August 2025

Fondazione Eni Enrico Mattei

Working Paper

17.2025

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Summary

The transition to a zero-emission vehicle fleet represents a pivotal element of Europe's decarbonization strategy, with Italy's participation being particularly significant given the size of its automotive market. This study investigates the potential for battery While population growth is a known driver of CO2 emissions, prevailing models often treat "population" as a homogeneous factor. This study addresses a critical gap, providing the first comprehensive empirical analysis to disaggregate the contributions of native-born and migrant populations to domestic CO2 emissions. Using an extended STIRPAT model for 172 countries (1990-2022), separated by OECD and non-OECD blocs, we uncover two novel insights.

First, native-born populations consistently exhibit a substantially higher emissions elasticity than migrants in both country groups. Second, a dynamic shift occurred in OECD countries: migrants' initially higher per capita emissions impact steadily declined over time, becoming lower than native-born individuals after 2003-2004. This refutes simplistic notions that migration inherently increases emissions. Our findings underscore the urgent need for differentiated, equitable climate policies that acknowledge the heterogeneous and evolving consumption patterns of diverse demographic groups, enabling more efficient mitigation strategies.

Keywords: CO_2 emissions; international migration; STIRPAT model; population elasticity

JEL Classification: C33, J11, J15, Q54

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Native-borns and migrants do not contribute equally to domestic CO_2 emissions

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ABSTRACT

While population growth is a known driver of CO_2 emissions, prevailing models often treat "population" as a homogeneous factor. This study addresses a critical gap, providing the first comprehensive empirical analysis to disaggregate the contributions of native-born and migrant populations to domestic CO_2 emissions. Using an extended STIRPAT model for 172 countries (1990-2022), separated by OECD and non-OECD blocs, we uncover two novel insights.

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1. Introduction

For millennia, human population growth remained relatively stable, but the Industrial Revolution fundamentally altered this dynamic, ushering in an era of rapid population increase driven by enhanced availability of food, water, energy, and medical care. This unprecedented growth has exerted immense pressure on Earth's systems, leading to resource extraction, increased freshwater usage, expanded land conversion for agriculture and urbanization, and, critically, a dramatic rise in pollutants and waste, most notably CO2 emissions that accelerate climate change

Human beings impact the Earth system in a variety of ways. First, they extract resources from the environment, including minerals, fossil fuels, trees, water, and wildlife. Second, they use freshwater extracted from lakes, rivers and ground reservoirs for drinking and hygiene, agriculture, recreation, and industrial processes. Third, they increase land usage for agricultural activities to grow crops and livestock, and fishing and hunting, exploiting several species populations. Fourth, natural habitats are converted into urban areas including the construction of homes, businesses, and roads to accommodate growing populations. Finally, production and consumption processes, burning fossil fuels, increasingly release pollutants and waste, which reduce air and water quality, harm the health of humans and other species and contribute to climate change.

The consideration of the growing population environmental impact dates back at least to the eighteenth century with the Malthusian concern about the rate of growth of food supply vis-à-vis the growth of population. Much later in the early 1970s, a debate focused on two competing explanations of the environmental impact, namely overpopulation or polluting technologies, which were eventually captured by the well-known IPAT equation (Erlich and Holdren, 1971). The relationship highlights the contribution of population, affluence, and technology to explain environmental impacts and to guide policy action. In the IPAT equation population acts in a sense as a “scale factor” for the environmental impact, whereas affluence is a “deepening factor” with technology controlling for the “intensity” of the environmental impact.

A large literature has documented the effects of population on the environment. Within the stochastic version of the IPAT equation, first proposed by Dietz and Rosa (1994), several papers have been interested in assessing the population elasticity of CO_2

emissions versus the per capita GDP elasticity, the latter proxying affluence in the equation. However, this established understanding has largely treated population as a homogeneous entity, overlooking crucial demographic distinctions. While some research has touched upon factors like urbanization, age structure, and household composition, there remains a critical gap in the literature: a thorough empirical analysis of the potential different impacts of international migrants on a country's CO_2 emissions compared to native-born individuals.

The aim of the paper is to fill this gap, estimating a new model which can distinguish the impact of migrants on the environment relative to that of native-born individuals. Demographers and sociologists have long studied migrants' integration and acculturation, with research largely examining migrants from the Global South moving to the Global North. As noted by Winkler and Matarrita-Cascante (2020), cultural differences are important determinants of energy consumption at the household level (Lutzenhiser, 1993; Stephenson et al., 2010; Warde, 2015). Cultural understandings of what kind, how many, when, and how often we use a variety of energy-intensive devices (cars, electronic devices, hot water, appliances, air conditioning, etc.) shape consumption patterns beyond differences due to income, market, or policy. In other words, what we want/need is shaped by cultural norms and prior experiences and daily practices (Warde, 2005). The focus on consumption generally follows the dominant assumption that immigrants (wanting to become a part of the new culture) adopt the habits of the majority norm (Wallendorf and Reilly, 1983).

This paper proposes two new contributions to literature. First, we estimate a variant of the STochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) equation, analyzing separately the impact of native-borns and migrants on carbon emissions of a (destination) country. Estimating the emission elasticity of these two groups of people allows us to assess whether the difference is statistically different from zero. Second, this paper looks at the different impact within the OECD and the non-OECD as the group of destination countries. The reason is that OECD "rich" countries have been traditionally the destination of international migrants, though an increasing portion of international migration has been taking place across countries also belonging to the non-OECD group.

Our findings challenge the simplistic assumption that migration necessarily increases emissions. We reveal an important asymmetry: in both OECD and non-OECD countries, the emissions elasticity of native-born populations is significantly higher than that of migrants. Furthermore, our study uniquely demonstrates that while migrants in OECD countries initially contributed more per capita to emissions than natives, this impact has steadily and significantly declined over time, becoming smaller than that of native-born individuals after 2003-2004. This dynamic shift is a novel finding that contrasts with earlier static assumptions.

These insights underscore the urgent need for differentiated climate policies that consider the evolving energy consumption behaviors and socio-economic realities of both native-born and migrant populations. By recognizing this demographic heterogeneity, governments and firms can craft more efficient and equitable mitigation strategies, focusing interventions where they will have the most significant impact.

The paper is organized as follows. In Section 2 we selectively review the relevant literature. In Section 3 we describe the methodology and the estimation strategy. Section 4 presents the data and Section 5 the estimation results. Section 6 discusses the results. Concluding remarks follow.

2. Selected literature review

This paper lies at the intersection of two strands of literature.

The first strand is the impact of population on the environment. A growing population has significant and multifaceted impacts on the environment, from resource depletion to environmental degradation – pollution, land use, deforestation, biodiversity loss – and climate change. These impacts stem from the increased demand for resources like food, water, and energy, as well as the greater production of waste and pollution.[1]

Because climate change represents the biggest challenge faced by humanity, the role of its main drivers has given rise to a large body of research, focusing specifically on population along with affluence, technology, and other factors. In the case of a global pollutant like there are two types of evidence for how CO_2 emissions are affected by demographic factors such as population growth or decline, ageing, urbanization, and

[1] On this topic there is an extensive literature starting perhaps with Holdren and Ehrlich (1974).

changes in household size (O'Neill et al., 2012). The first type is provided by results of empirical analyses of historical trends which tend to show that energy-related carbon dioxide emissions respond almost proportionately to changes in population size and that ageing and urbanization have less than proportional but statistically significant effects. The second type of evidence is provided by scenario analyses showing that alternative population growth paths could have substantial effects on global emissions of CO_2 several decades from now, and that ageing and urbanization can have important effects in particular world regions.

Focusing on the first type of evidence, the impact of population on the environment has been central to the debate that developed during the late 1900s when the so-called IPAT identity was first proposed by Ehrlich and Holdren (1971) as a framework to distinguish between the impact of population and that of income (or GDP). Specifically, the environmental impact (I) was taken equal to the product of population (P), affluence (A), and technology (T). Twenty years later Dietz and Rosa's (1994) proposed the econometric version of the IPAT identity known as the STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology) equation. This representation enabled researchers to use data to estimate the sensitivity of the environmental impact to the main IPAT drivers.

While the empirical studies based on the STIRPAT model abound (see Vélez-Henaoa et al., 2019, for a recent review), a small subset focus on population as a crucial driver of climate change and aim to estimate the elasticity of CO_2 emissions to population. This elasticity is often evaluated against that of affluence (per capita GDP). The general finding is that the population elasticity is larger than the affluence elasticity, with the former often exceeding unity. In this vein the early study by Dietz and Rosa (1997) found a population elasticity of CO_2 emissions equal to 1.15 and York et al. (2003) presented estimates ranging from 0.97 to 1.02 depending on the presence of additional controls. While Shi (2003) produces an elasticity in the range 1.41-1.65 while the GDP elasticity is much lower around 0.71-0.82. Cole and Neumayer (2004) apply a STIRPAT equation in first differences producing an elasticity of emissions with respect to population to be unity across different specifications in which they control for urbanization, household size, and age structure. Other cross-country studies are Martínez-Zarzoso et al. (2007), Poumanyvong and Kaneko (2010), and Bargaoui et al. (2014). More recently, Liddle

(2015)'s findings indicate that the carbon emissions elasticity of income is highly robust and less than one for OECD countries and not significantly different from one for non-OECD countries. By contrast, the carbon emissions elasticity of population is not robust, but likely not statistically significantly different from one for either OECD or non-OECD countries. Casey and Galor (2017) use a STIRPAT equation in first differences and show that the elasticity with respect to population is nearly seven times larger than the elasticity with respect to income per capita and that this difference is statistically significant. Thus, the regression results imply that 1% slower population growth could be accompanied by an increase in income per capita of nearly 7% while still lowering carbon emissions.

As noted by Jiang and Hardee (2011), the findings from statistical analyses of historical data reported above are important because they have been used to inform the projections of future carbon emissions and climate change, including the IPCC Special Reports on Emission Scenarios (SRES). In addition, and importantly, the evidence implies that policies that slow population growth would probably also have climate-related benefits.

The second strand of literature looks at the impact of migration on the environment. The environment-migration relationship is a complex one and causality runs both ways. A large and increasing body of research looks at the role of climate change as a push factor of international migration. Recent surveys include Millock (2015), Berlemann and Steinhardt (2017), Cattaneo et al. (2019) and Piguet et al. (2011). We do not review this literature here as we look at the impact that migration has on the environment. The difference is between the impact of climate change on migration *flows* and the impact that a population *stock* has on CO_2 emissions. The literature in this second area is also abundant. Actually, according to Hugo (2008), this body of research is considerably greater than that on the environment as a cause of migration, though it mostly focuses on internal migration, rather than on the ecological consequences of international migration. There are many case studies where expanding land settlement into fragile ecosystems in LDCs have led to desertification, deforestation and other environmental degradation.[2]

While the U.S., Canada, and more recently Europe, are characterized by large inflows of international migrants, China has large cross-provincial internal migration flows.

In the U.S. case, Kolankiewicz and Camarota (2008) consider immigration to the United States and the implications for GHG emissions. They increase because population transfers from lower-polluting parts of the world to the United States, which is a higher polluting country. The study finds that on average immigrants increase their emissions four-fold by coming to America. The estimated CO_2 emissions of the average immigrant (legal or illegal) in the United States are 18% less than those of the average native-born American. However, immigrants in the U.S. produce an estimated four times more CO_2 in the United States as they would have in their countries of origin. On the whole, the impact of immigration to the United States on global emissions is equal to approximately 5 percent of the increase in annual world-wide CO2 emissions since 1980.

Squalli (2009) investigates the immigration-environment relationship using data for a about 200 U.S. counties and a STIRPAT-type approach. Census data for the year 2000 on U.S.-born and foreign-born populations are combined with county-level data CO_2, NO_2, PM_{10}, and SO_2 emissions. The author finds that counties with a relatively larger U.S.-born population have higher NO_2 and SO_2 emissions. On the other hand, counties with a relatively higher number or share of foreign-born residents have lower SO_2 emissions.

Dedeoğlu et al. (2021) examine the relationship between immigration, human capital, economic growth, financial development, energy, and environmental pollution in the USA with the STIRPAT model. The data cover the years 1975–2014. According to the results, while migration, financial development, and energy consumption have an increasing effect on environmental pollution, economic growth has a decreasing impact on pollution. There is no statistically significant relationship between human capital and the environment. On the other hand, immigration contributes to human capital accumulation in the long run.

[2] One type of international migration which has attracted attention because of its environmental impacts is the refugee movement. The sudden unplanned arrival of large numbers of people into a generally spatially restricted area, often already vulnerable to environmental degradation, can have huge environmental impacts.

Morris (2021) uses data at both global (175 countries) and national (Canada and the USA) scales to analyze the anticipated effects of human migration on the abilities of nations to attain the 2030 UNFCCC CO_2 emission targets. The analyses reveal that mean per capita CO_2 emissions are nearly three times higher in countries with net immigration than in countries with net emigration. This implies that any increase in population size and its associated demand for energy, whether through births or net immigration, will necessitate an even greater effort to reduce CO_2 emissions. Immigration, except during the 2020–2021 COVID-19 pandemic, is higher than ever and represents a substantial contributor to population growth in many of the World's richest and high carbon-emitting nations, and especially so in Canada and the USA.

Hill (2024) studies the impact of migration of people within the U.S. on energy consumption and therefore the environment, combining county-level migration data, structural energy consumption estimation techniques, and the AP3 environmental damage model to estimate the emissions impact of migration by county over time. When people move to a new county, they change the size of their house, their commute to work, the quantity and fuel used for home heating, and the emissions content of the electricity they consume as well as its amount. The effect of this change, along with the environmental impact of total personal energy consumption, is a priori unknown. The analysis showed that migration was a net environmental positive in the U.S. in the 1990s but turned negative beginning in the 2010s.

Considering a small selection of papers on China, Wang et al. (2020) examine the relationship between urban environmental pollutant emissions and migrant populations at the prefectural level using data for 90 Chinese cities evidencing net in-migration. By dividing the permanent populations of these cities into natives and migrants in relation to the population structure, they estimate an improved STIRPAT equation that also includes variables on the cities' attributes. The findings are that migrant populations have significant impacts on environmental emissions both in terms of their size and concentration. Specifically, impacts are negative for $PM_{2.5}$ emissions and positive on emissions of NO_2 and CO_2. In addition, the impacts of migrant populations on urban environmental pollutant emissions are 8 to 30 times weaker than that of local populations. Finally, urban environmental pollutant emissions in different cities differ significantly according to variations in the industrial structures, public transportation facilities, and population densities.

Long at al. (2022) begin by noting that human activities and associated carbon emissions are mainly concentrated in cities. As big cities usually offer more job prospects than small cities, residents are increasingly migrating from small cities to big cities within a country. During such an internal migration process, production and consumption patterns typically change, inducing change in ecological footprint (see also Falco et al. 2019). Using the Index Decomposition Analysis (IDA) method to identify impacts of internal migration across cities in China on carbon emission changes, the authors find a positive impact of internal migration on the national carbon emissions, which increased China's aggregate carbon emission by 16% from 2001 to 2016. The positive impact of internal migration is achieved through greater demand for energy services (e.g., transportation, heating, cooling, etc.) in big cities than in small cities. They also find that the positive impact of internal migration on carbon emissions was even larger than that of net population growth.

Based on the panel data of 30 provincial regions in China from 2000 to 2019 Bu et al. (2022) perform a spatial econometric investigation to capture the spatial spillover effects of population migration on emissions. The authors find that population migration increases energy consumption and energy poverty, but energy poverty is more severe in provinces with net outward population migration. On the other hand, population migration increases the carbon emissions and carbon reduction barriers of the provinces with net outward population migration and has no significant impact on the carbon emissions and carbon reduction barriers of the provinces with net inward population migration.

Yuan et al. (2023) investigate the impact of interprovincial population migration on household energy footprints (HEFs) in China in 2010 and 2015. The findings show that interprovincial migration resulted in an 8% and 6% increase in HEFs in the two years considered respectively, with the main impact occurring in developed coastal regions due to massive immigration from neighboring provinces. In 2010, increased HEFs were mainly due to consumption of housing and services, while in 2015 consumption of household facilities and transport became major contributors.

We close by mentioning lifestyle migrants. In this vein Winkler and Matarrita-Cascante (2020) investigate the role that migration from highly developed countries with high consumption lifestyles to lower income regions plays in shifting the latter's adoption of energy-intensive residential goods. Because lifestyle migrants tend to be relatively wealthy, they are expected to consume at higher levels than the typical household in either the sending or receiving nation. The study considers the case of Costa Rica, a well-established recipient country for lifestyle migration and finds that lifestyle migrants not only consume more energy-intensive goods than native Costa Ricans, but that their presence elevates consumption among native neighbors as well.

3. Methodology

Following the bulk of the literature we adopt the stochastic extension of the well-known IPAT equation originally proposed by Erlich and Holdren (1971). Our version of the STIRPAT model originally put forth by Dietz and Rosa (1994) accommodates the stocks of native-borns and of migrants when considering their impact on emissions of carbon dioxide. Assuming a cross-country panel dataset is available, the model is:

$$(1) \qquad CO_{2,it} = \left(N_{it}^{\beta_1} M_{it}^{\beta_2}\right) A_{it}^{\beta_3} T_{it}^{\beta_4}$$

where $CO_{2,it}$ are the CO_2 emissions of country i at time t, N and M are the stocks of native-born and of migrated people, or migrants, respectively, A is affluence proxied by real per capita GDP and T is technology.[3] Note that unlike 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 energy/environmental R&D, population structure such as urbanization rate or population density), others consider technology to be included in the error term. Here we follow Casey and Galor (2017) by assuming that:

$$(2) \qquad lnT_{it} = \alpha_i + \gamma_t + Z'_{it}\delta + \epsilon_{it}$$

[3] The STIRPAT specification (1) postulates that the stocks of native-born and migrant people are characterized by a separate impact on CO_2 emissions captured by the two elasticities β_1 and β_2. The original IPAT formulation allows substantial flexibility as to the variables which should be actually included in the equation. If one, however, recognizes that the sum of native-born and migrants amounts to the overall population, a "standard" STIRPAT equation is specified. On the basis of the estimated population coefficient one can compute separate emission elasticities to native-born and migrants. We take this different tack and present the results in Appendix B.

where α_i is a fixed effect capturing time-invariant differences between countries, γ_t is a fixed effect capturing differences in global technology over time that affect all countries, and Z'_{it} is a set of control variables affecting carbon emissions. Our STIRPAT specification thus becomes:

$$(3) \qquad lnCO_{2,it} = \alpha_i + \gamma_t + \beta_1 lnN_{it} + \beta_2 lnM_{it} + \beta_3 \ln A_{it} + Z'_{it}\delta + \epsilon_{it}$$

While the previous literature has been especially interested in the population elasticity and in the difference between the elasticities of emissions with respect to (total) population on the one hand and to affluence on the other, we are especially interested in comparing the emissions elasticities of native-borns and of migrants and assessing whether or not they differ from each other.[4]

4. Data and sources

We collect annual data for a panel of 172 countries covering the period 1990-2022 (33 years of data). Specifically, we have all the 38 OECD countries and 134 Non-OECD countries where this number depends on the availability of the variables included in our empirical analysis.[5]

The primary interest of this paper is the potential different impact on domestic emissions of native-born and international migrant populations. Separate annual (destination) country-level data for the stock of native-borns and the stock of migrants are not available. We first describe how we obtained this data.[6]

[4] Our specification is similar to the one implemented by Wang et al. (2020). These authors consider emissions of several air pollutants including CO_2 in several Chinese cities for the two years 2005 and 2015 pooled together. The problem is that the way the migrant population data is constructed is ad hoc. Rafiq et al. (2017) estimate variants of the STIRPAT equation where they include as separate regressors both the Chinese provincial total population and the number of internal migrants (calculated by subtracting from total population the total number of permanent residents in the province). Here the interpretation of the migrant elasticity is unclear, given that total population rather than native population is included as an additional regressor. A similar problem applies to Guo (2024).

[5] The list of countries is presented in Appendix A, separately for OECD and Non-OECD.

[6] The primary sources for the data are: (1) United Nations, Department of Economic and Social Affairs, Population Division (2024). World Population Prospects 2024, Online Edition, available at: https://population.un.org/wpp/. (2) Census reports and other statistical publications from national statistical offices, (3) Eurostat: Demographic Statistics, (4) United Nations Statistical Division. Population and Vital Statistics Report (various years), (5) U.S. Census Bureau: International Database, and (6) Secretariat of the Pacific Community: Statistics and Demography Programme. See: https://databank.worldbank.org/source/world-development-indicators/Series/SP.POP.TOTL.

Total population (POP) is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values we use are midyear estimates and come from the World Bank. The World Population Prospects 2022 of the U.N. Population Division provides annual data on the Net Number of Migrants (thousands) (NM) for the period 1950-2022. For each country, they represent the difference between the people who have migrated into the country and the people who have migrated from the country in a given year.[7] In addition, the International Migrant Stock 2020 dataset provides estimates of the number (stock) of international migrants disaggregated by age, sex and country or area of origin. We denote these stocks as OP and DP for origin or destination country respectively. The data are available at five-year intervals for 1990, 1995, 2000, 2005, 2010, 2015 and 2020 and are available for 232 countries and areas of the world.[8]

To obtain annual data on the number of migrants to a country by destination country, we proceed as follows.

Let DP_T and OP_T be the year T stocks of migrants by destination and origin country respectively, where T = 1990, 1995, 2000, 2005, 2010, 2015, 2020.

1) For every five-year interval we compute the change for both stocks: $DP_T - DP_{T-5}$ and $OP_T - OP_{T-5}$;

[7]See: https://population.un.org/wpp/downloads?folder=Standard%20Projections&group=Most%20used and https://population.un.org/wpp/Download/Files/1_Indicators%20(Standard)/EXCEL_FILES/1_General/WPP2024_GEN_F01_DEMOGRAPHIC_INDICATORS_COMPACT.xlsx

[8] The United Nations Population Division provides data on net migration and migrant stock. Because data on migrant stock is difficult for countries to collect, the United Nations Population Division takes into account the past migration history of a country or area, the migration policy of a country, and the influx of refugees in recent periods when deriving estimates of net migration. The data to calculate these estimates come from a variety of sources, including border statistics, administrative records, surveys, and censuses. When there is insufficient data, net migration is derived through the difference between the overall population growth rate and the rate of natural increase (the difference between the birth rate and the death rate) during the same period. Such calculations are usually made for intercensal periods. The estimates are also derived from the data on foreign-born population - people who have residence in one country but were born in another country. When data on the foreign-born population are not available, data on foreign population - that is, people who are citizens of a country other than the country in which they reside - are used as estimates. The data are based on national statistics, in most cases obtained from population censuses. Additionally, population registers and nationally representative surveys provided information on the number and composition of international migrants. See: https://www.un.org/development/desa/pd/content/international-migrant-stock

2) We obtain the annual change (flow) in the migration stock by origin country as: $OM_t = (OP_t - OP_{t-5})/5$ where $t \in \{T, T-5\}$;
3) We construct an annual series of migration to destination DM_t as the sum of the annual net migration NM_t plus the change in migration by origin OM_t, that is: $DM_t = NM_t + OM_t$;
4) We use the constructed series DM_t to interpolate and construct a series of annual stock of migrants by destination country DP_t subject to the constraint $DP_t = DP_T$ when $t = T$. We set $MIG_t = DM_t$.
5) Once we have annual data of migrants to a (destination) country, we obtain the population of natives as follows: $NAT_t = POP_t - MIG_t$.

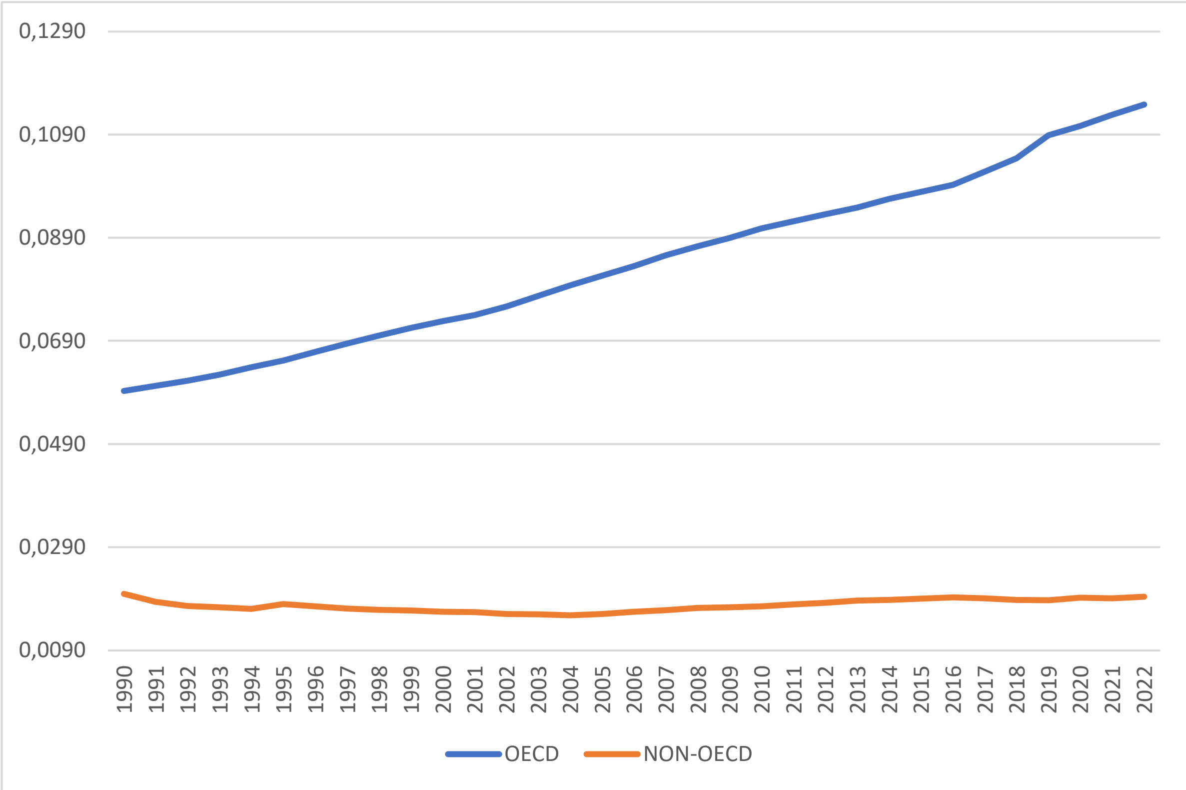
In Table 1 we present summary statistics for these variables for the two country groups. We can see that the migrant ratio, i.e. the ratio of the migrants' stock to total population, is on average 9% in rich countries and only 2% in Non-OECD countries. The variability is quite large in the OECD block as it goes from 6% to 11%, not so for the Non-OECD group where the ratio is very stable. In Figure 1 we present the migrant ratio for the two blocks.

Table 1: Descriptive statistics: OECD and Non-OECD countries

Variable	Mean	Std. Dev.	Min	Max
	OECD Countries			
POP	32.927	53.406	0.254	333.288
NAT	30.123	47.836	0.245	281.420
MIG	2.804	6.661	0.010	51.868
Migration ratio	0.087	0.039	0.059	0.115
	Non-OECD Countries			
POP	38.863	152.975	0.009	1417.173
NAT	38.171	152.554	0.007	1412.105
MIG	0.692	1.606	0.000	14.599
Migration ratio	0.020	0.000	0.016	0.020

Source: calculations based on the sample of 1254 observations for OECD and 4422 observations for Non-OECD.

Figure 1: Migrants ratio – OECD and Non-OECD countries



Source: ratio of total migrants over total population for OECD and Non-OECD countries based on our data sample.

The ratio between migrant population to total population has been systematically higher in OECD countries compared to the other block. It also shows a continuous increase over time, whereas the ratio has remained low and stable in Non-OECD countries. This is due to the attractor role of migration historically played by rich countries and to the fact that in relevant non-OECD countries such as China within-migration is more important than between-migration.

Data for carbon dioxide emissions (CO_2) come from Climate Watch, Historical GHG Emissions.[9] These emissions, expressed in Mtons, are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. The data on GDP per capita ($GDPpc$) are sourced from the World Development Indicators database of the World Bank. They are in constant 2017 international dollars based on purchasing power parity (PPP).[10] As additional covariates used in empirical work, we consider both

[9] https://www.climatewatchdata.org/ghg-emissions.

[10] https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD.

energy-related and demographic variables. Specifically, the renewable energy share ($RESH$) is the share of renewable energy in total energy consumption sourced from the IEA Extended Energy Balances. The urbanization rate (URB) from the World Bank is the urban population as a percentage of the total population, the people living in urban areas as defined by national statistical offices.[11] The median age ($AGEMED$) is an indicator of the age distribution of a population: it gives the age where there are the same number of people who are older than the median age as there are younger than it. These two series are sources from the World Bank World Development Indicators and the United Nations Population Division.

Descriptive statistics are presented for OECD and Non-OECD countries in Table 2.

Table 2: Descriptive statistics: OECD and NON-OECD countries

Variable	Mean	Std. Dev.	Min	Max
	OECD Countries			
CO_2	321.364	843.646	1.447	5775.807
GDPpc	37188.35	18217.06	6853.473	120647.8
RESH	18.668	15.836	0.4	82.9
URB	75.663	11.170	47.915	98.153
AGEMED	35.974	5.409	18.7	48.4
No. Countries	*38*			
No. Years	*33*			
No. Observations	*1254*			
	NON-OECD Countries			
CO_2	110.799	657.654	0.006	11396.939
GDPpc	11542.95	15390.9	430.4135	111879.75
RESH	38.213	32.618	0.000	98.3
URB	49.475	22.073	5.416	100
AGEMED	22.988	6.902	13.6	44.5
No. Countries	*134*			
No. Years	*33*			
No. Observations	*4422*			

Note: *CO2* emissions are expressed in Mtons. *GDPpc* is in constant 2017 PPP dollars. *RES* is renewable energy relative to total energy consumption in percentage terms. *ENINT* is energy intensity expressed in ktoe per constant 2015 dollars of GDP. *URB* is urban population as a percentage of the total population. *DENS* is population per square km. *SEX* is ratio of male births to female births. LEXP is life expectancy at birth expressed in number of years.

[11] For the urbanization rate the data are collected and smoothed by United Nations Population Division, World Urbanization Prospects: 2018 Revision. See: https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SP.URB.TOTL.IN.ZS.

5. Estimation results

We estimate (3) where the stocks of natives and migrants are denoted by NAT and MIG, affluence is proxied by per capita GDP $GDPpc$, and our controls are $Z = \{RESH, URB, AGEMED\}$, all in log terms. These variables control for the technology component of the IPAT equation and for the structure of population. Following the standard procedure, unobserved country heterogeneity is dealt with by including fixed country and time effects in all estimated equations.

Considering the presence of non-stationarity and cross-sectional dependence, in this paper we follow the estimation strategy described in Eibinger et al. (2024) for estimating macro panel data models which typically characterize STIRPAT applications.

As a preliminary step the standard approach requires testing for the non-stationarity of the variables involved. This can be done with usual Dickey-Fuller ADF tests or variants thereof, possibly allowing for cross-sectional dependence. If all variables are found to be I(1), then a test of cointegration is performed. Also in this case, besides the standard Engle-Granger test, there are several other statistics proposed in the literature. If the null hypothesis of no cointegration is rejected, a long-run relationship among CO_2 emissions and the determinants specified in (3) is said to exist. At this point one proceeds with the estimation of the modified STIRPAT equation (3).

A convenient alternative to the above approach is the Bounds Testing methodology of Pesaran et al. (2001) as it can accommodate a mixture of I(0) and I(1) variables, thus requiring no prior unit root test, and where different variables can be assigned different lag lengths as they enter the model.

Once a long-run relationship is established, the STIRPAT equation (3) it can be estimated with one of several panel estimation methods available, ranging from the classical Least Squares Dummy Variable (LSDV) estimator to cointegration techniques such as Dynamic Ordinary Least Squares (DOLS) (Kao and Chiang, 2000), Fully Modified Ordinary Squares (FMOLS) (Pedroni, 2000), and Canonical Cointegration Regression

(CCR).[12] We will use panel DOLS, which is a cointegrating estimator that is robust to endogeneity and autocorrelation without requiring the use of instruments.

A well-known result of Engle and Granger (1987) is that if cointegration cannot be rejected the long-run relationship also admits an Error Correction Mechanism (ECM) representation.[13] This is a dynamic specification involving both levels and first differences of variables, thus providing a separation of the long-run equilibrium and the short-run dynamic components. More generally, the ECM specification is nothing but a reparametrization of an appropriate Auto-Regressive Distributed Lag (ARDL) model. The dynamic approach assumes that CO_2 emissions of the last year have an impact on this year's emissions. However, dynamic models suffer from a bias which is caused by the endogeneity of the lagged dependent variable. This problem can be solved by an Anderson-Hsiao estimator that instruments the lag endogenous variable. However, Generalized Methods of Moments (GMM) instrumental variable estimators such as the Arellano-Bond and Blundell-Bond methods use more instruments and are more efficient.

In this paper we are interested in quantifying for the first time the CO_2 elasticities of native-borns and migrants and thus base our analysis of the evidence provided by the long-run augmented STIRPAT relationship (3). The separation between short-run and long-run effects are relevant in this respect.

5.1 Existence of a long-run augmented STIRPAT relationship

The first step of the estimation procedure is to test for the existence of a long-run relationship among the variables involved. For the reasons explained we implement a Bounds Testing methodology of Pesaran et al. (2001) which requires estimation of the ARDL version of (3) where we assume that the maximum lag length is 2. The ARDL(2,2) specification reads as follows:

[12] The panel methods we use include fixed (country and time) effects (FE). Relative to random effects (RE) approach a fixed effects is appropriate because we consider nearly all existing cross-sectional units (countries). The LSDV estimator, which is an OLS method applied to a model with countries and time dummy variables, is equivalent to the Within estimator for FE models.

[13] Some STIRPAT papers, e.g. Casey and Galor (2017), estimate the model directly in first differences, thus omitting the long-run level component. The problem with this strategy is that, if the variables are indeed cointegrated a first-differenced specification will suffer from omitted variable bias, as the long-run equilibrium elements are missing.

$$(4) \qquad \Delta lnCO_{2,it} = a_i + b_t + \sum_{j=1}^{2} c_j \Delta lnCO_{2,it-j} + \sum_{j=1}^{2}\sum_{k=1}^{6} d_{kj}\Delta lnX_{kt-j} + \theta_0 \ln CO_{2,it-1} + \sum_{k=1}^{6}\theta_k \ln X_{kt-1} + e_{it}$$

where $X_{it} = \{NAT, MIG, GDPpc, RESH, URB, AGEMED\}_{it}$. This expression is in fact an "unrestricted" ECM model. Before estimating (4), we have to preliminarily make sure that none of the variables involved is I(2), which would invalidate the methodology. To this end, we take the second log difference of each variable and apply the panel unit root test proposed by Im, Pesaran, and Shin (2003) (IPS). For both OECD and Non-OECD samples all tests had a p-value equal to 0.000 in all cases.[14] We thus conclude that no variable was I(2).

We then estimate the ARDL(2,2) model (4) and determine the appropriate lag structure. We allow for either time dummies or a time trend As said, given the use of annual data, our starting assumption is a maximum of two lags. We estimate four ARDL(p,q) specifications where $p, q = 1{,}2$ and select the specification characterized by the lowest value of the BIC "information criterium".[15] The criterion selects an ARDL(1,1) both for OECD and Non-OECD countries cases, regardless of the specification of time effects.

We proceed to perform a "Bounds Test" to see if there is evidence of a long-run relationship as given by (3). To that end we carry out an F test of the null hypothesis $H_0\colon \theta_0 = \theta_k = 0 \ \forall k$ against the alternative that H_0 is not true. The distribution of the test statistics is non-standard and exact critical values for the F-test are not available for an arbitrary mix of I(0) and I(1) variables. However, Pesaran et al. (2001) provide lower and upper bounds on the critical values for the asymptotic distribution of the F-statistics. Small-sample critical values are given by Narayan (2005). In each case, the lower bound assumes that all of the variables are I(0) and the upper bound is based on the assumption that all of the variables are I(1). If the computed F-statistics fall below the lower bound we conclude that the variables are I(0), so no cointegration is possible.

[14] The IPS test does not assume a common autoregressive parameter, nor does it require balanced panels. The null hypothesis is that all panels contain a unit root whereas the alternative hypothesis is that some panels are stationary. We conducted the test with and without a trend and controlling for serially correlated errors with the number of lags selected by the BIC criterion. We do not report these results here, but they are available, as all unreported results in this paper, from the authors upon request.

[15] Information criteria are based on a high log-likelihood value with a "penalty" for including more lags to achieve this. The form of the penalty varies from one criterion to another. Each criterion starts with -2log(L), and then penalizes, so the smaller the value of an information criterion the better the result. The results of the lag length selection are not reported to conserve on space.

If the F-statistics exceeds the upper bound, we conclude that we have cointegration. Finally, if the F-statistic falls between the bounds, the test is inconclusive. We conduct the F test for all our specifications and the results are presented in Table 3.

Table 3: Bounds F Test

	OECD		Non-OECD	
	Time dummies	Time trend	Time dummies	Time trend
ARDL(2,2)	15.89 (0.000)	14.79 (0.000)	41.78 (0.000)	42.42 (0.000)
ARDL(2,1)	17.05 (0.000)	16.16 (0.000)	42.85 (0.000)	43.89 (0.000)
ARDL(1,2)	16.41 (0.000)	15.23 (0.000)	41.79 (0.000)	42.52 (0.000)
ARDL(1,1)	17.15 (0.000)	16.20 (0.000)	42.55 (0.000)	43.59 (0.000)
Narayan (2005)'s critical values of the F test				
	Case III		*Case IV*	
	Lower bound	*Upper bound*	*Lower bound*	*Upper bound*
	2.06	*3.24*	*2.33*	*3.46*

Notes: The values reported are the F test statistics of the null hypothesis that all long-run coefficients are zero. The associated p values are in round brackets. Narayan (2005)'s critical values refer to the case $k = 10$ and $\alpha = 5\%$. Case III is the option with intercept and no trend, whereas Case IV has intercept and trend.

Irrespective of the lag length of the ARDL model, the bounds tests in the table reveal that in all cases the existence of a long-run relationship among the variables involved is a hypothesis that cannot be rejected.

5.2 Estimation of the long-run augmented STIRPAT relationship

The second step of the procedure is the estimation of the long-run "levels relationship" (3). To this end we use three different estimators to also account for cross-sectional dependence, as discussed below.

We first use a standard least squares dummy variable (LSDV) estimator. In a country-by-country setup, estimating the long-run "levels relationship" (3) corresponds to applying the Engle-Granger procedure which generates a consistent estimator of the long-run parameters, which, in a panel context, have been shown to be biased. Heterogeneity and persistence in short-run dynamics can create substantial variability in single-equation cointegration vector point estimates. This small sample fragility can be encountered despite the super consistency of these estimators. It is recommended to correct these problems using an alternative method, such as the Fully Modified OLS

(FMOLS) or the DOLS estimators which can provide more precise estimates. In the latter case a correction is made by assuming that there is a relationship between the residuals from the static regression and first differences of the leads, lags and contemporaneous values of the regressors in first differences:[16]

(5) $$\Delta lnCO_{2,it} = a_i + b_t + \sum_{k=1}^{6} \varphi_k \ln X_{kt-1} + \sum_{h=-H}^{+H} \sigma_{kh} \Delta lnX_{kt-h} + u_{it}$$

where $H = 1$ or 2 with annual data.

In addition, there is the possibility of cross-sectional dependence (CSD) among the units of a panel. When the units are countries, variables like GDP per capita and CO_2 emissions are likely to exhibit cross-sectional dependence because of regional and macroeconomic linkages due to common global shocks, common institutions (World Trade Organization, World Bank, International Monetary Fund, Paris Agreement) or local spillover effects between countries or regions (see e.g. Liddle, 2015).

We perform Pesaran (2007)'s CIPS test which belongs to the class of so-called second-generation unit root tests, i.e. those that account for the potential presence of cross-sectional dependence. The results show that non-stationarity is never rejected in the OECD sample, whereas the are a few cases where homogenous non-stationarity is rejected in the Non-OECD sample.[17] This evidence motivates the usefulness of the Bounds testing approach above.

There are essentially two proposed methods for panel regressions that are cross-sectionally correlated. These are the Common Correlated Effects (CCE) (Pesaran, 2006) and the AMG (Eberhardt and Teal, 2010) approaches. They have been shown to perform equally well. In Table 4 we present the results of estimating our basic specification (3) using three methods: a standard LSDV estimator, DOLS and AMG.

[16] Properties of panel DOLS have been discussed by Kao and Chiang (2000) and Mark and Sul (2003). Panel DOLS is straightforward to compute, and relevant test statistics have standard asymptotic distributions.

[17] The results are not shown to conserve on space. They are available from the authors upon request.

Table 4: Estimation of long-run "levels" relationship

	OECD Countries					Non-OECD Countries				
	LSDV		DOLS		AMG	LSDV		DOLS		AMG
	(1)	(2)	(1)	(2)		(1)	(2)	(1)	(2)	
lnat	0.999***	1.040***	0.885***	0.902***	1.196**	0.987***	0.994***	0.905***	0.980***	0.994**
	(0.053)	(0.054)	(0.190)	(0.161)	(0.571)	(0.036)	(0.036)	(0.166)	(0.076)	(0.432)
lmig	0.124***	0.121***	0.094***	0.091***	0.258**	0.063***	0.063***	0.086***	0.040**	0.138*
	(0.010)	(0.010)	(0.028)	(0.023)	(0.129)	(0.010)	(0.009)	(0.024)	(0.020)	(0.078)
lgdppc	0.163***	0.227***	0.574***	0.594***	0.515***	0.332***	0.337***	0.587***	0.774***	0.465***
	(0.027)	(0.026)	(0.074)	(0.063)	(0.101)	(0.019)	(0.018)	(0.065)	(0.039)	(0.071)
lresh	-0.173***	-0.179***	-0.260***	-0.206***	-0.337***	-0.198***	-0.198***	-0.205***	-0.241***	-1.576***
	(0.009)	(0.010)	(0.023)	(0.021)	(0.059)	(0.009)	(0.009)	(0.022)	(0.018)	(0.253)
lurb	0.497***	0.524***	0.052	0.104	4.494	0.871***	0.866***	0.078	0.387***	-0.393
	(0.092)	(0.095)	(0.374)	(0.309)	(3.331)			(0.320)		(0.734)
lagem	1.282***	1.298***	0.223	0.751**	-0.189	0.540***	0.543***	0.826**	0.656***	-0.413
	(0.115)	(0.118)	(0.322)	(0.326)	(0.771)	(0.080)	(0.080)	(0.337)	(0.170)	(0.529)
year/trend		-0.020***		-0.018***	-0.006		-0.003***	-0.017***		
		(0.001)		(0.003)	(0.010)		(0.001)	(0.003)		
N	1254	1254	1102	1102	1188	4418	4418	1064	3857	4418
F test	4211.6***	6666.0***				2357.3***	2910.5***			
Wald test			357.52***	359.78***	66.54***			340.17***	334.40***	83.91***
R-sq	0.996	0.996				0.990	0.990			
CD test					-1.697					0.086
p-value					(0.000)					(0.931)

Notes: Estimates in columns (1) and (3) are obtained including time dummies, while estimates in columns (2) and (4) allow for a linear time trend. Standard errors or p-values in parentheses. The DOLS specifications assume 1 lead and 1 lag. The results do not change with 2 leads and 2 lags. F and Wald tests are test of the joint significance of the included regressors. The null hypothesis of the CD test is weak cross-sectional dependence, the alternative is strong cross-sectional dependence. Asterisks indicate statistical significance with p-values as follows: * p<0.1, ** p<0.05, *** p<0.01.

All estimated coefficients, with some exception for the median age control, are strongly significant. This is especially notable for the parameters that refer to native and migrant population and affluence. The elasticity of per capita GDP is smaller than that of native population, although the difference is less marked in the DOLS case relative to the LSDV one. Finally, and most importantly for the present purposes, we see that the emissions elasticity of native-borns is eight to ten times larger than that of migrants. One first conclusion we can draw is that, in the OECD "rich" countries natives contribute to CO_2 emissions more than migrants *in percentage terms*.

Turning to the group of OECD countries the evidence is equally sharp. In this case we see that migrants' elasticity is significantly lower than in OECD. All the other parameters are strongly significant and confirm the previous pattern. Population is more impactful on carbon emissions than affluence in elasticity terms. According to Table 5, in the Non-OECD country group natives also appear to contribute to CO_2 emissions more than migrants *in percentage terms.*

All the models perform well in statistical terms according to F and Wald tests, with some specific weaknesses related to cross-sectional dependence and to the AMG estimator. The AMG estimation of the OECD sample excludes Denmark and Sweden, because within Northern Europe these two countries have developed an increasing share of renewables (hence a sharp decrease in the trend of CO_2 emissions) that contribute to generate a large part of electricity exports from Sweden to Denmark and then from Denmark to Germany. For these two countries there is a negative correlation between CO_2 emissions and population which could be partly attributed to the peculiar electricity export pattern toward Germany. As to the Non-OECD panel we see that while the AMG coefficients are statistically significant, Pesaran (2015)'s CD test of cross-sectional dependence is not significant. Thus, the AMG method is not able to completely purge cross-sectional dependence in the estimated residuals.

6. Discussion

The novelty of the present investigation lies in the analysis of the contribution of a country's population to CO_2 emissions by considering separately the role of native-borns and of migrants. Table 5 summarizes our estimated elasticities stemming directly from estimation of equation (3), the STIRPAT model with separate elasticities. The emissions elasticity of natives in on average equal to 0.89/1.20 for the OECD sample and 0.91/0.99

for the NON-OECD sample. In the case of migrants, we have an elasticity of 0.09/0.26 for OECD and 0.06/0.14 for Non-OECD. The estimated elasticities are slightly higher for the estimation methods LSDV and AMG and slightly lower for the estimation method DOLS. This pattern holds for both elasticities of natives and migrants and also in both areas OECD and Non-OECD.

Table 5: CO_2 emission elasticities of native-borns and migrants

	OECD					NON-OECD				
	LSDV1	LSDV2	DOLS1	DOLS2	AMG	LSDV1	LSDV2	DOLS1	DOLS2	AMG
	Estimated emissions elasticities from Equation (3)									
Natives	1.00	1.04	0.89	0.90	1.20	0.99	0.99	0.91	0.98	0.99
Migrants	0.12	0.12	0.09	0.09	0.26	0.06	0.06	0.09	0.04	0.14

Notes: Estimated coefficients from Table 6 based on equation (3) and computed elasticities from Table 9 based on equation (7) and the overall average ratios between emissions and natives and between emissions and migrants respectively. (+) indicates an elasticity computed using a statistically insignificant coefficient as reported in Table 7.

We see that *in percentage terms* native-born individuals have a one-to-ten larger impact on carbon emissions than migrants within a country. On the basis of this solid evidence, one might be led to conclude that for a variety of reasons, including economic conditions, cultural attitudes, habits and beliefs, individuals who migrated to and now reside in a country contribute to domestic emissions way less than individuals who are native to a country. Notice that this holds regardless of whether or not the country belongs to the club of the rich.

However, given the discrete nature of the population variable, it is also interesting to think of marginal contributions to emissions, that is, the increase in domestic emissions brought about by an additional individual residing in that country. Given our estimated elasticities from (3) we can easily calculate the marginal effects as follows:

$$(6) \qquad \frac{\partial CO_{2,it}}{\partial N_{it}} = \beta_1 \left(\frac{CO2_{it}}{N_{it}}\right) \quad \text{and} \quad \frac{\partial CO_{2,it}}{\partial M_{it}} = \beta_2 \left(\frac{CO2_{it}}{M_{it}}\right)$$

The marginal effects are country and time-varying. If we use the time average of the “carbon intensity” of the two population groups we obtain the results of Table 6.

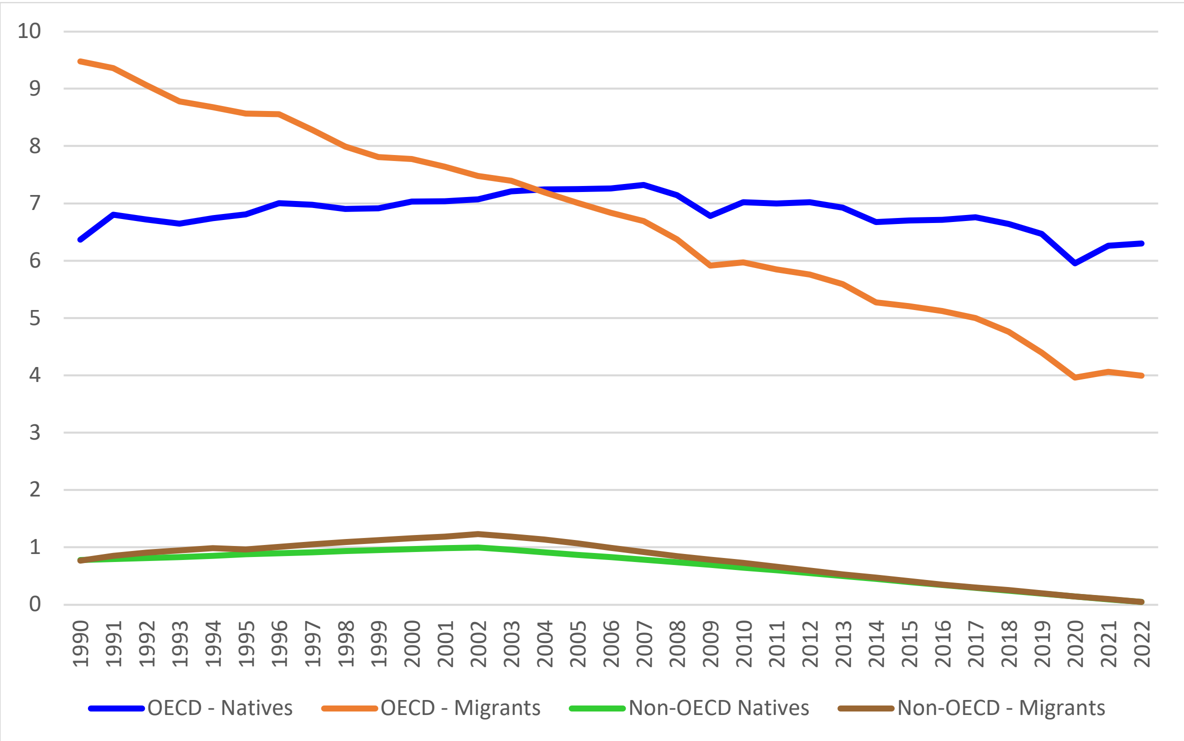
Table 6: Average marginal effects of one additional native-born and one additional migrant on CO_2 emissions

	OECD					Non-OECD				
	LSDV1	LSDV2	DOLS1	DOLS2	AMG	LSDV1	LSDV2	DOLS1	DOLS2	AMG
Natives	7.05	7.23	5.53	5.62	4.39$^{(+)}$	0.35	0.35	0.29	0.29	0.48
Migrants	8.30	8.52	6.51	6.61	5.17	0.34	0.34	0.29	0.29	0.47

Notes: $^{(+)}$ indicates a coefficient statistically insignificant at conventional levels.

Here we obtain a very different picture showing that, on average, one native individual contributes an additional 6.33 tons of carbon dioxide emissions if she resides in one of the rich countries, while a migrant contributes an additional, slightly larger, 6.74 tons. The contribution is dramatically smaller in NON-OECD countries where the contribution to emissions is only 0.41 on average, regardless of the origin of the individual. These relevant findings hide interesting trends over time that are shown in Figure 2.

Figure 2: Marginal effect on CO_2 emissions of native-borns and migrants



Source: values computed according to equation (3), using the estimated coefficients from regression results of Table 5 and the OECD and Non-OECD average CO_2/N and CO_2/M for period 1990-2022.

In fact, while the marginal contribution to emissions of NON-OECD country residents has been small and stable throughout the period considered, we see that the marginal impact of migrants has been steadily declining over time, while that of native-borns has remained relatively stable. The consequence of this fact is that the marginal impact to emissions of the average migrant in an OECD country that during the 1990s was higher than that of native individuals, it has become smaller after 2003-2004 to show at the end of the sample a contribution by 2-2.5 tons of carbon dioxide smaller than that of a native-born person.

These findings demonstrate a clear relationship between population dynamics (native-borns versus migrants) and CO_2 emissions, offering a critical contribution to the literature on environmental economics and migration studies. The evidence indicates that while native-born populations generally contribute more to emissions than migrants in percentage terms, the marginal impact of migrants has declined over time in OECD countries. These trends align with cultural, economic, and policy dynamics that shape energy consumption patterns across demographic groups. For instance, the lower emissions elasticity of migrants may reflect differences in consumption behaviors, resource access, or the adoption of more sustainable practices due to economic constraints or cultural norms. In general, a diminishing marginal contribution is indication of a phenomenon characterized by diminishing marginal returns, which in this case points to the idea that additional migrants in time are integrating in the hosting society better than their predecessors.

In NON-OECD countries, the stable, low contribution of migrants to CO2 emissions points to significant regional differences in economic and infrastructural development. This stability may be tied to limited industrialization, smaller energy footprints of households, and less energy-intensive urbanization. On the contrary, OECD countries face more dynamic shifts due to advanced infrastructure, evolving energy policies, and migrants' integration into existing high-consumption norms.

7. Conclusions and policy implications

This study represents an advancement in understanding the complex relationship between human population dynamics and CO_2 emissions, moving beyond conventional analyses that treat population as a homogeneous entity. Our methodological contribution lies in the estimation of an extended STIRPAT model that explicitly accounts for the distinct roles of native-born and migrant populations, utilizing robust econometric techniques across a comprehensive 1990-2022 dataset for 172 OECD and

Non-OECD countries. This approach provides a more granular and accurate view of demographic influences on emissions, aligning with recent tendencies in the literature to refine the demographic components of the IPAT and STIRPAT frameworks (O'Neill et al., 2012). In addition, the study employs advanced econometric techniques to ensure robustness against issues of non-stationarity and cross-sectional dependence, presenting empirical results of Dynamic OLS and Augmented Mean Group estimations.

The findings show that in OECD countries the emissions elasticity of native-born populations is on average 0.9–1.2, while that of migrants is significantly lower, averaging 0.10–0.26. Moreover, the marginal contribution of migrants to emissions in OECD countries has declined from over 8 tons of CO2 per individual in the 1990s to approximately 6 tons by 2022. In NON-OECD countries, native-born populations exhibit emissions elasticities of approximately 0.91–0.99, compared to migrants whose elasticities range between 0.04 and 0.14, highlighting the stark differences in carbon intensity across regions.

The findings of this study introduce a novel perspective to the literature on population and CO_2 emissions by distinguishing between the contributions of native-born individuals and migrants. Previous research has consistently demonstrated that population growth is a significant driver of carbon emissions, often exhibiting an elasticity close to or above one. However, those studies have largely treated population as a homogeneous entity, without differentiating the emissions impact of different demographic subgroups. By explicitly modeling the separate effects of native-born individuals and migrants, this paper reveals an important asymmetry: in both OECD and non-OECD countries, the emissions elasticity of native-born populations is significantly higher than that of migrants.

This key finding aligns with broader evidence that affluence and consumption patterns are primary drivers of emissions. Native-born populations in OECD countries tend to have well-established consumption habits that contribute to higher energy use, particularly in transportation, residential energy demand, and consumer goods. In contrast, migrants, especially those from lower-income countries, may maintain more conservative consumption behaviors due to economic constraints or cultural preferences (Hill, 2024). This aligns with research suggesting that migrants often consume less energy than native-born populations even after settling in high-income countries (Squalli, 2009).

An additional finding of this study is that in NON-OECD countries the marginal contribution of migrants to CO_2 emissions remains relatively stable over time, whereas in OECD countries it has significantly declined. This suggests that migrants in wealthier nations initially adopt higher emissions lifestyles upon arrival but, over time, their emissions footprint diminishes, possibly due to economic assimilation patterns or the adoption of energy-efficient behaviors. This finding is novel and contrasts with earlier studies, such as Kolankiewicz and Camarota (2008), which suggested that migration to high-income countries generally leads to an increase in per capita emissions. The present study, however, highlights that this effect is not static and evolves over time, with migrants' emissions contributions declining in later periods.

The evidence provided here that migrants have a lower emissions elasticity than native-born individuals, and that their marginal emissions contributions decline over time in OECD countries, provides a compelling new angle to discussions on climate policy and migration. These results challenge simplistic narratives that equate migration with increased emissions and suggest that policy approaches should consider the dynamic nature of consumption patterns among migrant populations. Future research could further explore the underlying behavioral and economic mechanisms driving these differences, particularly in terms of long-term integration and adaptation to local energy consumption norms.

We confirm the existing literature that emphasizes the greater relative impact of population growth compared to affluence. In both OECD and NON-OECD countries, the emissions elasticity of population exceeds that of GDP per capita, reinforcing earlier work by several authors. However, by disaggregating population into native-born and migrant subgroups, this study provides additional nuance: while population growth among native-born individuals remains a strong driver of emissions, migrant populations appear to integrate into existing economic structures with a lower or declining emissions intensity. This introduces an important policy dimension, suggesting that migration, rather than being an unqualified environmental burden, may have complex and evolving effects on emissions that require further examination.

The findings of this study yield distinct implications for both market actors and policymakers, particularly when considering the regional divide between OECD and Non-OECD countries. Significant policy implications arise from our findings. First, the higher emissions elasticity of native-born populations in OECD countries calls for targeted interventions that encourage sustainable consumption and energy efficiency within these groups. For example, fiscal policies such as carbon taxes or subsidies for energy-efficient appliances could be tailored to address the higher consumption patterns of native-born populations. In addition, climate policies should prioritize targeting established consumption patterns among natives. Policymakers could implement differentiated carbon pricing, energy efficiency incentives, or behavioral nudges tailored to long-term residents who contribute more heavily to emissions. For market players, this opens avenues for expanding green consumer products and services aimed at established households, especially in sectors like transportation, home energy systems, and durable goods.

Simultaneously, integrating migrants into green energy initiatives and urban planning strategies could harness their potential for adopting sustainable behaviors while mitigating emissions. Policies such as subsidized public transportation, access to affordable renewable energy sources, and culturally tailored outreach programs to educate migrant communities about energy-saving practices can be highly effective. The differentiated policies increase efficacy by aligning strategies with the consumption habits, cultural norms, and socioeconomic realities of each group, ensuring broader adoption and impact.

In Non-OECD countries, sustainable urbanization and investment in low-carbon technologies should be prioritized. Policies encouraging compact urban development, renewable energy projects, and the provision of affordable, energy-efficient housing can preemptively address the environmental pressures associated with rapid industrialization and urban migration. For these countries, the opportunity lies in leapfrogging into low-carbon development pathways by investing in renewable energy, affordable efficient housing, and mass transit solutions before high-emissions lifestyles become entrenched. By proactively planning for future population growth, these measures reduce long-term carbon footprints and enhance resilience to climate change.

Overall, by recognizing the demographic heterogeneity of emissions contributors, governments and firms can craft more efficient and equitable mitigation strategies that reflect the underlying behavioral and structural drivers revealed by this study.

This paper represented a first cut to the issue. We think that future research could gain more interesting insights using more granular data, such as the income of different demographic groups, sectoral employment and wages for migrants and native-borns, disaggregated energy consumption patterns and leveraging granular household-level data on energy use and carbon footprints.

In conclusion, this study provides a critical contribution to the literature on population-environment interactions by revealing the heterogeneous impacts of demographic groups on CO_2 emissions. The results underscore the need for differentiated policy approaches that account for demographic diversity, regional economic contexts, and evolving consumption patterns. By aligning policy measures with the specific behaviors and contributions of different demographic groups, policymakers can enhance the efficacy of climate change mitigation strategies. These targeted interventions not only improve environmental outcomes but also promote equitable and inclusive approaches to achieving global sustainability goals.

Acknowledgments

The authors acknowledge the financial support of the EU Grant Next Generation EU Mission 4 Component 1 CUP G53D2300676001 and CUP J53D23015200001 (prot. P2022A82P3).

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Appendix A: List of countries

OECD countries:

Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States of America.

Non-OECD countries:

Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, The Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, China, Comoros, Congo Democratic Republic, Congo Republic, Côte d'Ivoire, Croatia, Cyprus, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eswatini, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyzstan, Lao, Lebanon, Lesotho, Liberia, Libya, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Nauru, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Qatar, Romania, Russia, Rwanda, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Solomon Islands, South Africa, Sri Lanka, St. Kitts and Nevis, St. Vincent and the Grenadines, Sudan, Tajikistan, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, Uruguay, Uzbekistan, Vanuatu, Vietnam, Zambia, Zimbabwe.

Appendix B: Robustness

Our STIRPAT specification (3) in the main text postulates that the stocks of native-born and migrant people are characterized by a separate impact on CO_2 emissions captured by the two elasticities β_1 and β_2 in (1). The original IPAT formulation allows substantial flexibility as to the variables which should be actually included in the equation: the only message is that an environmental impact is due to the combined effect of demographic, economic, and technological factors.

If we recognize that the sum of native-borns and migrants amounts to the overall population, we should specify a standard STIRPAT equation:

(B.1) $$CO_{2,it} = P_{it}^{\gamma_i} A_{it}^{\gamma_2} T_{it}^{\gamma_3} = (M_{it} + N_{it})^{\gamma_i} A_{it}^{\gamma_2} T_{it}^{\gamma_3}$$

The estimated STIRPAT specification becomes:

(B.2) $$lnCO_{2,it} = \alpha_i + \mu_t + \gamma_1[lnM_{it} + lnN_{it}] + \gamma_2 \ln A_{it} + Z_{it}'\theta + \epsilon_{it}$$

On the basis of (B.2) we can evaluate the population elasticity γ_1 which can be directly compared with the estimates available in the literature and discussed in Section 2 of the main text. In addition, we can evaluate the elasticity of carbon emissions with respect to both native-borns and to migrants by computing the following quantities:

(B.3) $$\gamma_1^M = \frac{\partial lnCO_{2,it}}{\partial lnM_{it}} = \frac{\partial lnCO_{2,it}}{\frac{1}{M_{it}}\partial M_{it}} = M_{it}\frac{\partial lnCO_{2,it}}{\partial M_{it}} = M_{it}\left[\gamma_1 \frac{1}{M_{it}+N_{it}}\right] = \gamma_1\left(\frac{M_{it}}{P_{it}}\right)$$

(B.4) $$\gamma_1^N = \frac{\partial lnCO_{2,it}}{\partial lnN_{it}} = \frac{\partial lnCO_{2,it}}{\frac{1}{N_{it}}\partial N_{it}} = N_{it}\frac{\partial lnCO_{2,it}}{\partial N_{it}} = N_{it}\left[\gamma_1 \frac{1}{M_{it}+N_{it}}\right] = \gamma_1\left(\frac{N_{it}}{P_{it}}\right)$$

We followed the same estimation procedure of the main text. We estimate ARDL(p,q) specifications based on (B.2) with p,q = 1,2. Table B.1 shows the values of the BIC.

Table B.1: Lag length selection

	OECD Countries		Non-OECD Countries	
ARDL(p,q)	Time dummies	Time trend	Time dummies	Time trend
(2,2)	-3364.795	-3436.448	-5445.589	-5578.057
(2,1)	-3396.269	-3467.807	-5490.176	-5622.041
(1,2)	-3369.985	-3441.899	-5448.273	-5580.417
(1,1)	-3401.394	-3473.049	-5492.937	-5624.046

Notes: See Table 3 in the main text.

We first note that the two specifications of time effects give the same outcome. Secondly, the Bayes Information Criterion selects an ARDL(1,1) both for OECD and Non-OECD countries. We proceed to perform a "Bounds Test" to see if there is evidence of a long-run relationship as given by (B.2). To that end we carry out the Bounds F test as seen above and the results are presented in Table B.2.

Table B.2: Bounds F Test

	OECD		Non-OECD	
	Time dummies	Time trend	Time dummies	Time trend
ARDL(2,2)	18.29 (0.000)	17.55 (0.000)	51.88 (0.000)	52.83 (0.000)
ARDL(2,1)	20.06 (0.000)	19.30 (0.000)	53.12 (0.000)	54.33 (0.000)
ARDL(1,2)	19.06 (0.000)	18.24 (0.000)	51.79 (0.000)	52.85 (0.000)
ARDL(1,1)	20.31 (0.000)	19.48 (0.000)	52.63 (0.000)	53.86 (0.000)
Narayan (2005)'s critical values of the F test				
	Case III		*Case IV*	
	Lower bound	*Upper bound*	*Lower bound*	*Upper bound*
	2.06	*3.24*	*2.33*	*3.46*

Notes: See Table 4 in the main text.

From the outcome of the bounds tests in the table we can conclude that in all cases the existence of a long-run relationship among the variables involved is a hypothesis that cannot be rejected. We can then proceed to the estimation of the long-run "levels relationship" (B.2). As done in the main text, we present in Table B.3 the results obtained from standard least squares dummy variable (LSDV), Dynamic OLS, and Augmented Mean Group estimator.

Table B.3: Estimation of long-run "levels" relationship

	OECD Countries					Non-OECD Countries				
	LSDV		DOLS		AMG	LSDV		DOLS		AMG
	(1)	(2)	(1)	(2)		(1)	(2)	(1)	(2)	
lpop	1.251***	1.284***	0.981***	0.997***	0.780	1.202***	1.204***	1.022***	1.023***	1.660***
	(0.048)	(0.050)	(0.177)	(0.156)	(0.596)	(0.033)	(0.033)	(0.084)	(0.106)	(0.385)
lgdppc	0.184***	0.250***	0.603***	0.578***	0.558***	0.410***	0.411***	0.746***	0.746***	0.409***
	(0.026)	(0.026)	(0.076)	(0.062)	(0.096)	(0.018)	(0.018)	(0.038)	(0.038)	(0.066)
lresh	-0.171***	-0.178***	-0.251***	-0.195***	-0.350***	-0.199***	-0.198***	-0.221***	-0.213***	-1.644***
	(0.009)	(0.009)	(0.023)	(0.020)	(0.064)	(0.009)	(0.009)	(0.018)	(0.018)	(0.258)
lurb	0.283***	0.314***	0.009	0.078	7.795**	0.860***	0.858***	0.401***	0.412***	0.472
	(0.090)	(0.093)	(0.388)	(0.303)	(3.848)	(0.044)	(0.044)	(0.132)	(0.135)	(0.737)
lagem	1.936***	1.940***	0.116	0.818***	0.535	0.583***	0.583***	0.475***	0.613***	-0.642
	(0.107)	(0.110)	(0.315)	(0.316)	(0.803)	(0.074)	(0.074)	(0.167)	(0.225)	(0.461)
year/trend		-0.024***		-0.019***	-0.010		-0.009***		-0.011***	
		(0.001)		(0.003)	(0.011)		(0.001)		(0.003)	
N	1254	1254	1102	1102	1188	4418	4418	3857	3857	4418
F test	4399.87	7079.3				2623.85	3216.59			
p-value	0.000	0.000				0.000	0.000			
Wald test			297.13	314.59	82.56			1541.58	1208.89	100.5
p-value			0.000	0.000	(0.000)			0.000	0.000	(0.000)
R-sq	0.996	0.996				0.990	0.990			
CD test					-2.077					1.176
p-value					(0.038)					(0.240)

Notes: See Table 5 in the main text.

The performance of all models is quite good when judged on the basis of F tests and Wald tests of joint significance of coefficients. The estimated parameters referring to population and affluence are generally strongly significant. Notably, the LSDV method returns a population elasticity that is higher than the one estimated with DOLS, while the opposite occurs for the affluence elasticity.

The emission elasticity of population is always significantly higher than the emission elasticity of per capita GDP, confirming previous findings in the literature. A summary of the findings of selected STIRPAT studies in the existing literature reviewed in the main text is presented in Table B.4.

Table B.4: Estimated impact of population on carbon emissions from literature

	Percentage increase in carbon emissions per 1% increase in population
Dietz and Rosa (1997)	1.15
York et al. (2003)	0.98
Shi (2003)	1.43
Cole and Neumayer (2004)	0.98
Martínez-Zarzoso et al. (2007)	1.37 – 1.87
Poumanyvong and Kaneko (2010)	1.07 – 1.27
Bargaoui et al. (2014)	0.97 – 1.16
Liddle (2015)	1.38 – 1.85
Casey and Galor (2017)	1.36 – 1.47

Note: (i) when different cross-country panels are estimated, the elasticities in the table refer to all countries samples; (ii) when different specifications are estimated, elasticities in the table refer to static models. Elasticities stemming from dynamic models are typically lower.

It is generally recognized that the population elasticity is larger than the affluence elasticity. We confirm this finding, as summarized by our estimated coefficients in Table B.5.

Table B.5: CO_2 emission elasticities of population and affluence

	OECD					Non-OECD				
	LSDV1	LSDV2	DOLS1	DOLS2	AMG	LSDV1	LSDV2	DOLS1	DOLS2	AMG
POP	1.25	1.28	0.98	1.00	0.78(+)	1.20	1.20	1.02	1.02	1.66
GDPpc	0.18	0.25	0.60	0.58	0.56	0.41	0.41	0.75	0.75	0.41

Notes: Estimated coefficients from Table B.3. (+) indicates a coefficient statistically insignificant at conventional levels.

The average of the coefficients in the table for population is 1.12 for the OECD sample and 1.43 for the Non-OECD block, whereas it is for affluence 0.37 in the OECD case and

0.41 in the Non-OECD case. Relative to the literature on population elasticity, our findings are in line with the figures in the literature as summarized in Table B.4. In passing we note that, unlike the studies in literature, we cover all OECD countries and the large majority of Non-OECD countries for which data is available. Moreover, our sample is updated to the last publicly available data released at the time of writing.

Turning to the distinction between native-borns and migrants, the elasticities are time-varying. Therefore, we used the sample average of the ratios in equations (B.3)-(B.4), as shown in Table B.6.

Table B.6: CO_2 emission elasticities of native-borns and migrants

	OECD					Non-OECD				
	LSDV1	LSDV2	DOLS1	DOLS2	AMG	LSDV1	LSDV2	DOLS1	DOLS2	AMG
	Implied emissions elasticities from Equation (B.3)									
Natives	1.13	1.16	0.89	0.90	0.71(+)	1.18	1.18	1.00	1.00	1.63
Migrants	0.12	0.12	0.09	0.09	0.07	0.02	0.02	0.02	0.02	0.03

Notes: Estimated coefficients from Table B.5 based on equation (B.3) and computed elasticities from Table B.5 based on equations (B.3) and (B.4) and the overall average ratios between emissions and natives and between emissions and migrants respectively. (+) indicates an elasticity computed using a statistically insignificant coefficient as reported in Table B.3.

The results confirm the pattern already evidenced in the main text where a STIRPAT specification with separate elasticities for native-born and migrant populations was estimated. In percentage terms native-born individuals have about an impact on carbon emissions one-to-ten larger than that of migrants within a country. This fact holds regardless of whether or not the country belongs to the club of the rich.

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