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Faculty of Economics

Department of Public Policies and Economic History

PhD Thesis:

Monitoring domestic material consumption at subnational level

Enabling the territorial perspective

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“While territories,

with their social, cultural and institutional realm,

are crucial for successful innovation,

innovation is in turn a key source of competitive advantage

for territories and regions”.

(Crescenzi and Rodríguez-Pose, 2011)

“All models are wrong, but some are useful”

(George E. P. Box, 1976)

Preface

The thesis is submitted to the Faculty of Economic and Business, Department of Public Policies and Economic History at the University of the Basque Country (UPV-EHU). The work was mainly carried out at the Tecnalia Research & Innovation center, under the supervision of Prof. Ikerne del Valle (UPV-EHU) and co-supervision of Dr. Carlos Garcia Tapia (TECNALIA & NORDREGIO). The thesis benefited in part from the ESPON project *Circular Economy and Territorial Consequences* (CIRCTER), within which the first research concept was initially conceived.

Abstract

Searching for sustainable modes of consumption and production represents nowadays the only way to meet an ever-increasing demand of goods without incurring in further environmental deterioration. The growing awareness that "business as usual" is both, unwise and unsustainable, has placed the role of the environment and the efficient use of natural resources at the centre of political and economic strategies. At the same time, mitigation strategies and monitoring frameworks geared to sustainability are generally implemented at national or supranational levels, failing short in providing significant guidance for local policy makers. The need of granular data and, therefore, the adoption of a territorial perspective in the analysis of resource consumption patterns has been the main motivation for this thesis. The dearth of studies at subnational level constitutes a critical research gap not only to recognise the needs and opportunities reflecting the unique features of regions, but also because the regional scale is often considered as the optimal level of governance for planning, coordinating and assessing actions towards sustainable developments.

This thesis provides a methodology for scaling national environmental indicators to lower levels considering territorial heterogeneity, going far beyond the simplistic approaches that provide granular data based on, for example, per capita values. At the same time, the methodology remains sufficiently systematized to be applied to large datasets and different indicators. Specifically, our methodology is applied (and validated) to downscale the Domestic Material Consumption (DMC) indicator. DMC, which measures the direct consumption of material by an economy, is a prime example of an environmental indicator only delivered at national level, but strictly tied to specific territorial configurations. One of the outcomes of this thesis is to provide DMC figures for more than 280 European regions from 2006 to 2015. This database represents a critical input to expand the understanding on the complex relationship between resource consumption, territorial contexts and socioeconomic drivers. The analysis highlights the existence of a significant technological gap between urban and rural regions, the latter struggling the most to recover from economic crises and to retain human capital. Going further, a closer inspection on the impacts of socioeconomic drivers on resource efficiency across different regional economic structures, reveals that increased access to capital would generate higher resource efficiency returns in material-intensive economies, compared with service-based economies. Differently, increased agglomeration levels represent the best resource efficiency leverage across urban, service-based, territories.

Overall, the thesis brings into discussion a renewed interest for the consideration of territorial aspects for a better understanding of the dialectics between the underlying forces driving regional resource efficiency and the different opportunities and challenges that regions might face according to their specific endowments.

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I want to express all my thankfulness to my family. Words cannot express how grateful I am to my parents, Loretta and Fabio, for all the sacrifices that you have made throughout my life and for your unconditional support.

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List of Abbreviations

CE: Circular Economy

CG: Conditional efficiency gap

CRS: Constant Return to Scale

DEA: Data Envelopment Analysis

DMC: Domestic Material Consumption

DMI: Domestic Material Input

EFTA: European Free Trade Association

EU: European Union

GD: European Green Deal

EW-MFA: Economic-Wide Material Flow Analysis

GDP: Gross Domestic Product

IE: Industrial Ecology

MF: Material Footprint

MFA: Material Flow Analysis

NUTS: Nomenclature of territorial units for statistics

LQ: Location Quotient

PPS: Purchasing Power Standard

RME: Raw Material Equivalent

SEM: Socioeconomic Metabolism

SOE: Specification-Optimization-Extrapolation model

TG: Technological gap

TMR: Total Material requirement

UMAn: Urban Metabolism Analysis

VRS: Variable Return to Scale

WEEE: Electric and electronical Equipment Waste

Introduction

The concept of Sustainable Development, i.e. “meeting society’s needs without compromising the needs of future generations”, has become an important item on the global political agenda. The remarkable socioeconomic changes witnessed during the second half of 20th century – the so-called “Great Acceleration” – raised concerns about the long-term sustainability of our economy, and more in general, our global society (Brown and Ulgiati, 2011; Steffen et al., 2015).

World population increased from 2.5 billion at the middle of the 20th century to 7 billion by the end of the first decade of the new millennium. Meanwhile, global real gross national product expanded roughly eightfold. On average, humans have been enjoying improved medical conditions, prolonged expected lifespans, rising living standards, and more diverse services provided by numerous technology innovations and modern infrastructures (Zhang et al., 2018). However, these extraordinary socioeconomic advances have not come without a profound deterioration in natural capital, as ever-accelerating exploitation of natural resources has accompanied many of these achievements (Krausmann et al., 2009; Sverdrup et al., 2013).

In 1990, 37.2 billion metric tons of minerals, fossil fuels, and biomass were extracted and subsequently consumed or used in production processes. This number rose to 69.7 billion tons in

2008, an increase of 87.4% (Pothen and Welsch, 2019), and projected to more than double between 2015 and 2050 (European Commission, 2018a). Similarly, global greenhouse gas emissions continue to rise at an alarming rate, with energy use but also overconsumption of resources and destruction of ecosystems as main key drivers (UNEP, 2016). The extraction, processing, and utilization of raw materials are responsible for diverse consequent environmental impacts in the form of, among others, natural resources depletion, waste and toxic emissions, biodiversity reduction and pollution. The more natural resources that move through our economy, the more impact – including waste, emissions and hazardous pollutants – we can expect on our environment and, in turn, our well-being. Human interference with global biogeochemical cycles has grown to a level that is triggering epochal changes, including climatic change and state shifts in the Earth's biosphere (Barnosky et al., 2012; Pauliuk and Hertwich, 2015a).

These trends are having substantial impact on humanity; not only they are forcing humans to adapt and mitigate environmental strain, but they also influence geopolitical equilibria, exacerbating conflicts over critical raw materials control and reducing the possibilities of future well-being and economic growth (Fernández-Herrero and Duro, 2019; Flachenecker and Rentschler, 2018). If left unaddressed, the consequences of climate change and degradation of natural capital will seriously impact the economy, reducing the quality of life all over the planet and increase the intensity and frequency of natural disasters, putting more lives in jeopardy. While turning these negative trends around comes at a cost and requires strong collective effort, the cost of inaction and the associated social fallout might be much higher (European Commission, 2019a).

The growing environmental concerns have led politicians around the world to implement several international and multilateral initiatives, among which the 2030 Agenda for Sustainable Development and the Paris Agreement on climate change are, perhaps, the most important examples of these efforts. Similarly, in Europe, the overarching vision and strategy for moving towards a sustainable economy can be resumed in several key policy strategy documents: (1) the

Europe 2020 strategy for smart, sustainable and inclusive growth (European Commission, 2010); (2) the flagship initiative on resource efficiency (European Commission, 2011) and (3) the Circular Economy Action Plan (European Commision, 2015; European Commission, 2020). All these initiatives complemented areas of traditional focus of EU environmental policy (Domenech and Bahn-Walkowiak, 2019). For example, the flagship initiative on resource efficiency was made operational through several roadmaps and communications ranging from the energy and low-carbon economy transitions to the optimisation of the transport system.

More recently, the European Green Deal (GD) initiative raised the bar by providing a new growth strategy that sets the basis for the necessary departure from the linear economy and existing economic structures towards a resource-efficient and carbon-neutral economy and where economic growth is decoupled from resource use (European Commission, 2019b). Compared to previous action plans, what stands out in the GD is the explicit reference to the territorial dimension of future implementations of socioeconomic systems. Indeed, the recent experience with the Circular Economy package made clear that the effective implementation of circular solutions depends, to great extent, on the specific assets available at local and regional level. In this sense, it is essential that sustainable strategies, and the economic sectors involved in them, are defined and rely on a detailed analysis of the territorial contexts, i.e. socioeconomic needs to be addressed, potential endowments to be exploited, challenges to be tackled and, when feasible, smart specialisation priorities. Hence, the main motivation of this Thesis is to introduce a territorial perspective in the analysis of material consumption patterns. Territorial-based approaches generally rely on the analysis of subnational spatial units, such as regions and/or cities, which better reflect the available local endowments. In this Thesis, we consider the regional level (NUTS -2[1]) as unit of analysis. This classification comprises 330 European regions. Thanks to

[1] The NUTS system was established by EC Regulation 1059/2003 that defined a common classification of territorial units for statistics (NUTS), based on the administrative divisions applied in the Member States. The 2nd level in the classification (NUTS 2) groups regions with population between 80,000 and 3 million.

the reduced geographical extension, regional units better reflect the uneven distribution of natural, economic and social assets that characterise territories and, unsurprisingly, they are also often considered the optimal level of governance for planning, coordinating and assessing actions towards sustainable development (Mascarenhas et al., 2010; Mickwitz et al., 2006). We believe that the analysis of material efficiency and its socioeconomic drivers through a territorial lens constitutes an important contribution to the fields of Industrial Ecology and Ecological Economics, which, so far, have concentrated their efforts more on the investigation of nationwide material flows.

In general terms, material efficiency can be defined as the ability of firms, industries, regions or economies to produce more goods and services – understood in a functional sense – with fewer impacts on the environment and less consumption of natural resources (Allwood et al., 2011; Söderholm and Tilton, 2012). For example, the objective of the roadmap to a resource efficient Europe is "improving economic performance while reducing pressure on natural resources" (European Commission, 2011, p. 4). Similarly, the United Nations (2010) defined material efficiency as "producing more wellbeing with less material consumption (…) while respecting the ecological carrying capacity of the earth". Material efficiency can be expressed either in an intensity or a productivity form. The former is the ratio between a physical indicator (numerator) and an economic indicator (denominator) and it reflects the amount of material input per unit of economic output. Contrarywise, the productivity perspective corresponds to the reciprocal form of the intensity indicator, and it measures the amount of economic output generated per unit of material input.

Today, material efficiency indicators represent the operational means to measures society's progress towards more sustainable production/consumption configurations. During the last decade, three relevant concepts emerged as strategic goals of European initiatives:

“dematerialization”, “decoupling” and “circularity” [2]. Dematerialization refers to the absolute or relative reduction in the quantity of materials used and/or the quantity of waste generated in the production of a unit of economic output (Cleveland and Ruth, 1998). Decoupling emphasizes a break in the link between an environmental pressure and its economic driving force (OECD, 2002; Schandl et al., 2016), for example when the rate of economic output is higher than the rate of respective natural resources consumption. Circularity advocates instead for “an economy where the value of products, materials and resources is maintained in the economy for as long as possible, and the generation of waste minimised” (European Commision, 2015; Korhonen et al., 2018).

Despite the central position that strategies aimed at sustainable development occupy today in the policy debate, concerns about material efficiency and, more generally, the depletion of natural resources are not new. Early in the 1860s, the British economist William S. Jevons expressed the worry that Britain could not sustain its economic development when its coal resources are being exhausted (Polimeni et al., 2012). He pointed out that efficiency improvements would not be able to alleviate the problem because economic growth and increased consumption occurred at higher rates than efficiency gains, a phenomenon known as “rebound effect” (Alcott, 2005). Since then, the debates regarding resource scarcity continued to evolve. The “Oil peak” curve proposed by M. King Hubbert in the 1950s (Bardi, 2009), the sobering prospects modelled in The Limits to Growth by experts from the Club of Rome in the 1970s (Meadows et al., 1972), and a 1980s bet on the future prices of five basic metals between Julian Simon, a resource optimist, and Paul Ehrlich, an ecologist concerned about environmental degradation (Sabin, 2013) were among the most famous events, all igniting long-lasting discussions and arguments.

Thanks to a higher *human environmental literacy* than ever (Scholz et al., 2011), the 21st century witnessed a shift of the focal point of the material efficiency debate from questions whether

[2] Zhang et al. (2018) only refer to decoupling and dematerialization concepts. However, considering the recent evolution of scientific and policy discussion, we believe that “circularity” concept must also be considered.

natural resources are abundant enough for human use to issues surrounding the disutility that comes from adverse environmental and social impacts of accelerating resource extraction and mass production (Brown and Ulgiati, 2011). Facilitated by improved data collection and deeper understanding of the functioning and resilience of the earth system, the notion of planetary boundaries was established as a metaphor for the safe operating space for human societies to thrive (Rockstrom et al., 2009; Steffen et al., 2015). Empirical findings showed that at least six out of the nine planetary boundaries have already been approached or overshot by human interventions, including climate stability, biosphere integrity, land-system change, biogeochemical flows, ocean acidification and freshwater use (Jaramillo and Destouni, 2015; Steffen et al., 2015). These emerging crises are to a large extent caused by the expansion of material throughput to meet human needs. Based on the mass balance principle, all materials entering a socioeconomic system will ultimately exit as wastes into the natural environment. Larger gross material throughput leads to a larger potential of environmental pressures (Krausmann et al., 2017; Mayer et al., 2017; Schaffartzik et al., 2014).

The realization that natural resource depletion, emissions and the like are, of course, a consequence of human action, inspired in the early to mid- 1990s the specialty of socioeconomic metabolism (SEM), in which material input, processing, energy use, and loss are quantified and analysed from a socio-technical perspective (Clift and Druckman, 2015; Fischer-Kowalski and Hüttler, 1998; Pauliuk and Hertwich, 2015b). The ultimate task of this discipline is to relate resource transitions to societal change and to prospects for and measurement of sustainability. A principal manifestation of this approach is constituted by the studies of economy-wide material flows (EW-MFA) at the level of various societal units, generally on a national level.

The EW-MFA framework classifies materials into four groups – biomass, fossil energy carriers, metal ores, and industrial and construction minerals. The headline indicator Domestic Material Consumption (DMC) is calculated as the mass of all domestically extracted raw materials and harvested biomass plus the mass of imports (including raw materials, semi-products and finished products) minus the mass of exports. Other EW-MFA indicators include Domestic Material Input (DMI), which only covers domestic extraction and imports, and Total Material Requirement (TMR), which also accounts for unused hidden flows associated with raw material extraction (Wiedmann et al., 2015). Enormous efforts have been devoted to quantifying economy-wide material flows during the last decades. From early ones covering a small number of countries or snapshots of single years (Matthews et al., 2000; Schandl and Eisenmenger, 2006), to recent studies providing more comprehensive multinational datasets with long time series (Fischer-Kowalski et al., 2011; Giljum et al., 2014). The latest advances include the first global authoritative data set on material extraction and trade of materials covering four decades (1970–2010) brought together by the International Resource Panel hosted by United Nations Environment Program (Schandl et al., 2018; UNEP, 2016).

A generally agreed-upon conclusion from EW-MFA studies is that material productivity measured by GDP/DMC is higher in developed countries characterised by very advanced economies and lower in developing countries featuring urbanization and industrialization processes (Zhang et al., 2018). For example, G8 countries have successfully kept their aggregate DMC at a relatively stable level during the period of 1980–2008, while they doubled their total GDP over the same period (OECD, 2011). Some developed countries, such as Japan, Canada, and Germany, have even achieved absolute decoupling of material consumption from economic growth. In contrast, GDP per unit DMC in the Asia Pacific region roughly kept unchanged from 1970 to 1990, and then sink from 1990 to 2005, due to China’s soaring material consumption for its urbanization (Schandl and West, 2010). The historical evolution of the composition of countries’ material flows and levels of aggregated material consumption has often been referred to as the *sociometabolic transition* (Fischer-Kowalski and Haberl, 2007; Krausmann et al., 2008; Schaffartzik et al., 2014). In a nutshell, the sociometabolic transition concept suggests a shift in countries’ prevailing economic structure that reflects the state of underlying economic development. In this sense, Krausmann et al. (2008) describe a structural shift from an agrarian to an industrial regime. Whereas the former relies more on renewable resources, the latter depends more on non-renewable resources (fossil fuels and minerals) to build up and operate large amounts of human-made capitals. In general, the transition from an agrarian to industrial phase translates into an expansion of both, material consumption base and GDP, with an uncertain prevailing effect among the two forces. Although recognized as a general global trend, industrialized countries have almost finished this process and are now entering a new phase characterised by the so-called *knowledge economy* (Popkova, 2019; Powell and Snellman, 2004). This additional structural shift begins to be commonly indicated in most recent SEM studies as the natural stage following industrialisation. The rapid expansion of service sectors and similar knowledge-intensive activities, which is the characterizing factor of knowledge economies, stimulates productivity growth and, in turn, strengthens the decoupling of economic growth from the steady consumption of natural resources (Fernández-Herrero and Duro, 2019; Gan et al., 2013).

The analysis of development stages of an economy largely contributed to understanding material consumption patterns. However, economic development is far from being the only factor explaining the differences between countries. In one of the earlier EW-MFA contributions, Weisz et al. (2006) found that DMC per capita can be quite different even among mature economies such as EU-15 countries. The authors argue in fact that the level of use of biomass, industrial minerals, ores, and fossil fuels is largely determined by the structure of the economy rather than by national income or economic development. Similar findings were also presented by Bringezu et al. (2004), which examined dematerialisation for European and worldwide countries, including the USA, Japan and Australia, and Dittrich et al. (2011), which examined material use and material efficiency in emerging economies over the years 1985-2005.

The uneven evolution of material flow patterns observed among countries led scholars to examine more closely the relationship between resource consumption and its socioeconomic drivers (Steger and Bleischwitz, 2011; Steinberger et al., 2010; West and Schandl, 2018). The basic conceptual model employed in the literature for studying the impact of socioeconomic variables on the environment is constituted by the so called IPAT equation (Dietz and Rosa, 1997; York et al., 2003):

$$I = P \times A \times T$$

where I represent the impact of human activities on the environment, P is the human population, A is a measure of affluence (usually interpreted as average per capita GDP), and T is a measure of technological efficiency of consumption (Dietz et al., 2007; Dietz and Rosa, 1994). The IPAT approach has been extensively used in econometric studies in the form of STIRPAT – Stochastic Impacts by Regression on Population, Affluence, and Technology (York et al., 2003), which, thanks to its logarithm specification, allows to interpret results in the form of elasticities. Over time, extended STIRPAT models have been proposed by scholars. These include a broader range of explanatory variables, from geo-physical ones, e.g. latitude or climate, to structural ones, e.g. shares of economic activities over total GDP (West and Schandl, 2018). Among the most recent examples, Robaina et al. (2020) analysed the determinant factors of material productivity measured as GDP/DMC including novel explanatory variables such as the expenditure on R&D, value added by service and industry sectors or environmental tax revenues. Similarly, Fernández-Herrero and Duro (2019) explored the impacts of socioeconomic drivers in explaining international inequalities in material productivity levels considering openness to trade and value added by agriculture sector along with the other long-established explanatory variables.

As emerges from the literature examined, current material efficiency discourse, both in academia and policymaking, predominantly revolves around national and sectoral (or industry level) analysis. From international comparisons, we know a great deal about the aggregate drivers of material efficiency, but we know relatively little about the role played by places and regions in defining their own productivity performance. In spite of globalisation, territories (nations, regions and cities) still exhibit notorious differences in economic specialisation, competitiveness, institutions, cultures and overall historical heritages (Charron, 2016; Crescenzi and Iammarino, 2017). Such differences – often referred to as *territorial capital* (Castelnovo et al., 2020; Morretta et al., 2020) – all contribute to development strategies, and necessarily shape regional economies (Frenken et al., 2007; Gräbner et al., 2019; Hassink and Klaerding, 2015).

Regional science has a long experience in investigating the multitude of socioeconomic dynamisms which endogenously characterise economic growth and/or productivity (Camagni, 1991; Capello et al., 2007). Likewise, the neoclassical economic narrative recognises that 'factor conditions' exert great influence on local economies since Potter et al. seminal work, "*Competitive Advantage of Nations*" (1990). Factors of production are formed over historical periods through dynamic interactions between firms and institutions. Such long-term processes ultimately determine the availability of local infrastructures, resources and skills, hence shaping the capacity of certain regions to attract specific types of economic activity more than others (Porter, 1998). As a result, regional economies are influenced by a multiplicity of structural conditions and contextual circumstances, whose contribution toward national and global systems and networks is highly asymmetric (Crescenzi, 2020).

Material consumption patterns, and therefore material efficiency, are not an exception to this rule. If anything, the link between material efficiency and the territorial dimension is even stronger compared to its pure economic counterpart. In fact, the physical component of material efficiency, i.e. the consumption and/or production of goods, necessarily responds to the physical limits of territories. As an example, urban agglomerations and scarcely populated areas will behave very differently in terms of material consumption due to their underlying productive structures. Similarly, rural regions will present very different challenges to boost material efficiency compared to agglomerated areas, as they lack, for instance, the critical mass to enable waste sorting schemes and/or service-based business models. In this context, it can be claimed that it is not entirely possible to understand and interpret the relevance of the spatial distribution of material efficiency unless such territorial assets and related structural conditions are considered.

It becomes clear that existing national and supranational monitoring schemes tracking material efficiency performance do not live up to local policymakers as these latter generally face very different contexts compared to the national framework (Flachenecker and Rentschler, 2018; Rentschler et al., 2018). As has also been highlighted in recent contributions (see e.g. Bannò et al. (2015) and Crescenzi and Iammarino (2017)), region-specific factors and, thereby, territorial-based policy measures capable of stimulating regional competitiveness, are still poorly appreciated. Partly, this is due to the general scope of current national policies. Being mainly based on aggregated and international comparison research, these are unlikely to effectively stimulate regional material efficiency. Hence, an explicit focus on a subnational dimension must be an integral part of the material efficiency discourse, as it can provide a unifying lens to connect national policies to local contexts and, therefore, support local policymakers with tailored perspectives on the needs and potential opportunities of the respective jurisdictions.

However, comprehensive comparative research in the field of EW-MFA at European regional level is virtually absent. The main obstacle that prevented academic research from exploring the territorial dimension of material efficiency is the lack of data at subnational levels. Although some literature exploring material flows at regional or city level existed prior to this thesis (Kovanda et al., 2009; Rosado et al., 2014; Sastre et al., 2015), the very large spectrum of methodological approaches to measure EW–MFA indicators ultimately limited comparative analyses between areas (Kovanda et al., 2009; Rosado et al., 2014). To a large extent, this diversity of approaches is explained and driven by data availability in each setting. The high costs associated with data collection, alongside the limited capacity of intervention and incentives offered to regional and local governments to monitor and minimize material consumption in their own jurisdictions, make official statistics on material flows at subnational scales rather uncommon (Hammer et al., 2003; Sastre et al., 2015; Voskamp et al., 2017). This represents an important research gap for the characterisation of the metabolic profiles of territories, potentially hindering the design of place-based policies targeting material efficiency and/or sustainable consumption (Bachtler et al., 2017;

Binder et al., 2009; Kennedy et al., 2015). This research gap led to the formulation of the following research question, addressed by the first chapter in this Thesis:

Q1. How to deliver harmonised subnational material consumption indicators that recognise territorial heterogeneity?

- How to consistently scale down to subnational level material consumption indicators generally compiled at national level? How to elicit the multiple correlations existing between material consumption and its determinants? How to account for different national regimes in material consumption?
- What is the distribution of DMC across regions in EU countries?

The Thesis addresses this research gap by presenting a novel econometric approach to infer harmonised regional estimates from broadly available socioeconomic data. The method builds on the widely applied STIRPAT framework and expands it by integrating the different sociometabolic profiles characterising territories. The main novelty of the method is that, instead of adopting average elasticities for extrapolating lower-level estimates (Horta and Keirstead, 2017), we introduce an optimization algorithm that calibrates the elasticities of parameters to each national sociometabolic regime. In fact, to a large extent, it can be argued that regions tend to reflect the sociometabolic regimes of their respective nations. Modes and levels of production and consumption, as well as the economic momentum of subnational territories, necessarily follow macroeconomic trajectories observed at the national level. Therefore, national sociometabolic regimes can be a suitable predictor for subnational sociometabolic patterns. The method was applied to estimate DMC across more than 280 European regions. The comparison of our figures with previous studies confirms that, taking into account the due considerations, our estimates are consistent with those obtained by earlier studies making use of more data-intensive approaches (Kovanda et al., 2009; Rosado et al., 2014; Sastre et al., 2015). As a result, the proposed method represents a powerful tool to generate granular information that would otherwise be unavailable for empirical analyses.

The Thesis also delivers the first harmonised subnational DMC database for European – NUTS-2 – regions covering the decade 2006-2015 (Bianchi, 2020). We are convinced that the availability of granular data represents a critical input to advance the general understanding of sociometabolic systems as it permits to introduce the territorial dimension in cross-regional empirical analyses. As explained above, the consideration of territorial factors such as economic structures, demographic configurations, institutions, cultures etc. is critical to correctly interpret the relationship between material consumption and socioeconomic drivers, and ultimately, to better support resource management strategies. Hence, taking stock of the regional database developed in Chapter 2, the second part of this Thesis focuses on the analysis of the territorial implications of DMC patterns. Specifically, we address the following research questions:

Q2. What is the role played by territorial contexts in shaping the interdependencies between material efficiency and socioeconomic drivers?

- How the rural-urban regional dichotomy affects material efficiency of European regions?
- Do structural factors shape the relationship between material efficiency and its socioeconomic drivers?
- What are the implications for place-based material-efficiency strategies?

At first, we introduced the territorial perspective through the conventional rural-urban dichotomy. This *ad-hoc* territorial typology classifies regions according to the share of population living in rural or urban grid cells (Eurostat, 2018). At this stage, our main objective was to determine whether the comparison of material efficiency performance between urban and rural regions was consistent, or conversely, if such different territorial contexts were instead the main cause of the difference in efficiency. Therefore, a metafrontier Data Envelopment Analysis (DEA) framework (Battese et al., 2004; O’Donnell et al., 2008) was employed to compute regional efficiency with respect to (1) a common *metafrontier* – i.e. the whole regional sample, and (2) *group frontiers* – i.e. urban and rural groups. The underlying assumption of the metafrontier framework is that regions exhibit different technology sets depending on the availability of physical, human and financial assets, economic infrastructure, resource endowments and any other characteristics of the physical, social and economic environment in which production takes place. Such differences justify the estimation of separate production frontiers, which, in our case were determined according to the territorial typologies.

One of the main advantages of this approach is the possibility to disentangle the actual regional inefficiency in terms of *technological efficiency gap* and *conditional efficiency gap*. Technological efficiency gap is mainly driven by exogenous factors such as lack of economic infrastructures, human capital and/or other characteristics of the production environment. These technical constraints ultimately limit the access to higher production frontiers, independently from the region's overall ability to optimise resources. By contrast, the conditional efficiency gap measures the amount of inefficiency due to a non-optimal resources' management. While this approach has been extensively employed in empirical studies focusing on labour productivity (Battese et al., 2004; Kounetas and Napolitano, 2018; Walheer, 2018), its application to material efficiency, and alike environmental indicators, was so far missing in European regional studies. Hence our results provide a first evidence of the very polarised picture in terms of material efficiency between the better-off centric capital regions and the worse-off peripherical ones. Partly, this is explained by the fact that peripheral regions typically act as *suppliers* of materials for urban consumption. Agriculture and traditional manufacturing activities (e.g. footwear, leather, apparel, textiles, pulp and wood by-products etc.) are mainly located in intermediate and rural areas, which then export processed materials to urban agglomerations for final consumption and/or further refining. Therefore, the lower levels of material efficiency in rural and intermediate regions actually reflect an environmental burden that should be attributed to urban areas. However, the analysis also unveils that technological catching-up and underperformance processes are not necessarily associated with urban or rural characteristics as underlying socioeconomic patterns also influence material efficiency levels.

Once established that material efficiency levels depend, to a greater extent, on the regional territorial contexts, and therefore, on the underlying productive structures, we went a step further by paying a special attention to the effects that territorial contexts could have, in turn, on socioeconomic drivers of material efficiency. In other words, we analysed whether the elasticities of affluence, population density and technology differ across regions or whether they are stable. To this aim, we rely on a panel-data analysis covering the period 2006-2015, in which we employed material productivity (i.e. GDP over DMC) as a proxy for material efficiency and regional economic structures as a proxy for territorial contexts. To the authors' knowledge, this specific aspect was not yet been addressed by previous studies. Consequently, we believe that one of the main contributions of this work consists in the way in which we addressed economic structures. Unlike previous works that take account of structural factors as standard explanatory variables in regression models (Fernández-Herrero and Duro, 2019; Gan et al., 2013; West and Schandl, 2018), we considered the economic structures as interaction terms with socioeconomic drivers. This approach allowed to characterise the influence of heterogeneous economic structures on the relationships between material productivity and its socioeconomic determinants.

One of the most outstanding findings of this research was that affluence and population density impact the material productivity in considerably different ways based on the prevailing economic specialization of regional economies. Areas relying on primary and secondary sectors present higher returns in material productivity from increased levels of affluence, compared to service-based economies. By contrary, service-based economies tend to capitalise material productivity gains through physical densification. These patterns might be explained by the intrinsic nature of economies. In fact, material-intensive regions are mainly producers and exporters of raw material and manufactured goods, so that an increase in affluence would have direct repercussion on their productive means. Production would be enhanced by a greater access to financial resources, and therefore to technological improvements. By contrary, a GDP increase in tertiary economies would have a smaller impact on material productivity, as these economies present a rather weak presence of manufacturing and/or raw material extraction activities. Conversely, population density presents a higher leverage effect in urban regions, where space constraints limit the deployment of material-intensive activities and favour instead the development of strong service-oriented economies.

Overall, this Thesis provide compelling evidence that the underlying qualitative nature of economic development, e.g. in terms of the variety of sectors and technologies, or the different urban configurations of territories is critical for a complete understanding of socioeconomic metabolic systems. Material consumption and, therefore, material efficiency performances, not only behave differently according to territorial contexts, but also present different leverage mechanisms depending on local resources. We believe that a deeper understanding of the territorial dimension of material consumption is critical to support the design of effective place-based policies towards material efficiency goals.

After this *Introduction*, the manuscript is organised in 3 autonomous chapters. Each of them addresses a specific aspect of material consumption at lower territorial levels. A final section, named *Overall Conclusions*, is then presented summarising main findings and limitations of the whole research. Each chapter is organised as an independent “piece of research”. This means that Chapters 1, 2, 3 feature own introduction, material, methods and results. Besides facilitating the readability of the overall work, the decision of structuring the manuscript in autonomous chapters was also dictated by the fact that we relied on different literature and methods according to the specific research gaps addressed. In this sense, in Chapter 1 we develop a novel three-stage – specification, optimization, extrapolation (SOE) – econometric approach to infer harmonized regional level estimates from broadly available socioeconomic data. The approach is tested by estimating DMC in more than 280 European regions (at NUTS 2 level) for the years 2006 and 2014. Having established that our DMC estimates were consistent with previous studies, we applied the SOE methodology iteratively to build a regional DMC database for the period 2006-2015.

Taking advantage of the new dataset, in Chapter 2 and 3 we explore the territorial implications of material consumption patterns through two different perspectives. In Chapter 2 we propose an eco-efficiency indicator based on the frontier-approach to investigate material efficiency between urban and rural regions. First, Data Envelopment Analysis (DEA) is used to combine different types of indicators with the aim to generate a more inclusive measure of material efficiency compared to material productivity. In this respect, we included employment rates next to DMC and GDP measures as a proxy for the social dimension. Second, we introduce the metafrontier framework to evaluate the regional eco-efficiency performance according to the different operating environments of urban and rural contexts.

In Chapter 3, we offer a complementary perspective of the implications of territorial contexts by considering underlying regional economic structures. Differently from the urban-rural typology employed in Chapter 2, which is based on the distribution of urban population, in Chapter 3 we develop a taxonomy of economic structures based on the prevailing economic specialisation of regions. This is based on four overarching groups: agriculture-, industry-, intermediate- and service-based economies. In the following stage, we investigate the effects that these regional economic structures exert on the socioeconomic determinants of material productivity through a panel-data analysis in the period 2006-2015.

In *Overall Conclusions* section we summarise the main findings of our analysis. In addition, we reflect on possible lines of research that could be opened as a result of our analysis or as a complement to it.

At the end of the manuscript we also include a technical appendix with a detailed description of the Economic-Wide Material Flow Accounting (EW-MFA) framework. This should help any reader unfamiliar with EW-MFA indicators, facilitating the correct interpretation of DMC-based material efficiency indicators

Chapter 1

1. Monitoring Domestic Material Consumption at lower territorial levels

A novel data downscaling method

This chapter is based on the following published papers:

1. *Bianchi M, Tapia C, del Valle I. Monitoring domestic material consumption at lower territorial levels: A novel data downscaling method. J Ind Ecol. 2020;1–14. https://doi.org/10.1111/jiec.13000*
2. *Bianchi M, Tapia C. Producing regional data for circular economy monitoring in Europe, ESPON Scientific Report - Building the next generation of research on territorial development, section: New data sources. ISBN: 978-99959-55-90-8.*

1.1. Introduction

The increasing environmental pressure and resource scarcity resulting from human activities have led governments and international organizations to promote systemic changes towards new and more sustainable modes of production and consumption. As an example, circular and green economy transitions are among the leading strategies implemented at international level (European Commision, 2015; UNEP, 2011). Understanding how these systemic transformations impact regional economies and how different areas will evolve towards more sustainable trajectories are two among the major challenges that policy-makers dealing with territorial policies are currently faced with (Bachtler et al., 2017; Fratini et al., 2019). Against this background, monitoring and assessing material consumption and material productivity is critical, both from a macroeconomic perspective – to assess whether sufficient action has been taken –, as well as from a local perspective – to support local decision-makers in setting new priorities towards long-term objectives (Corvellec et al., 2013; Mayer et al., 2019; van Buren et al., 2016). However, although well-developed statistical infrastructures and monitoring schemes already exist worldwide, data availability on material consumption is still very limited, particularly at subnational levels. Hence, additional efforts are needed to characterise material consumption and material intensity indicators at more granular levels.

This chapter aims to fill this gap, first, by developing a methodology to provide harmonised regional level data, then, by applying the method to Domestic Material Consumption (DMC), by far the most relevant and used indicator informing on material use by a given economy (Bengtsson et al., 2018; Bringezu, 2017; European Commission, 2018b; PBL, 2018). DMC, defined as the sum of domestic material extraction and imports, minus exports (EUROSTAT, 2018), is often used to conduct quantitative analyses on the circularity and material efficiency of the economies (see e.g. Haas et al., 2015; Mayer et al., 2019) . Moreover, when combined with key variables such as population, surface area and/or Gross Domestic Product (GDP), it also allows to characterize the so-called sociometabolic profiles of territories (Fischer-Kowalski & Haberl, 1998; Krausmann, Fischer-Kowalski, Schandl, & Eisenmenger, 2008; Pauliuk & Hertwich, 2015). These inform on the complex systems of society-nature interaction characterizing a country and necessarily need to be taken in account when inferring respective subnational data. DMC is calculated according to the Economic-Wide Material Flow Accounting (EW-MFA), the standard methodology to account for material flows on a national or global scale (see Appendix for further details on EW-MFA).

Despite DMC provides valuable information to better understand present and future trajectories of regional or local economies (Baynes and Musango, 2018; Dong et al., 2017; Krausmann et al., 2009; Steinberger et al., 2013), it also has its shortcomings. On the one hand, DMC does not account for all those upstream raw materials related to imports and exports originated from outside the focal economy (Giljum et al., 2014; Wiedmann et al., 2015). This truncation might mislead assessments of national resource productivity – as countries might apparently reduce their DMC by outsourcing material-intensive extraction and processing abroad – and it must be considered when evaluating DMC results across countries (Talmon-Gros, 2014). On the other, given that the EW-MFA has been primarily developed to assess material flows of national and/or global economies (Schandl and West, 2010; Steinberger et al., 2010; Weisz et al., 2006), harmonised data on material flows are only available at highly aggregated level (EUROSTAT, 2018; Gierlinger and Krausmann, 2012; Krausmann et al., 2011).

Recent regional studies in Europe focusing on – among others – Paris and Île de France (Barles, 2009), Czech regions (Kovanda et al., 2009), Lisbon and its metropolitan area (Niza et al., 2009; Rosado et al., 2014), Amsterdam (Voskamp et al., 2017) and various Spanish regions (Sastre et al., 2015) favoured the development of a solid knowledge-base on the regional and urban metabolism across the European continent. However the large spectrum of methodological approaches applied – see e.g. Duarte (2016) and Niza et al. (2009) for a review on urban-based metabolism studies – undermines comparative analyses between areas (Kovanda et al., 2009; Rosado et al., 2014). To a large extent, this diversity of approaches is explained and driven by data availability in each setting. The high costs associated with data collection, alongside the limited capacity of intervention and incentives offered to regional and local governments to monitor and minimize material consumption in their own jurisdictions, make official statistics on material flows at subnational scales rather uncommon (Hammer et al., 2003; Sastre et al., 2015; Voskamp et al., 2017). This represents an important limitation for the characterisation of the metabolic profiles of territories, potentially hindering the design of place-based policies targeting material efficiency and/or sustainable consumption (Bachtler et al., 2017; Binder et al., 2009; Kennedy et al., 2015).

This chapter presents a three-stage – specification, optimisation, extrapolation (SOE) – econometric method to estimate harmonised and comparable DMC data at subnational level. The method builds on the widely applied STIRPAT framework that seeks to explain resource consumption as a function of population, affluence and technology and expands it by integrating the different socio-metabolic profiles characterising territories. We apply the SOE method to estimate DMC figures for most European NUTS-2 regions[3] for years 2006 and 2014[4]. The main advantages of the SOE method are that: (1) it uses a consistent approach that recognises territorial heterogeneity but at the same time allows comparability across different areas and over time, (2) it elicits the multiple correlations existing between materials consumption and its key explanatory factors, and (3) it is systematically applied, allowing to estimate larger datasets at once. Moreover (4), the methodology can be easily adapted to other fields and/or indicators, paving the way for further comparative analyses at subnational levels in face of data scarcity.

The main contribution of this chapter is twofold: First, unlike previous studies aiming to produce subnational level estimates for material flows, it introduces an optimization algorithm to account for the specific socio-metabolic profiles of territories. This allows not only to efficiently deal with data scarcity at subnational levels, but also to successfully deliver granular data that reflect territorial heterogeneity. Second, it provides a novel harmonised material consumption dataset at European regional level that potentially open the way for further comparative research in the field of regional resource use. The method and the new data are expected to advance the general understanding of metabolic systems and their influencing factors at regional levels (Fernández-

[3] The Nomenclature of Territorial Units for Statistics (NUTS) is a geocode standard for referencing the subdivisions of countries for statistical purposes. The standard is developed and regulated by the European Union, and thus only covers the member states of the EU in detail. The analysis covers all the EU and most European Free Trade Area (EFTA). Hereafter the terms “regions” and/or “regional level” will refer specifically to the NUTS-2 level.
[4] Note that after the publication of the article a whole dataset from 2006 to 2015 was generated by iteratively applying the SOE method. The whole dataset can be found in Bianchi (2020).

Herrero and Duro, 2019; Kennedy et al., 2015; Rosado et al., 2014), providing decision-makers with valuable information on the effects of measures and policies adopted across different regions.

The chapter is structured as follows: after this Introduction, we present a brief overview of the socio-metabolic concept. In Section 1.3 and 1.4 we discuss the data sources and thoroughly describe the SOE method, respectively. Section 1.5 presents our DMC regional estimates for 280 European regions, including a comparison with DMC figures provided by other peer-reviewed studies. Finally, Section 1.6 summarises the main conclusions and presents some ideas for future research.

1.2. The socio-metabolic regimes of territories

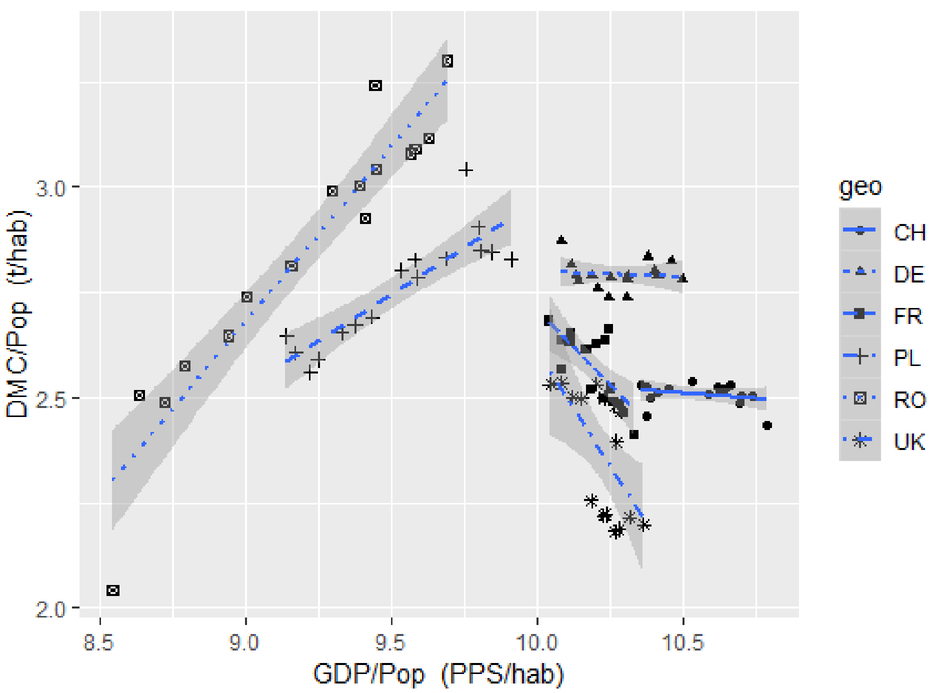
The proposed SOE method takes special advantage of the notion of socio-metabolic regimes firstly introduced by Sieferle (1997) and Fischer-Kowalski and Haberl (1998) and further elaborated by several other authors including, inter alia, Krausmann et al. (2008), and Pauliuk and Hertwich (2015). In general terms, socio-metabolic regimes refer to the structural coupling of a socioeconomic system with a certain compartment of the natural environment from which it draws its resources (Krausmann et al., 2008). This latter dimension can be related to material and/or energy throughputs, depending on the framework analysis. The main underlying hypothesis is that the amount of materials or energy consumed by a society is largely determined by the size of its population, along with its production-modes and consumption patterns (Fischer-Kowalski & Haberl, 1998). These socioeconomic characteristics are typically described in terms of population density and GDP per capita (Steinberger et al., 2013), two key synthetic indicators that can also be used in empirical modelling strategies (like ours) to indirectly infer environmental impacts (Dietz et al., 2007; West and Schandl, 2018; York et al., 2003).

High population density is often the result of extended periods of intensive agricultural colonization (Krausmann et al., 2008). By contrast, a low population density might be explained by either historical reasons (i.e., no long, uninterrupted history of agrarian colonization), or geophysical reasons, such as hostile natural conditions, e.g., aridity, cold climate, or adverse terrain (Krausmann et al., 2008). However, population density not only reflects geophysical conditions and agricultural history, but it also allows to systematically differentiate between areas of high and low per capita availability of natural resources (Weisz et al., 2006). In general, the per capita endowment of natural resources, being these mineral resources, biomass, or even livestock, is higher in sparsely populated regions than in densely populated areas. These patterns are further enhanced by the historical argument outlined above. Countries with a high population density usually have a longer history of resource exploitation and hence have often exhausted their domestic resource base (Krausmann et al., 2008). Finally, sparsely populated regions require a higher input of energy and materials for the same level of supply of services per person compared to densely populated areas. Therefore, population density can be expected to have a significant impact on metabolic profiles of regions (Weisz et al., 2006).

GDP per capita, on the other hand, is generally used to discern between different levels of average consumption of economies (Dietz et al., 2007; York et al., 2003). Moreover, this indicator is also a good proxy informing on the productive structure of a region. In general, economic activities belonging to the tertiary sector are the most productive ones. These can generate up to 86% of the total gross value added of metropolitan areas (Duarte, 2016). This suggests that regions with above-average income levels in general have strong service-driven economies, while lower income levels reflect economies that rely more on material-intensive activities such as agricultural and/or industrial activities (Bithas and Kalimeris, 2018). Roughly speaking, it could be expected that richer regions might directly consume less materials on per-capita basis, since it is likely that these areas import finalised products and/or semi-elaborated products instead of producing them locally. In fact, there is solid evidence that highly developed economies outsource material-intensive products to other areas (Giljum et al., 2014; Wiedmann et al., 2015).

Identifying specific socio-metabolic regimes is essential when explaining territorial diversity and development patterns (Krausmann et al., 2008). For instance Dong et al. (2017) distinguished between developing, primary developed and mature industrialized countries, while Steinberger et al. (2013) highlighted the difference between the metabolic regimes of China and Germany. Figure 1 shows a scatterplot of DMC per capita and GDP per capita for a sample of European countries over the 2000-2015 period. Similarly to these examples, our data depicts distinctive socio-metabolic regimes for individual countries. These can nonetheless be grouped in clusters of countries with similar behaviour. Economies like Germany and Switzerland are characterised by a rather stable DMC per capita despite a growing GDP per capita, whereas French and British economies show a declining pattern on DMC per capita vs GDP per capita (i.e. declining material consumption per capita and increasing GDP per capita), which could be an indication of economic tertiarization. In contrast, expanding economies such as Poland and Romania show a DMC per capita that grows at similar pace as the GDP per capita.

Figure 1: Examples of socio-metabolic patterns at country level (2000-2015)



Note: figures are in logarithmic forms. Fitted lines are generate by OLS regressions for each country. DMC/Pop: DMC per capita, GDP/Pop: GDP per capita. Data source: EUROSTAT.

The discussion outlined above becomes fundamental when it comes to the estimation of material consumption at subnational scales. To a large extent, regions necessarily reflect the socioeconomic regimes of their respective Nations because their modes and levels of production and consumption, as well as the economic momentum of subnational territories, present similar trajectories as those observed at the national level. In this respect, national socio-metabolic regimes can be a suitable predictor for subnational socio-metabolic patterns. This aspect has been specifically taken-up by our quantitative model, as described in section 1.4 below.

1.3. Data

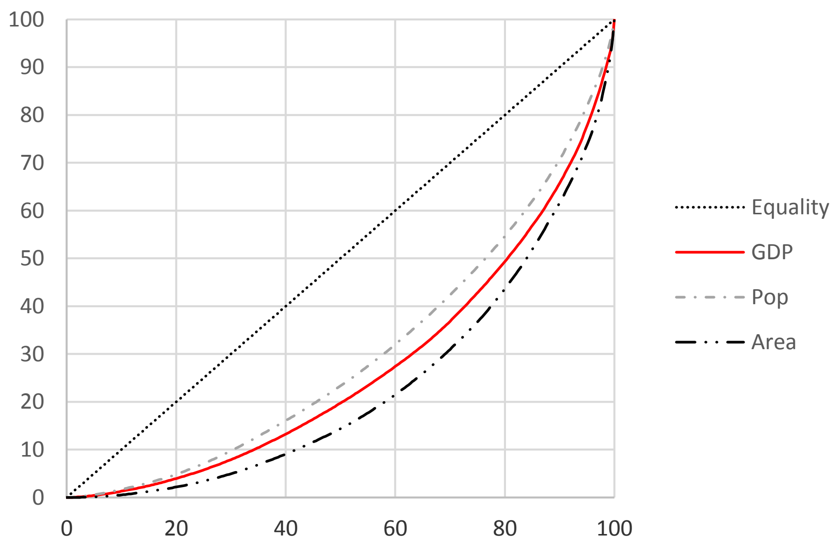
We built a dataset that includes DMC measured in thousand tonnes, GDP measured in purchasing power standard units (PPS), population measured in number of inhabitants (Pop), and surface area measured in square kilometres (Area) at both, national (NUTS 0) and regional (NUTS 2) levels. From these variables we computed the GDP per capita (GDP/Pop), population density (Pop/Area), DMC per capita (DMC/Pop) and DMC intensity (DMC/GDP) for 2006 and 2014. These years were selected as reference time-cuts for two reasons: Firstly, because they cover a significant time-span, allowing to capture potential structural changes in socio-metabolic regimes. Secondly, because data availability was acceptable: 2006 and 2014 are the oldest and the most recent year for which almost complete data sets were available[5]. Data were downloaded from the Eurostat “nama_10r_2gdp”, “demo_r_d3dens”, and “env_ac_mfa” datasets on March 2019. The download was performed by making use of the R package “Eurostat” v.3.3.5 (Lahti et al., 2019). Data gaps were filled by making use of OECD and/or national statistical databases.

Countries exhibit great heterogeneity in terms of socioeconomic and physical factors. The biggest EU economy, Germany, shows GDP and population values that are respectively 265 and 188

[5] 2006 is the first year in which Norway reports on DMC, while the years after 2014 present many *estimated* DMC figures.

times bigger than those recorded for the smallest European country in our dataset, Malta. On the other hand, Malta shows the highest population density in Europe (1.375 persons/km2). This is a clear example of how territorial assets might be unevenly distributed across geographies – and also explains why scholars often suggest the use of per capita variables (e.g. income per capita and population density) instead of absolute variables (e.g. area, population and GDP) when describing territorial patterns of material use (Steinberger et al., 2010; Weisz et al., 2006). The heterogeneity observed at the national level increases when we move down to the regional scale. Figure 2 illustrates the Lorenz curve of GDP, population and surface observed at regional level in Europe. Absolute surface area is the variable more unevenly distributed, with only four regions (Nordic regions of Scandinavia plus Castilla y Leon in Spain) representing around 10% of total European surface. GDP and population also show very skewed distributions. Around 20% of EU regions produce almost 50% of total GDP. Similar percentages hold for population data.

Figure 2: Lorenz curves of GDP, population, and surface (2014).



Data source Eurostat.

Table 1 offers an alternative perspective on the very assorted configuration of European territories by summarising the variation of GDP per capita and population density – two socioeconomic drivers of material consumption – across regions and countries. Regions with the highest GDP per capita, such as Inner London-West (UK), show values that are 21 times greater than those of the regions situated in the lower rank (e.g. Bulgarian and Romanian regions). In terms of population density, greater agglomerations such as Inner London and Brussels regions, with more than 7000 inhabitants per square kilometres, contrast with very low-density regions, such as Upper Norrland (SE) and Nord-Norge (NO), with only 3 and 5 inhabitants per square kilometres, respectively. It should be noted that the coefficient of variation (CV) and the variation factor (VF) increase dramatically at the subnational scale, above all for physical factors such as population density. For example, nationally, the most concentrated country has a population density of 81 times that of the most sparsely populated country. At regional level, this ratio is equal to 3593, i.e. the most populated region (Inner London - East (UK)) is 3593 times the least populated one (Upper Norrland (SE)).

Table 1: Comparative statistics for EU regions (2014).

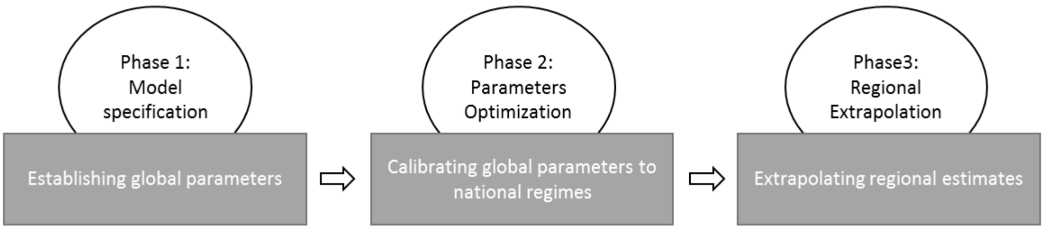
Concept	Level of analysis	GDP/Pop	Pop/Area	DMC/Pop	DMC/GDP
Mean	Countries	27949	168	16.32	0.67
	Regions	27462	452	n.a.	n.a.
CV	Countries	0.46	1.47	0.38	0.50
	Regions	0.48	2.68	n.a.	n.a.
VF	Countries	8	81	3.98	5.61
	Regions	21	3593	n.a.	n.a.
Variables	**Selected outliers**				
	Maximum		**Minimum**		
GDP/Pop	Inner London - West (UK)	173032	North-western (BG)	8214	
	Luxembourg (LU)	75571	Southern Central (BG)	8802	
	Hamburg (DE)	57608	Nord-Est (RO)	9290	
Pop/Area	Inner London - East (UK)	10780	Upper Norrland (SE)	3	
	Inner London - West (UK)	10283	Nord-Norge (NO)	5	
	Brussels (BE)	7393	Middle Norrland (SE)	5	

Data source: Eurostat. Note: GDP/Pop is measured in GDP PPS per capita; Pop/Area is measured in inhabitants per square kilometres; DMC/Pop is measured in tonnes per capita; DMC/GDP is measured in tonnes per 1000 GDP PPS. The mean refers to the mathematical average of the sample; The coefficient of variation (CV) = standard deviation/mean. The variation factor (VF) = Max/Min.

1.4. SOE Method

The methodology is based on a three-steps econometric model (Figure 3), including: (1) global model specification, (2) optimization of parameters, and (3) regional extrapolation. Step (1) focuses on the identification of the best regression model describing DMC patterns across European countries. The main output of this first task is the estimation of the global parameters (β_g) (i.e. the regression coefficients observed between DMC and its explanatory variables at European level). Step (2) calibrates the model in order to reflect the specific socio-metabolic regimes of the different countries. This calibration is implemented by an optimization algorithm that automatically adjusts the estimated parameters based on the specific characteristics of each country. This generates a set of country-specific parameters (β_{cs}). Finally, in Step (3) we extrapolate the regional figures for DMC by applying β_{cs} on the selected explicative variables, which are now measured at the regional level.

Figure 3: Methodological approach to estimate regional figures.



$Y_i = const + \boldsymbol{\beta}_{\mathbf{g1}} X1_i + \boldsymbol{\beta}_{\mathbf{g2}} X2_i + e$

$Country: i = 1{,}2{,}3 \ldots 31$

$Y_i = const + (\boldsymbol{\beta}_{\mathbf{cs1}})_{\boldsymbol{i}} X1_i + (\boldsymbol{\beta}_{\mathbf{cs2}})_{\boldsymbol{i}} X2_i$

$Country: i = 1{,}2{,}3 \ldots 31$

$\hat{\boldsymbol{y}}_{\boldsymbol{j}} = const + (\beta_{cs1})_i x1_j + (\beta_{cs2})_i x2_j$

$Country: i = 1{,}2{,}3 \ldots 31$

$Region: j = 1{,}2{,}3 \ldots 280$

Note: bold terms refer to the output of each phase; upper case letters (Y-X) refer to variables measured at national level (NUTS 0); lower case letters (y-x) refer to variables measured at regional level (NUTS 2).

Even though the method relies on the assumption of same model specification across scales – similarly to other top-down approaches (Horta and Keirstead, 2017) –, it offers an important advantage on how territorial heterogeneity is considered in the model. While previous studies often deal with the variability of territorial regimes by using a switching regression approach (see e.g. Chasco (2003)), we apply an algorithm that automatically adjusts the global parameters to the socio-metabolic profile of each country. In doing so, our approach does not only overcome the issue of limited data availability that often impedes the application of EW-MFA approach at subnational levels, but it also addresses two aspects that most MFA studies have so far ignored, namely: (a) the issue of national regimes dependency and (b) the multiple correlation accounting problem.

When it comes to item (a), it should be considered that correlations between drivers and response variables might not only vary across scales, but also across observations belonging to different "territorial regimes". When considering the nations-to-regions extrapolation, it is very likely that regional drivers are not only influenced by highly aggregated supra-national structures, but also and foremost by their own national regimes. For instance, any combination of territorial factors operating in Nation A, being these hard (as those in our model) or soft (e.g. governance and administrative traditions, milieus, etc.) could impact the respective regions in the country in a different way from how these same factors could affect regions in Nation B. In practice, this means that similar underlying drivers can affect regions in different and diverse ways, depending on the specific socio-metabolic conditions defined by the upper territorial structures.

Regarding item (b), most local metabolism studies use a single proxy factor (or driver) to estimate missing data by assuming bold hypothesis such as "consumption is almost proportional to population" (Barles, 2009; Courtonne et al., 2015). However, different correlation studies established important findings regarding material consumption and its potential drivers (Courtonne et al., 2015; Steger and Bleischwitz, 2011; Steinberger et al., 2010), which go well beyond the simplified consumption-population relationship. For instance, geophysical characteristics of regions, along with economic structures and standard of living, do affect the level of material consumption (Baynes and Musango, 2018; Weisz et al., 2006) and therefore must be somehow accounted when estimating DMC.

1.4.1. Step 1: Global Model specification

The global model specification concerns the definition of a regression model at the upper (national) level, where the indicator of interest is available. Variable selection is arguably the most difficult task in regression modelling exercises and several time-saving algorithms are often applied to support the analyst choice (e.g. forward selection, backward elimination, stepwise regression and “all possible regressions”) (Neter et al., 1996). In general, these build on selection criteria such as: (1) statistical tests (e.g. F-statistic, chi-square, and t-test), (2) statistical criteria (R-squared, adjusted R-squared), (3) statistical stopping rule (e.g. P-values thresholds for variable entry/deletion in a model) (Ratner, 2010). Notwithstanding, relying entirely on ad-hoc selection algorithms might (1) introduce some undetected bias and (2) result in including some drivers that have nothing in common with our response variable, but that apparently result to be correlated (Smaranda, 2013). Consequently, the suggested approach in drivers’ selection should be mainly driven by the analyst’s knowledge of the area under study and of each of the variables, leaving the use of selection algorithms to explorative and/or validating purposes.

Figure 4 shows a decisional flow-chart that resumes the steps needed to identify the best downscaling model across different time-periods. The selected model should satisfy a set of requirements. These are:

1. Goodness-of-fit: in regression, the R^2 coefficient is a statistical measure of how well the regression line approximates the real data points. R^2 close to 1 indicate that parameters explain well cross-country differences, therefore the first requisite is to find the best fitting model.

2. Model complexity: one drawback of R^2 coefficient is that it does not take in account the complexity of the model. In other word, it increases as the number of variables increase in the model (R^2 is monotone increasing with the number of variables included, i.e. it will never decrease). Using the AIC criterion, we account for the risk of model overfitting

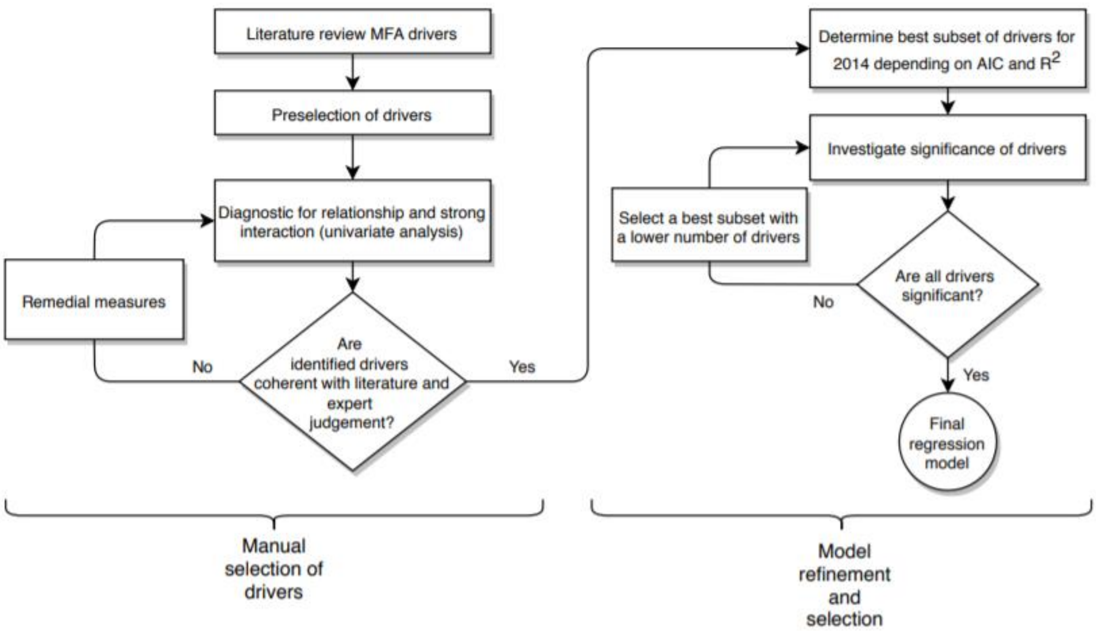
since it deals with the trade-off between the goodness-of-fit of the model and the simplicity of the model.

3. Coefficients' significance: selected drivers are used in the following steps to downscale national figures. Consequently, in order to reduce prediction variance, drivers with reduced standard error are highly recommended.

In addition, whenever the SOE method is applied to generate a time series, it is important that the model remains unchanged across years. This translates into a fourth requirement:

4. Comparability: if the final aim is to conduct comparative analysis across different time periods, the model should be equal across the years (i.e. same number and typology of drivers). The selection of different drivers across time, for a same dependant variable, would likely generate results biased from the type of drivers used, worsening in the end the comparison.

Figure 4: Decision flow-chart for model selection



Source. Own elaboration

Concerning the DMC indicator, the starting point of our empirical model is based on the STIRPAT framework (STochastic Impacts by Regression on Population, Affluence and Technology) firstly introduced by Dietz and Rosa (1997, 1994) and adopted later by, inter alia, Steinberger et al. (2010) to understand and quantify the relations between material consumption flows, socioeconomic drivers and geophysical factors, and Baynes and Musango (2018) to predict global material consumption by 2050 (see also Dietz et al. (2007)). The STIRPAT approach seeks to explain environmental impact (I) of a given socioeconomic system in terms of population (P), affluence (A) and available technology (T). Affluence stands for the level of consumption and it is generally approximated by GDP/pop. Technology, can be interpreted as the particular means by which affluence is generated (Baynes and Musango, 2018; Fischer-Kowalski et al., 2011) and it is often approximated by measures of economic structure (e.g. manufacturing or industrial share of GDP) (Cole and Neumayer, 2004; Shi, 2003). Given the limited set of covariates considered, the STIRPAT framework might be criticised as a reductionist approach in a context where it is plausible to assume that other factors would causally influence the response variable (i.e. DMC) (Hummel et al., 2013). However, recent studies show that, beside the long-established explanatory variables of Pop and GDP per capita, additional variables do not contribute significantly to explain the remaining variation between territories (West and Schandl, 2018). Therefore, considering that our goal in providing a robust, transparent, systematic and easy-to-apply approach to infer regional estimates, the development of a more complex and sensitive model was excluded.

The STIRPAT model has been applied so far using both total DMC or its intensive expressions, i.e. DMC/Pop and DMC/GDP (Baynes and Musango, 2018; Dietz et al., 2007). We will focus here on the intensive form DMC/GDP. This not only allows to better capture the relationships between DMC and its drivers, but it also constitutes the most important indicator informing on the decoupling of economic growth from environmental degradation (Bringezu, 2017; UNEP, 2016; Wiedmann et al., 2015).

Our STIRPAT equation is expressed as:

$$Log\left(\frac{DMC}{GDP}\right) = const + \beta_{g1}Log\left(\frac{Pop}{Area}\right) + \beta_{g2}Log\left(\frac{GDP}{Pop}\right) + e$$

Eq. 1.4-1

where $\beta_{g1,g2}$ are the parameters to be estimated respectively for population density (Pop/Area) and GDP per capita (GDP/Pop), while *e* is the error term. Logarithmic forms were used to reduce skewness and approximate linear relationships between variables. Note also that the logarithmic form also allows to interpret the parameters' coefficients (β) as "ecological elasticities" (York et al., 2003). When $|\beta|$ >1 the relationship is elastic, meaning that Y increases as the predictor X increases, but it does so at a faster rate than X. When $|\beta|$ <1, the relation is inelastic, i.e. as X increases, the response Y increases as well, but at a slower rate than X. When $|\beta|$ =1, the relation between the explanatory variables (X) and the response (Y) is proportional.

Table 2 shows the regression results for years 2006 and 2014. Overall, the STIRPAT approach is quite successful at explaining cross-country differences in material consumption, and our results are in line with past studies (Dietz et al., 2007; Steinberger et al., 2010). According to our fitted model, Pop/Area is inversely correlated with material consumption. As outlined above, this can be explained by assuming that denser areas are able to optimize material consumption (think for example on how the construction of transport infrastructures may have a greater impact on per capita values when deployed in low-density regions). Besides, denser regions are typically areas where material intensive activities such as primary and secondary transformations of raw materials are rarely conducted (Weisz et al., 2006). However, the fact that the coefficient is almost inelastic suggests that the mitigation effect of agglomeration economies on DMC remains limited in any case (Fernández-Herrero and Duro, 2019). According to the fitted model, the second explanatory variable, namely GDP/Pop, which reflects income elasticity, is inversely correlated with the DMC/GDP. This is consistent with the previous claim that higher levels of GDP per capita reflect economic structures that are based on the most productive sectors, therefore limiting direct material consumption. Furthermore, the negative sign is justified by the decrease in material intensity observed in recent decades which is largely explained by the steady growth of GDP, as the DMC has decreased at a much slower pace.

Table 2: OLS regressions results

Ind. variable	DMC/GDP			
Year	2006		2014	
Constant	7.73***	*(1.052)*	7.374***	*(1.289)*
Pop/Area	-0.225***	*(0.051)*	-0.251***	*(0.057)*
GDP/Pop	-0.688***	*(0.105)*	-0.663***	(0.129)
N	30		31	
R^2	0.721		0.664	
F-statistic	34.9		27.62	
JB X-squared	0.585		0.539	
SW	0.953		0.987	
B-P Koenker	6.763*		2.904	
RESET	0.900		1.126	
Chow-test	2.991**			

Note: '***' significant at 1%; '**' significant at 5%; '*' significant at 10%; Standard errors in parenthesis; JB: Jarque Bera; SW: Shapiro-Wilk; BP: Breusch-Pagan test using Koenker's studentized version; RESET test applied for quadratic and cubic powers; In 2006 figures for North Macedonia were not available.

Although we initially considered pooling the two, 2006 and 2014, cross-sections in a single sample, the Chow test suggested that a structural change between the two periods under analysis had actually occurred. We hence decided to keep the two cross-sections on separate analytical strands. While verifying the model robustness for each cross-section, we detected that albeit residuals exhibit normal behaviours, the 2006 model seemed to suffer from residual heteroskedasticity. This was reflected by the Koenker's version of the Breusch-Pagan statistic, which was significant for the 2006 cross-section (but not for the 2014 dataset). One frequently used approach to deal with the heteroskedasticity issue is to apply robust errors. However, this option was excluded to avoid undermining the following step in our methodology, namely model optimization. Since this phase depends on the confidence intervals of estimated parameters, it is only reliable in presence of tied intervals. The use of robust errors would have widened the intervals used as a boundary during optimization, and hence we opted to work with the heteroskedastic 2006 model. We also tested for non-linear combinations of drivers by performing the RESET test, which suggests that the two models for 2006 and 2014 data are correctly specified. Based on all the tests performed, we conclude that the model is sufficiently reliable to be applied in the optimization phase as a basis to estimate country-specific parameters.

1.4.2. Step 2: Parameters optimization

The parameters β_g for Pop/Area and GDP/Pop estimated in step 1 are global, that is to say, they apply indifferently to all countries, without taking into account country-specific socio-metabolic regimes. Hence, the use of global parameters computed at European scale would likely produce unrealistic regional estimates.

We propose an optimization procedure that automatically adjusts global parameters to account for country-specific socio-metabolic regimes. This systematisation is a pragmatic way to reflect country regimes and overcome the poor data context that would otherwise limit the application of more complex methods, like switching regressions (Chasco, 2003; Quandt, 1958). The optimization algorithm, which is based on the general nonlinear programming problem (Ye, 1988), has been implemented in R through the “Rsolnp” Package (Ghalanos and Stefan, 2015) and can be defined as:

$$\text{Min } f(x)_i \; for\ each\ country: i = 1,2,4 \ldots 31$$

such that:

$$l_{\beta_g} \leq \beta_g \leq \ u_{\beta_g}$$

$$f(x)_i = Y_i$$

Where $f(x)$ is the result of the regression model (i.e. $const + \beta_{g1} Log\left(\frac{Pop}{Area}\right) + \beta_{g2} Log\left(\frac{GDP}{Pop}\right)$); β_g are the estimated global parameters for Pop/Area and GDP/Pop; $\left[l_{\beta_g}, u_{\beta_g}\right]$ are the respective confidence intervals based on the standard errors; and Y_i the DMC/GDP observed at country level. Essentially, through this approach we are allowing the parameters for β_g to vary within their confidence intervals such that for each country the estimated DMC/GDP matches the observed DMC/GDP. In this way, the β_g coefficients are calibrated to better capture the country-specific socio-metabolic regimes. Table 3 shows the estimated elasticities for all countries on years 2006 and 2014.

1.4.3. Step 3: Data extrapolation and reconciliation

The next step in our procedure consists on the direct application of the country-specific parameters for Pop/Area and GDP/Pop to the exogenous variables measured now at the regional (NUTS 2) level, generating regional DMC estimates (i.e. from Eq. 1.4-1 to Eq. 1.4-2):

$$Log\left(\widehat{\frac{DMC}{GDP}}\right)_j = const + (\beta_{cs})_i \, Log\left(\frac{Pop}{Area}\right)_j + (\beta_{cs})_i \, Log\left(\frac{GDP}{Pop}\right)_j + e \, ;$$

Eq. 1.4-2

$$region\, j = 1,2, \dots 280;$$

$$country\, i = 1,2, \dots 31;$$

Where Eq. 1.4-1 represents the regression model estimated at EU level, and Eq. 1.4-2 represents the country-specific regression models applied to each country in order to extrapolate the regional $\left(\widehat{\frac{DMC}{GDP}}\right)$. As it can be seen in Eq. 1.4-2, we substitute β_g with β_{cs}, and the variables Pop/Area and GDP/Pop with their equivalents measured at regional level.

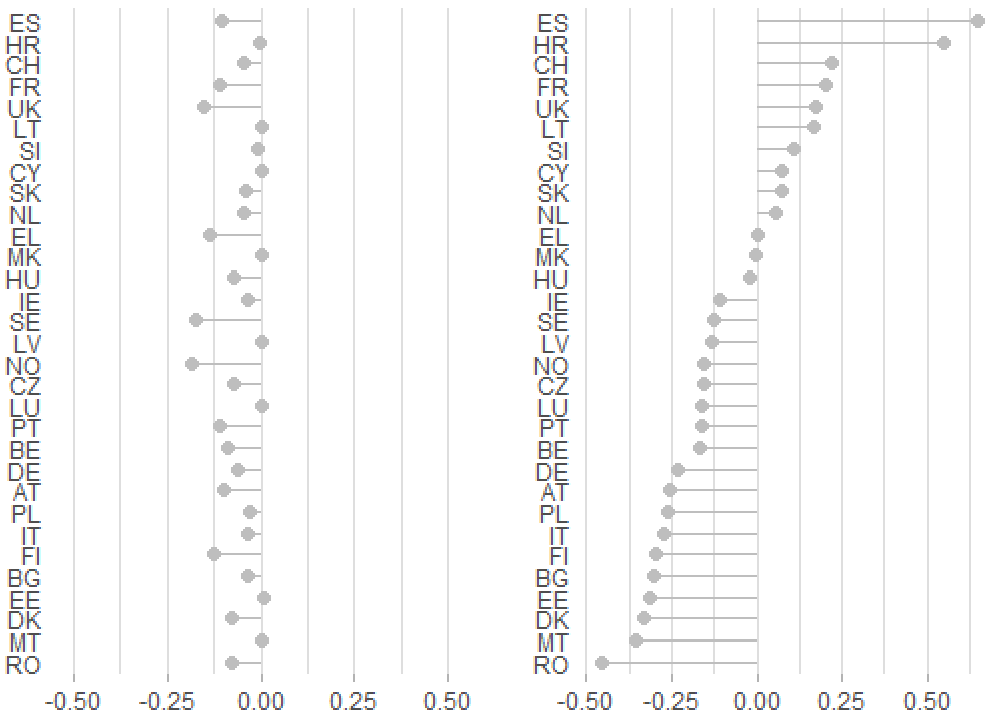
Table 3: Country-specific parameters generated by the optimization algorithm.

	Global parameters (β_G)							
	2006				2014			
	GDP/Pop		Pop/Area		GDP/Pop		Pop/Area	
Coefficients	-0.689		-0.225		-0.663		-0.251	
Confidence interval (5%)	-0.903	-0.474	-0.329	-0.122	-0.923	-0.400	-0.367	-0.134
	Country-specific parameters (β_{cs})							
GEO code	GDP/Pop		Pop/Area		GDP/Pop		Pop/Area	
AT	-0.670		-0.223		-0.646		-0.249	
BE	-0.678		-0.224		-0.655		-0.250	
BG	-0.670		-0.223		-0.630		-0.248	
CH	-0.723		-0.229		-0.685		-0.253	
CY	-0.668		-0.223		-0.670		-0.251	
CZ	-0.675		-0.224		-0.654		-0.250	
DE	-0.689		-0.225		-0.645		-0.249	
DK	-0.649		-0.221		-0.634		-0.248	
EE	-0.678		-0.224		-0.626		-0.248	
EL	-0.706		-0.227		-0.678		-0.252	
ES	-0.684		-0.225		-0.721		-0.256	
FI	-0.663		-0.224		-0.643		-0.250	
FR	-0.720		-0.229		-0.691		-0.253	
HR	-0.711		-0.228		-0.707		-0.255	
HU	-0.694		-0.226		-0.669		-0.251	
IE	-0.637		-0.221		-0.656		-0.250	
IT	-0.697		-0.226		-0.711		-0.256	
LT	-0.726		-0.229		-0.678		-0.252	
LU	-0.669		-0.223		-0.649		-0.249	
LV	-0.683		-0.225		-0.649		-0.250	
MK	n.a.		n.a.		-0.687		-0.253	
MT	-0.681		-0.224		-0.624		-0.245	
NL	-0.712		-0.229		-0.672		-0.252	
NO	-0.716		-0.227		-0.666		-0.251	
PL	-0.687		-0.225		-0.637		-0.248	
PT	-0.672		-0.223		-0.657		-0.250	
RO	-0.672		-0.223		-0.611		-0.246	
SE	-0.720		-0.227		-0.668		-0.251	
SI	-0.672		-0.223		-0.674		-0.252	
SK	-0.703		-0.227		-0.674		-0.252	
UK	-0.716		-0.229		-0.693		-0.254	

Source. Own estimation

To check consistency between the two different levels (i.e. national vs regional) we can examine whether the sum of regional estimates for each country reflects the real national value. Even if this approach does not ensure that regional figures are correctly distributed within a country, it can provide some insights on the goodness of the approach applied. In Figure 5 we provide an overview of the deviation of results generated by (1) our approach and (2) the results that would have been generated by global parameters (β_g) (i.e. without optimization procedure). According to the figures, the use of optimized parameters improves significantly the goodness of regional estimates, as these deviates significantly less from the real values. The perfect matching for countries having just one region (i.e. Republic of Macedonia, Lithuania, Latvia, Luxemburg, Estonia and Malta) simply indicates that the optimization algorithm adjusted the parameters to fit exactly the national value.

Figure 5: Deviations of estimates from real values in the case of global- and country-specific approach (year 2014).



(β_{cs}) (β_g)

Note: Deviation for each country has been computed as $\left(\frac{\widehat{DMC}-DMC}{DMC}\right)$.

Once the consistency of our regional estimates was confirmed, we performed a reconciliation of these values with the national figures. Reconciliation is a procedure that seeks to ensure coherence of results between different scales of analysis (Courtonne et al., 2015). In this specific study, reconciliation consisted on a rescaling the regional estimates to fit exactly the respective national values. Mathematically, $\tilde{y} = \frac{\hat{y}_i * Y}{\sum_{i=0}^{n} \hat{y}_i}$ where $\tilde{y}$ is the final rescaled regional estimate (i.e. DMC/GDP), $\sum_{i=0}^{n} \hat{y}_i$ is the sum of regional estimated values $\hat{y}_i$ of a country Y. Final results are presented in the following section, along with a discussion and a comparison of a set of estimated and real DMC values produced by previous studies for a sample of selected regions.

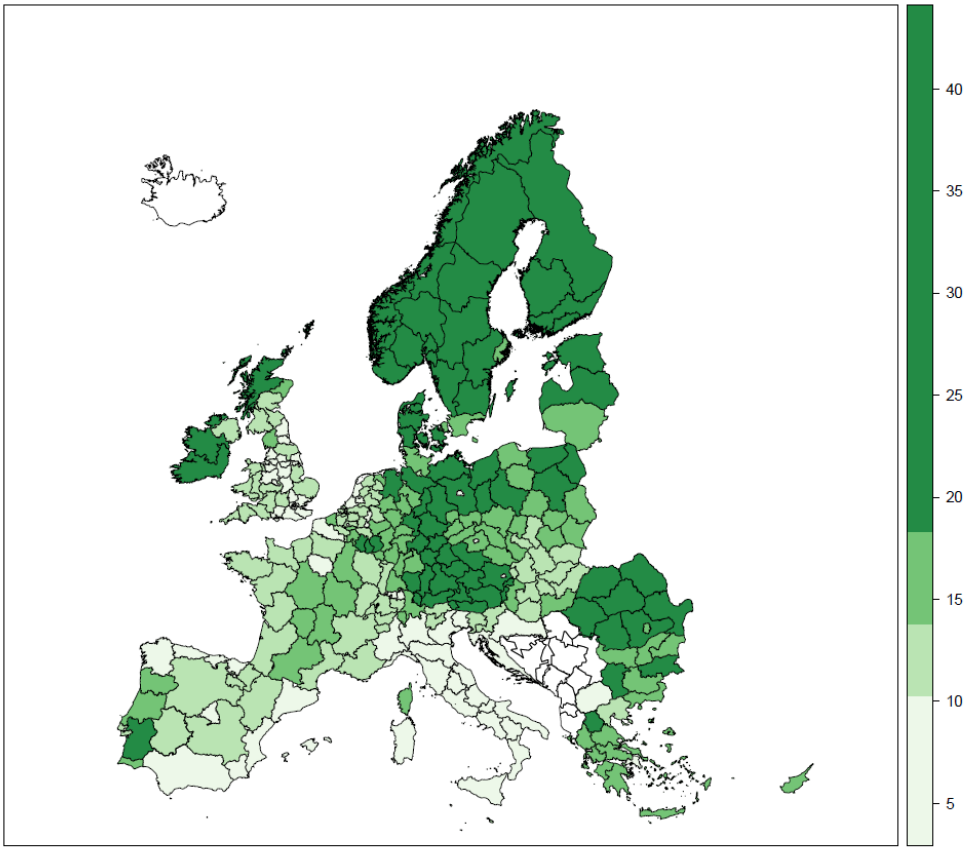
1.5. Results

1.5.1. Empirical results

Figure 6 provides the regional DMC per capita across Europe in 2014[6]. Regions with large urban agglomerations and strong tertiary economies are those characterised by lower material consumption per capita (i.e. Ile de France, Madrid, greater London etc.). As mentioned before, this could be a natural consequence of the economic specialization in these areas, in contrast to the less densely populated regions. In fact, rural, peripheral regions feature greater availability of land for the cultivation of biotic resources and extraction activities. Natural resources are pre-processed or pre-transformed locally as a strategy so as to minimise transportation costs, which could increase the DMC intensity of these economies in comparison to other regions that exclusively import or consume finished products.

[6] The reader can refer to Bianchi (2020) for the open access to the whole regional dataset of DMC (2006-2015).

Figure 6: Quantile map of DMC per capita (t/CAP) in 2014



Note: the four tonalities of green refer to sample quantiles corresponding to the four probability intervals [0% – 25%], [25% – 50%], [50% – 75%] and [75% – 100%]. The numbered scale reflects the DMC per capita measured in t/CAP. White regions indicates no data availability.

To better understand the connection between regional material consumption and sectoral specialisations, in Table 4 we present the average figures for DMC/Pop intervals, as displayed in Figure 6, along with the average figures for selected socioeconomic variables and sectoral specialisations. Sectoral specialisations were computed by means of location quotient (LQ), which makes reference to the proportion of gross value added generated in a particular sector in a given region compared with the European proportion of gross value added for the same sector (see also section 3.2.2 for further details on LQ). Focusing on the first DMC/Pop interval (0%-25%), it exhibits the lowest LQ across most of material intensive sectors (i.e. agriculture, industry and manufacturing), while having the highest score in services. Therefore, on average, regions presenting lower consumption of resources are also those less specialised in material intensive sectors in the European economy (LQ<1).

Notwithstanding, there is an interesting exception within the construction sector, as a result of there not being a significant difference in this sectoral specialisation between the DMC/Pop quantile intervals (1.00-1.30). This might be explained by the underlying regional urban structures. In fact, unlike the sparsely populated regions, the very high level of urban agglomeration that characterizes the first group (1,264 hab / Km2) is an advantage for economies of scale and therefore streamlines the consumption of material per capita.

Table 4: Mean values by DMC/Pop quantiles for selected socioeconomic variables and sectoral specialisation.

Quantile intervals	DMC/Pop (t/cap)	Pop/Area (hab/km2)	GDP/Pop (PPS/hab)	Sectoral specialisation				
				Agric.	Industry	Manuf.	Constr.	Services
0%-25%	8.17	1264	29496	1.12	0.82	0.77	1.16	1.09
25%-50%	12.25	274	27084	1.93	1.12	1.09	1.18	0.89
50-75%	16.04	180	24881	2.23	1.27	1.26	1.00	0.84
75%-100%	24.01	84	28394	2.07	1.33	1.26	1.30	0.80
Europe	15.12	451	27464					

Note: sectoral specialisations have been calculated by means of location quotients.

On the contrary, the third and fourth samples quantiles – which largely coincide with the Eastern regions, Southern Portugal, Ireland, Scotland and Scandinavia peninsula – tend to concentrate on material intensive sectors. A prime example of this could be the finding that most of Romanian regions exhibit among the highest LQ scores among intensive sectors (i.e. agriculture, manufacturing, industry and construction). The same goes for the Scandinavian peninsula and Irish regions, which are specialised in material-intensive sectors like timber and livestock, respectively.

Again, regional economic specialisation has a strong impact on DMC per capita and it largely explains the unbalanced distribution of environmental burden within European regions. Nevertheless, it should be pointed out that there also exist diverging cases where regions specialised in material intensive sectors present low material consumption per capita (e.g. Andalusia in Spain or Continental Croatia), or likewise, regions presenting diverging socioeconomic structures but similar material consumption rates (e.g. Dusseldorf region in Germany vs Northern Hungary). These aspects will be deepened in Chapter 2 and Chapter 3, which will provide specific analyses of DMC patterns along with their underlying socioeconomic structures across European regions.

1.5.2. Comparison of results with existing subnational metabolism studies

In general, the only reliable way to assess the validity of the estimates is to compare these with direct statistics for those same administrative areas (e.g. NUTS 2). However, mainly as a consequence of the existing material-flow studies being so diverse in terms of data sources, timeframes and applied methodologies to calculate DMC, a consistent validation across the full range of existing studies cannot be carried out. Still, a comparison of these studies with our results allows to assess the overall consistency of our estimates, as well as to understand and recognise some methodological limitations. Table 5 compares our results with DMC figures estimated by other material-flow analyses for a sample of selected regions.

Focusing on the results for Ile de France (10.69 t/cap in 2006 and 8.97 t/cap in 2014), we can see that our estimates are similar to the most recent studies based on Input-Output analysis (11.85 t/cap in 2011) (Duarte, 2016). Moreover, similarly to these studies our estimates also suggest a decreasing trend of DMC in this region. The major discrepancy is with Barles' results. This can be justified by the different assumptions made by this author when characterising waste flows. Indeed, Barles considers waste as an exported material, which is consequently subtracted from the calculation of the DMC indicator. In turn, the EW-MFA framework considers waste material flowing to landfill as a material flow within the economy and thus includes it in the calculation of the DMC indicator.

Table 5: DMC results for selected regions and comparison with other studies.

Geo code	Region name	Our results DMC (t/cap)		Other studies		Method. Approach	Sources
		2006	2014	DMC (t/cap)	Year		
FR10	Ile de France	10.69	8.97	7.10	2003	MFA	Barles (2009)
				11.85	2011	IO	Duarte (2016)
				14.72	2000	IO	Duarte (2016)
				15.50	2000	IO	Pina et al. (2015)
DE30	Berlin	8.91	8.73	17.86	2011	IO	Duarte (2016)
DE60	Hamburg	12.44	12.06	20.90	2011	IO	Duarte (2016)
				12.10	2001	MFA	Hammer and Giljum (2006)
PT17	Lisbon	16.23	10.91	10.40	2005	UMAn	Rosado et al. (2013)
				18.97	2011	IO	Duarte (2016)
				17.10	2000	IO	Pina et al. (2016)
ES30	Comunidad de Madrid	15.55	5.90	5.90	2010	EW-MFA	Sastre et al. (2015)
				12.91	2011	IO	Duarte (2016)
UKD7	Merseyside (Liverpool)	7.93	5.87	8.32	2011	IO	Duarte (2016)
UKD3	Greater Manchester	8.26	6.06	9.05	2011	IO	Duarte (2016)
UKE2	North Yorkshire (York)	16.91	13.32	11.94	2000	MFA	Barret et al. (2002)
NL32	Noord-Holland (Amsterdam)	10.69	9.80	16.00	2012	MFA	Voskamp et al. (2016)
SE11	Stockholm	14.77	16.08	19.19	2011	IO	Duarte (2016)
				10.34	2011	UMAn	Rosado et al. (2016)
				10.10	2011	UMAn	Kalmykova et al. (2015)
AT13	Wien	13.19	9.64	9.20	2003	MFA	Hammer and Giljum (2006)
Mean		12.32	9.76	12.09			

Note: MFA refers to ad-hoc bottom-up material flow analysis, IO refers to Input-Output table, EW-MFA refers to Economy Wide-Material Flow analysis and UMAn refers to Urban Metabolism Analysis.

With respect to Hamburg, Berlin, Stockholm and Amsterdam, we also noted some divergences with previous studies. The difference for Hamburg might be explained by the so-called "Rotterdam Effect" (EUROSTAT, 2019). In commercial harbour areas, material flows tend to be overestimated due to trade exchanges and the difficult statistical allocation of transit goods. Still, our estimates for Hamburg are in line with those provided by Hammer and Giljum (Hammer et al., 2003). In the case of Amsterdam, the difference between the predicted values and those from previous studies can be explained by the inclusion of water flows in the analysis conducted by Voskamp et al. (2017). Water flows are normally excluded from standard EW-MFA. The order of magnitude of water flows dominate the material accounts to a point that these 'dilute' the flows of other materials (EUROSTAT, 2018, p. 18). Finally, for the regions of Lisbon, Madrid, Liverpool and Manchester, all the estimated values are close to previous studies.

Our conclusion from this comparison exercise confirms the hypothesis that the divergence between the various assessments strongly depends on the specific methods and underlying assumptions that are made. We found that Input-Output approaches (e.g. Duarte (2016) and Pina et al. (2016)) tend to generate higher estimates in comparison to bottom-up material-flow studies. This might be due to the way in which trade statistics might inflate material-flows, therefore producing higher figures in regional trade-hubs (e.g. Berlin and Hamburg). This issue can also be detected in the Madrid case, where the Input-Output approach produced results that are more than twice as large as the EW-MFA approach. On the other side, bottom-up approaches rely on different sets of assumptions that ultimately hamper the comparison between regions.

1.6. Discussions and Conclusions

This chapter presents a novel econometric modelling approach to derive regional estimates. The method was applied to estimate DMC across more than 280 EU and EFTA regions (NUTS-2 level) in two periods (2006 and 2014). The approach provided reliable estimates for the DMC indicator. The comparison of the estimated figures with previous studies on regional metabolism confirms that our results are consistent with those obtained by earlier studies making use of more data-intensive methods. Hence, our results provide granular information on material consumption that would otherwise be unavailable for policy formulation. In particular, this input is critical in term of the design of place-based policies and strategies in support of sustainable resource use at subnational levels.

The approach addresses several methodological limitations concerning previous studies. First, by applying a consistent and systematic approach, we provide a harmonised material consumption dataset at European regional level, which is not only exhaustive (all EU and most EFTA regions are covered), but also comparable over time and across regions. This paves the way for comparative research that advances the general understanding of metabolic systems and their influencing factors (Kennedy et al., 2015; Rosado et al., 2014). Potentially, this provides decision-makers with valuable information regarding the effects of measures and policies adopted across different regions (Voskamp et al., 2017). Secondly, by accounting for multiple correlations between material consumption and its potential drivers, we provide regional estimates that not only capture the magnitude of the relationship between drivers and material consumption, but also account for their evolution over time. Thirdly, yet of utmost importance, we overcome major data constraints at subnational levels. The lack of regional and local data is arguably the most important barrier to conduct local metabolism studies (Hammer et al., 2003; Sastre et al., 2015). This issue affects many other policy domains as well. By taking advantage of general statistical information available and reflecting territorial heterogeneity through the optimization algorithm, we propose a method that can be sufficiently automated to allow the estimation of larger datasets at once. Furthermore, its systematisation makes it suitable for application to other territorial contexts, geographical scales, thematic domains and indicators.

The method could be further improved in various ways. For example, in this study only static indicators and annual explanatory variables (e.g. GDP and/or population in a specific year) were considered in order to build the models. While these static variables are the best alternative to regionalise a given indicator at a certain point in time, such variables say very little about the dynamics of change of the regionalised indicators. Further analyses might focus on the selection of progress variables such as population and/or income growth for a selected period as opposed to static time-cuts. This dynamic approach would allow to e.g. gauge the impact of specific drivers on material efficiency and better understand the impact of policies on material consumption.

Similarly, it would be useful to compare our regional estimates with freight transport data to determine whether regions are genuinely decreasing their material footprint or simply “shifting the burden” on other areas.

Chapter 2

2. Eco-efficiency in European regions: a territorial perspective

This chapter is based on the following published paper:

1. *Bianchi M, del Valle I, Tapia C, Measuring Eco-efficiency in European regions: evidence from a territorial perspective, Journal of Cleaner Production, https://doi.org/10.1016/j.jclepro.2020.123246*

2.1. Introduction

Today, environmental policies represent a critical lever for sustainable development. Policymakers are increasingly faced with the challenge of finding the right balance between pursuing economic growth and protecting the environment (Apergis and Garćıa, 2019; Sarkhosh-Sara et al., 2019). As Steinberger et al. (2013) illustrated, economic growth generally entails the use of natural resources and results in increasing environmental harms at all stages of product life cycle. However, the intensity and scale of environmental degradation ultimately depend not only on the structure and technical efficiency of economic productive structures, but also on the regulatory policies and quality governance in place (Apergis and Garćıa, 2019; Fabrizi et al., 2018; Schandl et al., 2016). In response to this challenge, the Europe 2020 Strategy identifies smart, sustainable and inclusive growth as a key instrument to achieve a resource efficient, greener and more competitive economy, while delivering high levels of employment, productivity and social cohesion (European Commission, 2010). Systemic shifts towards new and more sustainable businesses and patterns of production are therefore increasingly encouraged by governmental bodies (European Commision, 2015). However, such a systemic transformation requires a closer inspection on the challenges that these structural changes might suppose in providing EU citizens with secure and well-paid employment (Bachtler et al., 2017).

Eco-efficiency – or environmental productivity – is a well-known concept that encourages environmental improvements that yield parallel economic and social benefits (OECD, 2002; WBCSD, 2006). In general terms, it can be defined as the ability of firms, industries, regions or economies to produce more goods and services – understood in a functional sense – with fewer impacts on the environment and less consumption of natural resources (Camarero et al., 2013; Wursthorn et al., 2011). Along these lines, the roadmap to a resource-efficient Europe sets out a framework for the design and implementation of future actions in which *resource productivity*[7] constitutes the lead indicator to measure its principal objective, namely "improving economic performance while reducing pressure on natural resources" (European Commission, 2011, p. 4).

Conventional indicators of eco-efficiency involve comparing a measure of desirable economic output with a measure of environmental input. Two approaches – the ratio approach and the frontier approach– are mainly used to estimate such indicators. The main advantage of ratio approach indicators such as resource productivity is their straightforwardness. They can be easily understood by policymakers as well as by the general public (Camarero et al., 2013). However, ratio-based indicators neglect the combination of socioeconomic forces that might cause or drive

[7] Note that eco-efficiency, environmental productivity and resource productivity are often used interchangeably to indicate the same indicator. See Huppes and Ishikawa (2005) for a terminology review.

environmental impacts. As an example, it is well known that economy dematerialization occurs almost exclusively during periods of economic recession. Obviously, recessions do not look like an attractive strategy to curb environmental harms (Shao et al., 2017). For this reason, social indicators such as employment rates are also commonly included in monitoring frameworks. This ensures proper measurement of simultaneous progress towards environmentally sustainable and inclusive economic growth (see e.g. SDGs goals (Eurostat, 2019a) and Europe 2020 Strategy (Eurostat, 2019b)). Therefore, eco-efficiency indicators should be assessed by combining indicators from two or more dimensions (Mickwitz et al., 2006), including, when necessary, an appropriate weighing scheme (Kuosmanen and Kortelainen, 2005).

The frontier approach is one of the most used techniques to address this challenge, since not only it generates objective weights from the data – thus avoiding the subjectivity implicit in weighting decisions (Dyckhoff and Allen, 2001), but it also combines efficiently different types of indicators (e.g. economic- social- or environmental) in an aggregated eco-efficiency score (Masternak-Janus and Rybaczewska-Błażejowska, 2017). Frontier-based indicators are widely applied to estimate eco-efficiency in cross-country analyses (see e.g. Camarero et al., 2013; Halkos, Tzeremes, & Kourtzidis, 2016; Moutinho, Madaleno, & Robaina, 2017). However, only a few studies focus on the meso-economic, or regional economies, perspective. This dearth of studies at subnational level constitutes a critical research gap not only because more granular analyses would help local policy formulation processes by recognising the specific needs and opportunities defined by the unique features within each jurisdiction (Corvellec et al., 2013), but also because the regional scale is often considered as the optimal level of governance for planning, coordinating and assessing actions towards sustainable development (Mascarenhas et al., 2010; Mickwitz et al., 2006). Therefore, the delivery of indicators at subnational scale is key for the design of policy tools, including the European Regional Development Fund, the Common Agricultural Policy, the Circular Economy Package (European Commision, 2015) and the Bioeconomy Strategy (European Commission, 2017).

One critical aspect to bear in mind when estimating eco-efficiency at the lower meso-level is the presence of territorial heterogeneity within the sample. In fact, regions – especially in Europe – are characterized by different operating environments that necessarily shape their production structures (Bianchi et al., 2020a). While some regions host primarily service industries, others undergo more rural or manufacturing industries. From an eco-efficiency point of view, it is straightforward that the non-discrimination between different sectoral patterns of production might lead to an unequal distribution of environmental burdens (Camarero et al., 2013; Zhou et al., 2018). In fact, the outsourcing of primary commodities associated with little added value and large environmental impacts – carried out mainly in rural and/or peripherical regions – is at odds with the "cleaner" processing and services activities at the end of the value-added chain – mostly carried out in urbanized regions. Accordingly, if these different economic structures are not considered, the estimated eco-efficiency values may be biased by the heterogeneity of regional economies rather than being the result of efficient combination of inputs and outputs (Battese et al., 2004; Walheer, 2018; Zhang et al., 2015).

In this context, the metafrontier framework introduced by O'Donnell et al. (2008) represents an appealing approach to compare frontier-based efficiency measures of regions that can be classified into different groups. Essentially, the approach distinguishes between efficiencies measured with respect to a common *metafrontier*, defined as the boundary of an unrestricted technology, and efficiencies measured with respect to a *group frontier*, defined as boundaries of restricted technology sets, where the restrictions derive from exogenous factors such as economic infrastructures, human capital and/or other characteristics of the production environment (Battese et al., 2004; O'Donnell et al., 2008). The distance between the group-specific frontiers and the metafrontier provides a measure of the gap between the technology available to all regions and the technology available to a specific regional group. Consequently, this approach permits to disentangle the actual inefficiency (i.e. the one with respect to the metafrontier) in terms of the technological gap, i.e. the inefficiency due to diverse operating environments (exogenous factors), and conditional efficiency gap, i.e. the inefficiency resulting from a non-optimal resources allocation (endogenous factors). Recent examples of metafrontier-based applications in macroeconomic contexts include, among others, measurement of eco-efficiency (Han et al., 2019) and energy efficiency (Li et al., 2019; Zhang et al., 2015) in China regions, and labour productivity in Europe (Filippetti and Peyrache, 2015; Kounetas and Napolitano, 2018) (see Walheer (2018) for an exhaustive metafrontier applications review).

In this chapter our goal is to measure and analyse the eco-efficiency of European regions (NUTS level 2[8]) in 2006 and 2014 by considering both their territorial heterogeneity and the socioeconomic patterns associated with domestic material consumption. This study represents the first comprehensive research assessing eco-efficiency among European regions and it expands the existing research in 2 areas. Firstly, it proposes an eco-efficiency index that goes beyond common resource efficiency indicators by considering simultaneously material consumption, gross domestic product and employment rates of regional economies. The combination of these three indicators in a single score fills a policy demand in relation to the evaluation of trade-offs between the three sustainability domains. Secondly, it captures the heterogeneous territorial settlements of European regions through an *ad-hoc* urban-rural typology. This allows to better understand the dialectics between the underlying forces driving regional eco-efficiency (i.e. technological or conditional efficiency gaps), and, therefore, to distinguish the different opportunities and challenges that regions face according to their specific endowments.

The chapter is organised as follows: Section 2.2 presents the literature review and the underlying hypothesis of our approach. Section 2.3 introduces the data and the methods used to conduct the empirical analysis, namely, the data envelopment approach (DEA) and the metafrontier framework – these data are used to decompose the eco-efficiency index into the technology gap

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[8] The NUTS system was established by EC Regulation 1059/2003 that defined a common classification of territorial units for statistics (NUTS), based on the administrative divisions applied in the Member States. The 2nd level in the classification (NUTS 2) groups regions with population between 80,000 and 3 million. Readers are referred to Appendix A for additional information on this topic.

and the conditional efficiency gap; Section 2.4 presents the empirical results for European regions in 2006 and 2014; Section 2.5 discusses our main findings; the conclusions and limitations are presented in Section 2.6, along with suggested avenues for further research.

2.2. Literature review and hypotheses

Although originally formulated as a tool for evaluating companies performance, DEA is now extensively used in empirical analyses for assessing eco-efficiency at macroeconomic levels, and therefore, for supporting sustainable development policies (Wursthorn et al., 2011; Zhou et al., 2018). Differently from microeconomics studies concerning firms' productivity, economic policy commonly focuses on certain economic-wide indicators, such as gross domestic product (GDP) and employment, for quantifying economic prosperity (Eurostat, 2019a). Similarly, environmental impact indicators regularly used within national monitoring frameworks usually refer to material flows (European Commission, 2011; EUROSTAT, 2013) and greenhouse gases (GHG emissions) inventories (European Commission, 2014). While the former measures the consumption of raw materials and energy consumed domestically by an economy, the latter measures the GHG emissions generated by economic activities (Huppes and Ishikawa, 2005; Seppälä et al., 2005).

The selection of inputs and outputs, as well as the underlying assumptions relating to the type of technology, are conditioned by the specific goal and scope in which the DEA is conducted (Wursthorn et al., 2011; Zhou et al., 2008a). In general, the starting point is the free disposability of inputs and outputs, which means that inputs and outputs can freely be disposed-off. This implies that fewer outputs can always be produced with more inputs. If convexity is also assumed, then any weighted average of feasible production plans is feasible as well (Bogetoft and Otto, 2011). However, this conjecture does not always hold, especially when a reduction in waste or emissions forces a lower production of desirable output (Podinovski and Kuosmanen, 2011;

Seiford and Zhu, 2002). In this situation, directional efficiency measures are often employed to reflect the weak disposability assumption (Färe et al., 1989). This implies an inverse relationship between desirable and undesirable outputs (Färe and Grosskopf, 2004; Zhou et al., 2008b). An alternative approach might be also the treatment of undesirable outputs as inputs (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). However, this method is not recommended when the true production configuration is infringed (Seiford and Zhu, 2002).

Most of the existing macroeconomic studies focusing on eco-efficiency are generally conducted at the country-level. As an example, Moutinho et al. (2017) employed a DEA output-oriented model to estimate the eco-efficiency of 26 different EU countries. They combined input factors such as labour, capital productivity, and the share of renewable and fossil energy, with GPD per GHG as output. Their main conclusion was that the type of energy sources is critical in explaining differences in emissions. A composite sustainability efficiency index has been proposed by Halkos et al., (2016), which distinguished between a first-stage efficiency (production maximization oriented) and a second-stage efficiency (environmental pressure minimization). Interestingly, they reported that a high production efficiency not always translates in higher eco-efficiency performance. Several studies also analysed eco-efficiency from a longitudinal convergence perspective. Camarero et al. (2013) assessed eco-efficiency convergence for a group of 22 OECD countries over the period 1980–2008, employing three air pollutants as environmental impacts from economic activities. They found the existence of clubs of convergence for the (most eco-efficient) Scandinavian economies and the (worst eco-efficient) Southern European countries. Additional examples can be found in Gómez-Calvet et al. (2016), Camarero et al. (2014) and Yu et al., (2018).

Eco-effiency studies at subnational levels are rather sparse and most of them focus on Chinese provinces. Yang et al. (2015), measured eco-efficiency for 30 Chinese provinces considering as inputs energy consumption, fixed capital and sulfourus emission, while taking the GDP as output. They found distinct eco-efficiency patterns between the different spatially-located areas of China, resulting the eastern areas more eco-efficient. Similar results were found in Yang and Zhang (2018) and Zhang et al. (2015), notwithstanding the use of a different set of environamental indicators such as construction land area, water and energy consumption, next to those commonly employed. Concerning the European area, only two studies address eco-efficiency at regional level, both of them constrained to the regions of a single country. Masternak-Janus and Rybaczewska-Błażejowska (2017) assessed eco-efficiency for Poland regions employing as environmental indicators the consumption of natural resources. They found that, among others, consumption of cement and electricity were the most correlated with GDP. Eco-efficiency of UK regions was assessed instead by Halkos and Tzeremes (2013), which found a "U" shape relationship between environmental inefficiency and economic growth. Most likely, the scarcity of subnational studies in Europe is related to the lack of harmonized environmental data for all European regions, as these are generally only provided at national level (Bianchi et al., 2020a; Halkos and Tzeremes, 2013). Therefore, taking advantage of the regional DMC figures estimated in Chapter 2, this research represents the first attempt in providing a comprehensive analysis of eco-efficiency for European regions. However, due to the exclusion of GHG emissions from the analysis, the proposed eco-efficiency indicator should be interpreted as the *environmental productivity* variant of eco-efficiency (Huppes and Ishikawa, 2005). This is also in line with the macro-indicators used by the EU in support of its circular economy policy agenda (European Commission, 2018b, 2011; Eurostat, 2019a).

2.3. Material and Methods

This section describes the dataset and the empirical strategy employed. As a first step, a DEA model, combining socioeconomic variables (employment and GDP per capita) and domestic material consumption, is defined based on the best available approaches. Next, the metafrontier framework is employed in order to compare eco-efficiency across groups of regions. The metafrontier approach integrates the territorial heterogeneity characterizing European regions and allows to decompose eco-efficiency in two components: the conditional efficiency gap (i.e. the distance of a given region to its group frontier) and the technology gap (i.e. the distance between a group frontier and the metafrontier). The data download was performed by making use of the R package "Eurostat" v.3.3.5 (Lahti et al., 2019), DEA analysis was conducted with R package "Benchmarking" v. 0.28 (Bogetoft and Otto, 2019), while data plotting was performed with R packages "sp" v. 1.3-2 (Pebesma, 2019) and "ggplot2" v. 3.3.0 (Wickham, 2020). The following sections will present in detail each of these steps, starting with a description of the dataset used and the definition of the urban-rural territorial typology.

2.3.1. Data and variables

The dataset employed in this study comprises annual observations for the periods 2006 and 2014 and cover 282 European regions out of 331[9] at NUTS-2 level. The DEA model was estimated using two input and one output. For the latter, Gross Domestic Product (GDP) per capita was considered, measured in purchasing power standard (PPS). On the input side, employment rate (EMP) and Domestic Material Consumption per capita (DMC) were taken into account. The employment rate is measured as the ratio between the number of active employees and the total workforce that is potentially employable. The DMC, which measures the total amount of materials directly used by an economy, is defined as the annual quantity of raw material extracted from the domestic territory, plus all physical import minus all physical export, and it is expressed in tonnes per capita. The socioeconomic variables – GDP and EMP – were retrieved from Eurostat databases "nama_10r_2gdp" and "lfst_r_lfe2emp[10]" respectively. In general, data on DMC is only

[9] Regions of Albania, Bosnia and Herzegovina, Iceland, Lichtenstein, Montenegro, Serbia, Turkey, Republic of Kosovo and French outermost regions were excluded from this study because of missing data. Inner London West (UK) was also excluded from the study because it represents an outlier, being its GDP per capita more than 6 times the European average.

[10] Employment rate for Denmark and Croatia refers to 2007, while Slovenia and UKI3 to UKI4 refers to 2010.

available on national basis from material flow accounts collected under the regulation (EU) 691/2011 on European environmental economic accounts. Hence, the DMC database developed in chapter 1 was used instead.

These indicators were selected in order to reflect the main priorities of European strategies for sustainable growth, namely resource productivity, economic growth and job creation (European Commission, 2019b). These are also considered headline indicators in existing monitoring frameworks (European Commission, 2018b, 2011; Eurostat, 2019a). The use of ratio variables instead of absolute values is intentional, as the former reflect regional economic performance in a more appropriate way than the latter (Bithas and Kalimeris, 2018; Dzemydaitė and Galinienė, 2013; LeSage and Fischer, 2008).

2.3.2. Urban rural typology

In order to conduct the metafrontier analysis, European regions were classified according to a urban-rural classification of regions inspired by the "Tercet" classification (European Commission, 2016). The Tercet initiative integrates the urban-rural taxonomy across administrative units. The urban-rural typology distinguishes between (1) predominantly rural regions, (2) intermediate regions and (3) predominantly urban regions, depending on the share of population living in rural or urban grid cells. Predominantly urban regions are those regions where more than 80 % of the population live in urban clusters. Intermediate regions are those regions where more than 50 % and up to 80 % of the population live in urban clusters. Predominantly rural regions are those regions where at least 50 % of the population live in rural grid cells. This taxonomy is often used by EU policymakers' in the context of cohesion and territorial development policies to account for territorial diversity across European areas.

Given that the urban-rural taxonomy is only available at a NUTS-3 level, the classification was upscaled to the NUTS 2 level. To this aim, the prevalence of territorial typologies observed at the lower scale, along with the population density as an additional criterion[11], were considered to classify regions in any of the three categories. Comparable approaches have also been applied by previous studies with similar results (see e.g. Bachtler et al., 2017; ESPON, 2019b; Smit, Van Leeuwen, Florax, & De Groot, 2015). A detailed description of the criteria used to classify European region according to the urban-rural taxonomy is provided in Table 6, while Figure 7 shows the resulting typology distribution in Europe.

Table 6: criteria employed to classify urban-rural regions at NUTS 2 level

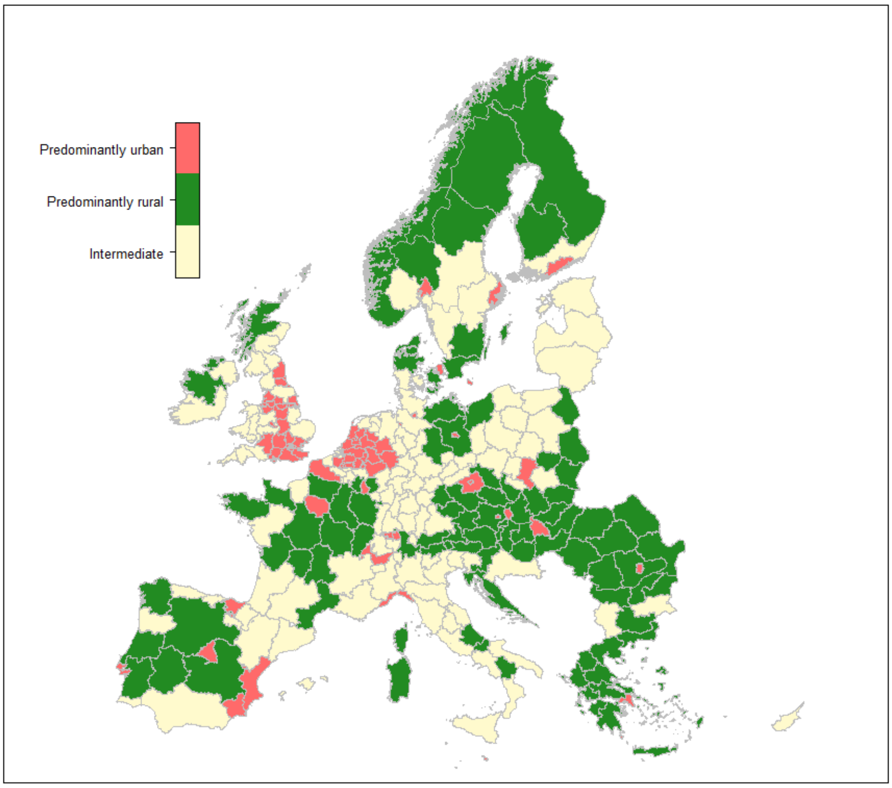
Region classification NUTS 2	Criteria applied at NUTS 3 level	Logic formula
U	Presence of only one category[12]	$\sum_{i=0}^{n} u > 0 \wedge \sum_{i=0}^{n} i = 0 \wedge \sum_{i=0}^{n} r = 0$
I	Presence of only one category	$\sum_{i=0}^{n} u = 0 \wedge \sum_{i=0}^{n} i > 0 \wedge \sum_{i=0}^{n} r = 0$
R	Presence of only one category	$\sum_{i=0}^{n} u = 0 \wedge \sum_{i=0}^{n} i = 0 \wedge \sum_{i=0}^{n} r > 0$
I	Presence of all categories or presence of urban and rural categories	$\sum_{i=0}^{n} u > 0 \wedge \sum_{i=0}^{n} i \geq 0 \wedge \sum_{i=0}^{n} r > 0$
I	Presence of urban and intermediate category scarcely populated	$\sum_{i=0}^{n} u > 0 \wedge \sum_{i=0}^{n} i > 0 \wedge \sum_{i=0}^{n} r = 0 \wedge D < Q_3$
U	Presence of urban and intermediate category densely populated	$\sum_{i=0}^{n} u > 0 \wedge \sum_{i=0}^{n} i > 0 \wedge \sum_{i=0}^{n} r = 0 \wedge D > Q_3$
R	Presence of rural and intermediate category scarcely populated	$\sum_{i=0}^{n} u = 0 \wedge \sum_{i=0}^{n} i > 0 \wedge \sum_{i=0}^{n} r > 0 \wedge D < Q_2$
I	Presence of rural and intermediate category densely populated	$\sum_{i=0}^{n} u = 0 \wedge \sum_{i=0}^{n} i > 0 \wedge \sum_{i=0}^{n} r > 0 \wedge D > Q_2$

Note: U=predominantly urban NUTS 2; u=urban NUTS; I= intermediate NUTS 2; i=intermediate NUTS 3; R=rural NUTS 2; r=rural NUTS 3; D=population density NUTS 2; Qn= n quartile population density of EU NUTS 2 regions; ∑n=sum of n regions within a country;

[11] This further criterion is introduced to overcome potential biases due to the very different geographical dimensions of NUTS 2 administrative regions.

[12] The only exceptions to this criterion are constituted by Luxemburg and Hovedstaden (DK) regions, which according to the Tercet taxonomy are classified as intermediate regions. However, considering that they are capital regions and present an underlying socioeconomic structure much more similar to urban typology, it was decided to classify them as predominantly urban region.

Figure 7: The geographic distribution of urban-rural regional typologies in Europe



Source: own elaboration

The predominantly rural, predominantly urban and intermediate groups are respectively composed by 100, 69 and 113 regions. The intermediate group accounts for approximately one third of European's population and GDP, and it largely reflects European averages across all variables considered. The urban group, despite being the smaller group in numeric terms (69 regions), accounts for almost half of European's population and more than half of its GDP. This is not surprising, given that urban regions cover most of European capital regions. On average, capital regions account for more than 26% of national GDP, and as centres of entrepreneurship and innovation, they show enterprise and employment creation more than 60% higher with respect to other areas (OECD, 2018). The rural group, which covers 42% of Europe's territory, is the least developed compared to urban and intermediate categories. In general, regions in this class have population densities, as well as an income per capita and labour productivities, well below European averages. Table 7 reports the summary statistics for our sample data.

Table 7: Descriptive statistics of variables by territorial typology, (2014).

	Inputs variables								**Output variable**			
	DMC per capita (t/cap)				**Employment rate (percentage)**				**GDP per capita (PPS/cap)**			
Group	Mean	Max	Min	CV	Mean	Max	Min	CV	Mean	Max	Min	CV
Europe	15.26	44.11	4.80	0.44	66.14	83.10	39.00	0.13	27192	75571	8214	0.37
U	10.69	22.24	4.80	0.35	69.09	81.20	50.00	0.09	34030	75571	19591	0.34
I	14.69	30.08	5.88	0.34	66.96	83.10	39.00	0.13	24559	49767	10977	0.33
R	19.06	44.11	8.89	0.40	63.17	81.80	46.10	0.14	22058	42325	8214	0.37

Note: U= predominantly urban, I= intermediate, R= predominantly rural, CV=coefficient of variation (standard deviation divided by the mean); t = tonnes; cap=capita; PPS = purchasing power standard units.

2.3.3. DEA model

To measure the eco-efficiency of European regions, a variable return to scale (VRS) DEA model (Cooper, William W.Seiford, Lawrence M. Tone et al., 2007) was applied based on a directional efficiency measure, namely the graph hyperbolic direction (Bogetoft and Otto, 2011; Zhou et al., 2008a) [13]. This DEA specification presents an important advantage respect to alternative evaluations of regional eco-efficiency. In fact, differently from most DEA models, which focus on input or output orientation, the graph efficiency approach allows to simultaneously reduce inputs and expand outputs. This avoids incurring on a 'reductive fallacy' due to oversimplification, i.e. efficiency measures based on a single perspective (Huang et al., 2014). Even more importantly, our approach considers potential trade-offs between multiple goals or policy priorities, i.e. *simultaneous* environmental impact minimization and economic output

[13] Relative to the type of efficiency, directional distance functions can also be used to reflect the weak disposability assumption, i.e. situations in which an increase in desirable outputs is coupled by a simultaneous decrease in undesirable outputs, based on a predetermined direction vector (Halkos and Tzeremes, 2013; Picazo-Tadeo et al., 2005; Picazo-Tadeo and Prior, 2009).

maximization. Likewise, given the diversity of production structures that characterise European regions, assuming a VRS represents a more realistic assumption than its counterpart constant return to scale (CSR), since VRS better captures the multifaceted productive structures of regions (Moutinho et al., 2017). In addition, the VRS represents a smaller technology set respect to the CVS, which according to the *minimal extrapolation* principle is a preferable setting. In fact, the choice of the smallest set implies a cautious or conservative estimate of the technology set, and therefore also a cautious or conservative estimate of the eco-efficiency scores and the potential loss due to inefficiency (Bogetoft and Otto, 2011)[14].

Assuming that there are n=1,2…, N regions in Europe, and each region uses input vector $x \in \mathbb{R}_{+}^{m}$ to produce outputs vector $y \in \mathbb{R}_{+}^{r}$, the technology set or production possibilities set can be expressed as $T = \{(x, y): x\ can\ produce\ y\}$ wherein free disposability of input (i.e. if a certain quantity of outputs can be produced with a given quantity of input, then the same quantity of outputs can also be produced with more inputs) and T being convex (i.e. for any two points in the technology set T, the planes on the line between them are also in T) are assumed. Therefore, T for N regions exhibiting VRS can be expressed as follows:

$$T = \{(x, y):\ x_m \geq \sum_{n=1}^{N} \lambda_n x_{mn,}\, m = 1, \dots, M,$$

$$y_r \leq \sum_{n=1}^{N} \lambda_n y_{rn}, r = 1, \dots, R,$$

$$\lambda_n \geq 0, n = 1, \dots, N\}.$$

Eq. 2.3-1

[14] For completeness, input- and output- oriented DEA models were also tested. Findings reveals that regions lying on the frontier do not change across the different orientations. However, while the difference in eco-efficiency scores between input and graph efficiency is minimal, it was found that output-orientation produced a biased ranking towards high-income regions.

Where λ is a nonnegative multiplier vector for constructing the production technology through a convex combination. In the case of VRS it is assumed that $\sum_{n=1}^{N} \lambda_n = 1$ (Cooper, William W.Seiford, Lawrence M. Tone et al., 2007). Using the hyperbolic distance function approach, improvements on the input and output side are considered simultaneously by basically combining the Farrell input and output efficiency measures into one measure:

$$G = \min\{G > 0 | Gx, y/G) \in T\}.$$

Eq. 2.3-2

In G, the goal is to simultaneously reduce inputs and expand outputs, when input side G are reduced, , the output side, 1/G, is expanded. Inserting the DEA technology (Eq. 2.3-1) in Eq. 2.3-2, the eco-efficiency index can be obtain as:

$$\min_{G, \lambda_1 \dots \lambda_n} \quad G$$

Eq. 2.3-3

$$s.t.\ Gx_m \geq \sum_{n=1}^{N} \lambda_n x_{mn}, m = 1, \dots, M,$$

$$\frac{y_r}{G} \leq \sum_{n=1}^{N} \lambda_n y_{rn}, r = 1, \dots, R,$$

$$\lambda_n \geq 0 \ \wedge \sum_{n=1}^{N} \lambda_n = 1, n = 1, \dots, N\}.$$

The solution value of G is the value of the eco-efficiency index for a region n. The weights are determined as the best when the resulting output-to-input ratio is maximised for each European region. DEA efficiency score is between 0 and 1, where 1 indicates that a region shows the best performance localized in the production frontier and reveals no potential reduction. Any result lower than 1 suggests that the region is not using the inputs efficiently. The objective function maximises the outputs ratio weighted by input as well as by the region analysed, under the condition that there are similar relations for all the regions in presenting efficiency scores equal to, or lower than 1.

Furthermore, it should be noted that employment was considered as a *desirable* input[15]. This means that reference aspects on input side for efficiency measurement should not be those defined by observed activities that consume smaller amount of material along with lower levels of employment, but smaller amount of material and higher levels of employment. In order to correctly introduce employment factor as a desirable input and, at the same time, preserving convexity relations, it was proxied by means of *unemployment rate*. This represents a linear monotone transformation as suggested in Hua and Bian (2007) and in Seiford and Zhu (2002).

2.3.4. Metafrontier DEA model

In this section, the concept of the metafrontier DEA approach is combined with the DEA model previously described to consider the existence of sub-technologies representing the production possibilities of specific groups of regions, namely the urban, intermediate and rural group introduced in section 2.3.2. The metafrontier framework was firstly introduced by Battese et al. (2004) and O'Donnell et al. (2008) to compare technical efficiencies of firms that might be classified into different groups. Similarly to Kumar and Russell (2002), they decompose technical efficiency into two components attributable to (1) technological gap (i.e. shifts in the production frontier) and (2) conditional efficiency gap (i.e. movements towards or away from the frontier)[16]. The underlying assumption of the metafrontier framework is that regions exhibit different

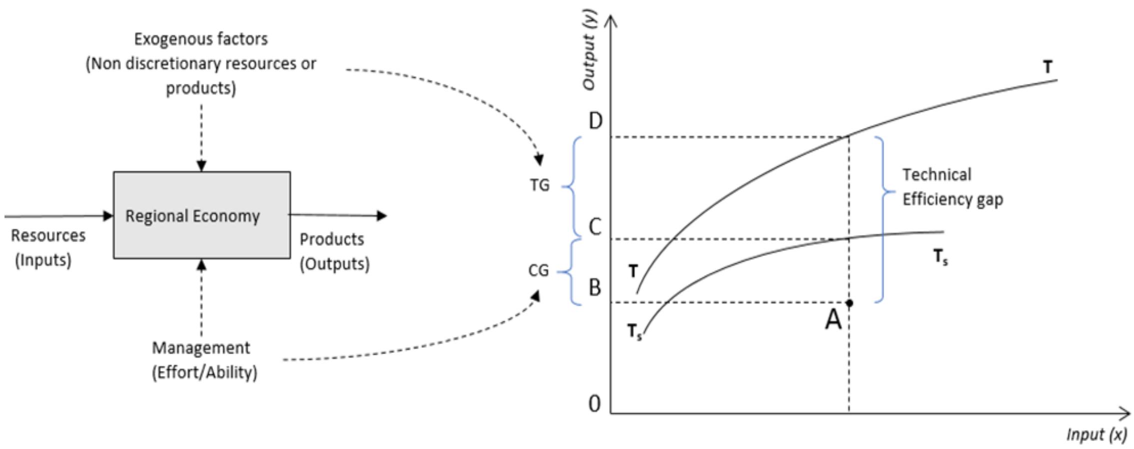
[15] Depending on the framework analysis, employment factor can be treated in different ways. In general, it is minimized (or held constant) when focusing on cost optimization at firm level. On the contrary, it is maximized when considering policy and cohesion goals. Since in this case the decision-making units are regions, the DEA model will pursue employment maximisation (more jobs in regional economies).

[16] Kumar and Russell further decomposed conditional efficiency into technological catch-up and capital accumulation.

technology sets depending on the availability of physical, human and financial assets, economic infrastructure, resource endowments and any other characteristics of the physical, social and economic environment in which production takes place (O'Donnell et al., 2008). Such differences justify the estimation of separate production frontiers for different groups of regions sharing similar characteristics.

Figure 8 presents a graphical view of the metafrontier framework in which two different frontiers are defined: (1) a single metafrontier T that considers the full range of technologically feasible input-output combinations (i.e. considering all European regions); and (2) a group frontier T_S that considers only a specific set of regions presenting similar operating environments (i.e. regions included in the same category). The area comprised between the two frontiers represents a technological constraint, i.e. a technological opportunity set which is not available to regions belonging to the group (e.g. lack of highly skilled human resources in rural regions). The gap between the two frontiers is what is defined here as the technology gap (TG). In turn, the conditional efficiency gap (CG) depends on the region's ability to optimize available resources. In other words, the CG is a proxy capturing regional ability to efficiently manage the available resources with respect to its regional peers, i.e. those regions facing the same range of technological opportunities.

Figure 8: Graphic overview of metafrontier approach



Own elaboration based on Bogetoft & Otto (2011) and O'Donnell et al. (2008).

Following O'Donnell notations, $T(x, y)$ is defined as the metafrontier or the unrestricted technology set containing all input-output combinations (i.e. the whole regional sample) (Eq. 2.3-1), while $T_s(x, y) \in T$ represents a sub-group frontier, or the technology set of a regional typology S whose regions present similar operating environments. Then, it is assumed that T and T_s display the same DEA specifications described above. Therefore, for a given region $A \in S \in N$ it can be easily calculated, by solving an analogous LP problem as in Eq. 2.3-3, the metafrontier eco-efficiency (MF_A) respect to T, for which N= 282, and the group eco-efficiency (GF_A) respect to T_s, for which, in the case of rural regions, would be equal to N=100. In this context, T constitutes the overall frontier that envelops all the European regions such that no point of group frontiers can lie above T (Battese et al., 2004). Therefore, the *metatechnology ratio* can be defined as the closeness between T_s and T, and it measures how close a group-s frontier is to the metafrontier[17] (O'Donnell et al., 2008):

$$MTR(x, y) = \frac{MF(x, y)}{GF(x, y)}$$

Eq. 2.3-4

Given that $0 < MTR \leq 1$ and $MTR = 1$ implies no difference between MF and GF, the distance of each region to the MF (dMF) can be decomposed into the technology gap (TG) and conditional efficiency gap (CG) (Han et al., 2019; Kounetas and Napolitano, 2018; Zhang et al., 2015) as:

$$dMF = 1 - MF = TG + CG$$

Eq. 2.3-5

[17] Considering figure 2, the group eco-efficiency (GF) is calculated as OB/OC, while the corresponding distance with respect to the metafrontier (MF) is defined as OB/OD.

$$TG = 1 - MTR$$

Eq. 2.3-6

$$CG = (1 - MF) - TG$$

Eq. 2.3-7

The calculation of the TG and CG is determinant to distinguish between two sources of inefficiency, namely (1) the differences between the production technology levels in regional groups and the European potential optimal production techniques (e.g. lack or availability of exogenous assets such as infrastructures, natural resources, etc); and (2) the loss in efficiency due to the low levels of production management (i.e. endogenous assets such as the ability of regions to maximise welfare gains given a limited set of resources).

In order to calculate the GF eco-efficiency, the urban-rural typology described in the previous section is used. It goes without saying that this classification cannot reflect all the potential differences among European regions. Hence, in order to establish whether the defined taxonomy effectively capture the different territorial configuration, it was tested the presence of significant differences between the efficiencies of the three territorial groups following Bogetoft and Otto work (2011). Namely, letting the density of the distributions of the efficiencies in the different groups be g_1, g_2 and g_3, it is tested $H0: g_1 = g_2$ against $H1: g_1 \neq g_2$. The same applies to g_1 vs g_3 and g_2 vs g_3. Since there are no priori assumption about the distribution of frontier efficiency outputs, the non-parametric Kolmogorov–Smirnov test statistic $T_{ks} = \max_{k=1,\dots,K}\{|G_1(F^k) - G_2(F^K)|\}$ was employed. Where G_1 and G_2 are the empirical cumulative distributions in the two subsets such that T_{ks} is the largest vertical distance between the cumulative distributions. Large values of T_{ks} indicate that $H0$ is false. Note that this test depends on the rank (i.e. the order) of F^K only, and not on the individual values of F^K. It follows Kolmogorov–Smirnov test statistic results:

Table 8: Kolmogorov–Smirnov test statistic results

Hypothesis	Test statistics	Interpretation
$H0: g_1 = g_2$	D = 0.44, p-value = 0	$g_1 \neq g_2$
$H0: g_1 = g_3$	D = 0.67, p-value = 0	$g_1 \neq g_3$
$H0: g_2 = g_3$	D = 0.46, p-value = 0	$g_2 \neq g_3$

Note: g1, g2 and g2 refer to the distribution density of eco-efficiency levels for Rural, Intermediate and Urban group, respectively.

Tests results lead to the rejection of the null hypothesis of identical groups, therefore confirming that regions present different technology assets based on the urban/rural category where they are included and, as such, hold different pre-conditions to achieve eco-efficiency.

2.4. Results

2.4.1. Metafrontier (MF) eco-efficiency

MF eco-efficiency is calculated under the assumption of equal operating environment across the whole sample of European regions. MF eco-efficiency varied from 0.41 (Central Region of Romania) to 1, which is the technological metafrontier defined by the regions of Luxembourg, Brussels, Zurich, London and Central Switzerland. This latter region joined the technology metafrontier in 2014, while the other regions did not change their respective rankings between the two years. Figure 9 shows the estimated MF eco-efficiency for European regions in 2006 (left side) and 2014 (right side), while Table 9 compare respectively some summary statistics for MF eco-efficiency, technological gap and conditional efficiency gap between 2006 and 2014.

Figure 9: Metafrontier (MF) Eco-efficiency in 2006 (left map) and 2014 (right map)

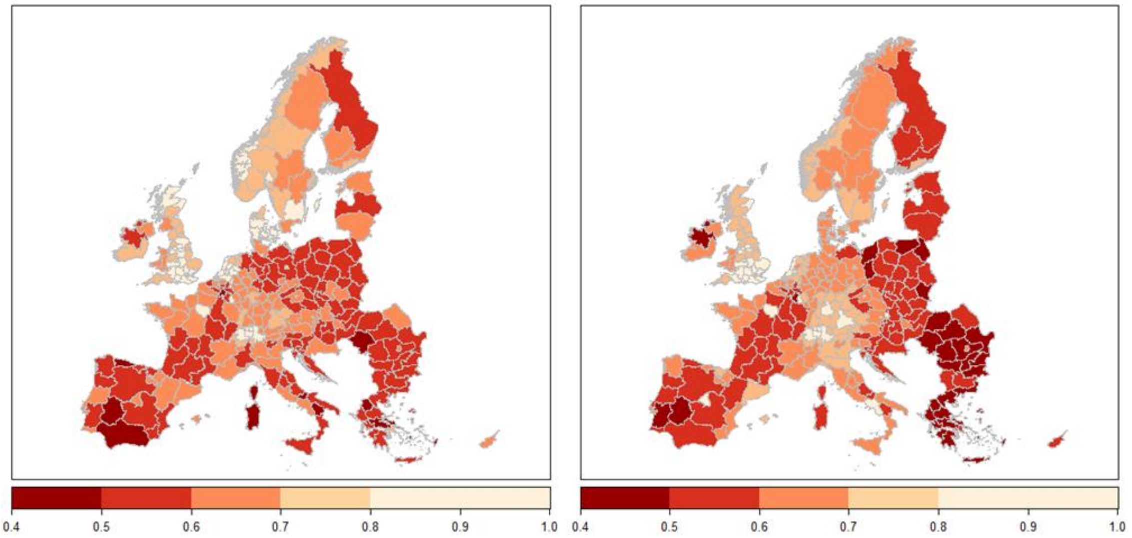


Table 9: Eco-efficiency: summary statistics

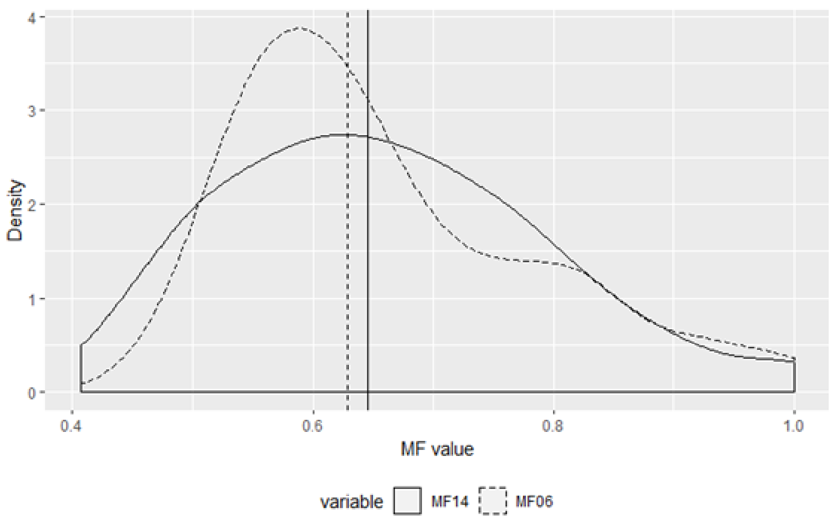
	MF06		**MF14**		**TG06**		**TG14**		**CG06**		**CG14**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Europe	0.66	*0.13*	0.66	*0.13*	0.17	*0.13*	0.16	*0.13*	0.17	*0.18*	0.18	*0.11*
Territorial typologies												
Pred. rural	0.60	*0.10*	0.57	*0.11*	0.26	*0.11*	0.26	*0.10*	0.15	*0.09*	0.16	*0.09*
Intermediate	0.64	*0.09*	0.66	*0.10*	0.20	*0.09*	0.16	*0.08*	0.16	*0.10*	0.18	*0.11*
Pred. urban	0.78	*0.13*	0.78	*0.12*	0.00	*0.00*	0.00	*0.00*	0.22	*0.13*	0.22	*0.12*

Note: MF: metafrontier eco-efficiency, TG: technological gap, CG: conditional efficiency gap, SD: standard deviation

As expected, results show a clear distinction between the most urbanised areas of Europe, which often coincide with capital cities (e.g. Greater London, Madrid, Ile de France, Brussel etc), and the remaining regions. The most urbanised regions present, on average, eco-efficiency scores ranging between 1 and 0.8. Interestingly, many of these areas, e.g. Oberbayern and Stuttgart (DE), Ile de France (FR) and Greater London (UK), consume among the highest amount of material in absolute terms. Some of them, like Luxembourg and Oberbayern also have high per-capita rates of material consumption. In general, most of these regions have economic structures based on financial sectors (e.g. Greater London and Luxembourg), or manufacturing process enabled by best available technologies and highly skilled human capital (especially in German regions). As a consequence, these regional economies are able to produce goods and services with very high added value. In addition, urban agglomerations are more accessible and attract more investments than peripherical regions. All these factors translate into high levels of economic development and high eco-efficiency scores (Masternak-Janus and Rybaczewska-Błażejowska, 2017). By contrast, the lower eco-efficiency scores of Eastern but also some Southern regions of Europe are responsive to their dominant industries, which exhibit production processes mostly connected with high consumption of energy and materials, and lower labour productivity.

The European eco-efficiency average is equal to 0.66, indicating that the theoretical aggregated eco-efficiency improvement might be 34 %. Comparing the kernel density distributions of the MF eco-efficiency scores across European regions in 2006 and 2014 (Figure 10), it can be observed a slight shift in the probability mass towards 1.0 between the two periods (the vertical lines on the plot represent the medians for 2006 and 2014, respectively). This suggests a progress of regional economies towards the MF eco-efficiency, in line with previous works that have described an improvement on material productivity over the last decades (Giljum et al., 2014; Steinberger et al., 2013).

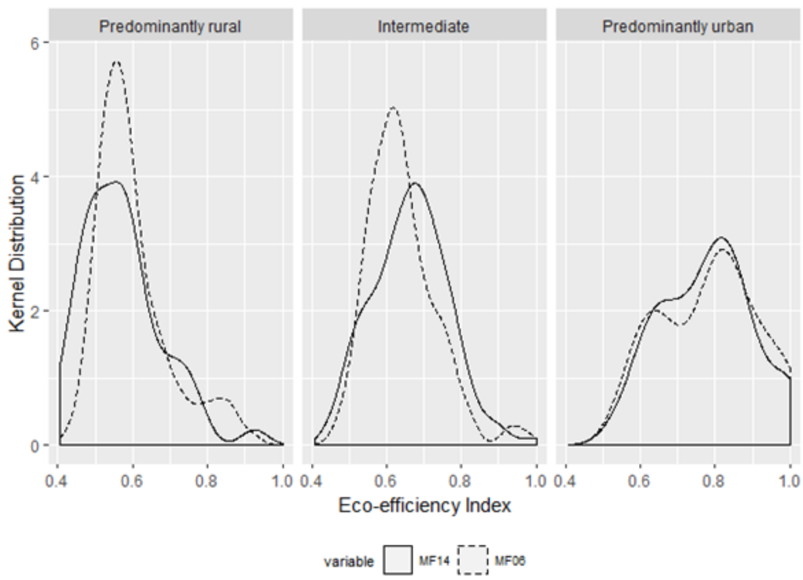
Figure 10: Density distribution of MF Eco-efficiency index in 2006 and 2014.



Note: shifts of density distribution to the right implies a progress towards the metafrontier, as more regions exhibit efficiency figures closer to 1.

However, this evidence does not necessarily imply that regions are converging equally to higher eco-efficiency levels. In fact, considering the evolution of MF densities by territorial typology (Figure 11), clear patterns can be discerned. First and foremost, urban regions present the highest MF eco-efficiency levels, with a mass density closer to 0.8. On the other hand, intermediate and rural regions exhibit distributions centred around lower eco-efficient levels (0.64 and 0.56 in 2014, respectively), with the rural group having the lowest average. As outlined above, this is mostly motivated by the economic specialization of the different groups of regions. Predominantly rural regions concentrate virtually all agricultural, forest- and mining-related activities, which are highly intensive sectors in terms of material consumption. The opposite holds true for urban regions and service-oriented segments of the economy (Bachtler et al., 2017; Walheer, 2018). Figure 11 also shows that regional typologies behaved differently between 2006 and 2014. While, intermediate group moved toward higher eco-efficiency levels (distribution's shift toward 1), the rural regions slightly deteriorated their performance (distribution's shift toward the left). Finally, predominantly urban regions did not show significant changes between the two periods.

Figure 11: Density's distributions of MF eco-efficiency by territorial typologies in 2006 and 2014.



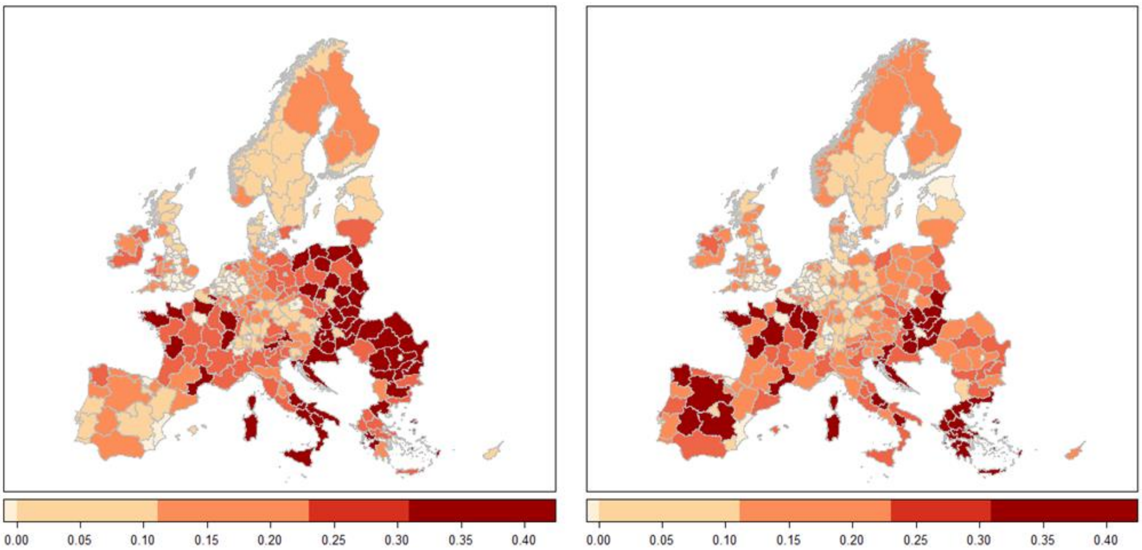
Note: shifts of density distribution to the right implies a progress towards the metafrontier, as more regions exhibit eco-efficiency figures closer to 1.

One of the main reasons explaining the diverging trends between rural areas and other regions lays on the labour migration patterns that European rural regions have experienced (ESPON, 2019b). In fact, the migration of highly qualified human resources is mainly channelled towards the most urbanised regions, which present more advantageous labour market conditions. Rural regions recorded highly negative net migration rates (e.g. Central Greece -20%, Calabria (IT) and Extremadura (SP) -13%), which ultimately affected their economic and eco-efficiency performances. In addition, peripheral regions were also among the most affected by the financial and economic crisis of 2008, which exacerbated outward migration towards agglomeration areas and eventually deteriorated the economic and eco-efficiency balances of remote, peripheral and rural areas.

2.4.2. Technological and Conditional efficiency gap

Figure 12 shows the evolution of TG – with respect to the metafrontier – in 2006 and 2014. On average, European technological gap slightly improved from 0.17 to 0.16 between the periods considered. The largest technological gaps are recorded across rural regions – Molise (IT), Sardegna (IT) and Adriatic Croatia (HR) display the highest TG figures equal to 0.42. Conversely, smaller TG (~0) are observed in most of urban regions and those intermediate regions featuring advanced manufacturing industries (e.g. Freiburg (DE) and Oberfranken (DE)). Focusing on the temporal patterns, it can be observed that most of Eastern European regions, especially Polish and Romanian regions, narrowed their technological gap. The improvement of the operating environment of Eastern regions can be largely explained by the process of integration and convergence advocated by the EU Cohesion Policy. In fact, as these areas joined the EU throughout the 2000s, they also gained access to Structural and Cohesion Funds. These funds are financial resources mostly directed towards structural investments and the construction of basic infrastructures (Filippetti and Peyrache, 2015). In contrast, a stagnating, even worsening, trend can be observed in the Western and Southernmost regions of Europe. In the specific case of Italian Mezzogiorno (i.e. Abruzzo, Basilicata, Calabria, Molise, Puglia, Sardinia and Sicily), our analysis reflects the so-called Italian divide, i.e. the systemic divergence between the southern and northern Italian regions in terms of macroeconomic variables such as unemployment, income growth, public finance and productivity. Consistently with Kounetas and Napolitano's study on regional productivity over the period 2000-2011 (2018), it was found that regions in the Mezzogiorno not only were laggards within Italy, but were also those experiencing among the largest technological gaps at European level in 2006 (e.g. Campania scored a TG equal to 0.39, while Puglia and Sicilia scored a TG equal to 0.37 in 2006). Nonetheless, it should be noted that most of Mezzogiorno regions reduced the TG over the period analysed.

Figure 12: Technology Gap (TG) in 2006 (left map) and 2014 (right map)

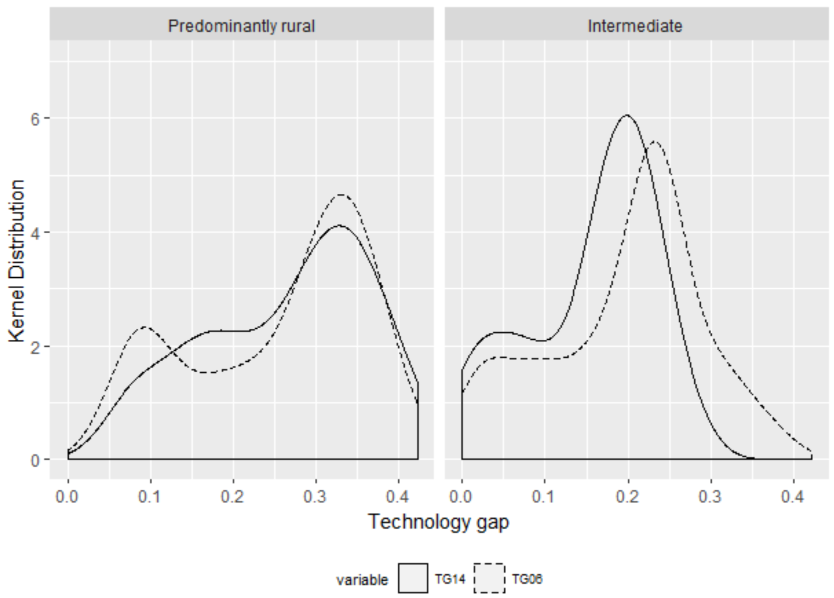


Source: own elaboration

In contrast, most Portuguese and Spanish regions widened their technological gap with respect to the European metafrontier. Although these areas have not reached the highest peaks of the regions of southern Italy recorded in 2006, they portray a similar pattern in which the territorial dualism, urban vs rural, has further deteriorated. In fact, urbanised Spanish regions such as Madrid, Valencia, Murcia and the Basque Country presented equal or improved technological gap over the period between 2006 and 2014. Conversely, rural regions such as Extremadura, Castilla la Mancha and Castilla Leon showed signs of worsening.

Overall, intermediate regions exhibited an improvement in the technological gap between 2006 and 2014, while the same cannot be said for the rural regions. Here the situation did not change significantly over the period (Figure 13).

Figure 13 Comparison of TG between 2006 and 2014 by territorial typology.



Note: shifts of density distribution towards the left (0 value) implies a reduction in the TG. Reversely, shifts towards the right (higher values) implies an increase in the TG. Plots of predominantly urban regions are not included, as these regions present a distribution highly skewed to the left. These regions in fact lie close to the metafrontier, and therefore exhibit very small technological gaps.

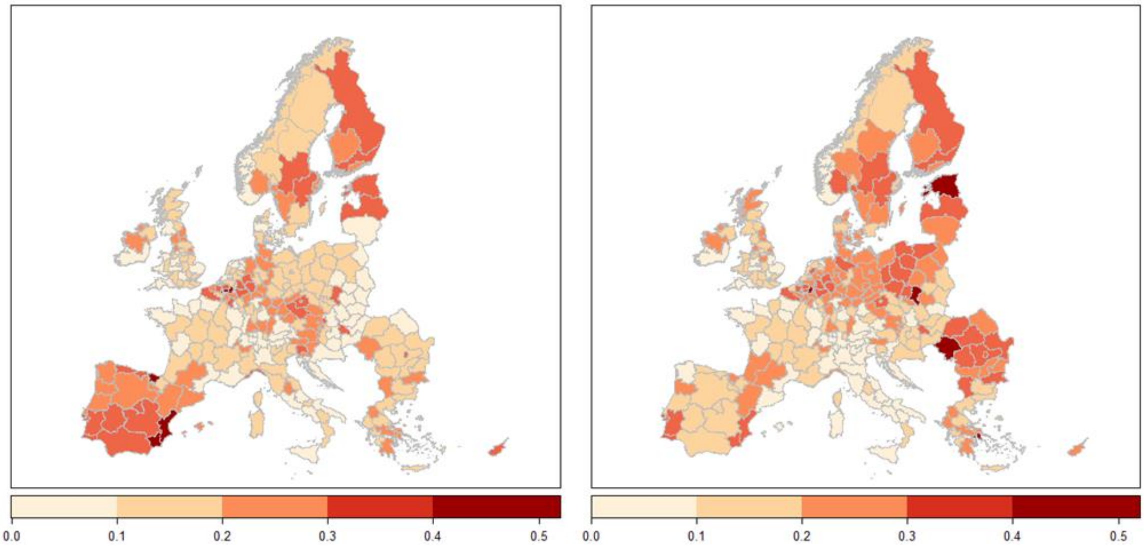
However, it is interesting to note that the rural distribution presents an evident bimodal structure in 2006, which then disappears in 2014. A more detailed analysis of the data reveals that in 2006 up to 19 rural regions recorded a technological gap lower than 0.1. However, due to a subsequent reduction in employment, many of these regions have significantly increased their technological gaps. The southern regions of Castilla la Mancha (ES), Centro (PT) and Alentejo (PT) are extreme cases of this situation. These regions suffered human capital losses of 18%, 9% and 7%

respectively. Similar illustrative patterns can be found in rural Scandinavian regions (Vestlandet (NO), Sjælland (DK) and Midtjylland (DK)). This result is an excellent example of the limited capacity of rural regions to maintain their employment levels, especially during periods of economic recession, and confirms the critical role played by the accumulation of human capital to keep pace with technological progress (Bachtler et al., 2017; Ballatore and Mariani, 2019).

When it comes to the conditional efficiency gap (CG, Figure 14), a different and somehow contrasting territorial pattern emerges. In fact, while Eastern regions significantly improved the operating environment of their economies, they appeared to be worsening in the area of optimal allocation of resources. The rural and intermediate regions of Romania and Poland experienced the highest deterioration in terms of their conditional efficiency gap, particularly in the Southeastern region in Romania, which went from 0.12 to 0.34. The macro-economic figures behind the eco-efficiency index largely explains this pattern towards exacerbation of intra-group differences. The Romanian region shows low rates of employment and GDP per capita in 2014 (54.4% and 13.600 PPS/hab respectively), with very high levels of DMC per capita (23.86 t/hab). Their peers (e.g. other rural regions in Romania and/or Poland) have not been penalised so much in terms of conditional efficiency because despite presenting similar pattern for GDP and DMC per capita throughout 2006 and 2014, they also improved employment rates, therefore largely explaining the increase in material consumption. Indeed, higher employment rates positively affects economic growth and material consumption by increased disposable income for purchasing material-intensive goods (Flachenecker, 2018).

Similar patterns and driving forces can also be found across intermediate regions. For example, Estonia and Latvia regions scored among the highest levels in conditional efficiency gap (above 0.38) as these areas exhibit a strong increase in material consumption per capita between 2006 and 2014, despite keeping similar levels of employment. For what concerns predominantly urban regions, the highest scores in conditional efficiency in 2014 were recorded in Athens (EL) and Śląskie (PL) regions, with 0.41 and 0.46 respectively. These regions represent a prime example of how similar levels of eco-efficiency performance can be explained and driven by differentiated socioeconomic patterns. Athens reduced its material consumption from 11.4 to 8.6 t/hab, which from an ecological point of view implies less environmental harms. However, this was achieved to the detriment of social welfare, as GDP per capita and employment collapsed by -17% and -23%, respectively. By contrary, Śląskie region experienced a strong increase in both GDP per capita and employment (0.32% and 0.13%) but did not manage to reduce its environmental footprint as DMC per capita increased by 0.12% over the same period.

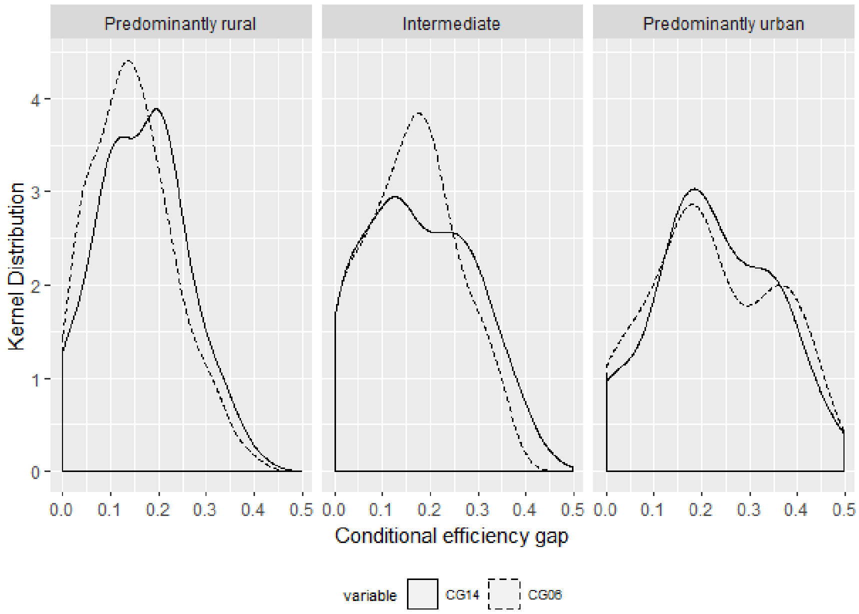
Figure 14: Conditional efficiency gap (CG) in 2006 (left map) and 2014 (right map).



Source: own elaboration

As shown in Figure 15, it is also interesting to note that CG scores are, on average, much higher within urban (0.22) and intermediate regions (0.22) than among rural regions (0.17). Recalling that CG is a measure of the efficiency loss due to low levels of resource management, the difference in CG recorded between rural and intermediate/urban regions might reflect the very different labour markets between the three typologies. In fact, it may be the case that technical differences in material intensive sectors (which are the base economy of rural regions) are not as significant/critical as those existing within the highly developed tertiary sector. In other words, regions specialised in material intensive sectors might benefit from similar levels of know-how and equipment in comparison to those regions operating mostly in knowledge-intensive sectors. In addition, the higher dispersion observed in the CG distribution density of the urban group reflects the more diverse economy structures characterizing these regions, wherein knowledge-intensive activities cohabit with lower-skilled sectors. Notwithstanding, the significant rightward shift in CG observed between 2006 and 2014 within intermediate and rural regions might suggest an increasing complexity of local economies also in those areas.

Figure 15: Comparison of conditional efficiency gap (CG) between 2006 and 2014 by territorial typology.

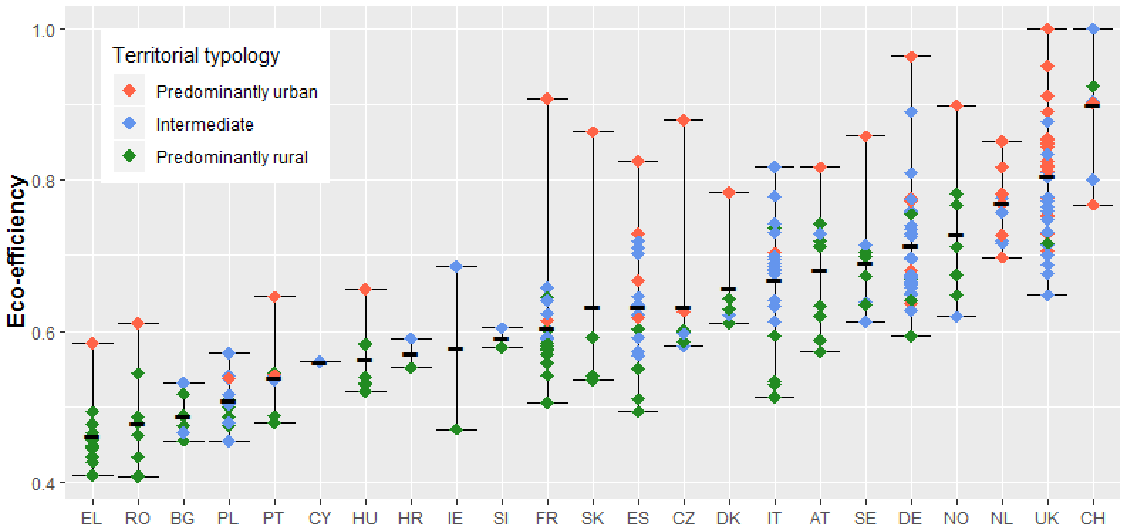


Note: shifts of density distribution to the left implies reduction of conditional efficiency gap, as more regions exhibit CG figures closer to 0.

2.5. Discussion

The metafrontier analysis reveals that territorial heterogeneity has direct implications on eco-efficiency and environmental productivity indicators. In fact, given the different sectoral specialisation patterns of regions, the analysis provides a polarised picture between the better-off centric capital regions and the worse-off peripherical ones. This mode is well reflected in Figure 16, which plots "within countries" MF eco-efficiency levels specifying the territorial typology.

Figure 16: Regional MF Eco-efficiency levels in 2014.



Source: Own elaboration

However, this specialization cannot be considered as the sole and key discriminating criterion between highly eco-efficient urban regions and less eco-efficient rural regions. The motivation is twofold: First, it should be bear in mind that productive structures of regional economies are a by-product of the *historical heritage* and *territorial capital* of regions (Castelnovo et al., 2020; Morretta et al., 2020), which often lead to competitive advantages and structurally higher levels of sectoral efficiency (Behrens et al., 2007). For this reason, it cannot be expected, nor pursued, that all regions adopt similar productive structures and specializations, so that these comparable structures level-out the effect of economic specialization on eco-efficiency scores. Second, and perhaps more importantly, it should be stressed that peripheral regions typically act as *suppliers* of materials for urban consumption. Agriculture and traditional manufacturing activities (e.g. footwear, leather, apparel, textiles, pulp and wood by-products etc.) are mainly located in intermediate and rural areas, which then export processed materials to urban agglomerations for final consumption and/or further refining. Therefore, the lower levels of material eco-efficiency in rural and intermediate regions actually reflect an environmental burden that should be attributed to urban areas.

The distinction between territorial typologies also unveil the specific sources of inefficiency, being these technological bottlenecks or low management levels, and the driving socioeconomic forces across rural, intermediate and urban areas. As expected, rural regions are those discounting larger technological gaps, –as most of them present economic structures that rely on primary and secondary sectors that show low technology intensities. However, two diverging patterns emerge during the period under analysis. On the one hand, most rural Eastern regions have been able to reduce their technological gap mostly thanks to an increased access to financial capital (Filippetti and Peyrache, 2015), which boosted local economies (e.g. the GDP per capita in many regions of Romania almost doubled over the study period). On the other hand, shrinking economies of rural Southern regions (e.g. Spain, Portugal and Greece) widened their technological gaps even further. These regions were much more directly hit by the financial and economic crisis of 2008 as, differently from urban agglomerations, have a limited capacity for shock adjustment (Bachtler et al., 2017). These trends prove that technological catching-up and underperformance processes are not necessarily associated with urban or rural characteristics, as internal socioeconomic conditions within each regional category may also differ. This evidence is further strengthened when focusing on the source of inefficiency related with low levels of management. The example of the Athens (EL) and Śląskie (PL) regions show that similar conditional efficiency gaps can be actually driven by opposite underlying socioeconomic forces.

Finally, the breakdown of inefficiency into an exogenous technological component and an endogenous component associated with the correct management of available resources shows that, although the contribution of both types of inefficiency was similar in 2006 (both CG and TG present an average equals to 0.17), the gains in technology efficiency are much more relevant than those achieved in management efficiency in 2014 (average for CG and TG is 0.18 and 0.16, respectively). A prime example of this phenomenon can be observed in the evolution of the composition of inefficiency between the regions of Romania. Even though these regions managed to halve the TG, they worsened in the management of resources compared to their peers.

From the above it follows that territorial policies aimed at eco-efficiency should go beyond a mere urban-rural differentiation, to focus on the complex linkages between the physical, social and economic environments. In particular, it cannot be expected, nor advocated, that a peripheral, rural and scarcely populated area improves its eco-efficiency level by suddenly shifting towards a service-, knowledge-based economy because, most likely, the region will lack the critical mass that this transition requires, including access to human, technology and financial capitals. These results reveal that future efforts to improve regional eco-efficiency levels should be aimed at encouraging an efficient use of productive factors within each regional *ecosystem*, rather than at reallocating resources among regions through –for example– financial transfer schemes. This requires a systemic, long-term and dynamic policy mix that not only consider regional strengths but that is also perfectly integrated and coordinated with supranational policies. As shown by Wostner (2017), a series of conditions need to be simultaneously in place, ranging from RTDI and human resource development to infrastructure provision, which need to be provided in line with the longer-term sustainable development priorities. Hence, renewed policies, administrative and monitoring systems of environmental protection are important catalysts for achieving eco-efficiency targets (Wang et al., 2019). Last but not least, the conditional efficiency gap should be further narrowed down. Despite an overall technology progress has been achieved by Europe as a whole, some regions are clearly lagging behind in terms of management levels. The less eco-efficient regions should take advantage of proximity with more advanced economies to further catch up with the most efficient economies in terms of global technological frontier. Interregional and intra-industrial spillover effects should therefore be favoured by technical roadmaps, facilitating the generation and transfer of knowledge to boost breakthroughs of environmental field techniques (Bachtler et al., 2017).

2.6. Conclusion

This study represents the first comprehensive research assessing eco-efficiency among European regions that explicitly considers territorial heterogeneity. An overall upward trend in eco-efficiency levels was found across European regions between 2006 and 2014. However, there is not enough evidence to conclude that regions are equally converging towards similar levels of eco-efficiency. Rather a complex core-periphery pattern seems to emerge from the data.

Firstly, the analysis seems to suggest that, from an eco-efficiency perspective, predominantly urban regions seem to be better placed to drive regional economies towards more sustainable pathways. The diversified composition of regional economies, with higher prevalence of knowledge-intensive sectors such as finance, technology, and business services, along with higher levels of employment and population density, allow these regions to make an optimal use of material resources on per capita level. By contrast, predominantly rural regions are penalized by sectoral specializations with high prevalence of material-intensive and low-skilled sectors. However, the lower eco-efficiency levels observed in rural and intermediate regions are, to a large extent, explained by *burden shifting* processes that are usually observed between the industrialized and developing countries (Behrens et al., 2007; Giljum and Eisenmenger, 2004). In fact, many urban agglomerations have been successful in maintaining or even increasing their regional eco-efficiency by outsourcing material intensive activities to other areas. These phenomena can be only understood by looking at material efficiency from the lenses of final consumption through a footprint approach (Wiedmann et al., 2015).

Secondly, in terms of technological gap, our results unveil a significant divide between Western Europe and New Member States. In the latter – and in particular in the rural and intermediate regions of Poland and Romania – the eco-efficiency performance seems to be driven by a process of structural and technological catching-up process with the remaining regions of the EU. These areas seem to be benefiting from the relatively recent integration into the EU. On the contrary, the southern regions of Spain, Portugal and Greece show little progress on their technology gaps. The opposite pattern is observed for the conditional efficiency gap, as Eastern regions scored worse in CG in 2014 than in 2006. These figures suggest that although Eastern regions improved the operating settings of their economies in technological terms, they have not kept the pace in terms of efficient resource management, resulting in similar eco-efficiency levels on the two periods. By contrast, intermediate and rural Southern regions further narrowed their conditional efficiency gaps. However, this was not enough to counterbalance their shrinking economies. The toll paid in these areas as a result of the economic and financial crisis of 2008 was high, and its impact was still clearly visible by the end of the period under analysis.

To conclude, a few limitations should be mentioned regarding the findings presented. First, despite the territorial typology represents a good proxy of the underlying productive structures of regions, it falls short in capturing the economic momentum of territories. As the results show, eco-efficiency drivers are very different depending on the specific socioeconomic profiles of the different European regions. Therefore, a more fine-grained analysis would be necessary in order to plan future strategies. These analyses should take in account the physical characteristics of regions, but also their sectoral structures and development trajectories. Second, by considering employment, material consumption and GDP, the DEA model reflected in a pragmatic way the main objectives of EU sustainability strategies. However, alternative models might be developed considering a broader range of environmental and socioeconomic variables such as carbon emissions, educational attainment levels, foreign direct investments etc. These could provide regional policymakers with a more detailed and far-reaching outlook on the overlap between eco-efficiency criteria and broader sustainability goals.

Chapter 3

3. Material productivity, socioeconomic drivers and economic structures

A panel study for European regions

This chapter is based on the following paper –under review in Ecological Economics:

1. *Bianchi M, del Valle I, Tapia C. Material productivity, socioeconomic drivers and economic structures: A panel study for European regions*

3.1. Introduction

Searching for sustainable modes of consumption and production represents the only way to meet an ever-increasing demand of goods without incurring in further environmental deterioration. The growing awareness that "business as usual" is both unwise and unsustainable has placed the role of the environment and the efficient use of natural resources at the centre of the political and economic debate (Domenech and Bahn-Walkowiak, 2019). Governments and international organizations are encouraging the adoption of alternative production systems and more inclusive policy models in order to achieve a *win-win* outcome – a combined environmental and economic benefit (Akenji and Bengtsson, 2014; Steffen et al., 2015).

One of the headline indicators that is systematically reported in empirical works and monitoring frameworks to track the progress towards more efficient and sustainable economies is Material Productivity (MP). MP refers to the economic value extracted from each unit of material resource consumed and it is calculated as the ratio between Gross Domestic Product (GDP) and an indicator of material consumption, generally Domestic Material Consumption (DMC)[18]. The use of DMC as a denominator entails certain limitations that need to be recognised for the correct interpretation of the respective MP measure. Indeed, DMC does not consider hidden material flows related to the use of raw materials at upstream extraction and processing stages. This truncation might lead to wrong interpretations and misleading policy messages, as economies could reduce their DMC by relocating or outsourcing material-intensive activities such as extraction and manufacturing. In this sense, MP indicator frequently becomes more responsive to the structure and sectoral specialisation of a given economy than to its underlying capacity to consume materials in a more efficient and/or sustainable way (Fernández-Herrero and Duro, 2019; Gan et al., 2013; Kovanda and Weinzettel, 2013). This shortcoming has been partly addressed by the calculation of Material Footprint indicator (MF), which takes into account the material "rucksacks" associated with imports (Wiedmann et al., 2015). However, up to date MF data are not provided at the country level. Consequently, the DMC-based MP remains the most used indicator not only in empirical studies, but also in policy discourses: The Sustainable Development Goals (SDGs), the G7 Resource Efficiency Alliance, the European Union's Roadmap to a Resource Efficient Europe, the Raw Materials Initiative and the Circular Economy Action Plan are some recent prominent examples of policy initiatives.

[18] DMC is calculated according to the Economic-Wide Material Flow Accounting (EW-MFA), a standardized methodology to quantify material throughput from a direct consumption perspective on a national or global scale (EUROSTAT, 2018). DMC indicates the annual quantity of raw material extracted from the domestic territory, plus material imports minus exports.

Understanding the influential socioeconomic factors driving resource productivity represents the first step in establishing and improving resource management policies (Domenech and Bahn-Walkowiak, 2019; Flachenecker, 2018; West and Schandl, 2018). Since the 1970s, when the study of socioeconomic metabolism of countries emerged as a new research field, there has been a bourgeoning literature analysing material consumption patterns and MP (Fischer-Kowalski and Haberl, 1998; Fischer-Kowalski and Hüttler, 1998). Among the many research branches focusing on material consumption at the macro-level (see e.g. Zhang et al., 2018 for a literature review), standardised Economic-Wide Material Flow Accounting (EW-MFA) has been the most widely used approach.

A generally accepted conclusion from EW-MFA studies is that MP is higher in high income developed countries and lower in developing countries (Zhang et al., 2018). According to this line of thought, more mature economic structures and minor reliance on material intensive activities, would lead to moderate and stable DMC levels and increasing GDP, mostly through the expansion of the service-based economy (Krausmann et al., 2008). By contrast, MP would be generally lower in developing countries due to the material-intensive processes of urbanization and industrialization, which often characterise these areas (Behrens et al., 2007; Krausmann et al., 2017). This dichotomy reflects the so-called *socio-metabolic transition* concept (Krausmann et al., 2008), which describes the evolution of material-flows patterns from an economic development perspective. These authors describe MP patterns at national level as a transition process characterised by (1) a shift from an agrarian to industrial phase, where decreased agricultural activity and increased industrial activity lead to higher resource productivity, followed by (2) a shift from industrial to tertiary sector, where decreasing industrial activity and an expanding service sector become the major impetus for resource productivity enhancement (Gan et al., 2013; Pothen and Welsch, 2019). An example of the first phase is provided by the Asia-Pacific region, which between 1990 and 2005 increased its material consumption intensity by nearly 30%, mostly driven by China's soaring industrial and manufacturing capacity (Schandl and West, 2010). On the other hand, structural change of economies towards service sectors can be observed in many advanced economies in Europe, North America and Japan (Giljum et al., 2014; OECD, 2011).

Although the development stages of an economy contribute largely to understanding material consumption patterns, they are far from being the only factors explaining the differences in MP levels observed between regions. As an example, Weisz et al. (2006) found that DMC per capita can be quite different, even among mature economies such as EU-15 countries. The authors argue that the level of use of biomass, industrial minerals, ores, and fossil fuels is largely determined by the structure of the economy rather than by national income or economic development. Similar findings were also presented by Bringezu et al. (2004), who examined dematerialisation for industrialised economies, and Dittrich et al. (2011), who examined material use and material efficiency of emerging economies over the years 1985-2005.

The uneven evolutions observed in MP levels led scholars to examine more closely the relationship between MP and its socioeconomic drivers (Gan et al., 2013; Steger and Bleischwitz, 2011; Steinberger et al., 2010). The basic conceptual model employed in the EW-MFA literature for studying the influence of socioeconomic variables on material consumption is constituted by the logarithmic STIRPAT model (Dietz and Rosa, 1997; York et al., 2003). Essentially, this approach seeks to explain environmental Impact (I) in terms of the main socioeconomic influential variables. These are: population (P), affluence (A) and technology (T) (Dietz et al., 2007; Dietz and Rosa, 1994). One of the key advantages of STIRPAT approach is its logarithm specification, which allows to interpret results in the form of elasticities. Over time, several extended STIRPAT models have been proposed. These include a broader range of explanatory variables, from geo-physical, e.g. latitude or climate, to structural factors, e.g. shares of economic activities over total GDP (West and Schandl, 2018). Focusing on recent examples, Robaina et al. (2020) analyse the determinant factors of MP including explanatory variables such as the expenditure on R&D, value added by service and industry sectors or environmental tax revenues.

Similarly, Fernández-Herrero and Duro (2019) explore the impacts of socioeconomic drivers in explaining international inequalities in MP levels considering openness to trade and value added by agriculture sector along with the other long-established explanatory variables.

Regardless of the specificities of different works and the differences in data availability, scholars generally recognise (1) economic status (often referred as affluence and proxied by GDP per capita), (2) economic structure (i.e. value added of specific economic sectors), and (3) demographic structure (i.e. population density) as the most important drivers of MP (Gan et al., 2013; West and Schandl, 2018). GDP per capita usually exhibits a positive relationship with MP as richer economies not only benefit more advanced means for production, but also outsource most of material-intensive products to other areas (Giljum et al., 2014; Wiedmann et al., 2015). Some studies also employ the quadratic term of GDP per capita in order to capture the decreasing marginal utility derived from higher levels of economic status (Fernández-Herrero and Duro, 2019; Steinberger et al., 2013). Therefore, this latter term generally exhibits negative sign. Regarding to the demographic structure, empirical findings suggest that increases in population density lead to higher MP, as more concentrated populations enable agglomeration synergies and high land prices generally 'expel' materially-intensive industries from these areas (Teixidó-Figueras et al., 2016; Weisz et al., 2006). Concerning the economic structures, the effects on MP differ depending on the economic development trajectories mentioned above. It is generally accepted that an expansion of agricultural and primary activities leads to lower levels of MP, while the opposite holds true for the service sector, i.e. increased relevance of services in the economic composition leads to higher levels of MP (Fernández-Herrero and Duro, 2019; Gan et al., 2013).

In general, the narrative on MP and its socioeconomic drivers has been framed within an economic development perspective that tends to juxtapose the higher MP performance of mature economies with the lower MP performance of developing regions. The underlying qualitative nature of economic development has only been marginally addressed by EW-MFA studies despite being widely recognised in neoclassical economic theory at least since Potter et al. seminal work "*Competitive Advantage of Nations*" (1990). According to this rationale, differences in economic structures, institutions, cultures and historical heritages – often referred to as *territorial capital* (Castelnovo et al., 2020; Morretta et al., 2020) – all contribute to delineate differential development trajectories (Frenken et al., 2007; Gräbner et al., 2019; Hassink and Klaerding, 2015). These patterns necessarily lead to notable differences in MP patterns but have little to do with the level of economic development. On the contrary they depend on the available – geographically bounded – stocks of physical and human capital. In general, the relevance of territorial assets are more visible at lower territorial levels and often lead to competitive advantages and structurally higher levels of sectoral efficiency (Behrens et al., 2007; Bianchi et al., 2020b). In this context, it can be claimed that it is not entirely possible to understand and interpret the relevance of the spatial distribution of MP unless territorial assets and related structural conditions are considered. In this chapter, we argue that the structural differences between regional economies are indeed highly relevant for understanding the impacts of socioeconomics drivers on material productivity.

The main contribution of this chapter is twofold: First, we provide an overview of the evolving geographical patterns of European regional economic specialisations over the 2006-2015 period; Second, we analyse the relationships between MP and its characterising factors considering the different economic arrangements. The analysis is organised in two phases. In phase one the predominant economic structures are defined for 280 European regions by means of location quotients and clustering techniques. In phase two, we investigate the impact of economic structures on the relationship between MP and its main drivers using a fixed-effects panel analysis. The analysis is performed for the decade 2006-2015, hence a period in which deep economic transformations occurred in Europe due to the financial crisis and its second-tier impacts. The main novelty of this work focuses on the way in which economic structures are considered in the analysis. Unlike previous works that take account of structural factors as standard explanatory variables in regression models (Fernández-Herrero and Duro, 2019; Gan et al., 2013; West and Schandl, 2018), we consider the economic structures as interaction terms with socioeconomic drivers. This approach allows to characterise the influence of heterogeneous economic structures on the relationships between MP and its socioeconomic determinants.

Our findings support the underlying assumption of this work, namely that the relationship between MP and its characterising factors change significantly according to the intrinsic economic structures that regions exhibit. In particular, our results suggest the existence of four well-defined economic structures across European regions, including agriculture, industry, intermediate and service-based economies[19]. We found that there is a significant difference in the elasticities of socioeconomic drivers between the more material-intensive economies, compared to the less intensive ones. On the one hand, an increase in affluence seems to favour agricultural and industrial economies more than service-based economies. On the other, tertiary economies seem to be able to better capitalise an increase in population density. We also observe a positive impact of R&D expenditure on MP, but in this case, there is no evidence of significant differences of its influence based on the economic structure of regions. Our results strongly suggest that, in order to develop informed policies geared at increased resource efficiency, it is essential to consider the heterogeneous economic configurations of European regions.

The remainder of the chapter is organized as follows. Section 3.2 presents data and methodology employed, while section 3.3 and 3.4 present and discuss empirical results, respectively. Section 3.5 gives some concluding thoughts and outlines suggestions for further research.

[19] The names of economic structures refer to the predominant economic activity observed in a region. The intermediate structure refers to those regions that have a rather balanced distribution among the various sectoral branches.

3.2. Materials and methods

This section describes the dataset and the empirical strategy employed. First of all, we classified European regions into four distinct clusters: agriculture, industry, intermediate and service cluster. This classification is assessed by means of specialisation indices (i.e. location quotients) and clustering techniques. Second, we employed a fixed-effects panel analysis to analyse the behaviour of MP socioeconomic drivers across the economic clusters defined. The analysis was performed using R Language and Environment for Statistical Computing (R Core Team, 2020). The data were collected using the R package "Eurostat" v.3.3.5 (Lahti et al., 2019). The cluster analysis was conducted using the R libraries "kmeans" and "hclust" from the "stats" package (R Core Team, 2020). Cluster validation was implemented through "clValide" package (Brock et al., 2008). The econometric analyses were conducted using the R package "plm" described in Croissant and Millo (2008).

3.2.1. Data

The dataset employed in this study comprises a panel data for 280 European regions out of 331[20] at NUTS-2 level[21] over the period 2006-2015. Data were collected from Eurostat database (access date 1/12/2019). The dependant variable, MP, is defined as the ratio of GDP to domestic material consumption (DMC). MP reflects the GDP generated per unit of resources used by an economy, expressed in €/kg. DMC accounts for the total amount of materials directly used by an economy, and it is defined as the annual mass of raw materials extracted from the domestic territory, plus

[20] Regions of Albania, Bosnia and Herzegovina, Iceland, Lichtenstein, Montenegro, Serbia, Turkey, Republic of Kosovo and French outermost regions were excluded from this study because of missing data. Inner London West (UK) was also excluded from the study because it represents an outlier, being its GDP per capita more than 6 times the European average.

[21] The NUTS system was established by EC Regulation 1059/2003 that defined a common classification of territorial units for statistics (NUTS), based on the administrative divisions applied in the Member States. The 2nd level in the classification (NUTS 2) groups regions with population between 80,000 and 3 million. In this chapter we refer to the nomenclature NUTS 2, year 2013. Recently a new NUTS 2 classification has been issued, however we preferred to employ the older one as data for year 2006 are not available according to the new nomenclature for certain countries.

all physical import minus all physical export. Data on DMC is only available on national level from material flow accounts collected under the regulation (EU) 691/2011 on European environmental economic accounts. Hence, the regionalised version of DMC developed in Chapter 1 was used to measure MP at regional level.

The following explanatory variables were selected as the MP driving factors to be analysed: GDP per capita (GDP), Population density (POP) and gross domestic expenditure on R&D measured in percentage of the country GDP (R&D). These variables were selected following the literature (see e.g. Fernández-Herrero and Duro, 2019; Gan et al., 2013; West and Schandl, 2018), and considering data availability at the regional level. GDP is expected to have a positive but decreasing effect on MP. The higher the affluence of an economy, the better the means for consuming natural resources and for using them in a more efficient way in production. GDP is included in its linear and quadratic forms. In order to avoid perfect multicollinearity between the two forms, the quadratic term was transformed following the method by Steinberger et al. (2013), as $(\log(GDP) - mean(\log(\mathrm{GDP}))^2$. POP is expressed as the number of inhabitants per square kilometres. This variable is expected to be positively correlated with resource productivity, as very concentrated populations tend to induce an increase in resource efficiency. On the one hand, agglomeration economies maximise the utility derived from material consumption and built stock (Krausmann et al., 2008; Weisz et al., 2006). On the other hand, higher costs of land in densely populated areas discourage the establishment of material-intensive industries, like forestry and agriculture. R&D is widely used to assess whether the productivity of a region is sensitive to investments in innovation activities. While empirical findings generally agree on the positive effects that R&D exert on economic measures of productivity, i.e. GDP over employment or hours worked (Bravo-Ortega and García Marín, 2011), the relationship between R&D and MP is not so straightforward. For example, recent studies found that R&D has different impacts depending on the speed of growth of the economies considered (Robaina et al., 2020). Therefore, less developed economies having larger margin for improvements seem to benefit more from R&D investments.

Similarly Kancs and Siliverstovs (2016) found that the relationship between R&D expenditure and productivity growth might be non-linear as there exist important inter-sectoral differences with respect to R&D investment and firm productivity. Accordingly, we also included the quadratic term of R&D, computed as $(\log(\text{R\&D}) - mean(\log(\text{R\&D}))^2$.

Next to MP and the explanatory variables, the gross value added by economic sectors (GVA) was also included to characterise regional economic specialisation (See following Section 3.2.2).

3.2.2. Regional cluster identification

The main goal of this phase is to define a taxonomy for the different underlying structures of the 280 regional economies in the 2006-2015 period. In order to capture and characterise the underlying productive structure of each region we first computed the Location Quotients (LQs). Differently from the GVA share, which simply indicates the relationship between an industry and the whole economy, the LQs reveals which industries make the regional economy unique, or in other words, what is the sectoral specialisation of a region in comparison to a National or international benchmark. We computed LQs for selected economic activities (NACE rev.2), namely: agriculture (A), industry (B-E) and services (G-J + K-N)[22], using the GVA generated by each of the economic branches. We also considered the inclusion of building and construction as a fourth economic segmentation. However, since this latter branch is rather homogenous across the sample and did not contribute significantly to distinguish regional economies, we decided to drop it.

As said, LQs are computed as a ratio that compares a region to a larger reference region according to some characteristic or asset (e.g. employment shares or GVA shares based on industrial activities). Hence, if for example, x is the GVA generated by sector k in a region i, y is the GVA

[22] The acronyms refer to the NACE rev. 2 taxonomy (European Commission, 2013). Service category includes financial and insurance activities; information and communication activities, real estate activities; professional, scientific and technical activities; administrative and support service activities.

generated by the whole economy in a region i, and X and Y are similar data points representative of European average, then the LQ or relative concentration of asset k in the region i compared to Europe is:

$$LQ_{i,k} = \frac{x_{i,k}/y_i}{X_{EU,k}/Y_{EU}}$$

Eq. 3.2-1

The use of LQs not only translates into very defined regional groups, but is also conductive to the economic phases that are usually referred in evolutionary studies that consider the different development stages of territories (Fernández-Herrero and Duro, 2019; Gan et al., 2013; Krausmann et al., 2008). High LQs in primary or secondary activities typically reflect export-oriented economies. The economic relevance of export activities is largely discussed in the literature (see e.g. Lee (2011) for a literature review). Studies using aggregated metrics of *specialisation* acknowledge that exporters are, on average, more productive than non-exporting areas. However, scholars also emphasise that productivity levels depend on the specific production structure of economies and, therefore, on the types of exports (Feenstra and Kee, 2008). In general, industries exporting relatively "low-tech" products show inferior levels of material productivity as they carry out most of the material-intensive activities related to extraction and/or primary processing of raw materials in situ.

In a second step, we proceeded to the definition of a taxonomy of regional economic structures. Identifying the predominant economic activity is straightforward for many regions. This is for example the case of most capital regions, which virtually in all cases are highly urbanised areas with service-based economies. However, intermediate regions exhibit a rather complex combination of economic activities, which ultimately prevents a transparent classification without incurring in subjective judgement and knowledge bias. In addition, we were also interested in capturing the regional structural changes occurred during the decade covered in our study (from e.g. prevalent industrial configurations to service economies, or vice-versa). This increased the complexity of performing a regional classification, as we could not infer regional structures to the entire panel based on a one-year analysis, nor we could treat each year separately, as fundamental changes at European level might change the classification of a region independently from its intra-regional patterns.

For these reasons, we pooled our data and applied alternative clustering techniques to identify a number of quantitatively robust groups of regions. This approach allowed to significantly reduce the complexity of the analysis focused on more than 2600 observations. Following Gräbner et al. (2019) and Steinberger et al. (2013), we relied on two conventional cluster techniques, hierarchical clustering (HCA) and k-means analysis. The general idea behind HCA is to separate a set of objects into disjunctive groups, where members of the same groups are similar to each other, but distinct to members of other groups. K-means procedures assign objects into clusters based on the average linkage between all pairs of objects in any two clusters, and standardized Euclidean distances. In addition, we also considered the PAM clustering algorithm (Kaufman and Rousseeuw, 2008), which, by using medoids[23] as cluster centres, is less sensitive to noise and outliers.

The final clustering approach and resulting number of regional clusters was established based on standard internal cluster validation procedures, such as the *Connectivity* (Handl et al., 2005), the *Silhouette Width* (Rousseeuw, 1987) and the *Dunn Index* (Dunn, 1974). In addition, since clustering techniques are purely inductive ways of analysing data that do not exploit theoretical insights other than those involved in variable selection, we validated our cluster results by comparing clusters features with theoretical assumptions and other classifications used in the literature.

[23] The medoid refers to an object within a cluster for which the average distance between it and all the other members of the cluster are minimal. In corresponds to the most centrally located point of the cluster.

3.2.3. Panel data modelling approach

Once identified the underlying economic structure for each region, we proceed to test the impact of these latter on the relationship between MP and its socioeconomic drivers. To the authors' knowledge, this specific aspect has not yet been addressed by previous studies. Therefore, for the sake of completeness, we present in Table 10 the summary of the functional forms employed. These considers the economic structures as (1) indexes (IND), (2) exogenous variables independent from other socioeconomic drivers (EXO) and interaction terms (INT). To note that all specification models are in logarithmic form. This allows to reduce skewness and approximate linear relationships between variables. In addition, the log-log form also allows to interpret the parameters' coefficients (β) as "ecological elasticities" (York et al., 2003).

Table 10: Summary of functional form employed

IND – Economic structures as **IND**exes (Pooled)

$$Log(MP_{itj}) = \alpha_i + \beta_1 \log(GDP_{it}) + \beta_2 \log(GDP_{it})^2 + \beta_3 \log(Pop_{it}) + \beta_4 \log(\text{R\&D}_{it}) + \beta_{5j} \log(\text{R\&D}_{it})^2 + \varepsilon_{it}, \quad for\ each\ j = 1, \dots N\ clusters$$

Separate model fitted to the data for each economic structures (j). Each model parameter is sample-specific. Comparison of parameters between different economic structures is not consistent.

EXO–Economic structures as **EXO**genous variables (Fixed-effects)

$$Log(MP_{it}) = \alpha_i + \beta_1 \log(GDP_{it}) + \beta_2 \log(GDP_{it})^2 + \beta_3 \log(Pop_{it}) + \beta_4 \log(\text{R\&D}_{it}) + \beta_5 \log(\text{R\&D}_{it})^2 + \beta_j j_{it} + \varepsilon_{it}$$

The effects of economic structures are absorbed into the exogenous factors ($\beta_j j_{it}$). The indirect impact on socioeconomic drivers is disregarded.

INT–Economic structures as **INT**eraction terms (Fixed-effects)

$$Log(MP_{it}) = \alpha_i + \beta_1 \log(GDP_{it}) \times j_{it} + \beta_2 \log(GDP_{it})^2 + \beta_3 \log(Pop_{it}) \times j_{it} + \beta_4 \log(\text{R\&D}_{it}) \times j_{it} + \beta_5 \log(\text{R\&D}_{it})^2 + \varepsilon_{it}$$

The effect of economic structures directly influences the socioeconomic drivers. Comparison of socioeconomic drivers across different economic structure can be done consistently.

Note: $i = 1, \dots n$ is the individual (region) index; $t = 1, \dots z$ is the time index; α is the intercept and β is the parameter/elasticity; ε is the error term;

The IND approach consists in considering separate models fitted to the data for each regional cluster j. In this way specific elasticities are estimated for each cluster. However, since this process is carried out separately for each group of regions, the comparison of parameters between different clusters is not straightforward. In addition, IND can only be estimated through a pooled model, as we lose the panel structure. In fact, the regional sample for each economic cluster changes for each year, following variations in the economic specialisation of the regions. The EXO approach estimates the average impact of regional economic structures on MP. This is the approach that is generally found in existing literature (Fernández-Herrero and Duro, 2019; Robaina et al., 2020). In this case, economic structures are included in the model as an additional independent explanatory variable, but the extent to which economic structures influence other socioeconomic drivers is disregarded. Finally, our approach INT introduces the economic structures through the interaction term $x_{it}\, j_{it}\beta_{it}$, which measure the impact β of a socioeconomic driver x according to the regional economic structure j.

Differently from the alternative models, the INT approach allows to consistently compare the effects of socioeconomic drivers on MP across the different economic structures. In other words, the INT approach allows to assess whether socioeconomic parameters differ significantly from each other as regional economic structures change. A statistic based on the t distribution is used to test the two-sided hypothesis that a slope β_{j1} of a cluster j_1 , equals a slope β_{j2} of a cluster j_2. The statements for the hypothesis test are expressed as:

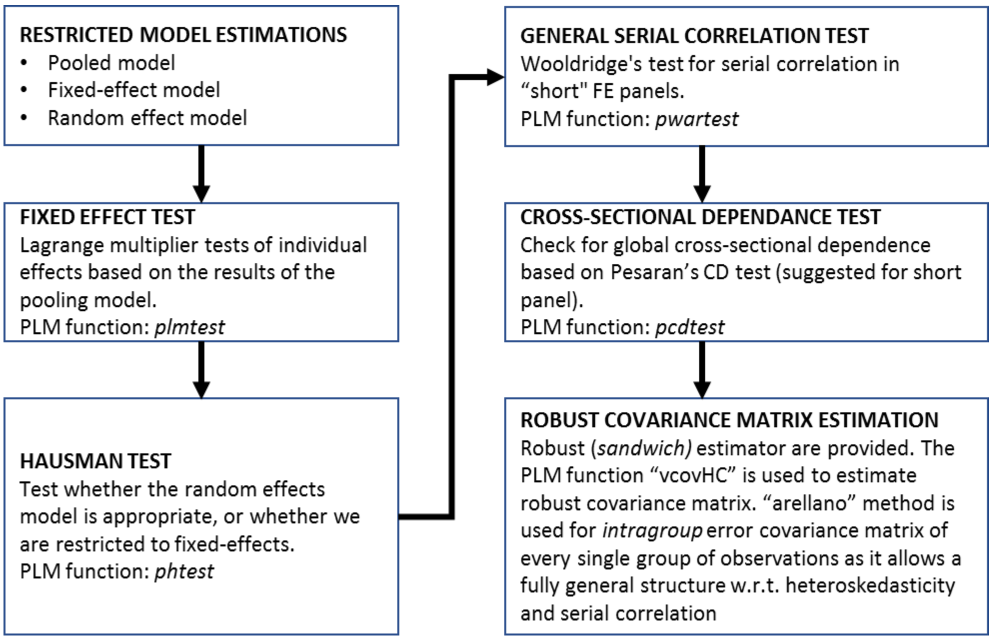
$$H_0\text{: } \beta_{j1} = \beta_{j2}$$

$$H_1\text{: } \beta_{j1} \neq \beta_{j2}$$

The test statistic used is $T_0 = \frac{\hat{\beta}_{j1} - \hat{\beta}_{j2}}{se(\hat{\beta}_{j1})}$, where $\hat{\beta}_{j1}$ is the least square estimate of β_{j1}, and $se(\hat{\beta}_{j1})$ is the standard error. The test statistics, T_0, follows a t distribution with $(n-2)$ degrees of freedom, where n is the total number of observations. The null hypothesis is accepted if the calculated value of the test statistic is such that $-t_{\frac{\alpha}{2},n-2} < T_0 < t_{\frac{\alpha}{2},n-2}$, where $t_{\frac{\alpha}{2},n-2}$ is the percentile distribution of the t distribution corresponding to a cumulative probability of $(1-\alpha/2)$, α is the significance level, and $-t_{\frac{\alpha}{2},n-2}$ and $t_{\frac{\alpha}{2},n-2}$ are the critical values for the two-sided hypothesis.

The econometric specifications –pooled, fixed effects and random effects– were iteratively applied to EXO and INT[24]. The choice of the most appropriate estimator for each approach was established based on statistical tests on parameters and error terms, according to the decision flow chart showed in Figure 17.

Figure 17: Decisional flow chart for the data and model combinations tested



Own elaboration based on Croissant and Millo (2008) and West and Schandl (2018)

Similarly to previous studies performing panel analyses on equivalent socioeconomic datasets (e.g. West and Schandl (2018)), we found that the pooled model and the random effects model were unlikely to provide valid results for EXO and INT approaches. Not surprisingly, the most

[24] The IND approach can only be computed through pooled model as it does not have a panel structure.

meaningful results from panel analyses were those obtained using the fixed-effects model. In addition, given that serial-correlation and cross-sectional dependence was detected across all fixed-effects models, *sandwich* estimators based on “arellano” method were computed by default, as it allowed for a fully general structure w.r.t. heteroskedasticity and serial correlation (Croissant and Millo, 2008).

3.3. Results

3.3.1. The taxonomy of regional economic structures

Table 11 shows the results of cluster validation procedures. As a rule of thumb, we tested up to six clusters, since a greater number would undermine the relevance of this procedure and would likely lead to overfitting issues in the following regression analysis. The hierarchical technique (Ward’s method) is the best approach according to Connectivity and Dunn Index measures, while the Silhouette measure suggests the use of K-means approach. On the contrary, the tests showed no evidence in favour of the PAM approach, so it was excluded from further analysis. Concerning the optimal number of clusters, results were not conclusive. This is mainly due to the evaluation approaches of the tests (see Handl et al. (2005) for a throughout overview of internal validation measures). In order to select the cluster configuration that best fit the heterogeneous economic structures of European regions, we analysed and compared the two solutions suggested by the validation metrics, i.e. the HCA with 3 clusters and the K-means with 4 clusters.

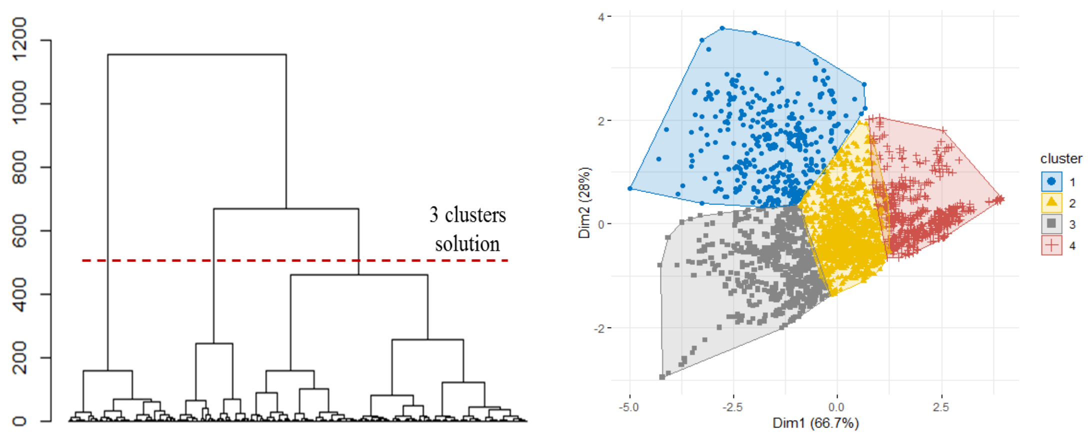
Table 11: Validation test for the definition of clustering approach and number of clusters

Cluster Technique	Cluster internal validation measures	Number of clusters 3	4	5	6
HCA	Connectivity	**99.726***	160.740	199.579	99.726
	Dunn	**0.011***	0.011	0.011	0.011
	Silhouette	0.309	0.295	0.221	0.309
K-means	Connectivity	230.937	263.699	317.357	230.937
	Dunn	0.003	0.004	0.004	0.003
	Silhouette	0.339	**0.354***	0.349	0.339
PAM	Connectivity	162.522	274.522	336.190	162.522
	Dunn	0.006	0.007	0.004	0.006
	Silhouette	0.337	0.346	0.299	0.337

Note: * optimal approach and cluster choice. The connectivity indicates the degree of connectedness of the clusters and has a value between 0 and infinity and should be minimized. The Silhouette and the Dunn Index combine measures of compactness and separation of the clusters. The Silhouette value measures the degree of confidence in a particular clustering assignment and lies in the interval [-1,1], with well-clustered observations having values near 1 and poorly clustered observations having values near -1. The Dunn Index is the ratio between the smallest distance between observations not in the same cluster to the largest intra-cluster distance. It has a value between 0 and infinity and should be maximized.

It follows a visual representation (Figure 18) and the summary statistics (Table 12 & Table 13) of clustering results based on the HCA and k-means methods.

Figure 18: Visual representation of HCA-based dendrogram (left) and k-means based scatterplot (right).



Note: given that there are more than two dimensions (variables), the axes of k-means plot rely on principal component analysis (PCA), i.e. data points are plotted according to the first two principal components that explain most of the variance.

Table 12: HCA clustering summary statistics

HCA clusters	LQ Agriculture		LQ Industry		LQ Services	
Nr. (Obs.)	2006	2015	2006	2015	2006	2015
1: (160)	1.56	1.60	1.13	1.13	0.89	0.89
2: (63)	0.69	0.67	0.62	0.58	**1.15**	**1.16**
3: (45)	**3.96**	**3.68**	**1.61**	**1.65**	0.70	0.71

Note: bold terms represent the highest values for each variable. The number of regions in each cluster (i.e. column 1) refers to year 2015. LQ Agriculture refers to NACE label "A" activities, LQ industry refers to NACE label "B-E" activities, LQ service refers to NACE label "G-J" + "K-N" activities

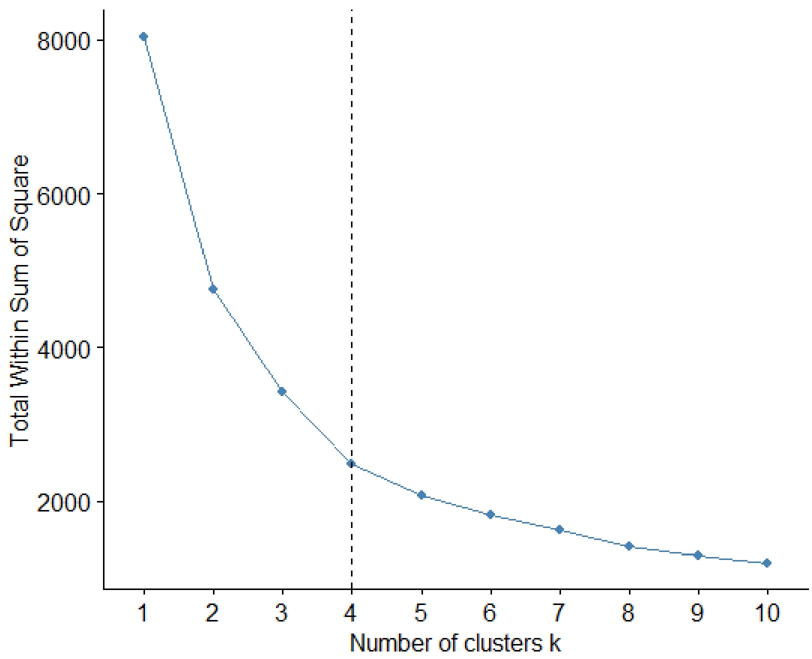
Table 13: K-means clustering summary statistics

K-clusters	LQ Agriculture		LQ Industry		LQ Services	
Nr. (Obs.)	2006	2015	2006	2015	2006	2015
1: (58)	1.48	1.53	**1.65**	**1.70**	0.75	0.74
2: (58)	0.69	0.67	0.60	0.57	**1.17**	**1.18**
3: (109)	1.26	1.23	1.04	1.03	0.93	0.93
4: (43)	**5.16**	**4.72**	1.13	1.12	0.78	0.80

Note: bold terms represent the highest values for each variable. The number of regions in each cluster (i.e. column 1) refers to year 2015. LQ Agriculture refers to NACE label "A" activities, LQ industry refers to NACE label "B-E" activities, LQ service refers to NACE label "G-J" + "K-N" activities

According to the summary statistics, the four groups defined by the k-means approach better define the prevailing economic structures characterising European regions, compared to the three HCA groups. In fact, the HCA approach does not distinguish effectively between industrial- and agricultural- based economies, as the third group presents the highest LQs among both, agricultural and industrial sector. In addition, the HCA presents a skewed distribution towards group 1 (which we might term as "intermediate"). This is almost three times larger than the other groups. Conversely, the k-means approach translates into well-defined regional clusters, where each group show a specific economic specialisation (except the group 3 "intermediate", which presents values close to European averages). The number of clusters defined in the k-means approach is also supported by common visualisation tool generally employed in similar exercises, such as the elbow method showed in Figure 19.

Figure 19: Optimal numbers of k-means clusters according to the Elbow method.



Source: own elaboration

Table 14 provides the summary statistics for the economic specialisations and socioeconomic variables according to the regional taxonomy based on k-means clustering. Cluster (1) encompasses the economies strongly specialised in agricultural sectors and presents an average agriculture's LQ greater than 4. This means that, in regions belonging to this cluster, agriculture is four times more concentrated than the European average. It should be noted that this cluster also features the lowest population density (roughly 70 hab/km2) and the lowest GDP per capita (~18.000PPS/cap in 2015). Cluster (2) comprises the regions with the highest specialisation in industrial sectors (LQ industry ~ 1.7). These regions are also specialised in material intensive activities and are characterised by lower levels of population density and GDP per capita with respect to European average. Cluster (3) groups intermediate economies, i.e. those presenting similar LQs across all sectors, falling close to the European average. Finally, economies specialised in the service sector are gathered in cluster (4). Service-based economies usually develop in very densely populated areas, where the lack of available land impedes the proliferation of material-intensive activities. All in all, cluster (4) presents the highest scores for population density, GDP per capita and MP.

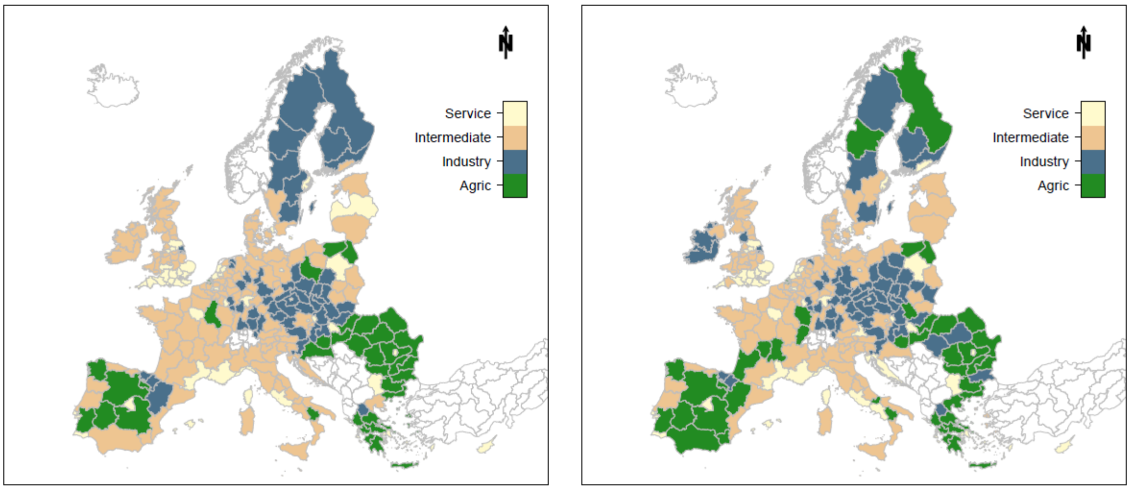
Table 14: Summary statistics of LQs, population density (POP), GDP per capita (GDP) and material productivity (MP) by regional clusters

	LQ Agriculture		LQ Industry		LQ Service		POP (hab/Km2)		GDP (PPS/hab)		MP (PPS/Kg)	
Cluster	2006	2015	2006	2015	2006	2015	2006	2015	2006	2015	2006	2015
1 Agriculture	**5.16**	**4.72**	1.13	1.12	0.78	0.80	68	65	14494	18376	0.79	1.33
2 Industrial	1.48	1.53	**1.65**	**1.70**	0.75	0.74	149	144	22766	27174	1.21	1.63
3 Intermediate	1.26	1.23	1.04	1.03	0.93	0.93	245	260	24155	27852	1.49	2.29
4 Service	0.69	0.67	0.60	0.57	**1.17**	**1.18**	1067	1167	30301	34308	2.22	3.23

Note: LQ Agriculture refers to NACE label "A" activities, LQ industry refers to NACE label "B-E" activities, LQ service refers to NACE label "G-J" + "K-N" activities.

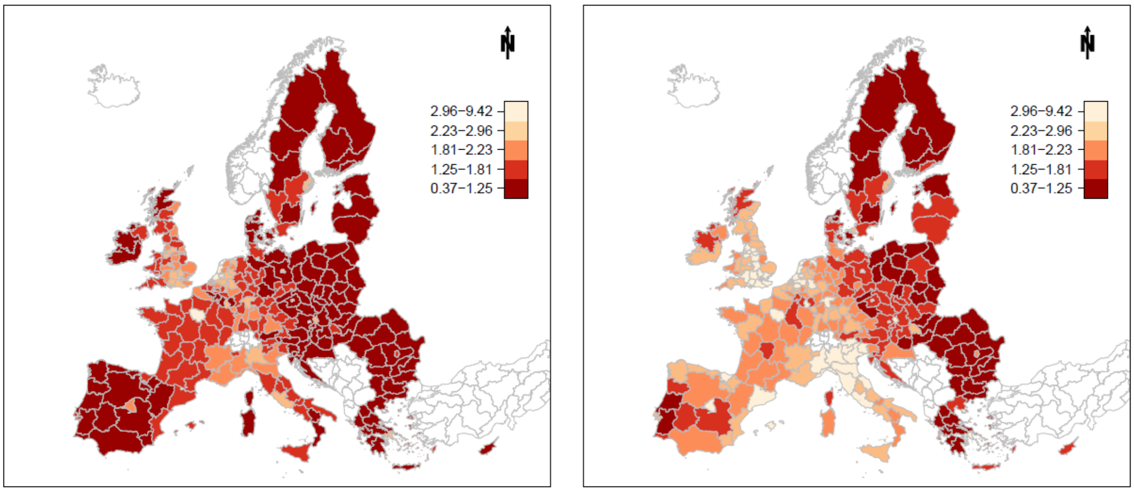
Figure 20 provides a geographical distribution of regional economic structures at the beginning (2006) and at the end (2015) of our study-period, while, in Figure 21, we show the respective regional patterns for MP. In line with previous studies (Fernández-Herrero and Duro, 2019), a significant improvement in MP can be observed across most of European regions between the two periods. As shown in Table 14, this progress was generalised, even if it occurred at different pace depending on the structural features of regions. Interestingly, the clusters also capture outstanding demographic patterns of regions, particularly out-migration in rural and industrial areas (ESPON, 2019b). In fact, regions in agriculture and industrial clusters show decreasing population density between 2006 and 2015.

Figure 20: The geography of regional economic specialisations in 2006 (left map) and in 2015 (right map).



Note: White regions indicate no data availability.

Figure 21: Regional patterns of MP in 2006 (left map) and in 2015 (right map)



Note: colours reflect the quantile breaks. White regions indicate no data availability. MP measured in PPS/Kg.

Comparing the evolution of economic structures (Figure 20) and MP (Figure 21), we see that a structural change toward material intensive sectors not necessarily translates into lower MP levels if such transformations are coupled and/or based on more efficient technologies. Ireland is an outstanding example of such structural change, as it went from an intermediate economic structure in 2006 to a very industrialised one in 2015, being its industrial LQ among the highest in Europe

(2.08). In fact, the manufacturing share of GVA of Southern and Eastern Irish regions increased threefold over the period considered. Nonetheless, these regions also improved their MP rates (0.98 in 2006 and 2.88 in 2015). The same can be said for the southern Spanish regions Andalucía and Murcia, which exhibited among the highest MP increase between 2006 and 2015 (roughly 10%) despite a structural shift towards agricultural specialisation (agriculture LQ for Andalucía and Murcia equal to 4.16 and 3.44 in 2015 respectively). Conversely, many European eastern regions showed reversed trajectories, i.e. from primary agricultural-based economies to industrial, intermediate and service-based economies. As an example, Southwestern region of Bulgaria, where the capital Sofia is located, is clearly evolving towards a service-based economy comparable to most European capitals. A similar situation can be observed in Bucharest, while other Romanian areas such as Northwest, Central and West region transitioned towards predominant industrial structures.

The taxonomy defined also illustrates very well the spatial agglomeration patterns of manufacturing activities towards the so-called "Central European Manufacturing Core" (Stehrer and Stöllinger, 2015). This area is led by German regions and includes large portions of Austria, the Czech Republic, Slovakia, Hungary and Poland. In all these regions the concentration of manufacturing activities increased significantly since the 2000s, probably as a response to expanding market shares in manufacturing industries (Cutrini, 2019). Stehrer and Stöllinger also reported a significant decline in manufacturing for most other European countries (in particular high-income countries, such as the Nordics and Benelux area, alongside France and United Kingdom). This trend is also reflected in Table 14 and Figure 20.

3.3.2. Material productivity, socioeconomic drivers and economic structures

For the sake of comprehensiveness, we present the results for the three approaches IND, EXO and INT. However, it should be borne in mind that the parameters estimated by the IND approach cannot be consistently compared each other as the data samples are very different between the groups of economic structures.

Table 15 presents the result of IND approach. All OLS models exhibit good performance in terms of explanatory power, being the Intermediate group, the cluster with lowest R-square (0.56). This is likely because the intermediate structure constitutes the largest group in terms of the number of regions (i.e. 1147 observations), and consequently is characterized by a wider regional heterogeneity, which is more difficult to capture by the selected parameters. Most of explanatory variables are statistically significant (at $p < 0.05$) for the four clusters (except R&D expenditure, which does not show clear patterns). This indicates, in general, the good specification of the model. As expected, the sign (and magnitude) of some variables differ across the regional groups, suggesting that economic structures might play a key-role in defining MP patterns. In particular, the weight of GDP per capita shows a stark difference between material-intensive economies (i.e. agriculture and industry cluster) and more diversified economies (i.e. intermediate and service clusters). Interestingly, the GDP quadratic term changed sign between the material-intensive and less-intensive groups (even if it is only significant for the intermediate cluster). The reason for this might reside in the fact that the decreasing utility of income per capita only materialise at the higher income levels of service and intermediate clusters. By contrast, given the lower GDP per capita levels of agricultural and industrial regions, there is no evidence of decreasing marginal utility. Population density is also statistically significant (at $p < 0.05$) across all clusters considered, but its weight varies less, compared to GDP per capita. Industrial cluster recorded the lowest weight for population density (0.22), while agriculture the highest (0.29). According to the results of the IND approach, we could already argue that the selected socioeconomic parameters behave considerably differently according to the economic structure characterising the region. Affluence, for instance, shows a higher leverage effect across agricultural and industrial regions rather than service and/or intermediate areas. These relationships will be further analysed within the following approaches EXO and INT.

Table 15: IND approach - Pooled regression results

Coefficients	Model IND J=1 Agriculture		Model IND J=2 Industry		Model IND J=3 Intermediate		Model IND J=4 Service	
(Intercept)	-9.616***	(1.57)	-8.787***	(0.77)	-7.000***	(0.88)	-4.669***	(1.66)
GDP	0.877***	(0.15)	0.799***	(0.07)	0.635***	(0.09)	0.392**	(0.17)
GDP^2	0.007	(0.14)	0.163	(0.15)	-0.405***	(0.15)	-0.034	(0.18)
Pop	0.292***	(0.05)	0.223***	(0.02)	0.233***	(0.02)	0.256***	(0.02)
R&D	0.078	(0.11)	-0.042	(0.03)	-0.056*	(0.03)	0.012	(0.04)
R&D^2	-0.039	(0.04)	-0.040**	(0.01)	-0.015	(0.03)	-0.046	(0.03)
R	0.730		0.786		0.563		0.730	
R^2	0.726		0.784		0.561		0.728	
DF	334		528		1152		526	

Note: values in brackets refer to heteroskedastic robust standard error. * p < 0.1; ** p < 0.05; *** p < 0.01. DF: Degrees of freedom.

Table 16 shows the results obtained from approaches EXO and INT. Similarly to previous studies (Fernández-Herrero and Duro, 2019; Gan et al., 2013; Robaina et al., 2020), in EXO we treat the economic structures as exogenous variables, estimating their direct impact on material productivity. In this case, the use of the taxonomy of regional economic structures developed in section 3.3.1 is not suggested, as reliable fixed-effects estimation requires sufficient variability over time in the predictor variables (Hill et al., 2019)[25]. To overcome this limitation, we estimated EXO by directly applying the LQs. Being *continuous* variables, LQs can be effectively employed in fixed-effects models. Finally, in approach INT we applied the economic structures (as categorical variables) to the explanatory variables, generating four interaction terms for each socioeconomic driver. These interaction terms measure the influence of socioeconomic drivers on material productivity, according to the economic structures.

[25] It should be considered that the cluster taxonomy is based on four categorical variables that are nearly constant. Therefore, they would not contribute much information to the analysis within a fixed-effects approach.

The two models present similar explanatory power (R-adjusted ~0.2) and all explanatory variables are significant and show the expected sign. The quadratic forms of GDP and R&D behave in a consistent and similar fashion across the two models. A decreasing marginal utility is observed for GDP per capita (~-0.14) and an increasing marginal utility is noted for R&D (~0.04). Population density has the largest explanatory power (> 2.5) in all models. This means that, *ceteris paribus*, a 1% increase in population density would at least produce a 2.5% improvement in material productivity. This is in line with previous fixed-effect models that have promoted population density as the sole elastic socioeconomic driver for material consumption (West and Schandl, 2018). The second most relevant variable is GDP per capita, which shown an average coefficient value of 0.6. This is fully consistent with the 0.56 and 0.60 scores proposed in Pothen and Welsch (2019) and Wiedmann et al. (2015), respectively.

Looking at the coefficients of LQs it emerges that specialisation in material-intensive economies can be considered an inelastic driver. In other words, further specialisation in agriculture or industrial economy leads to an improvement of MP of inferior magnitude. On the contrary, the relationship between service specialisation and material productivity is almost proportional, i.e. an 1% increase in service specialisation would produce roughly a 1.11% improvement in MP. As this is presumably the first study in which LQs are used as proxies for economic structure, we do not have a valid reference to compare the parameters. However, the estimated elasticities are consistent with the theoretical argumentation introduced by similar studies (Fernández-Herrero and Duro, 2019; Gan et al., 2013; Robaina et al., 2020), namely that service-based economies are structurally advantaged when it comes to MP performance. However, differently from Fernández-Herrero and Duro and Gan et al., which found a negative relationship between MP and material-intensive structures, our LQ elasticities are all positive. Our interpretation is that higher degrees of economic specialisation may translate into productivity gains, thanks to advancements in technological capacity and know-how in the concerned market segments. In fact, the use of GVA shares as explanatory variable for MP – instead of LQs – ‘penalises’ the regions with higher concentrations of economic activity on material intensive sectors, ignoring that such regions are most likely those that show higher levels of competitivity and productivity in those same economic activities. In turn, the use of LQs allows to simultaneously characterise regional economic structures *alongside* their degree of specialisation, which is an important advantage of this approach over alternative options.

Table 16: EXO and INT approaches - Fixed-effects regression results

Coefficients	**EXO**		**INT**	
GDP	0.713***	(0.06)		
GDP^2	-0.144**	(0.07)	-0.133**	(0.07)
Pop	2.991***	(0.34)		
R&D	0.175***	(0.03)		
R&D^2	0.041***	(0.01)	0.038***	(0.01)
LQ Agriculture	0.110***	(0.03)		
LQ Industry	0.396***	(0.13)		
LQ Service	1.111***	(0.23)		
GDP: CL Agriculture			0.630***	(0.07)
GDP: CL Industry			0.615***	(0.06)
GDP: CL Intermediate			0.546***	(0.06)
GDP: CL Service			0.554***	(0.06)
Pop: CL Agriculture			2.623***	(0.34)
Pop: CL Industry			2.673***	(0.34)
Pop: CL Intermediate			2.808***	(0.34)
Pop: CL Service			2.787***	(0.35)
R&D: CL Agriculture			0.151***	(0.05)
R&D: CL Industry			0.181***	(0.04)
R&D: CL Intermediate			0.181***	(0.04)
R&D: CL Service			0.135***	(0.05)
R	0.311		0.278	
R2	0.228		0.189	
F-statistic	128.99		62.79	
DF	2288		2282	
Poolability test (F test)	21.70***		20.29***	
Hausman test (chisq)	523.38***		478.03***	
Wooldridge's SC test (F test)	1452***		1366***	
Pesaran's CD test (z test)	174.48***		197.33***	

Note: values in brackets refers to heteroskedasticity and serial (cross–sectional) robust standard errors (Arellano). * p < 0.1; ** p < 0.05; *** p < 0.01. Poolability test computes F tests of effects based on the comparison of the within and the pooling models. Wooldridge's SC test refers to the general serial correlation test in "short" panels. Pesaran's CD test refers to the global cross-sectional dependence test in "short" panels (see Croissant and Millo (2008) for test statistic description).

While EXO estimated the exogenous impact of economic specialisation on material productivity, INT allows to model the co-evolution of socioeconomic drivers and economic structures. Several conclusions can be drawn by looking at model INT parameters. First of all, we observe a relevant difference in GDP per capita between material-intensive clusters (0.63 for agriculture and 0.62 industry) and intermediate and service regions (both 0.55). This seems to suggest that the more 'material-intensive regions' could be better placed to boost material productivity through increased levels of affluence. An opposite pattern is observed for population density. In this case, an increase in this indicator has a greater leverage effect on intermediate and service-based economies compared to the same increase happening in agriculture and/or industrial regions (2.81 for intermediate and 2.62 for agriculture). This suggests that the concentration of population favours greater levels of MP in urban economies, but not so much in rural and sparsely populated regions. In other words, there seems to be a synergetic effect between changes in population density (which increases material efficiency) and regional economic specialisation (i.e. increased service-orientation of regional economies leading to economic de-materialisation). Concerning the effect of R&D expenditure on MP, we found a positive relationship. This seems reasonable as more investment in R&D can deliver goods and services more efficiently, and produce goods which have an increased knowledge component in their value added. However, R&D impact is very marginal and present little variation across the economic structures considered (0.14-0.18).

Results in Table 16 suggest that the impact of socioeconomic drivers on MP are likely to change according to the economic structures of regions. However, to understand the bearing of such differences we need to establish if they are statistically significant. Table 17 presents the T_0 statistic results computed by linear hypothesis testing with heteroskedasticity and serial (cross–sectional) robust standard errors.

Table 17: Linear hypothesis testing results

Socioeconomic driver: GDP				
	CL Agric	CL Industry	CL Interm.	CL Service
CL Agric.		**0.509**	**4.538****	**2.978***
CL Industry	**0.509**		**5.013****	**2.798***
CL Interm.	**4.538****	**5.013****		**0.165**
CL Service	**2.978***	**2.798***	**0.165**	
Socioeconomic driver: POP				
	CL Agric	CL Industry	CL Interm.	CL Service
CL Agric.		**1.045**	**4.463****	**2.848***
CL Industry	**1.045**		**4.698****	**2.320**
CL Interm.	**4.463****	**4.698****		**0.226**
CL Service	**2.848***	**2.320**	**0.226**	
Socioeconomic driver: R&D				
	CL Agric	CL Industry	CL Interm.	CL Service
CL Agric.		**0.675**	**0.528**	**0.085**
CL Industry	**0.675**		**0**	**1.070**
CL Interm.	**0.528**	**0**		**1.239**
CL Service	**0.085**	**1.070**	**1.239**	

Note: Values refer to T_0 statistics computed considering heteroskedasticity and serial (cross–sectional) robust standard errors. * p < 0.1; ** p < 0.05; *** p < 0.01

According to Table 17, we can say that:

- The effect of GDP and POP on MP is significatively different between material intensive economies (i.e. agriculture and industry cluster) and the less material intensive economies (i.e. intermediate and service economies);
- The impact of R&D on MP does not change significantly between the economic structures considered.

3.3.3. Robustness checks

We conducted a number of checks to scrutinize whether our results are robust to potential endogeneity issues. Some authors caution that current MP levels might be affected by past levels of MP (Flachenecker, 2018; Robaina et al., 2020). The hypothesis that past values of technological levels influence present technological performance is plausible, as the technological trajectory of a given territory is the result of a long historical process (Porter, 1990). In fact, MP has been often used as proxy indicator for technological level at country level (Dong et al., 2017; Schandl and West, 2010; Steinberger and Krausmann, 2011). Even if the use of lagged MP values has not been considered in recent EW-MFA STIRPAT applications (Fernández-Herrero and Duro, 2019; Gan et al., 2013; West and Schandl, 2018), we took into account potential issues of endogeneity by applying the difference-generalized method of moments (GMM) developed by Arellano and Bond (1991). Differently from the traditional "fixed-effect" econometric method, the difference-GMM is able to produce empirical output considering the dynamic relationship between variables and it also eliminates the problem of endogeneity and autocorrelation thanks to the use of the lagged values of explanatory variables as instrumental variables.

Table 18 shows the comparison of empirical results obtained for EXO and INT models calculated by the traditional fixed-effect and GMM method. As expected, MP(t-1) is significant in both models with a similar magnitude (~0.4). Concerning the other explanatory variables, we can clearly observe a change in magnitudes, especially for those variables constructed by GDP, since part of their explanatory power is now captured by MP(t-1). However, we can observe that, first, the GMM-based Location Quotients (LQ) acknowledge the findings of the fixed effect model. In fact, specialisation in service sector produces the higher gain in MP, followed by industry and agriculture (although this latter is not significant according to the GMM model). Second, within the INT model, material-intensive regions (agricultural and industrial based economies) present higher affluence elasticities (GDP per capita) compared to less material intensive regions (intermediate and service-based economies). By contrary, population density presents higher leverage effects across services and intermediate regions compared to material intensive regions. Finally, concerning R&D driver, we could say that the elasticities remain generally stable across the fixed-effect and GMM method.

Table 18: Comparison of fixed effects and GMM results for EXO and INT models.

Coefficients	EXO		EXO.GMM		INT		INT.GMM	
MP(t-1)			0.478***	(0.08)			0.412***	(0.08)
GDP	0.713***	(0.06)	0.257***	(0.08)				
GDP^2	-0.144**	(0.07)	0.417***	(0.08)	-0.133**	(0.07)	0.360***	(0.09)
Pop	2.991***	(0.34)	1.670***	(0.49)				
R&D	0.175***	(0.03)	0.107***	(0.03)				
R&D^2	0.041***	(0.01)	0.039**	(0.02)	0.038***	(0.01)	0.039**	(0.02)
LQ Agriculture	0.110***	(0.03)	0.024	(0.02)				
LQ Industry	0.396***	(0.13)	0.262***	(0.09)				
LQ Service	1.111***	(0.23)	0.595***	(0.15)				
GDP: CL Agriculture					0.630***	(0.07)	0.242***	(0.08)
GDP: CL Industry					0.615***	(0.06)	0.233***	(0.07)
GDP: CL Intermediate					0.546***	(0.06)	0.215***	(0.07)
GDP: CL Service					0.554***	(0.06)	0.208***	(0.07)
Pop: CL Agriculture					2.623***	(0.34)	1.776***	(0.55)
Pop: CL Industry					2.673***	(0.34)	1.796***	(0.55)
Pop: CL Intermediate					2.808***	(0.34)	1.833***	(0.56)
Pop: CL Service					2.787***	(0.35)	1.845***	(0.55)
R&D: CL Agriculture					0.151***	(0.05)	0.116**	(0.05)
R&D: CL Industry					0.181***	(0.04)	0.125***	(0.03)
R&D: CL Intermediate					0.181***	(0.04)	0.110***	(0.03)
R&D: CL Service					0.135***	(0.05)	0.077*	(0.04)
R	0.311				0.28			
R2	0.228				0.19			
F-statistic	128.99				62.79			
DF	2288				2282			
Poolability test (F test)	21.70***				20.29***			
Hausman test (chisq)	523.38***				478.03***			
Wooldridge's SC test (F test)	1452***				1366***			
Pesaran's CD test (z test)	174.48***				197.33***			
Sargan test (chisq)			72.46***				138.90***	
AR (1) test			-5.200***				-4.481***	
AR (2) test			1.623				1.213	
Wald test (chisq)			629.881***				528.967***	

Note: values in brackets refers to heteroskedasticity and serial (cross–sectional) robust standard errors (Arellano). * p < 0.1; ** p < 0.05; *** p < 0.01. Poolability test computes F tests of effects based on the comparison of the within and the pooling models. Wooldridge's SC test refers to the general serial correlation test in "short" panels. Pesaran's CD test refers to the global cross-sectional dependence test in "short" panels. Sargan test refers to overidentification test. AR (1) and AR(2) refer to first and second order Arellano-Bond's test of serial correlation. (see Croissant and Millo (2008) for test statistic description).

The GMM results did not reject our underlying hypothesis, as the type of economic structures still seem to exert a significant impact on socioeconomic drivers. In addition, it should be noted that according to the Sargan test, the GMM-model does not satisfy the overidentification requisite ($p < 0.05$). Despite the use of different combinations of instrumental variables, we have not been able to identify a satisfactory output. This might be due to the presence of heteroskedasticity in our sample. In fact, as also explained in Croissant and Millo (2008, p. 33), the assumption of strict exogeneity of regressors, which is essential for consistency of the Maximum Likelihood models, is often inappropriate in economic settings. Therefore, as a result, we preferred to stick to our simpler and more interpretable fixed-effect INT model.

Similarly to previous works (Flachenecker, 2018; Pothen and Welsch, 2019), we also tested the robustness of our empirical models (EXO & INT) to potential exclusion of countries and/or periods of time. First, we dropped the period 2008-2010 as this was characterised by a significant decline in economic output and material consumption levels. Second, we conducted the analysis for EU-15, to see whether the results might change considering only most advanced EU economies[26]. This check also confirmed that our results are generally robust. The exclusion of the period 2008-2010 from the analysis seemed to only affect the magnitude of elasticities, but it did not affect the relationship among them, nor their significance. The major change produced by the exclusion of non-EU-15 from the sample was the loss of significance for the quadratic term of GDP. This change might be due to the reduced variation of GDP levels within the sample. In fact, as EU-15 present similar GDP levels, the explanatory power of this parameter could be affected. Table 19 shows the results of robustness checks.

[26] We also considered the exclusion of single years characterised by significant “jumps” in linear trends, such as 2008 and 2011, and the exclusion of the five regions having the highest GDP per capita and the 5 regions having the lowest GDP per capita.

Table 19: Robustness check by excluding the financial crisis (2008-2010) and the new member states

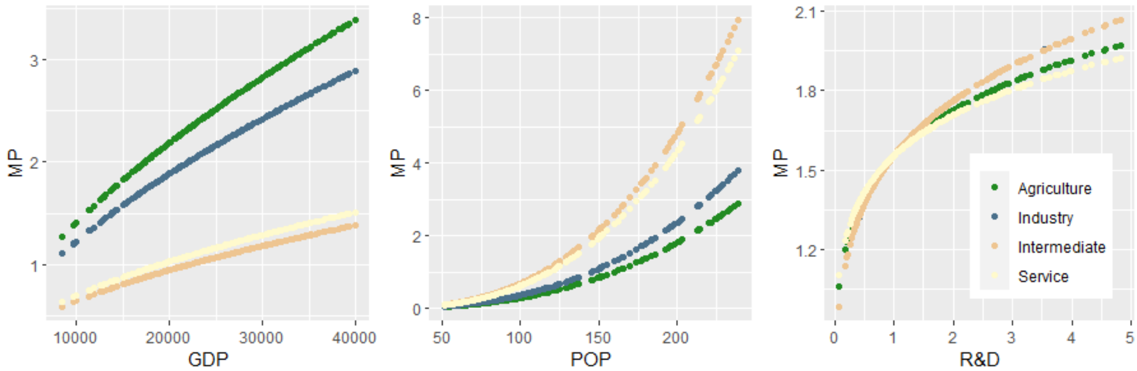
Coefficients	EXO Excl. 2008-2010		EXO EU-15		INT Excl. 2008-2010		INT EU-15	
GDP	0.742***	(0.05)	0.639***	(0.07)				
GDP^2	-0.199***	(0.05)	0.153	(0.10)	-0.199***	(0.05)	0.187*	(0.10)
Pop	3.265***	(0.17)	3.823***	(0.17)				
R&D	0.203***	(0.02)	0.182***	(0.02)				
R&D^2	0.051***	(0.01)	0.033***	(0.01)	0.047***	(0.01)	0.017	(0.01)
LQ Agriculture	0.116***	(0.02)	0.139***	(0.02)				
LQ Industry	0.368***	(0.06)	0.282***	(0.06)				
LQ Service	1.145***	(0.12)	1.300***	(0.13)				
GDP: CL Agriculture					0.639***	(0.05)	0.410***	(0.06)
GDP: CL Industry					0.632***	(0.06)	0.403***	(0.07)
GDP: CL Intermediate					0.558***	(0.06)	0.372***	(0.07)
GDP: CL Service					0.565***	(0.06)	0.350***	(0.07)
Pop: CL Agriculture					2.934***	(0.18)	3.776***	(0.18)
Pop: CL Industry					2.961***	(0.18)	3.796***	(0.18)
Pop: CL Intermediate					3.111***	(0.17)	3.838***	(0.18)
Pop: CL Service					3.097***	(0.17)	3.889***	(0.18)
R&D: CL Agriculture					0.186***	(0.03)	0.087*	(0.04)
R&D: CL Industry					0.222***	(0.03)	0.142***	(0.03)
R&D: CL Intermediate					0.219***	(0.03)	0.215***	(0.02)
R&D: CL Service					0.140***	(0.04)	0.070**	(0.03)
R	0.375		0.352		0.341		0.324	
R2	0.264		0.273		0.221		0.239	
F-statistic	116.473		121.042		57.181		60.854	
DF	1553		1782		1547		1776	

Note: values in brackets refers to heteroskedasticity and serial (cross–sectional) robust standard errors (Arellano). * p < 0.1; ** p < 0.05; *** p < 0.01.

3.4. Discussion

Our findings provide compelling evidence that the use of economic structures as simple exogenous factors explaining MP falls short in providing a comprehensive picture of the relationship between material productivity and its determinants. In particular, the analysis showed that different structural economic configurations are likely to change the effect of GDP and POP on material productivity. To give an idea of the scale of such differences across regional clusters, we present in Figure 22 the prediction of MP calculated by applying the values of interaction terms obtained in model INT. Each scatterplot represents the trends of MP calculated by using, respectively, the four elasticities obtained across economic structures for each socioeconomic driver (i.e. GDP, POP, and R&D), while keeping the remaining parameters constant.

Figure 22: Material productivity trends according to economic structures elasticities



Note: figures for GDP (PPS/hab), POP (hab/Km2) and R&D (%) refer to 2015.

The influence of GDP and POP on MP varies considerably depending on the socioeconomic structures of regions. Concerning GDP elasticity and assuming other conditions being equal between economic structures, at a GDP per capita level equal to €20.000, material intensive economies would be about twice as resource productive than intermediate and service-based economies. Conversely, the different elasticity of POP across regional groupings implies that, at a population density of 200 hab/Km^2, this factor would be associated with MP levels being 2.5 times higher in intermediate and service economies compared to material-intensive regions. Obviously, these predictions are only hypothetical, as the *ceteris paribus* assumption is not realistic. Furthermore, it should be borne in mind that the divergent effects observed between socioeconomic factors would largely offset each other, with a likely predominance of population density – as this variable presents greater elasticities in all types of regions. This also explains why very conglomerated areas such as metropolitan cities usually exhibit the highest MP scores (e.g. Brussels, Madrid or Ile de France).

The higher elasticity of GDP for agricultural and industrial regions might appear counterintuitive, considering that in general these regions show lower levels of MP. However, this is explained by the intrinsic physical nature of their economies. In fact, these regions are mainly producers and exporters of raw material and manufactured goods, so that an increase in affluence would have direct repercussion on their productive means. Production would be enhanced by a greater access to financial resources, and therefore to technological improvements. By contrary, a GDP increase in tertiary economies would have a smaller impact on material productivity, as these economies present a rather weak presence of manufacturing and/or raw material extraction activities. Conversely, population density presents a higher leverage effect in urban regions, where space constraints limit the deployment of material-intensive activities and favour instead the development of strong service-oriented economies. In addition, the significant difference of POP elasticity between denser (service-based regions) and less dense (agricultural and industrial regions) areas is consistent with previous findings confirming that firms and workers are, on average, more productive in agglomerated economies (Combes, Pierre-Philippe Duranton et al., 2012; Duranton and Puga, 2014).

Interestingly, R&D elasticities present a significant but marginal effect on MP, which does not change significantly across different types of regions. This could be explained by a combination of factors. On the one hand, investments in R&D do not necessarily occur in areas addressing material efficiency. In fact, as described by Domenech and Bahn-Walkowiak (2019), green technologies only attract a small share of R&D budgets. For instance, in Finland, which is the country that invests more resources on green innovation, green technologies attract only 12.5% of the total budget for R&D. On the other hand, it should be noted that the impact of R&D investment does not necessarily translate into local impacts. Technological innovations often generate impacts in locations that are distant from the place where such innovations were designed. For example, technologies to increase material efficiency of industrial processes are seldom developed in the same areas where industrial plants are based.

A number of relevant policy messages emerge from our findings. Our models confirm that agricultural and industrial areas show greater potential for improving material productivity thanks to the concentration of material-intensive activities in those areas. This calls for investments on technologies and innovations aiming at material efficiency, particularly in material-intensive sectors and regions. However, we have seen how investments on green technologies still attract a small share of R&D investments. At the same time, agricultural and industrial regions often experience underinvestment (Flachenecker and Rentschler, 2018), mostly due to their less dynamic markets (Bachtler et al., 2017). Hence, better access to finance in those areas would not only support resource productivity goals, but also mitigate the growing polarization between core and peripheral regions in Europe (Bassi and Durand, 2018; Lee and Luca, 2019). Another conclusion from our models is that the economies of scale in consumption clearly benefit MP. From this it can be inferred that spatial planning policies should promote urban densification, even in sparsely populated areas. In peripheral and shrinking regions, scale-appropriate systems will need to be re-formulated to support smaller population while land take should be minimised through compact urbanisation (Williams, 2019). Regions with urban and service-oriented economies, which are typically those with a greater concentration of population, should focus on the adoption of innovations geared at the organisation and optimisation of urban life. In particular, changing consumption habits of those living in cities will be critical to decouple economic growth from resource consumption (Zaman and Lehmann, 2011). In this sense, urban agglomerations present the right conditions for the development of business models that are based on product sharing, pooling and other forms of collaborative consumption that may contribute to curb demand for raw materials at the source (Cohen and Muñoz, 2016).

3.5. Conclusion

Research on the effects that economic structures exert on the relationship between material productivity and socioeconomic factors has been historically neglected by EW-MFA studies. This work argues that the idiosyncratic features of the individual regions, and therefore, the diverse economic configurations that the regions show, necessarily influence MP. Understanding the complex relationship between MP and its socioeconomic drivers under different structural economic configurations is essential for managing the current societal challenges and, hence, for providing policymakers with context-sensitive recommendations.

Our results provide evidence that the impact of socioeconomic drivers on material productivity changes according to the intrinsic socioeconomic structure of regions. In particular, affluence and population density impact the material productivity in considerably different ways based on the prevailing economic specialization of regional economies. Areas relying on primary and secondary sectors present higher returns in MP from increased levels of affluence, compared to intermediate and service-based economies. By contrary, intermediate and service-based economies tend to increase material productivity through physical densification. Overall, population density has a greater influence on MP levels than affluence. Not surprisingly, regions with higher population density have higher material productivity levels.

From a methodological perspective, this work provides two novelties in relation to traditional STIRPAT approaches: (1) the use of LQs instead of the share of gross values added as parameter capturing the structure of regional economies; (2) the consideration of these structures as endogenous factors shaping the relationship between MP and socioeconomic drivers. LQs provide superior information on the economy of a region, as they also recognise the level of specialisation, which to some extent is related to material efficiency. Similarly, examining the socioeconomic drivers of MP considering the underlying economic structures offers critical insights into the leading MP leverages of territories. In general, our method increases the explanatory power of socioeconomic drivers on MP, enabling more detailed and place-specific interpretations of regression coefficients.

Our approach also opens-up several research avenues for the future, as it encourages the exploration of alternative endogenous structures of socioeconomic drivers. In this analysis, we considered economic structures resulting from regional economic specialisation, but other configurations might be considered. As an example, Liddle and Lung employed a STIRPAT approach to investigate the consumption-related environmental impacts by population age-structure (Liddle and Lung, 2010). Similarly, considering the aforementioned MP limits, other resource productivity measures could be employed to further expand the understanding of regions' productivity levels. In this sense, Malmquist Productivity Index (MPI) could represent a promising approach since it not only allows to integrate several factors related to productivity, but also to decompose productivity into technical and efficiency components (Kumar, 2006; Mahlberg et al., 2011; Zhang et al., 2011). Likewise, access to improved regional data could open a number of additional channels of analysis, such as adding further explanatory variables better describing regional modes of consumption (e.g. import/export shares, transport statistics, type of energy consumption etc.).

Ideally, the analysis presented here should be complemented by adopting a consumption perspective. In particular, the use of alternative material indicators such as Material Footprint (MF) could shed light on the extent to which final consumption drives MP differently from production-based indicators like DMC. As showed in Wiedmann et al. (2015), assessments frequently differ depending on which modelling approach and indicators are used. In general, since MF indicators focus on final consumption, regional economic structures become less prominent drivers of MP. The production perspective adopted in this research seems more appropriate for identifying the role of territorial features on MP. Our main conclusion is that MP gains should be sought aiming at efficiency improvements rather than at structural economic transformations. Even if a shift towards increased service economies would automatically lead to increased DMC-based levels of MP, in most European regions this would be neither feasible nor desirable. First, most areas lack the critical mass required by such transformations, including access to human, technological and financial capitals. Similarly, the extent to which material-intensive activities such as mining and forestry can be localised in a given territory is also conditioned by its intrinsic characteristics, among which resource availability is the most obvious expression of those. Moreover, material-intensive activities, such as manufacturing, contribute to increase regional and national economic resilience. These activities make a very significant contribution to regional economies and, by localising and visualising the positive and negative externalities of massive resource use, they indirectly increase demand for new technologies and innovations that may further reinforce economic resilience and the overall economic dynamism of regions.

Overall Conclusions

The overall objective of this dissertation has been to expand the general understanding of material consumption patterns and its related socioeconomic drivers by introducing a territorial perspective. To achieve this aim, the *Specification-Optimisation-Extrapolation* (SOE) methodology was firstly developed as a systematic tool to quantifying subnational Domestic Material Consumption (DMC) in a comprehensive framework across the European Union. The development of a new harmonised regional inventory constituted a first research milestone, as the lack of cross-regional studies has so far prevented analysts from drawing broader policy conclusions that hold beyond national and regional borders. Cross-country analyses conceal wide territorial heterogeneity within countries, which may potentially obstruct the effect of resource mitigation policies. Results confirmed that the combination at the regional level of environmental indicators such as DMC and socioeconomic data represents a key element for delivering comprehensive insights into the complex mechanisms that shape sociometabolic models. We showed that several territorial features such as urban configurations and/or underlying economic structures play a pivotal role in determining resource consumption patterns. Hence, granular analyses, which better reflect the highly heterogenous territorial domains faced by policymakers, are essential to provide effective guidance, especially for resource management strategies very tied with regions' territorial capital such as the Circular Economy.

One of the main contributions of this Thesis is the quantification of DMC at the regional level. The provision of a harmonised and comprehensive dataset covering most of European regions is critical, not only because industrial policies and economic development strategies are increasingly recognising the role played by territories in guaranteeing successful transition to more inclusive and sustainable modes of development, but also because environmental accounting is comparatively less developed than social and economic perspectives within the policy and academic debate at the regional levels. In the European Union, the analysis of the key barriers hindering an efficient management of resource at the local level has been generally addressed by firm surveys (European Commission, 2018c). Such information has been critical in informing and driving resource efficiency roadmaps and related investments by both, firms and governments (European Commission, 2011). However, it only represents a limited perspective of the broader socioeconomic configurations driving material consumption patterns across regions. On the other hand, established EU monitoring frameworks mostly provide data at the very aggregate national level. But are these aggregated data really a guide for local policy makers? According to our results the answer is most probably no. Or, at least, they provide very limited guidance.

Going further, the European Green Deal calls explicitly for "*systemic solutions for the territorial deployment of the circular economy*", which should "*increase resilience and provide concrete solutions for the socioeconomic recovery and sustainable and inclusive growth of a specific territory*". Such territorial dimension will be unlikely constituted by a whole country. The distribution of general socioeconomic factors, such as population density, income, R&D expenditure, technological and educational levels, elderly population and employment, is very uneven across subnational territorial contexts. Agricultural economies are regularly those regions undergoing the lowest levels of human capital . Conversely, they exhibit the largest share of elderly population. An opposite situation is constituted by service-based regions, as these present extremely high levels of population density, high level of employment and the lowest share of elderly population. On the other hand, industrial regions benefit from very high levels of investments in R&D and, therefore, technological levels (measured by patent emissions).

Ultimately, this heterogenous distribution of territorial factors translates into very different challenges at the local levels. Challenges that politicians are often ill-equipped to deal with, given the general scope of current national policies. To design effective subnational and place-based policies, a deeper understanding of the territorial dimension of material consumption is needed. Hence, the provision and analysis of more refined data becomes critical to inform policy makers on the leveraging mechanisms, regional and local assets supporting resource efficiency goals.

The provision of an environmental regional dataset also contributes to fill a gap within the empirical body of regional studies, where environmental metrics are still far behind their socioeconomic counterpart. The lack of comprehensive regional environmental databases risks biasing the academic and policy debate towards the socioeconomic sphere, neglecting the environmental perspective. This is a crucial gap if we really aim to reconcile our economies and human activities with the planetary boundaries and to respond to citizen concerns and needs in the wake of systemic crisis such as climate change, biodiversity loss and adverse socioeconomic and environment impacts. Our regional DMC database represents a modest step in this direction.

Concerning the methodological development, the SOE method represents a pragmatic but efficient approach to generate information at the subnational level and it addresses several methodological limitations concerning previous studies. First of all, as shown with the DMC example, it is able to generate harmonised and comprehensive datasets that can potentially pave the way for further comparative research. The very wide range of methodological approaches employed in similar analyses usually prevented a consistent comparison among different regions. The empirical study conducted on DMC represents a prime example of the potential applications of the SOE method and its consequent functionality in providing granular information tailored to local contexts. This directly links to the second key advantage of the proposed approach, that is the capacity to account for territorial heterogeneity. The use of (1) explanatory factors measured at the regional level and (2) the optimisation algorithm reflecting the national regimes, positions the SOE method well beyond simpler extrapolation methods based on bold hypothesis such as “consumption is almost proportional to population”. Ultimately, these simplistic approaches fail in capturing territorial specificities, as disregard the specific relationships between regional factors and the response variable. By eliciting the multiple correlations existing between materials consumption and its key explanatory factors and calibrating these to the varying national regimes, the SOE method is able to reflect (at least partially) the various territorial settings, and therefore provide place-sensitive information.

The systematisation of the SOE method makes it suitable for application to other geographical scales (e.g. from regions to cities), thematic domains and indicators. In this sense, a simplified version of the SOE method has been applied within the CIRCTER project (ESPON, 2019a) to provide a comprehensive set of Circular Economy indicators at the regional level. The method was applied to downscale nine indicators for two time-periods (2006 and 2014). Five indicators focusing on material flows, namely: Domestic Material Consumption (DMC), Domestic Extraction, Biomass Consumption, Metal-ores Consumption and Non-metallic Mineral Consumption. Four indicators informing on waste generation: Total Waste Generation excluding major mineral waste, Waste generation by household, Food Waste, and Electric and Electronic Equipment Waste (WEEE). Despite the application showed decreased performance for very specific indicators (e.g. metal-ores consumption), it proved to be a reliable solution to deal with data scarcity at subnational levels, contributing to the identification of regional patterns of resource use that would have been otherwise remained unknown (ESPON, 2019c).

Lastly, but perhaps most important, this Thesis expanded the theoretical framework of Ecological Economics and Industrial Ecology by introducing the territorial perspective into the academic debate. We demonstrate that neglecting the territorial dimension prevents a proper understanding of the sociometabolic systems of regions, as material efficiency originates – to a varying degree

– in the local and regional realities. In Chapter 2 we showed that efficiency performance within-country can be very different from what national statistics say. While agglomerated areas are lowering their relative resource consumption thanks to ever-increasing economies of scale, peripherical areas show little, if nothing, progress. This trend not only reflects the growing socioeconomic polarity observed between urban and rural regions, but it could also result into a zero-sum game. Indeed, as long as the gains in resource productivity are achieved primarily by increasing levels of wealth and population (i.e. the engines of urban agglomeration), rather than a significant reduction in the overall amount of resource consumed, we will only see an *apparent* shift in environmental burdens from urban to rural areas. We underline "*apparent"* shift because agriculture and traditional manufacturing activities (e.g. footwear, leather, apparel, textiles, pulp and wood by-products etc.) are mainly located in intermediate and rural areas, but the throughput produced is mainly directed to satisfy the demand of goods of central urban areas. Anyhow, going beyond the exact allocation of environmental- burden/responsibility, this dichotomy suggests that effective resource mitigation strategies should be place-based. Just as it is more efficient for a city to derive most of its agricultural and manufacturing products from the hinterland, a region can have a much greater impact in reducing material consumption by influencing consumption behaviours rather than improving production processes. This evidence is further strengthened in Chapter 3, where we show that the elasticities of socioeconomic drivers actually differ according to the regional economic structures.

Regions relying on material-intensive production processes exhibited affluence's elasticity significantly higher than economies based on service structures. This means that industrial policies aimed at improving the efficiency of resource management should ensure access to financial resources for these peripheral regions, which often have difficulty in obtaining funding. Financial constraints are not the only barriers preventing peripheral areas from boosting their resource productivity. Chapter 2 showed that these areas are also characterised by a rather stationary market, which not only is less resilient to economic shocks, but it also struggles to retain human capital. As a result, many peripheral regions run the risk to fall in a downward spiral where these interlinked constraints reinforce each other, draining local resources.

Moreover, as demonstrated by the experience of the eastern regions, channelling financial resources to lagging regions is not in itself sufficient to ensure the transition to more sustainable production models. In fact, following the entry into the European Union, eastern regions have increasingly improved their technological assets, but have missed significant gains in resource productivity. This means that in order to guarantee the replication of successful solutions for sustainable growth, financial transfers should also be complemented by technical roadmaps that facilitate the transfer of knowledge between the economies lying on the technological frontier and those less material efficient. Not surprisingly, the European Green Deal emphasizes the need to *demonstrate* and *replicate* territorial strategies across many areas within and outside Europe if the goals set in the various policy areas are to be achieved.

It goes without saying that winning solution not necessarily can be replicated equally anywhere. The two territorial taxonomies proposed in Chapter 2 and 3 well exemplify how regions should be considered as a sort of well-defined *ecosystems*, rather than homogenous entities. In Chapter 2, we showed that urban-rural configurations translate into very different operating environments, which make doubtful the direct comparison between regions belonging to different categories. Similarly, in Chapter 3, we showed that economic structures cannot be simply considered as exogenous factors impacting resource productivity, as they are likely to influence other socioeconomic determinants as well. It should be emphasized that such differences in territorial capital do not necessarily translate into better-off and worse-off regions. Instead, they should be interpreted as different opportunities and challenges that politicians need to understand first in order to later reap their potentials. It is along these lines that the Smart Specialisation Strategies and the Territorial Agenda advocate for a place-based approach where the identification of strategic areas for intervention should build on the assets and resources available to the regions and on their specific socioeconomic challenges in order to identify unique opportunities for development and growth.

Empirical results in Chapter 2 provide direct evidence that gains in resource productivity can also be achieved by material-intensive economies if regions focus on their competitive strengths and growth potentials. The cases of the Southern and Eastern Irish regions and the southern Spanish regions Andalucía and Murcia, which increased their levels of resource productivity despite shifting their economies toward material-intensive structures, constitute a successful example. This evidence is further supported by the coefficient obtained for the location quotients. Increasing levels of economic specialisations translate, to varying degree, in higher material productivity, which is different from saying that agriculture structures have a negative impact on resource productivity. Obviously, dematerialised economies are better positioned to boost material productivity, but repeatedly presenting primary sectors as hindrances to material productivity could send the wrong message to policymakers of expanding an economy's service base as the only way forward when it comes to increasing material productivity. This is not true, nor feasible.

Perhaps, part of the solution lies in using more inclusive indicators. In fact, material efficiency narrative should consider implications that go well beyond the simplistic objective of using the least possible amount of materials to produce an economic output. An efficient use of materials should guarantee an optimum combination of production inputs (labour, capital, material), while producing the maximum yield in terms of social welfare. In this context, the indicators used to measure social welfare assume a critical importance. So far, gross domestic product (GDP) is the most widely used economic indicator. However, it is well known that GDP is not an ideal measurement of social prosperity for several reasons (Costanza et al., 2014). First of all, GDP does not distinguish between economic activities, i.e. it “sums-up” also those activities actually carried out to remedy adverse environmental and social effects. Second, it does not account for the cost of natural costs of natural capital depletion. Third, it does not reflect social equality aspects of economic development. Despite many efforts have been made to developing more inclusive metrics (Kubiszewski et al., 2013; UNDP, 2016), constructing material efficiency indicators based on GDP remains the custom for setting policy goals of resource conservation and environmental protection. Therefore, an interesting avenue of research would be the analysis of socioeconomic metabolic systems considering the use of more inclusive indicators. This would help, for instance, to better distinguish between those areas that have managed to decouple their economy from material consumption thanks to a *pure* progress of the society and those that have reduced material consumption mainly due to an economic recession.

Similarly, we are aware that DMC is far from being a perfect indicator of material consumption, and, as showed in our work, it has to be considered in combination with other environmental and socioeconomic figures for cautious and accurate interpretation. Ideally, this analysis should be replicated by using a raw material consumption-based indicator of resource use such as the material footprint (MF). As showed in Wiedmann et al. (2015), results often diverge depending on the material indicator selection. The use of MF might reveal that agricultural and industrial regions are not that far from agglomerated service-based regions in term of material efficiency. In fact, the higher GDP per capita of advanced economies would be, to some extent, compensated by the higher levels of consumption of these regions and, therefore, the amount of hidden material flows related to upstream activities. This analysis would be very interesting for e.g. assessing interregional environmental responsibilities linked to behavioural consumption.

Some remarks should also be mentioned concerning the SOE methodology and, thereby, the regional DMC dataset. This tool was developed under the premise of staying within the confines of existing data sets, harvesting information from these instead of developing entirely new data flows. However, we should point out that further improvement of resource efficiency monitoring may be gained by also using alternative data streams to those included in currently existing official statistics. There is a wide recognition that alternative data sources such as open source APIs, big data providers, earth observation data, free-of-charge and commercial data sources, etc. might offer additional insights on the uptake of e.g. Circular Economy policies and their effect in the material cycle and energy flow in Europe's economy. Likewise, our downscaling methodology can be further improved in several ways. First, the optimisation algorithm might be enhanced by integrating the *reconciliation* step as an additional constraint of the overall model. This would permit to better calibrate parameter elasticities to regional contexts. Second, future analyses might focus on the selection of progress variables such as population and/or income growth for a selected period as opposed to static time-cuts. This dynamic approach would allow to e.g. gauge the impact of specific drivers on material efficiency and better understand the impact of policies on material consumption.

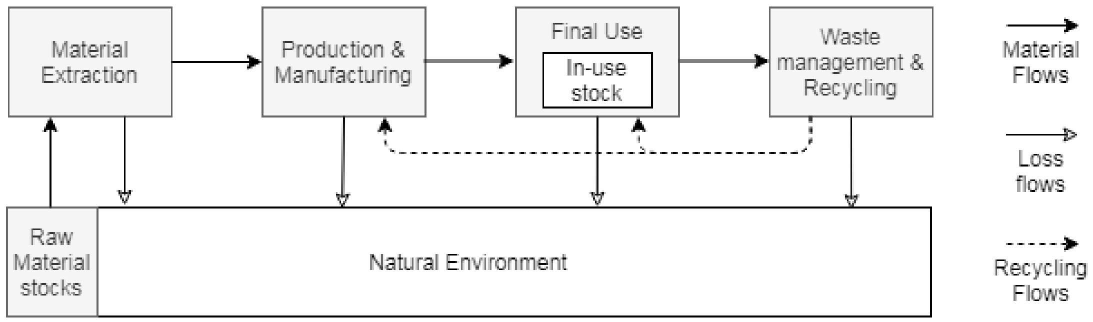
Summarising, this work represents a first attempt to connect the field of socioeconomic metabolism with that of regional studies. The territorial dimension of sustainable strategies is increasingly gaining importance within the policy discourse. Nonetheless, the physical – environmental – perspective of regional economies has so far been lacking in the current academic debate, mostly focused on socioeconomic aspects. However, sustainable development is not only about inclusive economic growth, but it also concerns the natural capital that we constantly withdrawn from the environment and its consequent effects. If these aspects are only monitored and analysed at national level, they will remain of limited guidance for local policy makers. Therefore, regional studies should promote the inclusion of a range of ecological indicators to better understand the dialectics between the socioeconomic and environmental systems. Conversely, Ecological Economics and Industrial Ecology studies should expand the analysis of sociometabolic systems by focusing on subnational levels in order to better reflect the multifaceted realms existing at lower geographical levels.

Appendix

Economic-Wide Material Flow Accounting

Material flow analysis (MFA) is a systematic assessment of the flows and stocks of material within a system defined in space and time (Brunner and Rechberger, 2010). Figure 23 presents a simplified overview of the anthropogenic materials cycle. Raw materials are extracted from the environment, and then processed into intermediate and final products through production and manufacturing activities. Final products or services enter the use stage to fulfil human needs. While durable goods (e.g. houses) and infrastructures accumulate in the anthroposphere, short-lived good will be collected and disposed-off according to waste management practices, and eventually recycled or reused as secondary materials. Each transformation from one stage to another will produce different "loss streams", i.e. material flows that return to the natural reservoir in the form of environmental charges, such as pollutants, solid waste and wastewater.

Figure 23: The anthropogenic material cycle.



Own elaboration based on Zhang et al. (2018)

Depending on the context and purpose, MFA can be implemented according to different approaches. The OECD distinguishes between six different tools of MFA (OECD, 2008). *Substance flow analysis*, *material system analysis and life cycle assessment* are associated with the measurement of certain substances, materials and manufactured goods, and in general are concerned with their environmental impact, supply security, and technology development. In contrast, *business level MFA*, *input-output analysis* and *economy-wide material flow analysis* (EW-MFA) consider the environmental and economic concerns of material flows at the level of specific business, economic activity sectors, countries or regions. EW-MFA approach is focused upon in this dissertation and will therefore be described in more detail. A comprehensive literature review on MFA tools can be found in Huang et al (2012).

EW-MFA is a standardized methodology to quantify material throughput from a direct consumption perspective (EUROSTAT, 2018). Its headline indicator, Domestic Material Consumption (DMC), is calculated as the mass of all domestically extracted raw materials and harvested biomass plus the mass of imports minus the mass of exports. The cut-off criteria adopted to define system boundaries for EW-MFA have been defined in order to reflect national administrative borders (i.e. countries) and in this sense are unambiguous. However, it should be recognised that the direct consumption perspective adopted by EW-MFA translates in an inconsistent accounting boundary for what concern the raw materials and finished products measurement. In other words, DMC adds up the weight of raw material extracted domestically with the weight of traded goods along the administrative boundaries. Clearly, traded goods are at different stages of processing compared to raw material extraction, and those resources used in the upstream life cycle stages to produce the imported goods are not explicitly captured in DMC indicators. As an example, Dittrich and Bringezu (2010) estimated that the mass of hidden upstream flows related with traded goods amounted to 41 billion tonnes in 2005, roughly 4 times as much as the weight of traded goods.

The accounting limitation of standardized EW-MFA drove academic efforts towards the definition of a more holistic measure of material consumption called material footprint (MF) (Wiedmann et al., 2015). MF indicators quantify both, direct and indirect flows of material consumption by combining the weight of traded goods with input-output tables containing detailed information of respective supply chains. Even if footprint indicators better connect environmental pressures to final consumption activities and, therefore, support a correct re-interpretation of material efficiency, they are not exempt from uncertainties. In fact, the lack of a standardised approach to estimate indirect flows coupled with the higher methodological complexity often result in a wide spectrum of estimates even for a single product, groups of products or economy. For instance, a comparative study conducted by Eisenmenger et al. (2016) found that Austria's MF ranged from 21 t/cap to 30 t/cap according to six different datasets employed. Analogously, MF indicators also inherit shortcomings related to input-output accounting, such as the aggregation bias and price fluctuation. The first refers to the uncertainty caused by the aggregation of sectors with very different material intensity (Piñero et al., 2015); the second relates to the variations in physical flows due to price fluctuation rather than real physical changes[27] (Weisz and Duchin, 2006).

[27] Physical flows in input-output table are represented or derived from monetary flows.

All in all, notwithstanding the incomplete interpretation of the real material dependence, EW-MFA indicators are by far the most consolidated and worldwide used metrics informing on material use by a given economy. In Europe, EW-MFA indicators are an integral part of environmental reporting systems (EUROSTAT, 2018) and, more recently, also included within the Circular Economy monitoring framework. By describing the material throughput of an economy, EW-MFA permits to delineate socio-metabolic profiles of territories, providing important information and statistical indicators on material use. That is why EW-MFA indicators are generally used as reference by EU's policies to monitor progress on, among others, circular economy, green growth, and resource productivity (EUROSTAT, 2018).

EW-MFA records the material flows at two points: (i) flows from the environment to the (national) economy, denominated domestic extraction, and (ii) the flows from the (national) economy to the environment called domestic processed output. Domestic extraction refers to the material input derived from the environment and used within the economy[28] (e.g. mineral extraction, fossil fuel extraction etc). Domestic processed output refers to the residual materials resulting from a production or consumption process released back to the environment (e.g. emissions to air and water). EW-MFA presents some recording conventions that must be kept in mind when interpreting the indicators, these are:

- Bulk material flows of water and air are excluded;
- In the case of minerals, in order to infer from product to domestic extraction in a standardised way, the so-called "run-of-mine" concept (ROM) is applied. The ROM is the amount of extracted material containing the wanted metal or mineral that is submitted to the first processing step. It excludes any overburden (hidden flow) which does not contain the wanted mineral or metal;

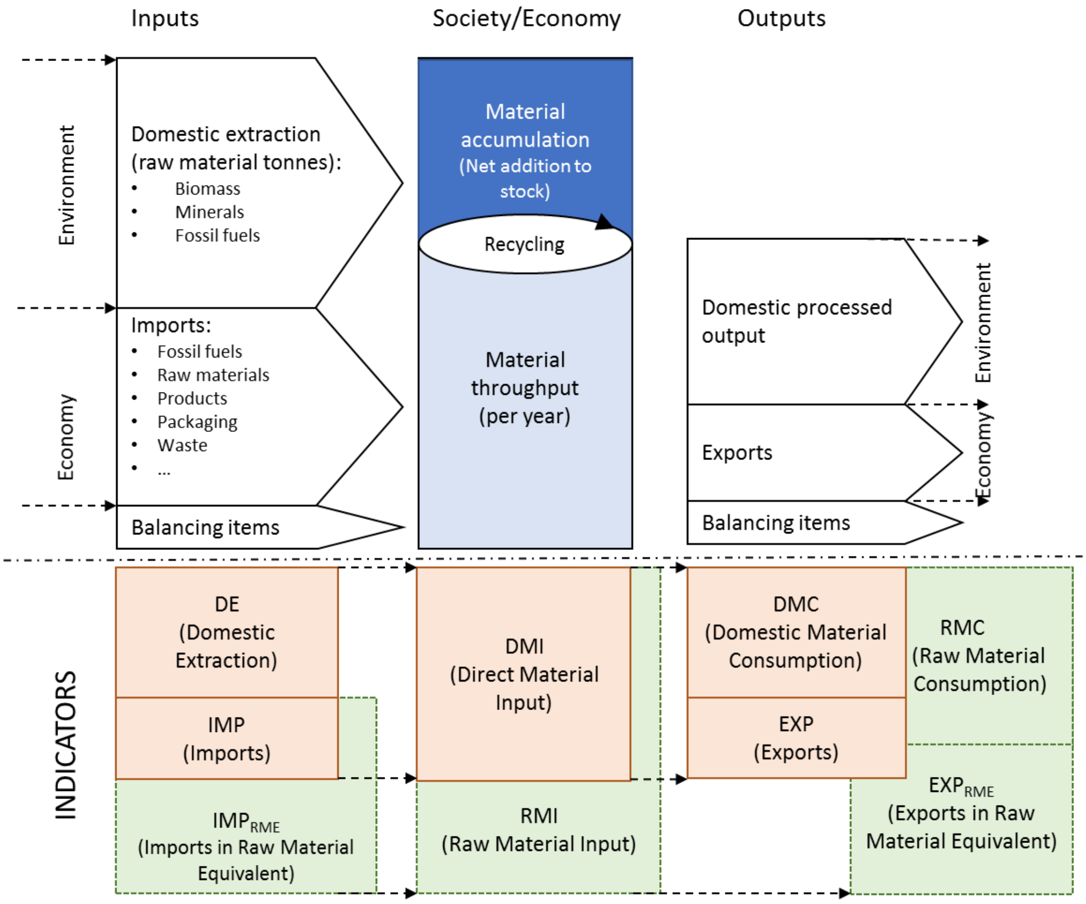
[28] A distinction can be made between "used" and "unused" material: used refers to an input for use in any economy, i.e. whether a material acquires the status of product; unused flows are material that are extracted from the environment without the intention of using them (also termed as "hidden flow" in some early publication). EW-MFA record only extractions of material used, therefore the term "domestic extraction" always refer to "used" extraction (EUROSTAT, 2018, para. 66ff)

- In the case of biomass, the “harvest approach” is applied. It implies that cultivated forests and agricultural plants are treated as if they were part of the environment, therefore domestic extraction occur at the point of harvest and it is equal to the amount of material harvested.
- Controlled landfills are produced assets and hence part of the economy. Material flows to controlled landfills are material flows within the economy and hence excluded from domestic processed outputs.

Alongside the material flows between environment and economy, EW-MFA record the material flows between the reporting economy and the rest of the world economy. Trade between economies is accounted according to the residence principle and to the change-in-ownership principle. EW-MFA record a physical trade flow when the ownership of a good changes from a resident unit to a non-resident unit (physical export) and vice versa (physical import). Hereby a resident unit is defined as an institutional unit that has its centre of economic interest on the economic territory of that country. Therefore, any economic activity is attributed based on the residence of economic units rather than on the location of the economic units at the time of their production, consumption or accumulation. In other words, some activities by resident units (e.g. international air and sea transport) may actually happen beyond the economic territory of the national economy concerned, and vice versa. Figure 24 gives a simplified overview of the EW-MFA framework and respective indicators.

While domestic extraction measures the weight (tonnes) of amounts of virgin materials as extracted from the environment, the physical trade indicators (IMP and EXP) measure the weight of products as crossing borders. This asymmetry is often considered as a shortcoming, especially when we consider derived indicators such as DMI and DMC. Indeed, the weight of a traded product does not reflect the extraction of materials that was necessary to produce the traded product. Also, almost all products go through different stages of manufacturing through which they become relatively lighter in terms of actual weight compared to the material extractions needed to produce that product. Due to this measurement asymmetry, a country that reduces domestic extraction and favours the imports of products in order to meet the same demand, would significantly reduce its DMI and/or DMC, even though the worldwide demand for material resource associated with its production and consumption does not change.

Figure 24: EW-MFA accounts and respective indicators



Own elaboration based on Eurostat (2018)

The conceptually different measurement of domestic extraction and physical trade also hampers comparability of DMI and DMC across countries. Some countries are endowed with natural resources which tend to result in comparably higher domestic material consumption. Good examples in Europe are Estonia, which exploits large oil shale fields for electricity generation, or several regions in Finland and Sweden that, thanks to the vast reserve of woodland, are the main EU producers of roundwood. Other countries do not have exploitable material deposits and need to import raw products or (semi-) manufactured and finished products, which are relatively lighter (e.g. Luxembourg, Malta, Cyprus etc.). Resource-rich countries tend to have a higher DMI and/or DMC compared to resource-poor countries, which have to rely on imports to meet the demand for material resources (EUROSTAT, 2018).

In order to overcome the different measurement of DMI and DMC components, traded products can be converted into equivalents of domestic extraction – called *raw material equivalents* (see Figure 24, green boxes). Raw materials equivalent (RME) capture the amount of extracted material needed to produce a certain product. Extraction of raw material throughout the product's entire production chain is taken into account, irrespective of whether the material extraction took place domestically or in the rest of the world. As such MFA-RME provide a consumption-based view of material requirement. However, to date, MFA-RME are not covered in Regulation (EU) 691/2011 and are collected only on a voluntary basis. As a result, EUROSTAT disseminates EW-MFA results measured in RME only for the aggregated EU economy.

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List of publications

This thesis is based on the three papers listed below as “Primary publications”, where Marco Bianchi was a main contributor in during his work as a PhD candidate. In addition, he has contributed as a co-author to several articles and project deliverables, listed below as “Additional publications”.

Primary publications

- Bianchi M, Tapia C, del Valle I. Monitoring domestic material consumption at lower territorial levels: A novel data downscaling method. J Ind Ecol. 2020;1–14. https://doi.org/10.1111/jiec.13000
- Bianchi, M., del Valle, I., Tapia, C., 2020b. Measuring Eco-efficiency in European regions: evidence from a territorial perspective. J. Clean. Prod. 123246. https://doi.org/10.1016/j.jclepro.2020.123246
- Bianchi M, del Valle I, Tapia C. Material productivity, socioeconomic drivers and economic structures: A panel study for European regions. In review at Ecological Economics journal.

Additional publications

- Bianchi M, Tapia C. Producing regional data for circular economy monitoring in Europe, ESPON Scientific Report - Building the next generation of research on territorial development, section: New data sources. ISBN: 978-99959-55-90-8.
- Bassi, A.M., Bianchi, M., Guzzetti, M., Pallaske, G., Tapia, C. Improving the understanding of Circular Economy potential at territorial level using Systems Thinking. Sustain. Prod. Consum. https://doi.org/10.1016/j.spc.2020.10.028

- Tapia, C., Bianchi, M., Bassi, A.M., Guzzetti, M., Pallaske, G., Exploring the role of territorial factors in a circular economy. Under review in *European Planning Studies*

Project deliverables

- CIRCTER – Circular Economy and Territorial Consequences – Final Report, 2019. Tapia C, Bianchi M, Zaldua M, Courtois M, Micheaux Naudet P, Bassi A, et al. https://www.espon.eu/circular-economy
- CIRCTER – Circular Economy and Territorial Consequences – Annex 1: A territorial definition of the circular economy, 2019. Tapia C, Bianchi M. https://www.espon.eu/circular-economy
- CIRCTER – Circular Economy and Territorial Consequences – Annex 2: Data on material and waste patterns and flows, 2019. Bianchi M, Tapia C. https://www.espon.eu/circular-economy