energy use to economic growth seems to be of particular relevance for advanced industries (e.g., Stern, 1993 and 2000; Toda and Yamamoto, 1995; Coondoo and Dinda, 2002; Lee and Chang, 2007; Apergis and Payne, 2010; Lee et al., 2008).

3.3. Methodological remarks

Overall, both ways of causality are plausible and there is good reason to assume a bidirectional relationship over a longer-term perspective, as the economy is passing through different stages of development. We therefore propose to check for the direction of causality before setting up the final (STIRPAT) model. One way to do so, is the application of the Granger-causality test, which provides valuable insights about the forecasting quality of one variable on another by the help of its past values. For example, a vector autoregression (VAR) model with two variables y and x allows to test whether, after controlling for past values of y, past values of x help to forecast y (Wooldridge, 2015). Formally, x Granger-causes y if

$$E(y_t|I_{t-1}) \neq E(y_t|J_{t-1}), \tag{5}$$

where I_{t-1} contains past information on y and x, and J_{t-1} contains only information on past y. Thus, Granger-causality does not mean causality per se and does not imply a contemporaneous causality between variables but rather a variable's feasibility of predicting the other variable according to its past development.

In order to test for Granger-causality most empirical studies either apply time series and cointegration analysis (Stern, 2000; Coondoo and Dinda, 2002; Oh and Lee, 2004; Lee and Chang, 2007) or use VAR models (Hamilton, 1983; Burbridge and Harrison, 1984; Stern, 1993). For the paper at hand we follow the VAR approach and estimate a panel vector autoregression (PVAR) model by the cross-sectional series of variables. The general PVAR structure is given by:

$$y_{i,t} = c_i + Ay_{i,t-1} + e_{i,t}, \tag{6}$$

where $y_{i,t} = (I_{i,t}, Y_{i,t})'$. $I_{i,t}$ is CO_2 emissions (or population or energy intensity) and $Y_{i,t}$ is GDP per capita of country i at time t. c_t is a country-specific intercept term, A is the coefficient matrix and $e_{i,t}$ is the residual term. In a next step equation (6) is transformed by taking logs and applying first-differences (7):

$$\Delta \ln y_{i,t} = A \cdot \Delta \ln y_{i,t-1} + \Delta \ln e_{i,t}. \tag{7}$$

Equation (7) is estimated by the generalized method of moments (GMM) while applying lagged values as instruments. The PVARs include first-order lags according to the Moment Model Selection Criterion (MMSC) and Akaike Information Criterion (AIC).

In case the empirical analysis reveals, for the considered period of time, a monocausal relationship running from anthropogenic factors to the environment, the conventional STIRPAT model (equation (4)) should be applied. If however, findings indicate a reverse causality for the relationship between GDP per capita and CO_2 emissions we suggest to add a new perspective to the STIRPAT approach. By analogy with the transformation from IPAT to STIRPAT (Dietz and Rosa, 1997), we setup a stochastic model based on equation (2) that explains stochastic impacts on economic growth (affluence) by regression on population, carbon emissions (as a proxy for energy use or ecosystem services) and technology:

$$A_{i,t} = c_t \cdot P_{i,t}^{\alpha} \cdot I_{i,t}^{\beta} \cdot T_{i,t}^{\gamma} \cdot e_{i,t}, \tag{8}$$

where $A_{i,t}$ is affluence of country i at time t, $P_{i,t}$ is population, $I_{i,t}$ is environmental input (e.g., energy use, availability of energy or ecosystem service measured by CO_2 emissions), $T_{i,t}$ is technology and $e_{i,t}$ is the residual error term.[18]

After taking logs and applying first-differences equation (8) yields:

$$\Delta \ln A_{i,t} = \Delta \ln c_t + \alpha \cdot \Delta \ln P_{i,t} + \beta \cdot \Delta \ln I_{i,t} + \gamma \cdot \Delta \ln T_{i,t} + \Delta \ln e_{i,t}. \tag{9}$$

where $\Delta \ln A_{i,t}$ is the change of log GDP per capita in country i from time t−1 to t. $\Delta \ln P_{i,t}$ is the change of log population, $\Delta \ln I_{i,t}$ is the change of CO_2 emissions, $\Delta \ln T_{i,t}$ is the change of log technology, $\Delta \ln c_t$ is the change of the log constant and $\Delta \ln e_{i,t}$ is the change of the log error term.

[18] In contrast to equation (2), P and T are not expressed inversely. This does not affect the estimation results.

3.4. Empirical application

3.4.1. Granger-causality, non-stationarity and cointegration

For the empirical part, a balanced yearly cross-country panel dataset of 30 advanced countries from 1982-2014 is used. The classification of advanced economies is according to the IMF (2016).[19] CO_2 emissions are measured in kilotons and the data stem from Oak Ridge National Laboratory (Boden et al., 2015). The variables GDP (in millions US$ 2011), population (in millions) and technology (defined as the energy intensity level of primary energy (in MJ per US$ 2011)), are taken from the Penn World Tables version 9.0 (Feenstra et al., 2015) and the World Bank data base (The World Bank, 2018), respectively.

Following equations (5)-(7), the Granger-causality between CO_2 emissions (environment) and GDP per capita (affluence), is estimated and tested in the first step (see appendix, tables (A.5.) – (A.7.) for the underlying PVAR estimations). Findings for the logarithmized and first-differenced variables confirm the "growth hypothesis" (with a causality running from CO_2 emissions to GDP per capita) but not the "conservation hypothesis" (implying a causal relationship running the other way around). Equally population Granger-causes GDP per capita but not vice versa. With regard to technology, however, Granger-causality only runs from GDP per capita to energy intensity (table (1)).

Table 1: Granger-causality Wald test (Chi2-statistic) based on PVARs (equation (7))

GDP per capita → CO_2-emissions	CO_2 emissions → GDP per capita	GDP per capita → population	population → GDP per capita	GDP per capita → Energy Intensity	Energy Intensity → GDP per capita
1.20	19.30***	0.01	8.82***	9.67***	1.67

***p<0.01.; H_0: Variable does not Granger-cause the other variables.

In general, the findings of the Granger-causality test support the idea to consider environmental impacts or inputs a main driving factor for affluence in industrially mature economies rather than vice versa (equation (8)). As the Hadri Lagrange Multiplier (LM) test, the Im-Pesaran-Shin (IPS) test and the Levin-Lin-Chu (LLC) test suggest that niveau parameters (order of differences: 0) are not stationary but first-differences variables are (see appendix, table (A.8.) for test results), we setup the modified STIRPAT model according equation (9).

[19] Though the IMF classifies 39 countries as advanced economies, full panel data are only available for 30 economies. A complete list with all considered economies is given in the appendix (table (A.4.)).

In addition, the variables are tested for panel cointegration. Cointegration can be interpreted as evidence of a long-run equilibrium relationship between variables (e.g., Liddle, 2011). In case of cointegration, the evaluation of short-run dynamics between variables by using a first-differences regression can be complemented by the evaluation of long-run dynamics by using error correction models. In order to check for cointegration, the Kao and the Pedroni tests are applied. Most (four out of six and five out of six) test statistics reject the null hypothesis assuming no cointegration (i.e. Modified Dickey-Fuller, Dickey-Fuller and Augmented Dickey-Fuller; see appendix, tables (A.9.1.) and (A.9.2.) for test results). Thus, there is evidence for a long-run cointegrating relationship among economic impacts, carbon emissions, population and structural/energy variables (see next section).

Consequently both, short-run and long-run impacts on economic growth are estimated. In order to evaluate the short-run dynamics, a standard random-effects (RE) estimator is used (estimation of equation (9)). In order to evaluate long-run dynamics, the fully modified ordinary least squares (FMOLS) estimator is applied.[20]

3.4.2. Reversed STIRPAT

Coefficients are estimated for three slightly different model variations (table (2)). In the first basic setup affluence (GDP per capita) is explained by CO_2 emissions, population, and energy intensity (table (2), column (1)). Not surprisingly, and in line with the results of the Granger-causality tests, CO_2 emissions positively and significantly affect GDP per capita. In fact, GDP per capita growth rises by 0.3 percent when CO_2 emissions growth rises by 1 percent. In contrast, impacts of population growth has a negative impact on affluence (GDP per capita growth declines by about 0.6 percent when population growth rises by 1 percent). Further, an increase in energy intensity has a negative and significant effect on GDP per capita. This means that an improvement of energy intensity (i.e. a *decrease* of energy intensity measured in MJ per $) positively relates to GDP per capita. Thus, in line with neoclassical growth theory, technological progress can be considered a key driver of affluence for the considered sample (Carlaw et al., 2003).[21]

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[20] In addition to FMOLS, dynamics ordinary least squares (DOLS) and canonical cointegration regression (CCR) estimators are applied. Results confirm the findings of FOMLS qualitatively (not shown). Further, the pooled mean group estimator is used. This approach allows for estimation of short- and long-run dimensions within one error correction model. Results confirm the validation of RE OLS first-differenced results (see appendix, table (A.11.)).

[21] Generally, the STIRPAT studies treat technology differently. This paper uses energy intensity in order to

The results are confirmed for a long-run perspective except for energy intensity (the coefficient for energy intensity has the same sign but is hardly significant; see appendix, table (A.10.), column (1)).

In the second model setup, the basic model is augmented by structural variables. In accordance with most STIRPAT models, we control for the share of urban population (% of total population; The World Bank, 2018) and thus for the effects of an increasing urbanization on economic growth. It can be assumed to have a positive impact on affluence due to agglomeration effects (Turok and McGranahan, 2013). Furthermore, the impacts of globalization (Globalization Index; Gygli et al., 2019) on economic growth are investigated.[22] At least in the long-run globalization is assumed to have positive effects on economic growth due to various scale and spill-over effects (Chang and Lee, 2010). Finally, we test for possible effects of life expectancy (at birth in years; The World Bank, 2018) on economic growth. Life expectancy is assumed to play a crucial role regarding the quality-quantity trade-off. Educational attainment rises if life expectancy increases. This process affects economic growth (e.g., Cervellati and Sunde, 2011).[23]

With regard to the size and sign of the coefficients, impacts of the key variables (CO_2 emissions, population and technology) remain almost unchanged compared to the basic model (table (2), column (2)). Further, results show that globalization has a negative impact on affluence in the short run. In contrast, life expectancy positively and significantly drives GDP per capita. At the same time, we find no significant impact of urbanization. Notably the long-run coefficients confirm the qualitative impacts of variables except for globalization, which has a positive effect on GDP per capita (see appendix, table (A.10.), column (2).

Assuming that CO_2 emissions reflect the utilization of terrestrial regulation services and fossil energy inputs, affluence might further be affected by the use of other (less carbon intensive) energy sources. For this reason, the third model setup additionally accounts for the share of renewable energy consumption (% of total; The World Bank, 2018) and electricity production from nuclear sources (% of total; The World Bank, 2018). The findings on short-run impacts suggest that the use of (comparatively cheap) nuclear

stay close to existing STIRPAT literature (Vivanco and Hernández, 2019). Often, technology is approximated and assumed to be partly captured of the error term.

[22] The Globalization Index contains an economic, social and political dimension and is taken from Gygli et al. (2019).

[23] Granger-causality test implies a unidirectional causality from life expectancy to GDP per capita in our sample (not shown).

energy positively and significantly relates to affluence (table (2), column (3)). With regard to renewable energy, no significant impacts can be observed in the short-run.

Results are confirmed for most variables in the long-run. Interestingly, globalization and renewable energy consumption turn significantly positive (see appendix, table (A.10.)). Generally, results are hardly affected qualitatively, if niveau parameters and size effects are taken into consideration (short- versus long-run model).

Table 2: Determinants of GDP per capita (RE Model)

Ln GDP p.c.	(1)	(2)	(3)
Ln CO_2	0.30*** (0.05)	0.28*** (0.06)	0.26*** (0.04)
Ln Population	-0.56*** (0.13)	-0.65*** (0.12)	-0.73* (0.42)
Ln Energy Intensity	-0.43*** (0.08)	-0.40*** (0.08)	-0.39*** (0.07)
Ln Urban		0.05 (0.44)	-0.33 (0.44)
Ln Globalization		-0.18* (0.10)	-0.11 (0.09)
Ln Expectancy		0.55*** (0.21)	0.60 (0.77)
Ln Nuclear			0.04*** (0.01)
Ln Renewable			-0.01 (0.01)
Constant	0.01* (0.01)	0.02** (0.01)	0.01 (0.01)
R^2 (*within*)	0.42	0.42	0.56
R^2 (*between*)	0.58	0.63	0.19
R^2 (*overall*)	0.43	0.43	0.54
observations	685	685	336
countries	30	30	15

***p<0.01, **p<0.05, *p<0.1; Robust standard errors clustered at country level in parentheses; Year fixed-effects are included; All variables first-differenced.

3.5. Discussion of results

The results indicate that GDP per capita growth rates are significantly driven by the development of CO_2 emissions, population and energy intensity. Coefficients remain rather robust with or without integrating structural and energy variables and for the short- and long-run perspective.

In conclusion, the empirical results confirm the "growth hypothesis", which considers (cheap) energy inputs a key driver of affluence. The positive impact of (comparatively cheap) nuclear energy further supports this hypothesis. In contrast, increasing shares of renewable energy have, in the short-run, no particular effect on welfare. However, results show that renewable energy consumption drives affluence in the long-run.[24] Reasons are, for example, a slow accompanying infrastructure or market accessibility needed for renewable energy sources.

Similar to conventional STIRPAT results, the findings should not be interpreted in a general way but with respect to the underlying country group (Singh and Mukherjee, 2019). This means, the results of this paper particularly hold for advanced economies but not necessarily for other countries. However, it is the governments of the advanced economies that have a particular responsibility to decarbonize their economies and to implement the intended energy turnaround towards renewable energy. This will not necessarily boost the welfare, but as long as prices are reasonably low, switching to renewables will not hamper the economic development either – renewables are more or less growth neutral in the short-run.

Further, findings indicate that population growth has a negative impact on economic growth. This is in line with unified growth theory, according to which positive impacts of a shrinking population on the economy are still visible for advanced industries, even long time after the demographic transition (i.e. process from high to low mortality and fertility rates) has taken place (Reher, 2004). Admittedly the findings are less conclusive on the role of technology. On the one hand, there is clear evidence that technical progress (in the form of decreasing energy intensity) relates significantly and positively to GDP per capita. On the other hand, causality analysis indicates that GDP per capita Granger-causes energy intensity rather than vice versa.

Increases in the share of urban population cannot be identified as a significant factor.

[24] Other studies confirm this long-run relationship between renewable energy and economic growth (e.g. Apergis and Danuletiu (2014)).

Again, this does not mean that the degree of urbanization is irrelevant for affluence. Rather advanced countries show generally very high levels of urbanization for the whole period of observation, so further increases might be less important in this case or even hamper economic growth (Nguyen, 2018).

In contrast, there is evidence that globalization affects economic growth negatively in the short-run and positively in the long-run. The various channels of globalization take time to gain momentum regarding clear positive effects on economic growth. For example, an increasing knowledge acquiration due to globalization cannot immediately translate into research improvements and thus economic growth (Grossman and Helpman, 2015).

Finally, life expectancy significantly and positively affects affluence in the short- and long-run. Exisiting literature points out that life expectancy increases economic growth due to effects on the age structure or improvements on educational attainment and labour productivity (Cervellati and Sunde, 2011).

3.6 Concluding remarks

The STIRPAT approach is commonly used to estimate anthropogenic impacts (growing affluence, increasing population and technological change) on the environment. Today, much of the debate in a continuously developing *STIRPAT* literature is on the choice of the control variables and the relative contribution of an increasing population, economic growth and technological change to the production of greenhouse gases and other environmental impacts. We largely stay clear of this discussion. Instead, our main interest lies in the causal relationship of the key variables.

Rather the presented paper proposes an alternative extension of the IPAT identity for empirical analysis. Similar to the STIRPAT studies a directional relationship between variables is presumed. However, in contrast to STIRPAT literature and based on a Granger-causality test it seems plausible, at least for advanced economies, to activate the IPAT identity towards affluence and to estimate stochastic impacts on economic growth (affluence) by regression on population, carbon emissions (as a proxy for energy use or alternatively ecosystem services) and technology. The significant and robust regression results (short- and long-run estimations) with respect to the main variables (CO_2 emissions, population and energy intensity) in all model variants demonstrate the reasonableness of applying this setup in addition and complementary to the traditional

STIRPAT model.

In addition, the findings confirm the ongoing high dependence of advanced economies on the availableness and consumption of cheap energy. Breaking the fossil path dependency and decarbonizing the economy, which in light of climate change is without alternatives, could in case of rising energy prices be accompanied with comparatively small growth rates of affluence (if measured as GDP per capita) in advanced economies in the near future. Policies should enhance the use of renewable energy and further support the substitution of non-renewable with renewable energy sources. So, a framework could be created that is able to foster economic growth during the energy transition.

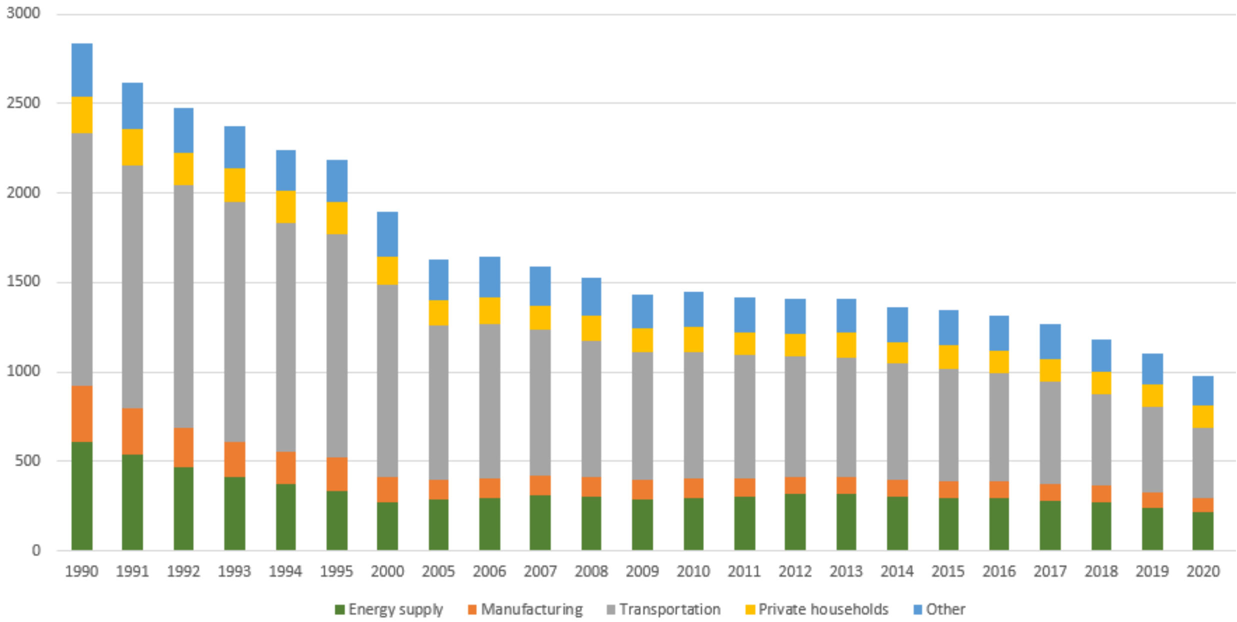
Without doubt, IPAT and particularly STIRPAT modelling has evolved to a powerful tool for illustrating and estimating anthropogenic impacts on the environment. However, this approach could be extended and also used to identify the relevance of environmental inputs on affluence. Following this line of thought further research might analyze other country groups (e.g., emerging economies) or earlier stages of development of industrialized countries. Furthermore, it might be interesting to use other, arguably more inclusive measures of environmental impacts, such as ecological footprints or ecosystem services, rather than fossil energy inputs.

4. The varying roles of the dimensions of affluence in air pollution: a regional STIRPAT analysis for Germany[25]

4.1. Introduction

Despite recent improvements in air quality, about 90 percent of the European Union's (EU) urban population are exposed to concentration levels above the World Health Organization's (WHO) latest annual guidelines for fine particulate matter ($PM_{2.5}$), ozone (O_3) and nitrogen dioxide (NO_x) (European Environment Agency, 2022). Therefore, air pollution is still a considerable threat to ecosystems and human health in the EU. In response, EU clean air policy set ambitious reduction commitments for main air pollutants that member states are required to integrate in their national environmental policies.

Figure 1: Sources of NO_x emissions in Germany (1990-2020, in thousand tons)



Source: Based on Umweltbundesamt (2022)

As one of the EU's main nitrogen oxide polluters, Germany is committed to reducing NO_x emissions by 65 percent by 2030 compared to 2005 (Umweltbundesamt, 2019).[26] Therefore, German law- and policy-makers are interested in learning more about the

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[25] The contribution is based on joint work together with Axel Schaffer (Bundeswehr University Munich) and is accepted for publication in *Environmental Science and Pollution Research* (Lohwasser, J. and Schaffer, A. (2022). The varying roles of the dimensions of affluence in air pollution: a regional STIRPAT analysis for Germany. Environmental Science and Pollution Research).

[26] In fact, Germany's average concentration of NO_x is among the highest in the EU, and almost all registered values are above the WHO guideline.

main sources of NO_x emissions at the sectoral level and about its socioeconomic drivers at the macro level. These emissions' sources are mainly the transportation, energy use, private households, and manufacturing sectors (figure (1)).

As for NO_x emissions' socioeconomic drivers at the macro level, the relationships of economic activities and population with environmental impacts (e.g., greenhouse gases, air pollution) are often analyzed using the environmental Kuznets curve (EKC) to measure the non-linear impact of the economy or population on the environment, or the STIRPAT model to measure the stochastic impacts on the environment by regressing population, affluence and technology. More recently, some studies also incorporate the EKC effect into STIRPAT modelling by adding non-linear effects of gross domestic product (GDP) or population size into the STIRPAT equation (e.g., Cole and Neumayer, 2004; Ge et al., 2018; Arshed et al., 2021).

Most empirical findings generally confirm the now well-established positive impact of population and affluence on the environment in the STIRPAT framework (e.g., Liddle and Lung, 2010; Andrés and Padilla, 2017). However, a close look at the large variety of empirical studies reveals that it is not the population as a whole that increases environmental pressures but certain groups in the population. Therefore, many authors differentiate population by region (global north vs. global south), by economic status (rich vs. poor; economically active vs. inactive), by settlement structure and density (urban vs. regional), by age group (young, middle, old), or educational achievement.

In contrast, affluence is almost exclusively defined as GDP per capita, which neglects the possibility that increasing prosperity affect the environment in different—even opposing—ways. Notable exceptions to this oversight include studies that disaggregate GDP by sector (Arshed et al., 2021; Wang et al., 2021), account for infrastructure capital per capita (Li et al., 2017), or expand the model using household size (Yousaf et al., 2021) or elements of consumer behavior, such as consumption of material goods (Kylbourne and Thyroff, 2020).

Against this background, the present study analyzes affluence in a differentiated way. This approach is in line with recent empirical findings on poverty and wealth (e.g., Peichl and Pestel, 2013; Törmälehto, 2017), which suggest that more differentiated measures than GDP per capita are needed to capture all aspects of affluence (e.g., living conditions, social exclusion and mobility) and takes into account that STIRPAT analysis originally differentiated affluence between national income and consumption patterns (Dietz and Rosa, 1994).

In taking this approach, we seek to identify the impacts on local air pollution (measured by NO_x emissions) of regional population and three aspects of affluence in German districts and autonomous cities between 1990 and 2020. We decompose affluence into (taxable) income per taxpayer, private car ownership, and the share of single-family houses per capita.

While our results confirm the long established positive relationship between NO_x emissions and population, the role of affluence is less conclusive. While the level of car ownership and the share of single-family houses per capita both have strong positive impacts on emissions, taxable income per taxpayer reveals a negative relationship between local NO_x emissions and taxable income per taxpayer (when we control for car ownership and the share of single-family houses per capita).

The remainder of the paper is organized as follows. Section 4.2. provides an overview of related literature, focusing on empirical findings and the treatment of affluence. Section 4.3. describes the decomposition of affluence we used. Section 4.4. introduces the STIRPAT model and describes the data and the empirical application of the model. Section 4.5. follows with a discussion of the results, and section 4.6. closes with concluding remarks and the study's policy implications.

4.2. Literature review

An extensive body of STIRPAT studies examine anthropogenic impacts on the environment. With regard to climate change, probably the most frequently studied issue in the STIRPAT environment, most studies confirm the role of a growing population and increasing affluence on CO_2 emissions (e.g., Kenworthy and Laube, 1999; Lankao et al., 2009; Karathodorou et al., 2010; Liddle and Lung, 2010; Travisi et al., 2010; Xu and Lin, 2016; Ge at al., 2018; Lv et al., 2019; Amin and as well as Scholl et al., 1996 for OECD countries; Timilsina and Shrestha, 2009 for Asian countries; Andrés and Padilla, 2017 for the EU; and Dogan, 2021 for regional studies).[27]

[27] While cross-country comparisons typically control for trade and economic structure or complexity, regional and city-based studies generally account for population (or urban) density and transport-related issues.

Compared to the rich portfolio of empirical studies related to greenhouse gases, the number of studies that analyze (local) air pollution is small, particularly for NO_x emissions, which are in the focus of the present study. However, Yang et al. (2020) analyze the potential impacts on NO_x emissions of 30 Chinese provinces and highlight the role of income and energy supply, which they suggest makes increasing denitrification tariffs a promising tool for reducing NO_x emissions. Applying a spatial regression technique for Chinese provinces, Diao et al. (2018) confirm the significant and positive impacts of income (GDP per capita) on NO_x emissions for the period from 2006 to 2015. While they also identify significant impacts from population size, energy efficiency and the industrial structure, their results indicate no significant impact from the number of private vehicles. This finding is in contrast to Montero et al. (2021), who analyze the drivers of NO_x emissions in communities in the Madrid area from 2000-2009 and find clear impacts of the number of vehicles. Their findings also point to spatial effects and a strong impact of affluence on NO_x emissions.

Most STIRPAT studies confirm the roles of a growing population and increasing affluence, typically measured by the number of inhabitants and GDP per capita, respectively, on the environment. The advantage of these measures lies in their simplicity, as well as availability of good data, which allows conclusive comparisons and policy implications at the macro level. For example, many empirical studies find that population has clearly higher ecological elasticity than economic growth, which some authors take as a reason to argue in favor of a slowed economy and reduced population growth (e.g., Casey and Galor, 2017). Even though some authors are critical of the feasibility and effectiveness of population policies, the broad consensus is that population growth must be considered as having significant environmental impacts.

At the same time, causal relationships between population and environmental impacts are not as simple as they appear. For example, empirical findings at the regional and city level suggest that population's environmental impacts do not necessarily relate to the number of residents so much as the age structure, household size, number of households, and education level (Cramer, 1998; Liddle and Lung, 2010; Liddle, 2011; Zagheni, 2011; York and Rosa, 2012) because consumption patterns vary substantially for different age cohorts, stages of life, and education levels (Liddle, 2013b). Some studies also pay attention to the EKC relationship between population and environmental outcomes and include a quadratic term of population. Although these studies' results are so far inconclusive, Cole and Neumayer (2004) demonstrate that, in the case of SO_2 emissions, a quadratic effect can be observed in some situations. This result suggests that the population-emissions elasticity is negative for small population sizes but rises rapidly as population increases.

In contrast to a differentiated understanding of population, most STIRPAT applications treat affluence as one-dimensional. Although several authors emphasize the limitations of GDP per capita as a measure of affluence (e.g., Kashima and Kashima, 2003; Majewska and Gierałtowska, 2022) and underscore the importance of differentiating the role of affluence more fully, particularly by accounting for consumption *and* production effects (Ehrlich and Holdren, 1971; Dietz and Rosa, 1994, 1997; Waggoner and Ausubel, 2002; York et al., 2003), empirical applications to date tend to stick to the easily available measure of GDP per capita.

Notable exceptions differentiate between GDP and public infrastructure per capita (Li et al., 2017), account for electric power consumption and sectoral value added (Montero et al., 2021), or use sectorally disaggregated GDP (Arshed et al., 2021; Wang et al., 2021). Some studies address the EKC relationship and include quadratic forms of (sectorally disaggregated) GDP per capita (e.g., Dietz and Rosa, 1997; York et al., 2003; Arshed et al., 2021; Wang et al., 2021), while others expand the STIRPAT approach to the marketing industry and include elements of consumer behavior, such as consumer spending and consumption of material goods (Kilbourne and Thyroff, 2020). However, the focus there is on the theoretical expansion of STIRPAT to the marketing industry and not on empirical application, as only a cross-country regression for one year is applied. Studies outside the STIRPAT literature that examine the environmental impacts of affluence also point to the role of housing conditions, mobility patterns, socioeconomic status, and income distribution (e.g., Dunlap and Mertig, 1995, Myers and Kent, 2003; Ransome, 2005; Boyce et al., 2006; Peichel and Pestel, 2013; Weinzettel et al., 2013; Hobza et al., 2017; Törmälehto, 2017; Majewska and Gierałtowska, 2022).

4.3. Decomposition of affluence

In an attempt to provide a differentiated view of affluence's impacts on the environment, we decompose affluence into three parts: taxable income per taxpayer (instead of the more common GDP per capita), car ownership (private passenger cars per capita) and the number of single-family houses per capita.

Because of rising profit shares in most OECD countries, in recent years, real GDP generally increased at a much faster pace than real household income did. However, the related literature indicates that household income, rather than GDP, is the basis of material wealth for most people and determines consumption patterns (Alda et al., 2004; Ribarsky et al., 2016). Therefore, we use taxable income per taxpayer instead of GDP per capita as a first measure of affluence.[28]

Second, affluence can also be measured by the level of personal car ownership in a region. This is because of the related cost of acquisition and maintenance (Galobardes et al., 2006; Lansley, 2016). Even though some recent findings of increasing rates of ownership among the poor and a carless but affluent young generation in metropolitan areas indicate a decoupling of car ownership and social standing, car ownership still relates strongly to regional income levels in developing nations (e.g., Li et al., 2010 (for Chinese regions); Huang et al., 2012 (for Chinese cities)), as well as highly industrialized nations (e.g., Yeboah et al., 2007 (for England and Wales)).

Finally, the number of single-family houses per capita reflects not only a region's settlement structure and housing situation. Due to higher construction and maintenance costs, a higher per-capita share of single-family houses further relates to a region's level of affluence (Kohler et al., 2017).

Eventually, decomposing affluence into car ownership, share of single-family houses and taxable income per taxpayer allows for a more differentiated analysis of environmental impacts. As the rate of car ownership substantially increases traffic density, it can be seen a key driver of local air pollutants (Mayerthaler et al., 2017). Given the unbroken increase in private car ownership in Germany, we propose that this aspect of affluence substantially contributes to the production of NO_x emissions. Considering single-family houses, buildings characteristic (e.g., living space per person or smart home devices) as well as the occupants' behavioral patterns (e.g., usage of home office, home entertainment systems or private spa areas) can increase the per-capita energy consumption of single-family houses over that of other residential buildings (Yohanis, 2008). Therefore, the share of single-family houses per capita can be expected to correlate positively with local NO_x emissions. In contrast to the impacts of car-ownership and the share of single-family houses, the impact of income seems not clear. On the one hand

[28] However, to allow a better comparison with other studies, we also run the model with GDP per capita (see section 4.4.3.).

empirical findings of most STIRPAT studies indicate that increasing income positively correlates with emissions. On the other hand, following the main EKC hypothesis, increasing income could come along with higher willingness to pay for environmental protection (see section 4.2.). This particularly holds for local pollution, where environmental spending transfers into noticeable improvements of the situation. Following this line of thought, we assume that taxable income relates negatively to the development of air pollutants such as NO_x emissions (if we control for the emission-intensive activities of affluence, such as car ownership and housing situation).

4.4. Theoretical model and empirical application

4.4.1. STIRPAT model

The STIRPAT approach was developed from the IPAT identity, which states that environmental impacts (I) are the multiplicative products of population (P), affluence (A) and technology (T) (Commoner et al., 1971; Ehrlich and Holdren, 1971). That is,

$$I = P \cdot A \cdot T. \tag{1}$$

While its clarity and simplicity add to the popularity of the IPAT approach, the pure identity undermines hypothesis testing and causal interpretation (e.g., York et al., 2003). Therefore, Dietz and Rosa (1994) suggest transferring the IPAT equation into the STIRPAT model, which explains stochastic impacts on the environment by regression on population, affluence and technology and provides the framework for empirical analysis:

$$I_{i,t} = c_t \cdot P_{i,t}^{\alpha} \cdot A_{i,t}^{\beta} \cdot T_{i,t}^{\gamma} \cdot e_{i,t}, \tag{2}$$

where $I_{i,t}$ is the environmental impact of country i at time t, $P_{i,t}$ is population, $A_{i,t}$ is affluence, $T_{i,t}$ is technology, c_t is the constant and $e_{i,t}$ is the residual error term. α, β and γ are the economic outcome elasticities with respect to population, affluence, and technology, respectively.

After taking the logarithm, the model is set up according equation (3):

$$\ln I_{i,t} = \ln c_t + \alpha \cdot \ln P_{i,t} + \beta \cdot \ln A_{i,t} + \gamma \cdot \ln T_{i,t} + \ln e_{i,t}. \tag{3}$$

The logarithmic form of the STIRPAT equation provides a tractable regression equation and dampens the potential for a skewed distribution of the variables (Jorgenson and Clark, 2010).

In decomposing affluence into the three dimensions, we estimate equation (3) by regressing NO_x emissions on population, taxable income per taxpayer, car ownership and share of single-family houses per capita. Given the significant role of industrial emissions, we control for the share of industrial manufacturing and assume a positive impact. Finally, and in line with most regional studies, the model includes urban density, as we assume the well-established negative relationship between urban density and CO_2 emissions (Kenworthy and Laube, 1999; Lankao et al., 2009; Karathodorou et al., 2010; Travisi et al., 2010; Liddle, 2013b) because of urban areas' more efficient energy use by the housing sector and more favorable conditions for public and non-motorized individual transport.[29]

4.4.2. Data

We use a balanced cross-regional panel dataset (1990-2020) of 367 German districts and autonomous cities for the empirical application (NUTS 3).

The German Environment Agency (Umweltbundesamt, 2021) provides data on regional emissions in the form of total NO_x emissions measured in kilotons. Although (local) concentrations of nitrogen oxides have generally declined over time, they still exceed policy targets and have been associated with serious impacts on health (e.g., asthma, hypertension, diabetes mellitus) in both rural districts and autonomous cities (Schneider et al., 2018). The data are available for a five-year interval.

Statistics from the Statistical Offices of the Federation and Lands (Statistische Ämter des Bundes und der Länder, 2021) identify increasing income per taxpayer (measured in €) for the 1990-2020 period we considered, albeit with regional differences. Population, which largely varies with the regions' sizes and urbanization levels, is generally increasing

[29] Aside from STIRPAT modelling, some studies control for climate functions and meteorological conditions that could, favorably or not, affect NO_x concentrations. For example, the findings of a recent study by the Leipniz Institute for Tropospheric Research (van Pinxteren et al., 2020) indicate that wind speed relates negatively and significantly to NO_x concentrations, so wind-protected regions in "bowl" or "basin" locations have higher concentrations. Empirical findings on other meteorological factors (e.g. temperature, precipitation and solar radiation) are not yet conclusive, although these factors seem to have small or no impacts. These conditional factors remain largely unconsidered in STIRPAT models, which have a clear focus on anthropogenic drivers.

in the cities but stagnating or even shrinking in rural districts (Statistisches Landesamt Baden-Württemberg, 2021).

Data from the Federal Motor Vehicle Office (Kraftfahrt-Bundesamt, 2022), shows that the average rate of private car ownership in Germany continuously increased from an already high level of just below 500 cars per 1,000 inhabitants in 1990 to more than 550 cars per 1000 inhabitants in 2020 (+14 percent) with no future breaks in the trend likely. Although the national trend is driven by rural districts, where the average rate of car ownership increased by more than 25 percent between 1990 and 2020, from 491 to more than 618 cars per 1000 inhabitants, car ownership is also increasing in most German cities.

The number of single-family houses per capita has increased over time and averaged 18 per 1000 residences in 2020 (Statistische Ämter des Bundes und der Länder, 2021).

Urban density can be defined in various ways in STIRPAT analyses (Dovey and Pafka, 2014). We follow the most common measure, inhabitants per km^2. Of course, average urban density (279 inhabitants per km^2) is much higher and increases faster in the cities than it does in other districts. However, these dynamics vary widely across regions. For example, districts that surround major cities have similar or even more dynamic trends than cities themselves, probably because of lower land prices, less congestion, and more possibilities for expansion (Statistisches Bundesamt, 2021).

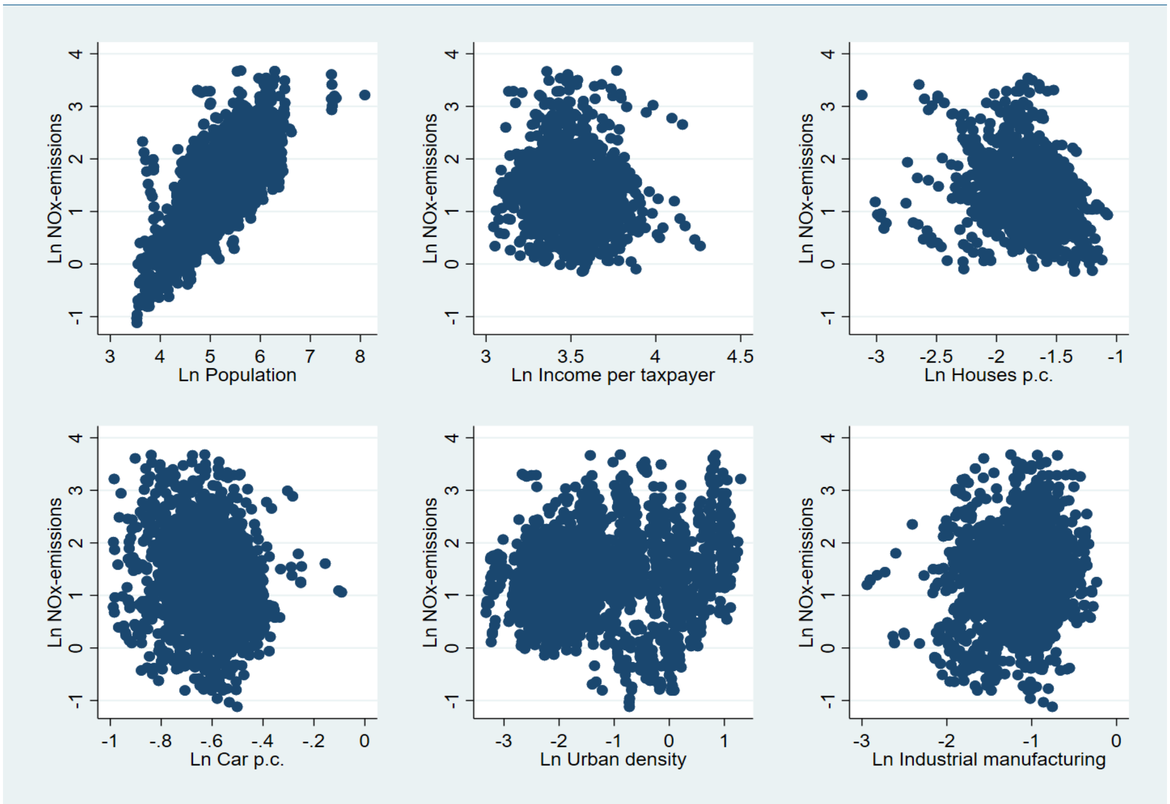
The State Office for Statistics Baden-Württemberg (Statistisches Landesamt Baden-Württemberg, 2021) reports that industrial manufacturing was 34 percent of GDP in 2020. The share of industrial manufacturing is a measure of the industrial structure of an economy (Cole and Neumayer, 2004).

Table 1 summarizes definitions, means, standard deviations, minima, maxima, skewness and kurtosis of the variables used in the study. The scatterplots in figure (2) indicate the correlations between NO_x emissions and the main explanatory variables.

Table 1: Definitions and statistical descriptions of the study's main variables

Variables	Definition	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
NO_x emissions	kilotons	5.13	4.69	0.33	39.66	3.06	15.93
Population	thousand	198.53	223.88	34.14	3629.16	9.59	128.93
Income per taxpayer	Income (€)/taxpayer	32803.55	6587.33	17172.94	70936.16	0.93	5.55
Car ownership	Cars/capita	0.55	0.07	0.21	1.14	0.45	9.29
Houses per capita	Houses/capita	0.18	0.05	0.04	0.34	0.03	3.26
Industrial manufacturing	% of GDP	34.13	11.08	5.29	79.09	0.38	3.52
Urban density	inhabitants/km^2	279.43	646.47	35.95	4072.58	2.35	8.52

Figure 2: Scatterplots of NO_x emissions and the main explanatory variables



4.4.3. Model application

Application of the model starts with unit root tests to determine the (non-)stationarity of variables, so we applied the Im-Pesaran-Shin (IPS) test (with the null hypothesis that panels are *not* stationary). The results show that the variables' levels (order of differences: 0) are stationary, allowing the null hypothesis to be rejected at the 0.01 significance level for all variables (table 2).

Table 2: Panel Unit Root Test

IPS-test Order of differences: 0 *H_0: Panels contain unit roots*							
	NO_x emissions	Population	Income per taxpayer	Car ownership	Houses per capita	Industrial manu-facturing	Urban density
Z-t-tilde-bar-statistic	-38.77***	-33.56***	-17.70***	-30.12***	-18.27***	-33.07***	-31.47***

***p<0.01; IPS test: The Im-Pesaran-Shin-test assumes panel-specific AR parameters, Akaike Information Criterion is minimized; all variables are logarithmized.

We also tested the variables for panel cointegration. When variables are not cointegrated, the long-term relationship is only weakly defined and the short-term relationship can be calculated by estimating a first-differences equation. However, when variables are cointegrated, estimating first differences would ignore a potential long-term relationship of the key variables, so an error-correction model should be applied to account for these dynamics (Engle and Granger, 1987; Liddle, 2011).

Table 3: Results of the Kao- and Pedroni Cointegration Tests

Kao-test *H_0: No cointegration*		**Pedroni-test** *H_0: No cointegration*	
NO_x emissions, population, income per taxpayer, car ownership, houses per capita, industrial manufacturing, urban density (all variables logged)			
Modified Dickey-Fuller t	-19.58***	Modified Phillips-Perron t	-19.39***
Dickey-Fuller t	-12.61***	Phillips-Perron t	-18.70***
Augmented Dickey-Fuller t	-7.14***	Augmented Dickey-Fuller t	-12.39***

***p<0.01; The Kao test assumes a constant cointegration vector, and the Pedroni-test assumes panel-specific AR parameters. Cross-sectional averages are substracted.

We applied the Kao and the Pedroni tests to check for cointegration (table 3). All test statistics clearly reject the null hypothesis, which assumes no cointegration. Thus, strong evidence suggests a long-run cointegrating relationship among the variables, and we proceed by estimating long-run impacts using an error-correction model.

Consequently, the fully modified ordinary least squares (FMOLS) estimator is used in order to estimate long-run elasticities. The FMOLS estimator can be applied to cointegrated panel data, and it addresses the cross-correlation between the cointegration equation error and the regressor innovations. The FMOLS estimator also accounts for any remaining non-stationarity issues and provides consistent estimates in small samples (Pedroni, 2001b; Chakraborty and Gosh, 2011). All variables are mean-centered to mitigate potential structural multicollinearity problems and to get stable estimates (Raudenbush, 1989; Cohen et al. 2002; Bell and Jones, 2015). The model is set up as in equation (3).

Table 4 presents the regression results with NO_x emissions as the dependent variable. In the first model setup, only population, taxable income per taxpayer and car ownership are estimated. Then, single-family houses per capita, industrial manufacturing and urban density are stepwise included. In addition, the model is estimated with GDP per capita instead of income per taxpayer.

In line with most STIRPAT analyses, population size positively and significantly affects NO_x emissions, a result that holds for all variations of estimation. For example, NO_x emissions rise by 0.90 percent when population rises by 1 percent.

The role of affluence is less conclusive. While private car ownership and the number of single-family houses per capita clearly translate into higher NO_x emissions for all estimations, the coefficients for taxable income per taxpayer are negative and significant in all cases. At first glance, the environmental impact of car ownership seems much greater than the impact of single-family houses per capita, but first estimations of standardized coefficients indicate no significantly different impacts of these variables (not shown). The results for population, private car ownership and single-family houses per capita also hold if we replace taxable income per taxpayer with the more common measure of GDP per capita. However, the coefficients on GDP per capita are insignificant in two of three cases.

The coefficient for industrial manufacturing is positive but not significant. With regard to urban density, the coefficient behaves as expected in indicating a negative impact on emissions. However, the coefficient is only strongly significant when GDP per capita is used instead of income per taxpayer.

Table 4: Determinants of NO_x emissions

Ln NO_x emissions	(1)	(2)	(3)	(4)	(5)	(6)
Ln Population	0.90*** (0.05)	0.96*** (0.04)	1.02*** (0.06)	0.91*** (0.03)	0.95*** (0.03)	1.02*** (0.06)
Ln Income per taxpayer (columns (1)-(3))	-0.57*** (0.19)	-0.41** (0.17)	-0.49** (0.22)			
Ln GDP per capita (columns (4)-(6))				-0.15*** (0.20)	-0.01 (0.22)	0.01 (0.11)
Ln Cars ownership	0.77*** (0.25)	0.52** (0.23)	1.07*** (0.23)	0.98*** (0.06)	0.59* (0.08)	0.69* (0.37)
Ln Houses per capita		0.32*** (0.09)	0.24** (0.12)		0.39*** (0.06)	0.28** (0.13)
Ln Industrial Manufacturing			0.08 (0.08)			0.11 (0.08)
Ln Urban density			-0.04 (0.06)			-0.09* (0.05)
Constant	0.072*** (0.08)	0.37*** (0.06)	0.36*** (0.07)	0.72*** (0.06)	0.41*** (0.07)	0.36*** (0.08)
R^2	0.60	0.61	0.61	0.55	0.60	0.60
Number of districts	367	367	367	367	367	367
Number of observations	1315	1176	1167	2240	1168	1168

***p<0.01, **p<0.05, *p<0.1. Robust standard errors are in parentheses. Year fixed effects are included. Variables are mean-centered before estimation, and estimations are based on the FMOLS technique. The varying number of observations is due to a lack of data for some variables.

Next, we evaluate the quality of the data and results using postestimation statistics and variations of estimations. First, we control for multicollinearity, so we calculate the independent variables' variance inflation factors (VIFs). The VIF indicates how much of the variance in the estimated regression coefficient would be inflated if the independent variables are correlated. The calculated values are clearly below 10 (maximum of 3.69), indicating that multicollinearity is unlikely to be a problem (Shrestha, 2020; table 5).

Table 5: Postestimation Statistics

	Results based on regression model Table 4 Column (3)	Results based on regression model Table 4 Column (6)
	VIF	
Ln Population	1.98	1.98
Ln Income per taxpayer	3.17	
Ln GDP per capita		1.91
Ln Car ownership	3.07	2.67
Ln Houses per capita	2.16	2.22
Ln Industrial manufacturing	1.13	1.10
Ln Urban density	3.69	3.20
	Model Specification (link test)	
Prediction squared	-0.01 (not significant)	0.01 (not significant)

Second, we test whether the regression equation is mis-specified because of missing variables or the assumption of the functional form. We perform a link test by regressing the independent variable to its prediction and its prediction squared. The results show that the null hypothesis, according to which there is no specification error cannot be rejected—that is, the prediction squared has no explanatory power (table 5)—so there is no evidence of misspecification in the model (Alho and Silva, 2014; StataCorp., 2017).[30]

Finally, we estimated the model for other time periods (e.g., 1995-2015 and 2000-2020; not shown). The results remain qualitatively and quantitatively similar, confirming the robustness of the coefficients.

4.5. Discussion of results

Our findings show that the development of NO_x emissions is clearly related to population, car ownership, the housing situation, income per taxpayer, and urban density in German districts and autonomous cities. While private car ownership, the number of single-family houses per capita and population positively affect NO_x emissions, taxable income per taxpayer and urban density have negative effects. Moreover, the significant results for the

[30] Similarly, we test for potential non-linear relationships between NO_x emissions and income per taxpayer and between NO_x emissions and population. Overall, we did not find evidence for the inclusion of squared terms, as only when population, population squared and income are used as explanatory variables does a significant negative impact of population squared appear (not shown). This result might be due to our use of disaggregated variables for affluence and control variables' (for technology) catching-up potential non-linearities (Cole and Neumayer, 2004). Further, the necessary threshold level for EKC is likely to be out of the sample range used here.

decomposed dimensions of affluence reveal a varying role of affluence in environmental degradation.

The positive impact of car ownership on NO_x emissions reflects an increase in motorized passenger transport in almost all counties and cities. Given the high share of cars with traditional combustion engines, which is particularly pronounced in rural districts but is also observed in most of the cities, individual motorized transport will remain a driver in local pollution in the near future. However, the emergence of e-mobility could change the game in the medium and long runs. In that case, even if private car ownership continues to increase, local emissions related to the internal combustion of fossil fuels may lose importance while other emissions (e.g., tire abrasion, brake dust) continue. For the moment, however, electric cars still account for less than 10 percent of new passenger-car registrations.

The positive environmental impact of the housing situation is likely to relate to the comparatively high energy use per capita in single-family houses, particularly because of over-average heating consumption, which is still powered primarily by fossil fuels. However, other household-related consumption of electricity in smart homes, digital devices, and household appliances also contribute.

The negative correlation between taxable income per taxpayer and local NO_x emissions (when controlling for car ownership and the housing situation) could be explained by the higher educational attainment and the willingness to pay for an intact environment by those with higher income. Therefore, contrary to the common findings of the STIRPAT literature (which usually uses only GDP per capita to measure affluence), our results indicate a varying role of affluence on local emissions. This result may be due to the three dimensions of affluence capturing different aspects of wealth. While private car ownership and single-family houses could reflect the material- and energy-intensive part of affluence, taxable income per taxpayer covers (if we control for car ownership and the housing situation) expenditures for material (e.g., food, consumables) as well as types of consumption more common among the financially affluent (e.g., services, cultural activities).

The divergent impacts of the dimensions of affluence on emissions are in line with a limited number of STIRPAT studies that investigate affluence in a differentiated way (see section 4.2.). So, Montero, et al. (2021) find a negative impact of gross disposable income and a positive impact of electric power consumption and sectoral value added on emissions (all of which indicate affluence) by analysing the municipalities of Madrid. Further, Arshed et al. (2021) show a U-shaped EKC for 80 countries when affluence is disaggregated into the sectorial shares of GDP (i.e., the industrial, agricultural and services sectors). In contrast, Kilbourne and Thyroff (2020) find no qualitative differences in the environmental impacts of components of affluence like consumer spending and consumption of material goods in 113 countries.

In line with the classic STIRPAT analysis, our regional findings confirm the important role of population with respect to local NO_x emissions. In the STIRPAT literature this effect is explained by the (high) level of energy consumption related to human activities.

Further, our findings confirm the negative correlation between urban density and local pollution (NO_x emissions) that most empirical studies in this field find. More densely populated regions are likely to allow for more competitive public transportation and, because of shorter distances between probable destinations, more non-motorized individual transport.

Largely because of a lack of data at the district level, our analysis does not address some explanatory variables. While public transport structures and related activities might be captured, at least in part, by urban density (even though the quality of services differs among regions with similar density), weather conditions remain unconsidered. For example, the wind conditions mentioned above can have a significant impact on the concentration of local emissions (van Pinxteren et al., 2020).

Overall, the results presented here are robust to variations in the estimations used and confirm the appropriateness of the STIRPAT approach for estimating impacts on the local environment in small-structured regional settings (i.e., NUTS 3).

4.6. Concluding remarks

The paper presents a region-based STIRPAT analysis that investigates anthropogeneous impacts on local air pollutants (NO_x emissions). Unlike most other regional studies, the analysis is not limited to a few cities but covers almost all German districts between 1990 and 2020. The paper decomposes affluence (one of the driving forces often identified) into three dimensions. Private car ownership, single-family houses per capita and taxable income per taxpayer facilitates a more differentiated consideration of affluence and its environmental impacts.

Because of existing cointegration dynamics between variables, our findings are based on long-run estimation techniques and largely confirm the findings of related empirical studies (e.g., on the role of population and urban density). However, they also provide new evidence of major driving forces of NO_x emissions from a regional perspective. In particular, we find a varying effect of three dimensions of affluence on NO_x emissions, as private car ownership and single-family houses per capita can be considered drivers of local pollutants, but such is not the case for taxable income per taxpayer or GDP per capita (if the income variable is controlled for the other two dimensions of affluence).

Although our results are not generalizable outside their underlying regional sample, the analysis highlights the crucial roles of private car ownership and settlement structures in decisions regarding policies for fighting local air pollution and leads to three conclusions:

- Urban policies should further strengthen integrated mobility concepts with high shares of intermodal transport, easily accessible car-sharing services, and so on. Mobility patterns can be highly persistent and, because of socio-demographic or topographic conditions, highly dependent on private cars, particularly for rural regions but also for smaller cities. Therefore, the call for better public services and more bike lanes could fall short of the mark, so they should be complemented with policies that support the transition to low-emission car technology.
- Policies should further support low-emission infrastructure (e.g., local and district heating networks) to mitigate its environmental impacts that are due to existing housing conditions and related consumption patterns. In addition, incentives should be established that favor investment into modern heating and self-sufficiency systems (e.g., insulation, photovoltaic installations, energy efficient appliances).
- Considering a more general aspect of STIRPAT modelling, our findings encourage a differentiated view of the role of affluence (or economic growth) in environmental degradation. While some dimensions of affluence can be considered drivers of emissions (e.g., private car ownership and single-family houses), other dimensions of affluence might work in the other direction (e.g., taxable income). Hence, future research is needed to understand fully the various impacts of affluence on the environment.

Like most empirical studies, the analysis could benefit from additional control variables that facilitate a more in-depth analysis of anthropogenic drivers of environment degradation. For example, detailed information on local freight transportation, which can be considered an important source of NO_x emissions, could be of value, as could knowing more about the age structure of single-family houses or the fuels used for heating. However, data, particularly time-series data, at the regional level is limited. Future analyses could focus on specific regions with better data availability (e.g., cities) to examine these factors. With regard to the rapid shift to electric cars and the mandatory installation of photovoltaic systems on new houses (at least in some regions), adopting a one-year interval and predicting future trends could be useful.

5. Drivers of local air pollution – a regional STIRPAT analysis for Germany[31]

5.1. Introduction

There is broad consensus that anthropogenic activities have substantially altered the environment. One important driving factor is transportation. In Germany, for example, the transport sector accounts for about 20 percent of total greenhouse gas (GHG) emissions and even higher shares for selected air pollutants (e.g., 40 percent of total NO_x) (Umweltbundesamt, 2022).

Though generally declining in absolute terms, reduction of transport-related emissions cannot always keep pace with the development in other sectors and more ambitious climate and environmental policy goals. This particularly holds for transport related CO_2 emissions that decreased by no more than 10 percent compared to the early 1990ies.[32] But it is also true for major air pollutants such as particulate matter ($PM_{2.5}$) and nitrogen oxide (NO_x), which until today regularly exceed existing threshold values, at least at regional level. Hence, the transportation sector has moved into the focus of environmental and climate policy, often by calling for technological improvements (e.g., alternative fuels and drive technologies). While there is no doubt that successful climate or environmental policy cannot succeed without new technologies and alternative fuels, transport-related emissions also depend on structural characteristics and regional context of transport activities and systems.

One way to analyze the relationship between technological progress, structural factors and emissions is the application of the well-known IPAT/STIRPAT model. Though normally applied to analyze environmental impacts (I) driven by population (P), affluence (A) and technology (T) in general, the IPAT/STIRPAT framework is increasingly and successfully being used to identify impacts on the environment caused by transport activities and the nature of transport systems (Timilsina and Shrestha, 2009; Liddle, 2013a; Fan and Lei, 2016; Andrés and Padilla, 2018). Following this research stream and in line with some recent series of city- and region-based STIRPAT analysis (Lankao et al., 2009; Liddle, 2013a; Zhang and Nian, 2013; Montero et al., 2021) the presented study adopts a regional STIRPAT model to assess evolution of NO_x emissions by regional

[31] The contribution is based on joint work together with Axel Schaffer (Bundeswehr University Munich) and Thomas Bolognesi (Grenoble School of Management).
[32] This is by far below the reduction of CO_2 emissions in the energy sector that decreased by more than 50 percent in the same period.

population, GDP per capita, level of motorization (i.e. car ownership) and structural factors (urban density as well as share of industrial manufacturing) for 367 German (rural) districts and autonomous cities between 1990 and 2020.[33] This procedure does not only allow for an analysis of the cities but also the rural districts. Not surprisingly, results confirm the positive relationship between NO_x emissions and key drivers (population, car ownership and share of industrial manufacturing) for urban and rural counties. Additionally, predictive margins analysis indicates that impacts of population increases with its level (i.e. percentiles). This is in contrast to urban density, where findings show the well-established negative relationship with environmental impacts mainly for rural but not for urban districts. Similarly, the findings reveal a negative relationship between local pollution and per capita income only for rural counties.

The remainder of the paper is organized as follows. Section 5.2. presents the relationship between urban structures and environmental development and briefly reviews the main findings of transport-related and region-based STIRPAT analysis in this context so far. Section 5.3. presents the model specification and describes the data. Sections 5.4. and 5.5. continue with the empirical application and the discussion of the results. Finally, the paper closes with concluding remarks and brief policy implications in section 5.6..

5.2. Literature review

5.2.1. Sustainable development at urban level

Urbanization is a primary driver of biodiversity loss and carbon emissions (Rees and Wackernagel, 2008; Seto et al., 2012). Cities source about three-quarter of global GHG emissions (IPCC, 2014). According to Moran et al. (2018), urban areas host 60 percent of the world population and produce 68 percent of the global carbon footprint, and the 100 biggest cities emit 18 percent of global GHG emissions. Air pollution is, to a large extent, an urban development question—the same holds for many environmental and sustainability topics. Urban areas concentrate people, human activity, and population in limited geographic regions. It leads to exceeding environment carrying capacity and increases the likelihood of irreversible damage. For instance, each Athenian has an ecological footprint of about 5 global hectares, i.e., the surface of nature necessary to support its lifestyle (Baabou et al., 2017). This mismatch between human needs and

[33] In spite of existing regional STIRPAT studies, there is little understanding whether STIRPAT models capture the human-economy-environment relationship at county and city level (Schneider, 2022).

environment capacity stresses development – competition for resources – and the environment -resource viability. Thus, the urban level is a relevant scale to study sustainability and development patterns.

Besides global assessments, inquiries on specific relations between urban development and the environment have been carried out. Urban forms and urban growth are intertwined, and the environment should play a role in or be affected by this relationship. Globally more difficult climatic conditions (heat and water scarcity) associate with more urbanization (Castells-Quintana et al., 2021). The association reveals non-linearities regarding urban concentration, size, and spatial structure. As a result, deteriorating climate conditions attract people to urban areas that will tend to sprawl and fragment simultaneously. At first glance, urban sprawl should increase air pollution, but the effect is not that straightforward if considering the change in congestion patterns (Nechyba and Walsh, 2004).

Urban forms affect GHG emissions heterogeneously across the globe (Peri and Robert-Nicoud, 2021). Studying 50 Japanese cities, Makido et al. (2012) found that residential-related CO_2 emissions per capita are negatively correlated with low fragmentation and regular urban forms and positively with densest and monocentric forms. They argue a non-linear pattern, especially when considering the transport sector. Density contributes to reducing per capita CO_2 emissions, but there is a turning-point from which more density leads to more CO_2 emissions. Mono-centricity is an aggravating condition. Lee and Lee (2014) investigate a similar relation by applying SEM (structural equation modelling) framework to the 125 largest urban areas in the US. They estimate doubling density in those places reduces households' CO_2 emissions by 48 percent regarding travel and 35 percent regarding residential energy consumption. The mediating effect of mono-centricity/fragmented urban structure reveals moderate. In Italy, similar null results hold, and urban sprawl comes with more CO_2 emissions (Burgalassi and Luzzati, 2015).

Next to GHG emissions, air pollution is of serious concern for health and economic activity. It reduces work productivity, even in service sectors that are less physically intense (Chang et al., 2019). This effect could be long-standing. Historical data on British industrial development proved that coal-induced air pollution lessened city employment and the working population in the long run (Hanlon, 2020). Cities growth improves overall population health but comes with air pollution as a countervailing force

(Ebenstein et al., 2015; Hanlon and Tian, 2015). Thereby, road vehicles are one of the major sources of air pollution in cities (Kumar et al., 2013; see next section).

Generally, environmental changes affect socio-economic outcomes. For example, the degree of land artificialization exacerbates cities' vulnerability while a high degree of economic development attenuates it (Bolognesi, 2015). The complex and heterogeneous relations between urban development and environmental conditions motivate the study of sustainability at the urban level, where both causes and consequences of unsustainable trajectories come with acute topicality (Truffer and Coenen, 2012; Brelsford et al., 2017; Peri and Robert-Nicoud, 2021). To tackle the challenge, modeling urban development as a social-ecological process is being developed (Cooper and Dearing, 2019). New types of indicators emerge to ease future empirical investigation and current decision-making. For instance, the Doughnut economics approach is being downscaled to the city level (Fanning et al., 2020), and so is the planetary boundaries framework (Hoornweg et al., 2016). Composite metrics that include social concerns enable the necessary rethinking of what is well-being at the urban level (Floridi et al., 2011; Le Roy and Ottaviani, 2022).

5.2.2. Transport-related and region-based STIRPAT analysis

Germany, like any other member State of the EU, is legally bound to reduce air pollution and meet tightened thresholds set by the National Emission Ceilings Directive (NEC Directive) for sulphur dioxide (SO_2), non-methane volatile organic compounds (NMVOCs), ammonia (NH_3) and nitrogen oxides (NO_x). While the 2020 and even 2030 targets have already been achieved for SO_2 and NMVOCs, additional efforts are necessary to meet national ceilings for NH_3 and NO_x.[34] While ammonia largely relates to farming activities, NO_x is mainly driven by transport-related emissions, which account for about 43 percent of the total. Transport-related emissions weigh twice those of the second leading contributor, the energy sector with no more than 21 percent.

Therefore, research interest for accounting transport-based NO_x emissions and investigating potential driving factors to ultimately evaluate the effectiveness of regulative measures (e.g., a reduction in the number of lanes or inner-city driving bans for older diesel vehicles) raises. Methodological tools are manifold and include, among others, bottom-up sector based analysis (e.g., Selvakkumaran and Limmeechokchai,

[34] Considering NO_x almost all EU member states must substantially reduce emissions to meet the 2030 target (EEA, 2020).

2015), integrated assessment and optimization models (e.g., Wang et al., 2015) or econometric analysis (e.g., Montero et al., 2021).

Belonging to the group of the latter, transport-related STIRPAT analysis often compare international trends and make use of country-specific panel data to identify anthropogenic factors of transport-related environmental impacts. Findings generally confirm the crucial role of a growing population and increasing affluence that trigger traffic density and related environmental impacts in passenger and freight transport (e.g., Scholl et al. (1996) for OECD countries, Timilsina and Shrestha (2009) for Asian countries, Andrés and Padilla (2017) for the EU). Besides, many studies find that emissions per passenger and tonkilometer are increasing, probably due to modal shifts towards more fossil energy-intensive modes (e.g., Scholl et al. (1996) for OECD countries, Lakshmanan and Han (1997) and Steenhof et al. (2006) for Northern America). In this context, some analyses highlight the importance of a growing road freight transport volume (Regmi and Hanaoka, 2015; Andrés and Padilla, 2017). Many authors, however, found a steady increase in private vehicle stock (Solis and Steinbaum, 2013; Xu and Lin, 2016).

Apart from population, affluence and transport-related factors, most studies further control for urban density and economic structures. Since average national levels of urbanization could be misleading, regional or city-based data gets preferred to gain in accuracy (e.g., Kenworthy and Laube, 1999; Lankao et al., 2009; Lankao et al., 2009; Karathodorou et al., 2010; Liddle and Lung, 2010; Travisi et al., 2010; Xu and Lin, 2016; Ge et al., 2018; Lv et al., 2019; Montero et al., 2021). Interestingly, empirical results indicate opposing effects for passenger and freight transport. The negative relationship between urban density and emissions related to passenger transit is now well-established (Kenworthy and Laube, 1999; Lankao et al., 2009; Karathodorou et al., 2010; Travisi et al., 2010; Liddle, 2013a). The primary drivers of the relationship are the shorter trip length and the more favorable conditions for public and non-motorized individual transport in urban areas permitted by higher density. In contrast, probably due to frequent deliveries to supermarkets and the retail trade sector, impacts from road freight transport seem to increase with the level of density (Lv et al., 2019). Furthermore, emissions also depend on the regions' economic structure, in particular on sectoral composition. This is due to

production-related emissions (in particular for energy supply and industrial production) and transport-related emissions (e.g., due to the generation of commuter traffic).[35]
Finally, the relationship of economic activities and environmental outcomes (like GHG or air pollutants) are often analyzed using the environmental Kuznets curve (EKC) in order to measure potential non-linear environmental impacts. The EKC thesis states that emissions initially increase with economic growth, whereas further economic expansion leads to a decline in emissions (Schneider, 2022). More recently, some studies also incorporate the EKC effect into STIRPAT applications by adding non-linear terms (e.g., Ge et al., 2018; Arshed et al., 2021).

5.3. Empirical design

5.3.1. Model specification

Ehrlich and Holdren (1971) propose a conceptual framework for calculating environmental impacts of human development. This IPAT approach presumes that environmental impacts (I) are the multiplicative product of population (P), affluence (A) and technology (T) (Commoner et al., 1971; Ehrlich and Holdren, 1971) and can be written as follows:

$$I = P \cdot A \cdot T. \tag{1}$$

While clarity and simplicity certainly add to the popularity of the IPAT approach, the pure identity undermines hypothesis testing and causal interpretation (e.g., York et al., 2003). This is why Dietz and Rosa (1994) suggest to transfer the IPAT equation into the so-called STIRPAT model that explains STochastic Impacts on the environment by Regression on Population, Affluence and Technology and provides the framework for empirical analysis:

[35] Largely aside from STIRPAT modelling, some studies control for climate functions and meteorological conditions that could – favorably or not – affect NO_x concentrations. Findings of a recent study by the Leipniz Institute for Tropospheric Research indicate, for example, that wind speed relates negatively and significantly to NO_x concentrations (van Pinxteren et al., 2020). This means NO_x concentration generally decrease with higher wind speed. In contrast, wind protected regions in "bowl" or "basin" locations seem to be affected the most by high concentrations. Empirical findings on other meteorological factors, e.g., temperature, precipitation and solar radiation, are less conclusive so far and seem to have (if at all) only small impacts. These conditional factors remain largely unconsidered in STIRPAT models. which have a clear focus on anthropogenic drivers. In addition, most STIRPAT models explain differences (rather than levels) of environmental impacts. Weather conditions are, however, relatively stable, and explain levels rather than differences of environmental impacts.

$$I_{i,t} = c_t \cdot P_{i,t}^{\alpha} \cdot A_{i,t}^{\beta} \cdot T_{i,t}^{\gamma} \cdot e_{i,t}, \tag{2}$$

where $I_{i,t}$ is the environmental impact of country i at time t, $P_{i,t}$ is population, $A_{i,t}$ is affluence, $T_{i,t}$ is technology, c_t is the constant and $e_{i,t}$ is the residual error term. α, β and γ are the economic outcome elasticities with respect to population, affluence or technology, respectively. The logarithmic form of the STIRPAT equation gives a tractable regression equation and dampens the skewed distribution of the variables (Jorgenson & Clark, 2010).

So, the model is setup according equation (3)

$$\ln I_{i,t} = \ln c_t + \alpha \cdot \ln P_{i,t} + \beta \cdot \ln A_{i,t} + \gamma \cdot \ln T_{i,t} + \ln e_{i,t}, \tag{3}$$

where technology ($T_{i,t}$) is assumed to be part of the error term, a combination of log-linear factors (like car ownership, urban density and share of industrial manufacturing) and time-fixed effects.

Transport-related STIRPAT analyses generally refer to this model setup but include transport-specific factors that explain GHG emissions or air pollutants.[36] For this purpose, they often use city-based or regional (rather than national) panel data to account for regional characteristics of transport systems, which might indeed drive environmental impacts but cannot be captured by (average) national levels or trends (e.g., Liddle, 2013a).

Following this line of thought, the proposed model identifies impacts of population, per capita income, car ownership, urban density as well as the share of industrial manufacturing on regional NO_x emissions of German districts between 1990 and 2020.

5.3.2. Data description

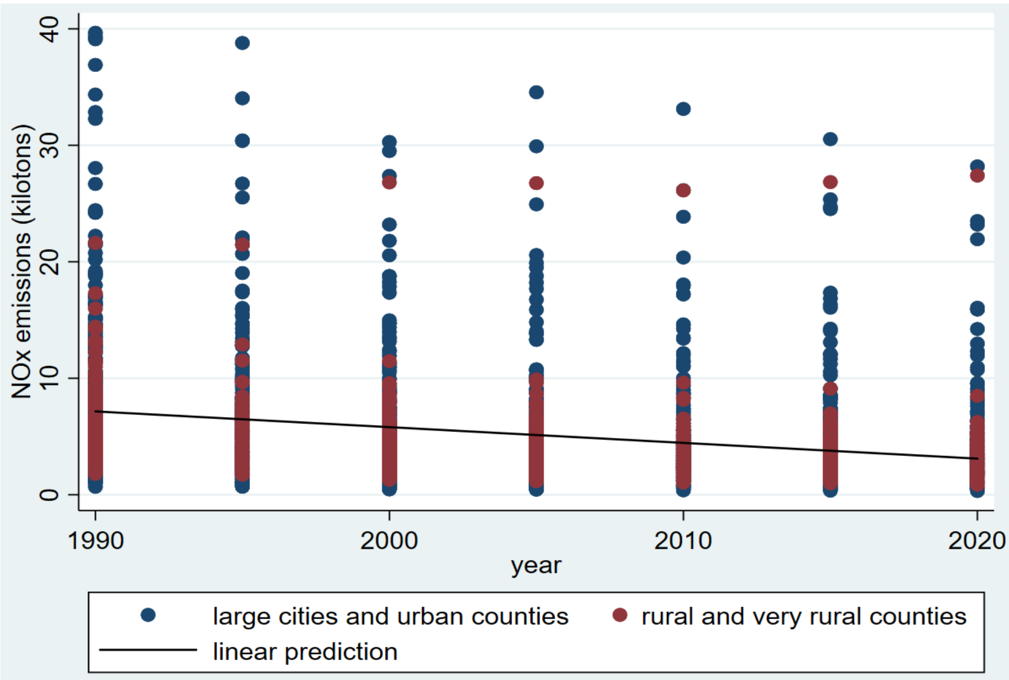
For the empirical application, a balanced cross-regional panel dataset (1990-2020) of 367 German districts and autonomous cities is used (NUTS 3). Additionally, the full sample is divided into two subgroups depending on a districts' settlement structure. The classification is derived from the criteria defined by the Federal Institute for Research on

[36] While some authors explicitly focus on transport-related emissions, others explain total emissions but are interested in the contribution of transport-related drivers. Our study belongs to the latter group.

Building, Urban Affairs and Spatial Development (Federal Institute for Research on Building, Urban Affairs and Spatial Development 2022). There are 229 *large cities and urban counties* (e.g., Dortmund or Munich) if the number of inhabitants per squared kilometers is larger than 150. Similarly, there are 138 *rural and very rural counties* if the number of inhabitants per squared kilometers is smaller than 150 (e.g., Harz or Miesbach).

Regional emissions are given by total NO_x emissions (measured in kilotons) and stem from the German Environment Agency (Umweltbundesamt, 2021). Transport-related NO_x emissions are responsible for the major part (of the change) of total NO_x-emissions regarding the considered time period (see section 5.1.). Though generally declining over time, local concentrations of nitrogen oxides still exceed policy targets and can be associated with serious impacts on health (e.g., asthma, hypertension, diabetes mellitus) in both, rural districts and autonomous cities (Schneider et al., 2018). The data are available for a five-year interval (figure (1)).

Figure 1: Development of NO_x emissions (in kilotons)



Source: Own illustration. Number of observations; 2240.

Official statistics generally identify an increasing GDP per capita (measured in €) for the considered time period with regional disparities (Statistische Ämter des Bundes und der Länder, 2021). Population, which largely varies with the regions' size and urbanization level, is generally increasing in the cities but rather stagnating or even shrinking in rural districts (Statistisches Landesamt Baden-Württemberg, 2021).

The average rate of private car ownership in Germany (used as a proxy for individual motorized transport) has continuously increased from an already high starting level of slightly below 500 cars per 1000 inhabitants in 1990 to more than 550 cars per 1000 inhabitants in 2020 (+14 percent) without any breaks in trends in sight. Though the national trend is certainly driven by a particular dynamic development in rural districts, where the average rate of motorization increased by more than 25 percent (from 491 cars per 1000 inhabitants in 1990 to more than 618 in 2020), car ownership is – maybe more surprising and despite an intensive debate on climate and environmental protection – also increasing in most German cities. The data are taken from the Federal Motor Vehicle Office (Kraftfahrt-Bundesamt, 2022).

While the number of private cars is still increasing, average annual NO_x emissions per private car are declining over time. This is due primarily to a cut of technology-driven specific emissions (NO_x/km) by more than 60 percent from 80 mg/km in 2012 to 28 mg/km in 2020 for new registered cars in Germany (Kraftfahrt-Bundesamt, 2022). This favorable development is attributable to the gradual renewal of the vehicle fleet and more stringent emission standards. In addition, we observe, at least on average, stagnating or even slightly declining annual mileage per car in recent years (from slightly above 14,200 km per car in 2013 to about 13,300 km/car in 2020; Kraftfahrt-Bundesamt, 2022). Both trends can be observed for rural and urban districts, but are more pronounced for the latter.

With regard to the remaining structural variables, urban density is defined as inhabitants per km^2. There are various ways of defining urban density (Dovey and Pafka, 2014). Here, the variable is supposed to reveal effects due to a concentrated public infrastructure such as the shortening of distances and a general increase of mobility. Thereby, average urban density (279 inhabitants per km^2) is much higher and develop faster for the cities compared to the other districts. However, dynamics vary strongly across all types of regions. Districts surrounding major cities, for example, show similar or even more dynamic trends (probably due to lower land prices, less congestion, better expansion possibilities) compared to the cities themselves. The data for the share of industrial manufacturing (34 percent of GDP in 2020) are taken from the State Office for Statistics Baden-Württemberg (Statistisches Landesamt Baden-Württemberg, 2021).

Table 1 summarizes definitions, means, standard deviations, minima, maxima, skewness and kurtosis of the variables used in the study.

Table 1: Definitions and statistical descriptions of the study's main variables

Variables	Definition	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
NO_x emissions	kilotons	5.13	4.69	0.33	39.66	3.06	15.93
Population	thousand	198.53	223.88	34.14	3629.16	9.59	128.93
GDP per capita	GDP (€)/capita	25538.82	13145.27	6822	182301	2.90	19.73
Car ownership	Cars/capita	0.55	0.07	0.21	1.14	0.45	9.29
Industrial manufacturing	% of GDP	34.13	11.08	5.29	79.09	0.38	3.52
Urban density	inhabitants/km^2	279.43	646.47	35.95	4072.58	2.35	8.52

5.4. Results

Model application starts with unit root tests to determine the (non-)stationarity of variables. Therefore, the Im-Pesaran-Shin (IPS) test (with the null hypothesis that panels are *not* stationary) is applied. It turns out that level variables (order of differences: 0) are stationary (i.e. null hypothesis can be rejected at 0.01 significance level) for all variables (table (2)).

In addition, the variables are tested for panel cointegration. In case variables are not cointegrated, the long-term relationship is only weakly defined and the short-term relationship can be calculated by the estimation of a first-differences equation. If, however, variables are cointegrated, the estimation of first-differences would ignore a potential long-term relationship of the key variables and an error correction model should be applied to account for these dynamics (Engle and Granger, 1987; Liddle, 2011).

In order to check for cointegration, the Kao and the Pedroni tests are applied (table (3)). All test statistics clearly reject the null hypothesis assuming no cointegration. Thus, there is strong evidence for a long-run cointegrating relationship among the respective variables, i.e., evolution patterns of the variables are associated.

Table 2: Panel Unit Root Test

IPS-test Order of differences: 0 *H_0: Panels contain unit roots*						
	NO_x	Population	GDP p.c.	Car ownership	Manufacturing	Urban density
Z-t-tilde-bar-statistic	-38.77***	-33.56***	-33.47***	-30.12***	-33.07***	-31.47***

***p<0.01; IPS-test: Im-Pesaran-Shin-test assumes panel-specific AR parameters, Akaike Information Criterion is minimized; all variables are logarithmized.

Table 3: Results of the Kao- and Pedroni Cointegration Tests

Kao-test *H_0: No cointegration*		**Pedroni-test** *H_0: No cointegration*	
NO_x, population, GDP per capita, car ownership, manufacturing, urban density (all variables logged)			
Modified Dickey-Fuller t	-53.77***	Modified Phillips-Perron t	-67.63***
Dickey-Fuller t	-26.97***	Phillips-Perron t	-39.68***
Augmented Dickey-Fuller t	-16.76***	Augmented Dickey-Fuller t	-37.39***

***p<0.01; Kao-test assumes a constant cointegration vector; Pedroni-test assumes panel-specific AR parameters; Cross-sectional averages are substracted.

Consequently, long-run impacts by using an error correction model are estimated. Therefore, the fully modified ordinary least squares (FMOLS) estimator is applied and long-run elasticities are estimated. The FMOLS estimator is applicable for cointegrated panel data and accounts for the heterogeneity that is present in the fixed effects as well as in the short-run dynamics. Further, the estimator addresses the cross-correlation between the cointegration equation error and the regressor innovations, mitigates potential remaining non-stationarity issues and provides consistent estimates in small samples. All in all, this estimator is very accurate in panels with heterogeneous serial correlation dynamics, fixed effects or endogenous regressors (Pedroni, 2001a and b; Chakraborty and Gosh, 2011).

Finally, the model is setup according to equation (3). As mentioned above, the term $T_{i,t}$ for technology is not estimated explicitly and is assumed to be part of control variables and time-fixed effects as well as the error term ($e_{i,t}$). Table (4) presents the results based on estimating equation (3) with NO_x emissions as dependent variable. Column (1) shows the results for the full sample. Columns (2) – (3) show the results for urban (i.e. large cities and urban counties) and rural districts (i.e. rural and very rural counties) respectively.

Population size positively and significantly effects NO_x emissions. This holds for the full sample as well as for the subgroups. For example, NO_x emissions rise by 0.94 percent when population rises by 1 percent (column (1)).

The coefficient for GDP per capita is insignificant in two of three cases. Only in case of rural districts a significant negative impact can be observed (column (3)).

Private car ownership and the share of manufacturing both translate into higher NO_x emissions. This holds for all specifications.

With regard to urban density, coefficients indicate a significant and negative impact. While this holds for the full sample and the rural districts, the coefficient is insignificant for urban districts.

Table 4: Results for all regions and specified areas

Ln NO_x	(1) Full sample	(2) Large cities and urban counties	(3) Rural and very rural counties
Ln Population	0.94*** (0.03)	0.93*** (0.04)	1.11*** (0.04)
Ln GDP p.c.	-0.01 (0.08)	0.04 (0.10)	-0.27*** (0.08)
Ln Car ownership	0.41* (0.22)	0.64** (0.31)	0.64*** (0.25)
Ln Manufacturing	0.17*** (0.06)	0.15* (0.08)	0.31*** (0.05)
Ln Urban density	-0.10 *** (0.03)	-0.04 (0.04)	-0.37*** (0.05)
Constant	-1.79** (0.73)	-2.40** (0.96)	1.65*** (0.85)
R^2	0.57	0.65	0.64
Number of counties	367	229	138
Number of observations	2240	1384	855

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Year fixed-effects are included; Large cities and urban counties: inhabitants per km^2 > 150. Rural and very rural counties: inhabitants per km^2 < 150.

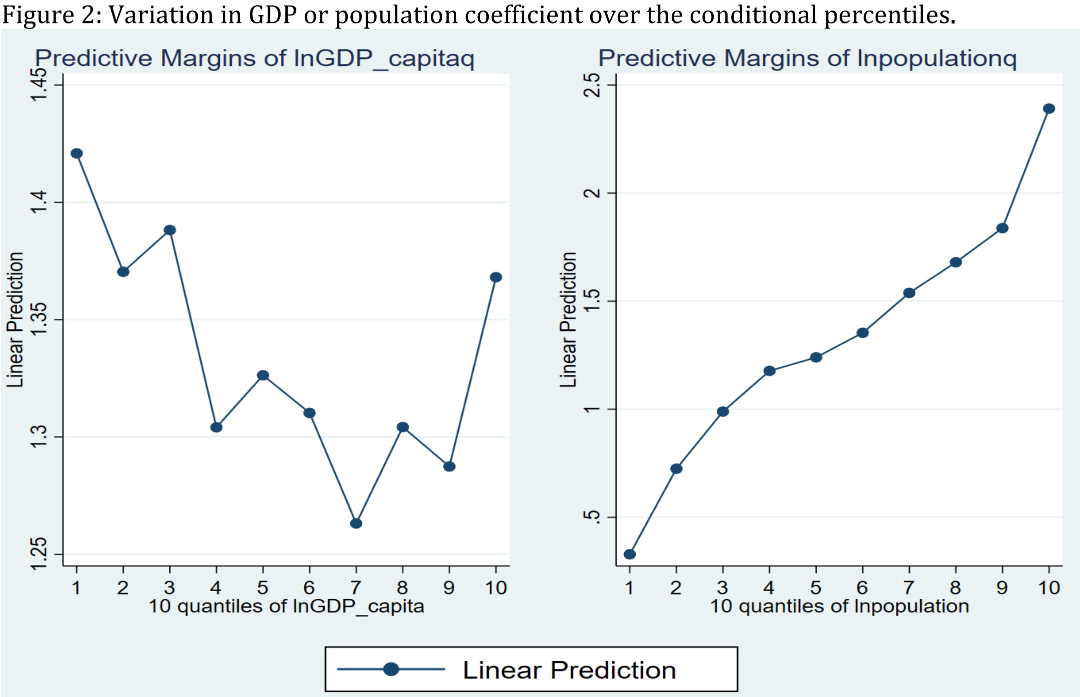
Additionally, we check for potential non-linearities. First, a squared term for GDP per capita is included in equation (3) in order to control for potential EKC dynamics. Results show a U-shaped effect of GDP per capita on NO_x emissions in the case of the full sample (table (5), column (1)). This dynamic cannot be confirmed for the subgroups.

Table 5: Results controlling for EKC

Ln NO_x	(1) Full sample	(2) Large cities and urban counties	(3) Rural and very rural counties
Ln Population	0.96***	0.94***	1.14***
	(0.03)	(0.04)	(0.08)
Ln GDP p.c.	-3.64*	-4.00	3.71
	(1.93)	(2.73)	(4.51)
(Ln GDP p.c.)^2	0.18*	0.19	-0.20
	(0.09)	(0.13)	(0.22)
Ln Car ownership	0.28	0.52*	0.69
	(0.23)	(0.31)	(0.45)
Ln Manufacturing	0.19***	0.18***	0.31***
	(0.06)	(0.08)	(0.10)
Ln Urban density	-0.10 ***	-0.04	-0.41***
	(0.03)	(0.05)	(0.09)
Constant	16.72**	18.71**	18.42***
	(9.97)	(14.23)	(22.61)
R^2	0.01	0.03	0.01
Number of counties	367	229	138
Number of observations	2240	1384	855

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Year fixed-effects are included; Large cities and urban counties: inhabitants per km^2 > 150. Rural and very rural counties: inhabitants per km^2 < 150.

Figure 2: Variation in GDP or population coefficient over the conditional percentiles.



***p<0.01 for all coefficients; Number of observations: 2240.

Moreover, figure (2) presents the predicted margins of GDP per capita and population on NO_x emissions. Specifically, the predicted margins indicate how the predicted elasticities for GDP per capita or population succinctly differ across their percentiles. The predicted margins of GDP per capita are ranging non-monotonically between 1.42 and 1.26. In contrast to, the predicted margins of population increase with the respective percentile. For example, the effect of the 90th-percentile of population is almost 4 times higher compared to the 10th-percentile.

5.5. Discussion of results

In general, the results of this paper show that the development of local pollutants (NO_x emissions) is clearly related to population, GDP per capita, car ownership, industrial manufacturing as well as urban density regarding German districts and autonomous cities in the long-run. In addition, findings show that the environmental impacts of variables partly depend on the underlying settlement structure (e.g., population density) or on the level of the explaining variable. Specifically, results indicate that there exist differences regarding environmental impacts between *large cities and urban counties* and *rural and very rural counties*.

On the one side, car ownership, population and industrial manufacturing show positive effects on NO_x emissions independently of the regions' structure.

The findings confirm the important role of population with respect to NO_x emissions for all estimation models. In line with existing studies, this driving effect may be based on the level of energy consumption related to human activities. Further, findings indicate that the environmental impact of population increases with its respective level. So, high populated areas (not necessarily corresponding with high density) intensify emissions-intensive activities.

Moreover, positive environmental impacts of motorization can be found for both, rural and urban districts.[37] The rate of motorization reflects the share of individual motorized passenger transport, which is not only affected by the level of income but also by sheer necessities and persistent mobility patterns. Given the ongoing increase of motorization and the high share of cars with traditional combustion engines, which is particularly pronounced in rural districts but can also be observed for most of the cities, individual motorized transport will remain a clear driving force of local pollution in the near future.

[37] If the subsample *rural and very rural counties* is again separated into *rural counties* and *very rural counties*, it can be shown that motorization rate has clearly the highest impact for *rural counties* compared to all other subgroups. The results are not shown due to less observations.

In the medium- and long-run, the emerging e-mobility could change the game. Even with still increasing private car ownership, local emissions related to the internal combustion of fossil fuels may then lose in importance and other emissions (e.g., tyre abrasion, brake dust) might come to the fore. For the moment, however, electric cars still account for less than 10 percent of new passenger car registration and much less considering private car fleet.

With regard to the structural factors, the findings show positive effects of industrial manufacturing on NO_x emissions. Though declining over time, industrial production still adds significantly to local pollution. In addition, locations of industrial manufacturing are related to (heavy) freight transportation further contributing to higher NO_x emissions.

On the other side, the results for GDP per capita and urban density depend on the considered regions. The findings show that the effect of GDP per capita is not significant in urban areas while being an important source of emission reduction in rural areas. Generally, people living in rural areas have not necessarily a higher level of education (although ongoing digitalization and increasing home-office opportunities may change this situation). However, people might have a deeper relationship with the existing natural environment and thus have higher preferences for environmental quality when living in rural areas. So, for example, larger amounts of higher income are spent for eco-friendly products and/or services. Moreover, the inclusion of car ownership potentially catches the emission-intensive part of affluence and thus reveals mitigating effects of GDP per capita on air pollution. In particular, this holds for rural areas with high private car ownership and low public infrastructure standards.

Additionally, results indicate a U-shaped effect of GDP per capita on NO_x emissions (only for the full sample). This is in contrast to most of empirical studies following the EKC theory (see section 5.2.). Probably, the threshold level for EKC is likely to be out of the sample range due to the relative high level of GDP per capita for German counties.

Further, our findings confirm the negative correlation of urban density and local pollution (NO_x emissions) found in most empirical studies in this field. It is likely that more densely populated regions allow for more competitive public transportation and (due to shorter distances) for more non-motorized individual transport. However, there is also a difference regarding a counties' settlement structure. Thus, a negative environmental impact of urban density can be shown for rural but not for urban districts. Probably, the mitigating effects of urban density on local pollutants are limited after passing a certain threshold.

Admittedly, the analysis misses, largely due to a lack of data at district level, explaining variables reflecting local weather conditions or public transport services. While public transport structures and related activities might partly be captured by urban density (even though the quality of services certainly differs among regions with similar density), weather conditions remain fully unconsidered. This could be particularly problematic for wind conditions (van Pinxteren et al., 2020), which can have a strong impact on local emission concentrations. However, it might be negligible if local weather conditions are relatively stable over time.

5.6. Concluding remarks

The paper presents a region-based STIRPAT analysis that investigates anthropogenous impacts on local air pollutants (NO_x emissions). Unlike most other regional studies, the analysis is not limited to selected cities but covers almost all German districts between 1990 and 2020. Overall, the robust estimations confirm the appropriateness of the STIRPAT approach for estimating environmental impacts with respect to a small-structured regional setting (i.e. NUTS 3).

The findings, which are, due to existing cointegration dynamics between variables, based on long-run estimation techniques largely confirm the findings of related empirical studies (e.g., on the role of population, urban density, sectoral composition) but also provide new evidence of major driving forces of NO_x emissions in a regional perspective. In particular we find positive impacts of population, private car ownership and share of industrial manufacturing for all regions. In contrast, GDP per capita and urban density show negative impacts on local NO_x emissions mostly for rural districts.

Though results should not be interpreted in a general way but with respect to the underlying regional sample, the analysis leads to the following conclusions.

With regard to policies fighting local air pollution, the results highlight the crucial role of private car ownership. Thus, policies should further strengthen integrated mobility concepts with high shares of intermodal transport, easily accessible car sharing services, etc. At the same time, mobility patterns can be very persistent and (due to socio-demographic or topographic conditions) highly dependent on private cars. Thus, uniform pricing policies or the call for better public services and more bike lanes could, depending on the regions' exogenous environment, fall short of the mark and should be complemented by fostering the transition to low-emission car technology.

Further, it can be concluded that heterogeneity of settlement structure is clearly relevant for environmental effects and associated health and social impacts. So, policymakers should be aware of the fact that the effectiveness of measures depends on the regions' structure. For example, the density of buildings (and people) should be increased in rural areas in order to exploit its mitigating effects on local pollutants. In contrast to, this cannot be recommended for urban areas.

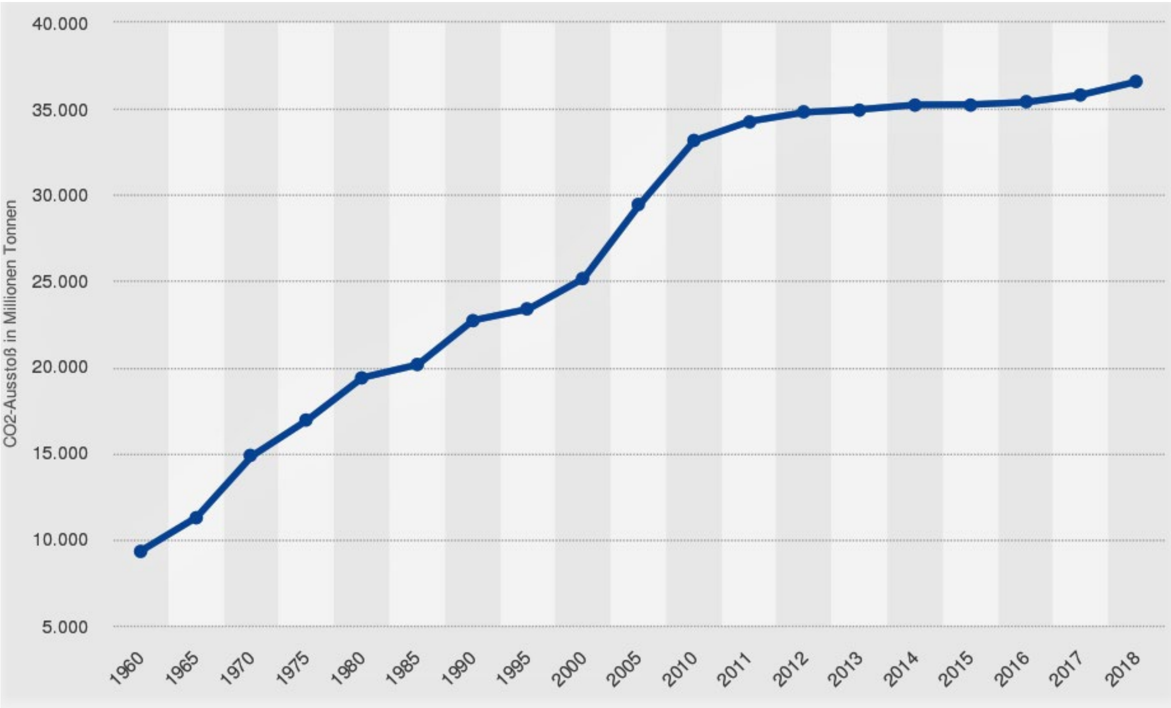
Last but not least, (urban) policymakers should be aware of the increasing predictive margins regarding the effect of population on air pollutants. How to balance population size and density for sustainable development is surely an important area of further investigation.

6. The effects of technological progress on CO_2 emissions: a macroeconomic analysis[38]

6.1. Introduction

Human-caused CO_2 emissions continue to increase steadily. Yearly CO_2 emissions more than tripled from 1960 to 2018 (figure (1)). In 2018, about 36,500 million of tons of CO_2 emissions went into the air. The major part of these emissions comes from the combustion of fossil fuels (United States Environmental Protection Agency, 2019).

Figure 1: Global CO_2 emissions (in millions of tons)



Source: Statista (2020)

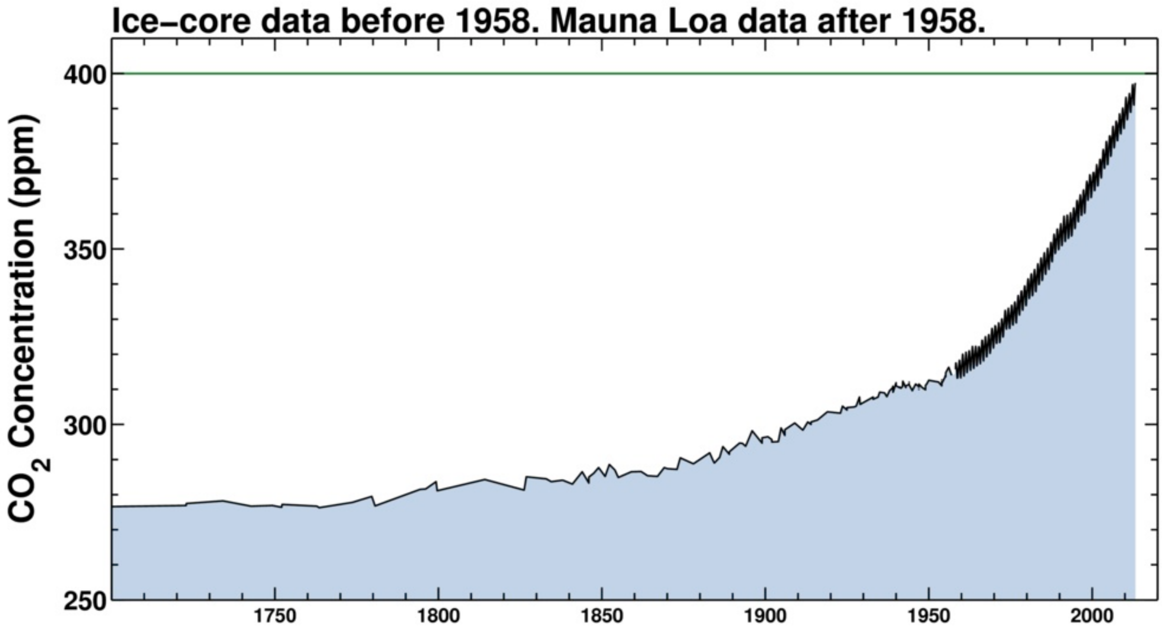
CO_2 emissions caused by humans are only a fraction of the total (natural) CO_2 cycle, but the additional amount of CO_2 emissions humans contribute means that the earth's natural absorption of CO_2 emissions is no longer guaranteed (Wayne, 2014). As a result, the CO_2 concentration in the atmosphere is increasing as never before in history. Today's CO_2 concentration is about 400 ppm (parts per million), as opposed to the historically natural level of about 270 ppm (Lindner and Schuster, 2019).[39] Figure (2) shows the

[38] The contribution (German version) is published in *Mensch und Technik – Perspektiven einer zukunftsfähigen Gesellschaft* (Lohwasser, J. (2020). The effects of technological progress on CO_2 emissions: a macroeconomic analysis. In: Hartard and Schaffer (eds.): Mensch und Technik - Perspektiven einer zukunftsfähigen Gesellschaft (2020). Metropolis).

[39] Atmospheric CO_2 concentration had not exceeded 300 ppm for the last 650,000 years (Schmidt, 2005).

accelerating increase of CO_2-concentration since the beginning of the industrial revolution.

Figure 2: CO_2 concentration in parts per million (ppm)



Source: Mairal (2013)

CO_2 represents the largest share of greenhouse gases and so is seen as major driver of climate change. Although the precise progression of climate change is difficult to predict, it is clear that it is an existential threat for humans, other life, and the environment. The direct impacts of climate change have multiplying indirect effects (e.g., rise in the sea level, crop failures, migration flows). The IPCC (Intergovernmental Panel on Climate Change), which regularly summarizes the latest scientific findings regarding this issue, states that it is still possible to limit global warming to 1.5°C (IPCC, 2018). To achieve this objective, CO_2 emissions must decrease significantly and approach zero in the mid-run. Therefore, transitional strategies that activate mechanisms related to energy and land use, cities, infrastructure, and industry are needed (IPCC, 2018).

Whether CO_2 emissions are reduced successfully depends on the choice of solution. One high-potential solution is in "combinations of new and already existing technologies" (IPCC, 2018, p. 17) and "acceleration of technological innovations (and behavioral changes)" (IPCC, 2018, p. 23), which could increase productivity in all sectors and decrease resource inputs.

This paper focuses on whether technological innovations have contributed to decreasing CO_2 emissions, so it investigates human and technological drivers of CO_2

emissions. In taking several periods in time into account, the analysis considers the potential environmental effects of three historical events. The report “The Limits to Growth” (Meadows, 1972) demonstrates for the first time that global actions motivated by material growth will be limited at some point (e.g., because of resource availability). This early wake-up call could have led to technological innovations that increased resource-saving production. As of 1989, with the fall of the Iron Curtain and the related acceleration of globalization, the prioritization of resource-saving production potentially decreased until the Kyoto-protocol was concluded in 1997 and the goal of reducing CO_2 emissions at the global level was fixed for the first time. This event could be a turning point in terms of environmental awareness, and the accompanying technical developments could again result in a focus on resource-saving production.

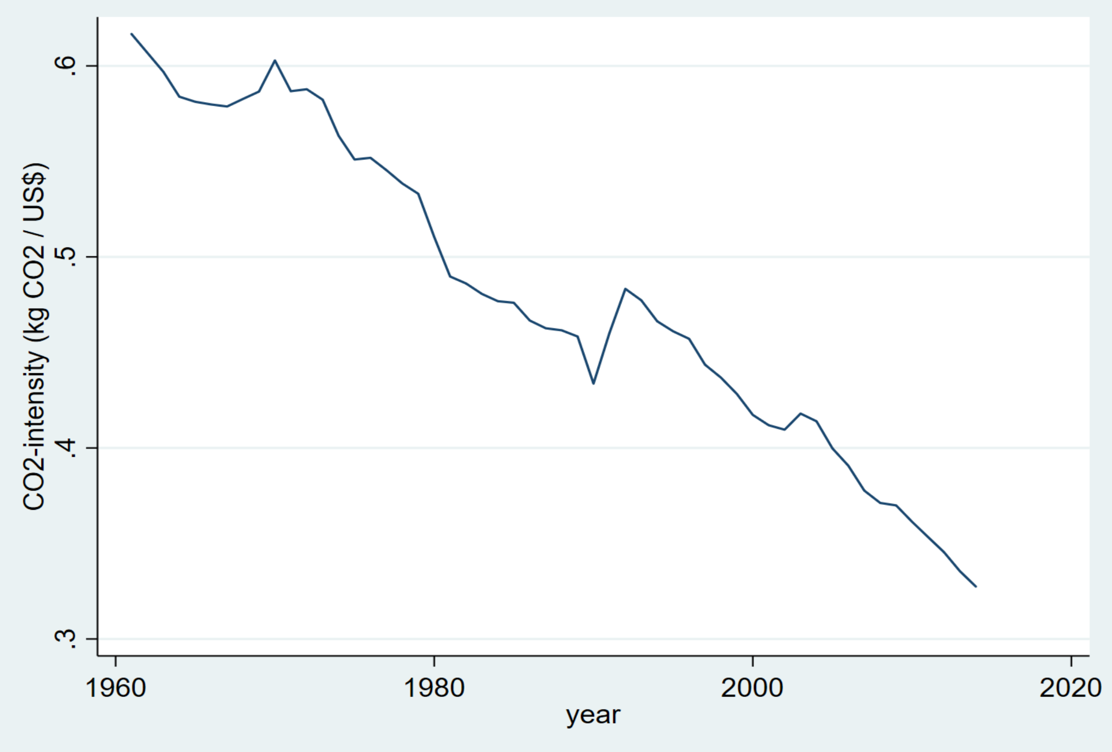
The remainder of the paper is organized as follows. Section 6.2. provides a brief overview of CO_2 intensity as a benchmark for resource efficiency and of the rebound effect in this context. Section 6.3. follows with a definition of productivity and a presentation of the methodological procedure. Section 6.4. shows the results, and Section 6.5. ends the paper with concluding remarks.

6.2. CO_2-intensity and the rebound-effect

CO_2 intensity indicates the relationship between technological progress and CO_2 emissions that, is the amount of CO_2 emissions per unit produced (in monetary units; CO_2/GDP).

Technological progress plays a central role in the efficient use of resources and, so, in reducing CO_2 intensity. Between 1960 and 2014, an era of rapid increases in productivity, CO_2 intensity decreased significantly (figure 3). However, the absolute amount of CO_2 emissions increased in spite of a more CO_2-efficient production, so the question is whether improving CO_2 intensity not only reduces CO_2 emissions but also fosters the components of CO_2 intensity (e.g., GDP) such that, in the end, improvements in CO_2 intensity turn into higher CO_2 emissions.

Figure 3: CO_2 concentration in parts per million (ppm)



Source: Own illustration based on data from the Penn World Table 9.0 (Feenstra et al., 2015) and the Oak Ridge National Laboratory (Boden et al., 2015)

As early as 1866, William Stanley Jevons states that efficiency gains in the production sector do not necessarily lead to savings in resources. Jevons explains this paradox using the example of the steam engine, whose invention led to more resource-saving production but also to more coal consumption (Jevons, 1866). Today, the logic of Jevons' "Paradoxon" is known as the rebound effect. Daniel Khazzoom (1980), among others, investigates this phenomenon and describes how efficiency gains in the energy sector can increase demand for energy.

Greening et al. (2000) divides the rebound effect into three categories with respect to energy consumption (Herring, 2006):

- *Direct (microeconomic) rebound effect:* The increase of energy efficiency in one sector results in a lower price of the produced good and, thus, to higher demand for the good. This mechanism counteracts the potential energy savings.
- *Indirect (microeconomic) rebound effect:* The indirect rebound effect derives from the direct rebound effect such that the savings that result from the lower price for the more energy-efficient good can be spent on other (more energy-intensive) goods.

- *Macroeconomic rebound effect:* The individual (especially indirect) rebound effects are relatively small, so the macroeconomic rebound effect considers the cumulative effects. The lower price of one good because of efficiency gains can result in a large global energy demand, and the efficiency gains can stimulate economic growth, leading again to increased energy demand.

In general, one refers to a (direct, indirect or macroeconomic) rebound effect if the decrease in resources used is less than the efficiency gains would imply. If higher efficiency turns into a higher demand for resources, the so-called backfire phenomenon results. For example, if the CO_2 intensity of a product decreases by 1 percent, CO_2 emissions per GDP decrease by 1 percent (ceteris paribus); the rebound effect occurs if the CO_2 emissions decrease less than 1 percent in this case (e.g., the rebound effect is 50 percent if the CO_2 emissions decrease by only 0.5 percent). In the case of the backfire phenomenon, the CO_2 emissions increase (i.e., the rebound effect > 100 percent). Therefore, the rebound effect should be taken into account in analysing the effects on resource savings of productivity gains from technological progress.

In addition to establishing the theoretical foundations of the rebound effect, a range of studies estimate the direct and indirect rebound effects.[40] However, these studies do not use a common methodological approach, so they offer no clear results regarding the macroeconomic rebound effect (Herring, 2006). Most studies that evaluate the (macroeconomic) rebound effect are regionally, sectorally, or temporally limited, while it is the macroeconomic (overall) rebound effect that must be investigated for fighting the drivers of climate change, especially in the global context of CO_2 emissions.

6.3. Identifying productivity using the STIRPAT approach

Plenty of studies investigate the human drivers of CO_2 emissions. The STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) approach, which estimates CO_2 elasticities with respect to population, affluence and technology, has not been used so far to investigate potential rebound effects even though this approach is highly flexible and facilitates global, regional, and temporal assessments (Velez-Henao et al., 2019). This section investigates the effects of productivity gains (defined as technological progress) on CO_2 emissions using the STIRPAT approach and estimates the

[40] For example, Sorrell et al. (2009) analyze related studies and conclude that the average direct rebound effect is smaller than 30 percent.

environmental elasticities, which indicate the percentage change of one variable (e.g., CO_2 emissions) when another variable (e.g., GDP per capita) increases by 1 percent.

The STIRPAT approach assumes that the most important drivers of CO_2 emissions are population, affluence (often defined as GDP), and technology (here: productivity). This relationship can be expressed by the following identity (based on Ehrlich and Holdren, 1971):

$$CO_2 = P * \frac{GDP}{P} * \frac{CO_2}{GDP}, \tag{1}$$

where P is population and GDP is the gross domestic product, so CO_2 emissions are the product of population, GDP per capita (GDP/P), and CO_2 intensity (CO_2/GDP). Since technological progress is defined as productivity, it is represented by the part of output (i.e., CO_2 emissions) that is not captured by physical inputs (Comin, 2006), so this paper defines productivity as CO_2 intensity (CO_2/GDP) *and* as part of GDP per capita (GDP/P).

CO_2 intensity, which states how much CO_2 emissions per unit of production are emitted, is given by the ratio of CO_2 emissions and GDP. Clearly, this kind of productivity—named "resource productivity" to distinguish between kinds of productivity—affects CO_2 emissions.[41]

GDP per capita measures monetary wealth and is used to approximate economic growth. GDP can be expressed by a production function that includes components like capital, labor, education level, and productivity. However, this kind of productivity is not directly measurable and so is identified here by means of decomposition; that is, productivity is measured as the residuum (the amount that is not identified by measurable factors like capital or labor) of the overall output. Productivity defined in this way does not directly apply to CO_2 emissions but to resources in general, but it contributes to economic growth and, thus, to CO_2 emissions. We name this kind of productivity "factor productivity," as GDP is decomposed into several directly measurable input factors to identify the remaining factor productivity. Thus, GDP per capita is expressed by the following production function *f*:

[41] The term "resource productivity" is commonly used to express how much GDP is obtained per unit of resource (e.g., raw material), but this paper uses this term in another way.

$$\frac{GDP}{P} = \frac{f(PR, L(P,H), C)}{P}, \tag{2}$$

where PR is productivity, L is labor (consisting of population (P) and human capital (H)), and C is physical capital.

Next, equation (2) is transformed into a stochastic version to estimate the effects of resource productivity and factor productivity on CO_2 emissions (cf. Dietz et al., 2007):

$$(CO_2)_{i,t} = c_t \, (\frac{GDP}{P})_{i,t}^{\alpha} \, (\frac{CO_2}{GDP})_{i,t}^{\beta} \, P_{i,t}^{\gamma} \, u_{i,t}, \tag{3}$$

where i is the respective country, t is the point in time, c is the constant and scales the model, and u is the error term. α, β, and γ are the respective CO_2 elasticities. After taking logs and including other variables (to isolate the factor productivity), equation (3) becomes the following regression equation:[42]

$$ln(CO_2)_{i,t} = \ln c_t + \alpha \ln (\frac{GDP}{P})_{i,t} + \beta \ln (\frac{CO_2}{GDP})_{i,t} + \gamma \ln(P)_{i,t} + \delta \ln(C)_{i,t} + \varepsilon \ln(H)_{i,t} + \ln u_{i,t}. \tag{4}$$

The coefficients γ, δ, and ε are the CO_2 elasticities with respect to population, physical capital, and human capital, respectively. α is the CO_2 elasticity with respect to the resource productivity, and β is the CO_2 elasticity with respect to the factor productivity (assuming including the other factors isolates this effect).[43]

6.4. Results

Table (1) presents the results based on estimating equation (4). Column (1) shows the results for the full sample (i.e., 1962-2014), for which the CO_2 elasticity with respect to the factor productivity (GDP p.c.) is higher than the resource productivity (CO_2/GDP). For example, the CO_2 emissions increase 0.78 percent when factor productivity rises 1 percent. Because an increase in factor productivity leads to an increase in CO_2 emissions, the backfire phenomenon shows up (rebound effect > 100 percent). If the resource

[42] All variables from equation (4) are from t-1 to t, subtracted for statistical reasons.
[43] The data for GDP per capita, population, physical capital, and human capital are taken from Penn World Table 9.0 (Feenstra et al., 2015) and the data for CO_2 emissions stem from the Oak Ridge National Laboratory (Boden et al., 2015).

productivity improves (i.e., *decreases* 1 percent), then CO_2 emissions decrease by 0.76 percent.[44] Again, the result indicates a rebound effect (of about 32%) because the CO_2 emissions decrease by less than 1 percent.[45]

Table 1: Determinants of CO_2 emissions

	(1) 1962-2014	(2) 1972-2014	(3) 1989-2014	(4) 1997-2014
Ln GDP p.c.	0.78*** (0.06)	0.77*** (0.06)	0.74*** (0.08)	0.78*** (0.08)
Ln CO_2/GDP (-)	0.76*** (0.08)	0.74*** (0.09)	0.70*** (0.12)	0.77*** (0.11)
Ln Population	1.00*** (0.12)	1.00*** (0.13)	1.08*** (0.13)	0.78*** (0.13)
Ln Physical Capital	0.14*** (0.05)	0.14*** (0.06)	0.10 (0.08)	0.12** (0.06)
Ln Human capital	-0.61 (0.43)	-0.73 (0.54)	-1.33*** (0.31)	1.41 (0.94)
observations	4757	4050	2465	1631
R^2 (*within*)	0.77	0.75	0.72	0.78
R^2 (*between*)	0.48	0.49	0.55	0.77
R^2 (*overall*)	0.77	0.74	0.71	0.78

***p<0.01, **p<0.05, *p<0.1; OLS regression. All variables are first-differenced. Year fixed-effects are included. Robust standard errors are in parentheses. Number of countries: = 118.

CO_2 emissions also increase when improvements in both kinds of productivity are considered (i.e., backfire) because of higher CO_2 elasticity with respect to factor productivity (0.78) compared to resource productivity (0.76).[46] As table 1 shows, this finding remains qualitatively similar for various time periods. For the 1997-2014 period, a backfire effect remains (column (4)), while for the 1989-2014 period (column (3)), the CO_2 elasticity with respect to resource productivity is smaller (0.70) than it was the 1972-2014 period (0.74; column (2)). The mitigating impact of the resource productivity on CO_2 emissions increases slightly beginning in 1997 (0.77; column (4)).

The coefficients regarding population and physical capital are positive and significant, while the coefficient of human capital is negative and significant for the 1989-2014 period.

[44] Resource productivity increases when CO_2/GDP decreases, so this term is marked with (-) in table (1) to simplify reading.
[45] Calculation of the rebound effect: (1-0.76)/0.76=0.32.
[46] The results remain qualitatively similar when standardized variables are considered (not shown).

6.5. Conclusion

CO_2 emissions must be drastically reduced to address climate change, and technological progress is a promising approach to doing so (IPCC, 2018). This paper analyzes the effects of technological progress, which is difficult to measure, on CO_2 emissions by identifying (parts of) technological progress with their productivity improvements and their effects on CO_2 emissions. The findings lead to several insights.

At first glance, the ongoing decrease in CO_2 intensity indicates environment-friendly production, but this development is contrasted with a clear rebound effect: An increase in resource productivity reduces CO_2 emissions, but not to the extent one could expect, and an increase in factor productivity even drives CO_2 emissions.

In addition, if the macroeconomic rebound effect is defined as the sum of both effects, then their sum is more than 100 percent, so the savings potential of resource productivity is smaller than the driving force of factor productivity. This finding holds for different periods of time.

Our analysis of different periods in time shows that the resource productivity's highest mitigating effect on CO_2 emissions holds for the latest period (i.e., from 1997-2014), and the smallest mitigating effect holds for the 1989-2014 period. These findings indicate that global developments like globalization and increasing environmental awareness (e.g., the Kyoto protocol) influence the effects of technological progress on the environment.

All in all, our results suggest that technological progress (defined as productivity) is probably not the way to limit CO_2 emissions. Because of the related rebound effect, it is not enough to make production more efficient. Of course, some technological innovations can reduce CO_2 emissions in another way, such as technologies that enable the storage of CO_2 emissions. However, other solutions are needed because of the urgent need for action. Moreover, new definitions of growth and affluence are necessary for a real resource-saving transformation.

Appendix

Table A.1.: The Effects of Standardization on Ecological Footprint

	Unstandardized		Standardized		Standardized (Partial	
Ln Footprint	(1)	(2)	(3)	(4)	(5)	(6)
Ln Population	0.83*** (0.10)	0.81*** (0.10)	0.13*** (0.02)	0.13*** (0.02)	0.08*** (0.01)	0.07*** (0.01)
Ln GDP p.c.	0.15*** (0.03)	0.14** (0.03)	0.16*** (0.03)	0.16*** (0.03)	0.15*** (0.03)	0.15*** (0.03)
Ln Urban		0.12 (0.08)		0.02 (0.01)		0.02 (0.01)
Ln Working		0.76*** (0.22)		0.05*** (0.01)		0.04*** (0.01)
Constant	- 0.01 (0.01)	-0.01 (0.01)	-0.17 (0.11)	-0.17** (0.11)	-0.17 (0.11)	1.49*** (0.22)
R^2 (*within*)	0.07	0.07	0.07	0.07	0.07	0.07
R^2 (*between*)	0.58	0.63	0.58	0.62	0.58	0.63
R^2 (*overall*)	0.09	0.09	0.09	0.10	0.09	0.09

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Year fixed-effects are included; Number of countries: 84; Number of observations: 2856; Partial SD: Partial Standard Deviation.

Table A.2.: Summary Statistics of the Predictor Variables and Variance of Inflation Factor (VIF)

Variable	Variance of Inflation Factor (VIF)	Mean	Standard Deviation	Partial Standard Deviation
	Two-Predictor-Model			
Δ Ln Population	2.96	0.02	0.01	0.01
Δ Ln GDP p.c.	1.13	0.02	0.08	0.08
	Full-Model			
Δ Ln Population	3.11	0.02	0.01	0.01
Δ Ln GDP p.c.	1.13	0.02	0.08	0.08
Δ Ln Urban	1.75	0.01	0.01	0.01
Δ Ln Working	1.41	0.01	0.01	0.01

Number of countries: 84; Number of observations: 2856.

Table A.3.: Ecological Elasticities by Using the Pooled Mean Group Estimator

	Unstandardized	**Standardized**
	(1) Δ Ln CO_2	(2) Δ Ln CO_2
LR		
Ln Population	0.21***	0.15***
	(0.07)	(0.05)
Ln GDP p.c.	0.32***	0.16***
	(0.03)	(0.01)
Ln Urban	1.49***	0.35***
	(0.11)	(0.03)
Ln Working	1.76***	0.08***
	(0.25)	(0.01)
SR		
Speed of Adjustment	-0.37***	-6.36***
	(0.03)	(0.51)
Δ Ln Population	-1.02	-0.08
	(2.63)	(0.21)
Δ Ln GDP p.c.	0.20***	0.11***
	(0.07)	(0.04)
Δ Ln Urban	-5.62	-0.50
	(4.23)	(0.37)
Δ Ln Working	0.30	0.01
	(1.83)	(0.06)
Constant	-2.46***	-0.77
	(0.23)	(0.65)

* p<0.10, ** p<0.05, *** p<0.01; Standard errors in parantheses;
Number of Countries: 84; Number of Observations: 2856;
LR: Long-Run, SR: Short-Run.

Table A.4.: 30 Advanced Economies

Australia	Germany	Netherlands
Austria	Greece	New Zealand
Belgium	Ireland	Norway
Canada	Israel	Portugal
Cyprus	Italy	Slovenia
Czech Republic	Japan	Spain
Denmark	Latvia	Sweden
Estonia	Lithuania	Switzerland
Finland	Luxembourg	United Kingdom
France	Malta	United States

Table A.5.: PVAR Model Results Regarding CO_2-emissions and GDP per Capita

	Dependent variable	
	Δ Ln CO_2	Δ Ln GDP p.c.
L. Δ Ln CO_2	0.01 (0.04)	0.11*** (0.03)
L. Δ Ln GDP p.c.	0.09 (0.08)	0.33*** (0.09)

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Number of countries: 30; Number of observations: 1256. The PVAR includes first-order lags according to the Moment Model Selection Criterion (MMSC) and Akaike Information Criterion (AIC).

Table A.6.: PVAR Model Results Regarding Patents and GDP per Capita

	Dependent variable	
	Δ Ln population	Δ Ln GDP p.c.
L. Δ Ln population	0.40*** (0.13)	1.17*** (0.39)
L. Δ Ln GDP p.c.	-0.01 (0.01)	0.37*** (0.09)

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Number of countries: 30; Number of observations: 1256. The PVAR includes first-order lags according to the Moment Model Selection Criterion (MMSC) and Akaike Information Criterion (AIC).

Table A.7.: PVAR Model Results Regarding Energy Intensity and GDP per Capita

	Dependent variable	
	Δ Ln energy intensity	Δ Ln GDP p.c.
L. Δ Ln energy intensity	-0.18*** (0.06)	-0.07 (0.05)
L. Δ Ln GDP p.c.	-0.22*** (0.07)	0.16** (0.07)

***p<0.01, **p<0.05, *p<0.1; Robust standard errors in parentheses; Number of countries: 30; Number of observations: 626. The PVAR includes first-order lags according to the Moment Model Selection Criterion (MMSC) and Akaike Information Criterion (AIC).

Table A.8.: Panel Unit Root Tests

	Hadri-LM-test Order of differences: 0 *H_0: All panels are stationary*	IPS-test Order of differences: 1 *H_0: Panels contain unit roots*	LLC-test Order of differences: 1 *H_0: Panels contain unit roots*
	z-statistic	Z-t-tilde-bar-statistic	Adjusted-t-statistic
Ln CO_2-Emission	131.91***	-18.94***	-26.89***
Ln GDP per capita	18.60***	-17.31***	-23.50***
Ln Population	149.18***	-0.90	-5.42***
Ln Energy Intensity		-14.04***	
Ln Renewable		-13.36***	
Ln Nuclear		-13.10***	
Ln Urban		-3.64***	
Ln Expectancy		-23.60***	
Ln Globalization		-16.68***	

***p<0.01; LLC-test: Levin-Lin-Chu-test assumes common autoregressive (AR) parameters across panels, Akaike Information Criterion is minimized; IPS-test: Im-Pesaran-Shin-test assumes panel-specific AR parameters, Akaike Information Criterion is minimized; Hadri-LM-test: Hadri-Lagrange-Multiplier-test.

Table A.9.1.: Results of the Kao- and Pedroni Cointegration Tests (Variation of Variables 1)

Kao-test *H_0: No cointegration*			Pedroni-test *H_0: No cointegration*		
GDP per capita, CO_2-emission, Population, Energy Intensity, Urban, Globalization, Life Expectancy (all variables logged)					
Modified Dickey-Fuller t	1.27	(0.10)	Modified Phillips-Perron t	4.78***	(0.00)
Dickey-Fuller t	1.30*	(0.09)	Phillips-Perron t	-2.25**	(0.01)
Augmented Dickey-Fuller t	1.09	(0.14)	Augmented Dickey-Fuller t	-2.87***	(0.00)

***p<0.01, **p<0.05, *p<0.1; p-value in parantheses; Kao-test assumes a constant cointegration vector; Pedroni-test assumes panel-specific AR parameters; Cross-sectional averages are substracted.

Table A.9.2.: Results of the Kao- and Pedroni Cointegration Tests (Variation of Variables 2)

Kao-test *H_0: No cointegration*			**Pedroni-test** *H_0: No cointegration*		
GDP per capita, CO_2-emissions, Population, Energy Intensity, Renewable, Nuclear (all variables logged)					
Modified Dickey-Fuller t	1.39*	(0.08)	Modified Phillips-Perron t	2.20**	(0.01)
Dickey-Fuller t	1.45*	(0.07)	Phillips-Perron t	-2.80***	(0.00)
Augmented Dickey-Fuller t	0.77	(0.22)	Augmented Dickey-Fuller t	-2.01**	(0.02)

***p<0.01, **p<0.05, *p<0.1; p-value in parantheses; Kao-test assumes a constant cointegration vector; Pedroni-test assumes panel-specific AR parameters; Cross-sectional averages are substracted.

Table A.10.: Determinants of GDP per Capita for the Long-run (FMOLS)

Ln GDP p.c.	(1)	(2)	(3)
Ln CO_2	0.37*** (0.07)	0.44*** (0.06)	0.55*** (0.06)
Ln Population	-0.34*** (0.07)	-0.42*** (0.06)	-0.51*** (0.07)
Ln Energy Intensity	-0.13 (0.10)	-0.20** (0.09)	-0.42*** (0.07)
Ln Urban		-0.09 (0.18)	-0.17 (0.21)
Ln Globalization		1.68*** (0.23)	1.17*** (0.25)
Ln Expectancy		6.18*** (1.58)	3.75*** (1.13)
Ln Nuclear			0.04** (0.02)
Ln Renewable			0.08*** (0.02)
Constant	6.83*** (0.58)	-27.14*** (7.08)	-14.99** (6.09)
R^2	0.53	0.30	0.06
observations	551	551	263
countries	30	30	15

***p<0.01, **p<0.05, *p<0.1; Standard errors in parentheses;
Year fixed-effects are included.

Table A.11.: Elasticities by Using the Pooled Mean Group Estimator for Core Variables

	Δ Ln GDP p.c
LR	
Ln CO_2	0.71*** (0.14)
Ln Population	-1.22*** (0.05)
Ln Energy Intensity	-1.31*** (0.07)
SR	
Speed of Adjustment	-0.17*** (0.04)
Δ Ln CO_2	0.34*** (0.07)
Δ Ln Population	-0.18 (1.41)
Δ Energy Intensity	-0.46*** (0.10)
Constant	1.18*** (0.25)

* p<0.10, ** p<0.05, *** p<0.01; Standard errors in parantheses;
Number of Countries: 30; Number of Observations: 529;
LR: Long-Run, SR: Short-Run.

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