Identifying rebound effects in consequential LCA

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Para mi madre y hermano

Para mi madre, Alba Libia Henao Zuluaga, por enseñarme a trabajar diariamente con ahínco por mis sueños sin importar las dificultades; y mi hermano Kevin Vélez Henao, quien me ha ensañado el valor de la familia.

DECLARATION

I, Johan Andrés Vélez Henao, declare that the work presented in this thesis is my own.
Some information has been derived from other sources; I confirm it has been clearly indicated in the thesis.
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Resumen

Una de las estrategias colombianas para diversificar y descarbonizar el sector energético es fomentar el uso de recursos renovables no convencionales (RNNC). Para ello, el gobierno emitió en 2014 la Ley 1715 para promover los RNNC y las mejoras de eficiencia energética en el sector. Si bien esto ayudará a cumplir el compromiso internacional y nacional de reducir las emisiones de CO2 en un 20% en 2030, este supuesto no puede ser probado de manera amplia sin tener en cuenta las consecuencias ambientales que tales iniciativas pueden producir en el sector doméstico, el mayor sector consumidor de electricidad en Colombia.

Esta tesis mide el efecto rebote ambiental (ERE) de aumentar la participación de energía eólica en la red eléctrica colombiana en el sector residencial (hogares). Para ello se aplicó un modelo de evaluación del ciclo de vida basada en procesos (P-LCA), un modelo de entrada y salida ambiental extendido (EEIO) y modelos de gastos adicionales (sistema de demanda casi ideal AIDS).

El efecto rebote directo se midió a través del precio de la elasticidad de la demanda de electricidad; además, el ahorro medioambiental por el aumento de la participación de energía eólica en la red se calculó a través de P-LCA. Para ello se realizó un P-LCA para un parque eólico en Colombia, mientras que la información para otros recursos energéticos (Hidro, Carbón, Gas, Solar) se tomó de la base de datos Ecoinvent 3.4.

Para calcular el efecto rebote indirecto ambiental se calcularon los ahorros monetarios obtenidos por la eficiencia ambiental. Para ello se aplicó un AIDS para obtener las participaciones presupuestarias marginales (MBS). Combinando las MBS obtenidas con el modelo EEIO, el ahorro monetario se tradujo en indicadores ambientales.

El ERE se presenta para diez categorías de impacto (cambio climático (CC), acidificación (A), ecotoxicidad (E), eutrofización marina (MEUT), eutrofización terrestre (TEUT), efectos cancerígenos (CE), efectos no cancerígenos (NCE), agotamiento de la capa de ozono (OD), creación fotoquímica de ozono (POC), y efectos respiratorios, inorgánicos (RES)). Además, se realizó un análisis de sensibilidad para medir la variabilidad del ERE con respecto a los diferentes valores del efecto rebote directo y los diferentes porcentajes de eficiencia de los precios.

Los resultados muestran que la inclusión del efecto de rebote ambiental tiene generalmente un impacto no despreciable en los indicadores ambientales globales a lo largo de todos los años estudiados. Estos impactos oscilan entre el 5% (eutrofización) y el 6,109% (creación de oxidantes fotoquímicos) para el modelo combinado, mientras que para el modelo único los valores caen en los rangos del 1% (eutrofización) y el 9,277% (creación de oxidantes fotoquímicos). Además, un análisis de sensibilidad del precio de la elasticidad de la electricidad y del precio de la electricidad revela que la ERE varía de diferentes maneras, específicamente, los cambios en estos parámetros podrían variar los impactos, respectivamente, hasta entre un <1% y 38%. En 8 de 10 los impactos ambientales estudiados está presente el “backfire effect” o “efectos contraproducentes” en diferentes magnitudes a lo largo de los años, dependiendo en gran medida de los ahorros disponibles para reinvertir.

Palabras clave. Efecto de rebote ambiental, mejoras en la eficiencia ambiental, recursos renovables no convencionales, LCA, STIRPAT.

Abstract

One of the Colombian strategies to diversify and decarbonize the energy sector is encouraging the use of non-conventional renewable resources (NCRR). For doing so the government issued in 2014 the Law 1715 to promote NCRR and energy efficiency improvements into the sector. While presumably it will help to achieve the international and national commitment to reduce the CO2 emission by 20% in 2030, this assumption cannot be tested broader without taking in account the environmental consequence that such initiatives may produce in the household sector, the greatest electricity consuming sector in Colombia

This thesis measures the environmental rebound effect (ERE) when increasing the shares of wind power into the Colombian power grid in the residential (household) sector. For doing so, a process-based Life Cycle Assessment (P-LCA), an environmental extended input output (EEIO) model and re-spending models (almost ideal demand system AIDS) were applied.

Direct rebound effect was measured thought the elasticity price of the electricity demand; furthermore, the environmental savings for increasing the shares of wind power into the grid were calculated via P-LCA. For doing so, a P-LCA for a wind farm in Colombia was performed, whereas the information for other energy resources (Hydro, Coal, Gas, Solar and Thermal) where collected from Ecoinvent 3.4 database.

To calculate the environmental indirect rebound effect the monetary savings obtained for the environmental efficiency were calculated. For doing so, an AIDS was applied to obtain the marginal budget shares (MBS). Combining the MBS obtained with the EEIO model the monetary savings were translated into environmental indicators.

The ERE is presented for ten impact categories (climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects, inorganics (RES)). Moreover, a sensitive analysis was conducted to measure the variability of the ERE to different values of the direct rebound effect and different percentages of price efficiency.

The results show that the inclusion of the environmental rebound effect has generally a non-negligible impact on the overall environmental indicators across all studied years. Such impacts ranging across impact categories from 5% (eutrophication) and 6,109% (photochemical oxidant creation) for the combined model, whereas for the single model the values fall on the ranges of 1% (eutrophication) and 9,277% (photochemical oxidant creation). Further, a sensitivity analysis of the elasticity price of the electricity and the price of the electricity reveals that the ERE varies in different ways, specifically, changes in these parameters could vary the impacts, respectively, by up to about <1% and 38%. Backfire effects are present for 8 of the 10 environmental impacts studied in different magnitudes across the years, depending meanly of the savings available to re-invest.

Keywords. Environmental rebound effect, environmental efficiency improvement, non-conventional renewable resources, LCA, STIRPAT.

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List of abbreviations

Abbreviation	Description	Abbreviation	Description
P	Population	EF	Energy efficiency
p^2	Quadratic form of population	L	Land
AE	Age structure	R&D	Research And Development
A^+	Affluence	HS	Household size
A^2	Quadratic form of affluence	FT	Foreign trade degree
U	Urbanization	CS	Consumption structure
U^2	Quadratic form of urbanization	D	Diet structure change
UD	Urban density	EP	Energy price
IN	Industrialization	FI	Foreign investment
IN*	Refers to the share of secondary and tertiary (services sector) industry	GDP	Gross domestic product
IN**	Refers to primary industry	PD	Population density
SV	Service sector	F	Represents the financial support for rural areas
EI	Energy intensity	A*	Per capita annual disposable income of rural households
ES	Energy structure	TEM	Annual average temperature (◦C)
CI	Carbon emission intensity	TN	Total nitrogen
ER	Environmental regulation	TP	Total phosphorus
PUB	Number of public transportation ownership per person	PSI	Investment in the private transport sector

Abbreviation	Description	Abbreviation	Description
FPR	Fuel price	RAIL	Rail infrastructure
NC	Numbers of cars and buses	EFI	Ecological footprint intensity
COD	Chemical oxygen demand	LR	Share of households with private garden
ED	Educational level	MENA	Middle East and North Africa
GSHP	Floor area of Ground-Source Heat Pump	HA	Central heating area
PI	Policy investment.	PEC	Per capita energy consumption
FAI	Total fixed asset investment	BM	Per capita city building and maintenance capital
PIUR	Per capita disposable income of urban resident	CPB	Carbon emission intensity in Chinese public buildings
CCR	Coal consumption rate,	LLR	Line loss rate
LAP	Labor productivity	URE	Urban employment level
PIC	Intensity of real economy	IST	Industrial structural transformation
ISR	Industrial structure rationalization	ISU	Industrial structural upgrading
ML	Technological progress	EIM	Denotes efficiency improvement
TI	Technology innovation	ETFP	Environmental total factor productivity
GA	Green areas per capita,	BU	Build up areas
TSE	The time-specific effect	EPR	Energy productivity
FD	Financial development	FD^2	Quadratic form of Financial development
LUPR	Land urbanization rate	LF	Land finance
CCB	Carbon emission intensity in Chinese commercial buildings	PCB	Per capita commercial buildings
ENI	PM2.5 concentrations	WI	Water intensity
RC	Residential consumption level	WA	Income ratio
EGN	Engel Coefficient	RE	Renewable energy
AG	Agricultural machinery	DD	Disaster degree
O	Degree of opening to the outside	V	Traffic density factor
NPV	Number of private vehicles	IU	Internet uses
PRE	Precipitation	MTA	Mean temperature anomaly

Abbreviation	Description	Abbreviation	Description
HDD	Heating degree days	CDD	Cooling degree days.
EU	Energy use	PGE	Power generation efficiency
LCA	Life cycle assessment	P-LCA	Process based life cycle assessment
IO-LCA	Input-output life cycle assessment	NCRR	Non-conventional renewable resources
AIDS	Almost ideal demand system	MBS	Marginal budget shares
EEIO	Environmentally-extended input-output	RE	Rebound effect
ERE	Environmental rebound effect	A	Acidification
CC	Climate change	E	Ecotoxity
EUT	Eutrophication	TEUT	Terrestrial eutrophication
MEUT	Marine eutrophication	CE	Carcinogenic effects
NCE	Non-carcinogenic effects	OD	Ozone layer depletion
POC	Photochemical ozone creation	RES	Respiratory effects, inorganics
IPCC	Intergovernmental Panel on Climate Change	EC	European Commission
EEA	European Environment Agency	IEA	International Energy Agency
UNEP	the United Nations Environment Programme	COP21	United Nations Climate Change Conference
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and. Technology	GHG	Greenhouse gas
OECD	Organization for Economic Co-operation and Development	LCIA	Life cycle impact assessment
ILCD	International Reference Life Cycle Data System	SUI	Superintendence of public services domiciliary
DANE	National Administrative Department of Statistics	PNCC	National climate change policy
PNACC	National Climate Change Adaptation Plan	ENREDD+	National Strategy for Reducing Emissions from Deforestation and Forest Degradation
ENFCC	National Climate Finance Strategy	UPME	Energy Mining Planning Unit
SDG	Sustainable development goals	LCI	Life cycle inventory
GTAP	Global Trade Analysis Project	EXIOBASE	Global multi-regional Environmentally Input Output database
Ecoinvent	Life cycle inventory database	IHLCA	Integrated hybrid LCA

Abbreviation	Description	Abbreviation	Description
HCE	Household consumption expenditures	COICOP	Classification of individual consumption by purposes

1. Introduction

One of the main challenges of the global economy is to achieve an economic growth without the depletion of the natural resources so that the future regeneration may meet their own needs. This paradigm become one of the most important goals of the human kind since the United Nations labeled it as “Sustainable development”, a concept introduced by Gro Harlem Brundtland chair of the World Commission on Environment and Development in his report “Our Common Future” to the United Nations in 1987 (United Nations, 1987).

Among the different strategies to achieve the sustainable development e.g. efficiency, consistency, and sufficiency. The efficiency which implies reduce the consumption of materials and energy to provide certain services “produce more with less” is suggested to be the key to decouple the economies to the depletion of resources and environmental impacts (IPCC, 2014). Thus, technology, via technical efficiency improvement have been thought to be play a decisive role to reduce the environmental impacts caused by anthropogenic activities (Sharon, 1994).

Several approaches e.g. The IPAT equation introduce by Ehrlich and Holdren (1971, 1972) define the environmental pressures (I) as function of the product of the population (P), affluence (A^+), and technology (T) in which T is commonly defined as the environmental impact per unit of economic activity (efficiency measurement) that translates human actions into environmental impacts (Commoner, 1972; Ehrlich & Holdren, 1971, 1972). Similarly, the Intergovernmental Panel on Climate Change (IPCC) uses a reformulation of the IPAT model, called the KAYA equation, as the basis for the greenhouse gas emissions (GHG) emissions calculation, projections, and scenarios (S. Lin et al., 2009). Different variations of the IPAT equation, e.g. ImPACT, ImPACTS, IPBAT, and STIRPAT, implicatively assume T as key to decouple economic growth from pollution (Vélez-henao et al., 2019). Consequently, several international and national policies, programs and strategies seeking to decouple resources consumption from economic growth focus their effort in efficiency improvements to achieve their goals.

However, the effectiveness to achieve those goals through efficiency improvements may be limited by the so called rebound effect (Maxwell et al., 2011). The rebound effect is a widely accepted phenomenon introduced by Stanley Jevons in the late nineteenth century (1865) and popularized in the last decades by Khazzom (1980) and Brookes (1990). An interesting debate about this topic can be found in Berkhout and colleagues (2000), and Muster (1995). General speaking the RE states that a change in the technical efficiency of an energy service can change the overall consumption pattern of this service, due to the behavioral responses of economic variables such as: income, price, financial gains, product costs, and material substitution (David Font Vivanco & Voet, 2014a). Similar definitions of the RE can be found in the literature (Berkhout et al., 2000; Binswanger, 2001; Brookes, 1990; Girod et al., 2010; Greening et al., 2000; Sorrell et al., 2009; Sorrell & Dimitropoulos, 2007; Weidema, 2008).

Different definitions of the rebound effect can be found in the literature (Berkhout et al., 2000; Binswanger, 2001; Brookes, 1990; Girod et al., 2010; Greening et al., 2000; Sorrell et al., 2009; Sorrell & Dimitropoulos, 2007; Weidema, 2008). A definition that can encompass all of them is the following: the rebound effect is the change in consumption and production of goods or services as a consequence of a change in economic variables (such as income, price and financial gains or costs of product and material substitution) caused by the improvement in efficiency of providing an energy service (David Font Vivanco & Voet, 2014a). Greening et al., (2000) provided a widely accepted classification of the rebound effect, classifying it into direct, indirect, and macroeconomic effects. The direct rebound effect can be measured through the efficiency or price elasticity of energy services. The indirect rebound involves further changes in consumption patterns caused by energy efficiency improvements. These patterns are captured through macroeconomic price variables rather than efficiency variables. Combination of Input Output models and re-spending models are commonly used to capture such effects (Freire-González, 2011). Macroeconomic effect refers to both direct and indirect responses to efficiency energy improvement.

Recently, the importance and complexity of the rebound effect has been handled by diverse actors such as academic, public, and private entities in different disciplines such as energy economics, transportation economics, and environmental sciences. According to Font Vivanco et al. (2016), many intergovernmental organizations and international agencies, such as the European Environment Agency (EEA), the European Commission (EC), the International Energy Agency (IEA) the United Nations Environment Programme (UNEP), the Department of Energy and Climate Change in the United Kingdom (UK), the Irish Department of Communications, Marine, and Natural Resources, and the U.S. Department of Energy, have advocated for the importance of taking into account the rebound effect, given its impact on achieving environmental goals. In the context of energy and climate change policies, projections from the Intergovernmental Panel on Climate Change (IPPC) that by 2030, energy efficiency gains will reduce global energy consumption by 30% below where they would otherwise be do not incorporate the rebound effect. Many rebound effect publications cite this as a serious oversight in light of the evidence for rebound effects for energy efficiency (Maxwell et al., 2011).

Moreover, some authors refer to the environmental rebound effect (E)RE, a concept that has its roots in industrial ecology and was first introduced by Goedkoop et al (1999) as the environmental pressure resulting from a function fulfillment optimization. This concept offers a more holistic view of the environmental impacts caused by an improvement in the efficiency of providing a service, expressing the rebound effect in different environmental dimensions, such as material extraction, emissions, and waste. Detailed information about the rebound effect and the environmental rebound effect can be found in (David Font Vivanco, Mcdowall, et al., 2016; Greening et al., 2000; Sorrell & Dimitropoulos, 2007). Moreover, Font Vivanco et al. (2014) presented a general framework to capture and assess the RE through the IPAT equation.

The ERE is possible to measure by the integration of LCA (Life Cycle assessment) approaches translating conventional measures of the rebound effect into different environmental footprints. LCA is a holistic approach developed to assess the environmental impacts caused by a product or service during the entire life of cycle, from the extraction of raw materials until the disposal or recycling (cradle to gate). LCA procedures are standardized by the ISO family 14040-14044 (ISO, 1998, 2000a, 2000b, 2006a, 2006b). The results found are analyzed below, in the presentation of each chapter of this document.

Different LCA approaches can be distinguish. (1) the process-based model (P-LCA) allows to model in a detailed way determinate technology across the entire life cycle of a product or services. Through P-LCA it is also possible to include the use and end-of-life (EoL) stages. (2) input output LCA (IO-LCA) allows including complete information of the system boundaries (whole economy) making possible to identify the environmental impacts of determinate consumption patter. According to Joshi (2000), traditional methods suffer, among other, from problems of subjective boundary definition and aggregation. Process-based LCA (P-LCA) often suffers from truncation as well as omission of resource use and emissions of upstream stages by setting subjective system boundaries (Huey et al., 2017; Lenzen, 2000). On the other hand, input–output LCA (IO-LCA) includes the whole economy as the system boundary, yet it suffers from aggregation issues as the product of interest is generally approximated by its commodity sector, an aggregation of a large number of heterogeneous products (Joshi, 2000; Lenzen, 2000). Finally, the (3) approaches, Hybrid LCA combines the strengths of both P-LCA and IO-LCA, resulting in a more robust method for environmental footprinting (Suh et al., 2004). Thus, the hybrid approaches allow to bring analyses one step ahead by (1) integrating social and economic aspects, (2) expanding the level of analysis across sectors and regions, and (3) including scenarios and rebound effects (Onat et al., 2017).

The ERE has been extensively studied for several regions, technologies, and environmental indicators. Estimations of the ERE can be found in the literature for general energy efficiency improvements in the household sector in US, China and Spain (Freire-González et al., 2017; Freire-González and Font Vivanco, 2017; Thomas and Azevedo, 2013a; Wen et al., 2018), smartphones reuse in the US (Makov and Font Vivanco, 2018), electric cars and transport innovations in Europe (Font Vivanco et al., 2016c, 2015; Font Vivanco and Voet, 2014), green consumption in Australia (Murray, 2013), and high-speed transport technologies (Spielmann et al., 2008). Whereas, the environmental rebound effect has not been yet explored in the area of renewable energy resources.

1.1 Problem statement

The energy sector is the second largest emitter of greenhouse gas (GHG) emissions in the country, accounting for about 35% of the 236.9 Mton of CO_2 emitted in 2014 (see figure 1).[1] About 28% of the GHG emissions of the energy sector come from electricity and heat production (IDEAM et al., 2018), mainly from the combustion of coal and natural gas, which still have a substantial presence in the energy grid (70% hydro, 18% coal, 12% Gas, <1% wind in 2014) (see figure 2) (UPME, 2019). Moreover, the current energy grid poses challenges for ensuring a continuous electricity supply during climatic variations such as the "El Niño" phenomenon, due to rainfall decrease which feeds the dams (Vélez Henao & Garcia Mazo, 2019). To meet the rising electricity demand while diversifying and decarbonizing the energy system, the Colombian government plans a sizeable increase in the share of non-conventional renewable resources (NCRRs, such as wind and solar power) (UPME, 2016b). Specifically, the government issued the law 1715, with the purpose of promoting energy and environmental efficiency in the energy sector (LEY 1715 de 2014, 2014). This policy seeks first to promote NCRRs to protect the electricity grid against the effects of the "El Niño" phenomenon. Second, to achieve the commitments made in COP 21 to reduce carbon emissions by 2030 (Vélez Henao & Garcia Mazo, 2019). Third, to align energy policies with the 7th sustainable development goal (SDG): guarantee the access for renewable and sustainable energy (United Nations, 2017).

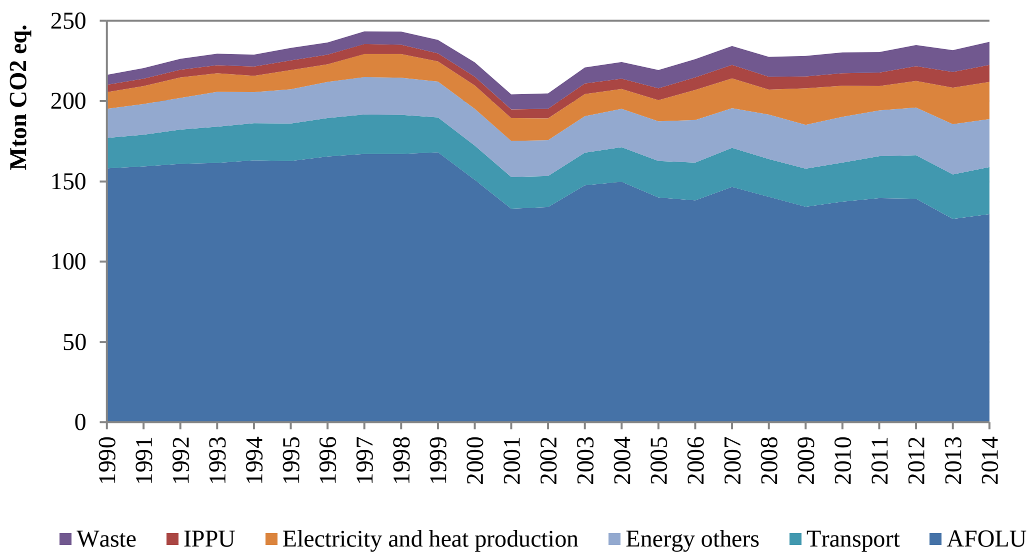

Figure 1-1. CO_2-equivalent emissions by economic sector in Colombia for the period 1990-2014. IPPU: industrial process and product use; Energy others: oil refining, solid fuel manufacturing,

[1] This was the last year available at the writing of this article.

manufacturing and construction industries, other sectors, and fugitive emissions; AFOLU: agriculture forestry and other land use (IDEAM et al., 2018).

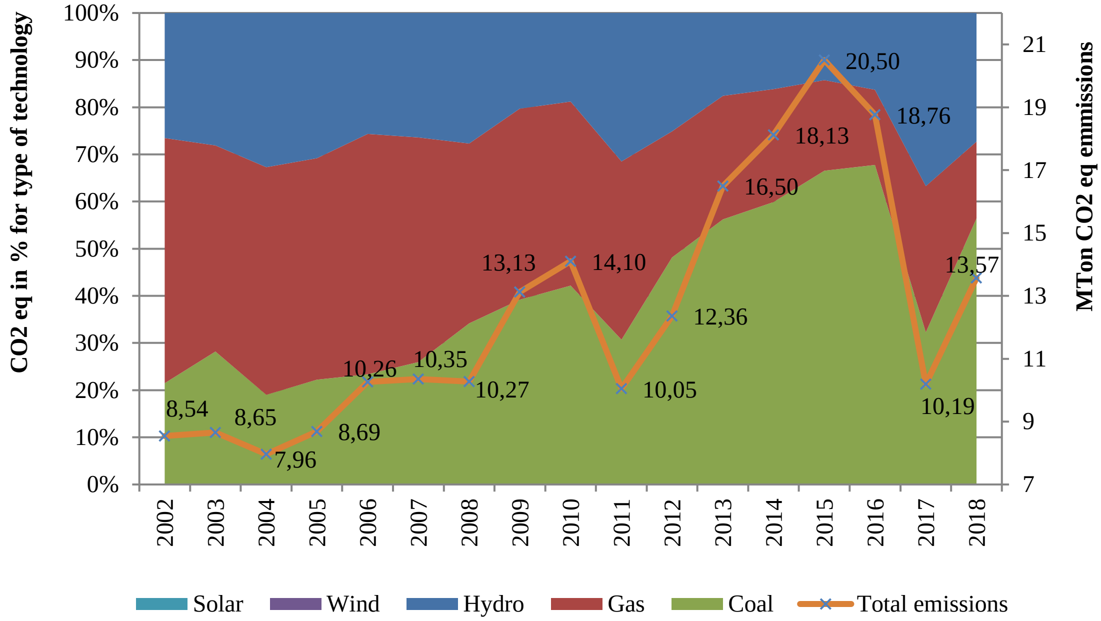

Figure 1-2. CO_2-equivalent emissions by electricity production technology. Source: own elaboration, based on UPME (2019) for the share of each technology in the energy grid and the CO_2 eq emissions for each technology, obtained from the ecoinvent 3.4 database.

Consequently, the Colombian government plans a sizeable increase in the share of NCRRs to meet the rising of electricity demand (UPME, 2016b). Among these, wind power is expected to receive a considerable boost, from a marginal share of 0.1% in 2016 to a share between 2% and 7% in 2030 (727 MW to 1,456 MW of new wind power installed). Such expansion will mainly depend on the available space in the Guajira region, where wind farms are expected to be installed. This expansion is expected to entail environmental savings in the production of electricity (UPME, 2016b).

The potential environmental savings from increasing the shares of NCRRs in the energy grid can, however, be totally or partially offset by the so-called rebound effect (Freire-González & Font Vivanco, 2017). The rebound effect has been extensively studied for energy uses (Berkhout et al., 2000; Binswanger, 2001; Brookes, 1990; Girod et al., 2010; Greening et al., 2000; Sorrell et al., 2009; Sorrell & Dimitropoulos, 2007; Weidema, 2008). This effect has caught the attention of scholars and public and private institutions during the last decades, due to its potential to fall short of key environmental targets (David Font Vivanco, Tukker, et al., 2016). Some examples include the United Nations Environment Programme (UNEP), the International Energy Agency (IEA), and the European Environment Agency (EEA). For further details about the rebound effect as a policy issue, see Font Vivanco et al. (2016).

Current trends show that NCRRs (particularly solar and wind) are both cheaper (Gielen et al., 2019; Kaberger, 2018) and have a better environmental performance than fossil fuels (Turconi et al., 2013). An increase in the share of NCRRs into the Colombian power grid may thus lead to a drop on the electricity price, causing an increase in available income, and consequently additional demand that offsets some or all of the initial expected environmental savings (Freire-González & Font Vivanco, 2017). An increase in the demand for the product subject to an efficiency improvement, electricity in this case, is generally known as the direct rebound effect (Greening et al., 2000). The increased demand of other goods and services (e.g., food or housing) is commonly known as the indirect rebound effect (Greening et al., 2000). In some cases, direct and/or indirect rebounds have the potential of not only entirely suppress the environmental savings achieved, but also generate additional environmental issues, a phenomenon known as backfire effect (Sorrell et al., 2009). Rebound effects can be expressed through a wide range of environmental issues, and are sometimes framed under the environmental rebound effect (ERE) concept (Font Vivanco and van der Voet, 2014; Freire-González and Font Vivanco, 2017; Goedkoop et al., 1999). Key strengths of ERE applications are the use of technology-detailed environmental-economic models, such as life cycle assessment, and the use of life-cycle environmental impact indicators (e.g. impacts on ecosystems and human health) (Freire-González & Font Vivanco, 2017; Weidema, 2008).

Given the fact that the ERE can undermine the efforts made by the Colombian government to decarbonize the electricity grid and the economy, the goal of this work is to obtain empirical evidence of the ERE from increasing the shares of NCRRs into the Colombian energy grid. To gain insight into the potential environmental consequences of a transition of the Colombian energy system to NCRRs (empowering by the issued law 1715).

1.2 Objectives

1.2.1 General objective

Assessment of the environmental rebound effect of the Colombian household sector cause by the increase of wind power into the electricity grid.

1.2.2 Specific objectives

1. Propose a methodology to describe the environmental rebound effect combining different current approaches.
2. Identify, through the variables population, affluence, and technology, the potential effect from electricity consumption on environmental impact.
3. Measure the environmental impacts of the wind power electricity production in Colombia.

4. Estimation of the environmental rebound effect related with the electricity consumption caused by the increase of wind power sources in the Colombian electricity grid in several environmental impact categories.

1.3 Hypothesis

H1. The direct rebound effects for the Colombian household electricity consumption are likely to be larger than in other developing countries due to the existence of a scheme of subsides for the final price to pay for electricity.

H2. Direct rebound effects would be higher at the interior of the country than in the coast due to demographic and economic conditions.

H3. The incorporation of non-conventional renewable energy sources in the electrical energy supply may produce a change in the electricity price due to the technologies introduced have a lower marginal production cost compared to conventional technologies.

H4. The environmental rebound effect of the Colombian household sector for the introduction of non-conventional renewable energy sources into the energy grid are expected to be significant high (backfires) due to the amount of savings achieve.

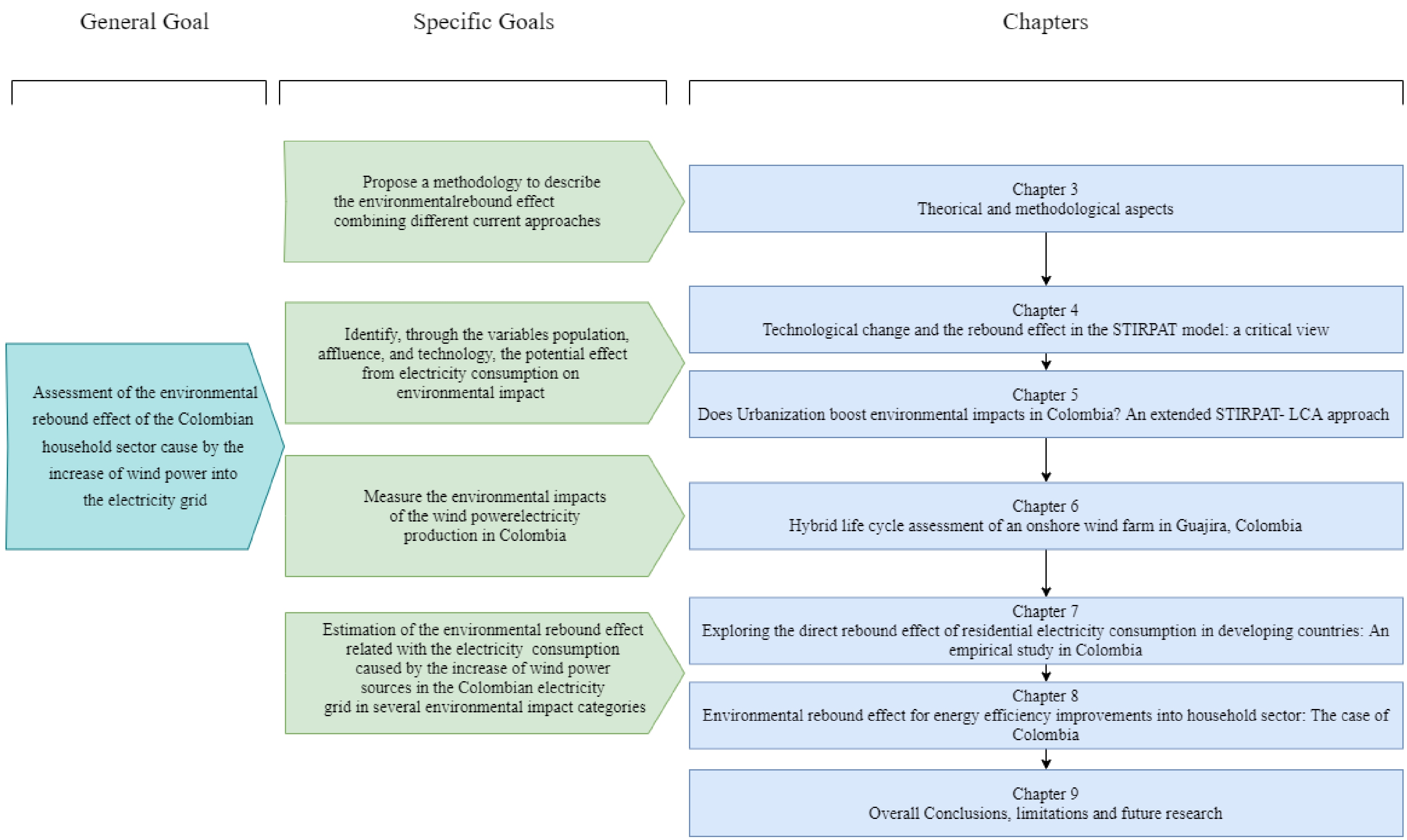

Figure 1-3. Thesis structure

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2. Description of the accumulative thesis.

This doctoral thesis comprises eight chapters. All chapters have paper format and are self-contained. Some chapters have already been published, others are in the process of publishing, another was written for this document. After the problem statement, Chapter three presents in detail the methodology followed to study the E(RE) in the Colombian household sector for increasing the shares of wind power into the power grid. For doing so, the approach to study the direct and indirect rebound effect through different models is explained.

Chapter three develops a systematic theorical framework to calculate the direct and indirect environmental rebound effect and provide the necessary elements need to measure the marginal budget shares.

Chapter four develops a critical review of Technological change and the rebound effect in the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and. Technology) model to understand the diversity and value of the variables, scopes, assumptions, statistical approaches, and the environmental impacts commonly studied. The findings highlight that, despite the multiple applications and the high potential of the STIRPAT model, inconclusive results and/or knowledge gaps remain, notably: (1) a geographical imbalance in the scope of studies, (2) the almost exclusive focus on carbon emissions, (3) a lack of agreement on the choice of data, additional explanatory variables, and regression models, (4) a lack of consensus on how to approximate T (technology), and (5) a lack of explicit analyses of the (E)RE (environment rebound effect).

Chapter five explores the relationship between urbanization and technological factors on Colombian household electricity consumption in several environmental impact dimensions (climate changes, eutrophication, acidification, and respiratory effects) by combining an extended STIRPAT model and LCA approach. The findings suggest that urbanization have an extreme significant and positive effect on electricity consumption (an increase in 1% in urbanization will increase in 1.61% the electricity consumption), whereas the effect of urbanization was found to have a moderate effect on climate change (1% increase in the urbanization rate is likely to increase carbon emissions by 0.99%). For eutrophication, acidification, and respiratory effects, urbanization was found positive but it is not statistically significant. This result may suggest that urbanization may not be a major driver of eutrophication, acidification, and respiratory effects in Colombia. Moreover, energy intensity was found to have significant effects on electricity use and environmental impacts, although in less proportion as the urbanization.

Chapter six carries out a hybrid life cycle assessment to estimate the environmental footprint associated with a wind farm of 19.5 MW of installed capacity in active duty. With respect to similar studies in other regions and general practice in the field, both direct (required on-site) and indirect (required in the supply-chain) services associated with the life cycle of the wind farm were included. The results show that the wind farm is associated with low global warming impacts (12.93 gr CO_2 eq/kWh) compared with similar studies, mainly due to high wind speeds. Moreover, the inclusion of both direct and indirect services increases the environmental impacts across indicators (with respect to the results without services) from 0% (carcinogenic effects) to 21% (terrestrial eutrophication). Further, sensitivity analysis suggests that the results are highly dependent on the capacity factor, lifespan, and percentage of losses. We conclude that the inclusion of both direct and indirect services is not negligible in the life cycle assessment of wind farms and similar projects, particularly given the substantial services required, such as surveying, legal compliance, etc. Given the difficulty to obtain data on services, we conclude with some recommendations aimed at relevant stakeholders, such as tax benefits and public procurement guidelines. This study provides novel insights on the truncation issues related to omitting service inputs in electricity generation, *an unprecedented feature*. Thus, the results contribute to the increasing discussion about the role of service inputs in LCA studies. Moreover, for first time, an LCA study for an electricity generation system in Colombia is provided. While there are several life-cycle studies for wind plants in the literature, this study fills the gap for Latin-American economies. Last but not least, this study highlights the importance of testing the sensitivity of the results of LCA for wind farms with some key parameters, since the capacity factor, the lifespan, and the percentage of losses are determining.

Chapter seven presents the framework for the direct rebound effect and reviews literature regarding the direct rebound effect for electricity consumption in the household sector, particularly studies for developing countries. Moreover, the direct rebound effect for all energy services consuming electricity in the household sector for different States in Colombia over the period 2005-2013 is empirically measured. The results suggest a national rebound effect of 83.4% and values ranging across regions between 64.7% (Atlantico) and 78.9% (Meta). This chapter provides novel insights of the rebound effect in developing countries. To the best of our knowledge; there are no such studies in South America. Furthermore, this study thus contributes to increasing discussion about the rebound effect in developing countries. Last but not least, this study also provides, for the first time, an empirically measurement of the direct rebound effect for 27 States in Colombia.

Finally, chapter eight combine the process-based life cycle approaches (P-LCA), re-spending models, and environmental extended input output models (EEIO) to study the environmental rebound effect in the household sector for increasing the shares of wind power into the Colombian power grid. The results show that the inclusion of the environmental rebound effect generally has a non-negligible impact on the overall environmental indicators across all the studied years. Such impacts ranging across impact categories from 4% (eutrophication) to 7,430% (photochemical oxidant creation) for the combined model, whereas for the single model the values fall on the ranges of 1% (eutrophication) to 9,277% (photochemical oxidant creation). Further, a sensitivity analysis of the elasticity price of the electricity and the price of the electricity reveals that the ERE varies in different ways, specifically, changes in these parameters could vary impacts, respectively, by up to about <1% and 38%. Backfire effects are presented for 8 of the environmental impacts studied in different magnitudes across the years, depending meanly of the savings available to re-spend. The results invite to look for the environmental consequences of increasing the shares of wind power into the power grid in the household sector. Given it relevance, the study concludes with some recommendations aimed at relevant stakeholders. This study provides, for the first time, a comprehensive evaluation of the potential consequences of an environmental energy law under the framework of the ERE.

Chapter nine summarized the main discussions and future lines of research. A graphic schema of the chapters and how it contributes with the objectives of this doctoral thesis is presented below. It is worth noting that each chapter presents the methodology applied. Moreover, main findings and conclusions are presented at the end of each chapter.

Related with the goals (see figure 1.1) and hypothesis formulated in this doctoral thesis the chapter three provide the necessary elements to satisfy the first specific goal (propose a methodology to describe the environmental rebound effect combining different current approaches).

Chapters four and five contribute to achieve the specific objective number two (Identify, through the variables population, affluence, and technology, the potential effect from electricity consumption on environmental impact). Chapter six serves to reach the third specific goal (measure the environmental impacts of the wind power electricity production in Colombia). Finally, jointly chapter seven and eight helps to achieve the specific goal number four of the research project (Estimation of the environmental rebound effect related with the electricity consumption caused by the integration of non-conventional renewable energy sources in the electrical energy supply in different environmental impact categories, in a study case). Particularly, chapter seven supports the H1 (The direct rebound effects for the Colombian household electricity consumption are likely to be larger than in other developing countries due to the existence of a scheme of subsides for the final price to pay for electricity), in developing countries the rebound effect is significantly higher RE>30% than developed countries RE<30% (see chapter seven). Additionally, this chapter provides a literature review that provides evidence to support the H2 (Direct rebound effects would be higher at the interior of the country than in the coast due to demographic and economic conditions).

Chapter eight provides evidence to support several hypotheses posed in this research. H3 (The incorporation of non-conventional renewable energy sources in the electrical energy supply may produce a change in the electricity price due to the technologies introduced have a lower marginal production cost compared to conventional technologies) are supported with the energy model, in the worst case the price of the electricity will fall by 20% comparing with the reference, yet the model assumes that the price of the other components of the price different from the generations will remain constant, situations that is unlikely to happened. Additionally, The H4 (The environmental rebound effect of the Colombian household sector for the introduction of non-conventional renewable energy sources into the energy grid are expected to be significant high (backfires) due to the amount of savings achieve). Backfire effects are presented for 8 of the environmental impacts studied in different magnitudes across the years, depending meanly of the savings available to re-spend.

The results obtained across the different chapters allow us to answer important questions such as: What are the critical drivers related with the environmental impacts caused by the electricity consumption? What can be the consequences related with implementation of the Law 1715/2014 by which the non-conventional renewable energies are integrated in the electrical system? Which can be the environmental impact caused by population, affluence, technology, and the approximation of the change of size in the electricity use? And what can be the best strategic policy to deal with the environmental rebound effect caused by the introduction of non-conventional renewable energy source in the energy national system in the electricity consumption in Colombia?

3. Theoretical and methodological aspects

3.1 Environmental rebound effect E(RE) model

The ERE was originally introduced by Goedkoop et al. (1999) as the environmental pressures resulting from a function fulfillment optimization. This concept offers a holistic view of the environmental impacts, caused by an improvement in the efficiency of providing a service. The ERE allows to express the rebound effect as different environmental burdens, rather than solely energy use (David Font Vivanco, Tukker, et al., 2016). The ERE is generally expressed as a percentage of the environmental savings that are "taken back" (David Font Vivanco & Voet, 2014b) as :

$$\%ERE = \left(\frac{PS-AS}{|PS|}\right) * 100 \; (3.1)$$

with

$$AS = PS - (PS + ERE) \; (3.2)$$

Where PS are the potential or engineering environmental savings from increasing the shares of wind power, on the energy mix, with respect to the current grid (in our case, through product-based LCA), and AS are the actual savings, including the rebound effect. Moreover, following Font Vivanco et al. (2016) and Font Vivanco and Voet (2014b) the ERE, expressed as a change in a given environmental indicator, can be calculated as:

$$ERE^{e,t} = ERE^{e,t}_{dir} + ERE^{e,t}_{ind} \; (3.3)$$

Where ERE_{dir} accounts for the direct ERE from the increased electricity consumption, due to the cheaper electricity price, and ERE_{ind} represents the indirect ERE, from the re-spending effect, in other products other than electricity. e represents the environmental burden, and t indicates time. Moreover, each single effect can be decomposed into a demand and an environmental or technology effect. The demand effect relates to the changes in demand due to changes in real income, whereas the technology effect is associated with the environmental burdens, associated with each unit of additional demand. Thus, ERE_{dir} and ERE_{ind} can be expressed as:

$$ERE^{e,t}_{dir} = \Delta d^{t}_{dir,ts} b^{e,t}_{ts} \; (3.4)$$

$$ERE^{e,t}_{ind} = \sum\nolimits_{s=1,\ldots,n} \Delta d^{t}_{ind,i} b^{e,t}_{i} \; (3.5)$$

With:

$$\Delta r^{t} = \Delta d^{t}_{dir,ts} + \sum\nolimits_{s=1,..,n} \Delta d^{t}_{ind,i} \; (3.6)$$

Where Δd_{dir} denotes the change in demand for a given technology shares in the energy mix ts, t indicates time, and Δd_{ind} denotes the change in demand for a consumption group i (both in monetary terms), b refers to the environmental burdens per unit of demand, n equals the total number of consumption groups, and Δr corresponds to the total change in real income, due to the increasing shares of wind power into the energy mix.

3.2 Environmental direct rebound effect

The direct RE can be study through direct or indirect approaches, the direct approach is based on surveys and primary data, whereas the indirect approach is based on econometric studies and secondary data (Freire-González, 2011).

Direct approach requires that the energy consumption must be known before and after the efficiency improvement to compare the actual energy savings respect to the expecting theorized savings. Measures of the direct RE through direct approaches are uncommon due to the data required (mainly through detailed and extensive surveys) consume high amount of resources (time and money) (Haas & Biermayr, 2000). Rebound effect can be simply measured by eq. (3.7)

$$Rebound\ effect(\%) = 100 * \frac{expecting\ savings - actual\ savings}{expecting\ savings} \qquad (3.7)$$

Particularly, a rebound effect of 0% means full achievement of energy reduction, while 100% means complete failure. Particularly, values greater than 100% means that the energy efficiency improvements increase the overall amount of energy use, this phenomenon is known as 'backfire effect' (Sang-Hyeon, 2007).

For the indirect approach, the direct RE can be study, under certain circumstances, through efficiency measures of the energy services (Berkhout et al., 2000; Khazzoom, 1980; Sorrell, 2007; Sorrell & Dimitropoulos, 2007).

$$\eta_{\varepsilon}(E) = \eta_{\varepsilon}(s) - 1 \qquad (3.8)$$

$\eta_{\varepsilon}(E)$ represents the efficiency elasticity of the demand for energy and $\eta_{\varepsilon}(s)$ is energy efficiency elasticity of the demand for useful work for an energy service. When $\eta_{\varepsilon}(s) = 0$, there is no direct rebound effect. When $\eta_{\varepsilon}(s) > 0$, and $\eta_{\varepsilon}(E) < 1$ there is a positive direct rebound effect. Finally, when $\eta_{\varepsilon}(s) > 1$ means that the demand is elastic and is called "backfire" (Saunders, 1992)

Since it is difficult to calculate ε (efficiency measurement), the direct rebound effect is often estimated from the price elasticity of energy service (Berkhout et al., 2000)

$$\eta_{\varepsilon}(E) = -\eta_{p_s}(s) - 1 \qquad (3.9)$$

This definition is easier to calculated than Eq. (4.8). However, this definition is based on two assumptions, symmetry and exogeneity. Symmetry implies that consumers respond in the same way to energy price decline and energy efficiency improvement, whereas exogeneity implies that energy prices' change can not affect energy efficiency (Wang et al., 2014). Furthermore, since data on energy demand is more available and accurate than data on useful work for a particular energy service a third definition based on price-elasticity of energy demand can be obtained, since $P_S = \frac{P_E}{\varepsilon}$ (Sorrell, 2007; Sorrell & Dimitropoulos, 2007)

$$RE_{dir} = \Delta d^{t}_{dir,ts} = -\eta_{p_E}(E) - 1 \qquad (3.10)$$

Where η_{p_E}(E) is the price elasticity of the demand for electricity. Following Haas and Biermayr (2000), the price elasticity of electricity demand can be estimated using the following energy demand function:

$$RE_{dir} = \eta_{p_E}(E) = LnE_t = \beta_1 LnY_t + \beta_2 LnI_t + \beta_3 LnZ_t + u_t \qquad (3.11)$$

Where α is a constant, β1- β3 are the parameters to be estimated, with β1 = η_{p_E}(E), and u_t represents the error term.E_t is the energy service in period t; Y_t is the price of the energy service in the period t; I_t is the income variable in the period t; Z_t is a vector of other drivers that is sometimes considered, usually the price of the substitute energy service or the climate variable. The term *u* is the error term (Berkhout et al., 2000; Binswanger, 2001; Brookes, 1990; Girod et al., 2010; Greening et al., 2000; Sorrell et al., 2009; Sorrell & Dimitropoulos, 2007; Weidema, 2008).

The direct price effect estimates using equation (2.11) are described as changes in electricity demand as a percentage from the initial electricity demand. This measure needs to be translated to environmental indicators by means of LCA-based coefficients, namely environmental impacts per kWh. LCA-based coefficients correspond to the coefficient $b_{ts}^{e,t}$ from eq. (3.4). That is the environmental impact per demand unit from the production of electricity.

3.3 Environmental indirect rebound effect

To calculate the ERE_{ind}, we need two different sub-models: a marginal consumption model and an EEIO model. The marginal consumption model allows us to know how the monetary savings obtained from the introduction of wind power are spend, by calculating the marginal budget shares (MBS) for each consumption group *i*. To calculate the MBS, we applied an Almost Ideal Demand System (AIDS). The AIDS is a popular consumer demand model introduced by Deaton and Muellbauer (1980), with properties that makes it preferable to competing models (Chitnis et al., 2012; Deaton & Muellbauer, 1980). To build the re-spending model, we calculated the marginal budget shares (MBS), or the share of total savings that will be allocated to each consumption category *i* (e.g., food or housing). To do so, we assume a fixed individual income, and no long-term savings, so all saved money is spent. The MBS for a given time period can be calculated following Deaton and Muellbauer (1980) as:

$$MBS_t^i = \alpha^i + \sum_{s=1,\dots,n} \gamma_s^i lnp_t^s + \beta^i \left(\frac{x_t^s}{P_t}\right) \text{ (3.12)}$$

Where n equals to the total number of consumption groups (s), *x* is total expenditures, *P* is defined here as the Stone's price index, *p* is the price of a given category, *t* indicates time, and α (constant coefficient), β (slope coefficient associated with total expenditure) and γ (slope coefficient associated with price) are the unknown parameters. The Stone's price index is defined as (Deaton & Muellbauer, 1980):

$$lnP_t = \sum_{s=1,\dots,n} MBS_t^s lnp_t^s \text{ (3.13)}$$

Once the MBS are obtained, the indirect effect, in monetary terms, can be calculated by multiplying the remaining change in real income (Δr_r), by each MBS, for each consumption group *i* as:

$$RE_{ind} = \Delta d_{ind}^{t} = \sum_{s=1,\dots,n} \Delta r_r^t MBS_i \quad (3.14)$$

With:

$$\Delta r_r^t = (\, d_{ats}^t - d_{ts}^t) - \Delta d_{dir,ts}^t (3.15)$$

Where *d* is the electricity demand in monetary terms for a given energy mix in *ts* (original energy mix without the introduction of additional wind power), and its corresponding alternative *ats* (energy mix with the additional wind power). Similar to the direct rebound in equation (3.11), indirect rebound in equation (2.14) needs to be translated into environmental indicators as the ERE_{ind}. To do so, an environmentally-extended input-output (EEIO) model is applied to obtain the environmental impact intensity (EII) (that is, the environmental impact per monetary unit) of each of the consumption categories (*m*). Details of the EEIO model can be found in Miller and Blair (2009). The ERE_{ind} can be calculated as:

$$ERE_{ind} = RE_{ind} EII \qquad (3.16)$$

With

$$EII = SL = S(I - A)^{-1} \qquad (3.17)$$

Where ERE_{ind} represents the indirect ERE, in environmental units, RE_{ind} is the indirect effect of the additional spend in monetary terms, *L* is the Leontief inverse matrix, *S* the set of coefficients of environmental intensities.

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4. Technological change and the rebound effect in the STIRPAT model: a critical view

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Abstract.

Technological change is key to understand the explanatory variables behind environmental impacts in the context of the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model. An adequate representation and analysis of the significance of the technology variable (T) in the STIRPAT model becomes crucial, even more if one aims to better understand underlying processes such as the (environmental) rebound effect (E)RE. A critical review of the application of the STIRPAT model has been conducted to understand the diversity and value of the variables, scopes, assumptions, statistical approaches, and the environmental impacts commonly studied. The findings highlight that, despite the multiple applications and the high potential of the STIRPAT model, inconclusive results and/or knowledge gaps remain, notably (1) a geographical imbalance in the scope of studies, (2) the almost exclusive focus on carbon emissions, (3) a lack of agreement on the choice of data, additional explanatory variables, and regression models, (4) a lack of consensus on how to approximate T, and (5) a lack of explicit analyses of the (E)RE. Our findings are useful to both policymakers and academics for method design, further research, and policy evaluation.

Keywords. Environmental impacts, STIRPAT model, Technology, Rebound effect

4.1 Introduction

The IPAT equation was proposed in the 1970s to better understanding the influence of changes in population (P), affluence (A^+), and technology (T) on environmental impacts (I) (Commoner, 1972; Ehrlich and Holdren, 1972, 1971). In most IPAT applications, T is defined as the environmental impact per unit of economic activity (normally expressed as gross domestic product [GDP]) through the ratio I/GDP. Technical efficiency improvements are thought to be key to reduce the environmental impacts caused by anthropogenic activities (Sharon, 1994). Among IPAT applications, climate change is particularly popular, specifically on energy-related carbon emission studies (Chertow, 2000), yet research areas are diverse.

The Intergovernmental Panel on Climate Change (IPCC) uses a reformulation of the IPAT model, called the KAYA equation, as the basis for the GHG emissions calculation, projections, and scenarios (S. Lin, Zhao, and Marinova 2009). Different authors have proposed various variations using the IPAT equation as a starting point. Waggoner & Ausubel (2002) proposed the ImPACT identity to identify the agents behind the driving forces and disaggregated T into consumption per unit of GDP and impact per unit of consumption. In this context, the impact is a consequence of the actions of parents, workers, consumers, and producers. Other authors proposed the ImPACTS identity (S. Lin, Zhao, and Marinova 2009; Z. Xu, Cheng, and GZ 2005), where *S* refers to social development and *m* to public management, arguing that social development and society have the capability to decrease environmental impacts, and that these variables are usually ignored in environmental assessments. Schulze (2002) proposed the IPBAT identity to capture the effect of behavioral choices (*B*), arguing that the IPAT equation does not explicitly encompass these choices. Nevertheless, *B* is not clearly defined, making its application problematic. Moreover, Diesendorf (2003) criticizes the IPBAT identity arguing that the behavior is already implicit in the IPAT equation.

While the IPAT model and its variants offer many insights on the pathways that translate human actions into environmental impacts, it nevertheless suffers from a considerable theoretical limitation. Specifically, IPAT model assumes linearity between variables, meaning that an increase in 1% of one right-side variable will produce a 1% increase in the environmental impact. This causal relationship is generally assumed for simplicity, and it is rarely tested (Chertow 2000). This assumption does not allow for testing hypotheses regarding the value of a certain variable, or proving the consequences of a certain decision (e.g. energy or environmental policies). The IPAT model also suffers from a limited focus and scope in its applications. First, it generally does not include additional factors that are considered as driving forces of environmental change (Dietz and Rosa 1994). Second, according to Roca (2002), the variable *T* is usually incorrectly treated as a residual term encompassing everything that affects environmental change other than population or affluence. Furthermore, *T* is in some cases unknown and derived generally from the studied environmental impacts divided by the other two drivers (T= I/P·A) (Wei 2011).

To overcome some of these limitations, Rosa and Dietz (1998) proposed the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence and Technology) as:

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (4.1)$$

The constant $a \neq 0$ scales the model; *b*, *c* and *d* represent, respectively, the effects of population elasticity, affluence elasticity, and technology elasticity. Positive values in any or all of these coefficients means that the value of the right side variable will increase, while negative values means that the variable will decrease in certain proportion. York et al. (2003a) refers to those coefficients as an “ecological elasticity (EE).” The term *e* is the error term and represents random variables not observable or controllable in the model (IPAT’s proportionality assumption sets a = b = c= d = e = 1). The subscript *i* indicates that those quantities (I, P, A, T and e) vary across observational units. Using regression methods, this approach allows for testing hypotheses regarding factors other than population and affluence that may contribute to environmental impacts (Dietz and Rosa, 1997). According to Wei (2011), the STIRPAT equation is used with two main purposes: First, to predict environmental impacts based on key driving forces; and second, to estimate causal effects between the driving forces. One of the strengths of the STIRPAT model is that it does not assume a causal linkage between the drivers that lead to the impact. Rather, it treats such linkages as hypotheses to be tested. In contrast to common applications of the IPAT equation, which assumes that technology is a factor related with technical parameters such as efficiency, the STIRPAT encourages consideration of cultural, institutional and political factors as drivers of environmental impacts (Dietz and Rosa, 1994). Furthermore, population and affluence can be broken down into forms that have more social meaning (Rosa and Dietz, 1998). However, the full potential of the STIRPAT model and its value for unravelling and better understanding the technology variable is not fully understood since no comprehensive literature review is available.

Similarly to the STIRPAT model, decomposition analysis tools decompose a variable under study into different explanatory factors, such as technological, demand, and structural effects (Ang 2015). Through decomposition analysis, the impact of a given factor is computed by letting that factor change while holding all the other factors at their respective base year values. While the STIRPAT model is used widely as a prospective tool, decomposition analysis has been applied mostly as a retrospective tool focusing on the study of the impacts of structural change (e.g. changes in industry product mix) and sectoral energy intensity change (e.g. changes in the energy intensities of industrial sectors) on trends in industrial energy use (Ang 2004). The STIRPAT model has been applied more broadly, while decomposition analysis has been historically applied in energy-related CO_2 emission studies. This paper focuses on the STIRPAT model, for detailed information on decomposition methods, see Hoekstra (2003).

This chapter carries out a critical review of 112 applications of the STIRPAT model with a focus on the role of technological change and related aspects. This approach is valuable for various reasons: First, T is usually treated as a residual term encompassing all factors other than population (P), and affluence (A^+), meaning that the real implications that technology has on environmental change is usually not adequately considered. Second, while T is considered as a key factor to reducing environmental impacts through efficiency improvements, studies however rarely consider the so-called rebound effect (RE), or in a broader sense, the environmental rebound effect (ERE) (Goedkoop et al., 1999). The (E)RE is the change in consumption and production of goods and services and their associated environmental impacts as a consequence of a change in economic variables caused by an improvement in the efficiency of providing a service (Font Vivanco and Voet, 2014). The (E)RE has gained relevance among academic, public and private entities in different areas such as energy economics, transportation economics and environmental sciences (Font Vivanco et al., 2016b).

The hypothesis put forward in this paper is that the STIRPAT model allows a more realistic measurement of the effect of technological change on environmental impacts, hence the role of the RE. This paper accompanies the critical literature review with a discussion on how to treat and measure the variable T, with a strong focus on the role of the RE. The findings help government and non-government agencies, policymakers, and academics in better understanding the role of technology as a driver of environmental change, as well as providing guidance for identifying and measuring the effects of the RE through the STIRPAT model. The main contributions of this paper are (1) a comprehensive review of 112 documents over the last 18 years in order to gain insights on how the variable T has been measured, including the diversity of regression methods, geographical scopes, and environmental issues studied, and (2) a discussion and guidance on how to approach the RE within STIRPAT models.

This chapter is structured as follows: Section 4.2 briefly describes the research method used to carry out the literature review. Section 4.3 provides a detailed analysis of the 62 articles related to the STIRPAT model, with a focus on the type of variables used in the models, the kind of impact studied, and the definitions of technological change (represented through the variable *T*). Section 4.4 and section 4.5 discuss, respectively, the treatment of the rebound effect and the variable *T*, and section 4.6 concludes. Detailed information of the documents reviewed and the list of abbreviations can be found in Supplementary data S4.1 and a S4.2 respectively

4.2 Materials and method

To better understand how the variable *T* has been treated in the STIRPAT model and its variants, a comprehensive literature review has been carried out. The targeted scientific documents correspond to peer-reviewed scientific papers as well as grey literature (e.g. academic and official reports). The review includes specific case studies with quantitative estimates of different environmental impacts and studies including variables related to urbanization or industrialization. These variables are the most commonly used in STIRPAT models due to the fact that the levels of industrialization (*IN*) and urbanization (*U*) are widely associated with emissions, respectively, from the perspective of producers and consumers. The review also includes documents that provide valuable conceptual and/or methodological aspects of the STIRPAT model. Two criteria were applied to select the documents: a time criterion covering the period 2000 to date, and a keyword criterion whereby documents must include the following keywords: (‘STIRPAT’ OR ‘Stochastic Impacts by Regression on Population, Affluence and Technology’) AND (‘urbanization’ OR ‘industrialization’ OR ‘rebound effect’). 112 relevant documents were identified during this review, covering up until the year 2018. This search was carried out using two approaches:

- Via the online catalogues Scopus and Science Direct using a searching criterion based on all the possible combinations, anywhere in the document, of the following keywords: (“STIRPAT” or “Stochastic Impacts by Regression on Population, Affluence and Technology”) and (“urbanization” or “industrialization” or “rebound effect”).
- Via cross-citation analysis from the documents identified through the previous approach.

The documents reviewed have been published in 42 different international journals in which the main subjects are Environmental Science, Earth and Planetary Sciences, and Energy. An increasing amount of publications over time is observed, with almost 50% of these during the period 2017-2018. Table 4.1 provides some general statistics.

Table 4-1. General statistics of the documents reviewed

Subject	number studies	%	year	number studies	%
Environmental Science	61	54%	2009	3	3%
Earth and Planetary Sciences	10	9%	2010	3	3%
Energy	25	22%	2011	4	4%
Engineering	7	6%	2012	7	6%
Economics, Econometrics and Finance Economics and Econometrics	3	3%	2013	5	4%
Business, Management and Accounting	3	3%	2014	6	5%
Agricultural and Biological Sciences	2	2%	2015	15	13%
Mathematics	1	1%	2016	14	13%
			2017	32	29%
			2018	23	21%
Total	112	100%		112	100%

4.3 Review overview

Table 4-2. Geographical Scopes

Geographical Scope	Number	%
Global	16	14%
Continental	4	4%
Mena region	1	1%
China	85	76%
Malasia	1	1%
Nigeria	1	1%
Pakistan	1	1%
Norwegian	1	1%
Taiwan	1	1%
Azerbaijan	1	1%
Total	112	100%

From the 112 documents identified, 16 studies (14% of the total) had a global scope, including 4 studies focusing on countries of the Organization for Economic Co-operation and Development (OECD) (see Table 4.2). The major sample of the category of global scope are covered by studies that included between 53 and 140 countries including developing and developed countries. Additionally, 4 studies (4% of the total) had a continental scope: two from Africa and two from Asia. One study on Africa covers Nigeria, Kenya, Congo, Egypt and South Africa, whereas the other covers 49 African countries. One study on Asia covers China, Indonesia, India, Malaysia, Pakistan, Philippines, Thailand, and Vietnam, whereas the other covers Bangladesh, Hong Kong, India, Indonesia, Iran, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka, and Thailand. Moreover, one study contains information of 20 countries of the Middle East and North Africa (MENA) region, and 6 studies have a national scope (6% of the total) on Malaysia Nigeria, Pakistan, Norwegian, Taiwan, and Azerbaijan. Most of studies (85 studies or 76% of the total), focus on China, yet with differing scopes: groups of provinces (32 studies) and cities (4 studies), specific provinces or cities (28 studies), and national scope (21 studies).

The most common variables included in the classic STIRPAT model are *U* and *IN*. The first is measured by the share of the population living in urban areas, while the second is measured in various ways. While the majority of studies refer to *IN* as secondary sectors, some authors refer to the share of the secondary and tertiary sectors, also known as the service sector (S. Lin, Zhao, and Marinova 2009; Yanan Wang and Zhao 2015). Only in one case the industrialization variable refer to primary sectors (M. Wang et al. 2010). Other variables used include household size, age structure, and working age (see supplementary data S4.1 for a complete description).

Regarding the environmental impacts analyzed, the most common practice is to set CO_2 emissions as the dependent variable (see Table 4.3). This treatment is mainly due two reasons. First, CO_2 emissions are a global political issue, and second, there is a lack of accurate data to measure other environmental impacts. This limitation is important because other types of environmental impacts, such as acidification or eutrophication, may rise due to the efforts to reduce CO_2 emissions. When addressing CO_2 emissions by setting energy consumption as a control variable, it merits noting that the results would be biased to support the hypothesis that environmental problems could be solved simply by business-as-usual growth, mainly because of two issues. First, a wrong interpretation of the parameters and resulting conclusions caused by the definition of CO_2 emissions. Since CO_2 emissions are measured indirectly from energy use in the datasets, CO_2 emissions are defined by a linear function of different fuel commodities. As a result, controlling for the level of energy use in the model means that only the proportions of fuel types, and subsequently the “carbon intensity” of the fuel mix, are allowed to vary. Consequently, the models can only analyze carbon intensity rather than CO_2 emissions. Second, a misspecification bias rising from the dependence between energy use and output measured commonly by GDP. Furthermore, the presence of an energy consumption variable into CO2 emissions models can lead to systematic volatility in its coefficients (Itkonen 2012; Jaforullah and King 2017). For practical considerations about addressing CO_2 emissions through energy consumption see Brown and McDonough (2016).

Recently, studies have increasingly addressed air pollutants. Qin and Liao (2015) studied the drivers behind the PM10 in 113 cities of China, while Effiong (2018) studied the same particles in Africa. Other studies focused on PM2.5 also in China but at different levels. Xu et al., (2016) focus at the provincial level, while Luo et al.,(2018), Xie et al.,(2018) and Xu and Lin (2018) focus at the national level. Outside of China, Ji et al., (2018) focus in 73 different countries. Other studies address a wide variety of air pollutants, such as SO_2, $N0_x$ and dust.(Diao et al. 2018; Ge et al. 2018; Wei Li and Sun 2016; S. Lin, Sun, et al. 2017; S. Lin, Zhao, and Marinova 2009; Mikayilov et al. 2017; Munir and Ameer 2018; B. Xu, Luo, and Lin 2016). The results also show that little progress has been made in determining the magnitude of the different environmental impacts in developing countries, especially in central and South America. An important reason for this is that the data necessary to conduct such analyses, are generally not easily available in developing countries, and in some cases the data suffers from quality issues. The findings show that the research on this topic is mainly focused on China. This is because China is the largest producer of CO_2 emissions and the Chinese government has set ambitious economical and development goals to reduce the emission intensity (CO_2 emission per unit gross domestic product) in 2020 by 40–45%, relative to 2005 (Seligsohn and Levin 2010). The studies focused on China apply three different approaches: panel data at provinces and city levels, specific data of a province or city, and nation-wide data.

Table 4-3. Types of environmental impacts analyzed in the selected studies

Environment pressure	Number of studies	%
Ecological footprint	4	4%
Energy ecological footprint	2	2%
CO_2 emissions	59	53%
Water footprint	1	1%
Change of lake area	1	1%
Carbon emissions	1	1%
Energy consumption of urban residential building, Urban residential energy consumption and CO2 Emissions, Household Energy Consumption	3	3%
Energy or fuel consumption	4	4%
CO_2 emissions and (Energy use, or energy consumption, or electricity consumption)	9	8%
Transport energy use, private transport energy consumption, CO2 emissions for transport	5	4%
Air Pollution (C02, SO2, dust), (NO2, SO2, and PM10), (C,SOx,NOx emissions),PM2.5 emissions	14	13%
exhaust gases, waste water and solid waste	1	1%
Pollutant comprehensive value: chemical oxygen demand; total phosphorus; total nitrogen.	1	1%
renewable and non-renewable energy consumption	1	1%
Demand for improved environmental safety	1	1%
Floor area of GSHP	1	1%
Municipal infrastructure development	1	1%
Natural gas consumption	1	1%
CO_2 emissions and Water use	1	1%
weak and strong sustainability	1	1%
Total	112	100%

4.4 STIRPAT and the Rebound Effect

The rebound effect is a concept that has its roots in the field of energy economics. It was first theorized by Stanley Jevons in 1865, when he stated that improvements in energy efficiency did not lead to a reduction in the demand for energy, but the contrary. Later, the concept of the rebound effect reappears in the 80s and 90s with the Khazzom-Brookes postulate (Brookes 1990; Jevons 1865; Khazzoom 1980) and in the context of subsequent energy and climate change crises (Berkhout, Muskens, and Velthuijsen 2000; Musters 1995). Greening et al., (2000) provided a widely accepted classification of the rebound effect, classifying it into direct, indirect, and macroeconomic effects. The direct rebound effect can be measured through the efficiency or price elasticity of energy services. The indirect rebound involves further changes in consumption patterns caused by energy efficiency improvements. These patterns are captured through macroeconomic price variables rather than efficiency variables. Combination of Input Output models and re-spending models are commonly used to capture such effects. (Freire-González, 2011)

Recently, the importance and complexity of the rebound effect has been handled by diverse actors such as academic, public, and private entities in different disciplines such as energy economics, transportation economics, and environmental sciences. According to Font Vivanco et al. (2016), many intergovernmental organizations and international agencies, such as the European Environment Agency (EEA), the European Commission (EC), the International Energy Agency (IEA) the United Nations Environment Programme (UNEP), the Department of Energy and Climate Change in the United Kingdom (UK), the Irish Department of Communications, Marine, and Natural Resources, and the U.S. Department of Energy, have advocated for the importance of taking into account the rebound effect, given its impact on achieving environmental goals.

Different definitions of the rebound effect can be found in the literature (Berkhout, Muskens, and Velthuijsen 2000; Binswanger 2001; Brookes 1990; Girod, de Haan, and Scholz 2010; Greening, Greene, and Di 2000; Sorrell and Dimitropoulos 2007; Sorrell, Dimitropoulos, and Sommerville 2009; Weidema 2008). A definition that can encompass all of them is the following: the rebound effect is the change in consumption and production of goods or services as a consequence of a change in economic variables (such as income, price and financial gains or costs of product and material substitution) caused by the improvement in efficiency of providing an energy service (Font Vivanco and Voet 2014). Some authors refer to the environmental rebound effect (E)RE, a concept that has its roots in industrial ecology and was first introduced by Goedkoop et al (1999) as the environmental pressure resulting from a function fulfillment optimization. This concept offers a more holistic view of the environmental impacts caused by an improvement in the efficiency of providing a service, expressing the rebound effect through different environmental dimensions, such as material extraction, emissions, and waste. Detailed information about the rebound effect and the environmental rebound effect can be found in (Font Vivanco et al. 2016; Greening, Greene, and Di 2000; Sorrell and Dimitropoulos 2007). Moreover, Font Vivanco et al. (2014) presented a general framework to capture and assess the RE through the IPAT equation.

Although the rebound effect has been recognized as an issue of matter by different public and private organizations(Font Vivanco, Kemp, and Voet 2016), it has not been fully explored in to SITRPAT framework. The reason may be explained by the fact that the STIRPAT itself allows to capture different impacts of technological chance by a multiple coefficients, which can represent an issue in order to interpret properly the rebound effect. However, taking in account the classification of the rebound effect provided by Greening et al., (2000) it won't represent a problem since different types of rebound effect are captured individually by different variables. In STIRPAT models, the direct rebound effect has been accounted by indirect measures of energy intensity (EI). Attempts to capture the indirect rebound effect individually or simultaneously with the direct rebound effect through the STIRPAT model have not been made.

In consequence only eight of the reviewed studies (7% from the total) included, though implicitly, some reference to the direct rebound effect. In Beijing, China, Wang et al. (2012) included the *EI* (energy intensity), among other variables, to approach the magnitude of the drivers related with the CO_2 emissions, and found a negative correlation. Concretely, a decrease of 1% in energy intensity lead to an increase of 0,095% in energy consumption. Moreover, Yang et al. (2015) concluded that a decrease of 1% in *EI* will lead an increase of 0.027% in carbon emissions. Wang and Yang (2014) mentioned the rebound effect when the variable *T*, measured as energy intensity, was found to be negatively correlated with the energy footprint of urban residents. Specifically, the authors found that a decrease by 1% in energy intensity led to an increase of 0,04% in energy consumption in China. Wang and Zhao (2015) measured *T* as the energy intensity and found a negative correlation between the energy intensity and the CO_2 emissions in China for three regions aggregated by grade of development (-0.052 in underdeveloped regions, -0.181 in developing region, and -0.216 in highly developed region). Wang et al., (2017) used *EI* to understand the influence of *T* on the CO_2 emissions in three regions of China. The authors found that the *EI* had a positive influence on the CO_2 emissions and therefore an improvement of the technical efficiency would have increased CO_2 emissions, a phenomenon also called backfire effect (Saunders 2008). The authors further acknowledged the complex relationship between technological progress and environmental improvements. For example, the introduction of LED lamps reduces energy consumption, yet their end-of-life requires additional energy. Furthermore, technological progress involves not only economic mechanisms (rebound effects), but also psychological mechanisms (mental rebound effects) (Santarius and Soland 2018). Erqian et al. (2017) found a negative correlation between *EI* and CO_2 emissions in China, ranging among regions from -0.134% to -0.294%. He et al. (2017) found that the energy intensity *EI* is one of the most significant drivers behind the CO_2 emissions in China, and claimed the need to introduce energy taxes to avoid the rebound effect. Lastly, Shahbaz et al. (2017) approximated *T* as the share of Industrialization *IN* and service sector *SV* and found a positive correlation between these variables and the energy consumption, arguing that the RE was not observed in this case.

While the treatment of the rebound effect in STIRPAT applications is limited, it nonetheless provides insights for its measurement. The direct rebound effect can be defined as an efficiency elasticity of energy demand, where the actual energy saving will equal the predicted saving when this elasticity is zero (Sorrell and Dimitropoulos 2007). In other words, a 1% increase in energy efficiency will lead to a 1% decrease in energy demand in the absence of the rebound effect. In this sense, a STIRPAT model can be used to measure the rebound effect by calculating energy (or any resource) efficiency as a function of energy demand, where the estimated coefficient can be interpreted as a constant elasticity (Small and Van Dender 2005; Z. Wang and Lu 2014). In this sense, the above STIRPAT results would imply a rebound effect in the range of 78-96%. Such results may however indicate measurement issues if compared with the literature. For instance, Li and Han (2012) found that the rebound effect in the China's tertiary's industry is 33%, while Shao et al (2014) found a rebound effect around 30-80% depending of the data used. More generally, the literature provides an average rebound effect of around 30% (Greening, Greene, and Di 2000). Key reasons for such mismatch are twofold. First, despite the clear correlation between energy and CO_2 emissions, establishing causality between variables expressed in different dimensions (e.g. emissions and energy intensity) can lead to over/underestimate the rebound effect. Second, adequate isolation of key variables is essential for measuring the rebound effect. For example, variables such as IN and SV are too aggregated to establish causality between efficiency and emission changes.

To adequately capture the rebound effect in STIRPAT model, the authors offer various recommendations for future research. First, decomposing the technology variable into variables of interest, such as resource efficiency, is often challenging. To overcome this issue, technology-detailed tools such as life cycle assessment (LCA) have proven valuable in the context of IPAT models (Font Vivanco et al. 2014). LCA data is also useful to address multiple environmental pressures, a valuable aspect to assess cross-rebound effects (Freire-González and Font Vivanco 2017). Also, choosing the variables to approximate *T*, in specific combinations of the variables *IN*, *EI*, and *ES*. *IN* is useful to measure the production of goods and services and defining the rate of energy consumed, in which the tertiary industry is less intensive in energy consumption. According to our review, this variable needs to be defined carefully in order to avoid misunderstandings in the results. *EI* is directly related to *IN*, which provides a measurement of the level of efficiency of the industries and is then translated into energy consumption. On the other hand, *ES* provides an understanding of the resources used to produce energy. Second, the choice of instrumental variable technique is key to avoid serial correlation, an issue it is discussed further in the following section. Lastly, it merits noting that indirect rebound and macro-economic effects may appear in a variety of other variables (overall economic growth, consumption of non-energy products, etc.), therefore the economy-wide rebound effect (direct + indirect + macroeconomic) (Greening, Greene, and Di 2000) may be in fact captured via multiple variables (Font Vivanco et al. 2014; Wei and Liu 2017).

No clear trends have been observed in the study of the rebound effect though the STIRPAT model. When the rebound effect has been taken into account, it has been modeled by measuring the energy efficiency, usually by indirect measures of the *EI*. Furthermore, all the reviewed studies focused on the direct rebound effect, thus overlooking indirect and economy-wide rebound effects (Greening et al., 2000).

4.5 Technology as a driving force

Rosa and Dietz (1994) point out the importance of reformulating *T* in the IPAT identity and the STIRPAT model. They recognize that *T* is not a single factor but comprises many separate factors that influence environmental impacts. In this sense, there are two different ways to assess the *T* using the STIRPAT model. First, *T* can be interpreted as the residual term in the STIRPAT model, since the residual term encompasses all factors other than *P* and *A*. Second, *T* can be interpreted as a set of variables theorized to influence impact per unit of production. Some authors argue that it is more suitable to assume *T* as the error term of the STIRPAT model, rather than estimating it separately because there is no clear consensus on which technology indicators are most adequate. Moreover, if *T* is interpreted by aggregating additional factors, it is necessary to ensure that these additional factors are conceptually consistent with the multiplicative specification of the model and that these variables do not bring multicollinearity issues into the model (Dietz and Rosa 1994; Wei 2011; York, Rosa, and Dietz 2003b, 2003a). This issue may be critical when using time series data for a single region, e.g. China.

From the reviewed studies, only four (4% of the total) used the error term to express the variable *T* following a conservative perspective of the implications of the technology. On the other hand, twenty studies (18% of the total) use a combination of different variables to measure *T* (see table 4.4). Jia et al., (2009) used *IN* and *U* to measure *T*, while Cao et al., (2011) used *EI* and *ES*. Liddle and Lung (2010) used *U*, *EI* and *ES* to approach *T*. Others authors used *IN* and *U* (Tang, Zhong, and Liu 2011; M. Wang et al. 2010). Poumanyvong et al. (2012) used *U* and *SV* as an approximation of *T* in their study of transport energy use in 99 countries. While Lin and Du (2015) applied these variables to approach the transport energy consumption in 30 provinces of China, and Li and Sun (2016) used the same variables to trace the air pollutants in Beijing.

Using *IN* and *EI* as a proxy of *T*, Li et al. (2015) studied the CO_2 emissions in Tianjin, China. Zhou and Liu (2016) and Zheng et al, (2016) used the same variables to approach *T* in a study of CO_2 in 30 provinces of China and 73 cities of China, respectively. Yansui Liu et al. (2015) study the exhaust gases, wastewater and solid waste in 30 provinces in China with *IN*, *SV* and *EI* as approximation of *T*. Yu Liu et al. (2015) applied *U*, *IN*, *SV* and energy structure *ES* as approximation of *T* to measure the energy consumption in 30 provinces of China. Zhou et al. (2015) study the CO_2 emissions and Energy consumption in 30 provinces of China using *U, IN*, *SV* and *EI* as approximation to *T*. Wang et al. (2017) combined *EI* with the time-specific effect *TSE* to understand the drivers behind three different industries (mining, manufacturing, and electricity and heat production) in China, arguing that *TSE* could be considered as a proxy of the technological progress on industrial carbon emissions controls. On the other hand, *EI* was taken as a proxy for technology-related environmental impacts. The study used two models based on A^2 and U^2 , yet it is not clear how they measured *TSE*. Some used energy efficiency *EF* and *IN* as an approximation of *T* to measure the CO_2 emissions in 29 provinces in China (S. C. Xu et al. 2016). Sheng and Guo (2016) combined *IN*, *ES* and environmental regulations *ER* to measure the CO_2 in 30 provinces of China. Finally, Miao (2017) approximates *T* by the energy price, temperature *TEM*, fuel price, and the number of public transportation ownership per person to measure the urban residential energy consumption and CO_2 emissions in China.

The most common practice is to use energy per unit of *GDP* as an approximation of *T*. However, Wei (2011) argues that *EI* can encompass carbon intensity *CI* represented by *T* only in the cases where the dependent variable under study is carbon emissions from energy consumption for a single region. In this case, carbon emissions need to be calculated with fixed emissions per unit of energy, and the energy structure does not change significantly over the period of the study. To overcome this issue, other authors used *EF* as an approximation of *T*, in which energy efficiency is denoted by the inverse of energy intensity (economic output per unit of energy consumption). However, the use of *EF* presents some inconsistencies. For example, Xu and Lin (2017a), and, Lin,(2017b) defined *EF* as energy consumption divided by GDP, which is actually the definition of *EI*, while Nasrollahi and Saeed (2018) and Xu and Lin (2018) incorrectly refer to *EF* as the inverse of *EI*, while the inverse of *EI* is more precisely defined as energy productivity. On the other hand, Li et al. (2011) and Li et al. (2012) used energy productivity *EPR* to proxy *T*. Other scholars measure *CI* directly as approximation of *T* (Shahbaz et al. 2016; P. Wang et al. 2013; S. Wang, Fang, and Wang 2016; L. Wen, Cao, and Weng 2015; L. Wen and Liu 2016).

Some authors chose to represent *T* with certain variables that encompass a better measurement of technology in their specific studies. For instance, York (2007) used *U* as approximation of *T*. To study the impact of demographic trends on energy consumption in the European Union, Chen et al. (2015) approximated *U* as the built up urban area, while Liddle (2013) used *UD* as a ratio between the population and the urbanized surface area of the metropolitan area. An important distinction between urbanization (share of population living in urban areas) and urban density (either urban or total) should be made since there is a much stronger relationship between density and emissions/energy than between urbanization and those same variables. Liddle (2014), in a detailed review of 28 papers, highlights that those that included urbanization and/or urban density found that urbanization was positively associated with energy consumption and CO_2 emissions, while higher population density was associated with lower levels of energy consumption and emissions. Furthermore, urban density was more correlated with energy efficiency than urbanization, *U* is defined as the percentage of the urban population in the total population that is itself a measure of proportion rather than an intensity measure, while *UD* is defined as a the Ratio between the population and the urbanized surface area and represent an intensity measure. Thus, researchers using *U* as a proxy of *T* are encouraged to use urban density since the variable *T* is associated by definition with efficiency/intensity.

Other authors, such as Li and Lin (2015), Ji and Chen (2015), Qin and Liao (2015), and Sheng et al.,(2017), used the share of industry *IN* as the percentage of *GDP* to approximate *T*. Li and Wang (2013) and Yang et al.,(2017) used the share of the tertiary industry *SV,* as approximation of *T*. Poumanyvong et al. (2010) prefer to use the combination of *IN* and *SV* variables as an approximation of *T* in their study of CO_2 emissions and energy use in 99 countries. Similar approaches are followed by Zhang and Lin (2012) for CO_2 emissions in 29 provinces of China, Salim and Shafiei (2014) and Shafiei and Salim (2014) on energy consumption in the OECD countries, Guan et al. (2016) in the study of CO_2 emissions in Ningxia Hui and Shahbaz et al. (2017) in a study of energy consumption in Pakistan, and Xing et al. (2017) investigated the effect of financial development (*FD)* on the CO_2 emissions in China.

There are many ways to express the impact of the technology. For instance, Ding et al. (2016) studied household energy consumption in 30 provinces of China approximating *T* as *TEM* measured as the annual average temperature (◦C), while Wang et al. (2012) and Long et al.,(2017) refer to *T* as ecological footprint intensity (*EFI*) to understand the drivers of the ecological footprint in 31 provinces in China and 72 countries, respectively. Lin et al., (2017) used *LAP* as *GDP* per person employed to proxy *T* in 53 countries to understand the drivers behind CO_2 emissions. In a novel study, Wang et al. (2012) used *R&D* output index measured by the stock of technical patents associated with CO_2 emissions as a representation of *T* to study the CO_2 emissions in Beijing. He et al. (2017) also used *R&D* in 29 provinces in China to assess the drivers behind the CO_2 emissions, and Jiang and Lei (2017) used *R&D* to study the drivers behind the need for Ground-Source Heat Pump in China. According to Wang et al. (2012), the advantages of expressing *T* as research and development *R&D* are: (1) patents are closely related to innovation, (2) the statistical data related to patents is open to the public, and (3) patents can reflect technological innovation to a great extent. Li et al. (2017), however, argues that the use of *R&D* to measure technological progress is too general and proposed to use instead the environmental total factor productivity *ETFP*. According to the authors, *ETFP* can be measured by the Malmquist–Luenberger productivity index (*ML)*. furthermore, the *ML* can be decomposed through mathematical operations into two different variables: technological progress into efficiency improvements (*EIM)* and technology innovations (*TI)*. The authors also provide a method to further decompose *IN* into different variables. Cui et al. (2018) also applied *ML* without decomposition to study the energy consumption patterns in Shanxi, China. Finally, some studies either exclude or do not specify the variable technology in their analyses. For example, Liu et al (2017) assumed that technology efficiency remains relatively stable since they only cover four time periods. Other examples include the studies from Wen et al. (2017), Li et al. (2017), Ma et al. (2017), Ma et al. (2017), Liu et al. (2017), Zhang et al. (2017), Zhang and Xu (2017), Mikayilov et al.,(2017), and Chai et al.,(2018).

Despite some authors adding different variables to proxy the variable *T,* a correct proxy for *T* should be a measure of efficiency, since the variable *T* is defined as the environmental impact per unit of economic activity through the ratio I/GDP, such as *EI*. Additional variables may give additional information to understand the *T* in terms of energy structure (*ES)* or industrialization (*IN)*. However, none of these variables can measure the effect of technology unless it is accompanied by some measure of efficiency. For example, *ES* is defined as the percentage of fossil fuels consumption (mainly coal) to total consumption, while *IN* is defined as a percentage of the increased value of industry to GDP, which are measures of proportion rather than an intensity measure. How to proxy *T* will also depend on the type of environmental pressure under study and the purpose of the study.

The authors observe some historical trends are observed on the treatment of the variable *T*. First, although historically *T* has been modeled though *U, IN, EI* or through a combination of them, as of 2012 some authors proxy technology by adding novel variables such as *R&D, CI,* and *TEM.* Second, relate with the quantity of explanatory variables included in the models. In the recent years, with the development of more complex regression models that deal with several issues, such as multicollinearity and heteroscedasticity, the number of explanatory variables included has increased significantly. For example, the average number of variables included into the models before 2013 four whereas, the average number of variables included after 2013 are six.

Table 4-4. Variables used to approximate *T* within applications of the STIRPAT model

T approximation by	number studies	%
Energy intensity *EI*	38	34%
Energy efficiency *EF*	4	4%
Error term	4	4%
Research and Development *R&D*	3	3%
carbon emission intensity *CI*	6	5%
Annual average temperature (◦C)	1	1%
Industrialization *IN*	6	5%
Combination of different variables	20	18%
Urbanization *U*	1	1%
Urban density *UD*	1	1%
Not clear or excluded	11	10%
Service sector *SV*	2	2%
Ecological footprint intensity *EFI*	1	1%

Industrialization and Service sector IN and SV	6	5%
Labor productivity *LAP*	1	1%
technological progress *ML*	2	2%
energy productivity EPR	2	2%
water intensity *WI*	1	1%
Energy use *EU*	1	1%
power consumption efficiency *PCE*	1	1%
Total	112	100%

This review shows that it is both valuable and possible to disaggregate *T* into multiple variables to better capture the effects of an explicit technological change. However, the issues of multicollinearity, autocorrelation and heteroscedasticity must receive detailed attention. There does not seem to be a common practice and the decision on how to overcome this issue appears a random consequence of the experience and background of the authors. The 42% of the authors seems to be inclined to use the *OLS, PLS* or *RR* the statistic issues of their regression models. While 16% of the samples choose to use the *FE, GMM* or *DK* in their studies. Others authors the 7% seems to be inclined to perform spatial *SEM* or *SDM* models to solve the issues. On the other hand the 31% of the samples use a diversity of methods into their models. An important highlight is that some authors (4% of the studies) do not specify or at least let clear the type of regression model applied. This should be treated carefully since without a correctly description of the models the solution to the statistical problems remain as a question.(S. Lin, Sun, et al. 2017; S. Lin, Wang, et al. 2017; Shuai et al. 2018; T. Wen et al. 2017). Table 4.5 summaries the methods applied in the samples.

Table 4-5. List of regression models applied

Method	Number studies	%	Method	Number studies	%
Ordinary Least Square OLS	8	7%	Generalized Method of Moments GMM	6	5%
Dynamic ordinary least Squares DOLS	1	1%	Augmented Mean Group AMG	1	1%
Fully modified ordinary least squares FMOLS	2	2%	Threshold regression model TR	2	2%
Partial Least Squares PLS	15	13%	multilevel latent class regression model MLC	1	1%
Weighted Least Squares WLS	1	1%	heteroskedasticity-robust Fixed Effect model HRFE	1	1%
Fixed effect model FE	8	7%	Random parameters model RPM	1	1%
Semi-parametric panel fixed effects SPFE	3	3%	vector error correction model VECM	2	2%

Dynamic fixed effect DFE	1	1%	Nonparametric additive regression models NPAR	1	1%
Semiparametric panel regression SPR	1	1%	two-stage least squares 2SLS	2	2%
First-difference F-D	2	2%	The geographically weighted regression GWR	1	1%
Ramdom effect RE	2	2%	Autoregressive Distributed Lag Bound Test ARDLBT	1	1%
Ridge Regression RR	25	22%	Newey-West standard errors N-W	1	1%
Spatial error model SEM	1	1%	Auto regressive distributed lag model ARDL	1	1%
Spatial Durbin model SDM	7	6%	Vector Autoregressive model VAR	1	1%
Panel-corrected standard errors PCSE	2	2%	NOT SPECIFIED	4	4%
Principal component analysis PCA	1	1%	Quantile regression QR	1	1%
Driscoll–Kraay standard errors DK	5	4%			
Total				112	100%

From the review, three main issues merit closer attention. The first issue relates to the theoretic model chosen, particularly whether to define *T* as the error term or as one or more independent variables. Using the error term may be suitable when there is no available or accurate data that allows to properly define *T*. It may also be suitable when the study encompasses a broad part of the economy, and the definition of technology can be interpreted in different ways. However, using the error term is problematic since it may represent no only the influence of the technology but other social and psychological aspects. If there is available information, it is recommended to represent *T* as a set of different variables that capture the multiple dimensions of technology. The second issue relates to the level of detail of *T*, which limits the coverage and scope of the analysis. At the macro level, the combination of different variables, such as *IN*, *EI*, and *ES*, represent the most complete and suitable way to define *T*. *IN* provides information about the economic productivity and energy consumption, while *EI* measures directly the efficiency of the industry and *ES* allows capturing the resource productivity. Lastly, issues of multicollinearity and heteroscedasticity can arise from inadequate treatment of instrumental variables. To overcome such issues, there are different statistical techniques such as the Ordinary Least Square (*OLS*), the Partial Least Squares (*PLS*), the Ridge Regression (*RR*), the Generalization Method of Moments (*GMM*), the Feasible Generalized Least Squares (*FGLS*), or the Two-Stage Least Squares (*2SLS*). It is recommended to apply firstly OLS regression to test if the variables used in the model are not correlated. If so, it is recommended to first use the PLS regression to confirm that the variables are correlated, and then apply the RR. An alternative approach by some authors is to confirm correlation with the 2SLS or FGLS, and then use the GMM.

It merits noting that, aside from statistical issues of multicollinearity and heteroscedasticity, heterogeneity, cross-sectional dependence, and nonstationary are other time-series cross-section issues that are often not addressed in STIRPAT studies. Liddle (2015) found a wide range of income and population elasticity estimates from 18 reviewed studies that applied the STIRPAT formulation to address the CO_2 emissions, and argued that an important reason of such variations was due to the treatment of heterogeneity and nonstationary. Heterogeneity could be solved by splitting the panel along income lines. Nonstationary issues can be solved by applying first difference, yet this approach would turn a given model into a short-run model (Brantley Liddle 2014, 2015). Lastly, the common correlated effects mean group estimator *CMG* and the augmented mean group estimator *AMG* can solve the heterogeneity, cross-sectional dependence, and nonstationary issues (Brantley Liddle 2015).

4.6 Conclusions and policy implications

Technological change, or technology (*T*) in the context of the STIRPAT model, is widely regarded as key to reducing environmental impacts mostly through efficiency improvements. Consequently, it is fundamental to pay close attention on how the variable *T* has been modeled within the STIRPAT model. Even more if this variable is considered closely related to key issues such as the (environmental) rebound effect (E)RE. In this sense, this paper carried out a critical review of the applications of the STIRPAT model in order to guide a discussion related with the diversity and value of the variables, scopes, assumptions, statistical approaches, and the environmental impacts commonly studied.

A critical assessment of the literature review points to various areas with inconclusive results and/or knowledge gaps. First, there is a geographical imbalance in the scope of the studies: while some regions such as China are relatively well-studied, others such as South America are unexplored. Second, CO_2 emissions are the most commonly studied pressure even though the STIRPAT model allows many different environmental impacts, such as other types of emissions, material use, and waste. In this sense, the use of tools such as Life Cycle Assessment (LCA) can be useful to approach multiple environmental impacts (Font Vivanco et al. 2014). Third, there is not a clear consensus on how to define the variable *T*, as this can be included in the error term or as a myriad of explanatory variables. Fourth, the STIRPAT model offers a valuable yet underused platform to address the (E)RE from changes in technological efficiency. For instance, not only energy efficiency improvements, but broader and more complex efficiency measures (e.g. material use efficiency and exergy efficiency) can be included by properly disaggregating *T*. Also, the model allows to test the effect of different variables (e.g. information, resources, physical space, time and skills) that can trigger the (E)RE.

Our findings can be useful to both academics and policymakers in different ways. For practitioners, the description of approaches and associated recommendations provided allows to better design specific applications of the STIRPAT model. Moreover, the identified knowledge gaps point the way to further research, especially regarding the geographical gap, the role of technological change and how to better represent it, capturing the (E)RE. For policymakers, how to curb environmental impacts effectively has been a persistent issue. The STIRPAT model offers a relatively simple and intuitive framework to understand key explanatory variables and refinements in scope and method can greatly aid policymaking. It is our understanding that, by refining the STIRPAT model to better capture the consequences of technological change, its application can shed new light into policy-relevant issues, including the rebound effect, but also the effectiveness of policies dealing with resource efficiency, circular economy, and resource nexus issues.

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4.8 Disclaimer

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5. Does Urbanization boost environmental impacts in Colombia? An extended STIRPAT- LCA approach

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Abstract

The relationship between urbanization and technological progress on environment, mainly CO2 emissions, has been extensively studied in the last decades; however, little effort has been made to understand such relationships in developing countries. This work focuses on understanding the effects of urbanization and some technological factors on the Colombian electricity consumption. This topic is addressed from several environmental impact dimensions rather than solely focusing on CO_2 emissions. An extended STIRPAT model, in combination with LCA approaches, was applied in a balanced panel dataset of 27 states, over the period of 2003 to 2018. Our findings suggest that urbanization is the major driver of electricity consumption and climate change in Colombia. Our results address the lack of information about this topic in developing countries and also, they contribute to understand the main features of emissions in Colombia and the key driving forces behind their environmental impacts. Finally, and given the current trends on population and urban growth, the author concludes with some recommendations aimed to relevant stakeholders.

Keywords. Life cycle assessment, STIRPAT model, Urbanization, Environmental impacts.

5.1 Introduction

Urbanization and technological transformations (energy efficiency improvements) are tied to development process (Brant Liddle & Lung, 2010; S. Lin, Wang, Marinova, Zhao, & Hong, 2017). As a result, people emigrate from rural areas (with agricultural-based economy) to urban areas (main cities with industrial economy) (Du, 2016). In the last decades, the urbanization process in Colombia has experienced an important acceleration; the percentage of population living in urban areas increased from 40% in 1960 to 80% in 2018 (World Bank, 2019). These dynamics have risen the demand for resources and have established new pressures on the ecosystems (Poumanyvong & Kaneko, 2010).

The observed expansion of urbanization boost the energy consumption in three different ways: First, the movement of people from urban to rural areas has forced agriculture activities to become more industrialized, as these are less labor intensive. Second, due to urban areas (food consumers) are separate from rural areas (food producers), more transport systems have been required to connect the two main economic agents (producers – consumers). Three, the industrialization process in urban areas has required more energy to produce economic outputs, making energy a normal good inside the market (Brantley Liddle, 2014).

Such a relationship between urbanization and energy consumption has been extensively tested during the last years. Particularly, for developed countries and those members of the Organization for Economic Co-operation and Development (OECD) and developed in Europe (Brant Liddle & Lung, 2010; Brantley Liddle, 2014; Salim & Shafiei, 2014; Shafiei & Salim, 2014; Y. Wang, Zhang, Kubota, Zhu, & Lu, 2015; York, 2007) (see section 2 for detailed review), whereas there is poor evidence between urbanization and environmental. Velez and colleagues (2019) evidenced in a systematic literature review of 112 articles, a geographical imbalance on studies related to the above relationship. They found that 76% of the studies focused on China, whereas no studies were developed in South America.

The objective of this work is to empirically analyze the effects that urbanization and technological changes have on electricity use in Colombia by evaluating different environmental dimensions rather than CO_2 emissions. To achieve this objective, this study combines a well-established and accepted model to study the drivers that trigger environmental pressures (The stochastic impact by regression on population, affluence, and technology (STIRPAT) model) (P. Wang, Wu, Zhu, & Wei, 2013) with the life cycle assessment approaches (LCA). The LCA is a holistic approach widely used to study the environmental impacts caused by the production of goods and services in a wide spectrum of environmental impacts beyond CO_2 emissions (Velez-Henao & Garcia-Mazo, 2019). A balance panel dataset of 27 states, registered over the period of 2003 to 2018 was used as our case of study. Our findings suggest that an increasing urbanization has a significant and positive effect on electricity use and environmental pollution.

The contribution of this work lies on three aspects. First, to the best of our knowledge, this is the first analysis of the effects of urbanization and technological changes in Colombia based on the STIRPAT model. Although there are several studies like this for developed economies (See section 3.2), our study fills the current lack of knowledge regarding these topics in developing economies, particularly in South America. Velez and colleagues (2019) pointed out that there is a geographical imbalance in this kind of knowledge (studies focus on European and Asian economies), with poorly evidence in Latin America economies. Second, this study provides unique data by examining the correlation between urbanization-pollution in Colombia, while a handful of studies includes it in a country panel data (K. Li & Lin, 2015; S. Lin et al., 2017; Long, Ji, & Ulgiati, 2016; Poumanyvong & Kaneko, 2010) this study allows to obtain more specific information regarding the impacts of urbanization on electricity consumption and the Colombia ecosystems. Finally, and not least, this study uses a LCA approach to measure the environmental impacts produced as a consequence of the consumption of electricity from several environmental dimensions (Climate changes, eutrophication, acidification, and respiratory effects). All this taking into account that previous studies focused in a limited range of environmental impacts such as CO_2 emissions, and others air pollutants contributing with climate e.g. SO_x, NO_x emissions (Vélez-henao et al., 2019), which are directly associated with the combustion of fossil fuels and lead to a systematic omissions of the effects produced in other stages of the supply chain such as the extraction and transport of the energy sources.

The development of this work is organized as follows: Section 5.2 present the literature review on the effects of urbanization in developing countries. Section 5.3 shows the materials and methods used to carry out the analysis. The STIRPAT model and the LCA approach which were applied to measure the different environmental impacts, are provided in this section. Furthermore, information regarding the data used is also presented. Section 5.4 shows the main results of our research and section 5.5 presents the discussion about our main findings. Finally, section 5.6 provides our relevant conclusions and the policy implications of this work

5.2 Literature review on the effect of urbanization and technological changes in developing countries

The effect of urbanization on developed countries has been extensively studied in the last years, this has been observed mainly for countries which are members of the Organisation for Economic Co-operation and Development (OECD) and developed economies in Europe. York (2007) analyzed the effect of urbanization on energy consumption, among other demographic factors (such as population and age structure), for fourteen European Union Nations during the period of 1960 to 2000. He concluded that urbanization does contribute to the increase of energy consumption in countries members of the European Union. In the same way, Liddle & Lung (2010) studied such influences for seventeen developed countries during the period of 1960 to 2005. Their results suggested that urbanization in developed countries is positively associated with energy consumption in the residential sector. Otherwise, Salim & Shafiei (2014) and Shafiei & Salim (2014) found that urbanization increased the consumption of non-renewable energy and the CO_2 emissions in OECD countries for the period between 1980 and 2011. Similar results can be found in Wang et al., (2015) for OECD economies along the period of 1960 to 2010. Whereas the empirical evidence for developing countries shows a geographical imbalance, studies focuses mainly in China and countries of the African and the South Asia continents (Vélez-henao et al., 2019).

Literature review points out that urbanization in China increase the amount of energy consumed and the pollutants emitted to the atmosphere. Lin et al., (2009) suggests that urbanization has a positive influence on the emissions of different pollutants (C, SO_x NO_x) in China. Analogous results can be found for different provinces, cities, and districts there. Jia and colleagues (2009) concluded that urbanizations has a positive influence on the ecological footprint in the province of Henan during the period of 1983 to 2006. Tang et al., (2011) found the same outcome in the province of Sichuan, Southwest China from 1995 to 2008. Liu, & Li (2015) for the city of Tianjin during the period of 1996 to 2012. Yang et al.,(2015) in Beijing from the period of 1984 to 2012. Sun et al.,(2013) in Beijing with not clearly specification for the period of time studied. Zhang et al., (2013) in the city of Jiangmen between 1990 and 2010 and Mingwei Wang et al., (2011) for the Minhang District in Shanghai between 1998 and 2009.

Additionally, similar results can be found at different levels of aggregation, Zheng et al., (2016) at the city level, Zhou and colleagues (2015) at the region level, Sheng & Guo (2016) at the province level, and Kang et al., (2016) in China as a whole. Surprisingly, Wang and colleagues (2010) suggested that enhancing the urbanization process is an effective way to reduce the environmental impact on the province of Jilin. Similarly, Yu Liu and colleagues (2014) indicated that the acceleration of urbanization restrains the increase of carbon emissions in a study at the level region in China.

Opposite to the results found for China, a positive relationship between urbanization and energy consumption and environmental impacts have been evidenced for developing countries located in Africa. This suggests that urbanization process decrease the amount of energy consumed and the environmental impacts produced. Madu (2009) suggested that an increasing in urbanization rates will reduce the CO_2 emissions in Nigeria. Similarly, Lin et al., (2016) concluded that urbanization has the potential to reduce the amount of CO_2 emissions in different countries in Africa (Nigeria, Kenya, Congo, Egypt, and south Africa). Likewise, Effiong (2018) suggested that urbanization decreases the amount of CO_2 and particulate matter (PM_{10}) emissions in 49 countries in Africa. Shahbaz et al., (2016) found a U-shape relationship in Malaysia, where urbanization initially reduces CO_2 emissions, but after a threshold level, it increases CO_2 emissions. Whereas Irfan & Shaw (2015) suggested that the relationship between urbanization and CO_2 emissions in South Asian countries (India, Pakistan, and Bangladesh) follows an inverted U-shaped, where urbanization increases CO_2 emissions but after a certain point, more urbanization leads to a fall in carbon dioxide emissions. Finally, Abdallh & Abugamos (2017) conducted a study for the countries of the MENA region (Middle East & North Africa) and concluded that urbanization process decrease CO_2 emissions.

To date, studies examining the urbanization-pollution relationship in Colombia are nascent. This study analyses the effect of urbanization and technological changes in several countries at different development stages and with low, middle and high income. There, Colombia is aggregated along other countries into the middle-income level. As an example, Poumanyvong & Kaneko (2010) suggested that the impact of urbanization on energy consumption and CO_2 emissions varies across the development stages of countries. Those, urbanization decreases energy use in the low-income group, while it is increased in the middle and high-income groups. Urbanization increased the CO_2 emissions in all the income groups. Similarly, K. Li & Lin (2015) and Lin et al., (2017) concluded that urbanization increase the demand of energy and the amount of CO_2 emissions in countries with middle level of income. Surprisingly, Long, Ji, & Ulgiati (2016) found that urbanization in all levels of income decrease the amount of environmental impacts, however the reason of such a results may be associated with the impact under study (ecological footprint).

Existing studies show that the effect of urbanization on energy consumption and environmental impacts are positive for developed countries, whereas for developing countries at low-income level an increasing rate of urbanization decreases energy consumption and environmental impacts. At the contrary, in middle income level countries such relationship is positive. Moreover, they also showed that the effects of urbanizations in Colombia have not been deeply studied, supporting the motivations of this work.

5.3 Materials and methods

This section presents the model and approaches applied to quantify different environmental pressures and their key drivers. Data collection and statistic evaluations are presented.

5.3.1 Environmental impacts related with electricity production

The Life Cycle Assessment (LCA) is a holistic approach, ruled by the ISO 14040 (ISO, 2006) to assess the environmental impacts of goods and services across the entire life of cycle, from the extraction of raw materials to the final disposal or recycling (cradle to gate). Over the past two decades, the LCA has been widely applied to assess the life cycle impacts of providing electricity through different energy resources (Arvesen and Hertwich, 2012; Turconi et al., 2013). This study uses the Ecoinvent 3.4 database (Ecoinvent, 2019) to measure the environmental impacts generated for the production of electricity. The Colombian energy system is composing for a mix of technologies such hydro, coal, thermal, wind, and solar which contributions vary across the years depending strongly on the climatic conditions (Figure 5.1). It is worth noting that the shares of wind resources in the energy system (green in the figure) have been historically low and barely accounts the 0,01% of the total shares, whereas the solar power was introduced into the national grid at the beginning of the 2018.

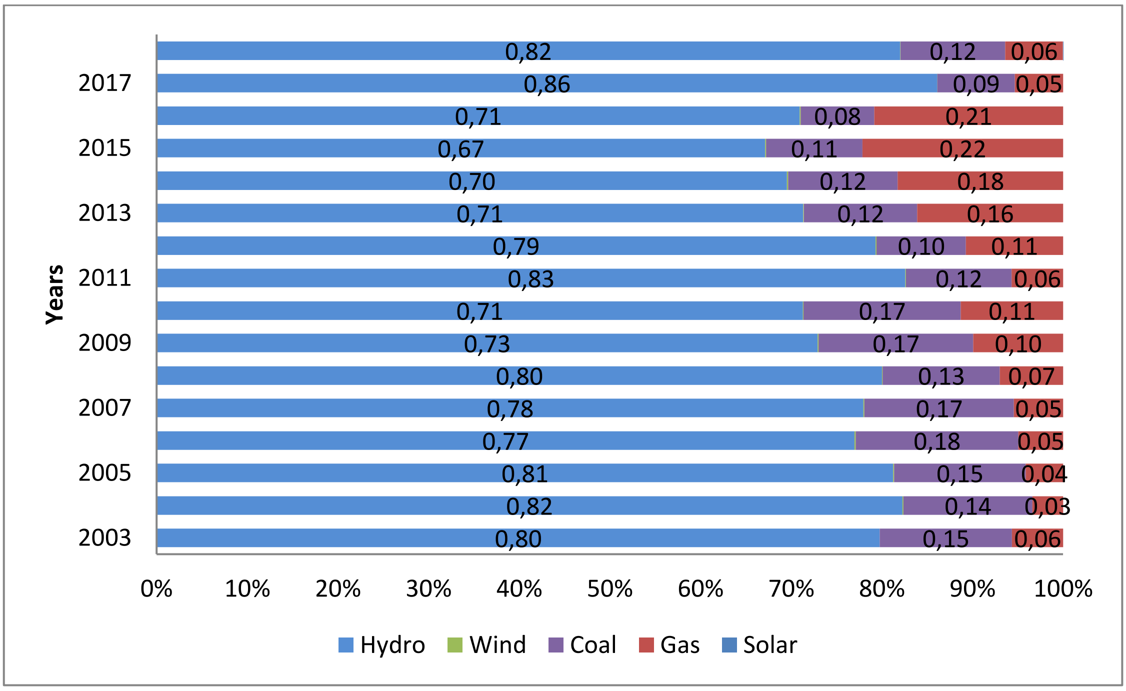

Figure 5-1.Share of technologies for electricity production in Colombia during the periods 2005-2013. Own elaborations base on (UPME, 2019a)

The environmental impacts selected for this study were climate changes (CC), freshwater eutrophication (EUT), freshwater and terrestrial acidification (A), and respiratory effects (RES), the most common impacts used to study environmental issues of the energy production. Due to Ecoinvent database does not have detailed information for Colombia, the impact factors for the different unitary process for the production of electricity (e.g. Wind, Solar, Hydro, Coal, and Gas) were taken from the Brazil. With such information the energy matrix for each year was built up base on the historical technology shares reported by the official entities (see table 5.1). This may introduce negligible uncertainties which are not significant due to the similitudes in the technology infrastructure and the geography conditions of both countries. The life cycle impact assessment (LCIA) was conducted using the life cycle impact characterization factors by International Reference Life Cycle Data System (ILCD) (European Commission, 2014) and provided by Ecoinvent 3.4, as a robust and widely used approach among LCA practitioners. Table 5.1 summarizes the impact factors for different electricity production resources.

Table 5-1. Impact factors for different electricity production resources that compose the Colombian energy system. Values in kg/KWh

Impact category	Hydro	Carbon	Gas	Wind	Solar
Climate changes (CO_2.eq.)	6.53E-02	9.26E-01	5.57E-01	1.57E-02	8.05E-02
Eutrophication(P-Eq)	1.69E-06	4.49E-04	4.14E-06	1.09E-05	7.12E-05
Acidification(mol H+-Eq)	2.87E-05	7.59E-03	6.82E-04	1.00E-04	5.98E-04
Respiratory effects (kg PM2.5-Eq)	6.24E-06	3.81E-04	2.61E-05	1.63E-05	7.83E-05

Source: own elaboration based on Ecoinvent 3.4 (2019)

5.3.2 STIRPAT model

The IPAT equation was introduced in the 1970s to study the environmental impacts (I) through population (P), affluence (A^+), and technology (T) (Commoner, 1972; Ehrlich & Holdren, 1971, 1972). The IPAT equation has been extensively used in climate change studies, particularly on energy-related carbon emission studies (Chertow, 2000). This equation has suffered several reformulations over the last years, such as the Kaya equation, ImPACT, ImPACTS, IPBAT (Vélez-henao et al., 2019). Yet, the IPAT equation and their variants contain theoretical limitations, their formulations does not include and test additional factors that may trigger environmental changes (Thomas Dietz & Rosa, 1994) and also it treats the technology variable incorrectly (Roca, 2002).

To tackle such limitations, Rosa and Dietz (1998) proposed the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence and Technology) as:

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (5.1)$$

Where, the constant $a \neq 0$ scales the model; *b, c* and *d* represent the effects of population elasticity, affluence elasticity, and technology elasticity, respectively. The term *e* is the error term. This approach allows for testing hypotheses regarding factors other than population and affluence which may contribute to environmental impacts (T Dietz & Rosa, 1997). According to Wei (2011), the STIRPAT equation is used with two main purposes: First, to estimate causal effects between the driving forces; Second, to predict environmental impacts based on key driving forces. STIRPAT model treats the linkage between variables as hypothesis to be tested and it allows a decomposition of population and affluence into forms that have more social meaning (Rosa & Dietz, 1998). This study extended the STIRPAT model to study the effect of urban dynamics and technology factors on the electricity consumption, global warming potential, freshwater eutrophication, freshwater and terrestrial freshwater and terrestrial acidification, and respiratory effects. For doing so, urban density, energy structure, and temperature were included as variables. Furthermore, the price of the electricity and energy intensity were added to test the existence of the rebound effect in the electricity household consumption.

The STIRPAT model can be extended as follows to study the drivers behind the household electricity consumption and different environmental impacts such climate change, eutrophication, acidification, and respiratory effects. Technology is broken down in energy intensity and energy structure. Urban density was included to test hypothesis of urban development minimizing the impact of demographic dynamics on the environmental impacts. The price of the electricity was included to test, rather than measure, the existence of the rebound effects in the household electricity consumption.

$$Ln\ (E_{it}) = \alpha + \ \beta_1 P_{it}\ + \beta_2\ Ln\ GDP_{it} + \beta_3\ U_{it} + \beta_4\ IN_{it} + \beta_5 Ln\ EI_{it} + \beta_6\ ES_{it} + u_{it}\ (5.2)$$

$$Ln\ (I_{kit}) = \varphi + \ \gamma_1 P_{it}\ + \gamma_2\ Ln\ GDP_{it} + \gamma_3\ U_{it} + \ \gamma_4 IN_{it} + \gamma_5 Ln\ EI_{it} + \gamma_6\ ES_{it} + v_{it} (5.3)$$

Where the subscripts i and t denote the region and time respectively, α und φ are the constant, β1 to β6 and $\gamma 1$ to $\gamma 6$ are the parameters to be estimated in the respective models. u_{it} and v_{it} represents the error term. $\mathrm{E_{it}}$: Represents the electricity consumption. I_{kit}: Stands for the environmental footprint, in which the subscript k represents Climate change, freshwater eutrophication, freshwater and terrestrial acidification and Respiratory effects. $\mathrm{P_{it}}$: represents the population size. GDP_{it}: Represent the income variable. U_{it}: represents the urban density. IN_{it}: Industrialization rate. EI_{it}: Energy intensity. ES_{it}: Energy structure (Table 5.2 presents the definition of all the variables used in the study).

Table 5-2. Definition of the variables used in the study for the period of 2003 to 2018

Variable	Definition	Unit of measurement
Electricity consumption (E)	Total household electricity consumption at the end of the year	GWh
Population (P)	Total population at the end of the year	Millions
Per capita Gross domestic product (GDP)	Total per capita GDP at the of the year	Millions COP(2005 constant prices)
Urbanization (U)	Proportion of population living in urban areas in each state at the of the year	Percent
Industrialization (IN)	Share of the GDP produced for the industrial sector divided the total GDP	Percent
Energy intensity (EI)	Total energy use divided by GDP	$GWh/10^6$
Energy structure (ES)	share of fossil fuels in the electricity grid at the of the year	Percent
Climate change. (CC)	Energy-related CO_2 Eq emission	Ton
Freshwater eutrophication (EUT)	Energy-related P-Eq emission	Ton
Freshwater and terrestrial acidification (A)	Energy-related mol H+-Eq emission	Ton
Respiratory effects, inorganics (RES)	Energy-related respiratory effects, inorganics PM 2.5	Ton

5.3.3 Data sources and description

Data used were gathering from different public entities. Total electricity consumption data was obtained from The superintendence of public services domiciliary (SUI by his acronym in Spanish) (SUI, 2018). Income variable data, population and area of the states were obtained from the National Administrative Department of Statistics (DANE by his acronym in Spanish) (DANE, 2018b). Environmental impacts data for the production of electricity were obtained from Ecoinvent 3.4 database (Ecoinvent, 2019). The data was collected yearly within 27 states of Colombia (Amazonas, Arauca, San Andrés y Providencia, Guania, Vaupés, and Vichada were excluded) along the period of 2003 to 2018. The exclusions are due to the lack or/and quality of the data associated with some important variables. The total number of observations per variable was 432. All the data is in constant prices of 2005. Table 5.3 present general statistics.

Table 5-3. Summary statistic (Variables in natural logarithms. U, IN, EI are in percentage).

Variable	Obs.	Mean	Max	Min	Std.des
E	432	6.697	9.560	2.707	1.338
P	432	0.130	2.102	-2.376	0.897
GDP	432	1.656	3.303	0.306	0.533
U	432	0.677	0.998	0.378	0.150
IN	432	0.093	0.286	0.005	0.067
EI	432	11.511	12.378	8.569	0.526
ES	432	0.229	0.328	0.129	0.055
CC	432	5.204	8.107	1.186	1.345
EUT	432	-3.038	0.071	-6.903	1.333
A	432	-0.148	2.924	-0.045	1.332
RES	432	-3.086	-0.019	-6.982	1.332

Correlation among variables represent an issue in econometric studies due to it can bias the results and affects the interpretation of the variables. Total correlations between the environmental impacts (Figure 5.2 present the correlation factor for each variable) are due to different impacts which are direct derived from the quantity of electricity produced for the respective sources. Nevertheless, this does not bias the interpretation of the results because each environmental pressure is independently studied.

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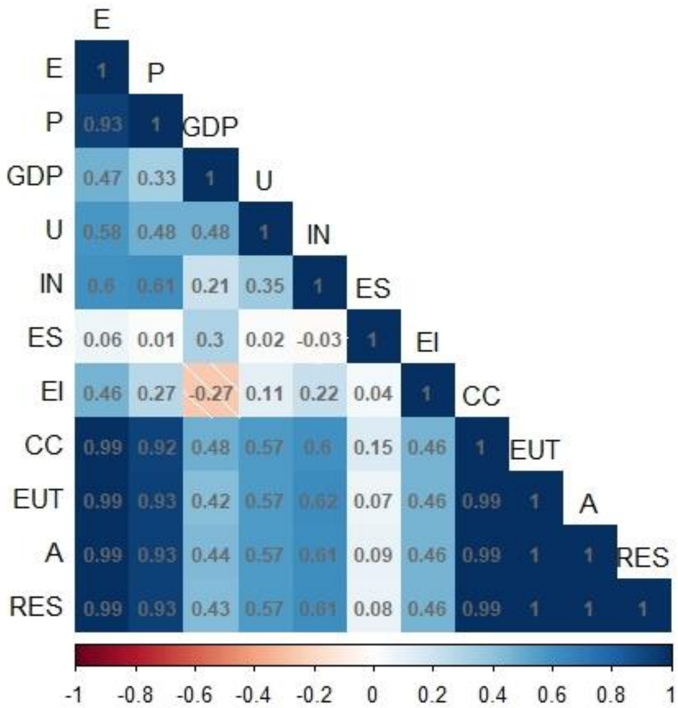

Figure 5-2. Correlation amount variables: E. Electricity consumption. P. Population. GDP. Gross domestic product per capita. U. Urbanization. CC. Climate changes. EI. Energy intensity. ES. Energy structure. EUT. Eutrophication. A. Acidification. RES. Respiratory effects

5.4 Results

Nine models were developed to test the effect of population, GDP, urbanization, industrialization, energy intensity, and energy structure on the electricity consumption according to different environmental impacts (climate changes, eutrophication, acidification, and respiratory effects). For each model different tests were carried out to find the most appropriated model for the data. Breusch-Pagan test was applied to evaluate the presence of heteroskedasticity. Hausman test was applied to choose the more suitable model (fixed or random effects).

The different tests suggest that the best model to represent the electricity use is the model (2). Breusch-Pagan test failed in rejecting the heteroskedasticity hypothesis; therefore OLS (model 1) estimations are bias. In order to tackle this issue, generalized least squares GLS model was evaluated. GLS is a well know model for being suitable in presence of heteroskedasticity. Moreover, Hausman test was used to determine whether GLS-FE (model 2) offers a better fit or RE (model 3) does. The hausman test suggested that GLS-FE (model 2) is more suitable than GLS-RE (model 3). So, results are discussed for GLS-FE (model 2) (See table 5.4 for results).

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Table 5-4. Estimation results for electricity use

Variable	OLS(1)	GLS-FE(2)	GLS-RE(3)
	-4.9384***		-5.2771***
Constant	(-32.0069)		(-94.6244)
	1.0381***	1.1329***	1.0336***
P	(112.8792)	(12.3546)	(141.4116)
	0.7924***	0.4492***	0.8078***
GDP	(56.0608)	(42.0027)	(108.0521)
	0.2950***	1.6127***	0.2035***
U	(5.9356)	(3.9526)	(4.7670)
	0.2619*	-0.7011***	0.9344***
IN	(2.3508)	(-4.4847)	(229.7294)
	0.9015***	0.9739***	0.9344***
EI	(68.6133)	(295.8569)	(229.7294)
	-1.8045***	-0.8921***	-1.8139***
ES	(-15.4701)	(-25.4268)	(-47.1943)
R2	0.9917	0.9969	0.9916
F-statistic	8649.07(0.000)		
Chisq			
BP test	95.62(0.000)		
Hausman test		255.35(0.000)	255.35(0.000)
Signif. codes:	***p<0.001 ;	**p<0.01;*p<0.05; .p<0.1	

By order of importance U, P, EI, and GDP were found positive and significant related with electricity consumption. These results suggest that an increase of 1% in U will lead to an increase of 1.61% in electricity consumption, whereas an increase of 1% in P, EI, and GDP will produce an increase in electricity consumption of 1.32%, 0.97%, and 0.44%, respectively. At the contrary, IN and ES were found negative and significant related with electricity consumption. Particularly, an increase of 1% in IN and ES will reduce the consumption of electricity to 0.70% and 0.89%.

For the CO_2 emissions evaluations, Breusch-Pagan test failed in rejecting the of heteroskedasticity hypothesis, delivering biased estimations of OLS (model 4). Therefore, GLS (model 5 and model 6) were performed to overcome the heteroskedasticity issues. Hausman test was applied to determinate if the model with fixed effects (model 5) is better than the model with random effects (model 6). Results showed that the model with fixed effects (model 5) offers a better fit for the data (Table 5.5).

Table 5-5. Estimation results for climate changes and key drivers behind the climate change for the Colombian with their respective test results

Variable	OLS(4)	GLS-FE(5)	GLS-RE(6)
Constant	-6.6767***		-7.0941***
	(-35.7802)		(-107.2965)
P	1.0379***	0.8587***	1.0352***
	(93.2731)	(8.7714)	(124.9418)
GDP	0.7381***	0.3795***	0.7548***
	(43.1573)	(40.1905)	(88.8091)
U	0.3531***	0.9968*	0.2637***
	(5.8713)	(2.2819)	(5.4739)
IN	0.4418**	-0.5666***	0.3456***
	(3.2769)	(-3.8509)	(5.1521)
EI	0.8766***	0.9773***	0.9159***
	(55.1407)	(327.9912)	(192.9747)
ES	0.6714***	1.7663***	0.6621***
	(4.7577)	(62.4650)	(17.7708)
R2	0.9889	0.9962	0.9879
F-statistic	5952.39(0.000)		
BP test	74.25(0.000)		
Hausman test		1230.8(0.000)	1230.8(0.000)

t-values are shown in parentheses.

Signif. codes: ***p<0.001 ; **p<0.01;*p<0.051; .p<0.1

P. GDP. U. and EI were found to be significant and positive related to climate changes as an effect. Particularly, an increase of 1% in P will lead to an increase of 1.13% on CO_2 emissions, whereas an increase of 1% in GDP will increase CO_2 emissions on 0.44%. Similarly, EI is positive and statistically significant related with CO_2 emissions. This suggests that a 1% increase in energy intensity will cause a 0.97% increase in CO_2 emissions. Thus, higher consumption of energy leads to higher levels of CO_2 emissions. Evaluating the variable of interest, it was found that U has a positive and statistically significant effect on CO_2 emissions. A 1% increase in the urbanization rate is likely to increase carbon emissions by 0.99%.

IN and ES were found to be negative related with CO_2 emissions. This result may suggest that industrialization and energy structure may not be major drivers of CO_2 emissions in Colombia.

For the other environmental impacts (EU. A and RES) Breusch-Pagan test failed in rejecting the heteroskedasticity hypothesis leading to biased OLS estimations. Hausman test suggested that FE model via GLS regression fits properly for all the above-mentioned impacts (Table 5.6 present the models results for EUT, A and RES).

Table 5-6. Estimation results for eutrophication (model7), acidification (model 8) and respiratory effects (model 9) GLS estimation.

Variable	GLS-FE(7)	GLS-FE(8)	GLS-FE(9)
Constant			
P	0.0534	0.1917*	0.2325*
	(0.5481)	(1.9934)	(2.4188)
GDP	0.1805***	0.2114***	0.2165***
	(13.4654)	(17.3174)	(17.8994)
U	-0.5960	-0.2787	-0.1660
	(-1.2836)	(-0.6142)	(-0.3665)
IN	0.3838*	0.2631.	0.2173
	(2.3675)	(1.6730)	(1.3840)
EI	0.9923***	0.9900***	0.9891***
	(316.296)	(322.6389)	(322.9398)
ES	0.9376***	1.3524***	1.0124***
	(31.6692)	(48.7855)	(36.7293)
R2	0.98321	0.98707	0.9874
BP test	40.311(0.000)	42.288(0.000)	42.767(0.000)
Hausman test	2796.2(0.000)	2958.7(0.000)	2007.7(0.000)

t-values are shown in parentheses.

Signif. codes: ***p<0.001 ; **p<0.01;*p<0.051; .p<0.1

For EUT (model 7), the variables GDP, IN, EI, and ES were found to be positive and statistically significant. Particularly, an increase of 1% on GDP will lead to an increase on eutrophication problems of 0.18%. Whereas an increase of 1% in IN, EI and ES will increase eutrophication by 0.38%, 0.99%, and 0.93%, respectively. Although, P was found to be positive correlated, both variables were statistically insignificant.

The results for acidification (model 8) and respiratory effects (model 9) are similar in terms of variables significance. IN was found to have a positive impact on the respective environmental impacts; however, it was only significant at a 90% level of acidification. Whereas it was found to be insignificant for the respiratory effect. By order of importance ES, EI, GDP, and P were found to be positive related with the respective dependent variable, acidification (model 8) and respiratory effects (model 9).

Urbanization was found to be negative for all the different environmental impacts but it is not statistically significant. These results may suggest that urbanization may not be a major driver of eutrophication, acidification, and respiratory effects in Colombia.

5.5 Discussion

Urbanization was found to have a significant and positive influence on electricity consumption (an increase of 1% in U will increase electricity consumption by 1.61%), and climate changes (1% increase in the urbanization rate is likely to increase carbon emissions by 0.99%), whereas for acidification, eutrophication and respiratory effects it was found to be negative but statistically insignificant.

The results found for acidification, eutrophication and respiratory effects (Table 5.6) may be explained for the fact that those environmental impacts are measured through the amount of electricity consumed. In this regard, the impacts for providing electricity in such impact categories may not be relevant compared with the impact of others activities that comes along with the urbanization process (e.g. pollutants generated in transport sector, which is a current issue in developing countries by its relationship with particular matter and human health) and which were omitted in this study. Moreover, given the fact that Colombia energy mix (See figure 3.1) is compound mainly by hydropower, the impacts associated with acidification and eutrophication are more likely to be present in rural areas, around the hydropower plants, than in urban areas, explaining why urbanization may not be a main driver in such impacts.

Our results do not match finding that suggest that urbanization decrease energy consumption and carbon emissions (Abdallh & Abugamos, 2017; Effiong, 2018; B. Lin et al., 2016; Madu, 2009; Shahbaz et al., 2016). Moreover, evidence suggests that the patters of urbanization in Colombia follow the same tendency described for China (Urbanization process increase energy use and pollutants at different levels of aggregation in China).

The reason for such discrepancy may be the fact that Colombia is a developing country which can be grouped as a middle income level, similarly to China, comparing to Nigeria, Kenya, Congo, and other countries in Africa studied by Madu(2009), Lin et al., (2016). Abdallh & Abugamos (2017), and Effiong (2018). Such differences in income level has been reviewed by Poumanyvong & Kaneko (2010). K. Li & Lin (2015) and Lin et al.. (2017), suggesting that urbanization decreases energy use in the low-income group, while it increases it in the middle and high-income groups. Furthermore, urbanization increases the CO_2 emissions in all the income groups.

In the last 20 years the number of people living in urban areas has increased by 37%. At the same time, urban density have been raised by 5% (DANE, 2018a). This implies that urban areas are rather growing horizontally than vertically. The main reason for the positive relation between urbanization and electricity use may be the fact that in urban areas the electricity is a normal consumed good used to supply several energy services such as: refrigeration, lighting and water heating. Urban areas (residential sector) is the economic sector who most electricity demand in Colombia (40% of the total amount of electricity) (UPME, 2019b).

The energy intensity was found to have a significant effect on electricity use and all the environmental impacts under study even if its proportion is lesser than the urbanization. The main reason of that is that energy intensity EI (The amount of energy needs to produce one unit of GDP) is a representation of the level of industrialization. This sector demanded the 29.36% of the total energy consumed in Colombia in 2016 (mainly carbon and natural gas). In terms of electricity demanded, it consumes a poorly proportion (12% of the total electricity demanded in 2016) (UPME, 2019b).

From the methodological point of view, the STIRPAT-LCA offers a more suitable and accurate framework to assess the environmental impact of different resources in the electricity production. First, LCA approach covers a wide range of environmental issues beyond CO_2 emissions. Resources that produce less CO_2 emissions comparing with fossil fuels could be linked to a larger emission of toxic substances (Font Vivanco & Voet, 2014). Second, CO_2 emissions in the STIRPAT studies are indirect estimated by multiplying the consumption of an individual resource (e.g. coal or gas) by their respective carbon emissions coefficient (H. Li, Mu, Zhang, & Li, 2011; S. Lin et al., 2009; Zhang et al., 2013). This approach neglects emissions associated with other stages of the supply chain for electricity production like facility infrastructure, transport and final disposal. The systematic omission of such details may lead to inaccurate recommendations for policy decisions.

The limitations of the study are associated with two factors. First, the availability and quality of the data, the information regarding the electricity obtained from the SUI (2018) only has records since 2003, preventing a more rigorous study with a larger time horizon. Moreover, the data obtained systematically omitted information for some regions in Colombia (Amazonas, Arauca, San Andrés y Providencia, Guanía, Vaupés, and Vichada). Second, Information regarding the environmental impacts produced for the generation of electricity reported by the UPME (2019) are available for a imitated number of periods (2008, and 2013 until 2019), moreover, this information is reported aggregated, which means that the UPME reported the emission factor for the SIN (national interconnected system by his acronym in Spanish) as a total amount of CO_2 eq/per kWh, it is worth nothing that the emission factor is published only for the CO_2 eq emissions. In order to tackle this issue, the information of the different environment impacts for the technologies that compose the Colombian energy system was obtained from the Ecoinvent data base 3.4, particularly the unit process for each technology was taking for Brazil as geography in absence of data for Colombia.

Further research is needed to study the effect of urbanization and other technical factors in Colombia. They have to be performed at different levels of aggregation, particularly at income level. Given the fact that the evidence suggests that impact of urbanization depends on the level of income (urbanization increase the energy use and pollutants in high income levels and reduce the amount of pollutants in low income levels). Moreover, efforts to increase the time horizon are encouraged.

5.6 Conclusions

In this work a STIRPAT-LCA model to address the influence of urbanization and technological changes on electricity consumption at different environmental impacts dimensions. A panel data with 27 of the 33 states in Colombia along a time span of 2003 to 2018 was used. The results suggest that urbanization is the main driver behind the electricity consumption (1.61%) and climate change (0.99%), whereas for acidification, eutrophication and respiratory, an explicit relationship was not found.

Giving the current trends on economic growth, it is likely that the population and urbanization process continue growing during the upcoming decades. This will lead to increasing pressures on the ecosystems and the economy which is facing a transition between the agro to the industry. In this matter, the Colombian government may focus in guaranteeing the urbanization process with a sustainable criterion. Energy politics may focus in decoupling electricity consumption from urbanization. E.g. promoting regulations for efficient building construction and the introduction of more efficient technologies in the households sector e.g. the replacement of old refrigerators to more efficient ones. Moreover, the government should strengthen and accompany the discussion processes around urban development strategies in such a way that the stakeholders can recognize the diversity of the territories and to ensure a coherent link between urban areas and ecosystems.

Joint efforts are needed to ensure sustainable urbanization processes; this will help us to create resilient and sustainable cities. Ass well as contributing to meet the commitments made by the country in the last COP21 which are concerning the reduction of the greenhouse emissions to 20% by 2030, respect to the reference year of 2010.

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6. Hybrid life cycle assessment of an onshore wind farm in Guajira, Colombia

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Abstract

To diversify and decarbonize its energy system, Colombia plans a sizeable increase in wind power by installing onshore wind farms in the Guajira region. While presumably superior to other alternatives in terms of environmental performance, this assumption cannot be tested due to the lack of studies in this region. We carry out a hybrid life cycle assessment to estimate the environmental footprint associated with an operational wind farm of 19.5 MW of installed capacity for various impacts. We include both direct (required on-site) and indirect (required in the supply-chain) services associated with the life cycle of the wind farm, an unprecedented feature in the LCA literature. The results show that the wind farm produces 13.45 gr CO_2 eq/kWh for global warming impacts, and the inclusion of both direct and indirect services increase the environmental impacts across impacts (with respect to the results without services) from 8% (photochemical ozone formation) to 1918% (eutrophication). Further, a sensitivity analysis suggest that the results are particularly affected by the chosen capacity factor, lifespan, and percentage of losses. Findings invite to include both direct and indirect services as well as perform sensitivity analysis of key technical parameters in future life cycle assessments of wind farms. Given the difficulty to obtain data on services, we conclude with some recommendations aimed at relevant stakeholders.

Keywords: Hybrid LCA, direct services, indirect services, wind power, case of study

6.1 Introduction

Colombia's energy sector was responsible for about 35% of the total greenhouse gas (GHG) emissions emitted nationally in 2014 (236.6 Mton), just behind the agriculture sector, which contributed 55% of the total (IDEAM et al., 2018). The Colombian government plans a considerable boost in the share of renewable energies to satisfy the growing electricity demand while diversifying and decarbonizing the energy system (UPME, 2016). Specifically, the government plans to diversify the grid to protect the electricity system against climatic variations.

Historically, the Colombian energy grid is highly dependent on hydro power (UPME, 2019), and such dependence makes the grid vulnerable to phenomenon such as the ”El Niño” and “La Niña”. Particularly,” El Niño” (south oscillation ENSO) takes place during the course of a year in both dry and rainy seasons, dramatically altering the reservoir levels. Such changes drive up the price of electricity because more carbon and gas resources are needed to support the system, and can even cause rationing of electricity (Velez-Henao and Garcia-Mazo, 2019). By increasing the shares of wind power in the power gird, the Colombian government also plans to endorse the sustainable development goals (SDG), especially SDG 7 (Ensure access to affordable, reliable, sustainable and modern energy for all) (United Nations, 2017) as well to satisfy the agreements made in the COP 21 to reduce national carbon emissions by 2030 (García Arbeláez et al., 2015). Among renewable energy sources, wind power is expected to receive a considerable boost, from a marginal 0.1% in 2016 to a 6% share of the grid in 2030 (UPME, 2016). Such an increase in capacity is planned to take place mostly by installing onshore wind farms in the Guajira region (UPME, 2016).

Wind farms are generally associated with lower life-cycle environmental impacts than alternative energy sources (Turconi et al., 2013), yet such better performance relies importantly on various aspects, such as the capacity and energy loss factors. Given the lack of LCA studies on wind farms in Colombia, their environmental performance is mostly ignored. Moreover, a largely overlooked aspect in life cycle assessment (LCA) studies is the environmental impact associated with services that are required both directly (surveying services prior to infrastructure building and environmental impact studies) and/or indirectly (services in the supply chain of products), whose omission can lead to significant truncation errors and misestimation of results (Pomponi and Lenzen, 2018). For example, Suh (2006) found that 38% of GHG emissions in the U.S are caused by services once supply-chain emissions are accounted for. Similarly, Nansai and colleagues (2009) highlighted that the supply chains of services in Japan consume a considerable amount of energy and materials. More generally, Font Vivanco (2020) found that systematically including services in the life cycle inventory (LCI) database ecoinvent 3.4 leads to a 4-16% median increase in environmental footprints, depending on the impact selected and the treatment of capital, whereas Agez et al., (2020) found an average truncation due to missing services of 14% for climate change in ecoinvent 3.5. Beyond current knowledge at the level of national and global economies, it remains unclear the role of services in particular LCA case studies. Our hypothesis is that services play a role in the environmental performance of wind farms and similar infrastructures. This is because wind farms are associated with a variety of indirect services in their complex supply chains, but especially numerous direct services required to build and operate the site, such as surveying, operation and maintenance, and legal compliance. The main research questions addressed here are thus: what is the contribution of onshore wind farms in the Guajira region towards sustainability goals and what is the specific role of services?

The goal of this study is to quantify the environmental performance of an operating onshore wind farm in the Guajira peninsula of Colombia with a focus on the role of services. To fulfill this goal, we carry out such an analysis using the integrated hybrid LCA approach proposed by Suh et al., (2002) and specifically the model developed by Suh et al., (2004). Hybrid LCA allows to improve system completeness (Joshi, 2000), in this case by incorporating indirect services from input-output data as done by Font Vivanco (2020) and Agez et al., (2020). Among the different methods of hybridization (tiered, path exchange, matrix augmentation, and integrated), the integrated LCA approach offers a versatile and transparent framework that has been used in a fairly consistent manner in several studies (Crawford et al., 2018). For example, to assess offshore wind turbines

(Wiedmann et al., 2011), biodisel (Acquaye et al., 2012), and solar PV and micro-wind technologies (Bush et al., 2014). According to Joshi (2000), traditional methods suffer, among other, from problems of subjective boundary definition and aggregation. Process-based LCA (P-LCA) often suffers from truncation as well as omission of resource use and emissions of upstream stages by setting subjective system boundaries (Huey et al., 2017; Lenzen, 2000). On the other hand, input–output LCA (IO-LCA) includes the whole economy as the system boundary, yet it suffers from aggregation issues as the product of interest is generally approximated by its commodity sector, an aggregation of a large number of heterogeneous products (Joshi, 2000; Lenzen, 2000). Hybrid LCA combines the strengths of both P-LCA and IO-LCA, resulting in a more robust method for environmental footprinting (Suh et al., 2004).

Hybrid LCA approaches allow to bring analyses one step ahead by (1) integrating social and economic aspects, (2) expanding the level of analysis across sectors and regions, and (3) including scenarios and rebound effects (Onat et al., 2017). Regarding renewable energy technologies, Wang et al., (2020) applied a matrix augmentation hybridization method to assess the effects of bioethanol expansion in terms of job creation, energy use, and economic stimulus across different regions of China. Faturay et al., (2020) studied the economic and energy impacts of an energy wind expansion across different USA regions. Mikulić et al., (2018) studied the economic effects of new wind energy developments in Croatia. On the other hand, Zafrilla et al., (2014) applied a tiered hybrid approach to study the GHG emissions of a nuclear power plant in Spain across different regions. Finally, Vélez-Henao et al., (2020) studied the direct and indirect environmental rebound effects associated with wind power expansion on the residential sector in Colombia.

By providing answers to our hypothesis, namely that services play a role in the environmental performance of wind farms, this study provides novel insights on the truncation issues related to omitting service inputs in electricity generation, an unprecedented feature. This study thus contributes to the increasing discussion about the role of service inputs in LCA studies. Compared with existing studies, this study includes the impacts of both the direct and indirect services. This study also provides, for first time, an LCA study for an electricity generation system in Colombia. While there are several LCA studies for wind plants in the literature (see section 2), this study fills the gap for Latin-American economies, the study found in Brazil is a fictive case. Last but not least, this study highlights the importance of testing the sensitivity of the LCA results of wind farms to key parameters.

Our study is relevant to various stakeholders: policymakers will gain insight on the actual role of wind energy in achieving sustainability goals, whereas the energy provider will better understand the environmental hotspots associated with the plant. Lastly, LCA practitioners will gain insight on the role of technical and location-specific aspects as well as services in energy and broader studies. This paper is organized as follows: section 6.2 provides a literature review of LCA studies on onshore wind farms. Section 6.3 describes the case study, materials, methods, and data. Section 6.4 shows the results, section 6.5 discusses the results, and section 6.6 concludes with the main findings of the study.

6.2 Literature review of life cycle assessments of wind farms

Wind power is associated with significantly less life-cycle GHG emissions compared to other electricity production technologies (Arvesen and Hertwich, 2012a; Turconi et al., 2013) (see Table 6.1 for climate change impact results). Such differences are associated mainly with two factors (Bonou et al., 2016; BWEA, 2005; Lenzen and Munksgaard, 2006): the technical aspects of the wind turbine (e.g. capacity, efficiency, and the materials used in the manufacturing of the wind turbine) and the technical parameters of the wind farm (e.g., factor capacity, wind speed, lifetime, and the losses assumed). Furthermore, the robustness of the studies relies on the capacity of the LCA method to represent the whole system as incompleteness leads to systematic truncation errors and misestimation of results (Lenzen, 2000). Because system boundary definition relays on suggestive decision (Joshi, 2000), two or more P-LCAs with the same purpose may not be comparable (Agez et al., 2020).

Table 6-1. Greenhouse gases (GHG) for different power plants, values in kg CO_2-eq/KWh.

	Carbon	Gas	Hydro	Wind	Solar
Max	1.05E+00	1.00E+00	2.00E-02	1.30E-02	1.30E-02
Min	6.60E-01	3.80E-01	2.00E-03	4.10E-03	1.90E-03

Table based on Arvesen and Hertwich (2012a) and Turconi et al.(2013)

Both P-LCA and IO-LCA highlight important aspects in an LCA for a wind power electricity production. P-LCA allows to model in a detailed way the technology and the technical and climatic parameters (capacity factor, percentage of losses, and wind speed) that influence the environmental performance of the plant. Through P-LCA it is also possible to include the use and end-of-life (EoL) stages. Within the latter, recycling processes have been recently acknowledged to highly influence the environmental impacts due to the possibility to grant positive credits (Garrett and Rønde, 2014). Recycling credits entail that recycling materials avoid the extraction of raw materials and that associated environmental impacts are avoided and can be given as credits. The implications of granting credits in the recycling stage of wind farms shows an increase in the environmental performance of about 30% (Garrett and Rønde, 2013; Oebels and Pacca, 2013). IO-LCA allows including complete information of the system boundaries, avoiding assumptions and technical omissions present in P-LCA models. The value of using IO-LCA to assess wind farms is however mostly ignored due to the lack of applications in the literature. In a pioneering study, Kumar et al., (2016) conducted an IO-LCA to include the stages of operation and maintenance (O&M) and decommissioning, with the latter representing around the 10% of the total emissions.

The evidence suggests that, regardless of the LCA approach applied, the results vary considerably according to the technical parameters and assumptions made in each study (see Table 6.2 for the results of different LCAs of wind power plants with differing parameters and assumptions). Moreover, potentially valuable information regarding the technical parameters is sometimes omitted. For example, Ardente et al., (2008), Rajaei and Tinjum (2013), Rønde (2013), and Oebels and Pacca (2013) do not mention the percentage of losses assumed. Also, Ozoemena et al., (2018) do not mention the wind speed assumed, whereas Xu et al. (2018) do not mention the percentage of losses included into the study. The latter study stated that 20% of the materials were recycled, but it does not provide the quantity granted. Ardente et al. (2008), Bonou et al., (2016), and Chipindula et al., (2018) do not specify the quantity of credits granted in the recycling stage, whereas Oebels and Pacca (2013) granted a total of 2.60E-03 kg CO_2-eq /kWh and Garrett, Rønde (2013) estimated total credits for recycling of 3.80E-03 kg CO_2-eq/kWh. and Al-behadili and El-osta (2015) estimated credits for recycling of 5.75E-03 CO_2-eq/kWh, the highest amount of credits granted from the reviewed literature. A few studies have applied hybrid LCA models in the context of wind power. Noori et al., (2015) quantified the direct and indirect environmental impacts of wind power in the USA. Arversen and Hertwich (2012b) studied the potential environmental impacts of a large-scale adoption of wind power in Europe. Lastly, Feng et al., (2014) calculated the CO_2 emissions and water consumption of several electricity generation technologies (including wind) in China.

This literature review points out to two key outstanding research gaps. First, existing studies show the importance of including complete information of the technical parameters as well as the environmental benefits credited by the recycling processes. Second, studies also show that services have been systematically omitted from wind power LCA studies, mostly because service industries are generally associated with low resource use and emissions (Nansai et al., 2009) and because current LCI databases applied in P-LCA have a poor description of service inputs aside from transport and waste management services (Font Vivanco, 2020). These findings support our approach of including comprehensive technical parameters, recycling credits, and service inputs to adequately assess the environmental performance of wind power.

Table 6-2. Summary of climate change impacts from existing life cycle assessment studies on wind power farms.

Study	Country	Lifetime (years)	Turbine Power (kw)	Wind speed (m/s)	Capacity factor (%)	Losses (%)	Climate change impact (kg CO_2 eq/kWh)	Approach
Lundie et al., (2019)	Germany	ND	2,000-3,000	ND	ND	ND	1.17E-02-1.83 E-02	IO-LCA
Gomaa et al., (2019)	Jordan	20	3,000	7-15	ND	ND	9.11E-03	P-LCA
Oguz and Eylul Sentürk (2019)	Turkey	20	600	8.4	ND	ND	1.06E-02	P-LCA
Wang et al., (2019)	China	20	2,000	ND	ND	ND	2.28E-02	P-LCA
Gao et al., (2019)	China	20	850 850 1,500	6.4 7.1 6.6	ND	ND	6.59E-02 8.65E-02 5.15E-02	P-LCA
Xu et al., (2018)	China	20	750-1,500	8.3	30	ND	8.6E-03	P-LCA
Ozoemena et al., (2018)	ND	25	1,500	ND	21-22	17	1.03E-02 – 1.66E-02	P-LCA
Chipindula et al., (2018)	USA	20	1,200-2,300	7.5	ND	35	5.84E-03- 7.35E-03	P-LCA
Bonou et al., (2016)	EU	20	2,300-3,200	8.5	ND	10	6.00E-03 – 5.00E-03	P-LCA
Ji and Chen (2016)	China	21	2,000	ND	25.8	ND	5.69E-03	IO-LCA
Kummar et al., (2016)	USA	25	1,500	ND	ND	ND	1.87E-02	IO-LCA

Table 6-2. continue

Study	Country	Lifetime (years)	Turbine Power (kw)	Wind speed (m/s)	Capacity factor (%)	Losses (%)	Climate change impact (kg CO_2 eq/kWh)	Approach
Al-behadili and El-osta (2015)	Libya	20	1,650	ND	ND	ND	1.04E-02	P-LCA
Noori et al., (2015)	USA	20	2,000-3,000	ND	ND	ND	1.73E-02	Hybrid LCA
Feng et al., (2014)	China	20	800	ND	ND	ND	4.64E-02	Hybrid LCA
Garrett and Rønde (2013)	Worldwide	20	2,000	7- 9.2	ND	ND	7.00E+03 – 1.00E-02	P-LCA
Rajaei and Tinjum(2013)	USA	26	1,800	6.5 -7	25	ND	1.87E-02	P-LCA
Oebels and Pacca(2013)	Brazil	20	1,500	7.8	34	ND	7.00E-03	P-LCA
Arversen and Hertwich (2012b)	Europe	20	1,200	N-D	23.6	ND	1.64E-02	Hybrid LCA
Ardente et al., (2008)	Italy	20	660	ND	19	ND	1.48E-02	P-LCA

ND No data available, *P-LCA* process-based life cycle assessment, *IO-LCA* input–output life cycle assessment.

6.3 Materials and methods

In line with the ISO 14040:2006 and 14044:2006 standards (ISO, 2006), first we present the goal and scope of the study, followed by a description of the life cycle inventory (LCI). Finally, we describe both the foreground and background systems, including the method to include direct and indirect services.

6.3.1 Goal and scope

The purpose of the study is assessing the life-cycle environmental impacts associated with an onshore wind farm in Colombia. The wind power plant studied is the only wind farm currently operating in the Colombian national grid. The wind farm has a total installed capacity of 19.5 MW and technical parameters for the operation as follow: a capacity factor of 42% (EPM, 2002), a percentage of losses of 10% due to the geographic conditions of the zone (Pinilla et al., 2009), and a lifespan of 20 years (Nordex, 2000; Pinilla et al., 2009). With which the wind farm produces 72 GWh/year. Detailed information of the technical specification of the wind farm is presented in supplementary data S6.1.

The study includes the manufacturing (manufacturing of the principal components and installation), operation and maintenance, transport (during all the stages of the system), and decommissioning and recycling (end of life [EoL]) stages and the foreground system is based on direct data collection from the project owners. The functional unit is 1 kWh of electricity delivered to the grid and the transmission has been excluded (see Figure 6.1).

The life cycle impact assessment (LCIA) phase was carried out using the International Reference Life Cycle Data System (ILCD) methodology (European Commission, 2014), a robust and widely accepted approach among LCA practitioners. Ten impact categories where considered for comprehensiveness: freshwater and terrestrial acidification (A, in mol H+-Eq), climate change (CC, in kg CO2-Eq), carcinogenic effects (CE, in CTUh), ecotoxicity (ECOTOX, in CTUh.m3.yr), marine eutrophication (MEUT, in kg N-Eq), non-carcinogenic effects (NCE, in CTUh), ozone layer depletion (OD, in kg CFC-11-Eq), photochemical ozone creation (POC, in kg ethylene-Eq), respiratory effects, inorganics (RE, in kg PM2.5-Eq), and terrestrial eutrophication (TEUT, in mol N-Eq).

6.3.2 Life cycle inventory

The LCI analysis was based on a comprehensive collection of data. Specifically, data in physical units were collected for the stages of manufacturing, transport, operations and maintenance, and recycling, whereas data in monetary units for the direct services were collected mainly from the environmental studies required by the authorities to grant the different licenses needed to operate the project.

6.3.2.1 Foreground System

The foreground system comprises the manufacturing of the wind turbines as well as the tower and generators. It also includes the transport, the construction of the wind farm, the operation and maintenance, and the EoL stages. In addition, the configuration of the foreground system was partly based on estimates and assumptions due to missing information from the plant owners. Specifically, some assumptions were needed to complete the construction as well as the operation and maintenance stages. Following Elsam (2004), each wind turbine was assumed to require 400 m^3 of soil removal and an associated use of 10 liters of diesel. Similarly, the mounting mobile cranes were assumed to consume 10 liters of diesel for the assembly of each turbine during the construction stage (Rydh et al., 2004). Moreover, according to Elsam (2004), each turbine consume 573 MWh of electricity. The maintenance stage was complemented with information provided by Ardente et al. (2008) regarding the replacement of one blade and 15% of the generator per turbine. Due to the fact that ecoinvent does not have unit process data for Colombia, alternative data was used. Specifically, the Colombian average electricity matrix between 2002 and 2017 (76.7% hydro, 13.5% Gas, 9.7% Coal, Wind 0.1%) (UPME, 2014) was build up based on unit processes from Brazil, a region witch best matches the geographic and climatic conditions of Colombia (Supplementary data S6.3 for detailed information of the unit process used from ecoinvent 3.4 in the entire study).

The foreground system includes service inputs associated with planning and studies carried out prior to the construction phase, mainly environmental studies required by the authorities to grant the different licenses required to operate the project. All the information was collected from a owners report (EPM, 2002) (see supplementary data S6.5). We differentiate between the service inputs directly associated with the wind farm and included in the foreground system (direct services) from those service inputs required upstream in the supply chain (indirect services), and included in the background system through the approach described in section 6.2.2. Detailed information of the foreground system is presented in supplementary data S6.2.

6.3.2.2 Background system

The background system is comprised by both LCI and input-output databases, which are inter-linked using the IHLCA approach proposed by Suh et al., (2002) and specifically the model developed by Suh et al. (2004). Specifically, we linked each product from the foreground system (see section 6.2.1) to the LCI via the concordances presented in supplementary data S6.2-S6.4. The IHLCA approach allows to systematically include service inputs to the LCI system by linking this to an IO system into a single matrix. We here follow the approach by Font Vivanco (Font Vivanco, 2020), see equation 1, which linked the ecoinvent 3.4 and EXIOBASE 3.4 databases by means of a upstream cut-off matrix (C_u) (Suh et al., 2004). Because Colombia is not explicitly described in EXIOBASE 3.4, we here use instead the Global Trade Analysis Project (GTAP) 9 database, containing 140 regions (including Colombia) and 57 industries. It is worth noting that the environmental extensions are taken from EXIOBASE since GTAP only describes CO_2 emissions. One of the main concerns regarding hybrid methods is double counting as parts of the economic system may be described twice (Crawford et al., 2018). In order to avoid this issue, we removed all the service inputs (other than transport and waste management) from the LCI system in order to prevent double counting when including these from the input-output system.

The procedure described by Peter et al. (2011) was applied to build the multi-region input output (MRIO) model using the GTAP database, particularly the approach with endogenous international transport pool. The underlying code can be found in a dedicated online repository (GitHub, 2018).

The upstream cut-off matrix (C_u) in eq.1, allows to extend the input structure of unit processes by including service inputs from the IO system. In other words, each element of the C_u represents monetary units of service inputs required to produce physical units of products. To build the C_u, Font Vivanco (Font Vivanco, 2020) proposes a three-step approach. First, existing service inputs are removed from the LCI database except for transport and waste management, which are relatively well represented. Second, service input structures for each unit process (except for transport and waste management services) are obtained from their corresponding industries. Third, service input structures are scaled according to the product's price and further corrected in case that economic balances are violated, namely when the cost of inputs exceed that of the product. Once all service input structures are obtained, these are introduced in the C_u. For detailed information of the approach and underlying assumptions we refer to Font Vivanco (Font Vivanco, 2020).

Using the IHLCA approach, a given environmental impact *e* (e.g., climate change) for any final demand was estimated using the Leontief model (Miller and Blair, 2009):

$$footprint_e = i_e^T x = i_e^T (Ly) = (c_e \circ s_e)^T (H^{-1} y) \ (6.1)$$

$$H = \begin{pmatrix} (I_{LCI} - A_{LCI}) & -C_d \\ -C_u & (I_{IO} - A_{IO}) \end{pmatrix} \ (6.2)$$

$$s_e = \begin{pmatrix} s_{LCI} \\ s_{IO} \end{pmatrix};\ c_e = \begin{pmatrix} c_{LCI} \\ c_{IO} \end{pmatrix} \ (6.3)$$

Where I_{LCI} is an $m \times m$ identity matrix, A_{IO} is a $k \times k$ technical coefficient matrix with the inter-industry inputs needed to supply one output unit, A_{LCI} is an $m \times m$ technical coefficient matrix with the inter-process inputs needed to supply one product unit, I_{IO} is a $k \times k$ identity matrix, y is any given $n \times 1$ final demand vector, with n being the total amount of unit processes (m) and industries (k), C_d is a $m \times k$ downstream cut-off matrix with product inputs to each industry (assumed to be a zero matrix),C_u is a $k \times m$ upstream cut-off matrix with industry inputs to each process, c_{LCI} and c_{IO} are respectively $m \times 1$ and $k \times 1$ impact characterisation factor vectors (impacts associated with each stressor), s_{IO} is a $k \times 1$ environmental stressors vector (stressors associated with a unit of output, s_{LCI} is an $m \times 1$ environmental stressors vector (stressors associated with a unit of product), s_i is an $n \times 1$ environmental stressor vector (stressors associated with a unit of product/output), c_i is an $n \times 1$ impact characterisation factor vector (impacts associated with a unit of stressor), the symbol $\circ$ represents the Hadamard product, *L is* the Leontief inverse matrix of direct and indirect inter-industry and inter-process inputs needed to satisfy a final demand unit, and i is an $n \times 1$ impact coefficient vector (impacts associated with a unit of output), and the superscript T indicates transposition.

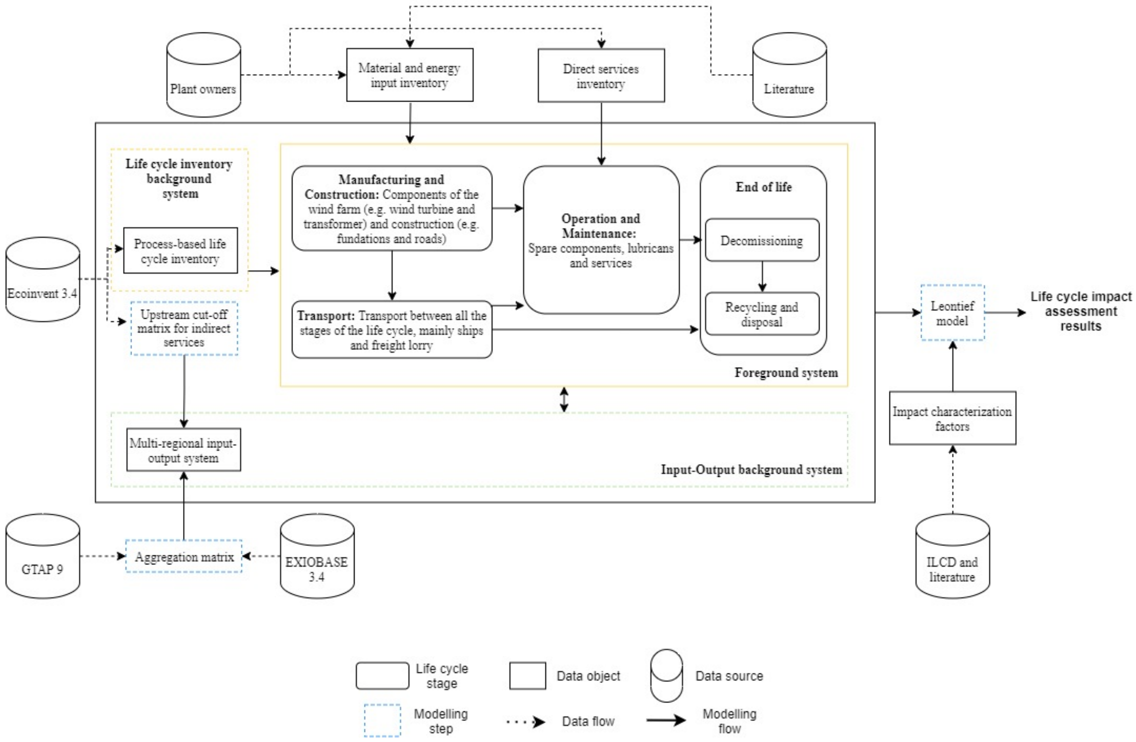

Figure 6-1. System boundary of the wind farm. LCA: Life cycle assessment, LCI: Life cycle inventory. GTAP: Global Trade Analysis Project database, MRIOT: multiregional input output table, IO-LCA: Input output life cycle assessment, P-LCA: Process based life cycle assessment

6.3.2.3 Sensitivity analysis

In order to increase robustness, support decision, and identify the most sensitive parameters that may affect the environmental profile of the wind farm, we conducted a sensitivity analysis of the capacity factor, the percentage of losses, and the lifespan of the plant. The reference parameters used in this study include a capacity factor of 42%, a percentage of losses of 10%, and a lifespan period of 20 years (see section 6.1). The values selected for the sensitivity analysis are based on the literature and correspond to percentage changes on the different parameters. The capacity factor ranges between 30% and 42%, with the high factor capacity of the wind farm being mainly related with the optimal climatic conditions of the region (EPM, 2002; Pinilla et al., 2009) while normal values ranges from 19% to 34% (see table 6.2). The percentage of losses ranges between 10% and 5% assuming efficiency improvements in the electrical system. The lifespan of the wind farms is commonly defined by the producer, with 20 years being the reference value even though wind turbines may continue operating after maintenance and replacement of deteriorated parts. Some authors select 25 and even 26 years as a lifespan (Kumar et al., 2016; Ozoemena et al., 2018; Rajaei and Tinjum, 2013).

6.4 Results

This section presents the results of the wind farm in the different environment impacts selected; moreover, results are presented for the direct and indirect services, and conclude with the results of the sensitive analysis.

6.4.1 environmental impacts by stages and components

The findings (see Figure 6.2 for the environmental impacts by stage) show that the inclusion of both direct and indirect services has a non-negligible impact on the overall environmental footprint of the onshore wind power plant with the exception of ecotoxicity and carcinogenic effects impacts. For all impact categories, this increase describes a median relative change (with respect to footprint results without services) ranging across impact categories from 8% (ODP, POC, RE) to 21% (TEUT). Manufacturing is the stage with a higher share of environmental impacts from the total: ranging from 15% (ECOTOX) to 97% (CE). Further, operation and maintenance have a notable contribution of 0% (ECOTOX) to 13% (MEUT and POC). The decommissioning and recycling stage represents 1% (CE) to 116% (ECOTOX). The impacts associated with the transport are negligible for all the impact categories (<1%). Decommissioning and recycling have negative values (positive credits) for all the impact categories because those stages avoid the extraction of new material and resources (see Supplementary data 6.3 for detail of the unit process used).

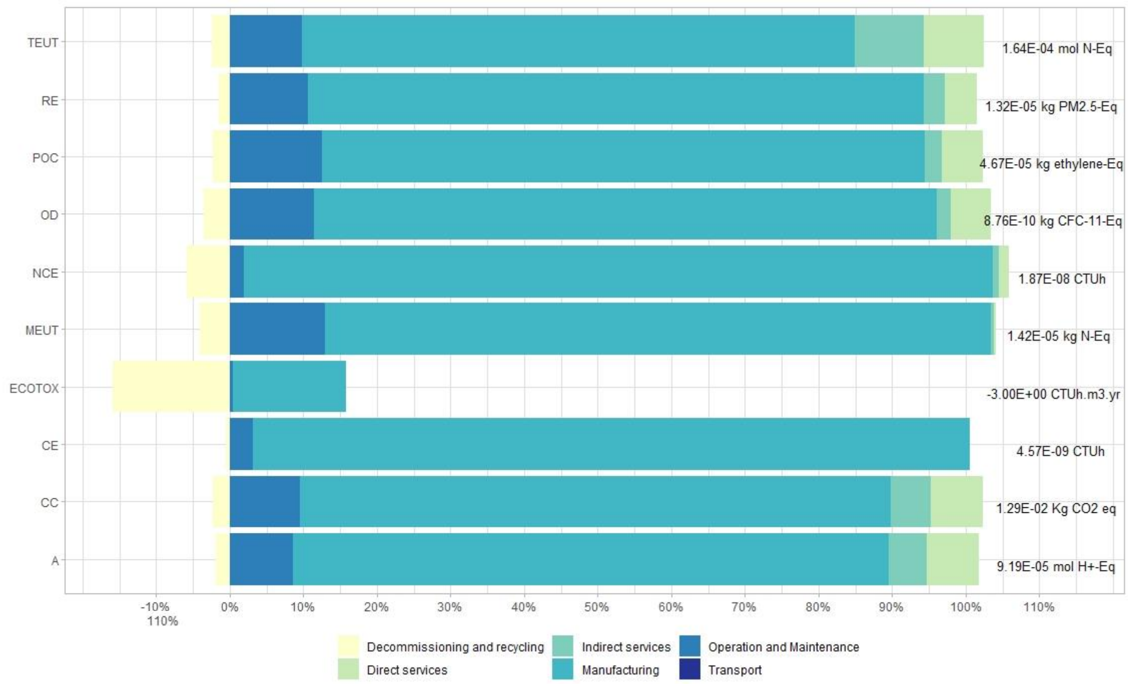

Figure 6-2. Life cycle environmental impacts associated with 1 kWh of electricity generated in the studied wind farm. A: freshwater and terrestrial acidification (in mol H+-Eq), CC: climate change (in kg CO2-Eq), CE: carcinogenic effects (in CTUh), ECOTOX: ecotoxicity (in CTUh.m3.yr), MEUT: marine eutrophication (in kg N-Eq), NCE: non-carcinogenic effects (in CTUh), OD: ozone layer depletion (in kg CFC-11-Eq), POC: photochemical ozone creation (in kg ethylene-Eq), RE: respiratory effects, inorganics (kg PM2.5-Eq), TEUT: terrestrial eutrophication (mol N-Eq).

Environmental impacts are largely associated with the different components of the wind farm (manufacturing stage). Taking CC impact category as an example, the tower represents the 40% of impacts, whereas the rotor and the nacelle accounts for the 27% and 21% of the impact, respectively. While impacts associated with the foundation represent the 10% of the total impacts, the cables and the transformer account jointly for just the 3% of the total impacts. Impacts by unitary process are similarly mainly associated with the unitary processes linked to the manufacturing stage (see Figure 6.3 for the top ten processes in terms of impacts in the different impact categories). Following with CC impacts, ten of the thirty-eight-unit processes associated with the wind farm represent the 94% of the total impacts, particularly the processes associated with the production of steel, reinforced glass fibre, concrete, and the epoxy resin represent jointly the 70% of the total impacts. Such high impacts are due to a combination of large amounts of physical inputs and the environmental impact intensity per unitary unit.

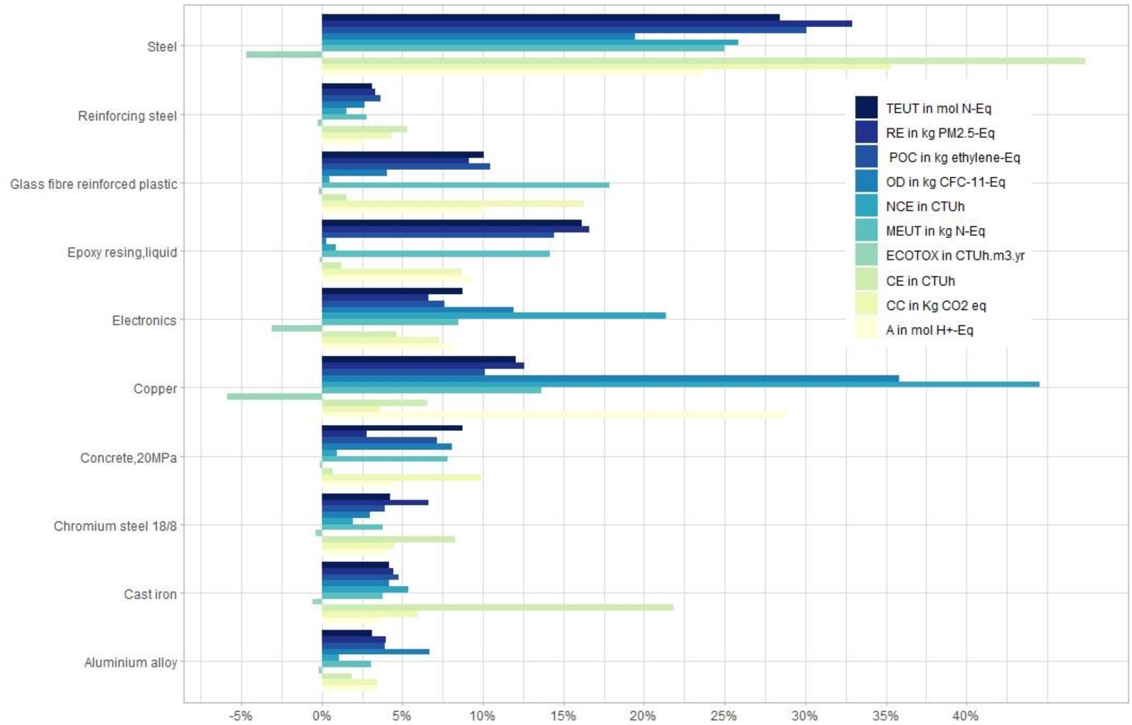

Figure 6-3.Top ten processes in terms of impacts associated with the materials (as a percentage of the total impacts). A: freshwater and terrestrial acidification (in mol H+-Eq), CC: climate change (in kg CO2-Eq), CE: carcinogenic effects (in CTUh), Ecotox: ecotoxicity (in CTUh.m3.yr), MEUT: marine eutrophication (in kg N-Eq), NCE: non-carcinogenic effects (in CTUh), OD: ozone layer depletion (in kg CFC-11-Eq), POC: photochemical ozone creation (in kg ethylene-Eq), RE: respiratory effects, inorganics (kg PM2.5-Eq), TEUT: terrestrial eutrophication (mol N-Eq).

6.4.2 Impact of direct services

The impacts associated with the direct services are largery associated with bussines services (OBS) and government services (OSG). Taking CC as an example, these industries combinedly represent about the 70% of the total impact (see figure 4 for the share of impacts associated with direct services by industry). The CC impacts related to OBS are mostly associated with activities related to contigencies (23%), coordination (22%), and the hiring of profesional services such as ingeniering, anthropology, biology, social communication, and translation services (22%). The CC impacts associated with OSG are mostly related to social management (74%) and the expansion and equipping of the school (11%). It merits noting that there is sometimes a mismatch between costs and associated impacts. For example, although the service costs associated with the electricity industry (ELY) are negligible (0.10% of the total direct services costs), this industry represents the 7% of the impacts. On the other hand, negligible results were found for the “water collection, purification and distribution” (WTR) industry (1%), albeit this industry represents the 11% of the total direct service costs (see suplementary data table S6.4 for a summary of the direct services and their respective GTAP code, for a complete detail of the direct services included see supplementary data S6.5).

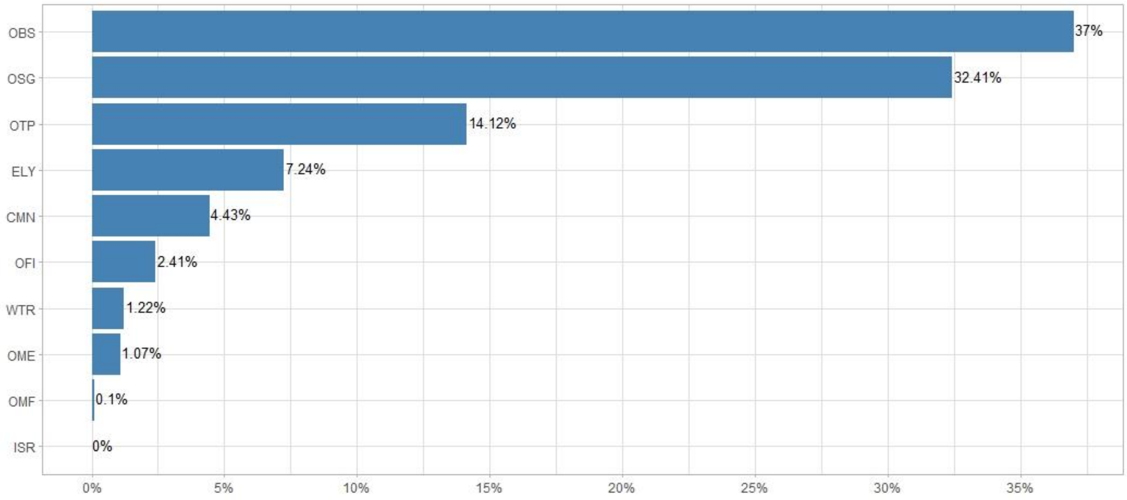

Figure 6-4. Shares of direct services by industry. Other Business Services (OBS), Other Services (Government) (OSG), Other Transport (OTP), Other Machinery & Equipment (OME), Communications (CMN), Financial Intermediation (OFI), Electricity (ELY), Water (WTR). Complete descriptions of the economic sectors are provided in supplementary data S3.

6.4.3 Impact of indirect services

A large share of impacts from indirect services are associated with unit processes related to manufacturing processes (see Figure 6.5 for the top ten processes in terms of impacts associated with indirect services). For example, the processes associated with the production of electronics units, low-alloyed steel, and concrete represent jointly the 63% of the total impacts associated with indirect services for CC impacts. Such high impacts associated with indirect services are due to a combination of large amounts of physical inputs, high life-cycle GHG emissions from services, and large shares of services in the input structures.

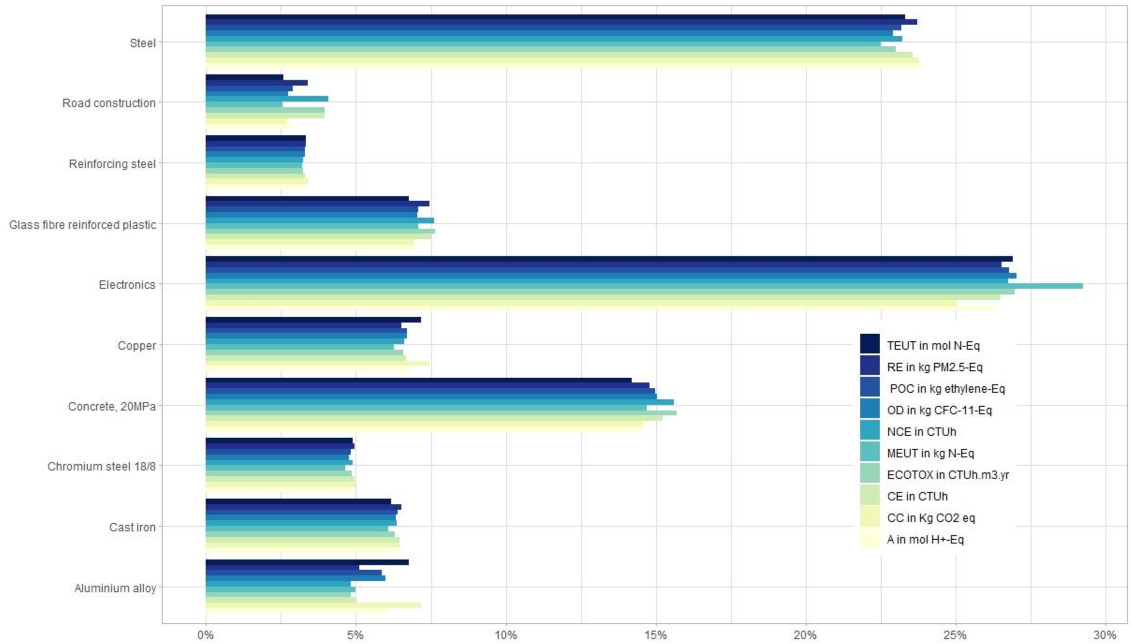

Figure 6-5. Top ten processes in terms of impacts associated with indirect services (as a percentage of the total impacts from indirect services). A: freshwater and terrestrial acidification (in mol H+-Eq), CC: climate change (in kg CO2-Eq), CE: carcinogenic effects (in CTUh), ECOTOX: ecotoxicity (in CTUh.m3.yr), MEUT: marine eutrophication (in kg N-Eq), NCE: non-carcinogenic effects (in CTUh), OD: ozone layer depletion (in kg CFC-11-Eq), POC: photochemical ozone creation (in kg ethylene-Eq), RE: respiratory effects, inorganics (in kg PM2.5-Eq), TEUT: terrestrial eutrophication (mol N-Eq).

6.4.4 Regional analysis

Environmental impacts take place mainly abroad (see Figure 6.5 and Figure 6.6 for impacts associated with materials and energy inputs and services, respectively). Taking CC as an example, only 4.78% and 1.64% of impacts take place in Colombia for materials and energy inputs and services, respectively. For some other impact categories, it merits noting that up to 15% of impacts take place in Colombia. This is largely because the main components of the wind farm (tower, rotor, and nacelle) are imported from other economies. The high impacts taking place in Colombia from materials and energy inputs for TEUT and POC are mainly associated with two activities: transport activities (52% for TEUT and 49% for POC) and diesel burned during the construction of the wind farm (38% for TEUT and 36% for POC). Moreover, the high impact for OD from direct and indirect services is associated mainly with the governmental services and unspecified business services, with 59% and 26% of the total impacts, respectively.

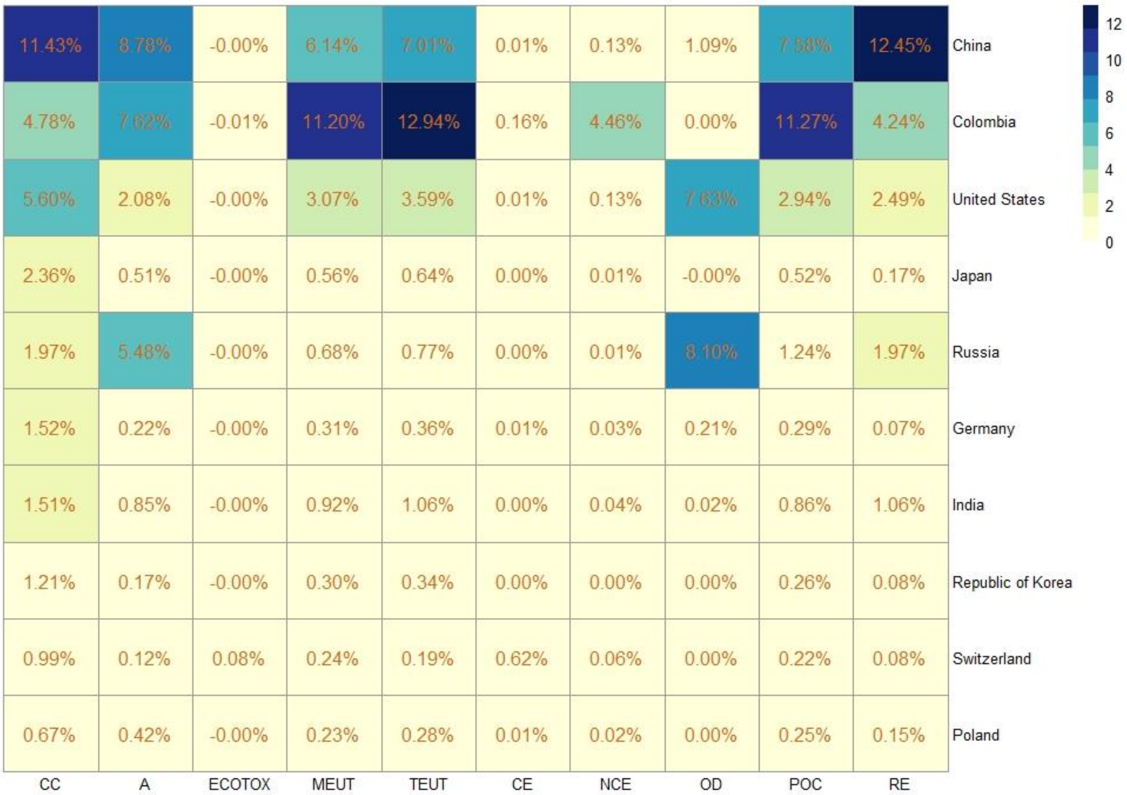

Figure 6-6. Heatmap by region of the impacts associated with material and energy inputs (as a percentage of the total impact) for the top ten contributing regions in terms of climate change. A: freshwater and terrestrial acidification (in mol H+-Eq), CC: climate change (in kg CO2-Eq), CE: carcinogenic effects (in CTUh), ECOTOX: ecotoxicity (in CTUh.m3.yr), MEUT: marine eutrophication (in kg N-Eq), NCE: non-carcinogenic effects (in CTUh), OD: ozone layer depletion (in kg CFC-11-Eq), POC: photochemical ozone creation (in kg ethylene-Eq), RE: respiratory effects, inorganics (in kg PM2.5-Eq), TEUT: terrestrial eutrophication (mol N-Eq).

Figure 6-7. Heatmap by region of the impacts associated with direct and indirect services (as a percentage of the total impact) for the top ten contributing regions, plus Colombia, in terms of climate change. A: freshwater and terrestrial acidification (in mol H+-Eq), CC: climate change (in kg CO2-Eq), CE: carcinogenic effects (in CTUh), ECOTOX: ecotoxicity (in CTUh.m3.yr), MEUT: marine eutrophication (in kg N-Eq), NCE: non-carcinogenic effects (in CTUh), OD: ozone layer depletion (in kg CFC-11-Eq), POC: photochemical ozone creation (in kg ethylene-Eq), RE: respiratory effects, inorganics (in kg PM2.5-Eq), TEUT: terrestrial eutrophication (mol N-Eq).

6.4.5 Sensitivity analysis results

The environmental performance of wind power plants depends importantly on the technical parameters selected. Parameters such as the capacity factor, the lifespan, and the percentage of losses are directly associated with the amount of electricity produced and hence the unitary environmental impacts associated with the power plant. The results suggest that the capacity factor is the most sensitive parameter (larger slope), followed by the lifespan and the percentage of losses (see Figure 6.8). Further, the ranges from the literature confirm the order of these parameters in terms of relevance for CC impacts: changes in these parameters could change impacts, respectively, by up to about -35%, 25%, and 5%.

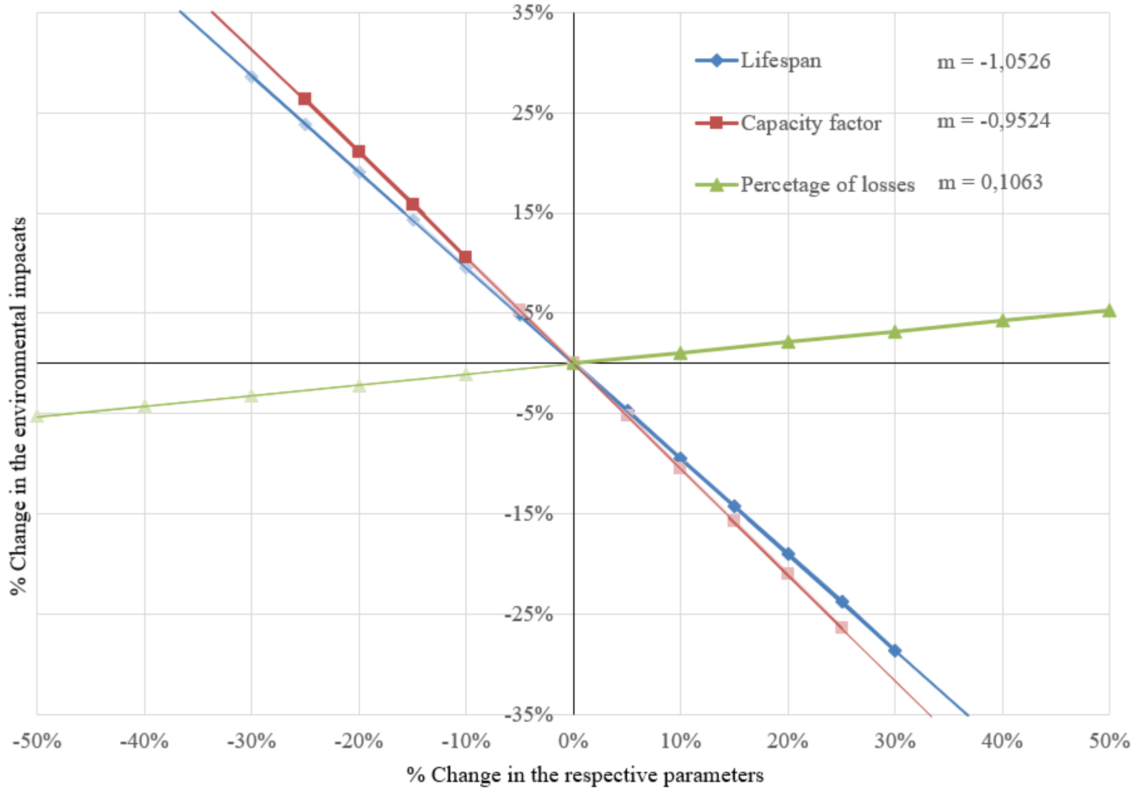

Figure 6-8. Sensitivity analysis for technical parameters (lifespan, capacity factor, and percentage of losses). The dark colored dots correspond to the ranges of the technical parameters typically found in the literature (19-34% for the capacity factor, 10-17% for the percentage of losses, and 20-26 years for the lifespan), m: Slope of the regression line.

6.5 Discussion

The impact results of the wind farm under study fall into the range found in the literature (see Table 6.1) despite accounting for both direct and indirect services, which suggests that our results are on the lower bound of such range. Taking CC as an example, our results (1.29E-02 kg CO2-Eq/kWh) are lower than those provided by comparable hybrid models such as those by Arversen and Hertwich (2012b) (1.64E-02 kg CO2-Eq/kWh), Noori et al.,(2015) (1.73E-02 kg CO2-Eq/kWh), and Feng et al., (2014) (4.64E-02 kg CO2-Eq/kWh). Differences can be largely attributed to the high capacity factor of the plant of 42%, while other studies report lower values.

Compared with P-LCA studies, our results are lower than those reported by Wang et al., (2019), Gao et al., (2019), Kummar et al., (2016), Rajaei and Tinjum (2013), and Ardente et al., (2008); but higher than those reported by Gomaa et al., (2019), Oguz and Eylul Sentürk (2019), Xu et al., (2018), Chipindula et al., (2018), Bonou et al., (2016), Ji and Chen (2016), Al-behadili and El-osta (2015), and Oebels and Pacca (2013). The inclusion of both direct and indirect services could be a defining difference.

Differences can be attributed to the parameter selection and the assumptions made during the operation and maintenance stage (see section 6.3). For example, Oebels and Pacca (2013) did not specify the percentage of losses assumed or the credits granted in the recycling process. Gao et al.,(2019) do not mention the percentage of losses, either the capacity factor. Also, Ardente et al.,(2008) and Rajaei et al., (2013) did not provide values for the percentage of losses and the recycling credits assumed.

By process, and taking CC as example, manufacturing processes account for 80% of all the impacts, from which the tower, the rotor, and nacelle contribute the most with 39%, 27%, and 21% from the total, respectively. This is somehow consistent with the literature, where manufacturing process are on the ranges from 60% to 80% (Ardente et al., 2008; Rajaei and Tinjum, 2013; Xu et al., 2018). Credits granted in the decommissioning and recycling stages are lower (2%) than reviewed studies (values ranging 5% and 35%) (Ardente et al., 2008; Xu et al., 2018). These lower values are justified because the chosen LCA model grants credits for recycling materials, avoiding the extraction of future resources (labeled as substitution by system expansion or avoided burden method in the LCA literature). However, according to Arvesen and Hertwich (2012a), such models commonly use inappropriate methods and lack transparency overall. It is worth noting that in this study we did not apply the avoided burden method. Credits granted come solely from the background activities regarding the recycling stages. Regarding the type of approach (P-LCA and IO-LCA), Dolan and Heat (2012) argues after an exhaustive review that P-LCAs of wind turbines are unlikely to differ substantially because the manufacturing stage, which accounts for about 60%-80% of all the environmental impacts, are to some extent similar. The main differences across studies are due to the technical parameters that affects the operation of the wind farm.

The regional analysis suggests that environmental impacts for the wind farm are rather exporter than produced in situ. Regions like China and US contribute significantly to the total environmental impacts. Taking CC impact as example, China contributes to 11% of the total impact associated with materials and to 15% of the impacts associated with both direct and indirect services, whereas US contributes to 6% and 14% of the impact associated with materials and services, respectively (see Figure 6.5 and 6.6). The environmental impacts taking place locally are mainly associated with the services rather than with the material and energy inputs. Colombia contributes with less than the 5% of the impact associated with materials and energy and the 1.64% of the impact associated with services. The results suggest that choices regarding both the inclusion of services and the selection of technical parameters lead to noteworthy differences in the environmental impacts associated with the studied wind farm. It is worth noting that this is not a point against the use of wind energy, as the inclusion of these activities will likely also significant for the production of energy by fossil fuels. Regarding the truncation error from omitting services, our results suggest an overall truncation error of about 6% and 7% respectively for direct and indirect services and for CC impacts. Despite such an increase in CC impacts, the results for the wind farm under study are within the ranges found in the literature (see Table 6.1). The implications of including service inputs in this study appear to be more or less consistent with the broader LCA literature. For example, Ward and colleagues (2017) found that ignoring service sectors not covered by LCI databases in the US is associated with 3% to 13% median truncation errors for carbon footprints, depending on the sector group being analyzed. Font Vivanco (2020) found a similar level of truncation in the ecoinvent 3.4 database for climate change, in the range of 10%. Agez et al., (2020) found an average truncation of 14% for ecoinvent 3.5. Yu et al., (2020) reports an increase of about 20% when the value of engineering is included in Australian buildings.

More broadly, hybrid LCAs considerably increase the environmental impacts of the studies by expanding the system boundaries, increasing robustness compared with traditional methods. Taking CC as example, our study suggests a difference around 14% compared with P-LCA. Such differences in this study appear to be more or less consistent with the broader hybrid LCA literature. For example Wiedmann et al., (2011) report an increase of 111% in the CC for a wind power generation in the UK. Palma-rojas et al., (2017) found a difference of 97% for a bagasse-derived ethanol produced in Brazil. Bush et al., (2014) present an increase of 20% for solar PV in UK. Huey et al., (2017) report differences on the ranges of 11% and 50% depending of the type of concrete. Li et al., (2020) found a difference on the range of 16%.

The use of sensitivity analyses should be encouraged to add robustness to LCA studies, particularly to test the variability of the results with respect to technical parameters and the assumptions made to build the system boundaries. With regards to the technical parameters, the results suggest special attention to the capacity factor, the lifespan, and the percentage of losses, by this order. This means that future studies should be careful when choosing the values of these parameters. Moreover, the assumptions required to build the system should be clearly described and presented in order to facilitate comparisons and provide transparency. In this study, the assumptions made are mostly associated with the operation and maintenance of the wind farm due to missing information from the owner of the project. These assumptions are not expected to have a significant effect on the results because the operation and maintenance stage accounts as much 13% (MEUT, POC) of the total environmental impacts. Particularly, the emission factor for CC associated with the electricity consumption during this stage was 2.15E-01 Kg CO_2/kWh, slightly higher than the value reported by the Colombian national authorities (2.10E-01 CO_2/kWh) (UPME, 2020). Values reported by ecoinvent were preferred instead mainly because ecoinvent report emissions factors for different environmental categories, whereas the Colombian authorities only report values for CC.

A limitation arises from using the environmental extensions from EXIOBASE 3.4 to complement the GTAP9 database, because both databases differ on the level of industry aggregation and base year, among other differences (Tukker et al., 2018) . Considering the scope of this study, such a limitation can be avoided by using a MRIO database which features both a high level of geographical coverage and extensive environmental extensions. For example, the Eora database (Lenzen et al., 2013) covers 190 countries, including Colombia, and includes several environmental extensions, of which only a few are homogenously reported for all countries. Using the Eora database, however, would limit the amount of environmental impact indicators used in this study. For example, Eora does not report PM2.5 emissions which are used to calculate respiratory effects from inorganic compounds.

Limitations regarding the inclusion of services inputs (direct services) are mainly due to the limited information regarding the expenditures associated with the project. While detailed information concerning the environmental studies required by the authorities to grant the different licenses needed to operate the project was obtained, it was not possible to obtain similar data for the planning and management stages of the project (service consumers). This omission can lead to the underestimation of the impacts related to direct services. Moreover, the limitations imposed by the IO-LCA regarding the high level of aggregation (Joshi, 2000; Lenzen, 2000) and the assumed proportionality between physical and monetary flows (Lenzen, 2000) may add uncertainties to the results. Aggregation issues exist because economic sectors, even in the most disaggregated IO tables, are actually a combination of heterogeneous production technologies and products with regards to input materials and environmental impacts (Suh et al., 2004; Suh and Huppes, 2005). Proportionality can alter the physical flow relationships between industries because of price inhomogeneity, particularly when inter-sectoral prices differ greatly between industries (Bicknell et al., 1998; Suh et al., 2004). According to Lenzen and Murray (2001), the proportionality assumption can lead to non-negligible errors (up to 40% for Australian energy and climate change impacts).

One of the advantages of using hybrid models is the possibility to perform life cycle sustainability analysis (LCSA) and similar analyses by including social and economic indicators which are often included in MRIO databases, such as value added and employment (Onat et al., 2017). We however did not include such additional indicators because there is currently no social nor economic extensions in ecoinvent that can be consistently integrated with those from EXIOBASE. The results show that the direct services associated with the environmental impact studies required by the authorities to build and operate large projects such as wind farms, which are usually excluded from LCAs, have a non-negligible impact on their environmental footprints. Including direct services may thus be relevant in projects with similar environmental compliance requirements, such as dams, roads, bridges, and tunnels, and particularly in projects that impact the lives of indigenous people. In the latter, consultation and land concessions are critical issues that require a comprehensive bargaining process, thus requiring high economic and time resources that may have a substantial associated footprint.

6.6 Conclusions

This paper carried out a hybrid LCA including services of an onshore wind farm of 19.5 MW of capacity installed, located in the high Guajira in Colombia. This wind farm is the first renewable energy project connected to the national grid. The main contributions of this study are being the first LCA study conducted in the country for any electricity production technology, second, we include both direct (required on-site) and indirect (required in the supply-chain) services associated with the life cycle of the wind farm, an unprecedented feature in the LCA literature, third, we highlighted the importance of the technical parameters of the wind farm on their respective environmental impacts. For policymakers as for the owners of energy projects and LCA practitioners this provides value knowledge on the role of wind energy in effectively achieving sustainability goals, by underlining the role of technical and location-specific aspects as well as services in energy and broader studies and providing environmental hotspots associated with wind projects.

The results suggest that omitting service inputs leads to non-negligible truncations issues. By order of importance, services increase the amount of emissions between 0% (ECOTOX and CE) and 21% (TEUT) with respect to the results without services, meaning that environmental declarations may be underestimated. By life cycle stages, the manufacturing processes accounts for 80% of the impacts in CC, being the tower, the rotor, and the nacelle the most relevant components with 39%, 27%, and 21% from the total, respectively. Moreover, results highlight the importance to perform a sensitivity analysis of the technical parameters. Particularly, changes in the capacity factor, the lifespan, and the percentage of losses could vary impacts, respectively, by up to about -35%, 25%, and 5%.

Owners of the project can achieve a better environmental performance by reducing the amount of steel required by the towers via improved design and/or by using recycled materials as well as by reducing and/or replacing the concrete with greener alternatives, such as mixing concrete with fly ashes (Lemay, 2017). Similarly, during the operation and maintenance stage, the use of renewable energy resources is encouraged. For example, the use of electricity inside the farm should be sourced whenever possible from electricity produced by the wind farm itself. Additionally, the transport inside the farm could be fulfilled with electric cars or even by smaller, low-emission vehicles (e.g. bicycle) given the small size of the plant.

In light of the relevance of direct services in LCA found in this study, our recommendation to improve the accuracy of LCA results and overcome the limited information regarding the expenditures associated with the project (direct services), is to create incentives for the publication of budget and expenditure data from the different stages of large infrastructure projects, such as public acknowledgement (e.g., eco-labels), requirements in public tenders, and tax benefits. For example, the World Bank discloses relevant information of the projects that receive their financial support. In Colombia, the law 1712 of 2014 (Law on Transparency and Access to Information) aims to guarantee the right of access to public information. This law, however, only regulates public organizations. In both cases, however, the time gap between data request and acquisition poses restrictions to the data collection and hinders related research. Moreover, tax benefits may be an effective instrument to incentivize data transparency, yet their application requires the agreement of different stakeholders: government, private sector, and civil society. Moreover, it requires a clear regulatory structure to make it effective. Increasing civil awareness may be first step to direct the efforts towards this alternative.

Further research would benefit from increased data gathering efforts on the full costs associated with services rather than just the services associated with the environmental studies needed to implement the project. Full cost information is commonly omitted by the project owners for confidentiality reasons. Moreover, extending the boundaries of the study to include the manufactured capital inputs, such as machinery and buildings used in production, as well as broadening the environment assessment with social and economic indicators can provide further information of the life-cycle sustainability impacts of wind power.

6.7 Acknowledgements

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6.8 Disclaimer

This chapter is fully published in the Journal of Environmental Management. Volume 284, 15 April 2021, 112058. https://doi.org/10.1016/j.jenvman.2021.112058 Therefore is under embargo according with the policies of the journal. For future consulting please refers directly to the journal.

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7. Exploring the direct rebound effect of residential electricity consumption in developing countries: An empirical study in Colombia

Under review, Energy efficiency

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Abstract

Energy efficiency technologies have been worldwide promoted by police makers, government and non-governmental institutions to decarbonize economies. In such context, Colombian government forecasted a total energy savings of around of 9% at the end of 2021 by promoting energy efficiency technologies across the different economic sectors. However, such efficiency goals may not be fully achieved due to the existence of the rebound effect. The rebound effect has the potential not only of entirely suppressing the energy savings expected, but also of generating additional energy demand, a phenomenon known as backfire effect. Although the rebound effect has been extensively studied for developed countries, there is no empirical evidence of this phenomenon for South American countries. Hence, this study measures the direct rebound effect for all energy services consuming electricity in the household sector in Colombia along the period 2005-2013 by applying econometric techniques in a panel data for 15 states around the country. The results suggest a national rebound effect of 83.4% and values ranging across regions between 64.7% (Atlantico) and 78.9% (Meta). Our study points out that the rebound effect in Colombia follows a geographic patter, with high values at the interior of the country, which is relevant to various stakeholders in order to make informed decisions. Policymakers will gain knowledge on the role of the rebound effect in planning sustainability goals, whereas academics and practitioners will benefit of novel data regarding the role of the rebound effect in Latin American economies. Given the significance of our finding about rebound effect in a Latin America country, we conclude with some recommendations aimed at relevant stakeholders.

Keywords. Electricity consumption; direct rebound effect; developing countries

7.1 Introduction

Colombian greenhouse gases (GHG) emissions accounted for about 236.9 Mton CO_2 (IDEAM et al., 2018) in 2014 (the last year for which such data is available at the writing of this article) and it is projected to increase by 50% in 2030 (García Arbeláez et al., 2016). Therefore, and in line with the worldwide efforts to defeat climate change, Colombian government compromised to reduce their GHG emissions in 20% by 2030. In order to achieve such compromises, the government recently issued several political instruments. Specifically, the government issued the national climate change policy (PNCC), the Colombian Low-Carbon Development Strategy (ECDBC), the National Climate Change Adaptation Plan (PNACC), the National Strategy for Reducing Emissions from Deforestation and Forest Degradation (ENREDD+), and the National Climate Finance Strategy (ENFCC) (MADS, 2017).

One of the key strategies to consider within the PNCC is the promotion of energy savings through efficiency improvements in all the consume energy sectors from which residential sector has greatest potentials. Concretely, according to estimations of the Energy Mining Planning Unit (UPME), the most important energy authority in the country, residential sector has a savings potential of 0.73% on the energy to be consumed by 2022 (UPME, 2016a).

Colombian residential sector accounted for 38% of the 58.7 TWh consumed in 2018 and it is expected to increase by about 2% yearly until 2030 (UPME, 2016b). Also, it is worth noting that electricity accounts for 51% of the total energy consumed in this sector, followed by natural gas (35%)(see figure 7.1) (UPME, 2016a). Among energy services, the consumption of electricity is mainly triggered by refrigeration, television, and lighting (see figure 7.2) (UPME, 2016a). Cooking is carried out with natural gas, LPG, and in a lesser extend with electricity. Such increase implies challenges in terms of climate change since the electricity sector accounted for about 9% of the total greenhouse gases (GHG) emitted (IDEAM et al., 2018) in 2014.

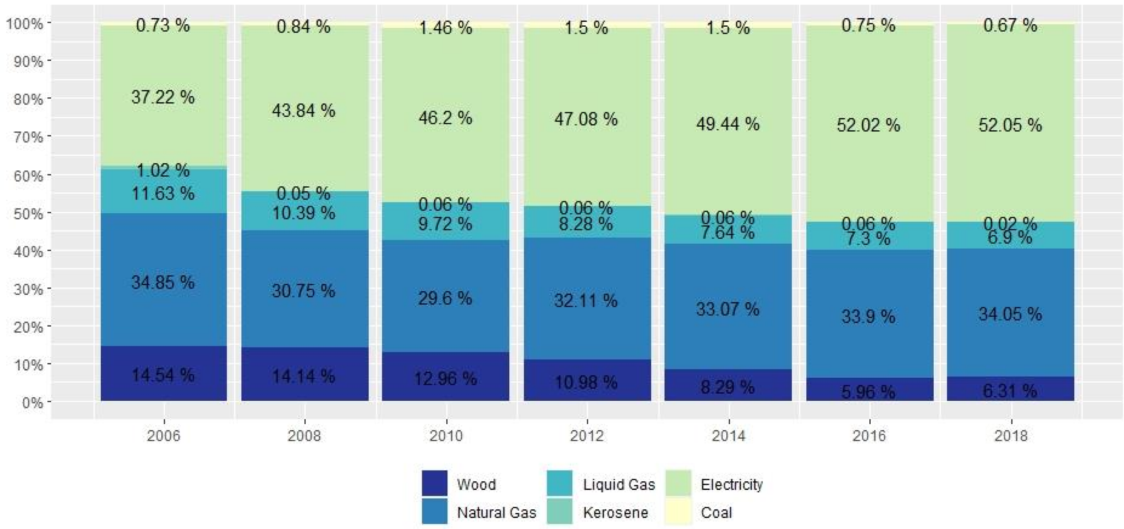

Figure 7-1. Amount of energy sources consumed in the Colombian residential (urban areas). Source: Energy Mining Planning Unit (UPME, 2019)

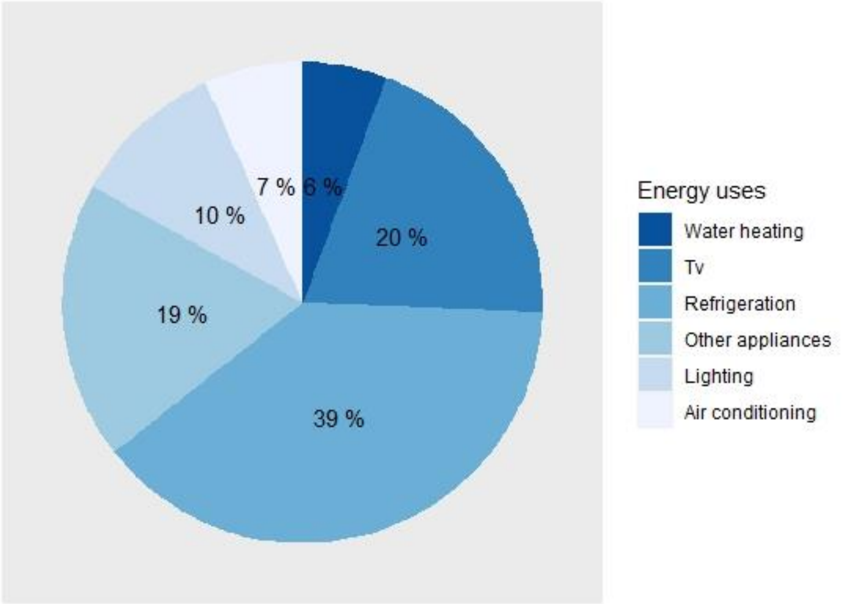

Figure 7-2. Colombian electricity consumption by the urban residential sector and destination uses in 2015. Others refer to services like ironing and washing - Source: Energy Mining Planning Unit (UPME, 2016a).

Savings in this sector are expected to be achieved through the implementation of several programs such as: replacement of incandescent bulbs, inefficient refrigerators, air conditioning and other appliance; the implementation of efficient burners, designs, and construction for sustainable housing; the substitution of the firewood in the rural and marginal areas with Liquefied Petroleum Gas – LPG (UPME, 2010).

Nevertheless, the effectiveness of such kind of programs may face two particular barriers. A low demand for efficient equipment, and a less than expected effectiveness (Belaïd et al., 2018). Efficient equipment requires investment that low income household groups cannot afford since 82% of the total residential sector is represented by low-income groups (SUI, 2018a). This situation forces the government to consider subsidies so these groups can buy new efficient equipment's. The less expected effectiveness may be due to the bad quality of energy retrofits, errors in measuring energy efficiency, and the rebound effect (RE). In this paper we focused on studying the direct rebound impact (Belaïd et al., 2018).

The rebound effect is a widely accepted phenomenon introduced by Stanley Jevons in the late nineteenth century (1865) and popularized in the last decades by Khazzom (1980) and Brookes (1990). An interesting debate about this topic can be found in Berkhout and colleagues (2000), and Muster (1995). General speaking the RE states that a change in the technical efficiency of an energy service can change the overall consumption pattern of this service, due to the behavioral responses of economic variables such as: income, price, financial gains, product costs, and material substitution (Font Vivanco & Voet, 2014). Similar definitions of the RE can be found in the literature (Berkhout et al., 2000; Binswanger, 2001; Brookes, 1990; Girod et al., 2010; Greening et al., 2000; Sorrell et al., 2009; Sorrell & Dimitropoulos, 2007; Weidema, 2008). Recently, the RE has reached the interest of an important number of academic, public and private entities due to the fact that it can negatively affect the possible environmental savings planned through sustainable production policies and technologies (Maxwell et al., 2011). Some examples of these policies are the United Nations Environment Programme (UNEP), the International

Energy Agency (IEA), the European Commission (EC) and the European Environment Agency (EEA), among others (Font Vivanco et al., 2016).

Thus, the main research question addressed here is: "which role the rebound effect plays in the developing Latin American economy?". Thereby, the goal of this study is to empirically measure the direct RE for all the household services consuming electricity in Colombia by analyzing a panel data generated at 15 different states along 2005-2013. Although, there are several studies about the direct RE for countries members of the Organization for Economic Co-operation and Development (OECD) and for developed countries, these studies unlikely represents the situations of developing countries where empirical measures of this phenomenon are scarce. That is why, this study starts filling the gaps observed around this topic in Latin American economies, by providing novel insights about the direct RE in Colombia, since its value has been historically theorized rather than empirically tested. Literature suggests that the RE varies by region and that it is lower than in developing countries due to an unsaturated demand for energy services (Font Vivanco & Voet, 2014; Lu & Wang, 2016; Sorrell et al., 2009; Thomas & Azevedo, 2013; van den Bergh, 2011; Yu et al., 2013). We aimed to test these statements since there is limited empirical evidence of them (Yu et al., 2013).

Our study is relevant to various stakeholders: government, non-government agencies, policymakers, and academics which can gain knowledge on the role of the rebound effect in achieving sustainability goals, whereas practitioners can gain insights into the role of the rebound effect in Latin American economies. The content of this paper is organized as follows. Section 7.2 provides a literature review of the rebound effect studies for electricity consumption in developing countries. Section 7.3 presents the theoretical and methodological aspects of the study. Section 7.4 provides the results found in this study, whereas section 7.5 presents their associated discussion. Finally, Section 7.6 provides conclusions and final remarks.

7.2 Rebound effect. Theorical aspect and literature review.

This section presents a short description of the direct RE and a literature review of the RE of electricity consumption in developing countries.

7.2.1 Rebound effect.

Three types of rebound effect can be distinguish: (1) direct effect, (2) indirect effect, (3) economy-wide effect (Greening et al., 2000). The direct effects are related with the change in consumption or production of a single energy service e.g. electricity. The indirect effects are associated with changes in consumption for other goods and services apart from the improved energy service. Both of these phenomena are considered microeconomic effects. The economy wide effects represent the effect on the macroeconomics and are the result of the joined direct and indirect effects. Direct effects are the most studied ones due to the lack of tools and the difficulty to measure the other types of rebound, which associate patters of consumption and macroeconomics (Font Vivanco & Voet, 2014).

The direct RE has been extensively measured through two main approaches: quasi-experimental approach based on measures before and after the implementation of energy efficiency improvements, and econometric approach based on econometrics (Sorrell et al., 2009) . The quasi-experimental approach is rare due to the requirement of high amount of data, typically collected by surveys (Freire-González, 2011; Haas & Biermayr, 2000). Methodological issues for such approach are associated with measures based solely before–after comparisons, without the use of a control group or explicitly controlling for confounding variables and measures are not randomly selected adding selection bias in to the studies, moreover, possible bias associated with: small sample sizes, large variation in the relevant independent variable, and monitoring periods that are too short to capture long-term effects (Sorrell et al., 2009). The econometric approach proxies the RE through the elasticity price of the energy services under study, commonly by econometrics techniques such panel data, time series, and cross-sectional analysis (Belaïd et al., 2018). The Rebound effect can be simply measured by eq. (7.1)

$$Rebound\ effect(\%) = 100 * \frac{expecting\ savings - actual\ savings}{expecting\ savings} \tag{7.1}$$

Particularly, a rebound effect of 0% means full achievement of energy reduction, while a 100% means complete failure. Values greater than 100% means that the energy efficiency improvements increase the overall amount of energy use, a phenomenon known as 'backfire effect' (Sang-Hyeon, 2007). It is worth noting that the RE is commonly study under two different conditions: short and long term. Difference relies on either the variables are fully adjusted and in equilibrium (long term) or not (short term).

Under certain circumstances, the direct RE can be studied using the econometric approach through efficiency measures of the energy services (Berkhout et al., 2000; Khazzoom, 1980; Sorrell, 2007; Sorrell & Dimitropoulos, 2007) as:

$$\eta_{\varepsilon}(E) = \eta_{\varepsilon}(S) - 1 \tag{7.2}$$

Where $\eta_{\varepsilon}(E)$ represents the efficiency elasticity of the demand for energy and $\eta_{\varepsilon}(s)$ is the energy efficiency elasticity of the demand for useful work on an energy service. When $\eta_{\varepsilon}(s)$ = 0, there is no direct rebound effect. When $\eta_{\varepsilon}(s) > 0$, $\eta_{\varepsilon}(E) < 1$ and there is a positive direct rebound effect. Finally, a $\eta_{\varepsilon}(s) > 1$ means that the demand is elastic and there exists "backfire" (Saunders, 1992). Due to the difficulty to measure ε, the direct RE is mainly approached by the price on price-elasticity of energy demand as follows (Berkhout et al., 2000; Sorrell, 2007; Sorrell & Dimitropoulos, 2007).

$$\eta_{\varepsilon}(E) = -\eta_{p_E}(E) - 1 \tag{7.3}$$

Where η_{p_E}(E) represents the price elasticity of the energy demand (in this paper the price elasticity of the demand for electricity). Eq. (6.3) is based on symmetry and exogeneity assumptions. Symmetry implies that consumers respond in the same way to energy price decline and energy efficiency improvement, whereas exogeneity implies that energy prices change can not affect energy efficiency (Z. Wang et al., 2014).

Lastly, as mention above the RE can be quantified, depending of the quality of data available, by different measures either the energy efficiency elasticity of the demand for useful work on an energy service or the price elasticity of the demand for electricity, among others (Sorrell & Dimitropoulos, 2007). It is worth noting that the latter one may overestimate the real value of the RE. preferer measures are the energy cost elasticity of the demand for useful work $\eta_{p_S}(S)$ or the energy cost elasticity of the demand for energy $\eta_{p_E}(S)$. See Sorrel & Dimitropoulos ((2007) for detail definition and limitations of the different definition of the RE.

7.2.2 Literature review of the rebound effect of electricity consumption in developing countries

Literature suggest that the RE may be higher in developing countries due to the unsaturated demand for energy services (Font Vivanco & Voet, 2014; Lu & Wang, 2016; Sorrell et al., 2009; Thomas & Azevedo, 2013; van den Bergh, 2011; Yu et al., 2013). According with Van den Berg (van den Bergh, 2011) the magnitude of the RE is higher in developing countries than in developed ones for several reasons. First, developing countries often show a higher growth rate than in developed countries, retaining higher potential for increased energy intensive-consumption. Second, the cost of energy in developing countries is relatively higher than in developed countries. Third, developing countries are far from saturation in their consumption of essential energy services such as lighting. Fourth, developing countries may "technologically leap-frog", in terms of energy-efficient technologies as well as new energy-using devices. Fifth, lower education and less availability of information in developing countries possibly contribute to decision-making by firms, households, and governments that do not take all relevant economic and associated energy use effects into account at the time to establish public policies.

Empirical evidence of the direct RE for energy services consuming electricity in households among developing countries has focused on countries from Asia and Africa (see table 7.1). The value of the RE varies significantly depending on the region, the level of income and the method applied to test it. Zhang and Peng (2017) applied a panel threshold for the time span 2000–2013 and suggested that the direct RE for the low-income household level in China is 68%, whereas for the high-income households level this effect was estimated to be 55%. Across regions (provinces), Wang et al. (2014) used a panel data with 30 provinces of China along the period 1996-2010, suggesting that the direct RE ranges 72% (short term) and 74% (long term).

Measurements for the direct and indirect RE in China suggest that this phenomenon is significantly higher than the indirect rebound RE. Lu & Wang., (2016) applied an energy input-output data E-I-O and scenarios simulation to study the direct plus indirect rebound effect in china with a provincial panel data from 1996 to 2010. Their results indicate that direct plus indirect partial rebound effect is 79% (long-term) and 78% (short-term) from which the direct effect is 72% in the long-term and 74% in the short term. Similarly, Wang et al. (2016), applied similar models for estimating a direct and indirect RE in Beijing for the period 1990-2013 suggesting that the direct RE is 40% (long-term) and 15% (short-term), whereas the indirect RE in the short-term ranged from 8% to 21%, and the long-term effect ranged from 6% to 15%. Their results imply that efficiency improvements in residential electricity use had little effect on the implicit energy consumption associated with other goods and services in Beijing.

Alternatively, Sang Hyeon (2007) found that the direct RE in south Korea ranged 38% (short term) and 30% (long term) during the period 1975–2005, and provide a direct RE estimation via surveys for air conditioners between 57–70%. Also, Alvi et al.,(2018) used the time series data from 1973 to 2016 generated in Pakistan and suggested a RE around 43% (short term) and 70% (long term).

Labidi and Abdessalem (2018) provide the only study that empirically measures the direct RE for an African country (Tunisia). Using a balanced panel data set for a sample of 21 cities in Tunisia over the period 1995, 2000, 2005 and 2010, the authors provided the highest measure of the studies reviewed (RE =81%). Moreover, they argued that the direct RE could be reduced to 71.9% if the subsidy granted for the residential electricity consumption is removed by the state.

Results provided by Su (2018) in Taiwan are significant valuable given the fact that the author measures the RE though a survey rather than through aggregate data. In this case, measures are provided by different energy services such as air conditioner (72%), lightning (11%), TV (3%), and refrigeration (70%). Its study was carried on via surveys with 7677 household data between the period 2014-2017. Moreover, the author suggests an average 33% RE for all appliance consuming electricity.

Finally, Fox and colleagues (2012) found a direct RE in US of 8%, whereas Freire-González (2010) estimated a direct rebound effect of 35% in the short term, and 49% in the long term in Catalonia Spain

Literature review points out two critical outstanding research gaps. First, existing studies show that the rebound effect is significantly higher (RE> 30%) in developing than in developed countries (RE< 30%). Second, studies also show that measures in Latin American economies have been systematically omitted, mainly because the data required to conduct such studies are not available and have poor quality (Economic Consulting Associates, 2014; Sorrell & Dimitropoulos, 2007). These findings support the motivations of this study.

Table 7.1. Studies in developing countries related with the electricity residential consumption

Author	Country	Rebound effect	Magnitude %	Method
Sang-Hyeon (2007)	South Korea	Direct	38 Short term 30 Long term	Price elasticity
Freire-González (2010)	Spain	Direct	35 Short term 49 Long term	Price elasticity
Fox and colleagues (2012)	US	Direct	8 Long term	Price elasticity
Wang et al.,(2014)	China	Direct	72 Short term 74 Long term	Price elasticity
Lu and Wang (2016)	China	Direct plus Indirect	78 Short term 79 Long term	Price elasticity and Energy Input output data
Wang et al.,(2016)	Beijing, China	Direct and Indirect	16 Direct short term 40 Direct long term 8-21 Indirect short term 6-15 Indirect long term	Price elasticity and Energy Input output data
Zhang and Peng (2017)	China	Direct	72 Long term	Price elasticity
Labidi and Abdessalem (2018)	Tunisia	Direct	81 Long term	Price elasticity
Alvi et al.,(2018)	Pakistan	Direct	42,9 Short term 69,5 Long term	Price elasticity
Su (2018)	Taiwan	Direct	33 Long term	Surveys

7.3 Theoretical and methodological aspects

This section presents the econometric method and the different variables used to measure it in the study.

7.3.1 Rebound effect

This section presents the estimation of the RE for all energy services consuming electricity in the Colombian household sector. Following Haas and Biermayr (2000), the price and income elasticities can be estimated through econometric models. Thus, to measure the long-term RE among all energy services consuming electricity in the Colombian household sector, the following model is applied:

$$Ln(E_{it}) = \alpha + \beta_1 Ln\, EP_{it} + \beta_2 Ln\, GP_{it} + \beta_3\, Ln\, GDP_{it} + u_{it} \qquad (7.4)$$

Where α is a constant, β1- β3 are the parameters to be estimated, with β1 = η_{p_E}(E), and u_{it} represents the random error term. E_{it}: Is the explanatory variable and represents the electricity consumption in GWh per habitant (number of households with electricity services) in the state i and period t of the households. EP_{it}: represents the price of electricity in the state i and period t. We calculate EP as a weighted average price for each year between the electricity price for the different household income levels. GP_{it}: Price of the household gas, as substitute good, in the state i and period t. GDP_{it}: Represents the income variable per capita (number of households with electricity services) measured for the gross domestic product GDP divided by the number of households with electricity service in the state i and period t. This variable is selected as an estimation of the household income since the desegregated data for the income variable, provide by the official entity in charge, is in terms of GDP as a whole.

Additionally, and given the fact that the consumption of electricity is strongly positive correlated with the winter or summer seasons, plenty studies include a climatic variable into their analysis. Several authors included the heating degree days HDD and/or the cooling degree days CDD as explanatory variables (Alvi et al., 2018; Freire-González, 2010; Haas & Biermayr, 2000; Hartman, 1988; Labidi & Abdessalem, 2018; Lu & Wang, 2016; Sang-Hyeon, 2007; Z. Wang et al., 2014; Zhang & Peng, 2017). Those studies have been conducted in countries of Europe and Asia which have seasonal temperatures. This implies that they experience extreme temperatures during the summer and winter, and therefore the consumption for calefaction or refrigeration raises the electricity consumption. In this study, the variable Heating Degree-Days (HDD_{it}) (base: 18°C) of Colombia in period t and state i has been included to account for the climatic variable; however, the statistical test suggested that the climatic variable is not significant for the Colombian case (see supporting information S7.1 for results of the model with HDD_{it} variable). Therefore, the climatic variable was removed from the final econometric model. This meanly because Colombia is located in the tropic region and it does not have seasons. Then, the temperature does not change significantly over the year.

It is worth mention that different models were develop in order to find the most suitable model for the analysis. A model without the variable GP and other with the GDP variable gross domestic product without any conversion were tested. Both models result less significance (see supporting information S7.2).

To determined which regression model applied (random effects, fixed effects, or pooled regression), we follow Montero (2011) procedure. We use fixed effects because the null hypothesis of both Breusch-Pagan and Hausman was rejected, indicating that there exist un-observable components associated with each department and there are systematic differences between the estimators (fixed and random). For a detail description of the procedure see the supporting information S7.3.

7.3.2 Data collection

Colombia counts with 33 states including the capital city (Bogotá). Information for all the variables mentioned above were collected for all the states along 2005-2017. However, and due to the lack of information and accuracy for some states, a sample of 15 states (Antioquia, Atlántico, Bogotá, Bolivar, Boyacá, Caldas, Cundinamarca, Cordoba, Huila, Magdalena, Meta, Risaralda, Santander, Tolima, and Valle del Cauca) was finally selected for the period 2005-2013. These states accounts for 56% of the gross domestic product and 80% of the total housing units in 2013 (DANE, 2018c, 2018a).

Data of the total household gas and electricity consumption, the number of households, price of natural gas and electricity was obtained for every year and state under study from the superintendence of domiciliary public services (SUI by his acronym in Spanish) (SUI, 2018b) see supporting information S6.4 for descriptive analysis for the number of households with electricity services and price by income level). Data of the income was obtained from the National Administrative Department of Statistics (DANE by his acronym in Spanish) (DANE, 2018d), all the monetary variables are in constant price from 2005 and was collected for every year and state under study. The time period of the data is annually (see table 7.2). present some descriptive statistics for the sample.

Table 7.2. Descriptive statistics of the variables of 15 States in Colombia, 2005–2013.

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
E	923.178	868.083	0.966	3,280.433
EP	384.934	98.953	217.026	576.969
GP	910.87	329.241	303.7163	2,2112.558
GDP	0.152	1.237	0.015	14.401

E. electricity consumption per subscriber of electricity services, EP. Electricity price, GP. Gas price, GDP gross domestic product per subscriber of electricity. All variables 2005 current prices. Source: author's calculus.

7.4 Results

Results for the RE at national level was estimate using a random effect model. The panel data regression suggests that the direct RE for all household energy services consuming electricity is

83.4% (see table 7.3). Thus, only 16.6% of the potential savings are achieved. Except for GDP, all the variables where significant at 90% or higher confidence level.

Table 7-3 Random Effects Model: Total electricity demand in households 2005-2013. Panel of 15 states of Colombia. Generalized Last Squares (GLS) estimation (cross-section weights). N=135.

Variable	Coefficient	z-statistics	Prob.
α	-6.3437	-6.14	0.000**
lnEP	-0.8345	-3.16	0.002
lnGP	0.5539	2.8	0.005
lnGDP	-0.3368	-4.42	0
Adjusted R-squared			
Within	0.0871		
Between	0.5673		
Overall	0.2371		
Wald Chi2	29.36		0.0000***

Signif. codes: *** at 1%, ** at 5%, *a t 10%.

To estimate price elasticities by states, we use the random-effects model with dummy variables for each of them; although the Breusch-Pagan test suggested not reject the null hypothesis that $Var(v_i) = 0$. However, pooled regression estimates were equal to random effects ones (supporting information S7.5). Since it was not possible to estimate the slope interactions by states using the pooled model, we apply a random effect model to account for such effects. Due to the perfect collinearity found in this model, the natural log of energy price was omitted, then the estimation shows the state-rebound effect for every cross-section units.

The results suggest that the direct RE for all household energy services consuming electricity in the long term, is present for all the states but in different ranges. We found values from 64.7% in Atlantico to 78.9% Meta (see table 7.4). Almost all the variables are significant at 90% of confidence except the log of GP and the states of Atlantico, Cordoba and Magdalena.

Table 7-4 Random Effects Model: Total electricity demand in households 2005-2013. Generalized Least Squares (GLS) estimation (cross-section weights) with interactions between State dummy variables and Log of energy consumption. Yearly data for 15 states. N=135

Variable	Coefficient	z-statistics	Prob.
lnGP	0.551	1.64	0.103
lnGDP	-0.270	-2.96	0.004**
lnEP_Antioquia	-0.742	-1.74	0.084*
lnEP_Atlantico	-0.647	-1.51	0.133
lnEP_Bogotá	-0.732	-1.72	0.088*

lnEP_Bolivar	-0.783	-1.83	0.07*
lnEP_Boyacá	-0.706	-1.83	0.069*
lnEP_Caldas	-0.749	-1.89	0.061*
lnEP_Cundinamarca	-0.725	-1.76	0.081*
lnEP_Córdoba	-0.710	-1.65	0.101
lnEP_Huila	-0.786	-1.83	0.07*
lnP_Magdalena	-0.659	-1.54	0.125
lnP_Meta	-0.789	-1.91	0.058*
lnP_Risaralda	-0.738	-1.84	0.068*
lnP_Santander	-0.775	-1.86	0.065*
lnP_Tolima	-0.783	-1.91	0.058*
lnP_Valle_del_Cauca	-0.718	-1.72	0.089*
α	-6.694	-6.42	0.000***
Adjusted R-squared	0.3025		
F-Statistic	4.42		
prob-F	0.000		
Root MSE	0.51565		

Signif. codes: *** at 1%, ** at 5%, *at 10%.

7.5 Discussion

Results for the direct RE at national level are slightly higher (83.4%) compared with existing studies for developing countries (see Table 7.1). RE in Colombia appears to follow a geographic pattern, with higher values in those states located at the interior of the country (Meta, Huila, and Tolima), whereas low values (Atlántico, Magdalena, and Cordoba) were observed for those states located on the coast of the country. The reason for such patters is a high demand of electricity in the coast where the yearly average temperature is above 28 degrees (NOAA, 2017), thus the high amount of electricity is associated with the demand of additional energy services for refrigeration and air conditioning. These services are not needed or are consumed in smaller quantities in the center of the country, leading to a saturated energy consumption in the coast. In 2013 the monthly amount of electricity consumed by household in the coast was 239.12 kWh (Atlántico), 216.62 kWh (Magdalena), and 182.14 kWh (Cordoba). At the interior of the country the consumption was 130.94 kWh (Meta), 118.58 kWh (Huila), and 100.26 kWh (Tolima) (DANE, 2018b; SUI, 2018a).

Difference between the result at national level (83.4%) and at the state level (64.7% - 78.9%) may be explained by the level of aggregation. Similar results were observed between the national and regional level for the long term RE for road freight transport in China. Wang & Lu (2014) estimated a long term RE of 84% at the national level, whereas for three different regions (eastern, central and western) the magnitude of the RE ranges from 52% to 80%. It is worth noting that results at national and state, other than at the regional level for the RE of residential electricity consumption were not found on the literature, therefore more adequate comparations were not possible.

In our model and different from the studies reviewed (see table 7.1), the coefficient of the variable GDP is negative; this may be explained by the particular conditions of the Colombian electricity sector. The household sector in Colombia is stratified in six levels according to the socioeconomic state and income. While levels one to three are considered low income, the level four, five and six jointly are labeled as middle and high income, respectively. Such disaggregation plays an important role in the residential electricity consumption given the existence of a scheme of subsides for the final price to pay for electricity. Particularly, there is a mixed subsidy system where the high-income levels and the commercial consumers pay an additional fee (contributions) on the price of electricity (20% of the price) to subsidize the low-income levels (cross-subsidy). Additionally, the Government subsidize a portion (direct subsidy) when the contributions are not enough (CREG, 1997a). This fact becomes significant given that low income households accounts for 80% residential electricity consumption in Colombia (SUI, 2018a) and receive up to 60% of subsides in the price of the electricity (CREG, 1997b). However, it is highlighted the coefficient of GDP was not significant in our model, which suggests that more research is needed to make significant conclusions.

Comparing with existing studies, the contrasting results found here have several explanations (i) the data processed, (ii) the method applied, and (iii) the particularities of each country. Regarding the data and method applied our study used panel data at state level along nine years (2005-2013), whereas other authors include large timespan. Sang-Hyeon (2007) included data for thirty years (1975-2005). Wang et al.,(2014) evaluated four years (1996-2010) of a provincial data set in China, whereas Alvi et al., (2018) used an aggregate data with forty-three years (1973-2016) in Pakistan. The above authors applied the method developed by Hass and Biermayr (2000) and Dargay and Gately (1997) to tackle the assumption of symmetry (demand responds in the same way as the energy price and energy service price declines or increases) imposed in the theoretical framework (see section 6.3). Specifically, the method decomposes the price of the electricity in three different components, Pmax (the highest price in history), Pcut (prices fall), and Prec (price recovery) from which the Pcut stands for the direct RE. In this way, only the factors affecting the energy price drop are taking in account and overestimations are avoided.

Other important difference is the type of data applied, while above studies use panel data for different states or provicens, Zhang & Peng (2017) used data for thirteen years (2000-2013) for income level (low, middle, and high). Particularly, Labidi & Abdessalem (2018) used a balanced panel data set for a sample of 21 cities in Tunisia over the period 1995, 2000, 2005, and 2010 and studied the rebound effect in two cases (with subsidies and without subsidies of the government for the electricity).

Regarding the variables included in the econometric models, it is noted that the studies reviewed commonly include a variable accounting for a substitute good (in this case natural gas) and a climatic variable into their analysis, since the consumption of electricity is strongly positive correlated with the winter or summer seasons. In the case of the Colombia household sector, natural gas is used as a substitute of electricity mainly for cooking and in less proportion for water heating (see section 7.1)(UPME, 2016a). Significance of these variables in our models (see tables 7.3-4) suggests that natural gas is positive correlated with the consumption of electricity, meaning that the consumption of electricity increase ones the price of the natural gas increase. A similar procedure is applied by Freire–Gonzáles (2010) but natural gas was excluded from the final models given his non-significance.

Moreover, several authors (see table 7.1) applied an error correction model (ECM) to capture the effect of the RE in the short-term. Yet, in these models all the variables should be non-stationary in order to perform correctly. In our study, these pre-conditions are not satisfied by all the variables (see supporting information S7.6), then the ECM cannot be performed since the variables are not co-integrated (they do not share a common stochastic path). The reason of such results may be explained by the small number of periods included in this study 2005-2013 (9 years).

Limitations of our study to be addressed in the future include. (i) The quality of the data obtained from national datasets has several gaps, especially for the information accounting for the number of households with electricity services; for some states, such data was available only along the period 2005-2013. Furthermore, when the data was available, there were gaps in information. Thus, the number of households with electricity services for all the income has missing values. (ii) Due to the lack of information for such level of desegregation, the household income variable had to be calculated as gross domestic product divided by the number of households with electricity services. More desegregated information for GDP in Colombia can be found for GDP/per capita, implying that this variable may add uncertainties into the results. (iii) The price of the electricity was estimated as a weighted average of the price of electricity for each household income level (Colombian electricity regulated market has six different prices for the electricity depending on the income levels). Low-income levels have a subsidy of up to 60% in the electricity price to pay. In contrast, the high-income levels have to pay a 20% extra contribution on the electricity cost (CREG, 1997b). Information to differentiate the price of the electricity without the number of subsidies and contributions was not possible to find.

Furthermore, uncertainties included by the assumptions of symmetry and exogeneity may be present in the study. Authors like Hass and Biermayr (2000) and Dargay and Gately (1997) have cited the assumption of symmetry, as a matter of interest when studying the rebound effect. In our study, a model with a price decomposition was build up but the result was not significant (see supporting information S7.7 for model with price decomposition). Reasons for such results may be attribute to the quantity and quality limitations discussed above. Other source of uncertainties comes from (i) the relationship between the rebound effect and the costs of capital (Freire-González, 2010). It would be necessary to estimate the indirect and economy-wide effects to obtain the total magnitude of energy efficiency improvements in households. It is worth noting that the direct and indirect RE are likely to be inversely proportional. A large direct RE (e.g this study) implies that an important part of the savings will be re-spending in additional electricity consumption leaving less income to be re-spending in others services and (ii) the correlation between rising energy prices and investments in energy efficiency. Preferred measures of the direct rebound effect may include efficiency elasticities, energy service price elasticities, and energy price elasticities, in searching for controlling self-selection of efficient appliance purchase (Thomas and Azevedo, 2013); such measures become significant when the rebound effect is estimated through hybrid methods (direct + indirect rebound effect) (L. Wang et al., 2019).

The combination of both limitations and uncertainties may bias the results. Therefore, it is worth mention that the R^2 obtained in the general model (see table 6.3) indicate that the variables included in the model explain only 9% of the electricity consumption. Contrary to similar studies (see table 6.1) where variables such as electricity price, GPD, and population (here as the number of households with electricity services) explain more than 80% of the electricity consumption. Such differences may be attributed to (i) the quality of the data (discussed above) and (ii) the omission of variables that could be related to the electricity consumption, such as rates of ownership of electrical appliances, number of persons per household, age of the members in the families, amount others (Su, 2018). Additionally, the variability associated to the variable number of households with electricity services may affect the results. Hight variability across the years and income level was found for some states: Risaralda (between 15% - 155%) and Santander (14% - 176%). Whereas, low values of variability are presented in the states of Antioquia (between 2% - 17%) and Bogota (between 3% - 9%), where two of the most important cities (Medellin and Bogota, respectively) are located; the states of Cordoba and Huila follow similar patterns of variability (see supplementary information S7.6.1).

Future research aims at different areas should cover efforts to improve the quality of the data and to insulate the effect of the subsidies and contribution from the electricity price. Furthermore, efforts should be made to study the direct rebound effect of residential electricity consumption at different levels of desegregation, as the RE change significantly depending on the level of income or the region. Results of this study suggest that the rebound effect follows a geographic pattern, yet the causes of such patters need to be studied. Future research should focus on studying the rebound effect at regional and city levels. Moreover, studying the rebound effect by income levels may reveal different patterns, particularly attributed to the fact that 80% of the Colombian population belongs to the low-income level. Finally, studies of different energy services, e.g., transport, should be encouraged mainly because the transport sector is responsible for around 12% of the GHG emissions in Colombia (IDEAM, 2016). Then, efficiency polices that seeks to reduce such values may not be achieved for the effect of the rebound effect.

7.6 Conclusions

The RE has been extensively studied in the last decades in developed countries for several energy services such as transport, household heating and cooling, and electricity (Sorrell et al., 2009). Measures for the RE in developing countries have been systematically omitted from literature and estimations are assumed rather than empirically measured. In this sense, this paper empirically estimates the direct rebound effect for all household energy services consuming electricity in Colombia, through a panel data of 15 states over the period 2005-2013. The results obtained indicate the existence of a direct rebound of 83.4% for the long-term, supporting the hypothesis that the rebound effect may be more significant in the developing than in developed countries.

The RE has several implications for police makers given the fact that it can undermine the environmental savings planned through sustainable production policies and technologies (Maxwell et al., 2011). In this regard, the results show that the RE for electricity consumption in the Colombian household sector has a non-negligible value, which implies that a drop of 1% in the price of the electricity will increase the demand by 0.834%. This result is significantly important for the Colombian government due to the high number of resources that are planning to be invested in efficiency improvements for the production and consumption of electricity. Concretely, electricity efforts have been put into strategies for consumption improvements such as the replacement of refrigerators and LED bulbs. Then, not considering the rebound effect may reduce the effectiveness of such energy and environmental policies.

Furthermore, it should be noticed that the potential savings gained by the above strategies are likely to be spent not only on energy services that are close to saturation such as lighting or refrigeration, but also on water heating, air conditioning and other services such as the internet. Additionally, income effects (indirect rebound effects) arising from such strategies should be taken in account since indirect energy requirements of households are bigger than the direct energy requirements (Dimitropoulos, 2007). Such additional consumptions may increase the productivity of the country alongside the energy demand. Moreover, understanding the environmental impacts (environmental rebound effect) associated with the additional consumption of energy (both direct and indirect rebound effects) will provide a better perspective on the real implications of such efficiency improvements on the economy (Vélez-Henao et al., 2020).

The Colombian Government is encouraged to account for the importance of the rebound effect and develop instruments to control it in order to achieve the commitments made in the COP 21 and the national efficiency targets. Some useful mechanisms to do it may be including economic instruments e.g., taxes and programs and campaigns, for the efficient use and saving of energy. Particularly, the last one has proven to have positive and significant impacts on the consumption of electricity e.g. the "Apagar Paga" campaign launched by the Government to reduce energy consumption through economic incentives, which also encouraged savings and penalize additional consumption based on average electricity consumption of the houses in the household sector. This example represents efforts that were translated into a significant reduction in the growth of consumption, a key factor to avoid given the emergency caused by the El Niño phenomenon in 2016-2017.

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7.8 Disclaimer

This chapter is under review by the journal energy efficiency. Therefore, will be under embargo, from the moment of his publication, according with the policies of the journal. For future consulting please refers directly to the journal.

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8. Environmental rebound effect for energy efficiency improvements into household sector: The case of Colombia

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Abstract

Colombia aims to diversify and decarbonize its energy sector by encouraging the use of non-conventional renewable resources. Policies and/or measures to achieve this will presumably help to achieve national and international environmental goals, yet potential rebound effects may reduce its efficacy by triggering additional demand and environmental burdens. One of such rebound effects may take place as household demand rises in response to cheaper electricity prices due to the increasing shares of wind power. This study assesses the environmental rebound effect (ERE) in the household sector from increased shares of wind power into the Colombian power grid, across six environmental impacts and for the period 2020-2030. The method used combines life cycle assessment, input-output modelling, energy system modelling, econometrics, and re-spending modelling. The results show that the ERE has the potential to partially, and even completely, offset any environmental savings (backfire effect), depending on the specific impact, year, and modelling choices considered. The magnitude of the ERE (as the percentage of potential environmental savings that are offset) ranges highly across impacts, from a negligible 1% (eutrophication) to a staggering 9,241% (photochemical ozone creation). The ERE has thus the potential to render decarbonization policies largely ineffective, which calls for rebound mitigation policies, such as environmental taxes.

Keywords: Environmental rebound effect, non-conventional renewable resources, wind power, households, backfire effect.

8.1 Introduction

The energy sector in Colombia is the second largest emitter of greenhouse gas (GHG) emissions in the country, accounting for about 35% of the 236.9 Mton of CO_2 emitted in 2014 (see figure

8.1).[2] About 28% of the GHG emissions of the energy sector come from electricity and heat production (IDEAM et al., 2018), mainly from the combustion of coal and natural gas, which still have a substantial presence in the energy mix (70% hydro, 18% coal, 12% Gas, <1% wind in 2014) (see figure 8.2) (UPME, 2019a). Moreover, the current energy mix poses challenges for ensuring a continuous electricity supply during climatic variations such as the "El Niño" phenomenon, due to rainfall decrease which feeds the dams (Vélez Henao and Garcia Mazo, 2019). To meet the rising electricity demand while diversifying and decarbonizing the energy system, the Colombian government plans a sizeable increase in the share of non-conventional renewable resources (NCRRs, such as wind and solar power) (UPME, 2016a). Specifically, the government issued the law 1715, with the purpose of promoting energy and environmental efficiency in the energy sector (Congreso de la Republica, 2014). This policy seeks first to promote NCRRs to protect the electricity grid against the effects of the "El Niño" phenomenon. Second, to achieve the commitments made in COP 21 to reduce carbon emissions by 2030 (Vélez Henao and Garcia Mazo, 2019). Third, to align energy policies with the 7th sustainable development goal (SDG): guarantee the access for renewable and sustainable energy (United Nations, 2017).

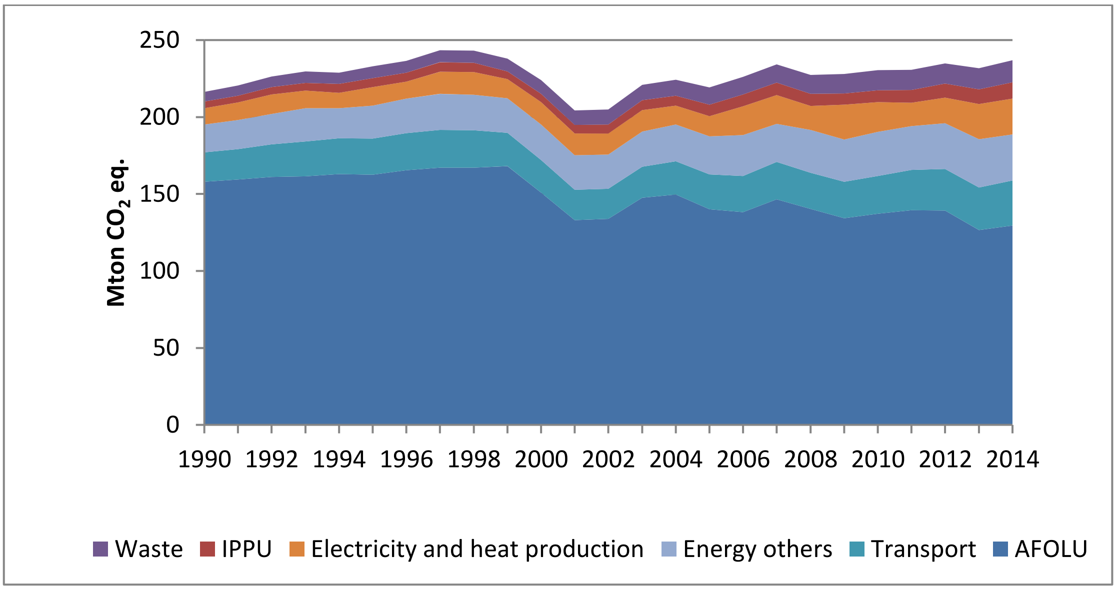

Figure 8-1. CO_2-equivalent emissions by economic sector in Colombia for the period 1990-2014. IPPU: industrial process and product use; Energy others: oil refining, solid fuel manufacturing, manufacturing and construction industries, other sectors, and fugitive emissions; AFOLU: agriculture forestry and other land use (IDEAM et al., 2018).

[2] This was the last year available at the writing of this article.

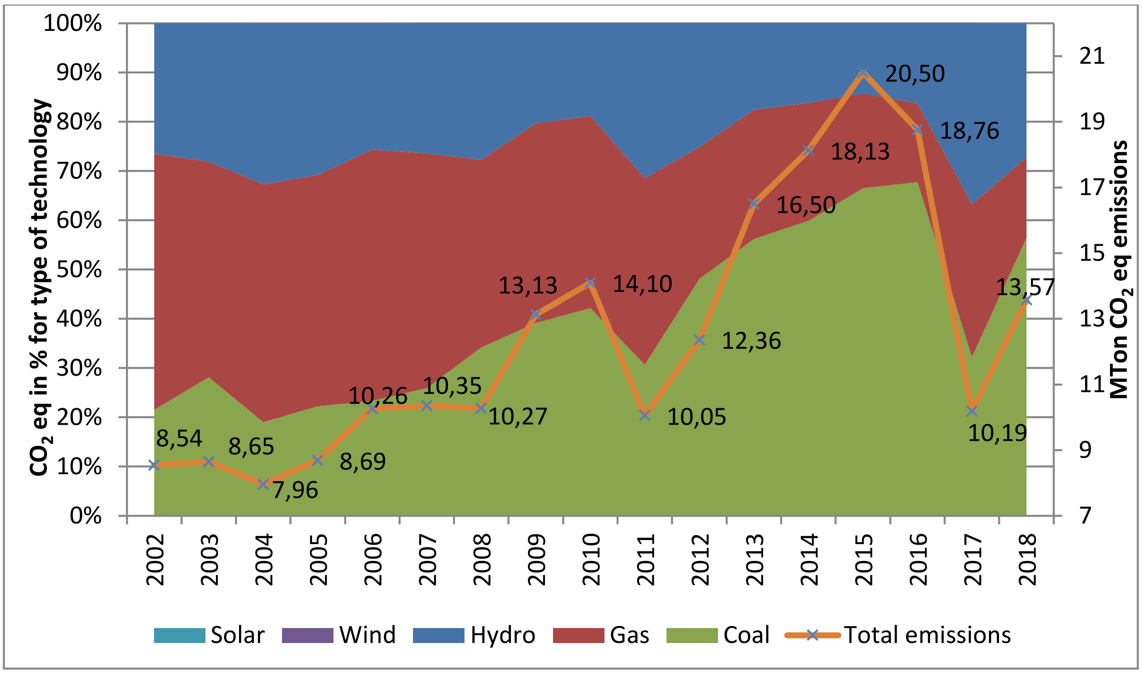

Figure 8-2. CO_2-equivalent emissions by electricity production technology. Source: own elaboration based on UPME (2019a) for the share of each technology in the energy mix and the CO_2 eq emissions for each technology obtained from the ecoinvent 3.4 database.

Consequently, the Colombian government plans a sizeable increase in the share of NCRRs to meet the rising of electricity demand (UPME, 2016a). Among these, wind power is expected to receive a considerable boost, from a marginal share of 0.1% in 2016 to a share between 2% and 7% in 2030 (727 MW to 1,456 MW of new wind power installed). Such expansion will mainly depend on the available space in the Guajira region, where wind farms are expected to be installed. This expansion is expected to entail environmental savings in the production of electricity (UPME, 2016a).

The potential environmental savings from increasing the shares of NCRRs in the energy mix can, however, be totally or partially offset by the so-called rebound effect (Freire-González and Font Vivanco, 2017). The rebound effect has been extensively studied for energy uses (Berkhout et al., 2000; Binswanger, 2001; Brookes, 1990; Girod et al., 2010; Greening et al., 2000; Sorrell et al., 2009; Sorrell and Dimitropoulos, 2007; Weidema, 2008). This effect has caught the attention of scholars and public and private institutions during the last decades, due to its potential to fall short of key environmental targets (Font Vivanco et al., 2016c). Some examples include the United Nations Environment Programme (UNEP), the International Energy Agency (IEA), and the European Environment Agency (EEA). For further details about the rebound effect as a policy issue, see Font Vivanco et al. (2016a).

Current trends show that NCRRs (particularly solar and wind) are both cheaper (Gielen et al., 2019; Kaberger, 2018) and have a better environmental performance than fossil fuels (Turconi et al., 2013). An increase in the share of NCRRs into the Colombian power grid may thus lead to a drop on the electricity price, causing an increase in available income, and consequently additional demand that offsets some or all of the initial expected environmental savings (Freire-González and Font Vivanco, 2017). An increase in the demand for the product subject to an efficiency improvement, electricity in this case, is generally known as the direct rebound effect (Greening et al., 2000). The increased demand of other goods and services (e.g., food or housing) is commonly known as the indirect rebound effect (Greening et al., 2000). In some cases, direct and/or indirect rebounds have the potential of not only entirely suppress the environmental savings achieved, but also generate additional environmental issues, a phenomenon known as backfire effect (Sorrell et al., 2009). Rebound effects can be expressed through a wide range of environmental issues, and are sometimes framed under the environmental rebound effect (ERE) concept (Font Vivanco and van der Voet, 2014; Freire-González and Font Vivanco, 2017; Goedkoop et al., 1999). Key strengths of ERE applications are the use of technology-detailed environmental-economic models, such as life cycle assessment, and the use of life-cycle environmental impact indicators (e.g. impacts on ecosystems and human health) (Freire-González and Font Vivanco, 2017; Weidema, 2008).

Given the fact that the ERE can undermine the efforts made by the Colombian government to decarbonize the electricity grid and the economy, the goal of this study is to obtain empirical evidence of the ERE from increasing the shares of NCRRs into the Colombian energy mix. To gain insight into the potential environmental consequences of a transition of the Colombian energy system to NCRRs (empowering by the issued law 1715), we conduct a case study based on a representative simplified energy model which accounts for half of the actual Colombian energy mix. We measure the ERE of a potential drop in the electricity price caused by the predicted increase of the share of wind power into the Colombian energy mix. An analysis like this has not yet been addressed in the literature. Compared to other measures of the ERE, this study provides, for the first time, a comprehensive assessment of the potential consequences of an environmental energy law under the framework of the ERE. Our study is relevant to both policymakers and practitioners. Policymakers will gain knowledge on the role of NCRRs in achieving sustainability goals, whereas practitioners will gain insights into the role of rebound effects in the context of multiple environmental pressures. The study of the ERE is in its infancy, with only a handful of empirical estimates available (Freire-González and Font Vivanco, 2017). This paper is organized as follows: section 8.2 provides the materials and methods applied to address the direct and indirect ERE from increasing the share of wind power in the Colombian energy mix. Section 8.3 shows the results for two case studies, section 8.4 the sensitivity analysis, section 8.5 discusses the results, and section 8.6 presents the main conclusions.

8.2 Case study design, sources of data and methods

This section briefly presents the electricity demand in Colombia by sectors, with a focus on the household sector. It further introduces the case of study, focusing on the ERE in the household sector due to a future increase in the shares of wind power in the energy mix. It concludes with a description of the data and methods used in the research.

8.2.1 Colombia electricity demand in brief

The Colombian final demand for electricity has been steadily increasing since 2006 (40.23 TWh) to 2018 (58.77 TWh),[3] and such demand is expected to further increase by about 2% yearly until 2030 (UPME, 2016a). The household sector represents the 42% of the total electricity consumption, whereas the industrial sector accounts for the 20%, and the construction,

[3] This is the last period with official data reported.

agriculture, and transport sectors represent jointly the 38% (UPME, 2019b). Consumption of electricity in urban households (85% of the total household sector) is dominated by energy services such as refrigeration, lighting, and cooking (UPME, 2016b). Low-income households consume more electricity (5.92%) compared with middle (3.01%) and higher (1.85%) income levels ones (The Word Bank, 2010). It is worth noting that around 88% from the total amount of households are connected to the energy mix (around 12 million of households) (SUI, 2018).

8.2.2 Introduction of non-conventional renewable resources in the Colombian power grid

This case study focuses on the ERE from households, due to the introduction of wind power in the Colombian power grid. The time horizon of the study is the period between 2019 and 2030, at the end of which the amount of wind power into the power grid will have achieved a relevant proportion (UPME, 2016a). Moreover, 2030 is the deadline to accomplish the carbon mitigation targets made in the COP 21 (MADS, 2017). A representative simplified energy model has been used[4]. It includes the main electric power plants within the current national energy system, representing 8,910.4 MW or 51% of the installed capacity in 2018. The rest of the plants are excluded due to the absence of data regarding their costs (installation, operation, and maintenance) (XM-Filial de ISA, 2018). Table S8.1 in the supplementary data shows the plants included in the study.

To keep the relative shares of wind power between the energy mix and our simplified energy model, we have chosen the installation of 536 MW of additional wind power, which corresponds to around the 50% of the total installed capacity that is expected in 2022 (1,073 MW) (UPME, 2019c). To measure the implications of the injection of 536 MW of wind power in the Colombia power system, we carry on a simulation of the electricity prices based on capacity factors and marginal production costs for selected periods (see supplementary data S8.1 for a detailed explanation of the energy system model, assumptions, and results). The study simulates an electricity demand of 28,557 GWh, with a yearly increase of 3.02% until 2030. The reference point corresponds to the case in which no additional capacity is installed, namely an energy mix with a limited participation of wind power (71.2% for hydro, 12.4% for coal, 6.4% for gas, and 0.2% for wind). Against this reference, we consider a hypothetical installation of 536 MW of wind power to an energy mix that is less dependent on hydro power (69% for hydro, 13% for coal, 15 % for gas, and 4% for wind) in 2019. The estimation of the ERE is based on the yearly savings obtained from the reduction of the electricity price as result of the injection of 536 additional MW of wind power. Such decrease stems mainly from the fact that wind power can be cheaper than conventional resources under specific operation, climatic, and economic conditions; even more considering the favorable wind conditions of the country. The price of electricity for household consumers is the sum of the different components of the energy market (generation, transmission, distribution, and commercialization), plus some components that reflect technical factors (losses and restrictions). Jointly, such components represent the 35%, 6%, 35%, 12%, 7%, and 5% of the electricity prices, respectively (supplementary data S8.3 presents the cost of the

[4] Energy model developed in Garcia-Mazo (2019)

electricity by component). For simplicity, it is assumed that, by introducing wind power, the cost of the electricity price components, other than generation, will remain constant.

For completeness, we will develop two different approaches to model the ERE. The first approach (combined model) measures the direct and indirect ERE separately, as done in Wen et al. (2018), Thomas and Azevedo (2013a), Font Vivanco et al. (2015), Font Vivanco and Voet (2014), Freire-González et al. (2017), and Freire-González and Font Vivanco (2017), by means of the own price elasticity of electricity demand and the marginal budget shares (MBS) (see section 7.3). The second approach (single model) uses solely the MBS to calculate the ERE, and therefore does not differentiate between the direct and indirect effects, as done by Makov and Font Vivanco (2018) and Brännlung et al (2007).

8.2.3 Data sources

Following Khazzoom (1980), at the microeconomic level, the direct rebound effect can be measured indirectly from the price elasticity of the demand for energy. This approach is the preferred among economists to measure the direct rebound effect since its allows to proxy the rebound effect without energy efficiency data (Freire-González, 2010). Consequently, in this study, we use a long-term price elasticity value of -0.959 for the rebound effect (see supplementary data S8.2 for econometric model and results), meaning that a 1% decrease in the electricity price will lead to a 0.959% increase in electricity demand. Later, in section 4, we carry out a sensitivity analysis to tackle the absence of measures for the direct rebound effect in the short-term, and possible misestimations.

The price of the electricity by components for households in the reference year was obtained from the Superintendency of Domiciliary Public Services SUI (2018) (see supplementary data S8.3 for detailed information of the price of electricity by component).

The life cycle impact assessment (LCIA) was conducted using the life cycle impact characterization factors from the International Reference Life Cycle Data System (ILCD) (European Commission, 2014) and provided by ecoinvent, a robust and widely used approach among LCA practitioners. Particularly, we present the ERE (expressed as a change in a given environmental indicator) in several impact categories: CC: climate change (in kg CO2-Eq); A: acidification (in mol H+-Eq); E: ecotoxicity (in CTUh.m3.yr); MEUT: marine eutrophication (in kg N-Eq); TEUT: terrestrial eutrophication (in mol N-Eq); CE: carcinogenic effects (in CTUh), NCE: non-carcinogenic effects(in CTUh); OD: ozone layer depletion (in kg CFC-11-Eq); POC: photochemical ozone creation (in kg ethylene-Eq); RES: respiratory effects (in kg PM2.5-Eq). Monetary savings were obtained by the difference between the price of the electricity for the reference year and the improved price of electricity for the different efficiency price scenarios developed, multiplied by the electricity consumption (See supplementary data S7.4 for detailed information of the scenarios developed and the monetary savings).

Marginal budget shares (MBS) were obtained via the almost ideal demand model (see supplementary data S8.5). Household consumption expenditures (HCE) were obtained from United Nations world information database, for the years 2000-2016 (UN, 2018) (see supplementary data S7.6), and price indices for the HCE by type of product for the respective year were obtained from Banco de la República database (2019) (see supplementary data S8.7).

Data for the environmentally-extended input-output (EEIO) model was obtained from the Global Trade Analysis Project (GTAP) 9 database, containing 57 industries across 140 regions (including Colombia). The construction of a MRIOT, using the GTAP database, was done following the procedure described by Peter et al. (2011), specifically the variant with endogenous international transport pool. The specific tool used, 'GDX_to_MRIOT_GTAPAgg', written with the programming language R, can be found in GitHub (2018).

8.2.4 Environmental rebound effect model.

The ERE was originally introduced by Goedkoop et al. (1999) as the environmental pressures resulting from a function fulfillment optimization. This concept offers a holistic view of the environmental impacts, caused by an improvement in the efficiency of providing a service. The ERE allows to express the rebound effect as different environmental burdens, rather than solely energy use (Font Vivanco et al., 2016c). A detailed review of the foundations of the ERE can be found in Font Vivanco et al. (2016b). The ERE has been extensively studied for several regions, technologies, and environmental indicators. Estimations of the ERE can be found in the literature for general energy efficiency improvements in the household sector in US, China and Spain (Freire-González et al., 2017; Freire-González and Font Vivanco, 2017; Thomas and Azevedo, 2013a; Wen et al., 2018), smartphones reuse in the US (Makov and Font Vivanco, 2018), electric cars and transport innovations in Europe (Font Vivanco et al., 2016c, 2015; Font Vivanco and Voet, 2014), green consumption in Australia (Murray, 2013), and high-speed transport technologies (Spielmann et al., 2008). The ERE is generally expressed as a percentage of the environmental savings that are "taken back" (Font Vivanco and Voet, 2014) as :

$$\%ERE = \left(\frac{PS-AS}{|PS|}\right) * 100 \text{ (8.1)}$$

with

$$AS = PS - (PS + ERE) \text{ (8.2)}$$

Where *PS* are the potential or engineering environmental savings from increasing the shares of wind power, on the energy mix, with respect to the current grid (in our case, through product-based LCA), and *AS* are the actual savings, including the rebound effect. Moreover, following Font Vivanco et al. (2016c) and Font Vivanco and Voet (2014) the ERE, expressed as a change in a given environmental indicator, can be calculated as:

$$ERE^{e,t} = ERE^{e,t}_{dir} + ERE^{e,t}_{ind} \text{ (8.3)}$$

Where ERE_{dir} accounts for the direct ERE from the increased electricity consumption, due to the cheaper electricity price, and ERE_{ind} represents the indirect ERE, from the re-spending effect, in other products other than electricity. *e* represents the environmental burden, and *t* indicates time. Moreover, each single effect can be decomposed into a demand and an environmental or technology effect. The demand effect relates to the changes in demand due to changes in real income, whereas the technology effect is associated with the environmental burdens, associated with each unit of additional demand. Thus, ERE_{dir} and ERE_{ind} can be expressed as:

$$ERE^{e,t}_{dir} = \Delta d^{t}_{dir,ts} b^{e,t}_{ts} \text{ (8.4)}$$

$$ERE_{ind}^{e,t} = \sum_{s=1,\dots,n} \Delta d_{ind,i}^{t} b_i^{e,t} \ (8.5)$$

With:

$$\Delta r^t = \Delta d_{dir,ts}^{t} + \sum_{s=1,..,n} \Delta d_{ind,i}^{t} \ (8.6)$$

Where Δd_{dir} denotes the change in demand for a given technology shares in the energy mix *ts*, *t* indicates time, and Δd_{ind} denotes the change in demand for a consumption group *i* (both in monetary terms), *b* refers to the environmental burdens per unit of demand, *n* equals the total number of consumption groups, and Δr corresponds to the total change in real income, due to the increasing shares of wind power into the energy mix.

Thus, from eq.(8.4) $\Delta d_{dir,ts}^{t}$ can be assessed, under certain assumptions (symmetry and exogeneity), by the following formula (Berkhout et al., 2000; Khazzoom, 1980; Sorrell, 2007; Sorrell and Dimitropoulos, 2007; Wang et al., 2014):

$$\Delta d_{dir,ts}^{t} = -\eta_{p_E}(E) - 1 \ \ (8.7)$$

Where η_{p_E}(E) is the price elasticity of the demand for electricity. Following Haas and Biermayr (2000), the price elasticity of electricity demand can be estimated using the following energy demand function:

$$Ln(E_t) = \alpha + \beta_1 Ln\, EP_t + \beta_2 Ln\, GP_t + \beta_3\, Ln\, GDP_t + u_t \qquad (8.8)$$

Where α is a constant, β1- β3 are the parameters to be estimated, with β1 = η_{p_E}(E), and u_t represents the error term. E_t is the electricity demand in period *t*. EP_{it} represents the price of electricity in period *t*. GP_t is the price of the household gas in period *t*. GDP_t represents the income variable in period *t*. For more details regarding the econometric approach applied and data sources, see supplementary information S8.2.

The price of electricity (EP), can be obtained as the sum of different components of the value chain (CREG, 2005): generation (G), transmission (T), distribution (D), commercialization (C), losses (PR), and restrictions (R), of the electricity sector (a table with the cost for the different component of the final EC can be found in supplementary data S8.3) (SUI, 2018) as:

$$EP = G + T + C + D + PR + R \ (8.9)$$

The direct price effect estimates using equation (8.8) are described as changes in electricity demand as a percentage from the initial electricity demand. This measure needs to be translated to environmental indicators by means of LCA-based coefficients, namely environmental impacts per kWh. LCA-based coefficients correspond to the coefficient $b_{ts}^{e,t}$ from eq.(7.4) and the values used can be found in supplementary data S8.4.

To calculate the ERE_{ind}, we need two different sub-models: a marginal consumption model and an EEIO model. The marginal consumption model allow us to know how the monetary savings obtained from the introduction of wind power are spend, by calculating the marginal budget shares (MBS) for each consumption group *i*. To calculate the MBS, we applied an Almost Ideal Demand System (AIDS) (see supplementary information S8.5 for the AIDS model and results). The AIDS is a popular consumer demand model introduced by Deaton and Muellbauer (1980), with properties that makes it preferable to competing models (Chitnis et al., 2012; Deaton and

Muellbauer, 1980). To build the re-spending model, we calculated the marginal budget shares (MBS), or the share of total savings that will be allocated to each consumption category i (e.g., food or housing). To do so, we assume a fixed individual income, and no long-term savings, so all saved money is spent. The MBS for a given time period can be calculated following Deaton and Muellbauer (1980) as:

$$MBS_t^i = \alpha^i + \sum_{s=1,\dots,n} \gamma_s^i lnp_t^s + \beta^i \left(\frac{x_t^s}{P_t}\right) \text{ (8.10)}$$

Where n equals to the total number of consumption groups (s), x is total expenditures, P is defined here as the Stone's price index, p is the price of a given category, t indicates time, and α (constant coefficient), β (slope coefficient associated with total expenditure) and γ (slope coefficient associated with price) are the unknown parameters. The Stone's price index is defined as (Deaton and Muellbauer, 1980):

$$lnP_t = \sum_{s=1,\dots,n} MBS_t^s lnp_t^s \text{ (8.11)}$$

Once the MBS are obtained, the indirect effect, in monetary terms, can be calculated by multiplying the remaining change in real income (Δr_r), by each MBS, for each consumption group i as:

$$RE_{ind} = \Delta d_{ind}^t = \sum_{s=1,\dots,n} \Delta r_r^t MBS_i \text{ (8.12)}$$

With:

$$\Delta r_r^t = (d_{ats}^t - d_{ts}^t) - \Delta d_{dir,ts}^t \text{(8.13)}$$

Where d is the electricity demand in monetary terms for a given energy mix in *ts* (original energy mix without the introduction of additional wind power), and its corresponding alternative *ats* (energy mix with the additional wind power). Similarly to the direct rebound in equation (8.8), indirect rebound in equation (7.13) needs to be translated into environmental indicators as the ERE_{ind}. To do so, an environmentally-extended input-output (EEIO) model is applied to obtain the environmental impact intensity (EII) (that is, the environmental impact per monetary unit) of each of the consumption categories (m). The EII values used can be found in supplementary data S7.10. Details of the EEIO model can be found in Miller and Blair (2009). The ERE_{ind} can be calculated as:

$$ERE_{ind} = RE_{ind} EII \text{ (8.14)}$$

With:

$$EII = SL = S(I - A)^{-1} \text{ (8.15)}$$

Where ERE_{ind} represents the indirect ERE, in environmental units, RE_{ind} is the indirect effect of the additional spend in monetary terms, L is the Leontief inverse matrix, S the set of coefficients of environmental intensities.

8.3 Results

This section presents the results for the environmental savings without taking in account the environmental rebound effect. Furthermore, the results of both the combined and single model for three different years (2020-2025-2030) and for six different environmental impacts (climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), carcinogenic effects (CE) ozone layer depletion (OD). Detailed results by year for all the environmental categories studied can be found in supplementary data S8.11 (combined model) and S8.12 (single model).

8.3.1 Environmental savings without the environmental rebound effect

Increasing the amounts of wind energy has positive effects on the environmental impacts produced by electricity generation (see table 8.3).Taking climate change (CC) as an example environmental savings ranging across the years under study from 0.7% (2006) to 2.8% (2024). Environmental savings are associated with the displacement of gas power by wind power (see supplementary data table S8.1.4 for the shares of generation in the reference and improved energy mix). Particularly the greater savings for the year 2024 is due to gas power is displaced to generate the 21% of the electricity to 19% in the improved energy mix. Similarly, the year with the smaller amount of savings, year 2026, is due to gas power is barely displaced to generate the 16% of the electricity to 14% in the improved energy mix. In both cases the displacement of gas power is due to the wind power, concretely the shares of wind power in the improved energy mix represents the 4% and 2% respectively.

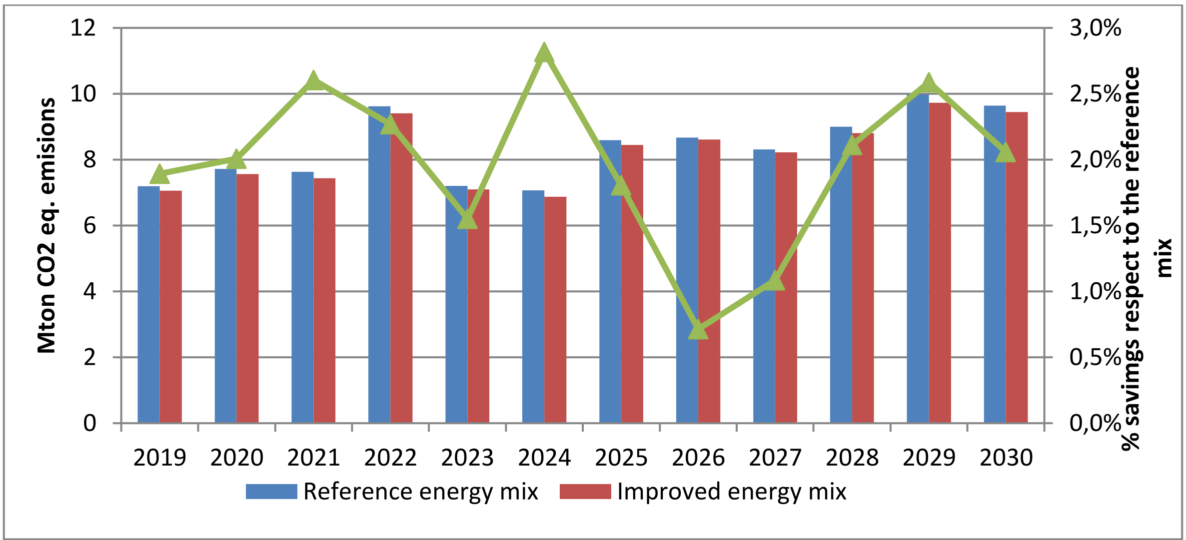

Figure 8-3 Environmental savings for increasing the shares of wind power into the energy mix without take in account the environmental rebound effect. CC: climate change (in kg CO2-Eq).

8.3.2 Environmental rebound effect results

The inclusion of both direct and indirect effects (combined model) has a notable impact on the environmental footprints from increasing the shares of wind power into the power grid (see figure 8.4.A). Taking the year 2030 as example, for all individual footprints, such an increase describes a relative change (with respect to the footprint results without the ERE) ranging across impact categories from 42% (E) to 385% (MEUT). By individual effects (direct and indirect), the ERE_{dir} is significantly higher than the ERE_{ind} for all the years studied. The values for the ERE_{dir} range across impact categories from 41% (E) to 379% (MEUT), whereas the ERE_{ind} values range across impact categories from 1% (E) to 58% (A).

The results for the ERE, when all the savings are allocated solely according to the MBS (single model), reveals slight differences compared with the combined model (see figure 7.4.B for the ERE based on the MBS for different years). Taking the year 2030 as example, for all individual footprints, such an increase describes a relative change (with respect to the footprint results without the ERE), ranging across impact categories from 11% (E) to 636% (A). In general, the single model shows higher values for the ERE than the combined model for half of the environmental impacts presented (A, CC, and OD), whereas, for the rest of the environmental impacts (MEUT, CE, and E), the impacts are higher in the combined model. Such differences are mainly due to the environmental impacts produced for the electricity infrastructure in each year. Specifically, the combined model takes into account the variability between the reference and improved energy mix for each year, and, therefore, the environmental efficiencies obtained by the introduction of wind power, whereas the single model does not take into account such environmental efficiencies, and uses a static value for the environmental impacts by the sector of electricity (see table S8.10.1 for the environmental impacts in different impact categories, per monetary unit, of the electricity sector).

Backfire effects, which mean that environmental impacts increased beyond the savings gained from increasing the shares of wind power, are present in the two models and in various years. Taking the year 2025 as an example, for all individual footprints, such an increase describes a relative change (with respect to footprint results without the ERE) ranging across impact categories from 1,478% (CC) to 177% (E) for the combined model, whereas, for the single model, backfire effects ranging across impact categories from 2,111% (A) to 230% (MEUT). Such high values are explained by the high savings available to re-spend in additional electricity and other goods. Particularly, savings from changes in electricity prices for the year 2025 are 20.5%, with respect to the reference price, in the respective year. Savings per kWh in the year 2020 and 2030 are 0.9% and 5.3%, respectively, with respect to the reference price, in the respective year. Generally speaking, greater savings are directly associated with higher environmental impacts in each impact category, by the increase of consumption of electricity and other goods.

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Figure 8-4. Environmental rebound effect (ERE) according to the combined model (A) (based on both price elasticities of demand and marginal budget shares) and the single model (B) (based entirely on marginal budget shares). CC: climate change (in kg CO2-Eq), A: acidification (in mol H+-Eq), E: ecotoxicity (in CTUh.m3.yr), MEUT: marine eutrophication (in kg N-Eq), CE: carcinogenic effects (in CTUh), OD: ozone layer depletion (in kg CFC-11-Eq).

Emissions across the different consumption groups depend on two factors (see supplementary information S8.13): the amount of consumption in each expenditure type (MBS) and the environmental impact intensity (EII). Taking climate change (CC) as an example, while the environmental impact for groups such as housing, other expenditures, transport, clothing and communications seem to be driven for the MBS, the groups of recreation and health & education are driven by the EII. The group of housing consumes the 20.41% of the total savings (the highest across consumption groups) and represents the 18.65% of the total emissions. Other expenditures consume the 14.9% of the available savings and account for the 12.91% of the total emissions. Among these, transport consumes the 11.61% of the expenditures and produces the 4.59% of the total impact. Recreation consumes 16.81% of the savings and produces the 23.85% of the impact (the highest across consumption groups).

Considering economic sectors (see supplementary informatio S8.13), the impacts vary significantly across the different consumption groups. The activities related with recreational, cultural and sporting activities produce the 99.99% of the impact in the group of recreation, whereas the activity of fishing accounts for <1% of the impacts. In the group of housing, the activities associated with construction and trade accounts for the 49.29% and 36.07% of the total impacts, whereas the consumption of electricity represents the 14.06% of the total impacts (or the 2.62% of the total impacts across the fifty-three economic sectors). The impacts in the group of other expenditures are driven mainly by two of the twenty economic sectors assigned to this group: other business and services (44.56%) and Petroleum & coke (32.62%). Activities related with the transport consumption group are mainly driven by the air transport (84.6%), while other types of transport such as road, rail, pipelines, auxiliary transport activities and travel agencies represent the 12.70% of the total impacts. Environmental pressures for the communication group are driven mainly by activities associated with post and telecommunications (91.60%). The activities of clothing, dressing and dyeing of fur; and textiles & man-made fibres produce, respectively, the 48.98% and 30.06% of the total impacts in the clothing consumption group. Finally, in the consumption group of food, impacts are significantly driven by two of the sixteenth activities assigned to this group. The production of sugar produces the 75.64% of the total impacts, whereas the cattle meat accounts for the 7.27% of the total impacts.

It is worth noting that only ten of the fifty-three economic sectors accounts jointly for the 91% of the total environmental impact associated with the savings expenditures. Recreation & Other Services (23.85%), Government services: public administration and defense; compulsory social security, education, health and social work, amount others (19.09%), Sugar production (14.34%), Construction (9.19%), Trade: retail sales, wholesale trade and commission trade, hotels and restaurants, amount others (6.73%), Other Business Services (5.75%), Petroleum & Coke (4.21%), Air transport (3.88%), Electricity (2.62%), Cattle (1.38%).

8.4 Sensitivity analysis

The ERE from increasing the shares of wind power into the Colombian power grid depends importantly on the amount of savings available for re-spending. Parameters such as the price elasticity of the demand for electricity and the price of electricity itself are directly associated with savings, and hence with the environmental impacts associated to the consumption of electricity (RE_{dir}) and other goods (RE_{dir}). In order to determine the sensitivity of the ERE to these variables, we conducted a sensitivity analysis. The year selected for the sensitivity analysis was 2020, and the environmental category selected was climate change. As a reminder, the reference parameter for the price elasticity is -0.959 and the price of electricity is 0.16 cent/kWh (see section 8.2.1). The results show that savings have a bigger slope (higher sensitivity to changes) than the price elasticity. The change of the ERE with respect to changes in the price elasticity of the electricity demand has, in general, insignificant changes (values close to zero) because this variable determines how much additional electricity is consumed (direct ERE). In this sense, the environmental impacts associated with the additional consumption of electricity are significantly lower compared with the environmental impacts per monetary unit of the savings re-spent in other goods and services (see Figure 8.5).

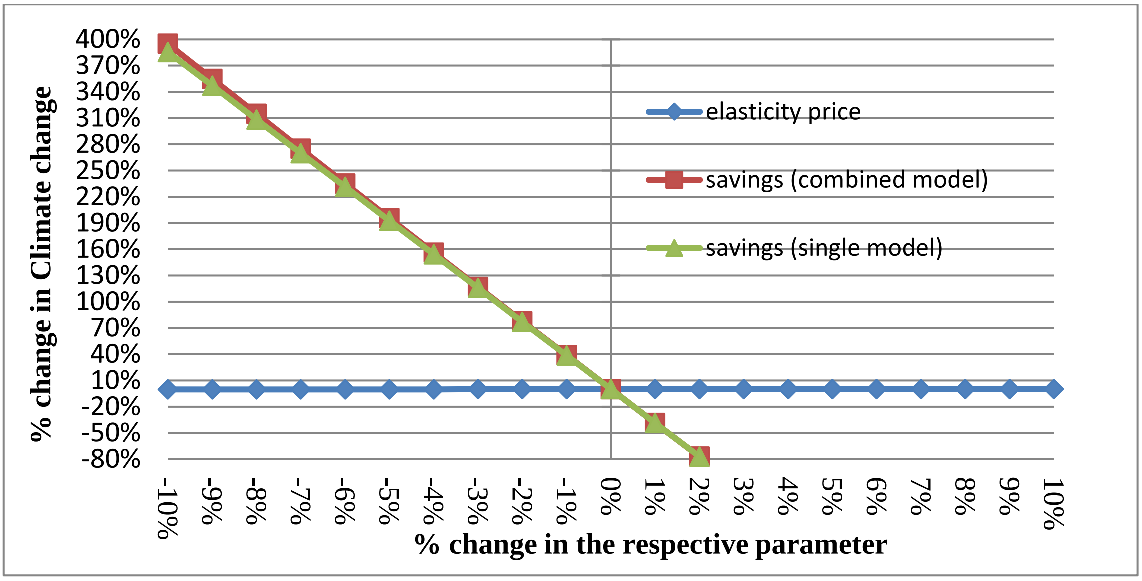

Figure 8-5 Sensitivity analysis for price elasticity for the demand (red and blue) of electricity and price (green)

8.5 Discussion

The results obtained in this research suggest that the ERE associated with an increase in the shares of wind power into the Colombian power grid lead to considerable differences in the environmental performance. For the combined model, differences range across impact categories from 5% (E) to 6,109% (POC). By type of effect, the ERE_{dir} is significantly higher than the ERE_{ind}. For ERE_{dir}, values range across impact categories from 5% (E) to 5,242% (POC), whereas the ERE_{ind} values range across impact categories from <1% (E) to 1,417% (POC). In general terms, there is a negative correlation between direct and indirect rebound effects (Freire-González, 2011; Lu and Wang, 2016). Indirect effects are higher at low values of direct rebound effect because more savings can be re-spent in consuming more goods and services.

The results for the single model show slight differences compared with the combined model. In general, the ERE is high for the impact categories of A, CC, OD, POC, TEUT, NCE and RES, whereas, for the rest of the environmental impacts (MEUT, CE, and E), the ERE is higher in the combined model. The main reason for such differences is the high emissions per monetary unit associated with the ERE_{ind}.

It is worth noting that the differences between the values of the ERE in both models across the years are due to the savings obtained in each year. In particular, in the year 2025, the savings per kWh are up to 20.5% of the reference price in this year, while for the years 2030 and 2020 the savings are the 5.3% and 0.9% of the reference price in each year, respectively. For the years 2024, 2026, and 2027 the ERE for all the environmental impacts is equal to zero due as there were no savings in those years. The variability across years is mainly due to the price of fossil fuels (coal and gas) and climatic variations across the years that affected the electricity production (capacity factor). For example, during “El Niño” there were lower precipitations, which increase the need for fossil fuels to satisfy the electricity demand, whereas during “La Niña” there were higher precipitations which lowered the need of fossil fuels and their price. Under such situation, an increase on the shares of wind power into the energy mix aims to prevent energy prices from rising in times of low rainfall, by replacing the use of fossil fuels with wind power (see table S8.1.2 for the capacity factor used in each year for the calculation of the electricity prices; and see table S8.1.5 for the price of the electricity in the reference and improved energy mix, along the timespan of the study).

Backfire effects can be found for the two models under study, yet with different a magnitude (amount of % change) depending on the year and the environmental impact analyzed. Particularly, backfire effects are likely to be higher in the single model. This is because, in the single model, all the savings are re-spent across the economy instead of a part of it, as in the combined model, in which part of the savings are consumed in electricity. In general terms, consuming electricity is associated with less environmental impacts than consuming additional goods and services from the entire economy.

The high EII in terms of climate change for consumption groups such as recreation (23.85%) and health and education (19.08%) are explained by the fact that such activities are service-intensive consumers. In such regard, Suh (2006) estimated that services are responsible for about 38% of GHG emissions in the US when supply-chain-induced emissions were included. Similarly, Nansai and colleagues (2009) highlighted considerable energy and material requirements in the supply chain of services in Japan. Conversely, for the housing consumption group, the impacts associated with the economic sector of electricity represent the 2.62% of the total impacts of the indirect ERE. Such impacts are associated mainly with the fossil fuels (carbon and gas) on the energy mix that, in average, represent the 23% of the total shares of technologies of the national energy mix (see figure 8.2).

Sensitivity analysis reveals that the ERE responds very differently to the selected parameters. The results suggest that the price elasticity has a negligible but positive influence on the ERE. Specifically, a 1% increase on the elasticity price will lead to an increase of the ERE of less than 1% (0.023%). On the other hand, the price of the electricity has a significant, negative influence on the ERE. A 1% decrease on the price of the electricity will lead to an increase of the ERE of 38.56%. This difference is explained by the fact that savings affect more significantly both the additional consumption of electricity (direct RE) and the amount of savings available to re-spend (indirect RE) than the elasticity price of the electricity.

The high TEUT, NCE, POC and RES impacts for the ERE_{ind} stem from the large emissions coefficients in EXIOBASE. These high emissions per monetary unit are largely due to a combination of completeness and aggregation issues, as discussed in the literature (Joshi, 2000; Lenzen, 2000). Higher completeness means that EXIOBASE accounts for economic sectors and flows that are systematically missing in LCI databases. Aggregation issues refer to the use of homogeneous sectors which aggregate many activities with different emissions coefficients.

The implications of increasing the shares of wind power into the power grid in the household sector from this study are consistent with the ERE literature, which describes both a high variability of magnitudes and a high prevalence of backfire. For instance, Alfredsson (2004) found that green consumption patterns in Sweden caused an ERE ranging from 7% to 300%. Tomas and Azevedo (2013a, 2013b) found an ERE ranging from 7% to 25% for transport and electricity in the US. A study by Font Vivanco and Voet (2014) on electric cars in Europe found ERE values ranging from -834,869% to 377%. Takase et al. (2005) described an ERE between 17% and 125% for transport, electricity, and food in Japan.

A number of sources of potential bias can be found. First, due the high level of aggregation of the household consumption expenditures (HCE) and their respective price indices. Second, due to the inherent uncertainties associated with the use of EEIO models, such as the level of sectorial aggregation, the linear production function assumption, the fixed technical coefficients, and vintage lags between emission data and IO tables (Thomas and Azevedo, 2013a). Double-counting in the combined were handled by removing the impacts associated with the ELY (Electricity: production, collection and distribution) economic sector from the total amount of impacts associated with the indirect ERE. Other limitations are the MBS available, which contain aggregated information of consumption, where the different patterns of consumption of the household income levels are less clear. Low-income households consume more electricity, housing, and food than high-income households, which consume more health and other services e.g. financial products. Specifically, low income households consume the 51%, 6% and 4% of their income in food, energy, and health, whereas high income ones expend the 22%, 2%, and 6% respectively in the same activities (The Word Bank, 2010).

From a technical point of view, some inherent particularities of wind power, like intermittency and its non-dispatchable nature (Abo-Khalil, 2013; Amusat et al., 2018; Flynn et al., 2016) pose challenges to the energy mix operation and control (Barelli and Ottaviano, 2019), thus increasing their cost (Amusat et al., 2018). Operation and control of the energy system could become more complex due to issues regarding its capacity to maintain generator synchronism when it is subject to a large disturbance (transient stability), the ability to restore steady-state conditions (voltage, current, power) after being subject to a small disturbance (small-signal stability), their ability to recover and maintain system frequency following a major generation–load imbalance (frequency stability), and their ability to maintain an acceptable voltage profile after being subjected to a disturbance (voltage stability) (Flynn et al., 2016). These problems during low consumption periods (Barelli et al., 2016) and/or times of system stress, have been traditional handled by wind power curtailment (Flynn et al., 2016). Detailed information regarding the technical impacts of wind power system stability can be consulted in Fynn et al., (2016). Moreover, rising costs in the operation and control of the energy system from the introduction of wind power, are due to several aspects. First, the construction of new transmission lines, given the fact that wind power plants are commonly located in isolated areas and so far from the consumption centers. Second, the integration of energy storage systems (ESS), mainly used to tackle intermittency issues (Amusat et al., 2018; Barelli et al., 2016, 2015; Barelli and Ottaviano, 2019; Ciupageanu et al., 2019). Third, the losses of efficiency operation and wear-and-tear costs of the thermoelectric plants, since they are often operated at part-load as fluctuating back-up power increasing the O&M cost (Barelli et al., 2015). It is worth noting that such challenges are likely to happen in energy mixs with wind power penetration higher than 20% (Barelli et al., 2016, 2015; Barelli and Ottaviano, 2019; Flynn et al., 2016), while other authors recommend limiting the contribution of wind generation to about 30% to ensure energy system stability (Amusat et al., 2018).

Future research could benefit from increasing efforts in gathering data from the different HCEs for different household income levels. More disaggregated HCE data, by type of expenditure and household level income, can provide more accurate and detailed information of the environmental impacts of the household sector. Moreover, including the whole energy system may yield more accurate data regarding electricity prices, since the total amount of savings has been proven to be the most sensitive parameter to measure the ERE.

8.6 Conclusions

In this paper, we have measured the ERE in Colombian households due to increasing shares of wind power in the power grid under different modeling assumptions and across ten environmental indicators. This is the first study conducted for Colombia that seeks to measure the potential environmental consequences of an environmental and energy law. The results suggest that increasing the share of wind power into the power grid leads to a notable ERE, and also that backfire effects can take place under certain conditions. Specifically, backfire is likely to happen for the majority of the environmental impacts studied (except for E and CE), across all analyzed years, depending mainly on the energy mix configuration in each year, which determines the amount of savings available to be re-spend.

In this regard, the Colombian government may work in several fronts. First, in fomenting the debate between academics and policy-makers. This would allow the stakeholders to recognize the importance of the ERE, and then support the development of transparent and simple tools to estimate it. Second, in increasing the awareness of consumers, e.g., by the implementation of smart meters to improve the visualization of consumption patterns, or by implementing energy efficiency campaigns. Third, in the development of economic instruments such as environmental taxation and energy pricing polices (Freire-gonzález and Puig-ventosa, 2015; van den Bergh, 2011). Environmental taxation has been theorized to minimize the effects of the ERE in developed economies (Font Vivanco et al., 2016a), and the question remains about their effectiveness and practical implementation in developing countries. Energy pricing polices will prevent that reductions in the price of electricity are not fully translated into increased electricity consumption (Freire-gonzález and Puig-ventosa, 2015). Subsides to incentivize or disincentivize additional consumption of electricity may also have positive effects in mitigating the ERE, though its poses challenges, such as increased complexity when designing tax schemes. Particularly, previous experiences have shown that reward and penalty mechanisms have a positive effect in the consumption of electricity in Colombia. For example, in 2017 the government launched the campaign "Apagar Paga" to reduce electricity consumption by encouraging savings and penalizing additional consumption in the household sector. It entailed a significant reduction in the growth of consumption, a key factor to avoid rationing, given the emergency caused by “El Niño” phenomenon in 2016-2017.

Optimal mechanisms to mitigate the ERE are based on target-oriented design and policy mixes, though it is important to highlight that any attempt to mitigate the ERE must take into account additional ERE and ways to mitigate it (Font Vivanco et al., 2016a). Such actions may help not only in mitigating the rebound effect, but also in contributing to effectively to achieve energy and environmental targets, e.g., those commitments made in COP21 and national targets.

More broadly, the results of this research contribute to the emerging literature on rebound effects from developing economies, which generally describe larger magnitudes mainly due to lack of saturation for resource-intensive products, such as energy products and meat (Boardman, 1991; Chakravarty et al., 2015; Roy, 2000). This, in turn, brings up the issue of the incommensurability associated with rebound effects, where detrimental environmental impacts and desirable social welfare increases occur simultaneously across income groups. It is thus key that rebound mitigation measures consider the overall effect across income segments, so as not to disadvantage vulnerable groups. In this sense, the analysis of the ERE would not only need to be decomposed by income groups, but also to integrate measurements of social welfare gains, in line with current efforts in sustainability science.

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8.8 Disclaimer

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9. Overall Conclusions, limitations and future research.

This section presents the overall conclusions of the whole research. Moreover, the limitations found are discussed and future lines of research are presented. It is important worth noting that each chapter contains their own section of conclusions and limitations and therefore this section summarizes the most general conclusions so as not fall into meaningless repetitions.

9.1 Overall conclusions

The STIRPAT model is a suitable and consist framework to understand the drivers that trigger a wide variety of environmental impacts. Comparing with other models, mainly variations of the IPAT equation, the STIRPAT model allows to include additional factors that may be considered as driving force of environmental changes. In particular, the variable technology may be decomposed in different factors that capture in better sense the effect of technological changes on several environmental footprints. Findings suggest that there is a geographic imbalance scope, studies focus mainly in china whereas studies for South America remind unexplored. Moreover, studies reviewed focus mainly in CO_2 emissions even though the STIRPAT model allows many different environmental impacts; extending STIRPAT-LCA model may be useful in addressing multiple environmental impacts. There is no clear consensus on how to define variable technology. Finally, the STIRPAT model, while providing a valuable framework, is still underused to address the rebound effect.

By applying a STIRPAT-LCA model to address the influence of urbanization and technological changes on electricity consumption in Colombia at different environmental impacts dimensions, the results suggest that urbanization is the main driver behind the electricity consumption (1.61%) and climate change (0.99%), whereas for acidification, eutrophication and respiratory, an explicit relationship was not found. Moreover, the energy structure was found to play an important role on the Colombian electricity consumption. The evidence suggests a negative correlation of (-0.89%) meaning that ones the energy structure, the shares of fossil fuels on the electricity grid, increase in 1% the consumption of electricity decrease by 0.89% this because the price of the electricity of fossil fuel is more expensive than the electricity produce by hydro power, thus, the final price of the electricity increase. Consequently, the energy structure is positive correlate (1.76%) with the amount of CO_2 emitted, this is because the fossil fuels are more polluting that renewable resources. Finally, results do not match with the hypothesis that urbanization decrease energy consumption and carbon emissions (Abdallh & Abugamos, 2017; Effiong, 2018; B. Lin et al., 2016; Madu, 2009; Shahbaz et al., 2016). Moreover, evidence suggests that the patters of urbanization in Colombia follow the same tendency described for China (Urbanization process increase energy use and pollutants at different levels of aggregation in China).The reason for such discrepancy may be the fact that Colombia is a developing country which can be grouped as a middle income level, similarly to China, comparing to Nigeria, Kenya, Congo, and other countries in Africa studied by Madu(2009), Lin et al., (2016). Abdallh & Abugamos (2017), and Effiong (2018). Such differences in income level has been reviewed by Poumanyvong & Kaneko (2010). K. Li & Lin (2015) and Lin et al.. (2017), suggesting that urbanization decreases energy use in the low-income group, while it increases it in the middle and high-income groups. Furthermore, urbanization increases the CO_2 emissions in all the income groups.

Regarding the hybrid life cycle assessment for the wind farm, the results suggest that omitting service inputs leads to non-negligible truncations issues. By order of importance, services increase the amount of emissions between 0% (ECOTOX and CE) and 21% (TEUT) with respect to the results without services, meaning that environmental declarations may be underestimated. By life cycle stages, the manufacturing processes accounts for 80% of the impacts in CC, being the tower, the rotor, and the nacelle the most relevant components with 39%, 27%, and 21% from the total, respectively. Moreover, results highlight the importance to perform a sensitivity analysis of the technical parameters. Particularly, changes in the capacity factor, the lifespan, and the percentage of losses could vary impacts, respectively, by up to about -35%, 25%, and 5%.

Additionally, the regional analysis suggests that environmental impacts for the wind farm are rather exporter than produced in situ. Regions like China and US contribute significantly to the total environmental impacts. Taking CC impact as example, China contributes to 11% of the total impact associated with materials and to 15% of the impacts associated with both direct and indirect services, whereas US contributes to 6% and 14% of the impact associated with materials and services, respectively. The environmental impacts taking place locally are mainly associated with the material and energy inputs rather than with the services. Colombia contributes with less than the 5% of the impact associated with materials and energy and the 1.64% of the impact associated with services. Regarding the truncation error from omitting services, our results suggest an overall truncation error of about 6% and 7% respectively for direct and indirect services and for CC impacts.

Results for the direct RE at national level are slightly higher (83.4%) compared with existing studies for developing countries. RE in Colombia appears to follow a geographic pattern, with higher values in those states located at the interior of the country (Meta, Huila, and Tolima), whereas low values (Atlántico, Magdalena, and Cordoba) were observed for those states located on the coast of the country. The reason for such patters is: (1) a relative high price of the electricity for the states at the interior of the country, 403 $/kWh (Meta),370 $/kWh (Huila), and 400$/kWh (Tolima) comparing with the states at the coast: 333 $/kWh (Atlántico), 351 $/kWh (Magdalena), and 341 $/kWh (Cordoba). (2) a high demand of electricity in the coast where the yearly average temperature is above 28 degrees (NOAA, 2017), thus the high amount of electricity is associated with the demand of additional energy services for refrigeration and air conditioning. These services are not needed or are consumed in smaller quantities in the center of the country, leading to a saturated energy consumption in the coast. In 2013 the monthly amount of electricity consumed by household in the coast was 239.12 kWh (Atlántico), 216.62 kWh (Magdalena), and 182.14 kWh (Cordoba). At the interior of the country the consumption was 130.94 kWh (Meta), 118.58 kWh (Huila), and 100.26 kWh (Tolima) (DANE, 2018b; SUI, 2018a). This supports the hypothesis stated by Van den Berg (2011) how suggest that the rebound effect is positive correlated with the price of the electricity and negative correlated with the saturation for the consumption of essential energy services.

It is worth mentioning that in our model the coefficient of the variable GDP is negative; this may be explained by the particular conditions of the Colombian electricity sector. The household sector in Colombia is stratified in six levels according to the socioeconomic state and income. While levels one to three are considered low income, the level four, five and six jointly are labeled as middle and high income, respectively. Such disaggregation plays an important role in the residential electricity consumption given the existence of a scheme of subsides for the final price to pay for electricity. Particularly, there is a mixed subsidy system where the high-income levels and the commercial consumers pay an additional fee (contributions) on the price of electricity (20% of the price) to subsidize the low-income levels (cross-subsidy). Additionally, the Government subsidize a portion (direct subsidy) when the contributions are not enough (CREG, 1997a). This fact becomes significant given that low income households accounts for 80% residential electricity consumption in Colombia (SUI, 2018) and receive up to 60% of subsides in the price of the electricity (CREG, 1997b). However, it is highlighted the coefficient of GDP was not significant in our model, which suggests that more research is needed to make significant conclusions.

Finally, the ERE of the Colombian household sector for increasing the shares of wind power into the Colombian energy mix has a non-negligible impact on the overall environmental indicators studied across all the years. Such impacts ranging across impact categories from 5% (eutrophication) to 6,109% (photochemical oxidant creation) when the combined model is applied (direct + indirect). Whereas, for the single model (only indirect) the values fall on the ranges of 1% (eutrophication) and 9,277% (photochemical oxidant creation). Furthermore, the sensitivity analysis of the elasticity price of the electricity and the price of the electricity reveals that the ERE varies in different ways, specifically, changes in these parameters could vary impacts, respectively, by up to about <1% and 38%. Backfire effects were present for 8 of the environmental impacts studied in different magnitudes across the years, depending meanly of the savings available to re-spend.

9.2 Limitations

Regarding the inclusion of services inputs (direct services) limitations are mainly due to the limited information regarding the expenditures associated with the project. While detailed information concerning the environmental studies required by the authorities to grant the different licenses needed to operate the project was obtained, it was not possible to obtain similar data for the planning and management stages of the project (service consumers). This omission can lead to the underestimation of the impacts related to direct services. Moreover, the limitations imposed by the IO-LCA regarding the high level of aggregation (Joshi, 2000; Lenzen, 2000) and the assumed proportionality between physical and monetary flows (Lenzen, 2000) may add uncertainties to the results. Aggregation issues exist because economic sectors, even in the most disaggregated IO tables, are actually a combination of heterogeneous production technologies and products with regards to input materials and environmental impacts (Suh et al., 2004; Suh and Huppes, 2005). Proportionality can alter the physical flow relationships between industries because of price inhomogeneity, particularly when inter-sectoral prices differ greatly between industries (Bicknell et al., 1998; Suh et al., 2004). According to Lenzen and Murray (2001), the proportionality assumption can lead to non-negligible errors (up to 40% for Australian energy and climate change impacts).

Moreover, from the methodological point, the limitations arising from using the environmental extensions from EXIOBASE 3.4 to complement the GTAP9 database, because both databases differ on the level of industry aggregation and base year, among other differences (Tukker et al., 2018) . Considering the scope of this study, such a limitation can be avoided by using a MRIO database which features both a high level of geographical coverage and extensive environmental extensions. For example, the Eora database (Lenzen et al., 2013) covers 190 countries, including Colombia, and includes several environmental extensions, of which only a few are homogenously reported for all countries. Using the Eora database, however, would limit the amount of environmental impact indicators used in this study. For example, Eora does not report PM2.5 emissions which are used to calculate respiratory effects from inorganic compounds.

Limitations associated with the measurement of the direct RE to be addressed in the future include. (i) The quality of the data obtained from national datasets has several gaps, especially for the information accounting for the number of households with electricity services; for some states, such data was available only along the period 2005-2013. Furthermore, when the data was available, there were gaps in information. Thus, the number of households with electricity services for all the income has missing values. (ii) Due to the lack of information for such level of desegregation, the household income variable had to be calculated as gross domestic product divided by the number of households with electricity services. More desegregated information for GDP in Colombia can be found for GDP/per capita, implying that this variable may add uncertainties into the results. (iii) The price of the electricity was estimated as a weighted average of the price of electricity for each household income level (Colombian electricity regulated market has six different prices for the electricity depending on the income levels). Low-income levels have a subsidy of up to 60% in the electricity price to pay. In contrast, the high-income levels have to pay a 20% extra contribution on the electricity cost (CREG, 1997b). Information to differentiate the price of the electricity without the number of subsidies and contributions was not possible to find.

Furthermore, uncertainties included by the assumptions of symmetry and exogeneity may be present in the study. Authors like Hass and Biermayr (Haas & Biermayr, 2000) and Dargay and Gately (Dargay & Gately, 1997) have cited the assumption of symmetry, as a matter of interest when studying the rebound effect. In our study, a model with a price decomposition was build up but the result was not significant (see supporting information S7 for model with price decomposition). Reasons for such results may be attribute to the quantity and quality limitations discussed above. Other source of uncertainties comes from (i) the relationship between the rebound effect and the costs of capital (Freire-González, 2010). It would be necessary to estimate the indirect and economy-wide effects to obtain the total magnitude of energy efficiency improvements in households. It is worth noting that the direct and indirect RE are likely to be inversely proportional. A large direct RE (e.g this study) implies that an important part of the savings will be re-spending in additional electricity consumption leaving less income to be re-spending in others services and (ii) the correlation between rising energy prices and investments in energy efficiency. Preferred measures of the direct rebound effect may include efficiency elasticities, energy service price elasticities, and energy price elasticities, in searching for controlling self-selection of efficient appliance purchase (Thomas and Azevedo, 2013); such measures become significant when the rebound effect is estimated through hybrid methods (direct + indirect rebound effect) (L. Wang et al., 2019).

On the other hand, related with the estimation of the ERE a number of sources of potential bias can be. First, the high level of aggregation of the household consumption expenditures (HCE) and their respective price indices. Second, the inherent uncertainties associated with the use of EEIO models, such as the level of sectorial aggregation, the linear production function assumption, the fixed technical coefficients, and vintage lags between emission data and IO tables (Thomas and Azevedo, 2013a). Double-counting may be present in the combined model between the additional consumption of electricity (direct rebound effect) and the re-spent savings, which include the industrial sector of ELY (Electricity: production, collection and distribution). Other limitations are the MBS available, which contain aggregated information of consumption, where the different patterns of consumption of the household income levels are less clear. Low-income households consume more electricity, housing, and food than high-income households, which consume more health and other services e.g. financial products. Specifically, low income households consume the 51%, 6% and 4% of their income in food, energy, and health, whereas high income ones expend the 22%, 2%, and 6% respectively in the same activities (The Word Bank, 2010).

9.3 Future research

Further research associated with the LCA of the wind farm would benefit from increased data gathering efforts on the full costs associated with services rather than just the services associated with the environmental studies needed to implement the project. Full cost information is commonly omitted by the project owners for confidentiality reasons. Moreover, extending the boundaries of the study to include the manufactured capital inputs, such as machinery and buildings used in production, as well as broadening the environment assessment with social and economic indicators can provide further information of the life-cycle sustainability impacts of wind power.

Regarding the direct RE, future research aims at different areas should cover efforts to improve the quality of the data and to insulate the effect of the subsidies and contribution from the electricity price. Furthermore, efforts should be made to study the direct rebound effect of residential electricity consumption at different levels of desegregation, as the RE change significantly depending on the level of income or the region. Results of this study suggest that the rebound effect follows a geographic pattern, yet the causes of such patters need to be studied. Future research should focus on studying the rebound effect at regional and city levels. Moreover, studying the rebound effect by income levels may reveal different patterns, particularly attributed to the fact that 80% of the Colombian population belongs to the low-income level. Finally, studies of different energy services, e.g., transport, should be encouraged mainly because the transport sector is responsible for around 12% of the GHG emissions in Colombia (IDEAM et al., 2016). Then, efficiency polices that seeks to reduce such values may not be achieved for the effect of the rebound effect.

On the other hand, associated with the ERE future research could benefit from increasing efforts in gathering data from the different HCEs for different household income levels. More disaggregated HCE data, by type of expenditure and household level income, can provide more accurate and detailed information of the environmental impacts of the household sector. Moreover, including the whole energy system may yield more accurate data regarding electricity prices, since the total amount of savings has been proven to be the most sensitive parameter to measure the ERE.

9.4 References

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10. Supporting information

Technological change and the rebound effect in the STIRPAT model: a critical view

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Supporting information S4-1 summary of surveyed STIRPAT model

Supporting information S4-2. List of abbreviations

Supporting information S4-3. Estimation model selection

Supporting information S4-4. Estimation model selection

Supporting information S4-1. summary of surveyed STIRPAT model

Table S4-1 supplementary data. summary of surveyed STIRPAT model

Reference	Data used	Time period	variables used	Technology	Environmental impact
1.Jia et al.,(2009)	Henan Province, China	1983 to 2006	P,A,A^2,U,IN	Proxy by IN and U	Ecological footprint
2.Lin et al.,(2009)	China	1978 to 2006	P,A,T,U,IN*,EI	EI	C,SO_x,NO_x emissions
3.Madu (2009)	Nigeria	Not specified	P,A,U	Included in the error term	Fuel consumption
4.Poumanyvong and (2010)	99 countries	1975 to 2005	P,A,U,IN,SV,EI	Proxy by IN and SV	CO_2 emissions and Energy use
5.Wang et al.,(2010)	West Jilin Province, China	1986 to 2006	P,A,A^2,U,U^2,IN**	Proxy by U, its quadratic form and IN	Ecological footprint
6.Liddle and Lung (2010)	OCDE (17 countries)	1960 to 2005	P,AE,A,U,EI,ES	Proxy by U, EI and ES	CO_2 emissions and electricity consumption
7.Wang et al., (2011)	Minhang District, Shanghai, China	1998 to 2009	P,A,EI,U	EI	CO_2 emissions
8.Tang et al.,(2011)	Sichuan Province, China	1995 to2008	P,A,A^2,U,IN	Proxy by U and IN	Ecological footprint
9.Li et al.,(2011)	China	1990 to 2008	P,A,U,IN,EF	EPR	CO_2 emissions
10.Cao et al.,(2011)	China	1985 to 2007	P,A,U,EI,ES	Proxy by EI and ES coal	CO_2 emissions
11.Wang et al.,(2012)	Beijing, China	1997 to 2010	A,A^2,U,IN,SV,EI,R&D	R&D	CO_2 emissions

Supplementary data S4.1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
12.Zhang and Lin (2012)	29 provinces of China	1995 to 2010	P,A,U,IN,SV	Proxy by IN and SV	CO_2 emissions and Energy use
13.Zhu and Peng (2012)	China	1978 to 2008	P,A,U,AE,HS	Included in the error term	Carbon emissions
14.M. Wang, Song et al.,(2012)	31 provinces of China	2010	P,A,U,EFI,L,AE	EFI	Ecological footprint
15.Li et al.,(2012)	30 provinces of China	1990 to 2010	P,A,U,IN,EPR	EPR	CO_2 emissions
16.Poumanyvong et al., (2012)	92 countries	1975 to 2005	P,A,U,SV	Proxy by U and SV	Transport energy use
17.Ren et al.,(2012)	Shenyang, China	2011 to 2030	P,A,A^2,U,EI	EI	CO_2 emissions
18.Liddle (2013)	35,85,47 countries respectively	1990, 1995 and 2001	P,A,UD	U	Private transport energy consumption
19.Sun et al.,(2013)	Beijing, China	Not specified	P,A,U,IN,EI	EI	CO_2 emissions
20.Zhang et al.,(2013)	Jiangmen, China	1990 to 2010	P,A,U,IN,SV,EI	EI	CO_2 emissions
21.Wang et al.,(2013)	Guangdong Province, China	1980 to 2010	P,A,U,IN,SV,FT,CI, ES	CI	CO_2 emissions
22.Li and Wang (2013)	Tianjin, china	1996 to 2011	P,A,U,EI,SV	SV	CO_2 emissions
23.Wang and Yang(2014)	China	1999 to 2010	U,A,IN,SV,EI,EGN	EI	Energy ecological footprint
24.Zhao et al.,(2014)	China	1990 to 2009	P,A,U,D	Included in the error term	Water footprint

Supplementary data S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
25.Liu et al.,(2014)	7 provinces of China	2006 to 2010	P,A,U,EI, IN,ES,EP,FI	EI	CO_2 emissions
26.Yahui and Weiguang (2014)	Chongqing, China	1998 to 2011	P,A,U,E	Included in the error term	Energy consumption of urban residential building
27.Salim and Shafiei (2014)	OCDE	1980 to 2011	P,A,U,IN,SV,PD	Proxy by IN and SV	Renewable and non-renewable energy consumption
28.Shafiei and Salim (2014)	OCDE	1980 to 2011	P,A,IN,SV	Proxy by IN and SV	CO_2 emissions
29.Li et al.,(2015)	Tianjin, China	1996–2012	P,A,A^2,U,EI,IN,FI	Proxy by EI and IN	CO_2 emissions
30.Lin and Du (2015)	30 provinces of China	1997 to 2011	P,A,U,SV	Proxy by U and SV	transport energy consumption
31.Wang and Zhao (2015)	30 provinces of China	1997 to 2012	P,A,U,IN*,FT,EI	EI	CO_2 emissions
32.Chikaraishi et al., (2015)	140 countries	1980 to 2008	P,A,U,IN,SV,EI	EI	CO_2 emissions
33.Dai et al.,(2015)	Jiangsu Province, china	1990–2009	P,A,A^2,EI,U,F	EI	COD, TN, TP
34.Wen et al., (2015)	China	1991 to 2011	P,A,U,IN,SV,ES,FT,CI	CI	CO_2 emissions
35.Liu et al.,(2015)	30 provinces of China	2006 to 2012	A,U,IN,SV,ES,EP	proxy by U,IN,ES and SV	Energy consumption
36.Yang et al.,(2015)	Beijing, China	1984 to 2012	P,A,U,HS,AE,EI	EI	CO_2 emissions
37.Wang et al.,(2015)	OCDE	1960 to 2010	A,U,U^2,EI	EI	CO_2 emissions
38.Qin and Liao (2015)	113 cities, china	2004 and 2010	PD,A,IN	IN	NO_2,SO_2, and PM10

Supplementary S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
39.Chen et al.,(2015)	Wuhan, china	1990 to 2013	P,A,U	U	Change of lake area
40.Zhou et al.,(2015)	30 provinces of China	1990 to 2012	A,U,IN,SV,EI	NOT CLEAR	CO_2 emissions and Energy consumption
41.Li and Lin (2015)	73 countries	1971–2010	P,A,U,IN,EI	I	CO_2 emissions and Energy consumption
42.Yansui Liu et al.,(2015)	30 provinces of China	1990–2012	PD,A,A^2,IN,SV,EI	Proxy by IN,SV and EI	Exhaust gases, waste water and solid waste
43.Ji and Chen (2015)	29 cities and provinces of China	1998 to 2010	P,A,U,IN	IN	Energy consumption
44.Wen and Liu(2016)	Hebei province, china	1995 to 2013	P,A^2,CI,U,ES,IN,FT	CI	CO_2 emissions
45.Guan et al.,(2016)	Ningxia Hui, china	1991 to 2011	P,A,A*,U,IN,SV	Proxy by IN and SV	CO_2 emissions
46.Kang, Zhao et al.,(2016)	30 provinces of China	1997 to 2012	P,A,EI,IN,U	EI	CO_2 emissions
47.Li and Sun (2016)	Beijing , China	1990 to 2013	P,A,A^2,SV,U	Proxy by SV and U	Air Pollution (CO_2,SO_2,dust)
48.Xu et al.,(2016)	29 provinces of China	1995 to 2011	P,A,A^2,U,EF,IN	Proxy by EF and IN	CO_2 emissions
49.Wang et al., (2016)	30 provinces of China	1995 to 2011	P,A,A^2,ES,CI,I,SV,EI	CI	CO_2 emissions
50.Ding et al.,(2016)	30 provinces of China	1997–2013	A,U,TEM	TEM	Household Energy Consumption
51.Shahbaz et al.,(2016)	Malaysia	1970 to 2011	U,U^2,A,FT,CI	CI	CO_2 emissions

Supplementary S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
52.Sheng and Guo (2016)	30 provinces of China	1995 to 2011	P,A,U,IN,ES,ER	Proxy by IN,ES and ER	CO_2 emissions
53.Zhou and Liu (2016)	30 provinces of China	1990 to 2012	P,HS,U,AEA,IN,EI	Proxy by IN and EI	CO_2 emissions
54.Zheng et al.,(2016)	73 Cities in China	2002 to 2012	P,A,A^2,U,IN,EI	Proxy by IN and EI	CO_2 emissions
55.B. Xu et al.,(2016)	29 provinces of China	2001 to 2012	P,A,U,EI	EI	PM2.5 emissions
56.Lin et al.,(2016)	Africa	1980 to 2010	P,U,A,A^2,EI,ES	EI	CO_2 emissions
57.Long et al.,(2016)	72 countries	1980–2008	P,A,IE,U,IN	EI	Ecological footprint
58.Xu and Lin (2017a)	30 provinces of China	2000 to 2014	P,A,U,IN,EF,ES	EF	CO_2 emissions
59.Miao (2017)	216 prefecture-level cities	2013	P,A,PD,EP,TEM,PUB	Proxy by EP,TEM, FPR and PUB	Urban residential energy consumption and CO_2 emissions
60.He et al.,(2017)	29 provinces of China	1995 to 2013	P,A,U,U^2,IN,EI,R&D	R&D	CO_2 emissions
61.Shahbaz et al.,(2017)	Pakistan	1972 to 2011	U,A,IN,SV,NC	Proxy by IN and SV	Energy consumption
62.Lin and Omoju (2017)	Asia	1990 to 2013	P,U,A,EI, PSI,RAIL	EI	CO_2 emissions for transport
63. Liu et al., (2017)	Norwegian	2006 to 2009	P,P^2,A,AE,U,UD,HS,LR	No clear or exclued	Transport energy use
64. Yeh and Liao (2017)	Taiwan	1990-2014	P,A,AE,IN,U	I	CO_2 emissions

Supplementary S4-1(continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
65. Zhang et al., (2017)	Henan Province, China	1995-2014	P,A,A^2,EI,U,SV	EI	CO_2 emissions
66.Lin et al.,(2017a)	China	2006-2014	P,A,EI,U,UD,IN,FT	EI	Air Pollution (C02,SO2,dust)
67. Wen et al.,(2017)	China	1995, 2000, 2005, 2010, 2014	P,A,A^2,U,ED	No clear or exclued	demand for improved environmental safety
68.Abdallh and Abugamos (2017)	Mena region	1980-2014	P,A, U,U^2, EI	EI	CO_2 emissions
69.Jiang and Lei (2017)	China	1998-2011	P,A,U,PEC,IN, R&D	R&D	GSHP
70. Li et al.,(2017)	China	2010	P,A,U,IN,SV,FAI,BM, PIUR	No clear or exclued	Municipal infrastructure development
71. Ma et al., (2017b)	China	2000-2015	P,U,SV,CI,CPB	No clear or exclued	CO_2 emissions
72. Yan et al.,(2017)	China	1981-2013	P,A,ES,EI,IN,U,CC,LLR	Proxy by ES,EI,CC,LLR	CO_2 emissions
73. Erqian et al.,(2017)	China	2000-2012	P,A,U,EI	EI	CO_2 emissions
74. Yu Liu et al.,(2017)	China	2006-2010	P,A,U,EI,IN,EP,FI	No clear or exclued	CO_2 emissions

Supplementary S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
75. Lin et al., (2017b)	53 Countries	1991-2013	P,A,U,IN,CI,EI,LAP,URE ,PIC	LAP	CO_2 emissions
76. W. Li et al.,(2017)	China	1997-2014	P,A,A^2,ISR,IST,ISU,EIM ,TI,ES,U,FI	ML	CO_2 emissions
77. Sheng et al., (2017)	78 Countries	1995-2012	P,A,IN,U	IN	Energy consumption
78. Long et al.,(2017)	72 Countries	1980-2008	P,AIN,SV,EI	EI	Ecological footprint
79. Yang et al.,(2017)	China	2000-2010	P,A,U,SV	SV	Energy consumption
80. Wang and Li,(2017)	China	1980-2014	U,SV,A,EI,GA,BU	EI	CO_2 emissions
81. Wang et al.,(2017)	China	2000-2013	A,U, A^2,U^2,EI,TSE	Proxy by EI, TSE	CO_2 emissions
82. Xu and Lin,(2017b)	China	2000-2014	P,A,EF,U,IN,ES	EF	CO_2 emissions
83. Yanan Wang et al., (2017)	China	1997-2012	P,A,U,AE,EI,TEM	EI	CO_2 emissions
84. Xing et al.,(2017)	China	2000-2013	A,IN,FD,FD^2	IN	CO_2 emissions
85. Wang and Lin,(2017)	China	1980-2014	P,A,U,ES,EI	EI	CO_2 emissions

Supplementary S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
86. N. Zhang et al.,(2017)	141 Countries	1961-2011	P,A,U,U^2,FT	No clear or exclued	CO_2 emissions
87. Zhang and Xu (2017)	China	2004-2013	P,A,SV,LUPR,LD	No clear or exclued	CO_2 emissions
88. Mikayilov et al.,(2017)	Azerbaijan	1990-2014	P,A,U,EI	No clear or exclued	Air Pollution ($C0_2$,SO_2,dust)
89. Ma et al.,(2017a)	China	2000-2015	P,U,,EI,SV,CCB,PCB	No clear or exclued	Energy consumption
90. Effiong (2018)	Africa	1990-2010	P,A,U,U^2,EI	EI	CO_2, and PM10
91. Chai et al.,(2018)	China	1984-2015	A,A^2,ES,ES,EI,IN	No clear or exclued	Natural gas consumption
92. Cui et al.,(2018a)	Shanxi, China	1990-2015	P,A,U,ML	ML	Energy consumption
93. Diao et al.,(2018)	China	2006-2015	P,A,IN,EI,U,NC	EI	NOx emissions
94. Ge et al.,(2018)	China	2010-2015	P,A,U,EI	EI	NOx emissions
95. Luo et al.,(2018)	China	1999-2011	P,A,A^2,U,IN,SV,ENI	EI	PM2.5 emissions
96.(Y. Wang et al., 2018)	Beijing, China	1996-2016	P,A,U,EI,WI	proxy by EI and WI	CO_2 emissions and Water use

Supplementary S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
97. W. Wang et al., (2018)	East and South Coastal China	2000-2015	P,A,U,IN,EI	EI	CO_2 emissions
98. Wang and Zhao,(2018a)	China	1997-2014	HS,RC,EI,U,AE,WA	EI	CO_2 emissions
99. Shuai et al.,(2018)	China	1995-2014	A,U,SV,FT	No clear or exclued	CO_2 emissions
100. Cui et al.,(2018b)	Hebei, China	1995-2015	CI,IN**,A,U,P,AG,DD,O	CI	CO_2 emissions
101. Xie et al.,(2018)	China	2003-2015	P,A,U,IN,FI,V,EI	EI	PM2.5 emissions
102. Wu et al.,(2018)	Qingdao, China	1988-2014	P,A,A^2,U,EI,ES,SV,FT	EI	CO_2 emissions
103. Nasrollahi and Saeed (2018)	MENA and OECD countries	1975-2015	P,A,A^2,IN,EF	EF	Weak and strong sustainability
104. Wang and Zhao (2018b)	China	1997-2012	U,IN,EGN,NPV,IU,SV,EI	EI	CO_2 emissions
105. Zhang et al.,(2018)	China	2005-2014	P,A,IN,EI,U,FT,LUPR	EI	CO_2 emissions
106. Xu and Lin (2018a)	China	2001-2015	A,P,EF,U,IN,ES	EF	PM2.5 emissions
107. Yang et al.,(2018)	Zhejiang, China	2006-2014	P,A,EI,U,ES,FT, PRE,MTA,HDD,CDD	EI	CO_2 emissions

Supplementary S4-1 (continued)

Reference	Data used	Time period	variables used	Technology	Environmental impact
108. Ji et al.,(2018)	79 Countries	2001-2010	P,A,AE,U,IN,SV,EI	IN,SV,EI	PM2.5 emissions
109. Munir and Ameer (2018)	Asia	1980-2014	P,A,U,FT,EU	EU	SO_2 emissions
110. Xu and Lin,(2018b)	China	1999-2015	P,A,EI,U,FT,IN	EI	CO_2 emissions
111. Wen et al.,(2018)	China	2000-2014	P,A,U,IN,ES,EI,PCE,PGE	PGE	CO_2 emissions
112. Liu et al.,(2018)	Fujian,China	1996-2016	P,A,U,IN,EI,FT,ES	EI	CO_2 emissions

A⁺ *affluence,* ***A²*** *quadratic form of affluence,* ***A**** *Per capita annual disposable income of rural households,* ***AE*** *age structure,* ***AG*** *Agricultural machinery,* ***BM*** *Per capita city building and maintenance capital,* ***BU*** *build up areas,* ***CC*** *coal consumption rate,* ***CCB*** *carbon emission intensity in Chinese commercial building ,* ***CDD*** *cooling degree day ,**CI*** *carbon emission intensity,* ***COD*** *chemical oxygen demand,* ***CPB*** *carbon emission intensity in Chinese public buildings ,* ***D*** *diet structure change,* ***DD*** *disaster degree,* ***E*** *consumption structure,* ***ED*** *educational level,* ***EF*** *energy efficiency,* ***EFI*** *ecological footprint intensity,* ***EGN*** *engel ratio,* ***EI*** *energy intensity,* ***EIM*** *efficiency improvement,* ***ES*** *energy structure,* ***EPR*** *energy productivity,* ***EP*** *energy price,* ***ER*** *environmental regulation,* ***EU*** *energy use,* ***F*** *financial support for rural areas,* ***FAI*** *Total fixed asset investment,* ***FD*** *Financial development ,* ***FD²*** *quadratic form of financial development,* ***FI*** *foreign investment,* ***FPR*** *fuel price,* ***FT*** *foreign trade degree,* ***GA*** *green areas per capita,* ***GSHP*** *floor area of Ground-Source Heat Pump,* ***HDD*** *heating degree days,* ***HS*** *household size,* ***IN*** *industrialization,* ***IN**** *refers to the share of secondary and tertiary(services sector) industry,* ***IN***** *refers to primary,* ***ISR*** *industrial structure rationalization industry,* ***ISU*** *industrial structural upgrading,* ***IST*** *industrial structural transformation,* ***IU*** *internet use,* ***L*** *land,* ***LAP*** *Labor productivity ,* ***LF*** *lad finance,* ***LLR*** *Line loss rat,* ***LR*** *share of households with private garden,* ***LUP*** *R land urbanization rate,* ***MENA*** *Middle East and North Africa,* ***ML*** *technological progress,* ***MTA*** *mean temperature anomaly,* ***NC*** *numbers of cars and buses ,* ***NPV*** *Number of private vehicles,* ***O*** *Degree of opening to the outside,* ***P*** *Population,**P²**quadratic form of population,* ***PCE*** *power consumption efficiency,* ***PD*** *population density,* ***PGE*** *power generation efficiency,* ***PIC*** *intensity of real economy,* ***PIUR*** *Per capita disposable income of urban resident,* ***PRE*** *precipitation,* ***PSI*** *Private sector investment in the transport sector,* ***PUB*** *number of public transportation ownership per person,* ***RAIL*** *Rail infrastructure,* ***RE*** *renewable energy,* ***R&D*** *Research And Development,* ***SV*** *service sector,* ***TEM*** *denotes annual average temperature (◦C),* ***TI*** *technology innovation,* ***TN*** *total nitrogen,* ***TP*** *total phosphorus,* ***TSE*** *the time-specific effect,* ***U*** *urbanization,* ***U²*** *quadratic form of urbanization,* ***UD*** *urban density,* ***URE*** *Urban employment level,* ***V*** *venden traffic density factor,* ***WA*** *wage ratio,* ***WI*** *water intensity.*

Supporting information S4-2. List of abbreviations

Table S4-2**.** List of abbreviations List of abbreviations

Abbreviation	Description	Abbreviation	Description
P	Population	EF	Energy efficiency
P^2	Quadratic form of population	L	Land
AE	Age structure	R&D	Research And Development
A^+	Affluence	HS	Household size
A^2	Quadratic form of affluence	FT	Foreign trade degree
U	Urbanization	E	Consumption structure
U^2	Quadratic form of urbanization	D	Diet structure change
UD	Urban density	EP	Energy price
IN	Industrialization	FI	Foreign investment
IN*	Refers to the share of secondary and tertiary (services sector) industry	GDP	Gross domestic product
IN**	Refers to primary industry	PD	Population density
SV	Service sector	F	Represents the financial support for rural areas
EI	Energy intensity	A*	Per capita annual disposable income of rural households
ES	Energy structure	TEM	Denotes annual average temperature (◦C)
CI	Carbon emission intensity	TN	Total nitrogen
ER	Environmental regulation	TP	Total phosphorus
PUB	Number of public Transportation ownership per person	PSI	Private sector investment in the transport sector
FPR	Fuel price	RAIL	Rail infrastructure

Supplementary data S4-2. (continued)

Abbreviation	Description	Abbreviation	Description
NC	Numbers of cars and buses	EFI	Ecological footprint intensity
COD	Chemical oxygen demand	LR	Share of households wiht private garden
ED	Educational level	MENA	Middle East and North Africa
GSHP	Floor area of Ground-Source Heat Pump	HA	The central heating area
PI	Policy investment.	PEC	Per capita energy consumption
FAI	Total fixed asset investment	BM	Per capita city building and maintenance capital
PIUR	Per capita disposable income of urban resident	CPB	Carbon emission intensity in Chinese public buildings
CC	Coal consumption rate,	LLR	Line loss rate
LAP	Labor productivity	URE	Urban employment level
PIC	Intensity of real economy	IST	Industrial structural transformation
ISR	Industrial structure rationalization	ISU	Industrial structural upgrading
ML	Technological progress	EIM	Denotes efficiency improvement
TI	Technology innovation	ETFP	Environmental total factor productivity
GA	Green areas per capita,	BU	Build up areas

Supplementary data S4-2. (continued)

Abbreviation	Description	Abbreviation	Description
TSE	The time-specific effect	EPR	Energy productivity
FD	Financial development	FD^2	Quadratic form of Financial development
LUPR	Land urbanization rate	LF	Land finance
CCB	Carbon emission intensity in Chinese commercial buildings	PCB	Per capita commercial buildings
ENI	PM2.5 concentrations	WI	Water intensity
RC	Residential consumption level	WA	Income ratio
EGN	The Engel Coefficient	RE	Renewable energy
AG	Agricultural machinery	DD	Disaster degree
O	Degree of opening to the outside	V	Traffic density factor
NPV	Number of private vehicles	IU	Internet uses
PRE	Precipitation	MTA	Mean temperature anomaly
HDD	Heating degree days	CDD	Cooling degree days.
EU	Energy use	PGE	Power generation efficiency
PCE	Power consumption efficiency	CMG	Common correlated effects mean group estimator
AMG	Augmented mean group estimator		

Hybrid life cycle assessment of an onshore wind farm in Guajira, Colombia.

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Supplementary data 6-1. Foreground data (LCI) wind farm

Supplementary data 6-2. Background concordances

Supplementary data 6-3. GTAP industries classification and direct services included in the foreground system

Supplementary data 6-1. Life cycle inventory

Different types of data were collect depending of the process. The background process that encompasses mainly the manufacturing of the wind turbine was obtained from the technical sheets of the N60/1300 KW provided by the Nordex Company. Information of the type of materials in each component were scaling up from a Vestas V82-1.65 MW turbine (2006).

Manufacturing

The manufacturing process encompasses the production of the rotor, nacelle (including the generator, gearbox yam system, control system, brakes) and the tower, it's also takes in account the lubricant and motor oils. Furthermore this study includes the construction of the foundations, the production of the 25000 KVA transformer and the internal and external cables of 13, 4 and 110 KVA respectively. For the manufacturing a total of 2.329 MWh/per turbine has been assumed from Elsam Engineering A/S (2004) with the electricity of Europe from ecoinvent 3.4.

Transport

Transport of the main components of the wind turbine was included (ex. foundation). Two types of transport were modeled, the transport of the components from Europe to Colombia, by sea from Hamburg Germany to Bolivar port in the Guajira region in Colombia, and the transport by road from the harbor to the wind farm. According to the owner of the project 7.4 Km of roads were needed to connect the port with the wind farm. The transport during the operation and maintenance includes a passenger transport from the operation facility of the wind farm to the wind turbines, and the transport needed from the wind farm to the recycling facility or the landfill depending of the material has been also included.

Construction.

During the construction process building machines are needed mainly cranes and digging machines. For the cranes follows Rydh et al., (2004) each wind turbine requires 16 hours and 10 L diesel oil. Furthermore for each wind turbine 400 m^3 of soil is removed (11,9 m x 11,9 m, and 2,5 m deep).Ecoinvent 3.4 was used for the digging machine. For the erection was necessary used mobile cranes, according with Rydh et al., (2004) each turbine requires the use of a crane for 16 hours and 10 L diesel oil/ h, 0,8 kg/L. 42 MJ/kg, 2,35 kg CO_2/L. finally 573 MWh/per turbine of electricity has been assumed from (Elsam Engineering A/S, 2004)

The electricity mix of Colombia used during the processs of construction, operation and maintenance is 70,39% hydropower, 15,15% natural gas, 8,41% hard coal, 5,27% fuel oil,0,7% sugarcane and 0,1% wind power. This process has been modeled taking in account the statistics of the last 4 years of the electricity production in Colombia taken from the Energy Mining Planning Unit UPME by his acronym in Spanish (UPME, 2016b)

Operation and Maintenance.

According to different authors for onshore wind turbines twice per year a technician must carry out inspection of each turbine. This mainly includes surveillance of turbines and cables. Transport for 1 km per year/ turbine has been included in a passenger car.(Ardente et al., 2008; Elsam Engineering A/S, 2004; Vestas Wind Systems, 2006)

During the lifetime of the farm a replacement of 1 blade and 15% of the generator per turbine has been included (Ardente et al., 2008). Using the information of Rydh et al., (2004) and the specifications of Nordex (2000) the change of lubricants and motor needed were 10,4 and 254 kg per turbine four times/20 years. In this process a total of 896 MWh/per turbine of electricity consumption has been assumed during the entire lifetime of the farm (Elsam Engineering A/S, 2004)

Decommissioning and recycling

Since the wind farm still have 4 years more of operation (assuming the life time 20 years) and no detailed data are actually available regarding Colombian wind farms the decommissioning and recycling process was modeled base on Vestas Wind Systems (2006) and Elsam Engineering A/S (2004) as follow, while other authors assumed a conservative value of 20% material recovery (Xu et al., 2018)

Table S6-1.1. recycling shares

Materials	scenario
Cast iron	90% recovery, 10% loss in landfill
Steel, engineering	90% recovery, 10% loss in landfill
Stainless steel	90% recovery, 10% loss in landfill
Steel	90% recovery, 10% loss in landfill
Cooper	90% recovery, 10% loss in landfill
Aluminum	90% recovery, 10% loss in landfill
Glass fibre	100% landfill
Epoxy resin	100% landfill
Plastic(polyethylene (PET) and styrene)	100% landfill
Electronics	100% landfill
Oil	
Foundation and roads	left in place

The foundation and roads are assumed to remain in place. For the decommissioning stage the same quantity of electricity and building machines used in the construction stage were assumed (ex. digging machine). A transport of 164 km was included to transport the materials from the wind farm to the landfill located in the capital of the state Rioacha.

According with the manufactured of the wind turbine Nordex (2000) each turbine has the capacity to produce a total 11,388 GWh/per year assuming a capacity factor of 100% which means that the wind turbine is operating the 8640 hour of the year. The wind farm under study has a total of 15 wind turbines (170,820 GWh/ per year). Taking in account the technical parameters of the wind farm: capacity factor of 42%, percentage of losses of 10% and a lifespan of 20 years the total amount of electricity produced by the wind farm is given by the following equation:

$$\text{Yield} = ((170820000*fc)-((170820000*fc)*losses))*años$$

$$\text{Yield} = ((170820000*0,42)-((170820000*0,42)*0,10))*20 = 1291399200 \text{ kWh/20 years}$$

Table S6-1.2. Overall LCI data for the production of 1 kWh of electricity.			
Item	Material	kg	Input
Rotor	Steel, engineering	kg	1.42E-05
	Steel	kg	3.98E-05
	Epoxy resin	kg	9.56E-05
	Cast iron	kg	1.07E-04
	Glass fibre	kg	1.43E-04
	Transport	tkm	2.57E-04
Nacelle	Electronics	kg	3.80E-06
	Oil	kg	3.80E-06
	Aluminum	kg	6.34E-06
	Epoxy resin	kg	9.13E-06
	Plastic	kg	1.27E-05
	Glass fibre	kg	1.37E-05
	Cooper	kg	2.03E-05
	Steel	kg	7.99E-05
	Stainless steel	kg	9.89E-05
	Steel, engineering	kg	1.65E-04
	Cast iron	kg	2.28E-04
	Transport	tkm	4.12E-04
Tower	Oil	kg	7.94E-06
	Copper	kg	1.03E-05
	Plastic	kg	1.59E-05
	Electronics	kg	1.75E-05
	Aluminum	kg	2.06E-05
	Transport	tkm	6.89E-04
	Steel	kg	1.00E-03
Internal clables	Cooper	kg	2.79E-05
	Plastic	kg	4.99E-05
	Aluminum	kg	5.73E-05
	Transport	tkm	8.67E-05
external cables	Cooper	kg	2.25E-07
	Aluminum	kg	8.99E-07
	Plastic high density	kg	1.43E-06
	Transport	tkm	2.46E-05
transformer 25 MVA	Rest: insulation,paint,wood,porcelain	kg	1.26E-06
	Cooper	kg	1.46E-06
	Transformer oil	kg	2.30E-06
	Steel	kg	5.59E-06
	Transport	tkm	1.02E-04
electricity(for all the manufacturing process)		KWh	1,89E-06
operation and maintenance	Electronics	kg	5.36E-08
	Aluminum	kg	8.94E-08
	Plastic	kg	1.79E-07

	Cooper	kg	2.86E-07
	Steel	kg	1.13E-06
	Stainless steel	kg	1.39E-06
	Steel, engineering	kg	2.32E-06
	Cast iron	kg	3.22E-06
	Diesel	MJ	4.37E-06
	Electricity	KWh	1.09E-05
	Oil	kg	1.16E-05
	Epoxy	kg	2.19E-05
	Fibre glass	kg	3.29E-05
	Transport	tkm	3.34E-04
recycling	Steel(recycling)	kg	1,43E-03
	Cast iron(recycling)	kg	3,22E-04
	Steel, engineering(recycling)	kg	1,72E-04
	Stainless steel(recycling)	kg	9,53E-05
	Aluminum(recycling)	kg	9,30E-05
	Cooper(recycling)	kg	7,99E-05
	Cooper(landfill)	kg	8.41E-06
	Aluminum(landfill)	kg	9.78E-06
	Stainless steel(landfill)	kg	1.00E-05
	Steel, engineering(landfill)	kg	1.81E-05
	Electronics(landfill)	kg	1.92E-05
	Cast iron(landfill)	kg	3.39E-05
	Plastic(landfill)	kg	9.01E-05
	Epoxy resin(landfill)	kg	1.14E-04
	Steel(landfill)	kg	1.50E-04
	Glass fibre(landfill)	kg	1.71E-04
	Transport	tkm	2.37E-03
	Oil	kg	1.05E-02

Supplementary data S6-2. Concordance between the foreground and the background

Table S6-2.1 concordances between the foreground and the background. Process from Ecoinvent 3.4

Material	process
Cast iron	Cast iron, at plant [RER]
Steel	steel converted, low alloyed, at plant [RER]
Steel, engineering	reinforcing steel at plant [RER]
Glass fibre	Market for glass fibre reinforced plastic, polyamide, injection moulded [GLO]
Epoxy resin	Market for epoxy resin, liquid [GLO]
Stainless steel	Market for sheet rolling, chromium steel [GLO]
	Market for steel, chromium steel 18/8 [GLO]
Cooper	Wire drawing, copper [RER]
	Market for copper [GLO]
Plastic	Polyethylene, HDPE, granulate, at plant [RER]
Aluminium	aluminum alloy ALMG3 at plant [RER]
Electrinics	Electronics production, for control units [RER]
Lubricanting oil	Market for lubricating oil [GLO]
Dielectric oil	Market for naphtha [RER]
	Bisphenol A production, powder [RER]
Concrete	Market for concrete, 20MPa [GLO]
Electricity Europa	Electricity, production mix RER [RER]
Electricity Colombia	Electricity production, hard coal [BR]
	Electricity production, wind, 1-3MW turbine, onshore [BR]
	Electricity production, oil [BR]
	Electricity production, natural gas, at conventional power plant [BR]
	Electricity production, hydro, reservoir, tropical region [BR]
	Cane sugar production with ethanol by-product [BR]
Transport	Transport, transoceanic freight ship [GLO]
	Market for transport, freight, lorry >32 metric ton, EURO3 [GLO]
	Market for transport, passenger car, small size, natural gas, EURO 3 [GLO]
Construction machines	Market for excavation, hydraulic digger [GLO]
	Diesel, burned in building machine [GLO]
	Market for road [GLO]
Recyling	Market for waste concrete [GLO]
	Market for electronics scrap from control units [GLO]
	Market for aluminum scrap, post-consumer [GLO]
	Market for scrap copper [GLO]
	Market for scrap steel [GLO]
	Market for waste glass [GLO]
	Market for waste plastic, mixture [GLO]
	Market for waste polystyrene [GLO]
	Market for waste polyethylene/polypropylene product [GLO]

Suplementary data S6-3 industries classification and direct services included in the foreground system

Table S6-3.1. Description of the GTAP classification system

GTAP	Code	Description
53	isr	Insurance: includes pension funding, except compulsory social security
1	pdr	Paddy Rice: rice, husked and unhusked
2	wht	Wheat: wheat and meslin
3	gro	Other Grains: maize (corn), barley, rye, oats, other cereals
4	v_f	Veg & Fruit: vegetables, fruitvegetables, fruit and nuts, potatoes, cassava, truffles,
5	osd	Oil Seeds: oil seeds and oleaginous fruit; soy beans, copra
6	c_b	Cane & Beet: sugar cane and sugar beet
7	pfb	Plant Fibres: cotton, flax, hemp, sisal and other raw vegetable materials used in textiles
8	ocr	Other Crops: live plants; cut flowers and flower buds; flower seeds and fruit seeds; vegetable seeds, beverage and spice crops, unmanufactured tobacco, cereal straw and husks, unprepared, whether or not chopped, ground, pressed or in the form of pellets; swedes, mangolds, fodder roots, hay, lucerne (alfalfa), clover, sainfoin, forage kale, lupines, vetches and similar forage products, whether or not in the form of pellets, plants and parts of plants used primarily in perfumery, in pharmacy, or for insecticidal, fungicidal or similar purposes, sugar beet seed and seeds of forage plants, other raw vegetable materials
9	ctl	Cattle: cattle, sheep, goats, horses, asses, mules, and hinnies; and semen thereof
10	oap	Other Animal Products: swine, poultry and other live animals; eggs, in shell (fresh or cooked), natural honey, snails (fresh or preserved) except sea snails; frogs' legs, edible products of animal origin n.e.c., hides, skins and furskins, raw , insect waxes and spermaceti, whether or not refined or coloured
11	rmk	Raw milk
12	wol	Wool: wool, silk, and other raw animal materials used in textile
13	frs	Forestry: forestry, logging and related service activities
14	fsh	Fishing: hunting, trapping and game propagation including related service activities, fishing, fish farms; service activities incidental to fishing
15	coa	Coal: mining and agglomeration of hard coal, lignite and peat
16	oil	Oil: extraction of crude petroleum and natural gas (part), service activities incidental to oil and gas extraction excluding surveying (part)
17	gas	Gas: extraction of crude petroleum and natural gas (part), service activities incidental to oil and gas extraction excluding surveying (part)
18	omn	Other Mining: mining of metal ores, uranium, gems. other mining and quarrying
19	cmt	Cattle Meat: fresh or chilled meat and edible offal of cattle, sheep, goats, horses, asses, mules, and hinnies. raw fats or grease from any animal or bird.
20	omt	Other Meat: pig meat and offal. preserves and preparations of meat, meat offal or blood, flours, meals and pellets of meat or inedible meat offal; greaves

Table S6-3.2. Total amount of direct services per activity

Component	US dollars*	GTAP Code
solid waste management program		
Coordination	12850	OBS
labor force	3984	OSG
technologist	9638	OBS
plastic buckets	281	OSG
plastic bags	107	OSG
tipper rental	8031	OTP
special waste container	268	OSG
hand compactor	4283	OSG
air quality management program		
technologist	6425	OBS
driver	2142	OTP
labor force	1328	OSG
tank car rental	8031	WRT
water transport	2677	WRT
equipment's various measurements	10709	OME
landscape impact management program		
specialized professional	5354	OBS
auxiliary	2677	OBS
logistical material	8031	CMN
Physical Plan Coordination	13653	OBS
Vegetative Protection Program		
labor force	12957	OSG
materials and equipment	5354	CMN
others	2677	OBS
contingencies	2099	OBS
research project propagation species	13386	OBS

Table S6.3.2 Continue

Component	US dollars*	GTAP Code
domestic and wild fauna protection program		
technical resource	6425	OSG
fiberglass spheres	2677	OME
Equipment for studies	1606	OME
warning signs	803	OMF
taller	803	OSG
coordination	27307	OFI
information and communication		
social communicator	6024	OBS
anthropologist	6024	OBS
technologist	3614	OBS
translator	803	OBS
printed material	8031	CMN
workshops visits	8031	OSG
Job Generation		
social communicator	3012	OBS
anthropologist	3012	OBS
technologist	1807	OBS
translator	1071	OBS
printed material	1874	CMN
environmental adduction		
social communicator	3012	OBS
anthropologist	3012	OBS
technologist	1807	OBS
graduate in ethno-education	4819	OBS
translator	803	OBS
printed material	8031	CMN
participation and community strengthening		
economist	6024	OBS
anthropologist	6024	OBS
technologist	3614	OBS
sanitary engineer	3012	OBS
translator	803	OBS
printed material	7496	CMN
information to officials		
anthropologist	3012	OBS
social communicator	3012	OBS
translator	402	OBS
printed material	2677	CMN

Table S6.3.2 Continue

Component	US dollars*	GTAP Code
implementation and monitoring of compensatory measures		
water treatment plant	80314	WTR
health post endowment	21417	OSG
endowment school amplification	42834	OSG
archaeological rescue and monitoring		
staff	23372	OBS
support staff	9544	OBS
transport	5328	OTP
laboratory analysis	6431	OBS
materials	535	CMN
Technological Dissemination		
social communicator	3012	OBS
anthropologist	3012	OBS
engineer	3012	OBS
translator	1071	OBS
printed material	18740	CMN
component	US dollars*	GTAP Code
servitude and payment occupation territory		
payments occupation of territory	12850	OBS
compensation	13921	OBS
logistics	19543	OBS
Contingencies 10%	51184	OBS
environmental management plan		
pms^{+} air quality		
environmental engineer	4016	OBS
sonometer	1285	OBS
hi-vol equipment	8031	OME
precision balance	3213	OME
membranes	2677	ome
sonometer	2409	OME
transport	8031	OTP
pms^{+} landscape quality control		
specialized professional	8031	OBS
auxiliary	2570	OBS
compass	161	OME
flexometer	37	OME
binoculars	535	OME
photographic camera	1606	OME
video recorder	803	OME
paper and materials	268	CMN
transport	5354	OTP

Table S6-3.2 continue

Component	US dollars*	GTAP Code
pms+ about vegetation		
forestry engineer	4350	OBS
forestry technician	5220	OBS
laborers	2158	OBS
transport	5354	OTP
materials and equipment	2677	CMN
contingencies	1976	OBS
pms+ about fauna		
biologist ornithologist	10709	OBS
auxiliary	3427	OBS
compass	80	OME
binoculars	134	OME
tape measure	37	OFI
transport	5354	OTP
Pms+ job generation	2677	OBS
pms+ compensatory measures	13386	OBS
pms+ technological divulgation	5354	OBS
pms+ conflicts generated project	7496	OBS
component	US dollars*	GTAP Code
Monitoring plan		
coordinating committee	38551	OBS
brigades	25701	OBS
materials and equipment	16063	CMN
operation and maintenance AO&M		
Line cost		
electric line use	304508	ELY
maintenances	68760	ELY
taxes	19646	ELY
plant cost	392914	
operation	275040	ELY
maintenance	628662	ELY
staff support	176811	ELY
Other cost		
surveillance	98228	OBS
insurances	78583	ISR
social management	294685	OSG
administrative and financial management	19646	OFI

*US 2011 constant dollars + Environmental management plans

The rebound effect on Latin American economies: Evidence from the Colombian residential sector.

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Supplementary information S7-1. Estimation model selection

Supplementary information S7-2 Test de Breusch-Pagan fixed effects dummies variables by state

Supplementary information S7-3 results model with climatic variable

Supplementary information S7-4 Error correction model

Supporting information S7-5 Model with price decomposition

Supplementary information S7-1 Estimation model selection

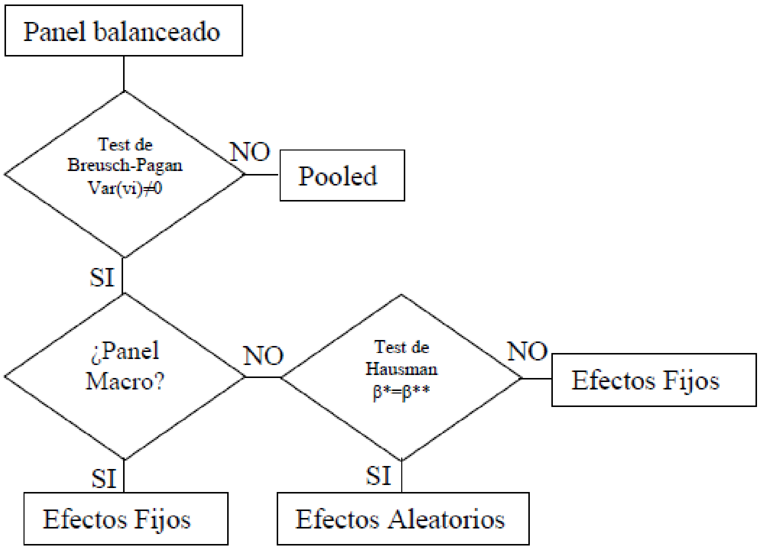

Figure S7-1 Procedure to determine the estimation model. Taking form Granados (2011)

According with Granados (2011) (see figure S7.1). The first step is to determined whether or not the panel data is balance, in this sense our panel data is a balance panel with 15 states and observations for all during the period 2005-2017. The next step is to determine whether or not the data set is a macro panel or not, in this sense 18 of the 33 states were excluded due to issues regarding the quality and availability of the data. Finally the Hausman test was to decide between random or fixed effect. The null hypothesis of both Breusch-Pagan (see table S7.1) and, Hausman (see table S7.2) is rejected, indicating that there exist un-observable components associated with each department, and there are systematic differences between estimators (fixed and random).

TableS7-1 Test de Breusch-Pagan Random effect

	Var	sd=sqrt(Var)
lnE	0.2037065	0.451335
e	0.0991868	0.3149394
u	0.0382649	0.195614
Test: Var(u)=0		
chibar2(01)=	49.65	
Prob>chibar2=	0.000	

Table S7-2. Test de Hausman

	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
fixed	fixed	random	difference	S.E
lnEP	-0.8088	-0.9590	0.1502378	0.167207
lnGP	0.5113	0.6015	0.0901877	0.141080
lnGDP	-0.4413	-0.0608	0.167562	0.014979

chi2(3)	=(b-B)'[(V_b-V_B)^(-1)](b-B)
	=7.52
Prob>chi2	=0.0569

Supplementary information S7.2 Breusch-Pagan Test

Table S7-3. Breusch-Pagan Test fixed effects dummies variables by state

	Var	sd=sqrt(Var)
lnE	0,2091746	0,4573561
e	0,1007596	0,3174265
u	0	0

Test: Var(u)=0	
chibar2(01)=	0,0
Prob>chibar2=	1,000

Supplementary information S7-3 results model with climatic variable

Table S7-4: Random Effects Model (RE): Total electricity demand in households 2005-2013 with climatic variable. Panel of 15 states of Colombia. Generalized Last Squares (GLS) estimation (cross-section weights).

variable	coefficient	t-statistics	prob.
α	-5.3835	-7.93	0.000**
lnEP	-0.8921	-4.30	0.000**
lnGP	0.5367	3.28	0.001**
lnGDP	-0.0605	-1.62	0.105
lnHDD	0.0130	1.23	0.220
Adjusted R-squared			
Within	0.0907		
Between	0.4853		
Overall	0.2976		
F-statistics	27.41		0.000***

Signif. codes: ***p<0.01. **p<0.05. *p<0.1.

Supplementary information S7-4 error correction model

To estimate the short-term effect of the direct rebound effect it is needed to develop an error correction model (ECM) (Freire-González, 2010; Sang-Hyeon, 2007; Wang & Lu, 2014). ECM is a specific econometrics model, which adopts a long-term co-integration equation as an instrument variable to solve the spurious regression problem (Wang & Lu, 2014). This model is the generalization of a partial adjustment model – Eq. (7.4) – with lags on endogenous and on exogenous variables, obtaining an estimation in differences.

$$\Delta Ln(E_{it}) = \alpha + \gamma_1 \Delta Ln\, EP_{it} + \gamma_2 \Delta Ln\, GP_{it} + \gamma_3\, \Delta Ln\, GDP_{it} + \gamma_3\, \Delta Ln\, E_{it-1} + \tau u_{it-1} + \varepsilon_{it}$$

Where u_{it-1} are the residuals resulting from estimations in eq 4, lagged one period – it represents the error correction term. In other to perform this model a precondition must be satisfied, all the variables should be non-stationary. To test such condition in the variables the Harris-Tzavalis unit roots test was performed. The results shows that dependient variable (electricity consumption is stationary) with which the ECM model cannot be performed (See table S5.4 for the results).

Table S7.4: Total electricity demand in households 2005-2013. Panel data fixed effects. 15 states. Yearly data. Error correction model

variable	statistic	z-statistics	prob.
lnΔE	0.0347	-8.5388	0.000**
lnΔEP	0.9127	2.7297	0.9968
lnΔGP	0.7724	0.9294	0.8237
lnΔGDP	0.3226	4.8442	0.000**
Adjusted R-squared			
Within	0.3862		
Between	0.0126		
Overall	0.3270		
F-statistics	9.56		0.0000***

Signif. codes: ***p<0.01. **p<0.05. *p<0.1.

The price of the electricity and the gas are non-stationary, whereas the electricity consumption and the GDP are stationary (see table S7.4), with which the ECM cannot be performed because the variables are not co-integrated (they do not share a common stochastic path).

Supporting information S7-5 Model with price decomposition

Table S7-5: Random Effects Model (RE): Total electricity demand in households 2005-2013 with climatic variable. Panel of 15 states of Colombia. Generalized Last Squares (GLS) estimation (cross-section weights). Model with price decomposition

variable	coefficient	t-statistics	prob.
α	-4.894	-7.18	0.000***
lnPmax	-1.0009	1.28	0.000***
lnPcut	1.398	4.3569	0.748
lnPrec	8.030	6.275	0.201
lnGP	0.6023	3.82	0.000***
lnGDP	-0.058	-1.56	0.118
Adjusted R-squared			
Within	0.1094		
Between	0.4852		
Overall	0.2941		
F-statistics	27.35		0.000***

Signif. codes: ***p<0.01. **p<0.05. *p<0.1.

Environmental rebound effect of energy efficiency improvements in Colombian households

Johan-Andrés Vélez-Henao[a,b*],Claudia Maria Garcia-Maso [a,c] ,David Font Vivanco[d], and Jaume Freire-González [e]

Supplementary information S8-1: Energy system model: method, assumptions and results

Supplementary information S8-2: Econometric model and results for the elasticity price of the electricity

Supplementary information S8-3: Price of the electricity by component for the year 2017

Supplementary information S8-4: Environmental footprints of current and improved energy matrix

Supplementary information S8-5: Yearly marginal budget shares of the AIDS model

Supplementary information S8.6: Colombian Household consumption expenditures (HCE) for the period 2000-2016 by DANE classification.

Supplementary information S8-7: Price indices for the HCE during the period 2000-2016

Supplementary information S8-8: Concordance between COICP and HCE classification system

Supplementary information S8-9: Concordance between HCE and GTAP classification system

Supplementary information S8-10: Environmental impact per monetary unit of each of the consumption categories (m).

Supplementary information S8-11: Environmental rebound effect results for the combined model

Supplementary information S8-12: Environmental rebound effect results for the single model

Supplementary information S8-13: Shares of the Marginal budget shares (MBS) and environmental impact intensity (EII) in percentage for each consumption group and their associated economic sectors in terms of climate change.

Supplementary information S8-1: Energy system model: method, assumptions and results

To measure the implications of the injection of 536 additional MW of wind power in the Colombian energy grid a representative simplified energy model has been used which includes the main electricity producing plants within the current national energy system (see table S8.1). Jointly the system model accounts for 8,910 MW of installed capacity (51% of the installed capacity at the end of the 2018) (CAISO, 2018; COLGENER S.A, 2008; CREG, 2013; García, Corredor, Calderón, & Gómez, 2013; Gensa, 2017; XM filiar de ISA, 2019). The whole system wasn’t possible to include due to the absence of data regarding the costs (installation, operation and maintenance) for all the plants that conform the energy system. The information for the capacity factor (See table S8.2) for the different technologies across the years was obtained from the (XM, 2019), moreover, data for the cost of the different components of the generation of electricity (installed cost, fixed and variable cost of operation and maintenance) was obtained(CAISO, 2018; eia & Administration, 2019; IRENA, 2018).The initial demand correspond to 28,557 GWh with a yearly increase of the electricity demand of 3.2% was assumed (see table S8-5).

To calculate the yearly generation cost of electricity a dispatch was made. The dispatch of the plants was done by calculating the yearly marginal costs and the amount of electricity offered by each plants according with the installed capacity and the capacity factor. In this sense the plants with the lowest cost of generation are the first to be dispatched, until the final cost with which the demand for electricity for the respective year is reached. The cost of the last plant with which the demand is satisfied becomes the price of generation for each year (see table S8-4 and S8-7). This procedure was applied for the reference model (8,910.4 MW) and the improved model (8,910.4 MW + 536 MW of wind power) (See table S8.6 for energy mix obtained from each model along the timespan).

The yearly monetary savings for introducing the 536 MW of wind power were obtained from the difference between the final price of electricity (generation, transmission, distribution, commercialization, losses and restriction) of the reference model and the improved model (see table S8-8). After accounting the monetary savings, the direct and indirect rebound effect was calculated. The direct rebound effect was calculated upon the elasticity price of the electricity (95.9%) see supplementary data S8-2. As an example, if electricity price are 1% cheaper, with the selected elasticity of electricity demand, electricity demand would increase by 0.959%. With the elasticity the additional yearly demand of electricity was obtained (see table S8-9). Finally the savings available to re-spend in other goods and services different from electricity were obtained after taking in account the additional consumption of electricity from the original savings calculated (see table S8-10).

Table S8-1.1 Power plans included in the model.

Plant	Resource	Capacity (MW)	Life time
San Carlos	Hydro	1,240	40
Guavio	Hydro	1,240	40
Chivor	Hydro	1,000	40
Pagua	Hydro	600	40
Guatapé	Hydro	560	40
Betania	Hydro	540	40
Tebsab	Gas	791	20
Alban	Hydro	429	40
Tasajera	Hydro	306	40
Jepirahi	Wind	18.4	20
Playas	Hydro	207	40
Termosierra AB	Gas	353	20
Zipaemg 5	Coal	63	30
Paipa 3	Coal	70	30
Jaguas	Hydro	170	40
Paipa 2	Coal	72	30
Calima	Hydro	132	40
Paipa 1	Coal	36	30
Termocalendaria 1	Gas	157	20
Termocalendaria 2	Gas	157	20
Flores 1 Gas	Gas	160	20
Paipa 4	Coal	160	30
Tasajero 1	Coal	163	30
Guajira 1	Coal	143	30
Guajira 2	Coal	143	30

Source. Own elaboration results from the energy model.

The capacity factor is defined as the resource (hydro, wind, thermal, etc.) availability both in terms of quantity and quality over a period of time of application(Gude, 2018), that is:

$$CF = \frac{Actual\ electricity\ production}{Maximum\ possible\ electricity\ output\ of\ a\ power\ plant}$$

See table S8.2. For the capacity factor of different generation technologies during period 2000 until 2015. With the above information the capacity factor for the period 2019-2030 were calculated according with the following steps. First, the calculation of the capacity factor for each technology for monthly, taking in account the seasonality of this variable. Second, the calculation of the probability distribution each capacity factor using the software @RISK. Finally, the calculation of the capacity factor for each techology until 2030 year (See table S8.3).

Table S8-1.2, we show the capacity factor of different generation technologies during period 2000 until 2015.

capacity factor	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Hydro	38.81%	18.26%	44.60%	48.58%	47.44%	52.02%	53.37%	56.88%	60.38%	53.39%	50.51%	59.85%	54.72%	52.29%	49.96%	46.58%
Coal	29.16%	25.42%	29.71%	37.95%	19.19%	28.11%	38.94%	45.34%	33.54%	57.67%	56.05%	20.24%	32.75%	61.50%	64.53%	71.18%
Gas	28.33%	18.15%	28.27%	19.96%	24.66%	27.26%	24.32%	23.71%	21.33%	36.03%	46.61%	20.81%	21.96%	21.39%	24.92%	32.19%
Wind					31.43%	30.71%	39.03%	30.92%	33.41%	35.76%	23.90%	25.58%	34.00%	35.71%	43.52%	42.38%

Table S8-1.3 Capacity factor 2019-2030

Capacity factor	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**
Hydro	50.06%	52.74%	48.64%	43.33%	52.97%	51.83%	49.72%	57.85%	55.34%	50.58%	48.13%	52.93%
Wind	40.68%	45.11%	45.37%	45.88%	34.27%	43.07%	37.42%	29.48%	27.51%	41.21%	45.73%	43.02%
Gas	42.59%	50.38%	55.97%	45.79%	42.10%	57.81%	50.19%	46.55%	56.08%	43.76%	53.94%	44.26%
Carbon	71.10%	78.88%	55.15%	96.82%	53.48%	28.25%	61.27%	76.70%	47.66%	59.35%	59.41%	64.77%

Electricity Cost

The electricity cost taking into account the cost investment and generation cost (See table S8-4).

Table S8-1.4. Marginal Cost ($US/MWh)

	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
ALBAN	55,37	52,73	56,90	63,48	52,51	53,60	55,73	48,35	50,40	54,84	57,47	52,55
BETANIA	51,34	48,90	52,75	58,82	48,70	49,70	51,67	44,86	46,75	50,85	53,27	48,73
Calima	81,99	77,99	84,29	94,24	77,67	79,31	82,54	71,39	74,48	81,18	85,16	77,73
Chivor	42,01	40,04	43,14	48,04	39,88	40,69	42,28	36,79	38,31	41,61	43,57	39,91
Guatapé	50,73	48,32	52,12	58,12	48,12	49,11	51,06	44,34	46,20	50,24	52,64	48,16
Guavio	39,19	37,37	40,25	44,79	37,22	37,97	39,44	34,35	35,76	38,82	40,64	37,25
Jaguas	75,32	71,66	77,43	86,53	71,36	72,86	75,82	65,62	68,44	74,58	78,22	71,42
Tasajera	61,92	58,94	63,63	71,05	58,69	59,92	62,32	54,02	56,32	61,32	64,28	58,74
Pagua	49,60	47,24	50,95	56,81	47,05	48,02	49,92	43,35	45,17	49,12	51,46	47,09
Playas	70,52	67,10	72,49	80,99	66,82	68,23	70,99	61,46	64,10	69,83	73,23	66,88
San Carlos	35,99	34,17	37,05	41,59	34,02	34,77	36,24	31,15	32,56	35,62	37,44	34,05
Eólica	61,89	56,03	55,72	55,12	73,05	58,58	67,09	84,58	90,45	61,13	55,30	58,64
Eólica 1	68,84	62,30	61,95	61,28	81,30	65,15	74,64	94,16	100,72	67,99	61,48	65,21
Guajira 1	192,97	166,21	151,57	180,87	194,97	147,39	166,76	178,22	151,30	188,35	156,53	186,45
Guajira 2	193,37	166,61	151,97	181,27	195,37	147,79	167,16	178,62	151,70	188,75	156,93	186,85
Paipa 1	118,01	103,17	95,05	111,30	119,12	92,73	103,47	109,83	94,90	115,45	97,80	114,40
Paipa 2	94,74	83,37	77,16	89,60	95,59	75,38	83,61	88,48	77,04	92,78	79,26	91,97
Paipa 3	93,36	82,10	75,94	88,27	94,21	74,17	82,33	87,16	75,82	91,42	78,02	90,62
Paipa 4	190,84	164,23	149,68	178,81	192,83	145,52	164,78	176,18	149,41	186,25	154,61	184,36
Tasajero 1	191,31	164,70	150,15	179,28	193,30	145,98	165,24	176,64	149,88	186,72	155,08	184,83
ZIPAEMG 5	92,45	81,52	75,54	87,51	93,27	73,83	81,74	86,42	75,43	90,56	77,56	89,79
FLORES 1	103,98	96,92	124,70	84,95	127,59	212,62	115,47	98,75	139,22	118,16	118,08	110,98
TEBSAB	50,09	48,33	55,26	45,34	55,99	77,21	52,96	48,79	58,89	53,63	53,61	51,84
Termocalendaria 1	99,17	92,89	117,59	82,25	120,15	195,75	109,38	94,52	130,49	111,77	111,70	105,39
Termocalendaria 2	100,72	94,29	119,59	83,40	122,22	199,66	111,19	95,96	132,81	113,64	113,56	107,10
Termosierra AB	64,43	61,16	74,02	55,62	75,36	114,72	69,75	62,01	80,74	70,99	70,95	67,67

Source. Own elaboration results from the energy model.

Table S8-1.5 Yearly electricity demand 2019-2030.

Year	Demand(MWh)
2019	28.557.600
2020	29.471.443
2021	30.414.529
2022	31.387.794
2023	32.392.204
2024	33.428.754
2025	34.498.474
2026	35.602.426
2027	36.741.703
2028	37.917.438
2029	39.130.796
2030	40.382.981

Source. Own elaboration results from the energy model.

Table S8-6. Energy grid for the references (without increasing the shares of wind) and the improved energy system (plus 536 MW wind). Sources. Results of energy model supporting information S8.1.

Reference												
years	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Technologies												
Hydro	71%	69%	69%	64%	75%	74%	70%	72%	73%	73%	69%	73%
Wind	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Coal	12%	13%	10%	17%	9%	5%	11%	12%	8%	10%	10%	11%
Gas	16%	18%	21%	18%	16%	21%	19%	16%	19%	17%	20%	16%
Total energy grid	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Improved (reference +Plus 536 MW Wind)												
Technologies												
Hydro	69%	67%	67%	61%	73%	71%	68%	71%	71%	70%	66%	70%
Wind	4%	4%	4%	4%	3%	4%	3%	2%	2%	4%	4%	4%
Coal	13%	13%	10%	18%	10%	5%	11%	12%	8%	11%	11%	11%
Gas	15%	16%	19%	16%	15%	20%	17%	14%	18%	15%	19%	15%
Total energy grid	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source. Own elaboration results from the energy model.

Table S8-7. Yearly price of electricity 2019-2030. Sources. Results of energy model supporting information S8-1 and supporting information S8-2.1.

Years	Reference generation price ($COP/KWh)	Improved generation price ($COP/KWh)	Reference electricity price ($COP/KWh)	Improved electricity price ($COP/KWh)	% savings
2019	183.5	163.7	494.5	474.8	4.0%
2020	174.3	169.9	485.3	480.9	0.9%
2021	217.0	188.1	528.0	499.2	5.5%
2022	279.1	244.7	590.2	555.7	5.8%
2023	229.6	197.6	540.7	508.6	5.9%
2024	213.0	213.0	524.1	524.1	0.0%
2025	371.7	231.4	682.7	542.4	20.5%
2026	183.4	183.4	494.5	494.5	0.0%
2027	220.2	220.2	531.3	531.3	0.0%
2028	427.1	421.9	738.2	732.9	0.7%
2029	426.8	421.5	737.8	732.6	0.7%
2030	435.9	396.4	747.0	707.5	5.3%

Source. Own elaboration results from the energy model.

Table S8-8. Yearly monetary savings.

Years	Savings current $Millions COP
2019	564876.33
2020	129835.43
2021	877680.54
2022	1080237.70
2023	1039144.14
2024	-
2025	4839958.73
2026	-
2027	-
2028	199555.89
2029	205941.68
2030	1595182.55

Source. Own elaboration results from the energy model.

Table S8-9. Yearly Direct rebound effect 2019-2030 in MWh.

Years	Direct rebound (MWh)
2019	1095396.01
2020	256559.797
2021	1594003.98
2022	1755372.04
2023	1843076.95
2024	0
2025	6798740.58
2026	0
2027	0
2028	259254.615
2029	267679.423
2030	2048030.45

Source. Own elaboration results from the energy model.

Table S8-10. Yearly indirect rebound effect 2019-2030 in $ Millions COP.

Year	Indirect rebound ($ Millions COP)
2019	44827.13
2020	6453.518
2021	81983.52
2022	104702.37
2023	101730.95
2024	0
2025	1152266.69
2026	0
2027	0
2028	9546.22
2029	9852.38
2030	146302.47

Source. Own elaboration results from the energy model.

Model validations

To validate the model, the amount of electricity generated by each plant included in the simplified model was initially compared with the amount of real energy generated by those plants in the year 2019. The results graphically show that the plants follow the generation trend of the real system (see figure S8-1.1)

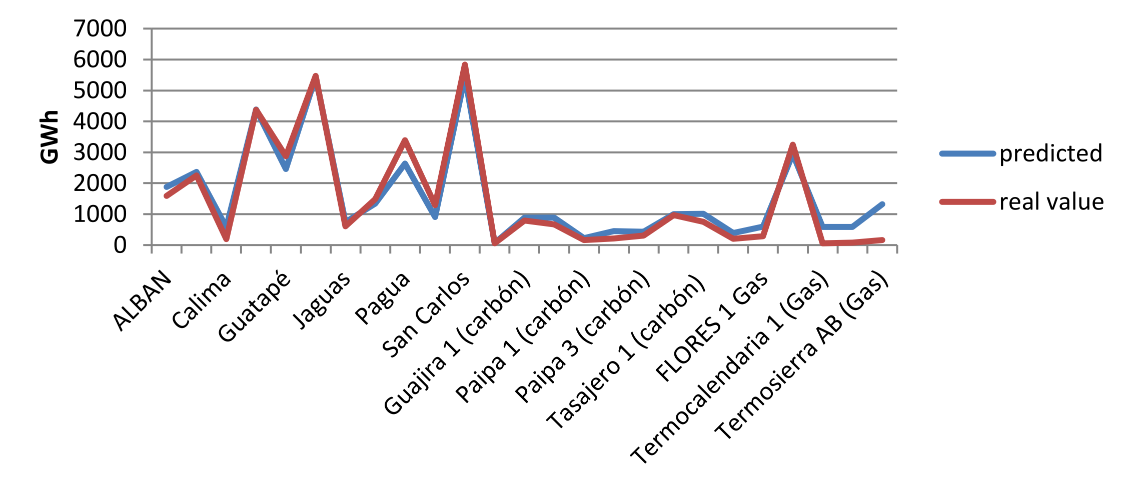

Figure S8.1 yearly electricity generation predicted vs real values in 2019

Additionally, the MSE "mean squared error" was calculated with a value of 119.4. An acceptable value for the proportions handled (values in GWh). After confirming that the values obtained comply with the assumptions of normality (Shapiro-Wilk normality test) and homocedasticity (Bartlett test), the model was validated by means of the "Test t de Student" test to determine whether the values obtained by the model are statistically significant when compared with the real data. According to the test performed at a 95% significance level, it can be concluded that there is no statistical difference between the model used and the actual values for energy generation.

Test the Shpairo-Wilk results

```
Shapiro-Wilk normality test

data:  datos$predichos - datos$reales
W = 0.94903, p-value = 0.2384
```

Test the Bartlett results

```
Bartlett test of homogeneity of variances

data:  values by ind
Bartlett's K-squared = 0.3368, df = 1, p-value = 0.5617
```

Test t.student test results:

```
Paired t-test
```

data: datos$predichos and datos$reales
t = 1.1746, df = 24, p-value = 0.2517
alternative hypothesis: true difference in means is not equal to 0. 95 percent confidence interval: -67.46915- 245.70166
sample estimates:
mean of the differences 8.911.626

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Supplementary information S8- 2: Econometric model and results for the elasticity price of the electricity.

Follow Haas and Biermayr (2000) the price and income elasticities are estimated using the following econometric model.

$$Ln(E_{it}) = \alpha + \beta_1 Ln\ EP_{it} + \beta_2 Ln\ GP_{it} + \beta_3\ Ln\ GDP_{it} + u_{it}$$

In which α is a constant, β1- β3 are the parameters to be estimated, and u_{it} represents the random error term. E_{it}: Is the explanatory variable and represents the electricity consumption in GWh per habitant (number of households with electricity services) in the state i and period t of the households.EP_{it}: represents the price of electricity in the state i and period t. EP was calculated as an average price for each year between the electricity price for the different household income levelsGP_t: Price of the household gas in the state i and period t. GDP_{it}:Represents the income variable per capita (number of households with electricity services) measured for the gross domestic product GDP divided by the number of households with electricity service in the state i and period t. This variable is selected as a proxy of the household income due to the fact that the more desegregated data for the income variable provide by the official entity in charge is in terms of GDP as a whole. HDD_t: Represents the Heating Degree-Days of Colombia in period t (base: 18°C) has been taking in account to include a climatic variable; however the statistical test demonstrated that the climatic variable is not significant for the case of Colombia (see table S8.2 for results of the model with HDD_t variable). Therefore the climatic variable has been removed of the econometric model.

Data collection

Colombia counts with 33 states including the capital city (Bogota). Information for all the variables mentioned above where collected for all the states during the years 2005-2017, however due to the lack of information and accuracy for some states a sample of 15 states for the period 2005-2013 were finally selected, jointly this states accounts for the 56% of the gross domestic product and the 80% of the total housing units in 2013 (DANE, 2018b, 2018a).

Data of the total household gas consumption, the number of households, price of natural gas and electricity for the period 2005-2017 was obtained of the superintendence of public services domiciliary (SUI by his acronym in Spanish) (SUI, 2018). Data of the income was obtained of National Administrative Department of Statistics (DANE by his acronym in Spanish) (DANE, 2018b), all the monetary variables are in constant price from 2005. The time period of the data is annually.

The panel data regression suggests that the direct RE for all household energy services consuming electricity is 95.9% (see table S8.2.1). Thus, only 5.1% of potential savings achieved. Except for GDP, all the variables proved where significant at 10% or more level of confidence.

Table S8-2.1: Random Effects Model (RE): Total electricity demand in households 2005-2013. Panel of 15 states of Colombia. Generalized Last Squares (GLS) estimation (cross-section weights).

variable	**coefficient**	**t-statistics**	**prob.**
α	-5.133	-8.03	0.000**
lnEP	-0.959	-4.78	0.000**
lnGP	0.6015	3.84	0.000**
lnGDP	-0.0608	-1.63	0.104
Adjusted R-squared			
Within	0.0901		
Between	0.4732		
Overall	0.2829		
F-statistics	24.69		0.0000***

Signif. codes: ***p<0.01. **p<0.05. *p<0.1.

Table S8-2.2: Random Effects Model (RE): Total electricity demand in households 2005-2013 with climatic variable. Panel of 15 states of Colombia. Generalized Last Squares (GLS) estimation (cross-section weights).

variable	**coefficient**	**t-statistics**	**prob.**
α	-5.3835	-7.93	0.000**
lnEP	-0.8921	-4.30	0.000**
lnGP	0.5367	3.28	0.001**
lnGDP	-0.0605	-1.62	0.105
lnHDD	0.0130	1.23	0.220
Adjusted R-squared			
Within	0.0907		
Between	0.4853		
Overall	0.2976		
F-statistics	27.41		0.000***

Signif. codes: ***p<0.01. **p<0.05. *p<0.1.

Supplementary information S8-3: Price of the electricity by component for the year 2017.

Table S8-3.1 presents the price of the electricity by components for the most representative companies during the year 2017.

Table S8-3.1. Average electricity price by component for the most representative companies during the year 2017.

	$COP/kwh average							% regarding the CUV						
Company	G	T	D	C	PR	R	Cuv	G	T	D	C	PR	R	Cuv
Electricaribe (caribe)	148.47	28.71	119.23	60.93	28.90	24.38	410.61	0.36	0.07	0.29	0.15	0.07	0.06	1.00
Epm unificado antioquia	158.98	28.71	175.03	40.36	31.10	24.38	458.55	0.35	0.06	0.38	0.09	0.07	0.05	1.00
Codensa bogota	160.08	28.71	162.61	42.32	29.70	24.38	447.79	0.36	0.06	0.36	0.09	0.07	0.05	1.00
Eemcali cali	186.66	28.71	162.06	40.15	35.16	24.38	477.10	0.39	0.06	0.34	0.08	0.07	0.05	1.00
Epsa valle	169.12	28.71	162.06	72.42	32.26	24.38	488.93	0.35	0.06	0.33	0.15	0.07	0.05	1.00
Essa santander	168.28	28.71	160.35	52.95	32.15	24.38	466.80	0.36	0.06	0.34	0.11	0.07	0.05	1.00
Cens n santander	169.22	28.71	160.35	52.40	32.32	24.38	467.36	0.36	0.06	0.34	0.11	0.07	0.05	1.00
Chec caldas	170.20	28.71	160.35	76.64	32.47	24.38	492.73	0.35	0.06	0.33	0.16	0.07	0.05	1.00
Enertolima tolima	175.01	28.71	190.14	65.17	33.28	24.38	516.68	0.34	0.06	0.37	0.13	0.06	0.05	1.00
Emsa meta	167.44	28.71	193.39	57.43	32.57	24.38	503.91	0.33	0.06	0.38	0.11	0.06	0.05	1.00
Electrohuila huila	167.11	28.71	162.61	74.71	31.16	24.38	488.67	0.34	0.06	0.33	0.15	0.06	0.05	1.00
Ebsa boyaca	171.88	28.71	162.61	83.36	32.73	24.38	503.65	0.34	0.06	0.32	0.17	0.06	0.05	1.00
Enerca casanare	187.20	28.71	193.39	51.51	35.26	24.38	520.44	0.36	0.06	0.37	0.10	0.07	0.05	1.00
Average	**169.20**	**28.71**	**166.47**	**59.26**	**32.23**	**24.38**	**480.25**	**0.35**	**0.06**	**0.35**	**0.12**	**0.07**	**0.05**	**1.00**

Prices in current COP/KWh. CUV:Unitary variable cost. generation (G), transmission (T), distribution (D), commercialization (C), losses (PR), and restrictions (R). Source (SUI, 2018)

Table S8-3.2. Average electricity of generation for the most representative companies during the year 2017.

Generation													
	January	February	march	April	May	June	July	August	September	October	November	December	average
Electricaribe (caribe)	128.1	132.62	163	153.06	142.47	134.29	135.18	138.16	159	164.27	166.1	166	148
Epm unificado antioquia	128.1	132.62	163	164.21	160.83	158.27	165.29	163.5	165	169.53	169.5	168	159
Codensa bogota	154.15	159.17	169.11	157.58	153.95	152.08	155.41	158.34	162	165.84	167.4	166	160
Emcali cali	152.03	189.94	195.04	192.83	190.29	187.88	185.49	186.75	182	186.14	195.4	197	187
Epsa valle	159.3	170.68	170.98	171.58	170.05	168.91	168.56	169.14	169	169.57	169.8	171	169
Essa satander	154.19	166.73	175.12	169.2	166.17	163.17	170.1	165.77	168	172.22	175.2	173	168
Cens n santander	151.08	170.5	173.56	171.11	166.18	170.52	170.94	171.36	171	171.8	172	170	169
Chec caldas	155.17	165.96	174.63	169.54	165.93	170.04	175.72	175.78	173	173.16	173.9	169	170
Enertolima tolima	164.87	174.11	177.56	176.95	170.64	175.15	174.81	176.46	177	177.71	176.5	178	175
Emsa meta	166.77	166.37	169.74	164.67	163.46	163.22	168.79	168.73	166	169.28	170.1	172	167
Electrohuila huila	152.03	189.94	195.04	162.43	158.98	165.43	163.89	164.2	158	164.16	166.5	165	167
Ebsa boyaca	154.04	168.79	175.45	167.9	168.46	175.77	173.22	174.14	177	176.15	175.7	176	172
Enerca casanare	187.84	190.81	187.53	184.9	189.2	187.01	186.33	183.73	192	185.77	185.2	187	187

Prices in current COP/KWh. CUV:Unitary variable cost. Source (SUI, 2018)

Table S8-3.3. Average electricity of commercialization for the most representative companies during the year 2017.

Commercialization													
	January	February	march	April	May	June	July	August	September	October	November	December	average
Electricaribe (caribe)	61.22	58.62	60.6	66.45	62.99	59.51	58.17	58.96	60	61.42	61.85	61.4	60.9
Epm unificado antioquia	39.58	39.22	40.19	41.31	39.62	40.48	40.48	40.56	40.8	40.55	40.55	40.9	40.4
Eodensa bogota	41.64	39.84	41.46	44.04	43.85	41.7	41.94	41.01	43.8	42.9	43.64	42.1	42.3
Emcali cali	40.31	39.55	37.13	41.84	40.24	40.92	41.19	40.5	40.8	40.45	39.34	39.6	40.2
Epsa valle	67.78	72.78	74.22	73.67	72.73	74.04	75.5	71.29	72.8	70.42	70.77	73.1	72.4
Essa satander	51.47	51.3	51.86	55.32	51.6	52.71	51.97	54.37	54.7	52.64	53.45	54	52.9
Cens n santander	48.55	49.42	54.48	57.49	55.23	53	51.7	52.08	53.1	51.58	50.72	51.4	52.4
Chec caldas	73.4	73.84	74.72	76.44	77.43	78.84	76.57	77.93	77.3	78.87	75.03	79.3	76.6
Enertolima tolima	64.31	65.05	64.36	64.75	66.08	65.7	65.21	65.76	65.7	63.96	65.34	65.8	65.2
Emsa meta	57.45	54.83	59.13	60.93	54.65	56.09	55.9	57.78	59	59.81	56.6	57	57.4
Electrohuila huila	70.31	75.51	72.62	75.46	77.64	77.32	78.25	74.77	75.9	74	71.25	73.5	74.7
Ebsa boyaca	79.71	83.5	81.72	79.93	86.88	82.78	84.59	84.31	85.7	82.4	84.25	84.6	83.4
Enerca casanare	47.29	48.69	49.1	50.05	52.51	51.14	48.57	52.62	53.6	53.55	55.87	55.1	51.5

Prices in current COP/KWh. CUV:Unitary variable cost. Source (SUI, 2018)

Table S8-3.3. Average electricity of restrictions for the most representative companies during the year 2017.

Restriction													
	January	February	march	April	May	June	July	August	September	October	November	December	average
	24.33	23.68	20.46	20.03	27.81	26.4	26.9	28.27	25.8	22.42	21.15	25.3	24.4

Prices in current COP/KWh. CUV:Unitary variable cost. Source (SUI, 2018)

Table S8-3.4. Average electricity of losses the most representative companies during the year 2017.

Losses													
	January	February	march	April	May	June	July	August	September	October	November	December	average
Electricaribe (caribe)	25.41	26.48	31.71	29.88	27.51	25.18	26.88	27.89	30.3	31.67	32.26	31.7	28.9
Epm unificado antioquia	28.7	31.32	32.91	31.35	29.97	29.01	31.51	31.75	31	32.06	32.06	31.6	31.1
Codensa bogota	28.67	29.8	31.65	29.52	28.29	27.09	29.12	30.12	29.6	30.73	31.24	30.6	29.7
Emcali cali	29.36	35.92	36.99	36.44	35.19	34.02	35.26	35.53	34	35.27	37.15	36.7	35.2
Epsa valle	30.52	32.71	32.95	32.88	32.03	30.83	32.37	33.01	32	32.47	32.8	32.5	32.3
Essa satander	29.69	32.09	33.75	32.67	31.13	30.26	32.64	32.45	31.8	32.84	33.61	32.8	32.2
Cens n santander	29.17	32.73	33.48	33.02	31.13	31.41	32.79	33.38	32.3	32.78	33.18	32.4	32.3
Chec caldas	29.85	31.95	33.88	32.56	31.11	31.27	33.57	34.12	32.6	33.05	33.47	32.2	32.5
Enertolima tolima	31.51	33.56	34.09	33.77	32.16	31.91	33.44	34.24	33.3	33.84	33.94	33.7	33.3
Emsa meta	34.85	35.13	32.76	31.79	31	30.71	32.41	32.93	31.5	32.4	32.84	32.6	32.6
Electrohuila huila	29.36	31.45	32.21	31.38	29.95	30.32	31.61	32.19	30.1	31.59	32.25	31.5	31.2
Ebsa boyaca	29.67	32.4	33.71	32.28	31.76	31.98	33.15	33.85	33.3	33.73	33.76	33.2	32.7
Enerca casanare	35.22	36.05	35.71	35.08	35.23	33.85	35.34	35.45	35.6	35.16	35.37	35	35.3

Prices in current COP/KWh. CUV:Unitary variable cost. Source (SUI, 2018)

Table S8-3.5. Average electricity of transmission for the most representative companies during the year 2017.

Transmission													
	January	February	march	April	May	June	July	August	September	October	November	December	average
	29.56	30.51	31.92	31.16	24.48	21.26	29.11	32.91	26.4	30.06	30.44	26.7	28.7

Prices in current COP/KWh. CUV:Unitary variable cost. Source (SUI, 2018)

Table S8-3.6. Average electricity of distribution for the most representative companies during the year 2017.

Distribution													
	January	February	march	April	May	June	July	August	September	October	November	December	average
Electricaribe (caribe)	118.21	121.57	121.47	124.07	117.96	116.94	118.21	118.98	119	119.83	115.9	118	119
Epm unificado antioquia	173.01	172.65	174.69	175.35	173.17	173.42	176.99	176.61	174	175.99	178.1	176	175
Codensa bogota	166.64	164.75	159.61	161.24	167.23	163.86	156.85	157.73	167	167.35	161.3	158	163
Emcali cali	164.45	160.54	158.12	164.13	163.73	159.8	157.87	162.75	168	166.17	160.1	159	162
Epsa valle	164.45	160.54	158.12	164.13	163.73	159.8	157.87	162.75	168	166.17	160.1	159	162
Essa satander	173.01	172.65	174.69	175.35	173.17	173.42	176.99	176.61	174	119.83	115.9	118	160
Cens n santander	173.01	172.65	174.69	175.35	173.17	173.42	176.99	176.61	174	119.83	115.9	118	160
Chec caldas	173.01	172.65	174.69	175.35	173.17	173.42	176.99	176.61	174	119.83	115.9	118	160
Enertolima tolima	189.12	188.92	189.59	188.09	191.48	190.29	191.68	189.72	190	190.11	190.1	193	190
Emsa meta	197.2	197.2	192.04	195.86	193.86	188.88	189.68	195.39	195	190.31	190.1	195	193
Electrohuila huila	166.64	164.75	159.61	161.24	167.23	163.86	156.85	157.73	167	167.35	161.3	158	163
Ebsa boyaca	166.64	164.75	159.61	161.24	167.23	163.86	156.85	157.73	167	167.35	161.3	158	163
Enerca casanare	197.2	196.04	193.21	195.86	193.86	188.88	189.68	195.39	195	190.31	190.1	195	193

Prices in current COP/KWh. CUV:Unitary variable cost. Source (SUI, 2018)

Supplementary information S8-4: Environmental footprints of current and improved energy matrix.

Table S8-4.1. Environmental impacts for different energy technologies (impact/KWh).

International Reference Life Cycle Data System (ILCD) impact characterization factors											
Tag	**Geography**	**CC**	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
Hydro	Brazil	0.0653	2.87E-05	0.0587	7.37E-06	8.09E-05	1.22E-09	2.19E-09	3.89E-10	3.60E-05	6.24E-06
Hard coal	Brazil	0.9261	0.0076	4.9570	9.75E-04	1.07E-02	5.96E-08	2.09E-07	2.58E-09	2.69E-03	3.81E-04
Wind	Brazil	0.0157	0.0001	2.0454	1.95E-05	1.93E-04	8.10E-09	1.87E-08	1.20E-09	6.35E-05	1.63E-05
Natural gas	Brazil	0.5575	0.0007	0.2910	2.09E-04	2.26E-03	2.06E-09	1.16E-08	3.71E-08	7.65E-04	2.61E-05

Source. Ecoinvent 3.4 (2019)

Table S8-4.2. Environmental impacts for producing 1 KWh of electricity with the reference and improved energy mix across the period 2019-2030.

	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
	BASE KWH									
2019	0.2518	0.0011	0.7066	1.60E-04	1.75E-03	8.59E-09	2.93E-08	6.63E-09	4.83E-04	5.59E-05
2020	0.2619	0.0011	0.7261	1.66E-04	1.82E-03	8.80E-09	3.02E-08	7.17E-09	5.03E-04	5.74E-05
2021	0.2508	0.0009	0.5825	1.43E-04	1.56E-03	7.02E-09	2.41E-08	8.26E-09	4.44E-04	4.65E-05
2022	0.3064	0.0015	0.9622	2.14E-04	2.34E-03	1.16E-08	4.01E-08	7.53E-09	6.35E-04	7.55E-05
2023	0.2224	0.0008	0.5516	1.29E-04	1.41E-03	6.76E-09	2.28E-08	6.37E-09	3.97E-04	4.41E-05
2024	0.2116	0.0005	0.3526	9.76E-05	1.06E-03	4.28E-09	1.44E-08	8.25E-09	3.21E-04	2.89E-05
2025	0.2491	0.0010	0.6263	1.48E-04	1.62E-03	7.59E-09	2.60E-08	7.51E-09	4.55E-04	4.98E-05
2026	0.2436	0.0010	0.6739	1.53E-04	1.67E-03	8.22E-09	2.80E-08	6.39E-09	4.63E-04	5.35E-05
2027	0.2262	0.0007	0.4825	1.21E-04	1.32E-03	5.88E-09	1.99E-08	7.62E-09	3.81E-04	3.89E-05
2028	0.2373	0.0009	0.6127	1.42E-04	1.55E-03	7.47E-09	2.54E-08	6.74E-09	4.35E-04	4.87E-05
2029	0.2551	0.0010	0.6211	1.49E-04	1.63E-03	7.49E-09	2.57E-08	8.08E-09	4.62E-04	4.94E-05
2030	0.2388	0.0010	0.6338	1.46E-04	1.59E-03	7.73E-09	2.63E-08	6.57E-09	4.44E-04	5.03E-05

	CC	A	E	MEUT	TEUT	CE	NCE	OD	POC	RES
	ENVIRONMENTAL EFFICIENCY KWh									
2019	0.2471	0.0011	0.7978	1.62E-04	1.78E-03	9.12E-09	3.09E-08	6.11E-09	4.87E-04	5.79E-05
2020	0.2567	0.0011	0.8189	1.68E-04	1.84E-03	9.34E-09	3.17E-08	6.62E-09	5.06E-04	5.95E-05
2021	0.2444	0.0009	0.6737	1.44E-04	1.57E-03	7.49E-09	2.53E-08	7.73E-09	4.43E-04	4.80E-05
2022	0.2996	0.0015	1.0687	2.16E-04	2.36E-03	1.22E-08	4.19E-08	6.81E-09	6.38E-04	7.79E-05
2023	0.2190	0.0009	0.6289	1.31E-04	1.43E-03	7.21E-09	2.41E-08	5.97E-09	4.01E-04	4.58E-05
2024	0.2058	0.0005	0.4326	9.77E-05	1.06E-03	4.64E-09	1.53E-08	7.86E-09	3.19E-04	2.98E-05
2025	0.2447	0.0010	0.7101	1.50E-04	1.64E-03	8.08E-09	2.73E-08	7.03E-09	4.59E-04	5.17E-05
2026	0.2418	0.0011	0.7477	1.57E-04	1.72E-03	8.75E-09	2.96E-08	5.95E-09	4.71E-04	5.59E-05
2027	0.2238	0.0008	0.5452	1.23E-04	1.34E-03	6.27E-09	2.11E-08	7.27E-09	3.85E-04	4.06E-05
2028	0.2324	0.0010	0.7013	1.44E-04	1.57E-03	7.95E-09	2.67E-08	6.27E-09	4.38E-04	5.04E-05
2029	0.2487	0.0010	0.7145	1.50E-04	1.64E-03	7.98E-09	2.70E-08	7.53E-09	4.61E-04	5.10E-05
2030	0.2340	0.0010	0.7232	1.48E-04	1.61E-03	8.22E-09	2.77E-08	6.09E-09	4.46E-04	5.21E-05

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES). Ecoinvent 3.4 source. Ecoinvent (2019)

Table S8-4.3. Environmental savings between the reference and improved energy mix across the period 2019-2030.

	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
SAVINGS KWh										
2019	0.0047	-3.24E-05	-9.12E-02	-2.45E-06	-2.66E-05	-5.33E-10	-1.52E-09	5.19E-10	-3.84E-06	-2.02E-06
2020	0.0052	-3.20E-05	-9.28E-02	-2.29E-06	-2.49E-05	-5.39E-10	-1.53E-09	5.52E-10	-3.25E-06	-2.02E-06
2021	0.0064	-2.05E-05	-9.12E-02	-9.12E-07	-9.68E-06	-4.68E-10	-1.25E-09	5.29E-10	4.43E-07	-1.46E-06
2022	0.0068	-3.74E-05	-1.06E-01	-2.44E-06	-2.66E-05	-6.31E-10	-1.79E-09	7.20E-10	-2.79E-06	-2.38E-06
2023	0.0034	-2.83E-05	-7.73E-02	-2.32E-06	-2.52E-05	-4.53E-10	-1.30E-09	4.00E-10	-4.11E-06	-1.74E-06
2024	0.0058	-1.01E-05	-8.00E-02	-3.81E-08	-1.01E-08	-3.59E-10	-9.09E-10	3.91E-10	2.14E-06	-8.86E-07
2025	0.0044	-2.96E-05	-8.38E-02	-2.20E-06	-2.39E-05	-4.90E-10	-1.39E-09	4.86E-10	-3.36E-06	-1.85E-06
2026	0.0017	-4.30E-05	-7.38E-02	-4.06E-06	-4.45E-05	-5.27E-10	-1.61E-09	4.35E-10	-8.78E-06	-2.43E-06
2027	0.0024	-2.76E-05	-6.26E-02	-2.38E-06	-2.60E-05	-3.95E-10	-1.16E-09	3.50E-10	-4.60E-06	-1.64E-06
2028	0.0049	-2.63E-05	-8.86E-02	-1.82E-06	-1.97E-05	-4.86E-10	-1.35E-09	4.76E-10	-2.33E-06	-1.71E-06
2029	0.0064	-2.21E-05	-9.34E-02	-1.05E-06	-1.13E-05	-4.85E-10	-1.31E-09	5.47E-10	1.48E-07	-1.55E-06
2030	0.0048	-2.77E-05	-8.94E-02	-1.97E-06	-2.14E-05	-4.97E-10	-1.39E-09	4.82E-10	-2.72E-06	-1.78E-06

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES).

Supplementary information S8-5: Yearly marginal budget shares of the AIDS model

$$MBS_t^i = \alpha^i + \sum_{s=1,\dots,n} \gamma_s^i lnp_t^s + \beta^i \left(\frac{x_t^s}{P_t}\right)$$

Where n equals to the total number of consumption groups (s), x is total expenditures, P is defined here as the Stone's price index, p is the price of a given category, t indicates time, and α (constant coefficient), β (slope coefficient associated with total expenditure) and γ (slope coefficient associated with price) are the unknown parameters.

Table S7-5.1. Coefficients of the AIDS model. Estimation Method: Linear Approximation (LA) with Stone Index (S).

Coefficients	Estimate	Std, Error	t value	Pr(>|t|)
alpha 1	3.2844	0.6813	4.8211	0.0000
alpha 2	1.6233	0.4025	4.0328	0.0001
alpha 3	-1.1452	0.5442	-2.1045	0.0386
alpha 4	0.9241	0.4782	1.9322	0.0570
alpha 5	-0.9004	0.5609	-1.6052	0.1125
alpha 6	-2.9390	0.6065	-4.8457	0.0000
alpha 7	-0.7185	0.4434	-1.6206	0.1092
alpha 8	0.8714	1.0004	0.8711	0.3864
beta 1	-0.1075	0.0237	-4.5441	0.0000
beta 2	-0.0493	0.0140	-3.5264	0.0007
beta 3	0.0421	0.0189	2.2250	0.0290
beta 4	-0.0294	0.0166	-1.7655	0.0814
beta 5	0.0369	0.0195	1.8934	0.0621
beta 6	0.1060	0.0211	5.0323	0.0000
beta 7	0.0265	0.0154	1.7180	0.0898
beta 8	-0.0253	0.0348	-0.7269	0.4695
gamma 1 1	0.1391	0.0385	3.6157	0.0005
gamma 1 2	-0.0394	0.0141	-2.7927	0.0066
gamma 1 3	-0.0356	0.0196	-1.8116	0.0739
gamma 1 4	0.0206	0.0161	1.2801	0.2044
gamma 1 5	-0.0109	0.0243	-0.4482	0.6552
gamma 1 6	-0.0745	0.0288	-2.5887	0.0115
gamma 1 7	-0.0353	0.0171	-2.0620	0.0426
gamma 1 8	0.0360	0.0441	0.8157	0.4172
gamma 2 1	-0.0394	0.0141	-2.7927	0.0066
gamma 2 2	0.1006	0.0173	5.8254	0.0000
gamma 2 3	-0.0877	0.0143	-6.1147	0.0000
gamma 2 4	-0.0115	0.0165	-0.6981	0.4872
gamma 2 5	0.1077	0.0196	5.4832	0.0000
gamma 2 6	-0.0620	0.0124	-4.9910	0.0000
gamma 2 7	-0.0326	0.0096	-3.3983	0.0011

gamma 2 8	0.0249	0.0276	0.9034	0.3692
gamma 3 1	-0.0356	0.0196	-1.8116	0.0739
gamma 3 2	-0.0877	0.0143	-6.1147	0.0000
gamma 3 3	0.1308	0.0213	6.1384	0.0000
gamma 3 4	0.0358	0.0165	2.1768	0.0326
gamma 3 5	-0.0978	0.0240	-4.0818	0.0001
gamma 3 6	0.0278	0.0187	1.4836	0.1420
gamma 3 7	0.0079	0.0131	0.6053	0.5468
gamma 3 8	0.0186	0.0294	0.6334	0.5284
gamma 4 1	0.0206	0.0161	1.2801	0.2044
gamma 4 2	-0.0115	0.0165	-0.6981	0.4872
gamma 4 3	0.0358	0.0165	2.1768	0.0326
gamma 4 4	0.0526	0.0266	1.9790	0.0514
gamma 4 5	-0.0298	0.0231	-1.2891	0.2012
gamma 4 6	-0.0293	0.0141	-2.0821	0.0407
gamma 4 7	0.0023	0.0114	0.2055	0.8377
gamma 4 8	-0.0407	0.0322	-1.2649	0.2097
gamma 5 1	-0.0109	0.0243	-0.4482	0.6552
gamma 5 2	0.1077	0.0196	5.4832	0.0000
gamma 5 3	-0.0978	0.0240	-4.0818	0.0001
gamma 5 4	-0.0298	0.0231	-1.2891	0.2012
gamma 5 5	0.1303	0.0388	3.3560	0.0012
gamma 5 6	-0.0297	0.0217	-1.3669	0.1756
gamma 5 7	-0.0030	0.0166	-0.1824	0.8558
gamma 5 8	-0.0669	0.0406	-1.6456	0.1039
gamma 6 1	-0.0745	0.0288	-2.5887	0.0115
gamma 6 2	-0.0620	0.0124	-4.9910	0.0000
gamma 6 3	0.0278	0.0187	1.4836	0.1420
gamma 6 4	-0.0293	0.0141	-2.0821	0.0407
gamma 6 5	-0.0297	0.0217	-1.3669	0.1756
gamma 6 6	0.0892	0.0384	2.3237	0.0228
gamma 6 7	0.0429	0.0184	2.3310	0.0224
gamma 6 8	0.0356	0.0349	1.0180	0.3119
gamma 7 1	-0.0353	0.0171	-2.0620	0.0426
gamma 7 2	-0.0326	0.0096	-3.3983	0.0011
gamma 7 3	0.0079	0.0131	0.6053	0.5468
gamma 7 4	0.0023	0.0114	0.2055	0.8377
gamma 7 5	-0.0030	0.0166	-0.1824	0.8558
gamma 7 6	0.0429	0.0184	2.3310	0.0224
gamma 7 7	0.0172	0.0169	1.0161	0.3128
gamma 7 8	0.0007	0.0262	0.0253	0.9799
gamma 8 1	0.0360	0.0441	0.8157	0.4172
gamma 8 2	0.0249	0.0276	0.9034	0.3692
gamma 8 3	0.0186	0.0294	0.6334	0.5284
gamma 8 4	-0.0407	0.0322	-1.2649	0.2097

gamma 8 5	-0.0669	0.0406	-1.6456	0.1039
gamma 8 6	0.0356	0.0349	1.0180	0.3119
gamma 8 7	0.0007	0.0262	0.0253	0.9799
gamma 8 8	-0.0082	0.0839	-0.0972	0.9228

	R-squared	
	values of expenditures shares	values of quantities
1	0.8377	0.9775
2	0.9797	0.9975
3	0.8642	0.9918
4	0.9676	0.9849
5	0.974	0.9993
6	0.9241	0.9833
7	0.5804	0.9492
8	-1.9243	0.9905

1: Food, 2: Housing, 3: Clothing, 4: Health and Education, 5: Recreation, 6: Transport, 7: Communication, 8: Other expenditure

Table S8-5.2. Marginal budget shares Colombian household income for the years 2000-2016.

year	Food	Housing	Clothing	Health and Education	Recreation	Transport	Communication	Other expenditures
2000	0.192	0.230	0.076	0.091	0.150	0.082	0.036	0.142
2001	0.195	0.226	0.075	0.091	0.150	0.086	0.037	0.140
2002	0.203	0.225	0.070	0.090	0.150	0.085	0.037	0.140
2003	0.195	0.223	0.069	0.087	0.152	0.094	0.040	0.140
2004	0.190	0.220	0.068	0.084	0.155	0.101	0.043	0.140
2005	0.187	0.216	0.067	0.084	0.158	0.105	0.044	0.140
2006	0.186	0.214	0.068	0.081	0.159	0.109	0.044	0.140
2007	0.186	0.209	0.068	0.080	0.160	0.112	0.045	0.141
2008	0.194	0.205	0.064	0.080	0.161	0.109	0.042	0.145
2009	0.191	0.209	0.063	0.080	0.163	0.110	0.042	0.142
2010	0.191	0.209	0.061	0.078	0.166	0.111	0.042	0.142
2011	0.186	0.203	0.063	0.077	0.168	0.117	0.043	0.143
2012	0.183	0.201	0.065	0.078	0.170	0.119	0.043	0.141
2013	0.178	0.201	0.065	0.078	0.173	0.122	0.044	0.139
2014	0.176	0.200	0.064	0.077	0.177	0.124	0.044	0.138
2015	0.183	0.199	0.061	0.076	0.177	0.122	0.043	0.140
2016	0.184	0.197	0.062	0.076	0.176	0.123	0.042	0.139
Average	0.185	0.204	0.064	0.078	0.168	0.116	0.043	0.141

Source. (DANE, 2018a)

Supplementary information S8-6: Colombian Household consumption expenditures (HCE) for the period 2000-2016 by DANE classification.

Table S7.6.1 Colombian Household consumption expenditures (HCE) for the period 2000-2016.

Year	Total expenditures $Billions COP	Food	Housing	Clothing	Health and Education	Recreation	Transport	Comunication	Other expenditures
2000	144135	0.1960	0.2307	0.0750	0.0902	0.1507	0.0813	0.0332	0.1429
2001	158693	0.1963	0.2268	0.0742	0.0907	0.1473	0.0855	0.0361	0.1430
2002	170777	0.1999	0.2243	0.0705	0.0898	0.1488	0.0877	0.0372	0.1418
2003	186790	0.1953	0.2243	0.0684	0.0879	0.1514	0.0920	0.0395	0.1411
2004	205750	0.1910	0.2216	0.0693	0.0848	0.1549	0.0970	0.0399	0.1416
2005	223748	0.1882	0.2178	0.0693	0.0832	0.1585	0.1026	0.0412	0.1392
2006	249279	0.1842	0.2142	0.0684	0.0820	0.1606	0.1059	0.0463	0.1383
2007	278688	0.1838	0.2071	0.0674	0.0803	0.1610	0.1127	0.0481	0.1396
2008	304921	0.1931	0.2019	0.0629	0.0796	0.1645	0.1115	0.0479	0.1385
2009	318887	0.1936	0.2060	0.0596	0.0798	0.1641	0.1112	0.0444	0.1413
2010	342565	0.1868	0.2075	0.0610	0.0777	0.1648	0.1180	0.0445	0.1398
2011	379450	0.1842	0.2022	0.0661	0.0760	0.1667	0.1234	0.0441	0.1374
2012	406316	0.1824	0.2015	0.0652	0.0757	0.1686	0.1239	0.0423	0.1403
2013	429195	0.1765	0.2006	0.0666	0.0775	0.1740	0.1201	0.0435	0.1412
2014	461575	0.1756	0.2002	0.0647	0.0773	0.1754	0.1227	0.0430	0.1411
2015	499215	0.1804	0.2007	0.0618	0.0783	0.1758	0.1200	0.0413	0.1417
2016	545678	0.1926	0.1987	0.0598	0.0762	0.1771	0.1146	0.0381	0.1430

Source. (UN, 2018) and Banco de la Republica database (2019).

Supplementary information S8-7: Price indexes for the HCE during the period 2000-2016.

Table S7.7.1 price indexes for the HCE for the period 2000-2016.

year	Food	Housing	Clothing	Health and Education	Recreation	Transport	Communication	Other expenditures
2000	53.11	68.56	91.94	57.27	76.58	58.49	62.48	65.32
2001	58.71	71.48	94.35	63.49	82.03	63.31	70.57	70.27
2002	65.12	74.39	95.00	69.35	86.34	66.52	78.46	76.59
2003	68.59	79.04	96.40	75.32	90.85	74.41	86.66	81.02
2004	72.31	82.92	97.75	80.59	94.74	80.69	91.72	84.96
2005	77.06	86.33	98.33	84.71	97.14	84.72	100.23	87.48
2006	81.44	89.93	98.62	89.18	97.59	89.97	93.93	91.63
2007	88.37	93.76	100.25	94.97	100.03	94.88	96.17	95.68
2008	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
2009	99.68	104.26	99.70	104.94	100.53	100.33	100.89	103.83
2010	103.76	108.10	98.37	109.46	101.11	103.13	100.61	107.13
2011	109.23	112.19	98.90	113.45	100.79	106.29	103.89	109.36
2012	111.98	115.58	99.64	118.29	101.33	107.83	105.53	110.75
2013	112.93	118.75	100.58	123.54	103.19	109.33	108.43	111.89
2014	118.23	123.13	102.08	127.82	106.09	112.87	110.93	114.35
2015	131.05	129.75	105.13	134.59	110.88	118.37	116.13	122.24
2016	140.51	136.02	109.31	145.55	115.37	123.66	121.61	131.11

Source Banco de la Republica database (2019).

Supplementary information S8-8: Concordance between COICP and HCE classification system.

Table S7.8.1 Concordance between COICP and HCE classification system.

HCE classification system	COICP code	COICP
Food	1	Food and non-alcoholic beverages
Other expenditures	2	Alcoholic beverages, tobacco and narcotics
Clothing	3	Clothing and footwear
Housing	4	Housing, water, electricity, gas and other fuels
Housing	5	Furnishings, household equipment and routine maintenance of the house
Health and Education	6	Health
Transport	7	Transport
Communication	8	Communication
Recreation	9	Recreation and culture
Health and Education	10	Education
Recreation	11	Restaurants and hotels
Other expenditures	12	Miscellaneous goods and services

Source. Banco de la Republica database (2019) and UN(2018)

Supplementary information S8-9: Concordance between HCE and GTAP classification system.

Table S7.9.1. Concordance between HCE and GTAP classification system.

HCE	GTAP	Code	Description
Clothing	7	pfb	Plant Fibres: cotton, flax, hemp, sisal and other raw vegetable materials used in textiles
Clothing	12	wol	Wool: wool, silk, and other raw animal materials used in textile
Clothing	27	tex	Textiles: textiles and man-made fibres
Clothing	28	wap	Wearing Apparel: Clothing, dressing and dyeing of fur
Clothing	29	lea	Leather: tanning and dressing of leather; luggage, handbags, saddlery, harness and footwear
Comunication	31	ppp	Paper & Paper Products: includes publishing, printing and reproduction of recorded media
Comunication	51	cmn	Communications: post and telecommunications
Food	1	pdr	Paddy Rice: rice, husked and unhusked
Food	2	wht	Wheat: wheat and meslin
Food	3	gro	Other Grains: maize (corn), barley, rye, oats, other cereals
Food	4	v_f	Veg & Fruit: vegetables, fruitvegetables, fruit and nuts, potatoes, cassava, truffles,
Food	5	osd	Oil Seeds: oil seeds and oleaginous fruit; soy beans, copra
Food	6	c_b	Cane & Beet: sugar cane and sugar beet
Food	9	ctl	Cattle: cattle, sheep, goats, horses, asses, mules, and hinnies; and semen thereof
Food	10	oap	Other Animal Products: swine, poultry and other live animals; eggs, in shell (fresh or cooked), natural honey, snails (fresh or preserved) except sea snails; frogs' legs, edible products of animal origin n.e.c., hides, skins and furskins, raw , insect waxes and spermaceti, whether or not refined or coloured

Food	11	rmk	Raw milk
Food	19	cmt	Cattle Meat: fresh or chilled meat and edible offal of cattle, sheep, goats, horses, asses, mules, and hinnies. raw fats or grease from any animal or bird.
Food	20	omt	Other Meat: pig meat and offal. preserves and preparations of meat, meat offal or blood, flours, meals and pellets of meat or inedible meat offal; greaves
Food	21	vol	Vegetable Oils: crude and refined oils of soya-bean, maize (corn),olive, sesame, ground-nut, olive, sunflower-seed, safflower, cotton-seed, rape, colza and canola, mustard, coconut palm, palm kernel, castor, tung jojoba, babassu and linseed, perhaps partly or wholly hydrogenated,inter-esterified, re-esterified or elaidinised. Also margarine and similar preparations, animal or vegetable waxes, fats and oils and their fractions, cotton linters, oil-cake and other solid residues resulting from the extraction of vegetable fats or oils; flours and meals of oil seeds or oleaginous fruits, except those of mustard; degras and other residues resulting from the treatment of fatty substances or animal or vegetable waxes.
Food	22	mil	Milk: dairy products
Food	23	pcr	Processed Rice: rice, semi- or wholly milled
Food	24	sgr	Sugar
Food	25	ofd	Other Food: prepared and preserved fish or vegetables, fruit juices and vegetable juices, prepared and preserved fruit and nuts, all cereal flours, groats, meal and pellets of wheat, cereal groats, meal and pellets n.e.c., other cereal grain products (including corn flakes), other vegetable flours and meals, mixes and doughs for the preparation of bakers' wares, starches and starch products; sugars and sugar syrups n.e.c., preparations used in animal feeding, bakery products, cocoa, chocolate and sugar confectionery, macaroni, noodles, couscous and similar farinaceous products, food products n.e.c.

Health and Education	56	osg	Other Services (Government): public administration and defense; compulsory social security, education, health and social work, sewage and refuse disposal, sanitation and similar activities, activities of membership organizations n.e.c., extra-territorial organizations and bodies
Housing	43	ely	Electricity: production, collection and distribution
Housing	44	gdt	Gas Distribution: distribution of gaseous fuels through mains; steam and hot water supply
Housing	45	wtr	Water: collection, purification and distribution
Housing	46	cns	Construction: building houses factories offices and roads
Housing	47	trd	Trade: all retail sales; wholesale trade and commission trade; hotels and restaurants; repairs of motor vehicles and personal and household goods; retail sale of automotive fuel
Housing	57	dwe	Dwellings: ownership of dwellings (imputed rents of houses occupied by owners)
Other expenditures	53	isr	Insurance: includes pension funding, except compulsory social security
Other expenditures	8	ocr	Other Crops: live plants; cut flowers and flower buds; flower seeds and fruit seeds; vegetable seeds, beverage and spice crops, unmanufactured tobacco, cereal straw and husks, unprepared, whether or not chopped, ground, pressed or in the form of pellets; swedes, mangolds, fodder roots, hay, lucerne (alfalfa), clover, sainfoin, forage kale, lupines, vetches and similar forage products, whether or not in the form of pellets, plants and parts of plants used primarily in perfumery, in pharmacy, or for insecticidal, fungicidal or similar purposes, sugar beet seed and seeds of forage plants, other raw vegetable materials
Other expenditures	13	frs	Forestry: forestry, logging and related service activities
Other expenditures	15	coa	Coal: mining and agglomeration of hard coal, lignite and peat
Other expenditures	16	oil	Oil: extraction of crude petroleum and natural gas (part), service activities incidental to oil and gas extraction excluding surveying (part)

Other expenditures	17	gas	Gas: extraction of crude petroleum and natural gas (part), service activities incidental to oil and gas extraction excluding surveying (part)
Other expenditures	18	omn	Other Mining: mining of metal ores, uranium, gems. other mining and quarrying
Other expenditures	26	b_t	Beverages and Tobacco products
Other expenditures	30	lum	Lumber: wood and products of wood and cork, except furniture; articles of straw and plaiting materials
Other expenditures	32	p_c	Petroleum & Coke: coke oven products, refined petroleum products, processing of nuclear fuel
Other expenditures	33	crp	Chemical Rubber Products: basic chemicals, other chemical products, rubber and plastics products
Other expenditures	34	nmm	Non-Metallic Minerals: cement, plaster, lime, gravel, concrete
Other expenditures	35	i_s	Iron & Steel: basic production and casting
Other expenditures	36	nfm	Non-Ferrous Metals: production and casting of copper, aluminium, zinc, lead, gold, and silver
Other expenditures	37	fmp	Fabricated Metal Products: Sheet metal products, but not machinery and equipment
Other expenditures	40	ele	Electronic Equipment: office, accounting and computing machinery, radio, television and communication equipment and apparatus
Other expenditures	41	ome	Other Machinery & Equipment: electrical machinery and apparatus n.e.c., medical, precision and optical instruments, watches and clocks
Other expenditures	42	omf	Other Manufacturing: includes recycling
Other expenditures	52	ofi	Other Financial Intermediation: includes auxiliary activities but not insurance and pension funding (see next)
Other expenditures	54	obs	Other Business Services: real estate, renting and business activities
Recreation	14	fsh	Fishing: hunting, trapping and game propagation including related service activities, fishing, fish farms; service activities incidental to fishing

Recreation	55	ros	Recreation & Other Services: recreational, cultural and sporting activities, other service activities; private households with employed persons (servants)
Transport	38	mvh	Motor Motor vehicles and parts: cars, lorries, trailers and semi-trailers
Transport	39	otn	Other Transport Equipment: Manufacture of other transport equipment
Transport	48	otp	Other Transport: road, rail ; pipelines, auxiliary transport activities; travel agencies
Transport	49	wtp	Water transport
Transport	50	atp	Air transport

Source. Own elaborations base on GTAP9.

Supplementary information S8-10: Environmental impact per monetary unit of each of the consumption categories (m).

Table S8.10.1. Environmental impact per monetary unit of each of the consumption categories (m). values in kg/1 million dollars (2011 constant prices).

Sectors	CC	A	E	MEUT	TEUT	CE	NCE	OD	POC	RES
ISR	164128.9053	1240.8056	37522.8501	17.0807	3903.7598	0.0003	0.0639	0.0114	610.9933	111.4053
PDR	634369.8025	4432.9872	191837.8623	76.9751	14128.2652	0.0012	0.3371	0.0153	1043.5406	413.6402
WHT	243277.9046	11503.1607	9703.1954	400.9032	51608.1918	0.0001	0.0141	0.0042	263.1471	330.7176
GRO	199952.4750	4224.1930	55744.8447	116.1425	17251.7032	0.0004	0.0979	0.0082	468.2421	223.3121
V_F	563051.7943	12698.4939	119901.4949	347.9621	51733.9800	0.0009	0.2096	0.0187	1233.5749	649.8500
OSD	407214.1609	9153.4598	972612.4828	80.4296	15991.5763	0.0052	1.7024	0.0137	1340.5261	1327.4987
C_B	5443155.8827	145088.3514	1159300.4189	4474.4164	614760.1027	0.0072	1.9942	0.2777	14607.0639	7404.4999
PFB	221325.9729	2745.6104	141323.3472	34.6209	6671.8888	0.0009	0.2513	0.0079	539.4031	275.7414
OCR	401050.2986	5384.8687	105182.6849	103.1829	19549.6264	0.0007	0.1849	0.0142	927.6463	419.9025
CTL	3135135.0592	76617.3466	463262.8412	2257.0435	320617.5951	0.0034	0.8433	0.0577	3740.4692	2905.6939
OAP	944865.6842	17675.7957	1764135.1960	139.2066	29937.8772	0.0097	3.0970	0.0375	3069.9849	2516.7446
RMK	1138340.4312	23972.6009	77704.6211	794.4415	105963.0054	0.0005	0.1351	0.0100	888.6414	684.7979
WOL	1203781.4809	24399.8272	3451344.5350	41.9302	20342.7188	0.0184	6.0376	0.0239	3595.4161	4647.0753
FRS	1560518.4848	122846.7411	114633.3200	3152.2470	591039.5113	0.0008	0.1997	0.0108	668.6510	2162.1326
FSH	197615.4606	2575.9159	115694.5023	23.8986	8181.6805	0.0013	0.2187	0.0075	467.5254	240.5899
COA	2624992.5249	1828.9657	36686.3371	12.1393	3651.9107	0.0002	0.0667	0.0046	1281.6904	303.3543
OIL	4403124.0645	4096.8837	134697.8651	21.6161	9887.2847	0.0008	0.2360	0.1815	9474.6542	363.9008
GAS	2052059.7824	2547.9156	76644.3909	13.0767	8427.8998	0.0004	0.1343	0.0634	3268.5063	157.4139
OMN	2424684.0274	163287.9801	27109655.1154	176.5949	73378.4423	0.1435	47.3782	0.1058	22449.9974	30901.7276
CMT	79185.3333	1070.7999	26462.6262	21.3260	3692.9314	0.0002	0.0494	0.0100	482.1454	169.7979
OMT	537039.3356	4447.1773	219376.3301	52.0826	11683.9567	0.0013	0.3920	0.0110	799.5463	437.6921

VOL	299691.4560	13239.4314	144585.2346	310.8774	58751.0907	0.0009	0.2558	0.0105	616.5847	422.9735
MIL	239347.2637	2730.9535	167629.2045	27.7531	6350.0108	0.0010	0.2974	0.0082	554.8100	325.3759
PCR	375792.7217	6909.6555	869568.2930	25.2595	7867.2682	0.0048	1.5249	0.0160	1377.1583	1152.0825
SGR	5468890.5385	58417.8883	6555312.0446	120.9712	73812.9075	0.0355	11.4898	0.2137	15111.2179	11373.5613
OFD	690199.1753	7459.6282	256051.4174	133.8330	23763.2486	0.0016	0.4549	0.0273	1599.7504	720.6132
B_T	1824683.9220	23036.1727	1522656.0291	180.7869	52594.5774	0.0085	2.6825	0.0446	3434.2925	3955.7728
TEX	50175.3878	653.2468	44961.6757	7.0232	1475.0906	0.0003	0.0794	0.0018	128.3251	75.7895
WAP	283702.9707	3183.2751	133609.7539	39.6490	8176.6031	0.0009	0.2378	0.0078	532.0580	294.5806
LEA	373324.8554	3923.9204	158004.0969	39.8096	9492.7519	0.0010	0.2818	0.0131	840.2833	411.1248
LUM	40788.3002	564.0006	24860.1563	9.9748	1742.1703	0.0002	0.0439	0.0017	104.7735	52.7490
PPP	140744.9370	1738.9358	33931.3959	10.3007	3533.4746	0.0002	0.0603	0.0060	385.2327	187.7401
P_C	4167954.4448	25085.6216	2491421.1324	46.3387	28204.1340	0.0135	4.3607	0.3232	17155.9037	3680.2856
CRP	757151.2304	6632.7497	227891.6978	36.8067	12000.0659	0.0013	0.4006	0.0192	1261.9160	580.7133
NMM	5190184.5027	20052.0308	318402.3550	38.1415	53655.8530	0.0021	0.5838	0.0131	2313.3853	4713.6846
I_S	2467143.3679	13847.1692	2526437.9289	88.3537	28962.9536	0.0140	4.4625	0.0293	3151.6586	3078.2674
NFM	865618.8911	75968.3453	566915.2391	45.2335	13711.8384	0.0063	1.3684	0.0130	6294.4642	4432.2456
FMP	146286.1640	1430.9411	100422.9624	13.6741	3037.2887	0.0006	0.1815	0.0071	436.5299	171.1585
MVH	148414.5962	1653.3329	140723.8463	5.4305	2965.1097	0.0008	0.2513	0.0161	872.6291	227.7275
OTN	96608.7608	1055.7571	48281.3283	14.2319	2910.1507	0.0003	0.0866	0.0049	286.7572	106.0947
ELE	197997.8027	2947.9172	41923.2121	56.8856	9493.9511	0.0003	0.0742	0.0089	523.9235	232.0023
OME	392158.4964	2871.7282	65961.0255	10.1056	5813.0331	0.0006	0.1330	0.0053	477.0042	236.0547
OMF	1469509.6380	9590.2995	95373.6620	40.1338	21170.1189	0.0007	0.1750	0.0309	1975.3264	685.4203
ELY	107723193.1423	570613.3088	1431203.7929	343.4960	811448.6656	0.0159	2.2877	0.3431	44082.7253	30712.7097
GDT	246193.0369	3094.2500	83826.6234	64.0560	10822.3658	0.0005	0.1489	0.0070	435.7186	204.3473
WTR	177927.9285	1982.9725	92419.4742	21.8533	4889.1058	0.0006	0.1639	0.0053	354.5778	231.4056
CNS	890962.3160	5458.4953	345767.9788	25.9469	18063.6891	0.0025	0.6648	0.0467	2751.9558	829.0108
TRD	2497462.2703	18692.5232	469213.2737	238.5771	71315.6627	0.0027	0.7641	0.1400	7363.2325	1995.7751

OTP	4184468.4331	25378.2624	259523.6722	89.6206	49296.8757	0.0019	0.4464	0.0750	4997.0705	1686.0914
WTP	176869.4818	2340.5255	169278.2320	19.9294	5911.5061	0.0016	0.3109	0.0059	429.4996	265.4497
ATP	572461.8149	3545.1383	63347.5944	36.7405	13614.6326	0.0005	0.1127	0.0129	818.5357	234.5290
CMN	651309.3244	20513.3940	212594.1258	46.1591	11819.6737	0.0020	0.4535	0.0314	2972.8291	1304.5113
OFI	1032342.9873	6542.2016	96330.4697	35.5369	13898.8003	0.0007	0.1668	0.0214	1371.5213	453.0284
OBS	1039718.2546	7060.7458	217614.0567	62.0936	17546.5834	0.0015	0.3946	0.0464	2668.6771	748.2287
ROS	2148576.9367	13426.5817	171088.1255	117.6962	32451.1697	0.0015	0.3248	0.0494	2937.4070	1049.9298
OSG	3695234.9683	19726.2766	456108.4055	218.9923	54672.4373	0.0035	0.8384	0.3491	16721.0572	1922.3934
DWE	88881.6136	1267.8181	81525.0192	20.7428	3388.2979	0.0005	0.1431	0.0038	246.4672	132.6881

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES). ISR: insurance, PDR: Paddy Rice, WHT: Wheat, GRO: Other Grains, V_F: Veg & Fruit, OSD: Oil Seeds, C_B: Cane & Beet, PFB: Plant Fibres, OCR: Other Crops, CTL: Cattle, OAP: Other Animal Products, RMW: Raw milk, WOL: Wool, FRS: Forestry, FSH: Fishing: hunting, COA: Coal, OIL:Oil, GAS:Gas, OMN: Other Mining, OMT: Other Meat, VOL: Vegetable Oils, MIL: Milk, PCR: Processed Rice, SGR: Sugar, OFD: Other Food, B_T: Beverages and Tobacco products, TEX: Textiles, WAP: Wearing Apparel, LEA: Leather, LUM: Lumber, PPP: Paper & Paper Products, P_C: Petroleum & Coke, CRP: Chemical Rubber Products, NMM: Non-Metallic Minerals, I_S: Iron & Steel, NFM: Non-Ferrous Metals, FMP: Fabricated Metal Products, MVH: Motor Motor vehicles and parts, OTN: Other Transport Equipment, ELE: Electronic Equipment, OME: Other Machinery & Equipment, OMF: Other Manufacturing, ELY: Electricity, GDT: Gas Distribution, WTR: Water, CNS: Construction, TRD: Trade, OTP: Other Transport, WTP: Water transport, ATP: Air transport, CMN: Communications, OFI: Other Financial Intermediation, OBS: Other Business Services, ROS: Recreation & Other Services, OSG: Other Services (Government), DWE: Dwellings. Source. Own elaboration base on GTAP9.

Supplementary information S8-11: Environmental rebound effect results for the combined model.

Table S8.11.1. Environmental rebound effect (ERE) combined model.

Environmental rebound effect ERE combined model										
	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
2019	220%	153%	34%	257%	315%	66%	123%	53%	545%	151%
2020	46%	34%	8%	64%	73%	15%	24%	11%	145%	31%
2021	223%	292%	39%	835%	1128%	85%	200%	89%	6109%	269%
2022	272%	266%	57%	501%	624%	109%	213%	64%	1449%	257%
2023	414%	222%	47%	327%	449%	92%	211%	104%	664%	245%
2024	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2025	1478%	1159%	177%	1399%	2752%	335%	1435%	453%	4108%	1499%
2026	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2027	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2028	35%	29%	5%	55%	68%	11%	22%	10%	144%	28%
2029	28%	35%	5%	98%	122%	11%	23%	11%	2383%	31%
2030	285%	239%	42%	385%	553%	85%	215%	83%	1021%	256%

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES). Source. Own elaboration.

Table S8-11.2. Direct Environmental rebound effect (ERE) combined model.

	Direct Environmental rebound combined model									
	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
2019	203%	131%	34%	255%	256%	66%	78%	45%	487%	110%
2020	43%	31%	8%	64%	64%	15%	18%	10%	135%	26%
2021	201%	234%	39%	824%	848%	84%	106%	77%	5242%	172%
2022	246%	226%	56%	496%	498%	108%	131%	53%	1279%	183%
2023	367%	173%	46%	322%	324%	91%	106%	85%	555%	150%
2024	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2025	1091%	656%	167%	1344%	1352%	325%	386%	285%	2691%	549%
2026	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2027	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2028	32%	25%	5%	54%	55%	11%	13%	9%	129%	20%
2029	26%	30%	5%	98%	100%	11%	14%	9%	2140%	22%
2030	246%	181%	41%	379%	383%	84%	101%	64%	831%	148%

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES).Source. Own elaboration.

Table S8-11.3. Indirect Environmental rebound effect (ERE) combined model.

	Indirect Environmental rebound combined model									
	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
2019	17%	22%	0%	2%	59%	0%	45%	7%	58%	41%
2020	2%	3%	0%	0%	9%	0%	6%	1%	10%	6%
2021	22%	59%	1%	11%	279%	1%	94%	13%	867%	97%
2022	25%	40%	1%	5%	126%	1%	82%	11%	170%	74%
2023	47%	49%	1%	5%	125%	1%	106%	19%	109%	95%
2024	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2025	387%	503%	10%	55%	1400%	10%	1048%	169%	1417%	949%
2026	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2027	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2028	3%	4%	0%	0%	13%	0%	8%	1%	15%	8%
2029	2%	5%	0%	1%	22%	0%	8%	1%	243%	9%
2030	39%	58%	1%	7%	170%	1%	114%	18%	190%	107%

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES).Source. Own elaboration.

Supplementary information S8-12: Environmental rebound effect results for the single model.

Table S8-12.1. Environmental rebound effect (ERE) single model.

	Environmental rebound effect ERE single model									
	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
2019	216%	272%	5%	29%	747%	5%	570%	94%	734%	516%
2020	44%	61%	1%	7%	177%	1%	126%	20%	193%	115%
2021	232%	627%	8%	114%	2992%	9%	1007%	134%	9277%	1039%
2022	259%	410%	8%	51%	1300%	8%	843%	117%	1759%	763%
2023	484%	505%	10%	50%	1280%	10%	1081%	197%	1112%	971%
2024	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2025	1625%	2111%	41%	230%	5881%	42%	4404%	709%	5952%	3986%
2026	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2027	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2028	55%	89%	1%	10%	269%	2%	170%	27%	322%	162%
2029	42%	106%	1%	18%	470%	2%	176%	24%	5085%	179%
2030	420%	636%	11%	72%	1856%	12%	1242%	202%	2067%	1169%

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES). Source. Own elaboration.

Table S8-12.2. Direct Environmental rebound effect (ERE) single model.

Direct Environmental rebound single model										
	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
2019	5.67%	4.35%	0.00%	0.03%	7.52%	0.01%	0.37%	0.16%	2.83%	3.75%
2020	1.15%	0.98%	0.00%	0.01%	1.79%	0.00%	0.08%	0.03%	0.74%	0.84%
2021	6.09%	10.01%	0.01%	0.14%	30.14%	0.01%	0.66%	0.23%	35.76%	7.55%
2022	6.80%	6.55%	0.01%	0.06%	13.10%	0.01%	0.55%	0.20%	6.78%	5.54%
2023	12.68%	8.06%	0.01%	0.06%	12.90%	0.01%	0.70%	0.34%	4.29%	7.05%
2024	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2025	42.60%	33.69%	0.03%	0.27%	59.24%	0.06%	2.87%	1.23%	22.94%	28.96%
2026	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2027	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2028	1.44%	1.42%	0.00%	0.01%	2.71%	0.00%	0.11%	0.05%	1.24%	1.18%
2029	1.10%	1.69%	0.00%	0.02%	4.73%	0.00%	0.11%	0.04%	19.60%	1.30%
2030	11.01%	10.15%	0.01%	0.09%	18.70%	0.02%	0.81%	0.35%	7.97%	8.49%

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES). Source. Own elaboration.

Table S8-12.3. Indirect Environmental rebound effect (ERE) single model.

Indirect Environmental rebound single model										
	CC	**A**	**E**	**MEUT**	**TEUT**	**CE**	**NCE**	**OD**	**POC**	**RES**
2019	211%	268%	5%	29%	739%	5%	570%	93%	731%	512%
2020	43%	60%	1%	7%	176%	1%	126%	20%	192%	114%
2021	226%	617%	8%	114%	2962%	9%	1006%	134%	9241%	1032%
2022	252%	404%	8%	51%	1287%	8%	843%	117%	1752%	757%
2023	471%	497%	10%	50%	1267%	10%	1080%	197%	1108%	964%
2024	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2025	1582%	2078%	41%	230%	5822%	42%	4401%	708%	5929%	3958%
2026	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2027	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2028	54%	88%	1%	10%	266%	2%	170%	27%	321%	161%
2029	41%	104%	1%	18%	465%	2%	176%	24%	5065%	177%
2030	409%	626%	11%	72%	1838%	12%	1241%	201%	2059%	1160%

Climate change (CC), acidification (A), ecotoxicity (E), marine eutrophication (MEUT), terrestrial eutrophication (TEUT), carcinogenic effects (CE), non-carcinogenic effects (NCE), ozone layer depletion (OD), photochemical ozone creation (POC), and respiratory effects-inorganics (RES). Source. Own elaboration.

Supplementary information S8-13. Shares of the Marginal budget shares (MBS) and environmental impact intensity (EII) in percentage for each consumption group and their associated economic sectors in terms of climate change.

Consumption group	Economic sector	% MBS	% EII	Consumption group	Economic sector	% MBS	% EII
Recreation		**16.81%**	**23.85%**		Lumber	0.47%	0.01%
	Fishing	0.01%	0.00%		Petroleum & coke	1.53%	4.21%
	Recreation & Other Services	16.80%	23.85%		Chemical rubber products	0.02%	0.01%
Health & Education		**7.82%**	**19.09%**		Non-metallic minerals	0.00%	0.00%
	Other Services (Government)	7.82%	19.09%		Iron & steel	0.00%	0.00%
Housing		**20.41%**	**18.65%**		Non-Ferrous metals	0.10%	0.05%
	Electricity	0.04%	2.62%		Fabricated metal products	0.56%	0.05%
	Gas distribution	0.66%	0.11%		Electronic equipment	0.18%	0.02%
	Water	0.00%	0.00%		Other machinery & equipment	0.48%	0.13%
	Contraction	15.62%	9.19%		Other manufacturing	0.63%	0.61%
	Trade	4.08%	6.73%		Other financial intermediation	0.66%	0.45%
	Dwellings	0.01%	0.00%		Other business services	8.37%	5.75%
Other Expenditures		**14.09%**	**12.91%**	**Transport**		**11.61%**	**4.59%**
	Insurance	0.01%	0.00%		Motor vehicles and parts	0.33%	0.03%
	Other crops	0.00%	0.00%		Other transport equipment	0.07%	0.00%
	Forestry	0.11%	0.11%		Other transport	0.21%	0.58%
	Coal	0.00%	0.00%		Water transport	0.75%	0.09%
	Oil	0.00%	0.00%		Air transport	10.26%	3.88%
	Gas	0.00%	0.00%	**Communication**		**4.31%**	**1.42%**
	Other mining	0.77%	1.24%		Paper & paper products	1.28%	0.12%
	Beverages and tobacco products	0.21%	0.25%		Communications	3.03%	1.30%

Supplementary information S8-13. Continued

Consumption group	Economic sector	% MBS	% EII
Clothing		**6.42%**	**0.53%**
	Plant fibres	0.06%	0.01%
	Wool	0.11%	0.09%
	Textiles	4.80%	0.16%
	Wearing Apparel	1.38%	0.26%
	Leather	0.06%	0.02%
Food		**18.52%**	**18.96%**
	Paddy Rice	0.00%	0.00%
	Wheat	0.12%	0.02%
	Other Grains	3.20%	0.42%
	Veg & Fruit	0.00%	0.00%
	Oil Seeds	0.00%	0.00%
	Cane & Beet	0.00%	0.00%
	Cattle	0.67%	1.38%
	Other Animal Products	0.37%	0.23%
	Raw milk	0.00%	0.00%
	Cattle meat	2.24%	0.12%
	Other Meat	0.70%	0.25%
	Vegetable Oils	2.26%	0.45%
	Milk	1.19%	0.19%
	Processed Rice	0.81%	0.20%
	Sugar	3.97%	14.34%
	Other Food	2.98%	1.36%

11. Authors Contributions

Overview of articles included in this cumulative Ph.D. thesis

(in accordance with the guideline for cumulative dissertations in Sustainability Science [January 2012], in the following termed "the guideline")

Title of Ph.D. thesis: "Identifying rebound effect consequential LCA" in Colombian and "Environmental rebound effect of renewable resources into the household sector " in Germany.

Papers included:

1- Vélez-henao, J., Font, D., & Hernández-riveros, J. (2019). Technological change and the rebound e ff ect in the STIRPAT model : A critical view. *Energy Policy*, *129*, 1372–1381. https://doi.org/10.1016/j.enpol.2019.03.044

2- Vélez-Henao, J. (2020) Does urbanization boost environmental impacts in Colombia? An extended STIRPAT–LCA approach. Qual Quant https://doi:10.1007/s11135-019-00961-y22

3- Vélez-Henao, J., González Uribe,G. (2020) The rebound effect on Latin American economies: Evidence from the Colombian residential sector. Energy efficiency. Under review submitted 27.02.2020.

4- Vélez-Henao, J., Font, D (2020) Hybrid life cycle assessment of an onshore wind farm in Guajira, Colombia. Journal of Environmental Management. Volume 284, 15 April 2021, 112058 https://doi.org/10.1016/j.jenvman.2021.112058

5- Vélez-Henao, J. Garcia-Mazo, C., Freire-González, J & Font,D. (2020) Environmental rebound effect for energy efficiency improvements into household sector: The case of Colombia. Energy policy. https://doi.org/10.1016/j.enpol.2020.111697

Author's contributions to the articles and articles publication status (according to §16 of the guideline):

Article #	Short title	specific contributions of all authors	Author status	Weighting factor	Publication status
1	Technological change and the rebound effect in the STIRPAT model : A critical view.	JV designed and undertook the research project, including establishing the theoretical framing. DF made a substantive contribution in terms of discussion of ideas and language. JH supervised the project and contributes with the english editions	First author with predominant contribution	1.0	Published in Energy Policy, 129, 1372–1381. https://doi.org/10.1016/j.enpol.2019.03.044 (Indexed -International Peer-Reviewed Scientific Journal)
2	Does urbanization boost environmental impacts in Colombia? An extended STIRPAT–LCA approach	JV designed and undertook the research project, including establishing the theoretical framing.	First author with predominant contribution	1.0	Published in Quality & Quantity. https://doi.org/10.1007/s11135-019-00961-y (Indexed -International Peer-Reviewed Scientific Journal)

3	The rebound effect on Latin American economies: Evidence from the Colombian residential sector	JV designed and undertook the research project, including establishing the theoretical framing. GG made contribution in terms of discussion of ideas, particularly regarding the significance of the models	First author with predominant contribution	1.0	Under review. Energy Efficiency.
4	Hybrid life cycle assessment of an onshore wind farm in Guajira, Colombia	JV designed and undertook the research project, including establishing the theoretical framing. DF made a substantive contribution in terms of discussion of ideas and language	First author with predominant contribution	1.0	Published: Journal of Environmental Management. Volume 284, 15 April 2021, 112058 https://doi.org/10.1016/j.jenvman.2021.112058 (Indexed - International Peer-Reviewed Scientific Journal)

5	Exploring the direct rebound effect of residential electricity consumption in developing countries: An empirical study in Colombia	JV designed and undertook the research project, including establishing the theoretical framing. CMG developed the energy model for the price of the electricity. DF made a substantive contribution in terms of discussion of ideas and language. JF made contribution in terms of discussion of ideas, particularly regarding the (AIDS) model	First author with predominant contribution	1.0	Published in Journal energy policy (Indexed - International Peer-Reviewed Scientific Journal) https://doi.org/10.1016/j.enpol.2020.111697

Explanations

Specific contributions of all authors

JV – Johan Velez

CMG-Claudia Maria Garcia

DF – David Font

JH – Jesus Hernandez

GG– Gabriel González

JF–Jaume Freire

Author status

According to §12b of the guideline:

- Single author = own contribution amounts to 100%.
- Co-author with predominant contribution = own contribution is greater than the individual share of all other co-authors and is at least 35%.
- Co-author with equal contribution = (1) own contribution is as high as the share of other co-authors, (2) no other co-author has a contribution higher than the own contribution, and (3) the own contribution is at least 25%.
- Co-author with important contribution = own contribution is at least 25%, but is insufficient to qualify as single authorship, predominant or equal contribution.
- Co-author with small contribution = own contribution is less than 20%.

Weighting factor

According to §14 of the guideline:

Single Author	1.0
Co-author with predominant contribution	1.0
Co-author with equal contribution	1.0
Co-author with important contribution	0.5
Co-author with small contribution	0.0

Declaration (according to §16 of the guideline)

I avouch that all information given in this appendix is true in each instance and overall.