Hertie School

Does Recycling Reduce Plastic Production? A European Panel Data Analysis of Circular Economy Rebound Effects

Master Thesis
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1. Executive summary

Despite significant policy efforts to scale up plastic recycling in Europe, plastic production continues to rise, raising concerns about the effectiveness of recycling initiatives in curbing the environmental impacts of plastic use. This thesis investigates to what extent plastic recycling in Europe may fall short of the anticipated reduction in primary plastic production.

Drawing on the theoretical framework from Zink & Geyer (2017), it is examined whether recycling triggers a circular economy rebound (CER) effect in plastic production and waste generation, thereby offsetting the expected environmental benefits. Notably, this is the first empirical study to examine the incidence of a CER effect in the plastic circular economy. To this end, I utilize European panel data covering the recent decade, and employ a research design that combines descriptive and correlational methods as well as two-way fixed effects regression for causal inference.

The findings reveal suggestive evidence for a CER effect triggered by plastic recycling. Descriptive and correlation analyses initially indicate an inverse relationship between recycling and production. However, the two-way fixed effects models yield more robust positive and largely statistically significant effects, indicating that increased recycling rates and quantities lead to higher total plastic production and waste generation.

These findings carry important implications for both the literature and policy-making. They highlight shortcomings in conventional circular economy models, which commonly assume perfect substitution of primary materials by recycled counterparts and thus overlook important market dynamics of the circular economy. Consequently, policymakers are urged to reassess existing circular economy strategies and environmental benefit claims in view of CER risks and to incorporate mitigation strategies into policy design and evaluation frameworks. Further recommendations emerging from this research emphasize the need for improved metrics and data.

2. Introduction

Plastic is ubiquitous and has become one of the most pervasive materials in the modern world found in almost everything from packaging and textiles to electronics and construction. However, the environmental and health problems associated with plastic are increasingly alarming. Plastic waste pollutes the environment, is one of the main drivers of biodiversity loss, and its production contributes significantly to global GHG emissions - an estimated 3.7% in 2019 (OECD, 2023). To address these problems, the European Union has made significant progress on its transition to a circular economy for plastics. According to Plastics Europe, the use of recycled plastics has already increased by 70% since 2018 (Plastics Europe, 2024). Yet, at the same time, the consumption of plastic continues to grow with the increase in plastic production. Over the past 70 years annual plastic production has increased nearly 230-fold and consumption is projected to double by 2050 (Ritchie et al., 2023; Stegmann et al., 2022). The simultaneous rise in both recycling and production casts doubts on the environmental effectiveness of plastic circular economy interventions - primarily recycling. This research investigates whether this seemingly contradictory development in the plastic circular economy may be indicative of a so-called *circular economy rebound* (CER). This phenomenon occurs when circular economy activities lead to additional resource use via behavioural and systemic responses (Zink & Geyer, 2017). While empirical evidence for CER remains limited, especially in the context of plastics, it raises important concerns regarding the assumptions and expected decoupling benefits of the circular economy.

Traditionally, plastic flows in a linear stream: extracted, produced, used, and then discarded. However this model is associated with severe environmental consequences. The simple and logical answer to the problem of the linear flow model is its reverse: a circular flow of materials. The circular economy has emerged as a promising alternative which aims to transform production and consumption systems towards more sustainability (Figge et al., 2023; Geissdoerfer et al., 2017; Kara et al., 2022). It is promoted as a regenerative growth model that can decouple economic growth from environmental impacts (Ellen MacArthur Foundation, 2019; European Commission, 2020). The circular economy's environmental merit lies in its potential to i) reduce waste and emission outputs and ii) reduce primary material inputs (Korhonen et al., 2018; Zink et al., 2018). Instead of the unsustainable extract-produce-use-dump pattern, a circular approach aims to optimize resource use by slowing, closing and narrowing material loops through activities like reusing, refurbishing, and recycling (Kara et al., 2022; Korhonen et al., 2018; Makov & Font Vivanco, 2018).

Policymakers have recognized the circular economy's potential and have increasingly embraced the concept (Ferrante & Germani, 2020; Geissdoerfer et al., 2017; Saunders, 2014). The EU is a prominent driver of circular economy initiatives such as the Circular Economy Action Plan (2020), in which it identified plastic as one of the priority areas (European Commission: Directorate General for Communication, 2020). A separate point of appeal of the circular economy is that it fits within the present growth paradigm (Ferrante & Germani, 2020; Geissdoerfer et al., 2017; Korhonen et al., 2018). A study commissioned by the Ellen MacArthur foundation found that the circular economy would enable Europe to increase GDP by up to 7 percentage points by 2030 (McKinsey Center for Business and Environment, 2015). While proponents of the circular economy champion this as a merit, it can also be criticized from a sustainability perspective, as it is questionable whether the circular economy can realistically deliver on its promise to decouple growth from environmental impacts.

Criticism around the concept also comes from the scientific community, which challenges the desirability of the circular economy in a reality with growing demand (Allwood, 2014; Corvellec et al., 2022). Scholars have pointed out that the circular economy in and of itself is not intrinsically sustainable but that the net environmental benefit of circular economy activities hinges on whether secondary plastic production actually reduces primary plastic production (Kara et al., 2022; Zink & Geyer, 2017). If not, we are left with the impact of increased secondary production in addition to the impact of primary production. Typical engineering models of the circular economy are premised on a 1:1 displacement of primary with secondary materials (Cooper & Gutowski, 2017; Makov & Font Vivanco, 2018; Thomas, 2003; Zink et al., 2018). But displacement is governed by market dynamics and is not guaranteed (ibid.). Hence closing material loops does not automatically lead to environmental improvements - as is commonly assumed.

Zink & Geyer (2017) have picked up on this point and made a case for why the circular economy is likely to experience a *CER,* a concept grounded in the rebound effect phenomenon studied in energy economics. Resource efficiency gains through circular activities like recycling can lead to increased production via market mechanisms, thereby offsetting the expected resource savings (ibid.). Research on CER is still nascent and empirical evidence for this phenomenon is limited, particularly in the context of materials (Lowe et al., 2024; Vivanco et al., 2018). To date, it remains unclear whether a CER occurs in the context of plastic recycling.

This research aims to address this gap by investigating whether plastic recycling in European countries is associated with a CER effect. A better understanding of CER is essential to accurately assess the environmental benefits of a circular economy and inform evidence-based policy making (Metic & Pigosso, 2022). In view of the expansion of circular economy related legislation, particularly in the EU, the issue of CER becomes increasingly relevant. Given that plastic is a central focus of circular economy legislation, this resource warrants particular attention.

The remainder of this research is structured as follows. Section 3 gives an overview of the state of the art in research on the rebound effect, the circular economy and the growing literature on CER. Section 4 develops the theoretical framework applied in this research. Section 5 outlines the research design, including data and methodology. In Section 6 the results from the descriptive, correlational and econometric analyses are presented and interpreted. Section 7 discusses the findings and situates them in the existing research on CER and provides an outlook for future research on this issue. Furthermore, practical implications and policy recommendations are presented. Lastly, Section 8 concludes with the key findings and implications of this study.

3. Literature review - from energy efficiency rebound to circular economy rebound

This section situates the present research in the current state of CER literature. The literature review outlines how the rebound effect phenomenon evolved from the energy economics discipline, to a broader resource focus in ecological economics, and more recently is applied in a circular economy context. Empirical evidence for CER is patchy, leaving an important gap in examining plastic recycling from a CER perspective.

The rebound phenomenon was first introduced by Jevons in 1865 under the term Jevons Paradox in the context of coal (Jevons, 1865). In the 1970s Khazzoom and Brookes revived the debate arguing that enhanced energy efficiency could increase consumption through price mechanisms (Saunders, 1992). Since then the number of journal articles published on the phenomenon has increased immensely (Lange et al., 2021; Metic & Pigosso, 2022). Nowadays the rebound effect is a well established concept and numerous empirical studies have demonstrated that improvements in efficiency almost always lead to a reduction in the expected energy savings due to changes in consumption patterns (Gillingham et al., 2016; Sorrell et al., 2009; Sorrell & Dimitropoulos, 2007).

To date energy economics is the dominating field studying the rebound phenomenon. Despite the intensive study of rebound effects in the context of energy, key resources like water, land use and particularly materials were overlooked (Lange et al., 2021; Vivanco et al., 2018). Ecological Economics broadened the focus to a wider range of resources and environmental issues (Metic & Pigosso, 2022; Vivanco et al., 2022). Subsequently, several studies demonstrated that environmental rebound effects can also be triggered by resource efficiency improvements (Meyer et al., 2007; Pfaff & Sartorius, 2015; Schettkat, 2011; Skelton et al., 2020). Despite their relevance to circular economy strategies, most of these works did not explicitly frame rebound within a circular economy context.

As scholarly interest in the circular economy grew, more research began questioning to what extent circular economy activities may trigger rebound effects as well (Metic & Pigosso, 2022; Zink & Geyer, 2017). Zink & Geyer (2017) developed a theoretical framework for the *circular economy rebound*, thereby establishing a common conceptual ground for further inquiry into this phenomenon. CER refers to a situation in which circular activities fail to offset growing consumption, ultimately leading to increased production and reducing the expected decoupling benefits (Zink & Geyer, 2017). Importantly, CER theory diverges in parts from the traditional concept, as it applies to circular instead of linear resource flows (Castro et al., 2022; Figge & Thorpe, 2019). While CER shares similar market mechanisms to energy and resource efficiency rebound, it may involve distinct mechanisms such as symbiotic rebound (ibid.). Furthermore, CER can arise not only in the consumption-side but also in production or waste generation (ibid.).

As an emerging research field, empirical research on CER is scarce and highly fragmented (Lowe et al., 2024; Metic & Pigosso, 2022; Vivanco et al., 2018). Preliminary evidence suggests that CER can arise from circular consumption patterns (Ottelin et al., 2020), circular business models (Siderius & Poldner, 2021), virtualization (Ahmadova et al., 2022), sharing schemes (Warmington-Lundström & Laurenti, 2020) and reuse in general (Cooper & Gutowski, 2017; Thomas, 2003). However most evidence remains indicative, partly owing to methodological challenges in estimating rebound effects (Lowe et al., 2024). One of the first efforts to quantify the magnitude of a CER effect comes from Makov & Font Vivanco (2018) who found that about one third of GHG emissions savings from smartphone reuse could be offset by rebound via re-spending and imperfect substitution mechanisms. The authors point out that such mechanisms can also be expected in recycling (ibid.). These early findings lay important groundwork supporting Zink & Geyer’s (2017) theory while also underscoring the need for a more comprehensive investigation of this phenomenon.

A subset of this research explored potential CER effects from recycling specifically - a widespread circular activity, However, empirical applications of the CER framework to recycling remain scarce. Zink, Geyer & Startz (2018) investigated whether increased recycling leads to the displacement of primary aluminium production, by quantifying displacement rates (the proportion of material production prevented by recycling). Their results suggest that 100% displacement is unlikely but zero or negative displacement rates are possible, thus suggesting a rebound effect. A possible explanation for this observation is offered by Dace et al. (2014) who studied packaging material efficiency. The authors found an increase in material usage per product unit when recycled material is used, due to its inferior quality (ibid.). As a result, the total consumption and waste generation of packaging materials would increase along with an increased fraction of recycled materials per product unit (ibid.). Similarly, Van Fan et al. (2021) found that while the EU’s (re)use of recycled material increased, waste generation increased as well. Collectively, these works provide suggestive evidence for rebound effects from material recycling.

While the CER literature is still in its early stages, a growing number of empirical studies suggest that circular economy activities can have unintended secondary effects in the form of higher material production and waste generation. However significant gaps remain due to the fragmented nature of current CER research. Although recycling is a central component of circular economy strategies, empirical investigations of CER in the context of recycling remain scarce. Moreover, several key resources, most notably plastic, have yet to be examined through the lens of CER. Hence, a systematic investigation of the rebound effect from plastic recycling could thus provide critical insights to the study of CER and advance this emerging research field. This suggests the following research question: *To what extent does plastic recycling lead to a circular economy rebound effect in European countries?*

4. Theoretical framework - integrating rebound effects and the circular economy

In this section the relevant concepts in this research are defined. Moreover, I will explain how recycling can trigger a CER effect, how an effect can be identified empirically, and what mechanisms are involved in CER, according to the theory of Zink & Geyer (2017). Lastly, the hypotheses are derived.

4.1. The rebound effect

Despite the vast amount of literature on the rebound effect in general, terminology around the concept is diverse and ambiguous (Lange et al., 2021; Metic & Pigosso, 2022). The *Rebound effect* is often seen as an umbrella term for a range of mechanisms which influence the size of energy savings achieved (ibid.). In line with Lange et. al. (2021), the term *CER* is used in this thesis to refer to the entire circular economy rebound phenomenon. This comprises both rebound effects and rebound mechanisms, which are oftentimes blurred but important to distinguish (ibid.). *CER effects* describe the magnitude of changes in resource consumption following an efficiency improvement whereas *mechanisms* generate such changes. Rebound effects can be caused by any type of resource efficiency improvements. Recycling for instance represents a form of resource efficiency gain because it is less energy and raw material intensive than primary production - a form of input/output efficiency (Zink & Geyer, 2017). Efficiency improvements then lead to cost reductions, which in turn set off the typical behavioural and market mechanisms for rebound effects (Gillingham et al., 2016). Efficiency improvements can be triggered either endogenously, through policy interventions, or exogenously due to technological innovation (Vivanco et al., 2016). This research leaves open whether a CER effect is triggered endogenously or exogenously.

4.2. The circular economy

There is no commonly accepted definition of the circular economy (Figge et al., 2023; Kara et al., 2022; Kirchherr et al., 2017). The most well known definition is probably the one by the Ellen MacArthur foundation, which defines it as an industrial economy that is restorative and regenerative by intention and design (Ellen MacArthur Foundation, 2019). While widely used, this definition is very broad and unspecific. For greater conceptual clarity I follow Geissdoerfer et al.'s (2017) definition of the circular economy as "a regenerative system in which resource input and waste, emission, and energy leakage are minimized by slowing, closing, and narrowing material and energy loops. This can be achieved through long-lasting design, maintenance, repair, reuse, remanufacturing, refurbishing, and recycling." (p.759)

At the core of most circular economy discussions lie the so-called four Rs - reduce, reuse, repair and recycle (Kirchherr et al., 2017). Recycling only refers to recirculation at the material, not product, level. The circular economy concept extends the traditional recycling concept by prioritizing reduction, reuse and repair and then only recycling of resources. Contrary to this hierarchy one of the most widespread circular strategies discussed in research and policymaking is recycling (Kara et al., 2022). It is frequently regarded as a key factor in lowering resource use, improving resource productivity, and achieving a more circular economy (Castro et al., 2022; Kirchherr et al., 2017; Robaina et al., 2020). The present research focuses on the recycling *R* of the circular economy, and does not seek to generalize findings to other circular activities.

4.3. The circular economy rebound

Zink & Geyer (2017) have drawn a strong parallel between the rebound effects from energy efficiency improvements and market dynamics in the circular economy and formalized the concept of CER. Analogous to energy rebound, CER effects occur when increases in production efficiency, for instance through recycling, are offset by increased levels of production, and by extension increased environmental impacts (Zink & Geyer, 2017).

Most discussions of the circular economy adopt an engineering-centric perspective, with material flows directly traveling from recyclers to producers and consumers (Zink et al., 2018; Zink & Geyer, 2017). In this view secondary production perfectly substitutes primary production, and the net environmental benefit of a circular activity solely depends on the difference in production impacts of secondary and primary material. Recycling would thus lead to environmental benefit as long as it has lower environmental impacts per production unit - a condition met by most recycling activities. Becauses primary production is based on raw material extraction and is very energy intensive, it is much more environmentally damaging than secondary production, which relies on product reuse and reprocessing (Cooper & Gutowski, 2017; Zink & Geyer, 2017) Thus, secondary production has lower per unit production impacts than primary production, a form of eco-efficiency.

However this view overlooks the fact that the circular economy is a system of markets, in which secondary materials compete with primary materials and substitution between such is governed by market forces rather than assured (ibid.). Consequently, the net environmental impact of recycling depends on the <u>combined</u> effects on production impacts <u>and</u> production quantities:

$$E_{net} = e_r \, \Delta Q_r + e_p \, \Delta Q_p$$

where e_r and e_p denote the environmental impact of producing one unit of secondary and primary material respectively, and ΔQ_r and ΔQ_p represent the change in secondary production and market mediated change in primary production respectively. Assuming that secondary plastic production is associated with less environmental impact than primary production, the net environmental impact hinges on whether total production increases as a result of recycling. In this view, recycling only reduces environmental impacts if $\Delta Q_p < 0$.

Typical engineering models assume perfect substitution in the form of $\Delta Q_s = -\Delta Q_p$, so that $\Delta Q = \Delta Q_r + \Delta Q_p = 0$. However, as mentioned above this assumption is not guaranteed in a system of competitive markets where substitution may be incomplete or even negative. As stipulated by Zink & Geyer (2017), "Any circular economy activity with $\Delta Q = \Delta Q_r + \Delta Q_p > 0$ is deemed to experience CER" (p. 596).

The two main mechanisms by which secondary production can cause rebound are the *imperfect substitution* and *price effect* (ibid.). The following discussion of these mechanisms serves to provide a better understanding for the theory of CER; and provide theoretical justification for the expectation of a CER effect in this study. Other potential behavioural mechanisms are not considered in this analysis.

On the one hand, recycling leads to rebound because secondary plastic is of inferior quality and therefore might be an insufficient substitute for primary plastic. This is commonly known under the word downcycling instead of recycling. For example recycled plastics rarely compete with primary materials due to degradation in the quality of the polymer and shortening of the fiber lengths (Allwood, 2014). Consequently, a larger amount of secondary plastic is needed to gain the same properties of primary plastic (Dace et al., 2014). Alternatively, secondary plastic could substitute material of a different kind, like glass or paper, in the field of packaging. Hence, recycled plastic is more likely to be produced in addition to, rather than instead of primary plastic, rendering perfect displacement unlikely.

Alternatively, the price effect causes rebound when increased secondary production affects (relative) prices. Recycling can influence prices of both primary and secondary material, and lower the costs of production (Zink et al., 2018, Vivanco et. al., 2018). Secondary material is often offered at a lower price than primary material, to compensate for the decline in quality. If secondary material is cheaper than primary material, producers who use secondary material are comparatively wealthier and can purchase more material and make more products than before, a so-called income effect. As a result more plastic is produced, sold and used. But even if secondary plastic is more expensive than primary plastic, recycling can induce a price effect. If secondary plastic competes in the same market as primary goods, basic economic principles would suggest that as the supply of a good increases, both its price and the price of its substitute in the market would fall. The price decrease would lead the market equilibrium to balance at lower prices and higher quantities, so that overall more plastic is produced, sold and consumed than before the secondary supply shock (Zink & Geyer, 2017).

In accordance with the framework of Zink & Geyer (2017), I argue that in a circular economy primary and secondary goods compete in the same markets. Following an increase in plastic recycling and a secondary supply shock, substitution and price effects occur. Therefore, plastic recycling would lead to an increase in overall plastic production and experience a CER effect, i.e. $\Delta Q = \Delta Q_s + \Delta Q_p > 0$. A complementary analysis of the effect of recycling on plastic waste generation is conducted, in order to assess a potential rebound effect in this domain. While the theoretical framework by Zink & Geyer (2017) primarily addresses production and consumption and does not explicitly theorize rebound effects in waste generation, I extend their logic by inferring that increased recycling could also lead to greater waste generation via the production and consumption channels. Followingly, I hypothesize that:

H1: An increase in plastic recycling leads to a circular economy rebound effect manifested in increased total plastic production.

H2:An increase in plastic recycling leads to a circular economy rebound effect manifested in increased plastic waste generation.

5. Research Design

This section outlines the research design employed to examine the relationship between plastic recycling and primary plastic production and identify a CER effect. It presents the data sources, and details the descriptive and econometric methods used to test the hypothesized relationship.

5.1. Data

The analysis in this study is based on panel data from Eurostat, the European Union's statistical office. Since this study relies on panel data from European countries, the results of this research only pertain to the European context. The analysis is conducted using R Language (R Core Team, 2021) and the package *plm* for panel-data analyses (Croissant & Millo, 2008). Two separate estimation samples are used: one with data on plastic recycling and waste generation of all types of plastic waste (hereafter referred to as the plastic sample) and another sample with recycling and waste generation data on plastic packaging waste specifically (hereafter referred to as the packaging sample). The packaging data is included due to its greater coverage, offering higher temporal resolution and a larger number of observations. Additionally, plastic packaging constitutes the largest flow of post-consumer plastic waste and therefore merits focused analysis (Hsu et al., 2021). While the plastic sample has less observations, it enables a broader generalization of findings across overall plastic waste.

The main independent variable in this analysis is plastic recycling. Recycling is operationalized in two ways: i) the quantity of plastic (packaging) waste recycled in a European country per year measured in metric tonnes and ii) the recycling rate, i.e. the quantity of waste recycled over the quantity of waste generated. The quantity of recycled plastic waste is measured as part of the Eurostat Waste statistics, which can be broken down by treatment type and waste category, for this purpose the "recovery - recycling" and "plastic waste" categories (Eurostat, 2024c, 2025b). The recycling quantity as measured by Eurostat reflects the input of waste to a recycling process. Plastic waste statistics and plastic packaging waste statistics treat waste imports and exports differently. Plastic waste statistics exclude exported waste but include the treatment of waste imported into the state. On the other hand, plastic packaging waste statistics include exports of waste for recycling but exclude imports of packaging waste. The recycling rate is used by the European Union as an indicator to measure progress against the circular economy. In both samples is computed manually by dividing the quantity of plastic waste recycled over the quantity of plastic waste generated. Due to the fact that waste generation only includes waste produced domestically, but recycling data also includes imported waste, the recycling rate in the plastic sample can exceed 100%.

The main dependent variable in this analysis is the production of plastic. In the absence of mass flow data on plastic production in physical units (Amadei et al., 2022), the production volume from the Eurostat short term business statistics was chosen as a reasonable proxy indicator for production quantity (Eurostat, 2025). This indicator measures real changes in production output across European countries, as it is adjusted for price changes. Furthermore, it is classified according to the statistical classification of economic activities (NACE) and classification of products by activity (PCA). This allows filtering the production statistics for "plastic in primary form" (NACE code C 20.16), referring to plastic in its pre-processed granulate form.[1] The production index is presented as a Laspeyres-type index with the base year 2015. Given its regular updates, cross country comparability, and methodological consistency, the short term business statistics provide high quality data.

Plastic waste generation is used as an additional outcome variable for a complementary analysis of the CER effect. Plastic waste generation is also recorded by the European Union as part of the waste statistics and measured in tonnes (Eurostat, 2024b, 2025b). The indicator includes waste generated by all economic activities as well as households, so pre- and post-consumer waste. Waste generation is attributed to the entity that hands over the waste to the waste management system (Eurostat, n.d..). This indicator refers to all national waste generated and therefore excludes imported waste. Member states are free to decide on the data collection methods, which can range from surveys, over administrative sources and statistical estimations to a combination of such. According to Eurostat, the comparability of data across time and countries is ensured through the application of standardized definitions and harmonized classification systems .

Eurostat also provides data for the relevant covariates Gross Domestic Product (GDP) and environmental taxes (Eurostat, 2024a, 2025a). GDP at market prices is also

[1] "Plastic in primary forms" is not to be confused with "primary plastic". The former comprises both primary as well as recycled material, whereas the latter only refers to primary material, i.e. plastic produced from fossil fuels.

indexed to the 2015 baseline, measured in chain linked volumes. Chain linking adjusts for inflation thus enabling comparability of annual data over time (Nierhaus, 2005). The environmental tax indicator captures the tax revenues from energy, transport, pollution and resource taxes. This indicator is broken down by economic activity according to the NACE classification of economic activities and for the purpose of this analysis filtered for environmental taxes on plastic production, measured in million euros.

The two final samples are panel data, clustered by state. The samples were limited to the years 2010 - 2022 as this period has the most complete production and recycling data. Most recent data from 2023 and 2024 is not published yet and data from before 2010 is not consistently available across countries. Countries with more than one missing value were omitted from the samples, in order to keep the panels relatively balanced. There are only two missing observations: one for Greece 2020 in the packaging sample and one for Türkiye 2022 in the plastic sample. The plastic sample has 48 observations and covers 2010 to 2022, observed biannually for France, Germany, Greece, Italy, The Netherlands, Spain and Türkiye (n = 7, T = 6-7). The packaging sample has 77 observations and stretches from 2010 to 2022, with annual observations for Germany, Greece, France, Italy and Spain (n = 6, T = 12-13).

5.2. Methodology

This thesis applies a quantitative approach in order to explore the relationship between plastic recycling and production/waste generation. There is no methodological consensus in the literature for measuring the rebound effect (Sorrell & Dimitropoulos, 2007). Rebound effects have been estimated using a variety of quantitative approaches, among which econometric techniques are widely used because of their flexible data requirements (Lowe et al., 2024; Sorrell et al., 2009). The choice of method is largely determined by data requirements and adequate data availability.

The research design in this study is similar to that of Van Fan et. al. (2022), employing a combination of descriptive, correlation and econometric analysis to examine CER effects, shown in Figure 1. To begin, a short descriptive analysis of the two key variables, production volume and recycling quantity, is presented to get a first impression of the data and the relationship between the variables. Next, Pearson's correlation coefficient is used to assess the strength and direction of association between all variable pairs. While this offers preliminary insights into their relationship, identifying a rebound effect requires establishing a causal relationship between plastic recycling and the outcome.

Among econometric methods, ordinary least squares (OLS) regression is the standard approach to estimate rebound effects, because it is suited for various data structures. However the conditions for OLS estimators to be unbiased and efficient for causal inference are frequently violated (Sorrell & Dimitropoulos, 2007). Fixed effects techniques provide more robust estimates and are suitable for panel data, such as the present dataset (ibid.). Hence, this study employs a two-way fixed effects (TWFE) model to test the hypothesis of a CER effect from plastic recycling.[2] Panel estimators permit causal inference that rests on weaker assumptions than usual regression estimators (Munzert, 2023). TWFE models can account for unobserved time-invariant heterogeneity across countries and common shocks over time, thereby mitigating omitted variable bias. Nevertheless, this approach cannot address measurement error or reverse causality, a relevant issue in this research design. With these limitations in mind, the TWFE estimators are cautiously interpreted as causal. Three models with different combinations of dependent and independent variables are estimated, shown in equation one to three respectively. Testing whether the effect holds across different model specifications is one way to improve robustness of the regression results. The dependent variables are the production of plastic in primary forms (*Prod*) and the quantity of plastic waste generated (*WasteGen*). The latter is transformed with a natural log, due to skewness in the data. The independent variables are the quantity of recycled plastic (*RecyclingQuant*) and the recycling rate (*RecyclingRate)*. Model 1 and 2 are specified in a linear-log functional form and Model 3 in a log-log functional form, to fulfill the OLS assumption of linearity between the independent and dependent variables. The coefficient β captures the effect of recycling on plastic production or waste generation. The control variables are *GDP* and the environmental taxes (*EnvTax*) levied on plastic production. The covariates were selected

[2] The plm package estimates the within estimator through a demeaning and ordinary least squares approach.

based on suggestions from the literature (Van Fan et al., 2021). Other environmental policy measures could also influence plastic production, however are difficult to measure and operationalize in a regression setting and therefore unaccounted for in these models. Environmental policy measures on the EU level are captured by time fixed effects to the extent that they are implemented equally across countries. As another potential confounder, the price of oil is expected to be captured by year fixed effects, assuming that oil prices do not vary across countries. α_s and α_y represent the intercepts for state and year fixed effects respectively. ln denotes the natural logarithm, whereas subscripts s and y represent state and year, respectively.

$$Prod_{s,y} = \alpha_s + \alpha_y + \beta lnRecyclingQuant_{s,y} + \gamma GDP_{s,y} + \delta lnEnvTax_{s,y} + \epsilon_{s,y} \qquad Eq. (1)$$

$$Prod_{s,y} = \alpha_s + \alpha_y + \beta lnRecyclingRate_{s,y} + \gamma GDP_{s,y} + \delta lnEnvTax_{s,y} + \epsilon_{s,y} \qquad Eq. (2)$$

$$lnWasteGen_{s,y} = \alpha_s + \alpha_y + \beta lnRecyclingQuant_{s,y} + \gamma GDP_{s,y} + \delta lnEnvTax_{s,y} + \epsilon_{s,y} \qquad Eq. (3)$$

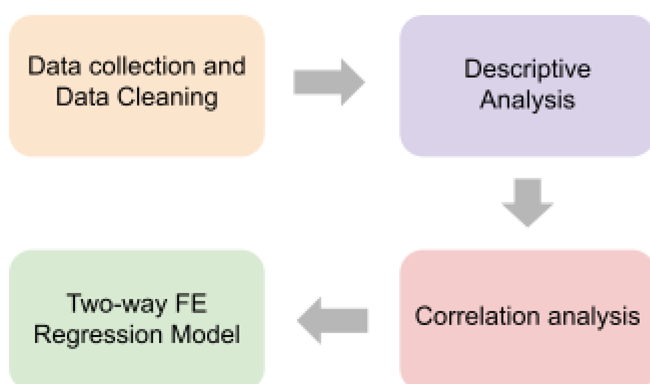


Figure 1: Research Design

6. Results

In the following Section I will present and analyze the results from the descriptive statistics. To maintain clarity and focus, I limit the descriptive analysis to the variables from the first model, which represent the primary variables of interest in this research. I will then continue with the correlation analysis and finally analyze the results from the TWFE regression models. The regression results will also be used to test the hypotheses that plastic recycling has a positive effect on production and waste generation.

6.1. Descriptive Analysis

Plastic sample

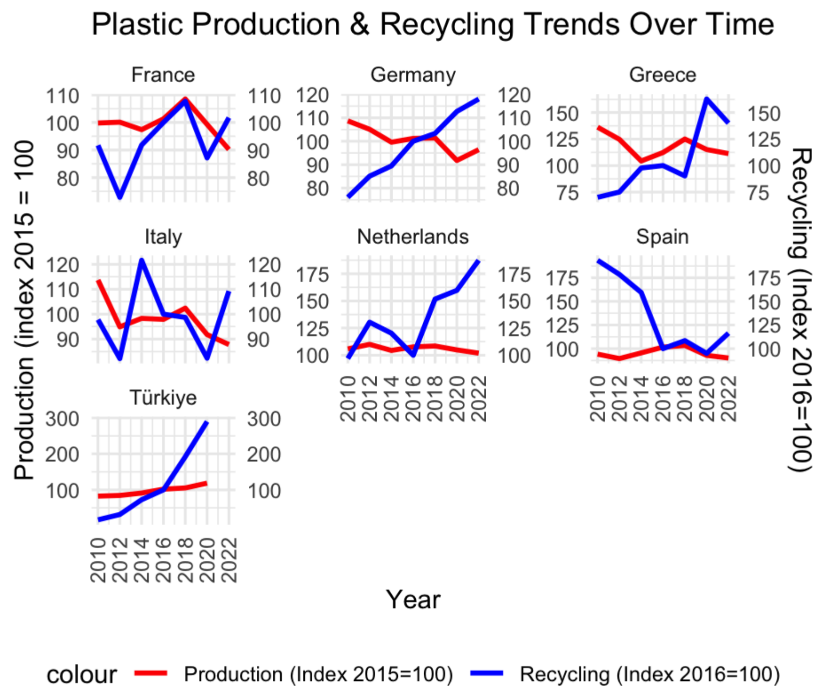


Figure 2: Plastic production and plastic recycling trends over time

The line graphs in Figure 2 display the trends in plastic recycling and production over time on a common scale.[3] Line plots are typically used to show trends and changes in data over time, allowing to quickly identify patterns. Displaying both variables on the same plot over time also offers an initial impression of their relationship. In addition the facet plots facilitate easy comparisons across countries. The majority of countries exhibit an upward trend in recycling over time - particularly Germany, Türkiye, Greece, and the Netherlands.

[3] To enable direct comparison, recycling data was converted to an index with a baseline value of 100 set in 2016. As 2015 was not observed for recycling, 2016 was chosen as the baseline.

Spain stands out as the only country where recycling declined between 2010 and 2022. In contrast, plastic production shows a slight downward trend in most countries, especially after 2018. The Netherlands and Spain show relatively stagnant production levels, while Türkiye is the overall exception, showing an increase in both recycling and production over time. Although in the majority of countries the data suggests an inverse relationship between recycling and production, there is no uniform pattern. There is strong cross-country heterogeneity in the recycling patterns, and to a lesser extent in the production trajectories.

Packaging sample

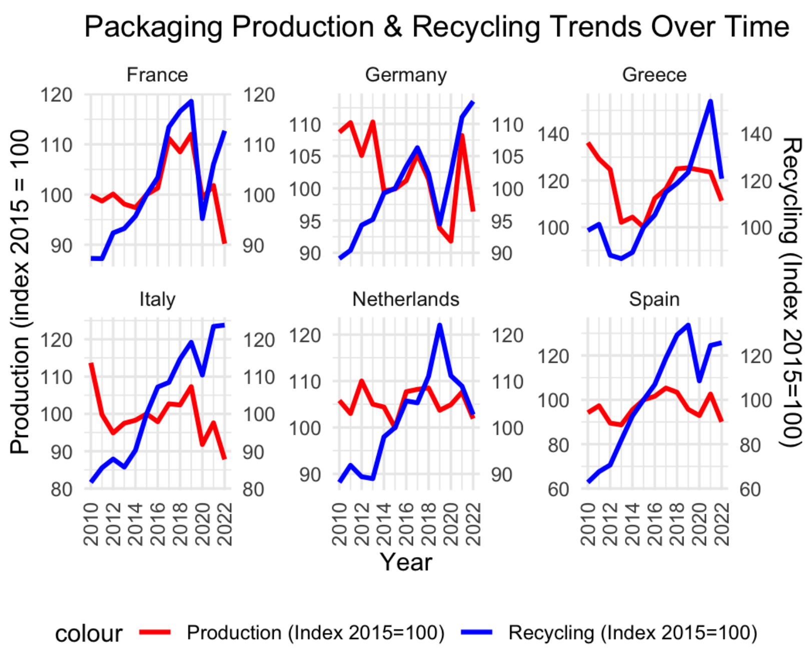


Figure 3: Plastic production and packaging recycling trends over time

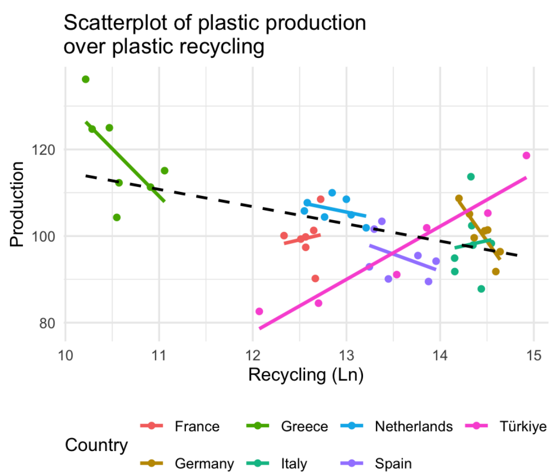
The line graphs in Figure 3 plot packaging production and recycling trends over time on a common scale.[4] Due to the higher frequency of observations, trends in this sample appear more erratic. Nevertheless, all countries except for Spain have consistently increased their recycling quantities from 2010 to 2022. The more consistent upward trend in recycling

[4] In this case, recycling data was indexed using 2015 as the base year to align with the production index

across countries may reflect stricter EU regulation on plastic packaging waste as opposed to overall plastic waste. All recycling trajectories experience a shock between 2019 and 2021. In the majority of countries this takes the form of a marked drop in recycling rates, whereas a few others peak during that time. Production trends mirror those observed in Figure 2 (since it is the same indicator), with slight decreases for most countries except the Netherlands and Spain. Also here an inverse relationship between recycling and production emerges, which would speak against a rebound effect and for the desired substitution effect of recycling.

6.2. Scatterplots and correlation analysis

<u>Production Volume and Recycling Quantity:</u>



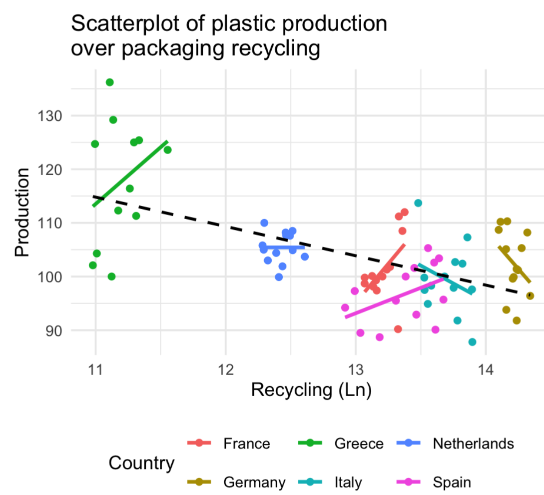


Figure 4a: Scatterplot of plastic production over plastic recycling

Figure 4b: Scatterplot of plastic production over packaging recycling

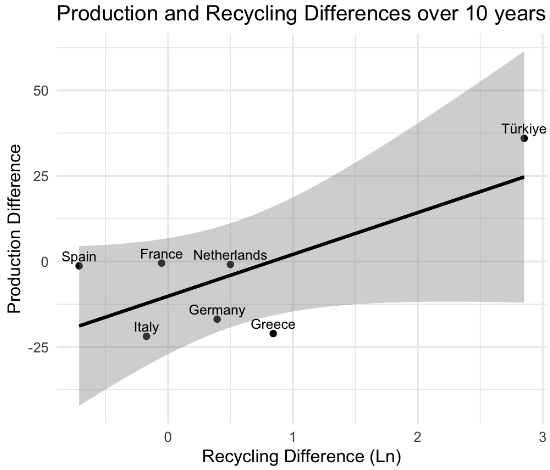


Figure 4c: Scatterplot of 10 year difference in plastic production and plastic recycling

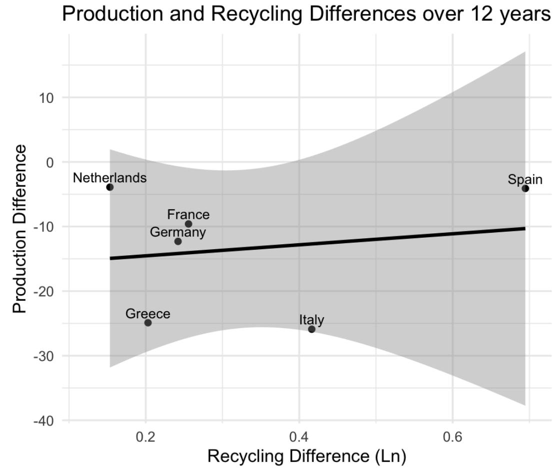


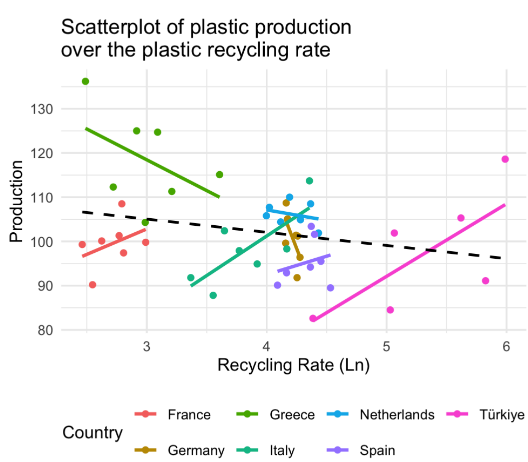
Figure 4d: Scatterplot of 12 year difference in plastic production and packaging recycling

The scatterplots in Figures 4a and 4b show the relationship between recycling and production across and within countries for the plastic and packaging samples, respectively. The scatterplots and correlation give insight into the strength and direction of the relationship between recycling and production. At first glance, it becomes clear that relying on cross-country correlations would lead to misleading interpretations in both samples. In both cases, the overall correlation suggests a negative relationship. However, within-country relationships can also be positive as seen in Türkiye, France, and Italy for plastics, and in Greece, France, the Netherlands, and Spain for packaging. Some countries exhibit much stronger correlations than others, as indicated by steeper slopes, highlighting substantial heterogeneity. This variation is also reflected in the correlation coefficients: plastic production and recycling are negatively correlated overall (Pearson's r = -0.49), but within-country coefficients range from -0.873 in Germany to 0.953 in Türkiye. Similarly, in the packaging sample, the overall correlation is negative (Pearson's r = -0.57), while within-country coefficients range from -0.338 in Germany to 0.520 in France. Though this range is smaller than in the plastic sample, it still underscores the heterogeneity in both direction and strength of correlation.

To gain another perspective, Figures 4c and 4d show 10- and 12-year differences between recycling quantities and production volumes. In Figure 4c, increases in recycling are accompanied by increases in production, suggesting a positive relationship. But this pattern is largely driven by Türkiye, which pulls the line upward. Without Türkiye, there would be close to no relationship between recycling and production, as seen in the packaging sample in Figure 4d. These over-time difference graphs suggest that recycling and production are mostly unrelated. However, it should be considered that the production and recycling trends shown in Figures 1 and 2 were very erratic. For example, using 2020 as the endpoint in the packaging sample would yield production differences that misrepresent the general trend.

Similar to the descriptive analysis the scatterplots reveal no uniform pattern in the relationship between recycling and production, as there is strong heterogeneity between countries. Whereas the average correlation would suggest an inverse relationship, the over-time difference plots imply a very weak or slightly positive association. The correlation coefficients indicate that recycling and production can be very strongly related, both negatively and positively. As a result, no unequivocal conclusions regarding the direction and strength of association between recycling and production can be drawn..

<u>Production Volume and Recycling Rate</u>



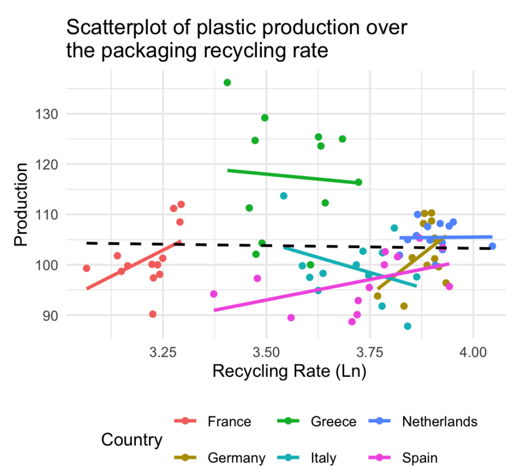


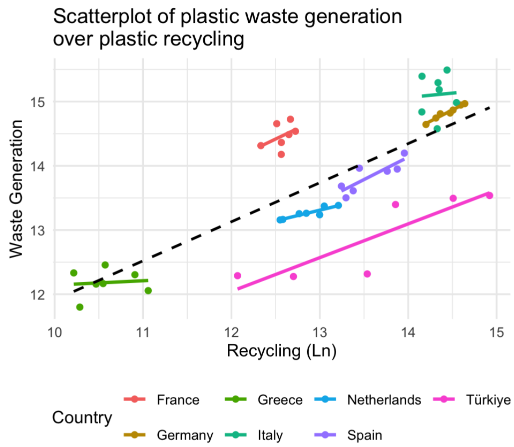
Figure 5a: Scatterplot of plastic production over the recycling rate

Figure 5b: Scatterplot of plastic production over the packaging recycling rate

Figure 5a and 5b plot the plastic production volume over the recycling rate. Again the overall correlation inaccurately represents within-country relationships. Furthermore, some countries exhibit a reverse direction of association compared to the recycling quantity. There is stark cross country heterogeneity in the relationship between production and the recycling rate. As shown in Figure 5a, plastic production and the recycling rate are positively associated in France, Italy, Spain and Türkiye, whereas in Greece, Germany and The Netherlands this is the opposite. Interestingly, in Spain and Greece the direction of association reversed in comparison to the analysis of the recycling quantity. In the packaging sample, the average and within country slopes are flatter, indicating that the association is weaker. Spain, France, and Germany display a clearly positive relationship between plastic production and the packaging recycling rate. In Italy and Greece, the relationship is negative, whereas in The Netherlands there is almost no relationship between the two variables. Also here two countries reversed the relationship compared to the recycling quantity, in this case Germany and Greece. The ambiguity in the scatterplots is mirrored in the Pearson's correlation coefficient. In the plastic sample the overall correlation is slightly negative (-0.24), and within countries it ranges from -0.65 in Germany to 0.75 in Italy. In the packaging sample the average correlation is close to 0 (-0.03), and within countries it ranges from - 0.381 to 0.49 in Spain.

Again the scatterplots and correlation do not reveal a clear pattern in the association between production and the recycling rate. Average correlations are slightly negative in the plastic sample or close to zero in the packaging sample. Within country correlation coefficients range from moderately negative to strongly positive. Interestingly, although both the recycling quantity and recycling rate aim to capture improvements in recycling, the indicators are not uniformly associated with production.

Waste Generation and Recycling Quantity



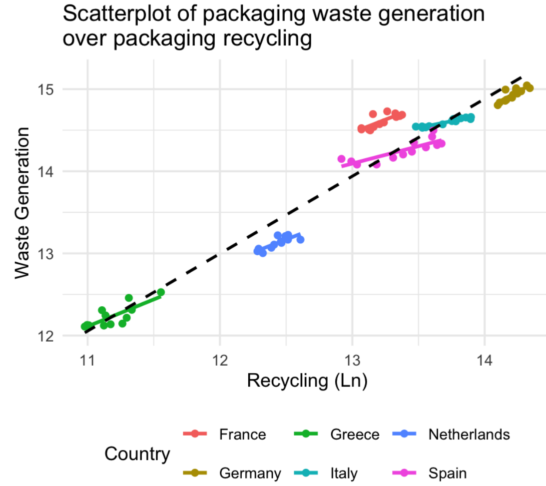


Figure 6a: Scatterplot of plastic waste generation over plastic recycling

Figure 6b: Scatterplot of packaging waste generation over packaging recycling

Lastly, the correlation between recycling quantity and waste generation shown in Figure 6a and 6b is analyzed. In contrast to the previous plots, this variable pair shows a much stronger and unequivocally positive relationship. In the plastic sample on average and also within countries, recycling and waste generation are positively correlated, which is reflected in the Pearsons's correlation coefficient of 0.76. In the packaging sample this association is even more significant with a Pearson's correlation coefficient of 0.96, an almost perfect linear relationship and a clearly upward sloping line in the scatterplot across and within countries. Although there are between-country differences in the strength of the relationship, all of them display a positive one. This would indicate a rebound effect in waste generation, however the correlation of recycling and waste generation has to be interpreted with caution, since it can be driven by reverse causation and is susceptible to omitted variable bias.

6.3. Regression analysis

As the insights from the descriptive and correlation analysis are inconclusive, the results from the TWFE regression models one to three are analysed to gain a clearer picture. The plastic and packaging samples are analysed individually and all results summarized at the end. Given that these are TWFE models, the coefficient represents a within estimator, which captures changes within and not across units. While acknowledging the risk of reverse causality and measurement error, I will proceed to interpret the within estimators below as causal for ease of exposition. In line with CER theory, any change in total production > 0 is deemed to experience rebound. This would be indicated by a statistically significant and positive regression coefficient (ß > 0). For the interpretation of the results I will use the significance level of 5%, most commonly used in research. Since the p-values reported by R are generated from two-tailed tests, the p-value is divided in half to obtain the correct p-value (Warren, 2021).[5] In the linear-log models, the coefficient can be interpreted as the change in index points, associated with a 1% change in the independent variable. In the double-log model, the coefficient directly reflects the percentage change in the dependent variable resulting from a 1% change in the independent variable. Standard errors are heteroskedasticity and autocorrelation robust and clustered on state level according to the arellano method.[6] A small sample correction (HC2) is also applied in the calculation of the standard errors.

The results and interpretations of the robustness checks can be found in the appendix. The models were estimated with heteroskedasticity robust standard errors, to ensure that cluster-robust standard errors do not erroneously shrink the standard errors in the case of a small number of cluster units (Table A1 and A2). Furthermore, the models were estimated with the omission of the covariates GDP and Environmental taxes to ensure the robustness of the main effect to the ex-/inclusion of control variables (Table A3 and A4). Given that Turkey was identified as a potential outlier in the plastic sample, the regression models were re-estimated excluding Turkey's observations (Table A5). For robustness checks, the error relevant OLS assumptions - homoskedasticity, no serial correlation of errors, no multicollinearity and normality of errors - were tested.

Plastic sample

[5] Since model fit is less pertinent in explanatory or causal modeling and not particularly relevant for this research, the R-squared value of the regression model will not be interpreted.

[6] Generic sandwich estimators are not applicable to plm models. Instead, cluster-robust standard errors are computed using the vcovHC() function from plm. Given the inclusion of fixed effects, the arellano method is appropriate, as it allows for clustering at the group level. Alternatively, the white method would yield heteroskedasticity standard errors only.

Regression Output from FE regression models (Plastic Sample)

	Dependent variable		
	Production	Production	Waste Gen. (Ln).
	(1)	(2)	(3)
Recycling (Ln)	1.732		0.355^{**}
	(3.507)		(0.185)
Recycling rate (Ln)		4.311^{**}	
		(1.977)	
GDP	0.676^{***}	0.664^{***}	0.005
	(0.131)	(0.070)	(0.010)
Environmental taxes	0.734	0.929	-0.076
	(3.342)	(3.378)	(0.065)
two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
R squared	0.576	0.598	0.435
Adj. R-squared	0.377	0.409	0.170
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 1: Regression table of the plastic sample regressions

Table 1 presents the results from three multivariate TWFE regression models based on data from the plastic sample. Model (1) examines the relationship between plastic recycling quantities and production. The coefficient suggests that a 1% increase in recycling quantity corresponds to a 0.01732 index point change in production volume relative to the 2015 baseline. However, this estimate is very uncertain with standard errors more than twice the size of the point estimate. Moreover, the effect size is very small compared to the standard deviation of production (sd = 10.5 index points) according to Cohen's d style interpretation of the effect size. As a result, Model (1) does not provide conclusive evidence that changes in recycling quantities affect plastic production, and the null hypothesis cannot be rejected at the 5% significance level.

Model (2) assesses the effect of the recycling rate on plastic production. Here, the estimated effect is positive and statistically significant at the 5% significance level. This allows to reject the null hypothesis of no or negative effect on production. Specifically, a 1% increase in the recycling rate is associated with a 0.04311 index point increase in production volume. Compared to the standard deviation of production (sd = 10.5 index points), this effect size is again very small. Regardless of the magnitude, the coefficient indicates an overall increase in production. As any increase in total production is deemed to experience a rebound effect, and the estimate here is statistically significant, this model provides indicative evidence for a rebound effect from plastic recycling.

Model (3) explores the link between recycling quantity and waste generation. The effect of recycling is positive and statistically significant at the 5% level. The coefficient indicates that a 1% increase in recycling is associated with a 0.355% increase in waste generation. Put differently, doubling recycling corresponds to a 35.5% rise in waste generation - a substantial effect. This result also allows to reject the null hypothesis of no or a negative effect on waste generation, and provides tentative support for a rebound effect in waste generation. However, the error terms in this model are non-normally distributed, and inferences from this model may be inaccurate (Nguyen, 2020).

Estimating the models without covariates changes the coefficients slightly qualitatively. The p-value of the recycling quantity increases slightly, however by conservative measures it is still insignificant. Both the coefficients on recycling quantity and rate change in effect size when omitting the covariates, indicating that an omission of such may lead to biased estimates in Model 1 and 2. Importantly however, none of the coefficients change in the direction of effect. The waste generation model hardly changes when the covariates are omitted, suggesting they drive little variation in the outcome. Estimating only robust standard errors does not change the results of the models qualitatively, as the cluster robust standard errors are larger than only robust ones. Excluding the observations from Türkiye, results in noticeable changes in the effect sizes of Model 1 and 2, however all regression coefficients in this sensitivity analysis are statistically insignificant and thus do not provide enough ground to compromise the robustness of the main results.

Packaging sample

Regression Output from FE regression models (Packaging Sample)			
	Dependent variable		
	Production	Production	Waste Gen. (Ln)
	(1)	(2)	(3)
Recycling (Ln)	26.904***		0.256***
	(9.024)		(0.077)
Recycling Rate (Ln)		17.406*	
		(10.850)	
GDP	0.451***	0.576***	0.006***
	(0.143)	(0.145)	(0.001)
Environmental taxes	1.676	1.178	-0.034
	(3.597)	(4.785)	(0.047)
Two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
R-squared	0.299	0.181	0.154
Adj. R-squared	0.049	-0.111	-0.300
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Regression table of the packaging sample regressions

Table 2 reports the regression results from the multivariate TWFE models based on data from the packaging sample. Model (1) again examines the relationship between production volume and recycling quantity. In this sample, recycling has a positive and statistically significant effect. The coefficient indicates that a 1% increase in recycling corresponds to a 0.269 index point change in production volume. Put differently, doubling the recycling quantity leads to a 26.9% increase in production volume. Compared to the plastic sample, this effect is substantially larger in size and statistically significant at the 1% level. The higher precision in this estimator may be due to the larger size of the packaging sample.

Model (2) estimates the effect of the recycling rate on production volume. Unlike in the plastic sample, the effect in this sample is less statistically significant, with a p-value of 0.057. Although this is close to the critical significance level of 5%, I fail to reject the null hypothesis that there is a null or negative effect of the recycling rate on production. Nevertheless, the inconclusiveness of this estimate should not be confused with evidence for no effect. At least in the sample at hand, the recycling rate leads to a relatively small increase in production. Here, a 1% increase in the recycling rate leads on average to a 0.174 index points. The imprecision of the estimate in this sample could be improved with a bigger sample size, in which case a positive effect may also be inferred to the population.

Model (3) investigates the relationship between recycling quantity and packaging waste generation. The coefficient on recycling is positive and statistically significant at the 1% significance level, indicating that a 1% increase in recycling leads to a 0.25% increase in packaging waste generation. Equivalently, doubling recycling would increase packaging waste generation by 25%. This is a meaningful effect both statistically and substantively and would lend further support for the alternative hypothesis that increased recycling leads to more waste generation.

In the packaging sample the effect size and significance of recycling quantity in the first and third model are insensitive to the exclusion of covariates. Only the coefficient on recycling quantity decreases in size and becomes even less precise than in the fully specified model. Importantly, as in the plastic sample, all coefficients remain positive. Also here, estimating only robust standard errors does not change the results of the models qualitatively.

6.4. Summary

Taken together, the analyses offer mixed evidence. At first, the descriptive statistics and average correlations pointed towards an inverse relationship between recycling and production in line with the conventional expectation of a substitution effect from recycling. However, a closer examination of within-country correlations revealed a more complex picture. The relationship varies considerably across countries with some displaying strong positive correlations between recycling and production. This is a classic example of Simpson's paradox, a statistical phenomenon that arises when an association between two variables in a population reverses when examined within subgroups. It typically occurs when confounding variables are omitted from the analysis which can lead to potentially misleading interpretations. In this case, it revealed significant heterogeneity across countries. Interestingly, the only consistently positive correlation both across and within countries is observed between recycling and waste generation. However, given that correlation alone cannot establish causality and offers inconclusive evidence, the formal hypothesis testing and causal inference rely on TFWE regression.

Contrary to the negative relationship suggested by the descriptive analysis, the TWFE estimators reveal a positive relationship between recycling and production. Interestingly, the recycling rate shows a significant effect only in the plastic sample, whereas the recycling quantity is only significant in the packaging sample, despite the fact that both indicators aim to capture improvements in resource efficiency. While no definitive explanation can be offered, the divergence in significance between recycling rate and quantity across the two samples may be attributed to differences in sample size, or the way imported and exported waste are accounted for in the overall plastic and plastic packaging waste statistics.

Focusing on the statistically significant results, both the recycling rate and recycling quantity have a significant positive effect on production in at least one of the samples. In the packaging sample, the recycling rate is only marginally significant, but still indicates a positive direction of the effect. Furthermore, recycling has a positive and highly significant effect on waste generation in both samples, aligning with the results of the descriptive and correlation analysis. While the effect size and statistical significance differs, it is important to emphasize that recycling consistently has a positive effect on both production and waste generation across all models. Generally, these findings are consistent with the alternative one-sided hypothesis that an increase in recycling leads to more production and waste generation. Keeping in mind methodological limitations, these results provide suggestive empirical evidence for a CER effect in the context of plastic recycling in Europe. Nevertheless, the precise magnitude of this effect cannot be determined in this research and remains unclear.

7. Discussion

This section presents a general discussion of the research question by analysing the insights gained in section 6 and situating the findings in the broader literature and previous empirical findings. Moreover, the practical implications of these findings for policymakers are outlined and policy recommendations are proposed.

7.1. Relevance for the literature

This research set out to examine whether plastic recycling in European countries gives rise to a CER effect in plastic production or waste generation. This study builds on a narrow body of literature that explored CER empirically with limited attention given to recycling activities (e.g. Dace et al., 2014; Van Fan et al., 2021; Zink et al., 2018; Makov & Font Vivanco, 2018; Ottelin et al., 2020; Siderius & Poldner, 2021). Although the potential for CER effects is frequently acknowledged in the literature, few studies have directly examined their incidence (Castro et al., 2022). To the best of my knowledge, this is the first study to systematically examine the incidence of CER in the context of plastic and provide suggestive evidence for its occurrence in European countries. It thereby addresses a crucial gap in the literature.

The results of this study offer suggestive evidence that increased recycling does not necessarily lead to reduced material production or waste generation. Instead, recycling activities appear to have a positive effect on both production and waste generation. These findings are indicative of a CER effect from plastic recycling in European countries. This finding lends further support for Zink & Geyer's (2017) theory, and aligns with the existing CER research, which has identified a CER effect from various circular economy activities and resources - except for plastic recycling. Specifically, my results advance the discussion on rebound effects in waste generation by offering a focused analysis of how recycling influences waste generation. It contributes to the work of Van Fan et. al. (2021) who found indicative evidence for a CER effect in waste generation due to an increase in the use of recycled material, but called for a more comprehensive assessment.

In line with the analysis of substitution rates from aluminium recycling by Zink, Geyer & Startz (2018), the findings indicate that a zero or negative substitution rate between primary and secondary material is unlikely but a positive substitution rate is possible in the case of plastic. Recycling may only prevent a fraction of primary production than what is assumed, or in the most extreme case might even induce more production than before. Further, an incomplete substitution of primary with secondary material would result in a shortfall of its expected environmental benefits, the extent of which depends on the exact magnitude of the rebound effect in environmental metrics - a potential avenue for future research.

This finding demonstrates that the widely held assumption of perfect substitution in circular economy models and studies, does not hold in the case of plastic, and is potentially violated in the context of other resources and circular economy activities as well. It reflects growing concerns that, while the circular economy is widely promoted as a more sustainable economic model, its environmental claims are often based on assumptions that are insufficiently scrutinized, most notably perfect displacement, and fail to accurately capture the market dynamics and environmental consequences of the circular economy - an area that remains poorly understood (Castro et al., 2022). A potential explanation for this is that the circular economy is predominantly studied from an engineering perspective, which overlooks its economic dynamics. Furthermore, as Korhonen (2018) argues, the circular economy has almost exclusively been developed and led by practitioners and as a result lacks scientific scrutiny. This thesis joins calls (Corvellec et al., 2022; Korhonen et al., 2018; Santarius et al., 2018) for a more critical, scientific and interdisciplinary examination of the circular economy.

Research focusing on CER specifically is critical, because insights from the rebound effect literature in energy economics cannot be directly applied to the circular economy context. CER is governed by different dynamics than traditional energy rebound, because it arises in circular instead of linear resource flows (Castro et al., 2022; Figge & Thorpe, 2019). The former involves the conventional price and substitution mechanisms, however these are insufficient to fully explain the phenomenon and additional mechanisms have been proposed (ibid.). Unlike energy efficiency rebound, the CER effect can arise in the demand and supply side, as is demonstrated in the present study, and the interaction between these two sides can develop new effects (Castro et al., 2022; Figge & Thorpe, 2019). Hence, the suitability of borrowing rebound effect definitions, classifications, and mechanisms from energy economics needs to be evaluated. Clearly, further research on the CER is needed to fully understand the underlying mechanisms, triggers, and potential mitigation strategies which could not be delivered in this thesis.

Methodologically, this study also demonstrates that econometric techniques, in particular TWFE regression, is a useful method to examine CER. In the energy economics literature, regression techniques are already common, however in studies of the CER they have only been applied to a limited extent. This research contributes to the efforts of Lowe et. al. (2022) in identifying methods that could be used to estimate CER effects and their according data needs. With access to mass based plastic flow data, TWFE models could offer an alternative way to quantify displacement rates and CER effect magnitudes .

7.2. Practical Relevance and Policy Recommendations

Practically, the finding that plastic recycling in European countries likely leads to a CER effect carries significant implications for policymakers and other stakeholders in the plastic circular economy. As mentioned above, plastic recycling and the associated policies will likely underperform the expected environmental gains. As such, CER poses a critical obstacle to achieving economic and environmental decoupling through the circular economy (Castro et al., 2022; Kara et al., 2022). However it is important to keep in mind that CER effects partially offset but do not necessarily completely cannibalize the expected environmental gains of a circular economy. A key concern raised is that conventional circular economy models and studies often rely on overly simplistic assumptions. Despite a lack of a comprehensive and scientifically robust understanding of the circular economy's functioning, it has gained widespread policy traction. This may risk leading to unintended and potentially counterproductive policy outcomes and by extension environmental impacts, which is especially salient in light of rapidly growing global plastic production. Thus, it is imperative that the potential for CER effect is taken into account in policy design, impact assessment and evaluation in the domain of plastic circular economy policies and perhaps even beyond. This is not only important for policymakers to consider but also for stakeholders in the plastic value chain who are transitioning (or aim to transition) to more circular material flows. Concrete policy recommendations drawn from this research are outlined below, some of which also echo recommendations from previous research on CER.

1. Take rebound effects into account in policy design and evaluation

Rebound effects must be recognized and taken into account in the design and impact assessment of circular economy policies. Environmental benefit statements of plastic circular economy policies should be reassessed and possibly moderated in light of potential CER effects from plastic recycling. For instance, mandatory recycled content targets introduced in the Packaging and Packaging Waste Regulation (Regulation (EU) 2025/40 of the European Parliament and of the Council of 19 December 2024 on Packaging and Packaging Waste, Amending Regulation (EU) 2019/1020 and Directive (EU) 2019/904, and Repealing Directive 94/62/EC (Text with EEA Relevance), 2024) should be reassessed in light of CER effects induced by packaging material efficiency (Dace et al., 2014). Circular strategies in other resource domains should consider CER effects a potential risk. Uncertainty around rebound effects should not be a pretext for inaction on the issue, as has been the case in the past (Vivanco et al., 2016). Moreover, the existence of a CER effect does render efficiency based policies invaluable for achieving environmental improvements. Rather it highlights the importance of understanding the extent to which anticipated environmental savings are offset when designing policies. Further research uncovering quantitative estimates of CER effects should be promoted, to support the formulation of rebound risk profiles related to different circular economy strategies and the development of appropriate risk management solutions (Lowe et al., 2024). Quantitative CER effect estimates can enable decision-makers to steer circular strategies towards more effective displacement.

2. Incorporate rebound mitigating measures into policies

Rebound mitigating measures must be incorporated in circular economy policies, if a rebound risk is identified. A frequently mentioned measure to mitigate rebound effects are (Pigouvian) taxes, in order to inhibit the development of price mechanisms (Dace et. al., 2014, Font Vivanco et. al., 2016, Brännlund et. al., 2007). Among the mitigation measures mapped by (Maxwell et al., 2011) mixed instruments approaches that combine fiscal, technology and behavioral aspects, have been found to be effective in addressing rebound effects. Within the fiscal measures taxes, consumption caps and bonus malus schemes are proposed (ibid.). However it is unclear to what extent these are also effective in the context of CER and the appropriate design of mitigating measures depends on the exact magnitude of the rebound effect. Zink & Geyer (2017) propose the following conditions to avoid CER generally: i) circular economy activities must produce products and materials that truly are substitutes for primary alternatives, ii) circular economy activities must have either no effect on or decrease aggregate demand iii) circular economy activities need to draw consumers away from primary production. Furthermore, to improve the environmental performance, circular economy policies should adhere to the waste hierarchy and prioritize reduction over recycling (Allwood, 2014; Vivanco et al., 2022). In line with this, academics are calling for an absolute cap on plastic production in the global plastic treaty currently under negotiation (Bergmann et al., 2022; Villarrubia-Gómez et al., 2022).

3. Improve quality and coverage of plastic flow data

This research underscores the critical role of high quality data in enabling an accurate and informative assessment of circular economy policies. Low resolution and limited coverage of plastic data constrain a scientific evaluation of progress on the circular economy for plastic. Data limitations regarding the circular economy for plastics are echoed by several studies (Amadei et al., 2022; Geyer et al., 2017; Hsu et al., 2021), which point towards a lack of complete and comparable information on plastic flows. In light of this, the coverage of the European Union monitoring framework for the circular economy should be extended and its implementation strengthened. Key metrics like the *circular material use rate* or *resource productivity* should be made available for a broader range of resources including plastic. In addition, mass based data on plastic flows, ideally distinguishing between primary and secondary plastic, should be collected. Databases like "Recotrace" and "MORE" already contribute to an improvement of the data environment for a plastic circular economy but need to be scaled up. This research also uncovered the need to harmonize the accounting of waste imports and exports in waste treatment statistics. In addition, Amadei et. al. (2022) and Korhonen et. al. (2018) recommend harmonizing plastic flow data categorization (e.g. life cycle stages or product categories) to improve data compatibility, and to include circular economy activities like product reuse and repair into statistical categorizations.

4. Re-evaluate existing circularity metrics

Furthermore, there is a need to re-evaluate the metrics and indicators used in the EU monitoring framework for the circular economy as these can be misleading. Circularity indicators such as the recycling rate and recycling quantity, are often assumed to reflect progress toward sustainability. However, the findings from this study suggest that more circularity does not necessarily translate into environmental benefits. Previous studies have already demonstrated that some of the available metrics used to track progress against the circular economy targets can be misleading (Horvath et al., 2019; Psyrri et al., 2024; Van Fan et al., 2021). For instance, high recycling rates do not necessarily equate to significant environmental benefits (Psyrri et al., 2024) and higher circular material use rates have been linked to higher waste generation (Van Fan et. al., 2021). Consequently, existing metrics should be revised and new metrics and indicators developed. Expanding the indicator set beyond downstream metrics (e.g., waste treatment and recycling volumes) to include upstream dimensions will be crucial for capturing the full spectrum of circular economy dynamics and ensuring more accurate policy assessments. It is important to consider that circularity serves as a means to more sustainability, rather than an end in itself.

7.3. Limitations

While this research makes a valuable contribution to the literature on CER, several limitations related to data, methodology and scope should be acknowledged. Addressing these limitations could present an important avenue for future research.

Firstly, the analysis was based on a relatively small dataset. A larger sample would likely improve the precision of the results. In addition, the indicators used in this study are subject to several limitations, which may introduce measurement error and in turn bias the estimated coefficients. Plastic production was not observed for primary plastic specifically but only on the aggregate level. Furthermore, the production indicator was not measured in mass based quantities, as portrayed in the theoretical framework, but instead a coarse approximation of such through production volumes. Recycling quantities on the other hand were measured in mass units. However the recycling quantity is not identical to secondary production quantity, since there are usually losses during the recycling process and not all material entering a recycling process also enters the secondary material market (Hsu et. al., 2021). Hence, this research could be significantly strengthened by using data that measures plastic production on the granularity of primary and secondary plastic mass flows, if such data is available. Ultimately, CER effects should also be estimated in terms of environmental impacts. Databases such as Exiobase V3, which link material flows to environmental impacts across multiple countries and decades, could facilitate such assessments.

Secondly, there are important methodological limitations. The assumption of exogeneity can only be justified theoretically, however recycling could still be endogenous in which case OLS would yield biased estimates. While most confounding variables are controlled for, the risk of omitted variable bias cannot be entirely ruled out. Reverse causality is a significant concern in the context of this study, as both plastic production volumes and waste generation could influence recycling activity, rather than the other way around. Future research could address these endogeneity issues by using quasi experimental methods such as instrumental variables.

Lastly, the results should not be extrapolated beyond the European context, as this research only used data from European countries. Furthermore, these results only pertain to recycling in the context of plastic and are not generalizable to other resources or other types of circular activities. A rebound effect from plastic recycling suggests that similar effects may also occur in other resources subject to resource efficiency policies, such as water, land, or materials. Similarly, this research's findings would give reason to expect that other circular economy activities such as reduction, reuse, or repair are also susceptible to rebound effects. However, these hypotheses require further scientific inquiry and empirical validation.

8. Conclusion

Building on CER theory this study investigated the incidence of a circular economy rebound (CER) effect in the context of plastic recycling. Using a combination of descriptive statistics, correlation analysis, and TWFE regression models, this research analyzed European panel data on plastic recycling, production and waste generation. The findings from the TWFE models provide suggestive evidence that increases in plastic recycling are associated with CER effects in both plastic production and waste generation. To the best of my knowledge, this constitutes the first empirical investigation of CER in the plastic domain lending further support for CER theory, which has only been proven in a limited number of studies to date. Nevertheless, these findings are subject to a number of limitations, most importantly inaccuracy in the measurement of plastic recycling and production and potential endogeneity issues in the estimation technique, which could be addressed by future studies. CER is still an emerging research field, and further empirical research is needed to deepen our understanding of circular economy (rebound) to support the design of more effective and realistic circular economy strategies.

This thesis highlights that the common understanding of the circular economy rests on overly simplistic assumptions which overlook important market dynamics. As a result plastic recycling likely falls short of its assumed sustainability gains. This insight carries important implications for policymakers, given that the circular economy enjoys significant attention by policymakers. Based on these findings a number of policy recommendations are suggested, in order to account for CER effects in policies and improve the EU's circular economy monitoring framework.

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10. Appendix

10.1. Robustness checks

Heteroskedasticity of errors - Breusch Pagan test

In a Breusch Pagan test the null hypothesis is homoscedasticity. So a p-value smaller than 0.05 would indicate heteroskedasticity. The homoscedasticity assumption for OLS holds in almost all models. Heteroskedasticity only appears to be an issue in the Model 3 of the packaging sample. Since I am estimating cluster-robust errors, the heteroskedasticity in model 3 is automatically corrected for, and standard errors are not inflated.

Model 1 Plastic

BP = 1.0138, df = 3, p-value = 0.7979

Model 2 Plastic

BP = 1.5147, df = 3, p-value = 0.6789

Model 3 Plastic

BP = 2.3774, df = 3, p-value = 0.4979

Model 1 Packaging

BP = 5.9835, df = 3, p-value = 0.1124

Model 2 Packaging

BP = 6.264, df = 3, p-value = 0.09945

Model 3 Packaging

BP = 9.5161, df = 3, p-value = 0.02316

Autocorrelation of errors - Durbin Watson test

The null hypothesis in a Durbin Watson test is that the errors are not serially correlated. So a p-value smaller than 0.05 would indicate serial correlation (highlighted below), a common issue in longitudinal data. Serial correlation seems to be a serious issue in the packaging data. This would mean that the regressions in the packaging sample violate OLS assumptions. However, by use of clustered heteroskedasticity and autocorrelation standard errors, this should be corrected for and serial correlation should not lead to incorrect inference in these models.

Model 1 Plastic

DW = 1.8504, p-value = 0.2428

Model 2 Plastic

DW = 1.786, p-value = 0.1863

Model 3 Plastic

DW = 1.6097, p-value = 0.06129

Model 1 Packaging

DW = 1.3968, p-value = 0.001863

Model 2 Packaging

DW = 1.2071, p-value = 6.924e-05

Model 3 Packaging

DW = 0.84283, p-value = 3.549e-09

<u>Normality of errors</u>

Normality of errors is an essential OLS assumption. The normality of erros can be inspected by using qqplots shown below. Model 2 and 3 from the plastic sample and Model 3 from the packaging sample raise concerns and are further investigated using a Shapiro Wilk test. Only Model 3 from the packaging sample, violates normality, which may result in incorrect inferences in small samples.

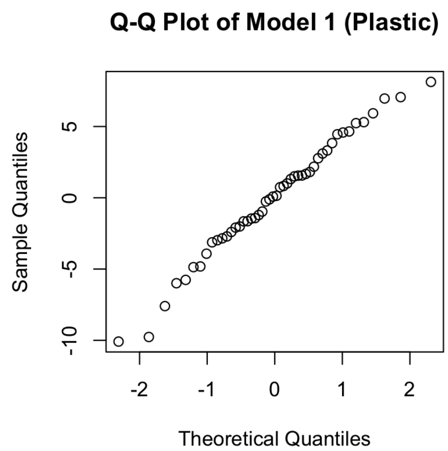

Figure A1: Quantile Quantile plot of Model 1 in the plastic sample

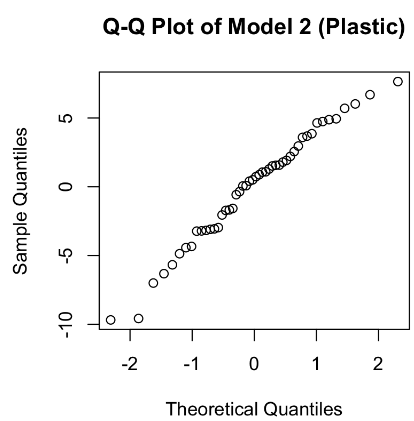

Figure A2: Quantile Quantile plot of Model 2 in the plastic sample

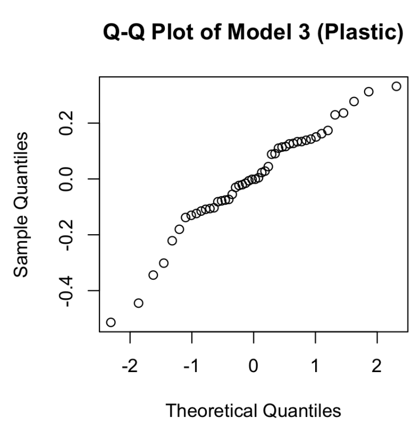

Figure A3: Quantile Quantile plot of Model 3 in the plastic sample

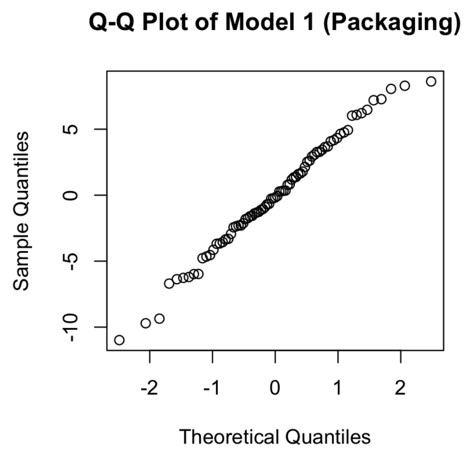

Figure A4: Quantile Quantile plot of Model 1 in the packaging sample

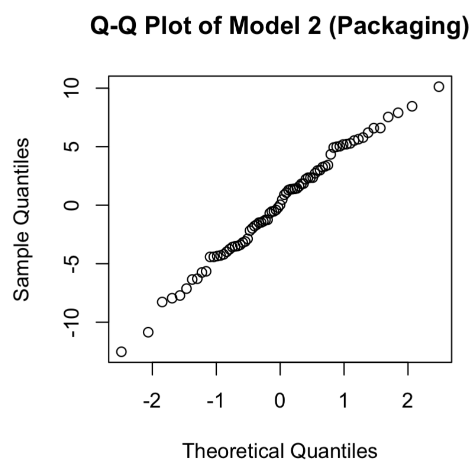

Figure A5: Quantile Quantile plot of Model 2 in the packaging sample

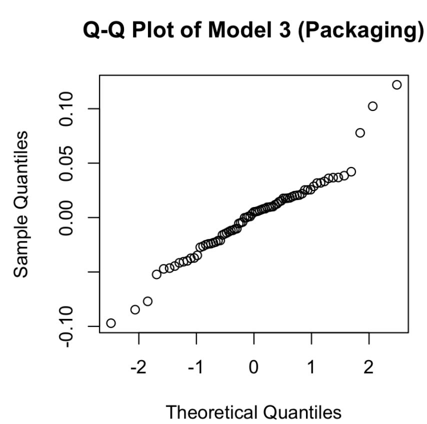

Figure A6: Quantile Quantile plot of Model 3 in the packaging sample

Multicollinearity - Variance inflation factor

Generally a VIF exceeding 10 is a sign of multicollinearity requiring correction, however a more conservative threshold of 5 would already warrant further investigation. Multicollinearity seems to be problematic in the Model 1 and 3 of the packaging sample with a vif > 5. However, since the same variables are used in the plastic sample, the multicollinearity seems to be an artifact of the data and not the model itself. Furthermore, multicollinearity is problematic since it reduces the precision of the estimators, however, statistical precision of the coefficients in Model 1 and 3 in the packaging sample are already statistically significant at th 5 % level, so the multicollinearity does not cause major inference problems in this case.

Model 1 Plastic

log(recycling_tonne)	GDP_index2015	log(env_tax_mioEUR)
2.517409	1.012889	2.514390

Model 2 Plastic

log(recycling_rate)	GDP_index2015	log(env_tax_mioEUR)
1.009822	1.001784	1.009669

Model 3 Plastic

log(recycling_tonne)	GDP_index2015	log(env_tax_mioEUR)
2.517409	1.012889	2.514390

Model 1 Packaging

log(recycling_tonne)	GDP_index2015	log(env_tax_mioEUR)
6.391703	1.023028	6.383237

Model 2 Packaging

log(recycling_rate)	GDP_index2015	log(env_tax_mioEUR)
1.127803	1.039468	1.144556

Model 3 Packaging

log(recycling_tonne)	GDP_index2015	log(env_tax_mioEUR)
6.391703	1.023028	6.383237

10.2. Sensitivity checks

Sensitivity check I: TWFE regression models with (heteroskedasticity) robust standard errors

The models are estimated without standard error clustering, because in samples with few cluster units such as this one, clustering can falsely lead to very small standard errors. However, in all models the robust standard errors are smaller than the cluster robust standard errors, indicating that cluster-robust standard errors are not biased downwards.

FE regression results (Plastic Sample) robust SE

	Dependent variable		
	Production	Production	Waste Gen. (Ln)
	(1)	(2)	(3)
Recycling (Ln)	1.732		0.355^{***}
	(2.533)		(0.127)
Recycling Rate (Ln)		4.311^{**}	
		(1.845)	
GDP	0.676^{***}	0.664^{***}	0.005
	(0.109)	(0.082)	(0.008)
environmental tax	0.734	0.929	-0.076
	(2.388)	(2.207)	(0.125)
Two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A1: Regression output from sensitivity check I, plastic sample

FE regression resuts (Packaging Sample) robust SE

	Dependent variable		
	Production	Production	Waste Gen. (Ln)
	(1)	(2)	(3)
Recycling (Ln)	26.904^{***}		0.256^{***}
	(6.244)		(0.070)
Recycling Rate (Ln)		17.406^{**}	
		(8.353)	
GDP	0.451^{***}	0.576^{***}	0.006^{***}
	(0.116)	(0.143)	(0.001)
environmental tax	1.676	1.178	-0.034
	(2.908)	(3.197)	(0.038)
Two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A2: Regression output from sensitivity check I, packaging sample

Sensitivity check II: TWFE regression models omitting covariates GDP and environmental taxes

Omitting the covariates from the models serves as a sensitivity check. The models in Table 5 and Table 6 have no covariates but only TWFE. In the plastic sample, the coefficient in Model 1 and 2 changes moderately in size. Notably, the p-value of Model 1 changes quite a lot when omitting covariates, however it would still not be significant at the 5% level. In Model 3 of the plastic sample the effect increases from 35% to 45%, when omitting covariates but p-values are similar. In the packaging sample, there are almost no changes in Model 1 and 3. Model 2 becomes statistically insignificant and the coefficient almost halves when omitting covariates. This suggests that the results are quite sensitive to model specification.

FE regression results (Plastic Sample) sensitivity check

	Dependent variable		
	Production	Production	Waste Gen. (Ln)
	(1)	(2)	(3)
Recycling (Ln)	9.559^{*}		0.433^{***}
	(5.100)		(0.097)
Recycling Rate (Ln)		10.744^{*}	
		(5.997)	
Two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A3: Regression output from sensitivity check II, plastic sample

FE regression results (Packaging Sample) sensitivity check

	Dependent variable		
	Production	Production	Waste Gen. (Ln)
	(1)	(2)	(3)
Recycling (Ln)	28.032^{***}		0.268^{**}
	(9.350)		(0.115)
Recycling Rate (Ln)		9.865	
		(13.273)	
Two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A4: Regression output from sensitivity check II, packaging sample

Sensitivity check III: Plastic sample regression models exluding observations from Turkey

Regression Output from FE regression models (Plastic Sample)

	Dependent variable		
	Production	Production	Waste Gen. (Ln).
	(1)	(2)	(3)
Recycling (Ln)	-4.629		0.247
	(3.684)		(0.296)
Recycling rate (Ln)		2.672	
		(2.665)	
GDP	0.433^{**}	0.468^{**}	0.003
	(0.173)	(0.226)	(0.012)
Environmental taxes	1.241	1.843	-0.069
	(2.742)	(3.665)	(0.058)
two-way FE	Yes	Yes	Yes
Model	Within	Within	Within
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A5: Regression output from sensitivity check III

10.3. Disclosure statement on the use of AI in this thesis

This thesis used AI tools, specifically the large language model chatGPT by OpenAI, for text editing and R-code generation.

Statement of Authorship

I hereby confirm and certify that this master thesis is my own work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and clearly designated. I confirm that the digital copy of the master thesis that I submitted on 28th April 2025 is identical to the printed version I submitted to the Examination Office on 29th April 2025.

DATE: 28th April 2025

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