The application of Machine Learning methods to the analysis of Business: A study of the implementation of the Circular Economy.

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Abstract

The thesis examines the application of different machine learning tools to the analysis of the implementation of circular economy in firms, to be able to better understand and solve the challenges these types of models pose for businesses, governments, and society. Particularly, this thesis studies how institutional pressures in different policy and business areas affect the development and promotion of circular economy models in firms, making special emphasis on the interaction of policies and the non-linearity and complementarity of the process. Hence, a combination of regression methods and machine learning (i.e., Artificial Neural Networks, K-means clusters, and Tree regression analysis) is used to analyse data from 870 companies in the European Union.

The research is structured around three papers, which analyse three different key dimensions of the institutional environment of the company when developing a circular economy. That is, the effect of the typology of the institutional pressure, the economic actors (i.e. consumers and producers), and two economic activities (i.e. innovation and financial support). For this, the thesis brings together several perspectives of institutional theory (i.e., institutional pressures, institutional entrepreneurship, and institutional complexity) with stakeholder theory and dynamic capabilities theory.

The combination of the three papers in the thesis shows that the application of machine learning tools has an important contribution in solving complex analytical questions involving multivariate non-linear relationships, complementarity, and interaction. Hence, an adequate combination of conventional regression analysis with machine learning can serve as an instrumental framework that helps increase the explanatory power of models suitable for the study of the circular economy. Moreover, the thesis contributes to the circular economy and institutional theory literature, particularly the extant literature on circular economy institutional pressures and policies, by better understanding and explaining their effect on circular economy models in firms, as well as providing interesting environmental policy and managerial implications.

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List of Publications

The following publication has resulted from the work contained in this thesis at the time of submission. It should be noted that there are two other papers currently under different stages of the publication process.

Arranz, C. F. A., Sena, V., & Kwong, C. (2022). Institutional pressures as drivers of circular economy in firms: A machine learning approach. *Journal of Cleaner Production*, 355, 131738. doi: 10.1016/j.jclepro.2022.131738

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Abbreviations

AENOR	Asociación Española de Normalización y Certificación (Spanish Standardization Association)
AFNOR	Association Française de Normalisation (French Standardization Association)
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
ANOVA	Analysis of Variance
ARIMA	Autoregressive Integrated Moving Average
B2B	Business to Business
B2C	Business to Customer
B2G	Business to Government
CE	Circular Economy
CEAP	Circular Economy Action Plan
CEBM	Circular Economy Business Model
CMB	Common Method Bias
CMV	Common Method Variance
DT	Decision Trees
EC	European Commission
ELTs	End-of-Life Tires
ELVs	End-of-Life Vehicles

EMAS	Eco-Management and Audit Scheme
EU	European Union
ISO	International Organisation for Standardisation
KMO	Kaiser-Meyer-Olkin test
ML	Machine Learning
MLP	Multilayer Perceptron
OLR	Ordinal Logistic Regression
PACE	Platform of Accelerating the Circular Economy
RBF	Radial Basis Function
RBV	Resource-Based View
RD	Royal Decree
SCP	Sustainable Consumption and Production
SDGs	Sustainable Development Goals
SEM	Structural Equations Models
SMEs	Small and Medium-Sized Enterprises
UN	United Nations
UNEP	United Nations Environment Programme
VIF	Variance Inflation Factor

Chapter 1: Introduction

1.1 Introduction

"Machine intelligence is the last invention that humanity will ever need to make."

(Bostrom, 2015)

In recent years, machine-learning research has erupted. Although there are several reasons for this explosion in research, the main two causes are: First, different communities of scholars in critical fields such as machine learning, computational learning theory, neural networks, and statistics have begun to work together and with other areas of research such as Medicine, Business and Economics, Engineering, etc. (Berry et al., 2020). Therefore, machine-learning approaches are now being implemented for novel problems, including knowledge discovery in databases, language processing, robot control, and combinatorial optimisation, as well as more traditional problems such as speech/face recognition, data analysis, and learning of complex stochastic models, among others. Second, the machine learning emerging phenomenon comes in hand with the increasingly central role that data has taken in the last few years in terms of its growing volumes, variety, and velocity (Deepa et al., 2022). Scholars are trying to exploit the large volumes of data and data resources possessed by businesses, governments, and societies as a whole, to analyse them and generate value of a broader nature via the utilisation of machine learning approaches (Yui, 2012). Machine learning approaches are being utilised in a wide range of applications, including predicting consumer choices, predicting the likelihood of a medical condition or the effect of public policy, analysing social networks and social media, and better-managing traffic networks.

As noted by Sandhu (2018), machine learning is a subset of artificial intelligence that employs computerised methods to address problems based on historical data and information without requiring unnecessarily changes in the core process. Unlike artificial intelligence applications, machine learning involves learning hidden patterns within the data (data mining) and then utilising the patterns to categorise or forecast an event linked to the problem (Alpaydın, 2014)[1]. In short,

[1] It is worth noting that all machine-learning approaches are artificial intelligence techniques, however, not all artificial intelligence techniques qualify as machine learning approaches.

machine-learning algorithms are integrated into machines and data streams to extract knowledge and information and feed it into the system for quicker and more efficient process management (Libbrecht and Noble, 2015).

Regarding the study of business, most of the problems of companies are based on decision-making[2] (Kunc and Morecroft, 2010; Putka et al., 2018). These decisions, most of the time, involve the interaction of various variables through a dependency relationship. These types of business problems are solved via traditional methods of regression, looking for the relationship between dependent and independent variables (Hair, 2006; Minbashian et al., 2010). Thus, linear regression, logistic regression (Logit, Probit, Tobit), etc., are conventionally used, supplemented with methods of Structural Equations Models (SEM). Each method assumes its own restrictions such as collinearity, endogeneity, etc. (Hair, 2006; Asteriou and Hall, 2015; Wooldridge, 2015). Moreover, in many cases, the decisions of the companies involve non-linearity, not a direct causality, and multi-interactions (for example, Minbashian et al., 2010; Verlinden et al., 2008). All of this means that the explanatory capacity of the models is reduced by around *20% to 40% of the explained variance* (Hair, 2006; Asteriou and Hall, 2015). If these are combined with several techniques, such as factor analysis and regression analysis, the explanatory capacity of models *is less than 10%* (Hair, 2006; Asteriour and Hall, 2015). This leads to the fact that only qualitative hypotheses are considered, analysing the sign of the relationship. More problematic is the explanatory ability of the model, when faced with hierarchical problems, in which the relative importance of two variables in their impact on the dependent variable is analysed (example, Poppo and Zenger, 2002).

From the perspective of statistical methods, several problems arise with the use of conventional regression analysis (Hair, 2006; Asteriou and Hall, 2015; Wooldridge, 2015):

- On the one hand, regression models allow limited use of models of variable relationships, from a linear relationship, or a tangential or sigmoidal, there are cases of more frequent relationships. Following Somers and Casal (2009), Verlinden et al. (2008), and Wang (2007), this involves serious problems in the case of non-linear relationships, such as optimisations or convex/concave functions.

[2] Other types of problems are solved through classification methods (ANOVA and Cluster) or through temporal analysis methods (e.g. ARIMA) (Hair, 2006).

- On the other hand, conventional methods do not work well when the relationship is not direct (Cavalieri et al., 2004; Zacharis, 2016), or when there is a phenomenon of persistence (Triguero and Córcoles, 2013). In this case, the adoption of non-linear forms of relationships tends to be the most appropriate solution.
- When variables are correlated, regression methods do not work well, which involves combining various methods (Zacharis, 2016).
- Economic systems and business models usually involve a large amount of data and many variables, making machine learning the best approach (Russell et al., 2018). Moreover, machine learning responds to situations where there is a lack of data, or in a variety of formats, as well as when there is a lack of definition of relationship models between variables. Therefore, these techniques will allow researchers to solve previous limitations of classical statistical models, providing a higher level of explanatory variance.
- Furthermore, the question of quantifying and prioritising how the variables affect the business models has not been resolved, which is an important issue from the perspective of business decisions and the development of environmental policies (Mazzanti et al., 2021; Elmagrhi et al., 2019), considering the limited resources and the need to identify the critical factors in the development of economic and business models.
- Finally, in business management, many dummy variables are used (sometimes derived from the brevity required by the questionnaire), which forces the transformation of these variables into continuous, combining several methods with the consequent loss of information (Hardy, 1993; Ciurana et al., 2008).

Due to the nature of machine-learning algorithms, which consist of the study of approaches that improve their performance automatically as they gain experience, all the reasons listed above make machine-learning methods most suitable to solve these problems. More specifically, Artificial Neural Networks (Multilayer Perceptron and Radial Basis Function networks), Tree Decisions methods, Bayesian Optimisation, K-means clustering, etc., exhibit an important ability to solve classification, regression, and forecasting problems (Blum and Langley, 1997; Mehrotra et al., 1997; Haykin, 2009; Shalev-Shwartz and Ben-David, 2014; Russell and Norvig, 2016; Tonidandel et al., 2018). Considering that the ultimate goal of business research is to look for a causal effect or impact between variables, as well as the understanding of the decision in the company. These methods provide an adequate response to the problems, obtaining errors not comparable to conventional methods and less than 10% (as indicated by Zacharis, 2016; Minbashian et al., 2010).

This is particularly relevant for businesses that aim to become more sustainable or to achieve the UN sustainable development goals (SDGs). Ecology problems and relationships are the results of multivariate and non-linear conditions (Gevrey et al., 2006). Therefore, the phenomena are rarely due to a simple cause or a unique perturbation. Hence, machine learning with its good pattern recognition and modelling of multivariate non-linear relationships serves as a good tool to study these effects. The thesis examines the application of different machine learning tools to the analysis of the implementation of the circular economy in firms, to be able to better understand and solve the challenges these types of models pose for businesses, governments, and society as a whole. Particularly, this thesis studies how institutional pressures in different policy and business areas affect the development and promotion of circular economy models in firms, making special emphasis on the interaction of policies and the non-linearity and complementarity of the process. Hence, this thesis combines regression methods with Machine learning (i.e., Artificial Neural Networks, K-means clusters, and Tree regression analysis) to analyse data from 870 companies in the European Union.

Although quite some research has been carried out in recent years on different aspects of the circular economy (see, for example, Marrucci et al., 2019; Kanda et al., 2021). However, only around 11.55% of the academic literature about circular economy investigates how to transition toward a circular economy from a policy perspective at the national and international level (Millar et al., 2019; Merli et al., 2018; Bigano et al., 2016; McDowall et al., 2017). This is quite problematic, as already argued by Huamao and Fengqi (2007), policy is a fundamental driver in realising a circular economy, and government bodies must play the role of facilitator with regard to overcoming the key lock-ins in the current economic and industrial systems (Genovese et al., 2017). Despite the importance of the research examining the relationship between institutional pressures and the implementation of circular economy models in the firm, little is known about how institutional pressures operate (Alonso-Almeida et al., 2021). Moreover, different authors have concluded that the scarce research has focused more on qualitative research and has generated contradictory results (Delmas and Toffel, 2004; Ahrens and Ferry, 2018; Zapata and Zapata, 2018; Wang et al., 2019). Therefore, Ferasso et al. (2020) have highlighted the necessity for more academic research in this line, and Ahrens and Ferry (2018) and Zapata and Zapata (2018) have emphasised the importance of empirically analysing how institutional actors drive these types of changes in firms and their effectiveness. In this regard, as recommended by Milios (2018), it should be investigated not only if such policies affect, but also how they affect, to understand which variables are more significant and if there are synergistic effects between them.

To do this, the research is structured around three papers, which analyse three different critical dimensions of the institutional environment of the company that have received little attention from scholars, have generated contradictory results, and are essential for the implementation of circular economy in firms. These are: (i) the effect of the typology of the institutional pressure, (ii) the effect on economic actors (i.e. consumers and producers), and the effect of two key economic activities (i.e. innovation and financial support). For this, the thesis brings together several perspectives of institutional theory (i.e., institutional pressures, institutional entrepreneurship, and institutional complexity) with stakeholder theory and dynamic capabilities theory. Hence, the first paper (Chapter 2) aims to clarify and settle the long-lasting debate in institutional theory on the effect of institutional pressures, arguing that the discrepancies are due to a methodological problem since previous research has analysed the relationship between institutional pressures without considering the interaction between them and the non-linearity of the processes. Therefore, deviating from previous studies, the thesis uses institutional entrepreneurship as a theoretical framework and considers two different typologies of institutional pressures (coercive and normative) to examine the effect of each pressure and their interactions on the development of circular economy in firms. Machine learning together with regression analysis are used to allow to examine this interaction effect. The second paper (Chapter 3) focuses on the consumption side of the circular economy, which has received less attention from scholars and policymakers. This paper investigates the effect of circular economy consumption policies on circular economy business models in firms, but also examines the interplay this type of policies have with circular economy production policies, to have a broader picture of the circular economy policy framework, and the relevance of each type of policy on firms. This is achieved by borrowing from stakeholder theory to relax the “rationality of consumers” assumptions used by previous research, and combining it with institutional theory. Moreover, the use of machine learning allows disentangling the effect of each type of policy to provide a deeper understanding of the effect of circular economy consumption and production policies. Lastly, the third paper (Chapter 4) focuses on examining two key areas for the circular economy, that is, innovation and financial support, through the combination of institutional complexity theory and dynamic capabilities. This paper not only analyses the effect of policies for innovation promotion and financial support, but utilising different machine learning methods, it investigates the intensity, diversity, and joint action effect of these policies on the development of circular economy in firms.

The combination of the three papers in this thesis shows that the application of machine learning tools has an important contribution in solving complex analytical questions involving multivariate non-linear relationships, complementarity, and interaction. Hence, an adequate combination of conventional regression analysis methods with machine learning can serve as an instrumental framework that helps increase the explanatory power of models suitable for the study of the circular economy. Moreover, the thesis contributes to the circular economy and institutional theory literature, particularly the extant literature on circular economy institutional pressures and policies, by better understanding and explaining their effect on circular economy models in firms, as well as providing interesting environmental policy and managerial implications.

The introduction chapter is structured as follows. First, section 1.2 introduces the conceptual framework of the thesis, that is, circular economy, introducing the concept, describing the current state of the art of the circular economy, and explaining the main challenges. Second, section 1.3 focuses on the theoretical framework, explaining the different theoretical perspectives employed. Furthermore, section 1.4 describes the methodological and instrumental framework of the thesis, making particular emphasis on the specific machine learning methods used. Then, section 1.5 presents the database employed in the thesis. Finally, section 1.6 describes the structure of the thesis, highlighting the objectives of the research and the three papers developed.

1.2 Conceptual Framework: Circular Economy

"Infinite growth of material consumption in a finite world is an impossibility"

(Schumacher, 1973, p.88)

Addressing the most pressing environmental concerns for society will necessarily involve radical adjustments to global production and consumption of energy, water, and natural resources. In this context, the circular economy is attracting increasing interest from government, business, society, and academia. Following Kirchherr et al. (2017a), the Circular Economy (CE) "is an economic system that replaces the 'end-of-life' concept with reducing, alternatively reusing, recycling, and recovering materials in production/distribution and consumption processes. It operates at the micro-level (products, companies, consumers), meso-level (eco-industrial parks), and macro-level (city, region, nation, and beyond), to accomplish sustainable development, thus simultaneously creating environmental quality, economic prosperity, and social equity, to the benefit of current and future generations. It is enabled by novel business models and responsible consumers." (p. 229).

Therefore, the CE is conceptualised as a business model for closed-loop production and consumption systems, where the management of waste (that is, the final phase in the economic cycle) constitutes a valuable resource (Bocken et al., 2017; Jabbour et al., 2019). Compared to the traditional linear economic model, whose production model consists of "take, make, discard", the CE model builds an economic system that is more resilient and adaptable to the shortage of raw materials and energy resources (Zucchella and Previtali, 2019; Clube and Tennant, 2020; Ferasso et al., 2020). The economic system proposed by CE models is one based on recycling, remanufacturing, reusing resources, and product maintenance, which reduces the demand for new raw materials and contributes to the reduction of the ecological deficit (Boons and Lüdeke-Freund, 2013; Zucchella and Previtali, 2019). Hence, according to CE theory, this reduction of the negative environmental impacts, as a result of the most efficient use of natural resources, can be achieved without compromising growth and prosperity, and at the same time, striking a more beneficial balance for society, the environment, and the economy (Kiefer et al., 2019; Geissdoerfer et al., 2018; Manninen et al., 2018). The CE can be defined as a cyclic system that seeks to eliminate waste by repurposing products, which have reached the end of their useful lives, into resources for new goods (Stahel, 2016). Therefore, closing material loops in industrial ecosystems, which ensures the continued use of resources, becomes imperative in CE settings (Geissdoerfer et al., 2017).

Thus, the CE model strives to achieve production and consumption sustainability by implementing the aforementioned closed cycles (closed-loops), with activities that promote resource efficiency and value chains based on more efficient uses of waste and by-products generated in the production processes (Bocken et al., 2014; Hazen et al., 2017; Kirchherr et al., 2018; Perey et al., 2018; van Capelleveen et al., 2020). This process of closing loops is shown in the figure below.

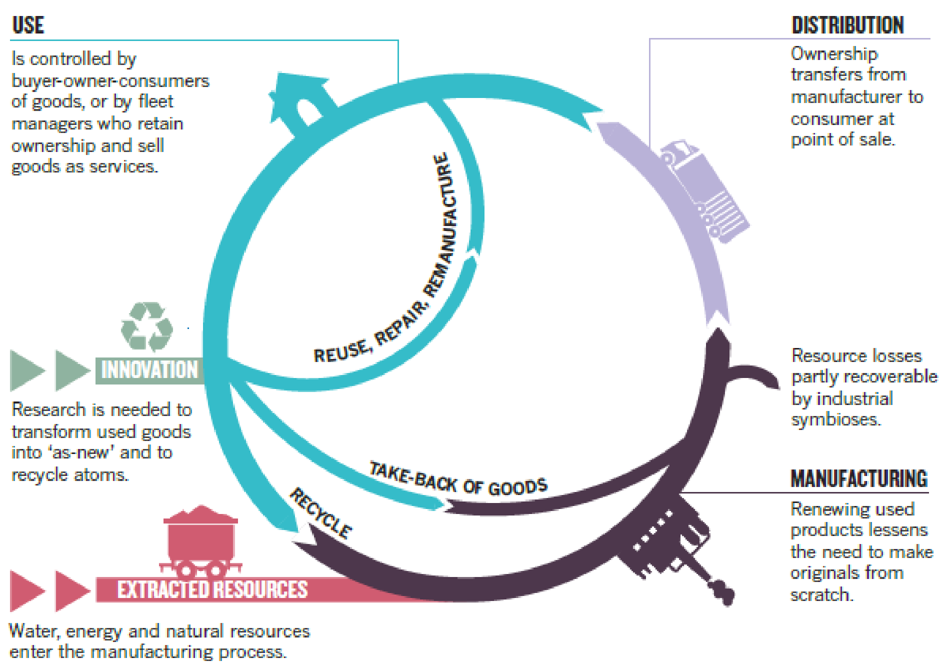


Figure 1.1 The Circular Economy Model (Stahel, 2016)

The growing relevance of CE models is reflected in the increased attention being paid to the implementation of CE in businesses and organisations by institutions, policy-makers, and public administrations (Bocken et al., 2016; Martins, 2018; Katz-Gerro and López Sintas, 2019; Millar et al., 2019). For instance, the European Circular Economy Action Plan (European Commission, 2015; Lieder and Rashid, 2016), the initiatives by major companies, such as Google or Renault (Esposito et al., 2016; Bocken et al., 2017), or the significant growth in the number of scholarly publications and journals covering this issue (Geissdoerfer et al., 2017). This growing relevance is also due to the fact that switching from a linear economy model to a circular one is widely recognised for bringing environmental, social, and financial benefits (Lewandowski, 2016). The use and reuse of resources, as well as the consequent decreased total resource inputs, energy, emissions, and waste leaks, could lessen the detrimental effects on the environment while maintaining prosperity and growth (Geissdoerfer et al., 2018; Manninen et al., 2018). However, implementing CE ideas frequently necessitates new visions, strategies, and policies, as well as a profound rethinking of product conceptions, service offerings, and channels for long-term solutions (Bocken et al., 2016; Lewandowski, 2016).

The development of CE business models implies two important challenges (Linder and Williander, 2017; Kirchherr, et al., 2018; Bressanelli et al., 2019; Figge, et al., 2021). The first challenge refers to the complexity of the design and creation of products congruent with the CE model. CE products can be viewed as eco-innovations (Scarpellini et al., 2020; Marzucchi and Montresor, 2017), which implies an associated cost (Boggia et al., 2018; Choi et al., 2016; Dangelico, 2016; Bönte and Dienes, 2013), and managerial complexity for firms. Bönte, and Dienes (2013), and De Marchi (2012), suggest that when there are no incentives to invest in eco-innovation, the social cost of pollution is reduced but the firms' private costs increase. Additionally, the literature on product innovation identifies a set of challenges and barriers that firms must confront, i.e., market complexity, the uncertainty of the process, and the management of organisational resources for innovation. Furthermore, because environmental knowledge is a public good, first innovators are easily imitable. Thus, followers do not incur the high cost and risks that this involves.

The second challenge stems from the closed supply chains, which are a pillar of the CE model (Lüdeke-Freund et al., 2018; Kirchherr, et al., 2018; Perey et al., 2018; van Capelleveen et al., 2020). The CE model encompasses not only all tasks involved in the production, distribution, and usage of products, but also the maintenance, reuse, recovery, and recycling. In other words, it embraces producer organisations, as well as users, intending to facilitate the development of CE-compatible products. Lewandowski (2016) noted the importance of collaboration and cooperation among organisations for the application of closed-loop systems. However, partnership-building is not without difficulties (Arranz et al., 2016, 2019). Finding the right partner, coordinating tasks, and preventing and resolving conflicts may inhibit organisations' interest in implementing CE models through cooperation.

1.3 Theoretical Framework

This research aims to apply tools of machine learning for solving CE problems and questions in the analysis of business, complementing the results of classical econometric models. More specifically, the papers developed in the thesis focus on analysing how the various institutions and administrations promote the development of CE in organisations. Thus, the prominent role that institutions and governments have undertaken in the introduction of circular economy business models (CEBMs) reflects the growing importance of CE initiatives in firms (Bocken et al., 2016; Lewandowski, 2016; Manninen et al., 2018 Katz-Gerro and López Sintas, 2019). In fact, as highlighted by Ariti et al. (2019), Levänen et al. (2018), and Kosow et al. (2022), governments and institutions develop a portfolio of policies, both aimed at the production system and consumption. However, while the literature has made important contributions in identifying factors that have influenced the development of CE, there are limitations in understanding how these factors act in promoting its development. The main limitation arises from the fact that previous research has analysed the relationship between drivers and CE without considering that this process is dynamic and complex[3], including the interaction between drivers in the development of CE. This complexity of interaction, following Almeida et al. (2020) is produced by the very diversity of institutions and organisations that promote the development of CE, and their need to coordinate. For example, the European Union, as a supranational institution, needs to coordinate with national institutions for the implementation of CE promotion policies, in the complexity of interactions at various levels. Moreover, in line with Greenwood et al. (2011), which highlights the institutional complexity, pointing out the need to understand the interactions and logistics of the various policies in their performance in the development of CE. Finally, Milios (2018) pointed out that little research exists on the use of policy to provide financial support or to enable systemic circular innovation to occur. As recommended by Milios (2018), it should be investigated not only if such policies affect, but how they affect, to understand which variables are more significant and if there are synergistic effects between them. In this context, Su et al. (2013) also identified the shortage of advanced technologies, combined with weak economic incentives, as a key barrier to

[3] Following Sterman (2000) a complex process is characterised, among other things, by constant changes, non-linearity, and self-organization. From a structural point of view, there are two characteristics of complex processes: the multiplicity of interactions and the diversity of agents that intervene in it (Arranz and Fernandez de Arroyabe, 2010).

realising CE goals. Therefore this, together with the lack of quantitative studies (Alonso-Almeida et al., 2021), has meant that results on the CE process have not been conclusive in determining factors and explaining how they interact (Arranz et al., 2021; Jové-Llopis and Segarra-Blasco, 2018; Horbach et al., 2016).

Against this background, institutional theory provides a natural and proper perspective to analyse the adoption of CE in firms (Phan and Baird, 2015; Zeng et al., 2017). Institutional theory (DiMaggio and Powell, 1983; Berrone et al., 2013) emphasises the social factors that affect organisations' actions. From this perspective, organisations seek approval from their environment and, therefore, are susceptible to social influence. Wang et al. (2019) conclude that organisational practices and behaviours are affected by the institutional and the external environment, that is, by values, norms, laws, cultures, social expectations, and common cognitions. This implies that organisations are inclined to comply with the institutional and external environment by means of changing their behaviours and structures, and implementing dominant practices, to gain and retain legitimacy independently of business outcomes (DiMaggio and Powell, 1983; Scott, 2005). These aspects have made this theory especially appealing to environmental scholars because ecological investments frequently cannot be justified from a financial point of view (Wahba, 2010; Berrone et al., 2013; Gallego-Alvarez et al., 2017; Liao, 2018; Wang et al., 2019; Gao et al., 2019; Lee and Raschke, 2020).

Institutional theory represents a well-established large body of literature, rich with concepts and models to explain the influence of institutions on organisations (Greenwood et al., 2011; Stål, 2015; North, 1991). The literature on institutional theory ranges from institutional logics (see, for example, Thornton and Ocasio, 2008; or Stål, 2015), institutional complexity (Greenwood et al., 2011; Smets and Jarzabkowski, 2013), institutional pressures (DiMaggio and Powell, 1983; Teo et al., 2003; Scott, 2005), and institutional entrepreneurship (Alonso-Almeida et al., 2021; De Jesús and Mendoça, 2018; Elliot, 2016; Battilana et al., 2009). Although all the papers that conform this thesis use institutional theory as the main theoretical perspective, each paper is then contextualised within one of these aspects of the general theory to be able to analyse the different research questions adequately. Hence, as shown in Table 1.1, institutional entrepreneurship, institutional pressures, and institutional complexity approaches are employed in the thesis.

More specifically, we can describe each of them as follows. The approach of Institutional Entrepreneurship (IE), introduced by DiMaggio (1988), is the process that contributes to radical changes in the institutional environment where this process takes place, including new organisational structures, new business models, new operating systems and procedures, among other types of innovations (Alonso-Almeida et al., 2021; Elliot, 2016; Covaleski et al., 2013; Battilana et al., 2009; DiMaggio, 1988). Battilana et al. (2009), consider that an organisation to be considered an institutional entrepreneur must meet the following requirements: first, promote the initiative of a divergent change and, second, participate actively in the transformation. Thus, an institutional entrepreneur is an actor who leverages resources to create or transform an existing institutional context by introducing new ideas (Elliot, 2016) favouring change (Covaleski et al., 2013) and introducing new concepts and innovations to change a certain situation (Alonso-Almeida et al., 2021). Thus, Dorado (2005) asserted that institutional entrepreneurs could be powerful actors with sufficient resources, such as governments, supranational organisations, corporations and other similar agencies, to promote change.

In line with the literature, we assume that institutional pressures are drivers in the CE in firms (Alonso-Almeida et al., 2020; De Jesus et al., 2019; Scott, 2005; Domenech and Bahn-Walkowiak, 2019; Teo et al., 2003). Researchers in the environmental field have categorised institutional pressures from various perspectives. The first perspective emphasises the final objective of institutional pressures, classifying them in actions that affect company processes to develop sustainable environmental practices for both the process and the product (Fischer and Pascucci, 2017); or directed to the market, to raise awareness of the consumption of green products (Gallego-Alvarez, 2017). Other approaches have addressed the very nature of the institutional pressures in terms of their implication for companies: from regulatory and coercive pressures, to merely informative (DiMaggio and Powell, 1983). One last dimension approached the study of the institutional pressures, considering these as promoting the development of environmental practices, focusing specifically on the acquisition of resources and capacities in companies (Gao et al, 2019; Liao, 2018).

The final institutional theory approach employed for this thesis is institutional complexity, which occurs when businesses are confronted with contradictory institutional pressures or policies from governments and institutions (Greenwood et al., 2011; Thornton, 2004). Organisations are frequently confronted with different pressures that may, or may not, be mutually incompatible

(Friedland and Alford, 2012; Kraatz and Block, 2008). When the prescriptions and proscriptions of multiple pressures are contradictory, or appear to be so, they unavoidably create obstacles and conflicts for organisations that are exposed to them. Therefore, institutional complexity arises when multiple institutional pressures are present and can interact and compete for influence in all socioeconomic domains of the organisation (Nigam and Ocasio, 2010). Moreover, institutional pressures are frequently in conflict, which means that their distinct systems of meaning and normative understandings embedded in company practices, create contradictory expectations for companies to adopt and create capabilities to cope with the changing environment (Greenwood et al., 2017). Institutional complexity emerges, unravels, and re-forms over time, resulting in new conditions to which organisations must adapt. For a review of the institutional theory literature and its various approaches, see Table 1.1

Moreover, Table 1.1 depicts stakeholder and dynamic capabilities theory, which are other additional perspectives employed as theoretical frameworks to complement institutional theory[4].

[4] For more information on these theories, the respective chapters, where they are employed, contain an in detail description of them. That is, Chapter 3 for stakeholder theory and Chapter 4 for dynamic capabilities theory.

Table 1.1. Theoretical perspectives employed in the thesis

Category	Theme	Description	References
Institutional Theory	Institutional Pressures	Social factors (such as values, norms, laws, cultures, social expectations, and common cognitions) that affect organisations' actions, behaviours, and structures.	DiMaggio and Powell, 1983 Teo et al., 2003 Scott, 2005 Liao, 2018 Wei et al., 2020 Daddi et al., 2020
	Institutional Entrepreneurship	Create or transform an existing institutional context by introducing new ideas and favouring change.	Alonso-Almeida et al., 2021 Dorado, 2005 De Jesus and Mendoça, 2018 Elliot, 2016 Covaleski et al., 2013 Battilana et al., 2009 Brown et al., 2019 De Jesús et al., 2019 Rodríguez-Antón et al., 2019 Boons et al., 2013
	Institutional Logics and Institutional Complexity	Ideas underpinning practices prevailing in the industry. Confronting incompatible prescriptions from multiple institutional logics.	Stål, 2015 Thornton and Occasio, 2008 Greenwood et al., 2011 Smets and Jarzabkowski, 2013 Pache and Santos, 2010 Kraatz and Block, 2008 Battilana and Dorado, 2010 Greenwood et al., 2017 Tracey et al., 2011 Friedland and Alford, 2012
Stakeholder Theory	Stakeholder Theory	Stakeholder pressure exercised by customers, regulators, suppliers, and competitors is a driver of more sustainable societies.	Delmas and Toffel, 2004 Horbach, 2008 Sarkis et al., 2010 Rennings and Rammer, 2011 Lin et al., 2014
Dynamic Capabilities Theory	Dynamic Capabilities	Firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments.	Faridian and Neubaum, 2020 Fainshmidt et al., 2016 Teece, 2014 Bitencourt et al., 2020 Barreto, 2010 Suddaby et al., 2020

This thesis is designed around three papers that examine the institutional environment of the company from three key perspectives: (i) the typology of the institutional pressure, (ii) the economic actors (i.e. consumers and producers), and (iii) the economic activities (i.e. innovation and financial support). These three dimensions are represented in graphically in Figure 1.2.

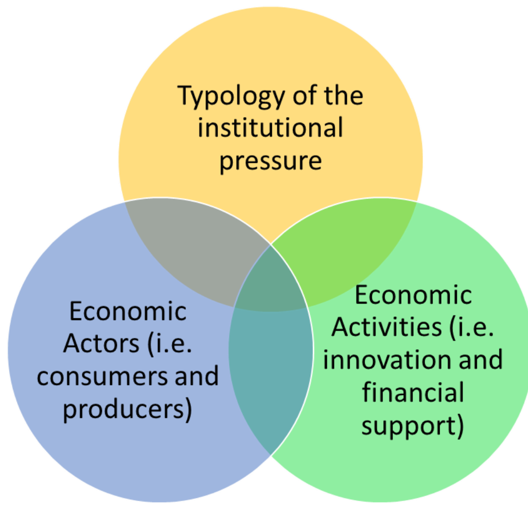


Figure 1.2. Institutional Theory dimensions analysed

In order to examine each different dimension, each paper employs different aspects of institutional theory (as previously mentioned) and other theories. These are explained in more detail below.

The first paper (which corresponds to Chapter 2) is titled “Institutional Pressures as Drivers of Circular Economy in Firms: A Machine Learning Approach”. This paper investigates how institutional pressures affect the development of CE in firms. Using Institutional Entrepreneurship as a theoretical framework, this paper considers two different typologies of institutional pressures (coercive and normative) to examine the effect of each pressure and their interactions on the development of CE. Seeking to clarify the debate on the effect of institutional pressures, we consider that the main limitation arises from the fact that previous research has analysed the relationship between institutional pressures without considering the interaction between them and the non-linearity of the processes. Deviating from previous papers, our analysis combines regression methods with Artificial Neural Networks. We find that while coercive pressure has a compulsory effect on the development of CE, normative pressures have an ambiguous effect by themselves. Normative pressures only have a clear positive effect on the development of CE in firms when interacting with coercive pressures. Moreover, our paper shows that the application of machine learning tools has an important contribution in solving interaction problems. From the perspective of environmental policy, this means that a comprehensive policy is required, which implies the coexistence or interaction of the three types of pressures.

The second paper (which corresponds to Chapter 3) titled “The effect of consumption and production policies on circular economy business models: A Machine Learning Approach” focuses more on the consumption side of CE. This paper investigates the effect of CE consumption policies on CEBMs in firms, but also examines the interplay this type of policies have with CE production policies, to have a broader picture of the circular economy policy framework, and the relevance of each type of policy on firms. While previous studies assume rational and passive consumer behaviour, this paper borrows from stakeholder theory arguing that consumers have a proactive attitude towards the consumption of environmentally friendly products. Moreover, we use institutional theory as an analytical framework, for modelling the effects of a particular policy framework on the CEBM. Our analysis combines classical econometric methods with machine learning approaches (i.e. Artificial Neural Networks and K-means clusters). The results show that CE policies aimed at promoting consumption have a direct and positive effect on CEBMs. This paper also confirms that a wide portfolio of CE policies on production and consumption has a greater effect on the development of CEBMs, due to the complementarity of CE consumption and production policies. Moreover, we show that in interaction with CE production policies, CE policies on consumption have an even greater effect on CEBMs in firms than would have been anticipated.

The third paper (which corresponds to Chapter 4) titled “Towards circular economy in firms: The role of innovation and financial support policies” focuses on innovation and financial support as impulse policies. The implementation of the CE in firms will require new visions, strategies, and policies. However, little research focuses on policies for the transition towards a CE, specifically, on policies to provide financial support or to enable systemic circular innovation, which has yielded discrepant and inconclusive results. This paper examines the effect of institutional actions, in the form of policies to promote innovation and financial support, on companies developing CE. As a theoretical framework, this paper combines the dynamic capability approach with institutional pressure theories, particularly, institutional complexity. Our methodology jointly employs machine learning (i.e., Regression trees and Artificial Neural Networks) with classical econometric methods, on data from the EU. The results, firstly, show that the intensity of institutional actions, in the form of innovation promotion and financial support policies, has a U-inversed shape effect, indicating that the development of CE improves as these institutional actions increase but that there is a threshold point. Any increase in these actions beyond the threshold point will deteriorate CE development in firms. Secondly, a greater diversity of the portfolio of both innovation and financial support policies has a positive effect on CE development. Finally, the joint action of innovation promotion with financial support policies generates synergistic effects, but not complementarity, on the development of CE in companies, greater than if financial support policies acted alone.

1.4 Methodological and Instrumental Framework

As indicated before, the thesis utilises Machine Learning (ML) techniques as the methodological and instrumental framework. ML is framed as a subfield of artificial intelligence, which is characterised as the capability of a machine to mimic intelligent human behaviour (Alpaydin, 2021; Mohri et al., 2018; Jordan and Mitchel, 2015). Hence, machine-learning algorithms are computational methods utilised to learn or uncover hidden patterns rooted in the data, which allows a machine to learn automatically from previous data without having to programme it explicitly. Moreover, machine learning encompasses a set of computational algorithms that by learning from existing data can perform pattern identification, classification, and prediction (Alpaydin, 2021; Sammut and Webb, 2011).

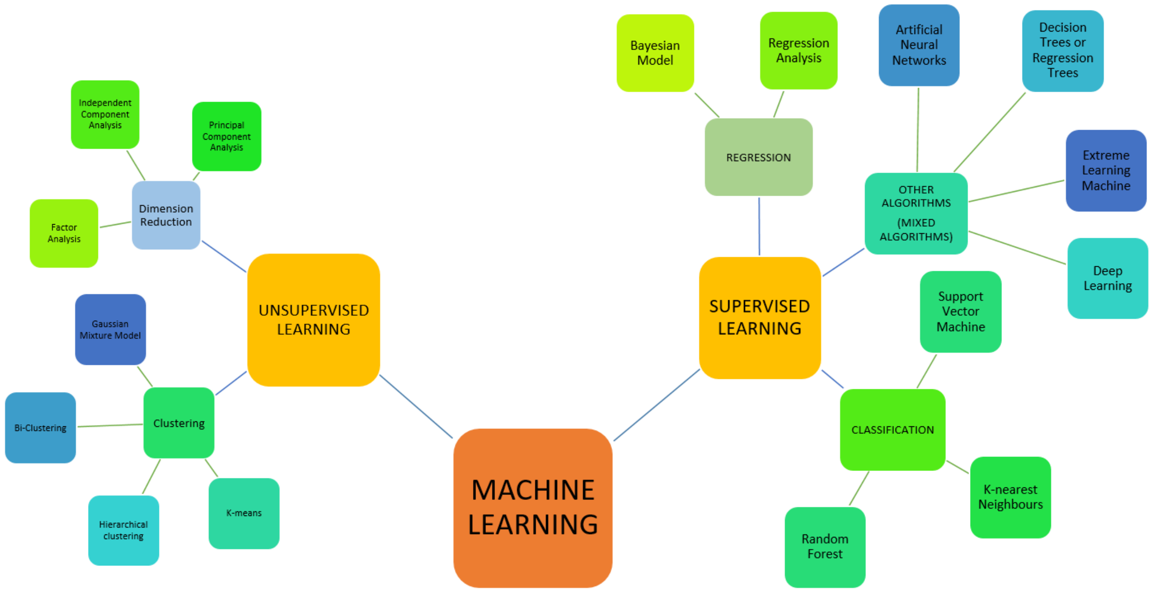


Figure 1.3. Main machine learning algorithms (based on Gao et al., 2020).

Figure 1.3 shows the classification of the main Machine Learning methods based on the characteristics and objectives of the algorithms. This thesis employs techniques from both branches of ML[5], that is, supervised and unsupervised learning algorithms. The primary difference between these two central types of ML algorithms is the presence of labels in the subset of the data used for training the algorithm. As Kotsiantis (2007) noted, supervised machine learning not only contains input characteristics, but also predetermined output characteristics. The supervised algorithms seek to classify and predict the predetermined attribute, as well as its accuracies and misclassification, along with other performance indicators. Once the algorithm achieves an adequate performance level, the learning process of the algorithm comes to an end (Berry, 2020). Technically, supervised algorithms, according to Libbrecht and Noble (2015), conduct analytical computations by employing training data first, and then generating contingent functions to map new instances of the characteristics. These algorithms need the pre-specification of maximum values for the intended output and performance levels (Libbrecht and Noble, 2015; Berry, 2020).

[5] It is worth noting that some scholars sometimes categorise other machine learning methods as reinforcement learning, since such techniques learn data and perform pattern recognition in order to react to an environment (Alpaydın, 2014). However, most of the literature recognise supervised and unsupervised machine learning algorithms as the two main categories within the methods available.

Moreover, supervised learning algorithms encompass a large number of algorithms or techniques that can be further classified into regression, classification, and mixed algorithms (Kotsiantis, 2007; Alloghani, 2020; Gao et al., 2020; Alpaydın, 2021). This is shown in Figure 1.3.

Unsupervised learning algorithms, on the other hand, employ pattern recognition without the use of predetermined characteristics. This means that all the variables employed for the analysis are utilised as inputs. Therefore, unsupervised learning methods are appropriate for clustering and association mining. Moreover, these learning methods can find groups or clusters within unlabelled data and then apply labels to each data value (Dougherty et al., 1995; Marshland, 2015). In fact, as noted by Hofmann (2001), this property of unsupervised learning approaches allows for generating labels, which can be used to conduct supervised learning. Although, on their own, unsupervised learning algorithms are useful for identifying rules and patterns that appropriately capture the relationship between characteristics. These types of methods can be further classified into clustering and dimension reduction algorithms, as shown in Figure 1.3 (Gao et al., 2020).

Thus, this thesis employs both supervised (i.e. decision trees and Artificial Neural Networks) and unsupervised (i.e. K-means clustering) machine learning methods. These methods are explained below.

1.4.1 Decision Trees (DT)

As a machine learning method, decision trees or regression trees are non-parametric supervised learning approaches utilised for regression and classification. This method aims to learn simple decision rules derived from data characteristics to build a model that predicts values of target variables with comparable class labels. This could include techniques such as stratifying the space of the observation from the training set into a smaller number of areas (known as terminal nodes or leaves). In this approach, the mean or mode of the training data in that node is used to categorise a new observation corresponding to a terminal node (James et al., 2017; Song and Ying, 2015).

Explaining decision trees in more detail, we can denote the 'p' possible values of the predictors in the training data as a set as ($x1,2,\ldots,xp$), where the structural elements are divided into non-overlapping number of K leaves or regions ($R1\ to\ Rk$) (Hastie et al., 2009). The decision tree classifier then assigns to the most frequently observed class response a new structural element within the training data in $Rk,$ given an unobserved data point that fulfils Rk. This procedure is depicted in Figure 1.4. The left panel of the figure depicts the complete dataset, including the different class labels and splits. The training observations are denoted in this figure by black triangles (representing, for example, CE) and black plus signs (representing no CE). The entire dataset is composed of different regions in our example in Figure 1.4, i.e., $R1.1$, $R1.2$, $R2.1$, and $R2.2$. In the first stage, the dataset is divided into two leaves or regions, $R1$ and $R2$. In the second stage, the purity of the leaves or regions is increased, therefore, $R1$ is split into two further regions, $R1.1$ and $R1.2$, while $R2$ is divided into regions $R2.1$ and $R2.2$ (Hastie et al., 2009; James et al., 2017). Hence, as shown in the figure, a new observation (represented as a red cross in the figure) is classified by the decision tree method as "CE" since that is the most common label in that region ($R1.1.$). Moreover, Figure 1.4, on the right panel, depicts the process of categorising new observations when utilising a decision tree method.

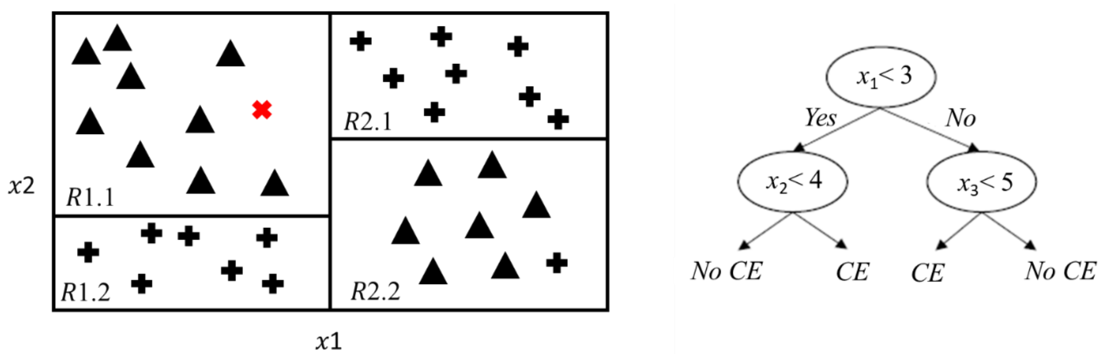


Figure 1.4. Representation of a Decision Tree

In order to minimise impurities such as the one in Figure 1.4, decision trees aim to generate a set of regions or leaves with the lowest possible class impurity in the resultant splits or divisions (James et al., 2017). Therefore, decision trees utilise recursive binary splitting, which is considered a top-down greedy strategy (Murphy, 2012; Hastie et al., 2009). The recursive binary splitting approach identifies an independent variable, $xj,$ with a cut-point value of s (where s corresponds to any value pertaining to xj). Then, given the feature space of an existing node, this approach splits this node into the terminal nodes $\{x \mid xj<s\}$ and $\{x \mid xj \geq s\}$, trying to maximise the purity of the classification for every single stage of the process (James et al., 2017). It is worth noting that the splits in this method occur only on the training observations in the regions or leaves available, instead of in the complete training dataset. Decision trees assess at each stage the purity of the

splits by using the Gini index or the entropy impurity function (James et al., 2017; Hastie et al., 2009). If in the new leaves or regions the level of purity is not adequate after each split, the splitting process is repeated to reduce the impurity of the new terminal nodes. Therefore, this procedure is repeated until no further progress is feasible, which results in a deep tree. Alternatively, this continuous repeating process can be terminated by specifying a termination condition, such as collecting a certain amount of observations in a given region (Murphy, 2012; James et al., 2017)[6].

Finally, Table 1.2 presents a summary of some of the advantages and disadvantages of employing decision or regression trees[7].

Table 1.2. Decision Trees: Advantages and Disadvantages[8].

Advantages of Decision Trees:
• Simple to understand and interpret. This is because Decision Trees can be visualised.
• They require little data preparation. Other techniques often require data normalisation, the creation of dummy variables, and the removal of blank values.
• The cost of utilising Decision trees (i.e., data prediction) is logarithmic in the number of data points utilised to train the tree.
• Decision Trees are capable of working with both numerical and categorical data.
• Decision Trees are capable of handling multi-output problems.
• Statistical tests can be used to validate a Decision Tree model. This allows accounting for the reliability of the model.
Disadvantages of Decision Trees:
• Overfitting can be a problem with Decision Trees if different standardised mechanisms from the literature are not followed properly, such as pruning mechanisms, setting a minimum number of samples required at a node, etc.
• Instability of the model can be present in Decision Trees, as small variations in the data might result in the generation of different tree models.
• The greedy algorithm utilised in Decision Trees, where locally optimal decisions are made at each node, cannot guarantee a globally optimal Decision Tree. This can be mitigated by training multiple trees in an ensemble learner, where the features and samples are randomly sampled with replacements.

[6] For further details on Gini and entropy impurity functions, please refer to James et al. (2017), Murphy (2012) and/or Hastie et al. (2009).
[7] For further information and explanation about Decision Trees or Regression Trees used in this thesis, please see the methodological section of Chapter 4 and Methodological Appendix IV, where more details are provided regarding the analysis performed.
[8] Based on James et al. (2017), Murphy (2012), Hastie et al. (2009), and Song and Ying (2015).

1.4.2 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are computational models that consist of numerous processing units that collect inputs and provide outputs given some predetermined activation functions (Heidari et al., 2020; Gurney, 2018; Rana et al., 2018; Paliwal and Kumar, 2009). ANNs employ similar processing to the one used by brains to create algorithms that can be utilised for modelling complex patterns and predicting problems. Yegnanarayana (2009) points out that ANN processes the information and permits the system to learn or carry out computation without being explicitly programmed for a task.

The term neural network refers to a loosely connected collection of models derived from research on brain functioning, which is characterised by a wide parameter space and a flexible structure. As the collection of models expanded, the majority of the new models were created for non-biological purposes and applications, albeit the accompanying language and terminology reflect the origin of these models (Gurney, 2018). The definitions of ANNs are as diverse as the disciplines in which these models are employed (see, for example, Müller et al., 1995; Yegnanarayana, 2009; Zhao et al., 2015; Park and Lek, 2016; Gurney, 2018; Rana et al., 2018; Heidari et al., 2020). While no one definition adequately encompasses the complete collection of models, this thesis makes use of the definition used by Haykin (2009), which indicates that an ANN is "a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use". Hence, as the author point outs, ANN models resemble brains in two ways: (i) the network acquires knowledge via a learning process, and (ii) Synaptic weights, which are the strengths of interneuron connections, are utilised to store knowledge[9].

It is worth noting that this broad definition could be used to describe conventional statistical methods. Hence, to distinguish ANNs from conventional statistical approaches, it is important to take into account what the definition of Haykin (2009) describes, as well as what it implies. For instance, conventional linear regression models can be said to acquire knowledge using the least-squares approach, and therefore, through the regression coefficients store this knowledge. Thus, in this sense, a conventional linear regression behaves as an ANN. In fact, Gurney (2018) suggests that linear regressions are a particular case of an ANN. Nevertheless, linear regression models have fixed model structures and a particular set of imposed assumptions that must be met before

[9] See Ripley (1996) for a discussion of whether this definition might be overly limiting.

learning from the data (Yegnanarayana, 2009). In contrast, the definition by Haykin (2009) places minimal constraints on the model structure and assumptions, which is the case of neural networks. As a result, ANNs have the ability to approximate a diverse range of statistical models, without the need for specific hypotheses or assumptions on the relationship between the dependent and independent variables in advance. The shape of the relationship between these variables is instead determined in the learning process of the ANN. Therefore, if a linear relationship between the variables exists, the ANN results should roughly resemble those of a linear regression model. On the other hand, if the appropriate relationship between the dependent and independent variables is non-linear, the ANN model is able to approximate this appropriate model structure (Ciurana et al., 2018). Although, this flexibility of ANNs is useful for the analysis of different models, at the same time comes with the trade-off that the synaptic weights can be difficult to interpret (Müller et al., 1995).

ANNs have grown in popularity and are the favoured method for many predictive data mining applications, due to the power, versatility, flexibility, and ease of use they permit (Gurney, 2018). Predictive ANNs are especially useful in applications with complicated underlying processes, such as forecasting consumer demand, or in the case of this thesis, detecting and understanding the different effects working in a CE scenario.

Although ANNs impose minimal constraints on the model structure and assumptions, neural networks can be classified based on the overall network architecture. There are two main types of ANN: Multilayer Perceptrons (MLP) and Radial Basis Functions (RBF)[10] (Buhmann, 2003; Zhao et al., 2015). These are also types of supervised ML approaches since the results predicted by the model can be compared against values that are known from the variables. Despite being classified differently based on their structure, both ANN-MLP and ANN-RBF are functions of some inputs (i.e., predictors or independent variables), which aim to minimise the prediction error of an output (i.e., dependent variable). Figure 1.5 shows the basic structure of an ANN, showing the input variable and the output variable. This basic structure is the same for MLP and RFB networks. These characteristics of the ANN can be also observed in Figure 1.6.

[10] These two types of ANN are utilised in this thesis, please refer to the methodological sections of Chapter 2 and 4, as well as to Methodological Appendices II and IV, for more information and detail explanations on the ANN-MLP models. Additionally, the methodological section in Chapter 3 and Methodological Appendix III provide further details and explanations on the ANN-RBF model utilised in the analysis.

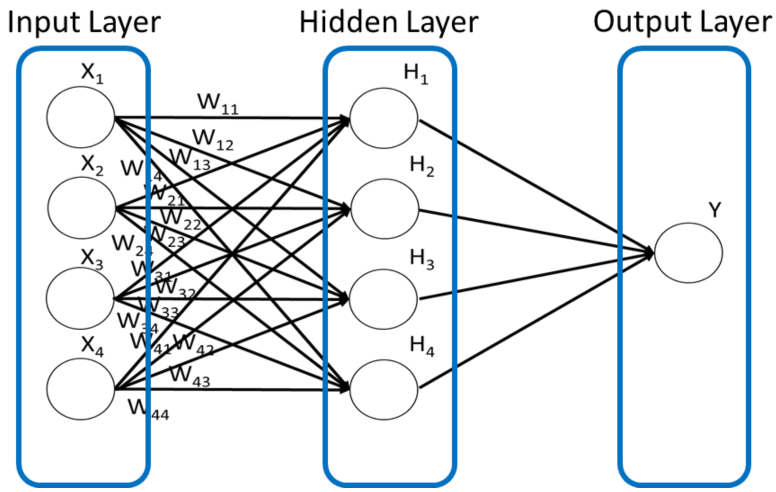


Figure 1.5. Structure of an Artificial Neural Network

Moreover, Figure 1.5 illustrates an important characteristic of the structure of an ANN, that is, the architecture of these networks is considered feedforward. This means that the connections in the ANN flow forward from the input layer to the output layer without incurring in any feedback loops. Hence, as depicted in Figure 1.5:

- The input layer includes the inputs, independent variables, or predictors.
- The hidden layer includes nodes or units[11] that are unobservable. Each hidden unit is some function of the input units or independent variables. The actual nature of the function is determined by the type of network and its specifications[12].
- The output layer includes the output or dependent variable. Each output unit is some function of the hidden units. Similarly, the actual nature of this function depends upon the type of network and its specifications.

Furthermore, as pointed out by Heidari et al. (2020), and Paliwal and Kumar (2009) a fundamental component of the ANN architecture is the neuron perceptron. The perceptron represents the small computational nodes or units that are connected with one another via weights. These weights dictate the strength of the connection between two different perceptrons. Each

[11] Each variable inside an ANN is represented as a neuron, node, perceptron or unit inside a layer.
[12] For more information and explanation about the hidden layer and its construction, please see Methodological Appendix II, which provides an in deep explanation of this and the other layers.

individual perceptron has a bias, which is utilised to alter the activation level for the perceptron (see Figure 1.6).

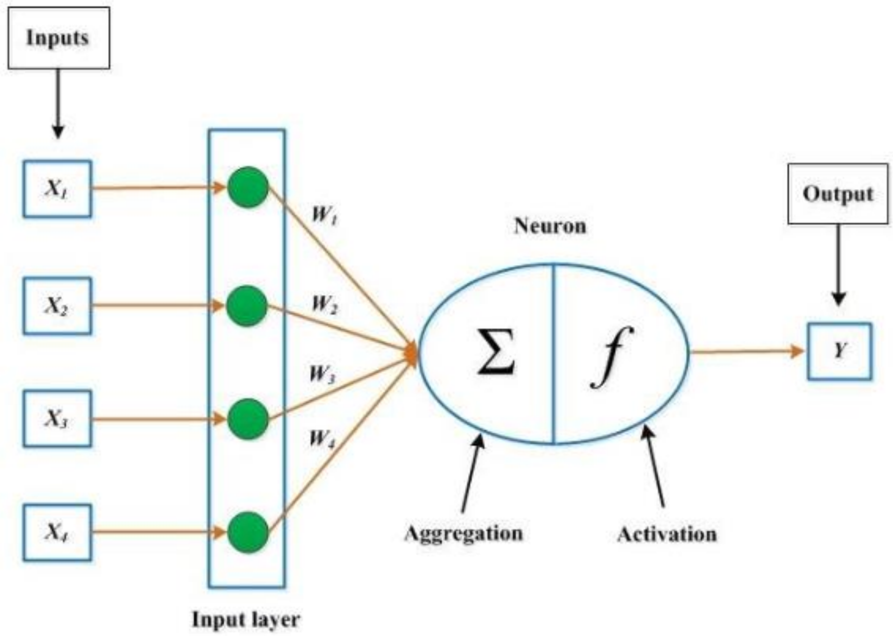


Figure 1.6. A single artificial neuron (perceptron) (Kumar et al., 2017)

As illustrated in Figure 1.6, these perceptrons combine to create layers. In the ANN computation process, the inputs or independent variables are multiplied by the weights, while the bias is added to them. The results are passed into the activation function, which not only defines the output of the perceptron, but also determines the activation state of the said perceptron. The output of the perceptron has the form of a linear function until the activation function is fed, at which point the non-linearity element is introduced. Due to its non-linearity, the ANN can represent sophisticated functions with high complexity that otherwise would have not been conceivable (Kumar et al., 2017). It is worth mentioning that the output layer activation function differs from that of the hidden layer(s) (Park and Lek, 2016; Zhao et al., 2015)[13].

From an operational point of view, ANNs require large amounts of training data for the learning process (Heidari et al., 2020; Rana et al., 2018; Müller et al., 1995). The data is initially sent through the input layer, after which an output with random weights and biases is formed. This

[13] The activation functions used throughout the analysis of this thesis are explained in more detail in Methodological Appendices II, III, and IV. Specifically, see Methodological Appendix II where a more general information and detailed explanation are provided regarding activation functions.

process is known as *forward propagation*. Then, an error is calculated, by comparing the actual output data with the predicted output[14]. This error is utilised to compute the error function[15]. After analysing the error function, the weights and biases of each individual layer are modified in a process known as *backward propagation*, which entails adjusting them beginning with the output layer. Madhiarasan and Deepa (2017) highlight that minimising the error function by modifying the weights and biases is a vital step in the creation of the neural network structure. Mathematically, this refers to the process of locating the minima of the error function, which can be done through

In mathematical terms, it refers to finding the minima of the cost function, which can be done through *Batch-Gradient descent* and *Stochastic-Gradient Descent*, the two most common methods used, although there are other methods (Yegnanarayana, 2009).

1.4.3 K-means Cluster Analysis

K-means cluster analysis, as a machine learning method, identifies structural features of a set of data points. K-means clusters can be seen as reduction techniques intended to group comparable cases in a dataset so that cases in the same group are as similar as possible, and cases in other groups are as distinct as possible (Kalra et al., 2018; Bansal et al., 2017). The k-means method divides the data into a predetermined number of clusters, *k*, where the cluster allocation minimises the total sum-of-squares distance to the cluster mean (Ahmad and Dey, 2007).

K-mean clustering has some particularities compared to other clustering methods. First, this type of clustering method does not require computing all feasible distances (Martinelli et al., 2016). Second, compared to hierarchical clustering, the number of clusters desired in K-mean clustering is required to be known in advance. Moreover, obtaining solutions for a range of clusters requires rerunning the analysis for each distinct number of clusters. Therefore, since the k-mean clustering method reassigns cases to clusters repeatedly, the same case may be reassigned from cluster to cluster throughout the cluster analysis (Munther et al., 2016). However, in agglomerative hierarchical clustering, cases are included in existing clusters, and thus, they are perpetually assigned to that cluster, with an ever-expanding circle of neighbours (Wahyudin et al., 2016). Finally, as the name of the clustering method indicates, k-means, the number of clusters targeted

[14] Hence, explaining why ANN are considered to be supervised machine learning methods, as there is an actual output data used in the analysis.
[15] Also known as cost function (Madhiarasan and Deepa, 2017).

is represented by *k*, and cases are allocated to the cluster with the smallest distance to the cluster mean. Hence, the computational process in this method revolves around finding the k-means (Bansal et al., 2017; Ahamad and Dey, 2007).

Regarding the calculation process of the K-means cluster analysis, the procedure commences with an initial set of means and classified cases based on their distances from the centres. To accomplish k-means clustering, the method randomly allocates *k* starting centres (where *k* is specified at the beginning of the analysis), either by randomly selecting the “Euclidean space” points defined by all *n* variables, or by selecting *k* points from all available observations. Then, the k-mean method allocates each individual observation to the closest centre iteratively. The new centre for each cluster is then calculated as the mean of the centroid regarding the clustering variables for each new set of observations for each cluster. This procedure is repeated by K-means, which allocates observations to the closest centre. It is worth noting, and as mentioned before, in this reiterative process some observations might change clusters. This procedure is repeated until there are no new observation reallocations to a new cluster. At this stage, the K-means clustering method is deemed to have converged and the final cluster allocations represent the solution for the clustering analysis. Finally, the cluster means are computed once again and the cases are allocated to their permanent clusters (Munther et al., 2016). Figure 1.7 (below) displays a K-means clustering analysis example with four groups. The Hartigan-Wong algorithm is the commonly used method when using K-means clusters. This algorithm seeks to minimise the Euclidean distance between all data points and their closest cluster centre, by reducing the sum of squared errors (SSE) within a cluster (Yadav and Sharma, 2013; Ahmad and Dey, 2007)[16].

[16] For further information and explanation about the K-means cluster used in this thesis, please see the methodological section of Chapter 3 and Methodological Appendix III, where more details are provided regarding the analysis performed.

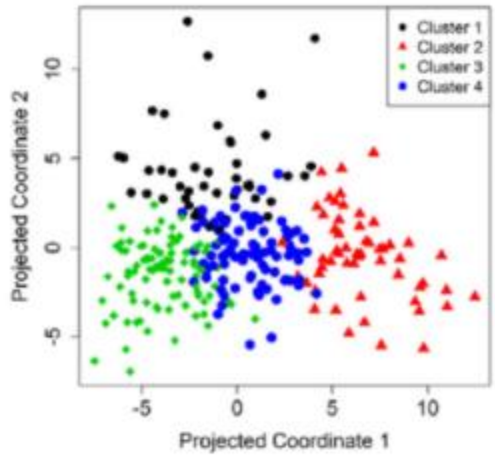


Figure 1.7. K-means clustering analysis with four groups

1.5 Database

The thesis employs data from the EU survey on *Public Consultation on the Circular Economy* database from the year 2015, carried out by the European Commission (European Commission, 2015). This cross-sectional database is used since it is the most recent one done at a European level regarding CE. The main purpose of the survey is to comprehend the extent of the adoption of CE in firms, the motives, and organisations' knowledge and awareness of CE, to understand how EU policies are influencing the implementation of CE models in European companies, as well as to explore ways of promoting CE business models. The survey questions can be grouped into three main topics, in line with prior research by Ghisellini et al. (2016), Rizos et al. (2016), Fonseca and Domingues (2018), and Lakatos et al. (2016). The first set of questions is intended to describe the organisation. The second set of questions seeks to gather data on knowledge, motivation, and intensity in the organisation's adoption of CE models. Finally, the last series of questions concentrate on the actions aimed at facilitating the adoption of CE models in firms.

The data was collected via an online database, over two weeks, following the methodology of "wave analysis" (Amstrong and Overton, 1977). Moreover, non-response bias has been verified, and no significant differences were found between early and late respondents. Previously, the survey was reviewed by a panel of CE experts.

The total database consists of 1280 organisations and companies[17] in different economic sectors, and comprises the 27 EU Member States, Norway, Iceland, Switzerland, and Liechtenstein. The companies included in this study had implemented environmental improvements in their companies leading to the implementation of the circular economy strategies in the last five years and/or were planning to implement them in the next five years. Respondents were directors of human resources or CEOs of companies. From the surveyed companies, around half of the companies (44.5%) were large companies with 250 employees or more, small and medium-sized companies, with between 10 and 249 employees, (32.2%), and micro-companies, with fewer than 10 employees (23.2%). The largest proportion of companies included in the survey belonged to the area of environmental management (recycling and other waste management, and repair services), with the other sectors, both industrial and service, represented in a balanced way.

Lastly, in terms of environmental management, the sample is balanced in terms of the use of environmental certifications, with 52.2% of companies having implemented some type of certifications (Eco-Management & Audit Scheme (EMAS), EU eco-label, or other environmental management schemes), and 47.8% do not follow any environmental management scheme[18].

1.6 Structure of the Thesis

The present thesis is structured as follows. Chapter 2 is titled “Institutional Pressures as Drivers of Circular Economy in Firms - A Machine Learning Approach” and deals with the effect of different typologies of institutional pressures on the development of circular economy in firms by combining ANN with regression analysis. Chapter 3 pays attention to two economic actors in the circular economy, consumers and producers, focusing on the consumption side of CE. This chapter is titled “The effect of consumption and production policies on circular economy business models: A Machine Learning Approach” and combines K-means clusters with ANN, together with conventional regression analysis. Chapter 4 centres on two key areas for CE: innovation and financial support policies. This chapter is titled “Towards the Circular Economy in firms - The

[17] After filtering and eliminating incomplete responses, microenterprises and individuals, the final sample used in this thesis contains 870 organisations.

[18] See Methodological Appendix I for more information, descriptive statistics, analyses, and robustness checks about the database.

role of innovation and financial support policies" and utilises ANNs with Tree Regression analysis, as well as traditional regression analysis. Finally, Chapter 5 presents the conclusion of the thesis. This last chapter covers the main conclusions from the three papers that compose the thesis, emphasising their main theoretical and methodological contributions, as well as it presents some limitations and recommendations for further research.

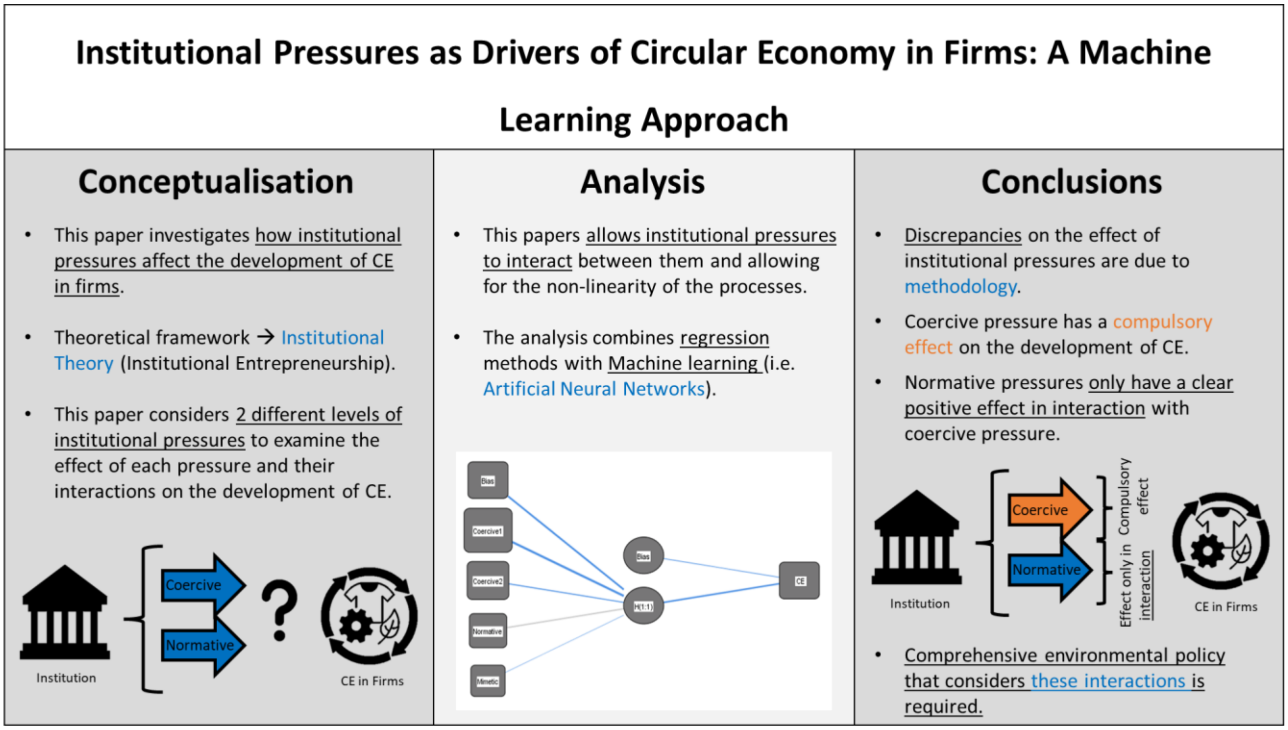
Chapter 2: Institutional Pressures as Drivers of Circular Economy in Firms - A Machine Learning Approach

2.1 Abstract

This paper investigates how institutional pressures affect the development of CE in firms. Using Institutional Entrepreneurship as a theoretical framework, this paper considers two different levels of institutional pressures (*coercive and normative*) to examine the effect of each pressure and their interactions on the development of CE. Seeking to clarify the debate on the effect of institutional pressures, this paper considers that the main limitation arises from the fact that previous research has analysed the relationship between institutional pressures without considering the interaction between them and the non-linearity of the processes. Deviating from previous papers, our analysis combines regression methods with Machine learning (i.e. Artificial Neural Networks), and employs data from the EU survey on *Public Consultation on the Circular Economy*. This research finds that while coercive pressures have a compulsory effect on the development of CE, normative pressures have an ambiguous effect by themselves. Normative pressures only have a clear positive effect on the development of CE in firms when interacting with coercive pressures. Moreover, this paper shows that the application of machine learning tools has an important contribution in solving interaction problems. From the perspective of environmental policy, this means that a comprehensive policy is required, which implies the coexistence or interaction of the two types of pressures.

Keywords: *Institutional pressures; Circular Economy; Machine Learning; ANN Model.*

2.2 Graphical Abstract



2.3 Introduction

The CE is an economic model conceived from a cycle of development and transformation, whose main objective is to optimise the use of resources and promote the efficiency of production systems (Gedam et al., 2021; Salvador et al., 2021; Kanda et al., 2021). The CE model seeks to eliminate negative externalities of economic activity while ensuring economic growth, preserving natural capital, and promoting greater well-being of societies (Martins, 2018; Millar et al., 2019). The CE model strives to achieve production and consumption sustainability by implementing closed cycles (closed-loops), with activities that promote efficiency in the utilisation of resources and value chains based on more efficient uses of waste and by-products generated in the production processes (Bocken et al., 2014; Hazen et al., 2017; Kirchherr et al., 2018; Perey et al., 2018; van Capelleveen et al., 2020). The growing relevance of CE models is reflected in the increased attention being paid to the implementation of CE in businesses and organisations by institutions, policy-makers, and public administration (Bocken et al., 2016; Martins, 2018; Katz-Gerro and López Sintas, 2019; Millar et al., 2019). This interest is also reflected in the development of various policy initiatives to promote the CE models in organisations (Levänen et al., 2018; Haque and Ntim, 2018).

The research has not been alien to these initiatives and has analysed the impact of these policies on the adoption of CE strategies. Institutional theory has been used as a framework to explore the willingness of companies to engage in environmental activities (Berrone et al., 2013; Phan and Baird, 2015; Daddi et al., 2016; Wang et al., 2019). These studies rest on the assumption that institutional pressures may influence the environmental activities of firms (such as CE). The institutional perspective highlights the role of normative, mimetic and regulatory factors in influencing the decisions of companies to pursue a particular strategy, independently of the strategy's efficiency (Scott, 2005; DiMaggio and Powell, 1983; Delmas and Toffel, 2004). Despite the importance of the research examining the relationship between institutional pressures and the implementation of CE models in the firm, little is known about how institutional pressures operate (Alonso-Almeida et al., 2021). De Jesus and Mendoça (2018) point out that the difficulties to understand how these pressures act, arises from the need for interaction between institutions in the development of CE, and from the diversity of measures that stimulate CE at all levels (i.e. regulations, standards, guidelines, certifications, and educational frameworks). Moreover, different authors have concluded that the research is scarce, has focused more on qualitative research, and has generated contradictory results (Delmas and Toffel, 2004; Ahrens and Ferry, 2018; Zapata and Zapata, 2018; Wang et al., 2019). Therefore, Ferasso et al. (2020) have highlighted the necessity for more academic research in this line, and Ahrens and Ferry (2018) and Zapata and Zapata (2018) have emphasised the importance of empirically analysing how institutional actors drive these types of changes in firms and their effectiveness.

Thus, this paper empirically investigates the effect of institutional pressures on the development of CE in firms. First, in line with previous research on CE and environmental sustainability policy (Stål, 2015; Alonso-Almeida et al., 2021; Daddi et al., 2020), this study assumes the perspective of institutional theory, particularly institutional entrepreneurship, which indicates how organisations at all levels can act as ‘institutional entrepreneurs’ (Ahrens and Ferry, 2018). This study is framed in the context of the European Union (EU), a supranational institution, which, following Battilana et al. (2009) and Dorado (2005), acts as an institutional entrepreneur. Institutional entrepreneurs promote changes in the environment using different politics, strategies, activities and pressures (Greenwood and Suddaby, 2006). Using this framework, this paper assumes the conceptualisation of institutional pressures or power of DiMaggio and Powell (1983) and Scott (2005). Thus, this research considers two levels of institutional pressure (*coercive and normative*), and examines the effect of each individual type of institutional pressure on the CE in firms. Second, this paper analyses how institutional pressures affect the CE in firms, explaining the dynamics of how these pressures act. In line with Delmas and Toffel (2004) and Gao et al. (2019) that highlight the importance of studying the interactions between variables to explain the impact of institutional pressures, this paper argues that each type of institutional pressure is due, not only to itself, but rather it is conditioned by the other institutional pressures. Based on this assumption, the research focus on the debate about the institutional effect on the development of CE in companies, which has yielded contradictory results (Wang et al., 2019). As mentioned before, this is problematic, especially because as noted by Boons et al. (2013) and Alonso-Almeida et al. (2021), an optimal combination of institutional pressures can influence the transformation of the CE, implying radical changes at all levels of an institutional environment. Hence, this paper postulates that the discrepancy in the results is due to a *methodological problem of the analysis*, since most of the prior quantitative research exclusively considers the direct effect of each type of institutional pressure on the organisation, without considering the possible interactions between institutional pressures, which might lead to indirect and even complementary effects. Thus, this paper examines the effect of the interaction between coercive and normative institutional pressures on the development of CE in firms.

To overcome these methodological concerns, this study combines conventional regression methods with ML. ML consists of algorithms that automatically improve their performance with experience (Alloghani et al., 2020). Hence, ML with its good pattern recognition and modelling of multivariate non-linear relationships serve as a good tool to study CE models, given the great challenges these models pose for conventional regression methods due to their innate characteristics (Garbero et al., 2021; Gevrey et al., 2006). Particularly, for this research, ANNs are utilised, which are a type of ML method that allows analysing the interaction among variables (Ciurana et al., 2008; Somers and Casal, 2009) and have been extensively used in environmental analysis (see, for example, Olden et al., 2004). For this study, data from the European Union survey on *Public Consultation on the Circular Economy* database in the year 2015 is employed, which includes 870 organisations in different economic sectors (European Commission, 2015).

2.4 Conceptual Background

2.4.1 Institutional Pressures

The institutional theory (DiMaggio and Powell, 1983; North, 1991; Scott, 2005; Berrone et al., 2013) emphasises the social factors that affect organisations' actions. From this perspective, organisations seek approval from their environment and, therefore, are susceptible to social influence. Institutional theory has become a well-established theory with a large body of literature, rich with concepts and models to explain the influence of institutions on organisations (Greenwood et al., 2011; Stål, 2015; North, 1991). The literature ranges from institutional logics (see, for example, Thornton and Ocasio, 2008, or Stål, 2015), institutional complexity (Greenwood et al., 2011; Smets and Jarzabkowski, 2013) and institutional entrepreneurship (Alonso-Almeida et al., 2021; Battilana et al., 2009; Elliot, 2016; De Jesús and Mendoça, 2018). This research is contextualised within institutional entrepreneurship.

Institutional entrepreneurship is a process that contributes to radical changes in the institutional environment where this process takes place, including new organisational structures, new business models, and new operating systems and procedures, among other types of innovations (Alonso-Almeida et al., 2021; Elliot, 2016; Covaleski et al., 2013; Battilana et al., 2009; DiMaggio, 1988). Battilana et al. (2009) consider that an organisation must meet the following characteristics to be considered an institutional entrepreneur: first, support the initiative of a divergent change, and second, actively engage in the transformation. Therefore, an institutional entrepreneur is an actor who leverages resources to create or transform an existing institutional context by introducing new ideas (Elliot, 2016), favouring change (Covaleski et al., 2013), and introducing new concepts and innovations to change a certain situation (Alonso-Almeida et al., 2021). Thus, Dorado (2005) asserted that institutional entrepreneurs could be powerful actors with sufficient resources, such as governments, supranational organisations, corporations and other similar agencies, to promote change. This is the case of the EU, where this research is contextualised.

From an operational point of view, and following De Jesus and Mendoça (2018), Dorado (2005), and Alonso-Almeida et al. (2021) institutional entrepreneurship exerts pressure or power to achieve a greater degree of acceptance and contribution to change. This type of power refers to the ability to promote change through technical and economic means, modifying values and practices, and shaping attitudes and preferences. Thus, Alonso-Almeida et al. (2021) point out that the institutional entrepreneur takes advantage of the resources to transform the institutional context, initiating and actively participating in the change and using his position to involve different actors to promote the desired change. This paper assumes the definition of DiMaggio and Powell (1983) and Scott (2005), which describe the forces pressing institutions to adopt shared routines and notions. This thesis selects two of the mechanisms proposed by the authors by which institutional change takes place: *coercive* and *normative pressures.* Coercive pressures result from political influence and originate from pressures exerted on organisations, both formal and informal (DiMaggio and Powell, 1983; Teo et al., 2003). Concerning the protection of the environment, coercive pressures are a direct response to government regulations and incentives. The second source, normative pressures, stems from professionalisation, understood as the conditions and methods of work defined by the members of a specific organisational framework (DiMaggio and Powell, 1983; Scott, 2005). The growth of professional networks encompassing organisations through which new models diffuse rapidly, and formal education, generate normative pressures that drive companies to implement predominant practices and behaviours (Teo et al., 2003).

2.4.2 Circular Economy and the challenges in the development of CE models

The CE is conceptualised, in this thesis, as a business model for closed-loop production and consumption systems, where the management of waste (that is, the final phase in the economic cycle) constitutes a valuable resource (Bocken et al., 2017; Kirchherr et al., 2017a; Jabbour et al., 2019). Compared to the traditional linear economic model, whose production model consists of "*take, make, discard*", the circular economy model builds an economic system that is more resilient and adaptable to the shortage of raw materials and energy resources (Zucchella and Previtali, 2019; Ferasso et al., 2020). Hence, the economic system proposed by CE models is one based on recycling and reusing resources, which reduces the demand for new raw materials and contributes to the reduction of the ecological deficit.

The development of circular economy models implies several important challenges (Linder and Williander, 2017; Kirchherr, et al., 2018; Bressanelli et al., 2019; Figge, et al., 2021). The first group of challenges refers to the complexity of the design and creation of CE models. CE can be viewed as an eco-innovation (Scarpellini et al., 2020; Marzucchi and Montresor, 2017), which implies an associated cost (Boggia et al., 2018; Choi et al., 2016; Dangelico, 2016; Bönte and Dienes, 2013), and managerial complexity for firms. Bönte and Dienes (2013), and De Marchi

(2012), suggest that when there are no incentives to invest in eco-innovation, the social cost of pollution is reduced but the firms' private costs increase. Additionally, the literature on innovation identifies a set of challenges and barriers that firms must confront, i.e., market complexity, the uncertainty of the process, and the management of organisational resources for innovation (Dangelico, 2016; Evans et al., 2017; Demirel and Kesidou, 2019). Furthermore, because environmental knowledge is a public good, first innovators are easily imitable. Thus, followers do not incur the high cost and risks that this involves. Moreover, the literature on CE highlights other challenges such as the organisational culture, lack of technologies and information, waste management, and consumer resistance (Hopkinson et al., 2018; Hina et al., 2022).

Another group of challenges stems from the closed supply chains, which are a pillar of the CE model (Lüdeke-Freund et al., 2018; Kirchherr, et al., 2018; Perey et al., 2018; van Capelleveen et al., 2020). The CE model encompasses not only all tasks involved in the production, distribution, and usage of products, but also the maintenance, reuse, recovery, and recycling. In other words, it embraces producer organisations, as well as users, intending to facilitate the development of CE. Lewandowski (2016) noted the importance of collaboration and cooperation among organisations for the application of closed-loop systems. However, partnership building is not without difficulties (Arranz et al., 2016, 2019). Finding the right partner, coordinating tasks, and preventing and resolving conflicts may inhibit organisations' interest in implementing CE models through cooperation.

2.4.3 Institutional Pressures and the Circular Economy

The relationship between institutional pressures and the circular economy has been extensively discussed in the literature. Thus, the literature, especially neoclassical contributions, has focused on the need for institutional support to implement environmental innovations in companies. Rennings (2000) introduced the concept of the "double externality problem" and the "regulatory push/pull effect", highlighting the specificity of environmental innovations compared to classic innovations. That is, green innovators produce an environmental positive externality creating an appropriate value for society (reduced environmental damage). However, firms that invest in cleaner technologies bear higher costs than polluting competitors. Hence, there is a disincentive for firms to invest in products or processes that reduce environmental impacts. Moreover, environmental knowledge has a public good nature, which allows for free riding from competitors, as it is relatively simple to replicate early innovations without suffering the substantial research costs and risks that this involves. (Tang et al., 2018; Bönte and Dienes, 2013; Porter and Van der Linde, 1995). The interaction of these two externalities together with the public good feature generates a market-failure which requires policy intervention to foster environmental innovations related to the circular economy (Rennings, 2000; De Marchi, 2012).

In this context, institutional pressures are considered as drivers of the CE in firms. The literature has analysed the effect of institutional pressures on various environmental practices: for example, Ren et al. (2019), Liao (2018), and Aragon-Correa and Leyva-de la Hiz (2016) examine the adoption of *green innovation* in firms under the effect of institutional pressures. Usually, to adjust to the external and institutional environment, and to gain legitimacy, companies are prone to modify their organisational configurations and behaviours by adopting the leading strategy (Berrone et al., 2013; Daddi et al., 2016; Liao, 2018; Wang et al., 2019; Wei et al., 2020). De Jesus et al. (2019), Domenech and Bahn-Walkowiak (2019), and Alonso-Almeida et al. (2021) highlight the importance of resources for the implementation of CE. Boons et al. (2013) and Brown et al. (2019) indicate that incentives can help partner engagement for the development of CE models. Wang et al. (2019) show that if companies refuse the external and institutional environment, they can be isolated. Thus, it could be concluded that it is more likely that firms develop CE under various types of institutional pressures. Despite the importance of institutional entrepreneurship in the development of CE, little is known about how institutional entrepreneurs operate (Alonso-Almeida et al., 2021). This could be due to different reasons. On the one hand, this could be because of the need for interaction between institutions in the development of CE. This is the case of the European Union, a supranational institution, where interaction with various national governments is necessary to promote CE (Bocken et al., 2018; Brown et al., 2019; De Jesus et al., 2019). On the other hand, the diversity of measures and policies such as rules, guides, standards, certifications, and educational structures that promote CE at all levels, could be at fault (De Jesus and Mendoça, 2018). While regulatory efforts, such as directives and policies, have a positive effect (coercive nature, in the case of CE) (Rodriguez-Antón et al., 2019; De Jesus and Mendonça, 2018), however, it is not clear how normative pressures affect companies to implement CE. In this sense, this is problematic, because as noted by Boons et al. (2013) and Alonso-Almeida et al. (2021) an optimal combination of institutional pressures can influence the transformation of the

CE, implying radical changes at all levels of an institutional environment. Table 2.1 classifies the main authors and themes of the literature review.

Table 2.1. Authors and themes of the literature review.

Category	Theme		Description	Papers
Institutional Pressures	Institutional theory		Social factors that affect organizations' actions, behaviours and structures	DiMaggio and Powell, 1983 North, 1991 Teo et al., 2003 Scott, 2005
	Institutional Entrepreneurship		Create or transform an existing institutional context by introducing new ideas and favouring change	Alonso-Almeida et al., 2021 Dorado, 2005 De Jesus and Mendoça, 2018 Elliot, 2016 Covaleski et al., 2013 Battilana et al., 2009
	Institutional logics and institutional complexity		Ideas underpinning practices prevailing in the industry Confronting incompatible prescriptions from multiple institutional logics	Stål, 2015 Thornton and Occasio, 2008 Greenwood et al., 2011 Smets and Jarzabkowski, 2013
CE and the challenges in the development of CE models	CE concept		Definition of CE and applications of CE models	Bocken et al., 2017 Zucchella and Previtali, 2019 Ren et al.,2019 Jabbour et al., 2019, 2020 Ferasso et al., 2020
	Complexity in the design and creation of CE	Barriers for CE	Factors that hinder or impede CE models (such as managerial and market complexities, associated costs, organisational culture, lack of technologies, consumer resistance, etc.)	Linder and Williander, 2017 Kirchherr, et al., 2018 Hopkinson et al., 2018 Bressanelli et al., 2019 Figge, et al., 2021 Hina et al., 2022
		Eco-innovations vs CE	Description and characteristics of eco-innovation (to compare with the development of CE products)	Dangelico, 2016 Boggia et al., 2018 Marzucchi and Montresor, 2017 Scarpellini et al., 2020
		Lack of incentives Public good quality	The absence of incentives suffered by companies to invest in ecological innovation	Bönte, and Dienes, 2013 De Marchi, 2011
	Closed supply chains (Challenge)	Sustainable production models	Models for closed-loop production comprising the maintenance, reuse, recovery, and recycling; embracing producer organisations as well as users and third parties	Lüdeke-Freund et al., 2018 Perey et al., 2018 van Capelleveen et al., 2020
		Collaboration and cooperation among organisations	Importance and difficulty of collaboration and cooperation for closed-loop systems	Lewandowski, 2016 Arranz et al., 2016, 2019
Institutional pressures and CE	Institutional pressures as drivers of CE		Effect of institutional pressures on shareholders, reporting policies, strategies, innovation, etc.	Liao, 2018 Wei et al., 2020 Daddi et al., 2020
	Institutional entrepreneurs and CE		Organisational practices are affected by values, norms, laws, cultures, social expectations, and common cognitions	Brown et al., 2019 De Jesus et al., 2019 Alonso-Almeida et al., 2021 Rodriguez-Antón et al., 2019 Boons et al., 2013

2.5 Hypotheses

2.5.1 The effect of Institutional Pressures on the development of CE

2.5.1.1 Coercive pressures for CE development.

Coercive pressures, employed by institutions and governments, offer a push for organisations to adopt environmental practices and strategies (Berrone et al., 2013; Levänen et al., 2018; Ariti et al., 2019; Wang et al., 2019). Using various environmental standards and regulations, firms react to this regulatory pressure, which might enforce mandatory and disciplinary measures on company behaviours that are deemed illegal or immoral (Li, 2014).

Extended literature in the area of environmental policy and sustainability has highlighted coercive institutional pressure as a driver that encourages companies to develop both green products and processes compatible with the environment, either by creating a regulatory framework through standards, or by encouraging the development of these products or processes with financial support (see, for example, Arranz et al., 2019). In this regard, there are several initiatives that various governments and institutions are launching in the form of coercive pressures to promote the development of CE products. This is, for example, the Eco-design Directive 2009/125/EC from the European Union, which creates a framework for establishing eco-design requirements applicable to products that use energy, aimed at reducing energy consumption and other negative environmental impacts of products. While the primary goal of this Directive is to minimise energy use, it also aims to enforce other environmental concerns included in the CE product development framework, such as materials and water use, polluting emissions, waste issues and recyclability. Similarly, Spain has adopted the Zero Waste certification through the Spanish Standardisation Association (AENOR) and, in accordance with Directive 2009/125/EC, has created a set of eco-design requirements for ecological goods (European Commission, 2015). The AENOR Zero Waste certification recognises organisations that manage waste, reducing its generation, preparing it for reuse and/or transforming waste into raw materials and reintroducing them into the value chain. Therefore, in line with Wang et al. (2019) and Berrone et al. (2013), these rules and regulations, many of which are mandatory, must be followed by companies to avoid being punished if they contravene them. Moreover, coercive institutional pressures can take the shape of incentive mechanisms, such as tax deductions, subsidies, and a low bank financing rate (Latan et al., 2018; Jabbour et al., 2020). Thus, creating direct incentives for the promotion and development of CE projects. For example, the EU has created the Circular Economy Action Plan (CEAP), which consists of a set of actions that establish the framework for the adoption of CE (European Commission, 2015, 2019). These actions are aimed at financing, informing, and enabling the CE products, which must be a key element that solves these drawbacks[19] or encourages the development of CE products in the firm. Therefore, coercive pressures create rules and support that serve as a reference framework for developing 3Rs, 6Rs, or 9Rs[20] products, which must have a positive effect on their development. Hence, this paper proposes:

Hypothesis 1a. Coercive pressures on CE products impact the development of CE.

As previously noted, the circular economy model is a closed-loop system. The development of the innovation process to implement CE models implies cooperation and collaboration with other organisations and institutions. Moreover, as extensively documented in the literature, the establishment of cooperation and collaboration agreements between companies entails a series of problems and barriers in their implementation (Bressanelli et al., 2019; Arranz et al., 2019). Thus, the primary challenges identified in the literature range from the search for the right partner to communication problems between partners and coordination of tasks, as well as the existence of financial risks. In this sense, coercive pressures could promote support for the development of innovative business models between partners. First, this occurs by enabling the search for partners (via digital platforms and databases) and facilitating communication and negotiation among partners. For example, the French certification AFNOR's XP X30-901 for the development and implantation of CE, emphasises this management tool that permits the organisation, implementation, evaluation, and improvement of CE projects. Facilitating cross-organisational discussion and communication to represent both the mode of consumption and production via a single language and shared meanings. Second, the companies involved in the development of these collaborative projects allocate financial resources, withdrawn from other budget items. In this regard, a coercive impulse through financing can be an incentive for the development of CE processes that support the development of CE. Hence, this paper proposes:

[19] Dangelico et al. (2017) have pointed out the difficulties of developing green products, in terms of technical and market uncertainty, as well as the costs involved with it.
[20] Following Fonseca et al. (2018, p.3), "the CE model is framed on the principles of the 3Rs (reduce, reuse, recycle), the 6Rs (reuse, recycle, redesign, remanufacture, reduce, recover) and the 9Rs (refuse, reduce, reuse, repair, refurbish, remanufacture, repurpose, recycle, recover)".

Hypothesis 1b. Coercive pressures on CE processes impact the development of CE.

2.5.1.2 Normative pressures for CE development.

Normative pressures originate from different social actors, such as customers and suppliers, as well as trade and industry associations (Scott, 2005). However, in the establishment of ground norms for the implementation of eco-innovations, trade and industry associations play crucial roles (Alda, 2019; Palmer and Truong, 2017; Chang et al., 2015), creating standard measures for voluntary use, or industry-led initiatives (self-regulation). For example, Wang et al. (2019) indicate that in the case of environmental management accounting implementation, behavioural norms will influence members in these associations. Normative pressures can take two different forms. First, as professional networks and sectoral levels that promote the development and implementation of standards and frameworks in companies (Palmer and Truong, 2017). Second, in the form of collaboration and professionalisation, understood as the conditions and methods of work defined by the members of a specific organisational framework (Scott, 2005). Companies can acquire better resources, knowledge and experience, as well as conditions and methods of work by collaborating with organisations and industry associations (Liang et al., 2007). However, normative pressures should not be an incentive to develop CE models in the organisation. As seen previously, the development of CE entails a double challenge. First, there is the creation of CE products, which involves substantial uncertainty for firms in terms of both, the technical solution, and the market acceptance of the new product, which adds to the costs of product development[21]. Second, it implies the development of closed-loop models, which entails collaboration and cooperation with other organisations. As indicated in previous hypotheses, this implies important obstacles and barriers in terms of cost and management that hinder implementation. Therefore, this research considers that the creation of sectoral standards of voluntary use or professionalisation and collaboration, as a normative impulse, does not provide sufficient incentive for companies to develop CE, given the important challenges that companies have in the

[21] The creation of green products requires a long development time, meaning significant costs of R&D investment, and extensive market research. The environmental literature refers to this effect as the double externality (Bönte, and Dienes, 2013; De Marchi, 2012; Porter and Van der Linde, 1995), which relates to the absence of incentives for firms to invest in environmental innovations. The minimisation of ecological damage by innovations lessens the burden on other polluting companies, as there is a societal benefit, without the latter needing to take any further measures. Furthermore, due to the public good feature of environmental knowledge, it is relatively simple to replicate the early innovations without suffering the substantial research costs and risks that this involves.

development of CE models, involving associated costs and substantial managerial complexity for the firm, which leaves the company with a clear disadvantage, considering the public nature of environmental knowledge. Hence, this paper proposes:

Hypothesis 2a. Normative pressures from sectors do not have an impact on the development of CE.

Hypothesis 2b. Normative pressures from professionalisation and collaboration do not have an impact on the development of CE.

2.5.2 The effect of the interaction between coercive and normative institutional pressures on the development of CE.

The interactions between variables in the fields of economics, management, and the environment, are an important and recurring topic. Interactions that produce synergistic and complementary effects between variables (see, for example, Hullova et al., 2016), or that moderate the effect of one variable on another are especially significant (Delmas and Toffel, 2004). In this paper, the interaction between an explanatory variable and an environmental variable is conceptualised as moderation. This means that the environmental variable moderates or modifies the effect of the explanatory variable (Delmas and Toffel, 2004). Therefore, to have an overview of the effect of institutional pressures on the development of CE, the case of interactions between the various types of institutional pressures has to be considered.

Unlike previous hypotheses, which postulated that there is no direct effect from normative pressures on the development of CE, the thesis proposes that if the existence of interrelationships between institutional pressures is introduced, both types of normative pressures, together with coercive pressures, have an impact on the implementation of CE.

The interrelationship between coercive and normative pressures facilitates the development of CE. For example, every year, about 800,000 end-of-life vehicles are deregistered in Spain. In 2000, Directive 2000/53/EC was approved, which was transposed into Spanish legislation through RD 1383/2002. Thus, because of this coercive institutional impulse, in 2007 one million vehicles were decommissioned, while in 2013 the figure did not reach 600,000 units. Compliance with said RD (*Royal Decree*) is done through the scrapping and recycling sector. End-of-life vehicles must be reused efficiently, especially concerning the reuse of parts through the scrapping network[22]. The lack of adequate financing by manufacturers, to cover the negative costs of managing these parts, means that they are practically not recycled. On the other hand, from the vehicle manufacturers' sector, initiatives have been carried out to advise on the dismantling of parts and even marking them, to facilitate their separation and subsequent recycling. This normative impulse developed by the manufacturing sector in combination and interrelation with the coercive impulse of RD 1383/2002, has meant that today there are about 950 authorised scrap yards and 28 fragmentation plants that recycle almost all the vehicles, creating an association that supports, advises, and collaborates on the management of end-of-life vehicles. Therefore, this example shows that the interrelation of coercive and normative pressures encourages companies to develop CE. While the action of the normative pressure had no effect on firms given the difficulties and costs of developing CE in firms, the combination with the coercive pressure makes firms assume the development of CE projects.

Hence, we propose:

Hypothesis 3: The interrelation of normative pressure with coercive pressures has a positive effect on the development of CE products.

[22] Furthermore, metal and iron parts constitute one of the most important sources of raw material that supplies steel mills. The non-ferrous metal parts (copper, aluminium, brass, and lead, mainly) are sent to specialised separation plants that, by means of flotation procedures in media of different densities, inductors and magnetic separators, manage to efficiently select the material obtained, and ensure its return to the production cycle infinitely. The challenge is with the non-metallic parts (mainly plastics and glass) that are sent to landfill.

Table 2.2. Case of End-of-Life Tires (ELTs) in Spain.

General basic data
Some 300,000 tons of End of Life Tires (ELTs) are discarded in Spain per year. This equates to roughly 25 million tires. Until 2005, the main destination of these tires was the landfill because, although recycled tires are a product with an economic value, the cost of collecting, transporting and crushing these tires exceeded the value derived from it. Concretely, at the end of their useful life, ELTs become recycled materials with different applications: recycling, civil works and energy recovery. Tires are subjected to a crushing process in the transformation plants to manufacture a product useful for civil works or as a replacement fuel. In parallel, a granulation process is carried out in which the materials that form the ELTs are separated into rubber, steel and fibres with multiple applications.
Coercive pressures for the CE development
In 2005, Royal Decree (RD) 1619/2005 entered into force, which required tire manufacturers to provide a fund to finance the proper management of tires. In addition, this RD prohibited the dumping of tires. Since then, due to the coercive institutional impulse, all the ELTs have been recycled or recovered, having finished with the out-of-used tires discharge.
Normative pressures for CE development
In response to RD 1619/2005, an Integrated Management Systems was created: the "Sistema Integrado de Gestión de los Neumáticos Usados" (SIGNUS Ecovalor) – or Integrated Used Tire Management System. Created by five main tire manufacturers: Michelin, Goodyear, Dunlop, Firestone, and Pirelli, which manages 70% of the tires out of use in Spain.
Result
It has been estimated that the number of tons collected during 2020 reach 188,631. This means that since the institutional pressures occur, from all the ELTs collected each year, around 7% of them have been reused and another 8% were retreaded to be used again. In terms of recycling, about 44% were chaffed and utilised for the construction of artificial grass football fields, running tracks, children parks, roads (by mixing rubber dust with asphalt), etc. Finally, 41% of the ELTs were used for energy recovery (properly prepared tires are an excellent substitute for coal, since they the same calorific value). Therefore, the combination of rules and incentives, together with the assumptions of organisational sector strategies and behaviours will facilitate CE product development

Source: based on SIGNUS (2020).

2.6 Methodology

The methodology of this paper is based on a quantitative analysis, which combines traditional statistical methods (regression analysis) with machine learning (Artificial Neural Networks), and uses an EU database about the Circular economy.

2.6.1 Database

As indicated above (section 1.5 of Chapter 1), this thesis employs for the empirical analysis the cross-sectional database from 2015 based on the EU survey on *Public Consultation on the Circular Economy* (European Commission, 2015). This database is used since it is the most recent one done at a European level regarding CE. Although, the total database consists of 1280 organisations and companies. After filtering and eliminating incomplete responses, microenterprises and individuals, the final sample used in this chapter contains 870 organisations. These companies are in different economic sectors and their geographic distribution corresponds to the 27 countries of the EU, Norway, Iceland, Switzerland, and Liechtenstein. The questions and data utilised for the creation of variables, as well as for the analysis, are described below.

2.6.2 Dependent Variable

The dependent variable measures the implementation level of CE. The questionnaire contains a series of items that determine if the goods developed by the company satisfy the characteristics listed in Table 2.3. The importance of each item is rated based on a Likert scale, which ranges from 3 (very important) to 0 (not important). One variable was generated, *CE,* as a factor analysis of all six previous items (Cronbach's Alpha: 0.948).

Table 2.3. Description of the dependent variable.

Dependent Variable	
CE	i) Durability. ii) Reparability: Product design facilitating maintenance and repair activities. iii) Reparability: Availability of spare parts. iv) Reparability: Information for reparation. v) Upgradability and modularity. vi) Reusability.

2.6.3 Independent Variables

The first variable measured in this paper is *coercive pressure*. Wang et al. (2019) and Ghisellini et al. (2016) highlight two types of direct actions from governments and institutions to promote CE. The first type of pressure tries to promote both the design and consumption of CE products.

Following the questionnaire, four items were used to create the *Coercive1* variable (shown in Table 2.4). The second variable that measures coercive pressure is *Coercive2*. This variable measures the importance of promoting CE solutions in production processes. Five items (displayed in Table 2.4) from the questionnaire are used to create this variable.

The next independent variable is *normative pressure*. Following Scott's (2005) description of the normative elements that shape the nature of organisations-oriented behaviour, two variables for *normative pressures* are generated. The first variable refers to normative elements from professional networks or sectoral organisations (*Normative1*). The questionnaire identifies elements from professional networks and sectoral levels that promote the development and implementation of standards and frameworks in companies. Two items are used to create the variable. The second variable (*Normative2*) stems from professionalisation and collaboration, understood as the conditions and methods of work defined by the members of a specific organisational framework (DiMaggio and Powell, 1983; Scott, 2005). Three items are used to generate this variable (see Table 2.4).

The importance of all independent variables is measured through a Likert scale, which ranges from 3 (very important) to 0 (not important).

Table 2.4. Description of independent variables.

Independent Variables	
Coercive1	i) Establish binding rules on product design (e.g. minimum requirements on 'durability' under Eco-design Directive 2009/125/EC). ii) Promote and/or enable the use of economic incentives for eco-innovation and sustainable product design (e.g. via rules on Extended Producer Responsibility schemes). iii) Review rules on legal and commercial guarantees. iv) Encourage the consumption of green products.
Coercive2	i) Support the development of innovative business models. ii) Improve the interface between chemicals and waste legislation. iii) Support the development of digital solutions. iv) Identify minimum standards for increasing resource-efficient processes. v) Provide access to finance for high-risk projects.
Normative1	i) Encourage industry-led initiatives (i.e., self-regulation). ii) Develop standards for voluntary use.
Normative2	i) Promote collaboration across value chains. ii) Promote collaboration between and among private and public sector. iii) Identify and promote the exchange of best practice.

2.6.4 Control Variables

Moreover, to properly measure the relationship between the dependent and independent variables of the model, the following two control variables are included in the analysis.

- *Sector*. The first control variable identifies the sector in which the organisation operates. This variable equals 1 if the organisation pertains to the industrial sector, and 0 for the service sector. This variable is used because effects on different sectors are to be expected (Rizos et al., 2017).
- *Environmental management*. The second control variable refers to the use of environmental management in the organisation, which following Marrucci et al. (2019), are useful tools

for the promotion of CE. The questionnaire proposes the following items: i) EU eco-label[23]; ii) Eco-Management and Audit Scheme (EMAS)[24]; iii) Another environmental management scheme[25]; and iv) No environmental management scheme. A binary variable is created that is equal to 1 when organisations use any of the above-mentioned environmental management schemes, and 0 otherwise.

2.6.5 Estimation Models

To test Hypotheses 1a, 1b, 2a and 2b that explore the direct effect of institutional pressures on the development of CE (Table 2.7), this paper shows how the variability of each type of institutional pressure explains the variability of the dependent variable. To do this, an OLS regression model is utilised. Thus, *CE* (Y_1) is utilised as the dependent variable, and the institutional pressures (*Coercive1, Coercive2, Normative1, and Normative2)* as independent variables, including, also, the control variables. The direct effect of each variable is measured by the regression coefficient. Table 2.7 shows the regression analysis with the developed models. The equations below show these models.

Model 1 (Basic Model):

$$Y_1 = constant + ß_1(Sector_s) + ß_2(Environmental\ Management_m) + e \tag{2.1}$$

Model 2:

$$Y_1 = constant + ß_1(Sector_s) + ß_2(Environmental\ Management_m) + ß_3(Coercive1) + e \tag{2.2}$$

Model 3:

$$Y_1 = constant + ß_1(Sector_s) + ß_2(Environmental\ Management_m) + ß_3(Coercive2) + e \tag{2.3}$$

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[23] Ecolabelling schemes are intended for consumers to obtain information regarding the environmental quality of particular products and companies at the time of purchase, allowing them to choose products that are environmentally friendly (Marrucci et al., 2019).

[24] The European Commission established the EMAS as a management tool for corporations and other organisations to review, report on, and improve their environmental performance. It applies to all industries globally and aims to improve performance, transparency, and credibility on an organisation's environmental performance (Marrucci et al., 2019).

[25] Such as ISO 14001 or ISO 50001.

Model 4:

$$Y_1 = constant + \beta_1(Sector_s) + \beta_2(Environmental\ Management_m) + \beta_3(Normative1) + e \qquad (2.4)$$

Model 5:

$$Y_1 = constant + \beta_1(Sector_i) + \beta_2(Environmental\ Management_m) + \beta_3(Normative2) + e \qquad (2.5)$$

Model 6 (Full Model):

$$Y_1 = constant + \beta_1(Sector_s) + \beta_2(Environmental\ Management_m) + \beta_3(Coercive1) + \beta_4(Coercive2) + \beta_5(Normative1) + \beta_6(Normative2) + e \qquad (2.6)$$

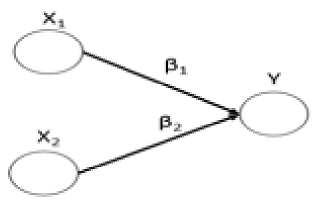
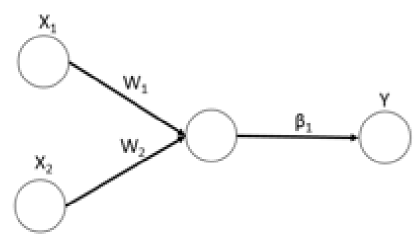
Direct Effect	Interaction Effect
	
$Y=\beta_0+\beta_1.X_1+\beta_2.X_2+e$	$Y=f(X1,X2)$ i) Interaction of variables X1 and X2 to variable Y: $Y=\beta_0+f(w_1.X_1+w_2.X_2)+e=\beta_0+\beta_1(w_1.X_1+w_2.X_2)+e$ Being, w_i, the weight of variable i in the interaction.

Figure 2.1. Direct and Interaction effects among variables

Hypothesis 4 studies the *interaction effects* of institutional pressures on the development of CE (Figure 2.1). To do this, this research assumes that an interaction effect occurs because there is an interrelation between various types of institutional pressure. Thus, this paper considers that one type of institutional pressure affects the probability of developing CE, conditioned by the interrelation with the other institutional pressure. Figure 2.1, shows this effect, in which variable

x_1 is combined with variable x_2, being w_i the weight that each variable has in the combination; and the new variable arising from the combination of both affects the variable Y. To model the interaction effects, an ANN is used, which is a type of ML. The ANN architecture is based on the MLP. This structure is considered feedforward since the connections of the network flow forward from the first layer or input layer (independent variables) to the last layer or output layer (dependent variables) (Minbashian et al., 2010). There may be several hidden layers between these two layers, whose role is essential in the MLP's generalisation capability. Figure 2.2 below displays the structure of the ANN-MLP model.

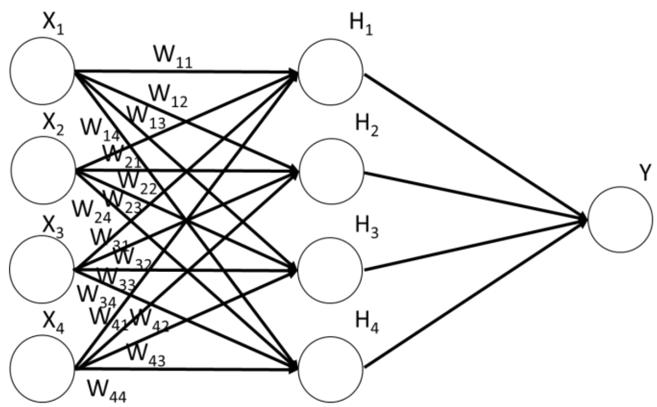


Figure 2.2. The structure of the ANN-MLP model

Regarding the structure of the ANN-MLP network, this paper employed the *trial and error procedure* (Wang, 2007; Ciurana et al., 2008), since there are no well-established approaches in the literature for identifying these structures (see Table 2.5). First, this research has to consider that the inputs of the proposed network are determined by the number of independent variables, and the number of neurons in the output layer (i.e., one) by the dependent variable. Second, regarding the number and size of hidden layers, different combinations of the number of hidden layers and the number of neurons are tested to find the right fit (Hornik et al., 1989). Although, as proposed by Ciurana et al. (2008) and Mehrotra (1997), a two-layer neural network is frequently enough to construct an accurate model. Finally, it is necessary to consider the activation functions. This paper assessed the same network architecture with three distinct configurations of activation functions (tangential, sigmoid logistic, and linear function) to analyse and determine the best ANN model, following Wang (2007) and Ciurana et al. (2008). The chosen configurations of architecture have been tested against different initial conditions to ensure that the proposed model is the best fit (Wang, 2007). The neural network is based on the model below (Model 7)[26].

Model 7 (ANN-MLP):

$$Y_1 = f\,(Coercive1;\ Coercive2;\ Normative1;\ Normative2) \tag{2.9}$$

Table 2.5. The Procedure of ANN design: The main stages.

Stages	**Choices**
1. *Choose the ANN typology*	• MLP
2. *Design of ANN-MLP architecture*	• Input and output variables • Number and size of hidden layers • Activation Functions
3. *The choice of the learning algorithm*	• Backpropagation Algorithm
4. *The learning stage*	• Training phase (60%) • Testing phase (20%) • Holdout phase (10%)

2.7 Analysis and Results

The robustness of the questionnaire and results were tested, which this paper explains before presenting the results of the analysis[27]. First, as proposed by Podsakoff et al. (2003), the common method bias (CMB) and the common method variance (CMV) were tested. These analyses show five latent constructs that represent 83.19% of the variance. As the first factor is below the recommended threshold of 50% (i.e., 26.04% of the variance), both CMB and CMV are not a

[26] For further explanation and description of the Artificial Neural Network model developed in this chapter, please see Methodological Appendix II, which describes in detail the model and its architecture, the chosen basic structure and design, the selection of the different algorithms used, the output of the neural network model, as well as a description of the selected activation functions.

[27] Another robustness check regarding the construction of the variables used for the ANN analysis is performed in Methodological Appendix II.

concern in the model. Second, to examine the statistical robustness of the regression analysis, this paper checked the collinearity test (VIF) and the autocorrelation test (Durbin-Watson). Table 2.7 displays the robustness of the results, showing adequate values for VIF and Durbin-Watson. Third, this paper has checked the robustness of the regression analysis adjustment by comparing the results of linear regression with other non-linear regression models (quadratic and cubic). Table 2.6 shows that the different regression models have similar results, both in the contribution to the variability of the model (R^2) and in the significance of the coefficients. The results do not reveal significant differences between these various types of analysis. Figure 2.3 illustrates the fit of the various regression models proposed in Table 2.6 (linear, quadratic, and cubic regression).

Table 2.6. Comparison of regression models.

Regression Model	Coercive1		Coercive2		Normative1		Normative2	
	R Square	β	R Square	β	R Square	β	R Square	β
Linear	.325	.501***	.194	.452***	.030	-.045***	.001	-.028
Quadratic	.327	.609***	.198	.470***	.044	-.242***	.005	-.065
Cubic	.356	.805***	.208	.542***	.068	-.412***	.005	-.070

*p <0.05; **p <0.01; *** p <0.001

Figure 2.3a. Regression model *CE*/*Coercive1*

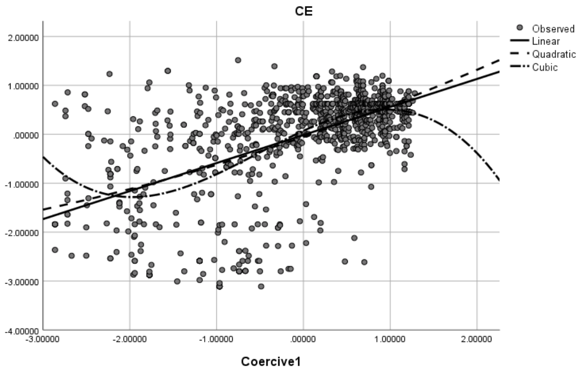


Figure 2.3b. Regression model *CE*/*Coercive2*

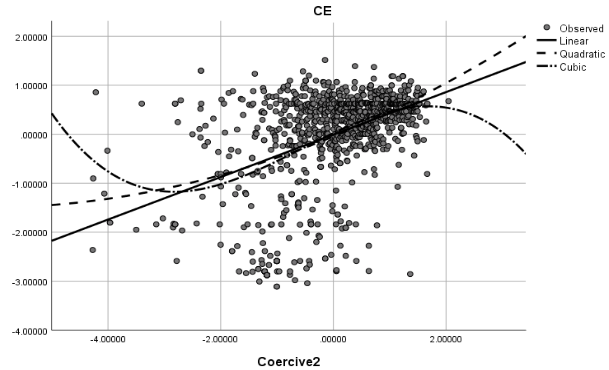


Figure 2.3c. Regression model *CE*/*Normative1*

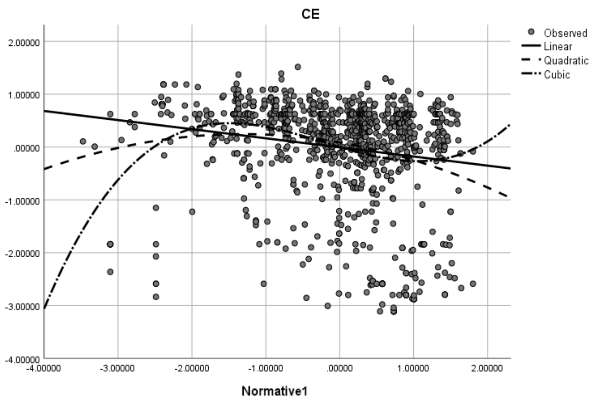


Figure 2.3d. Regression model *CE*/*Normative2*

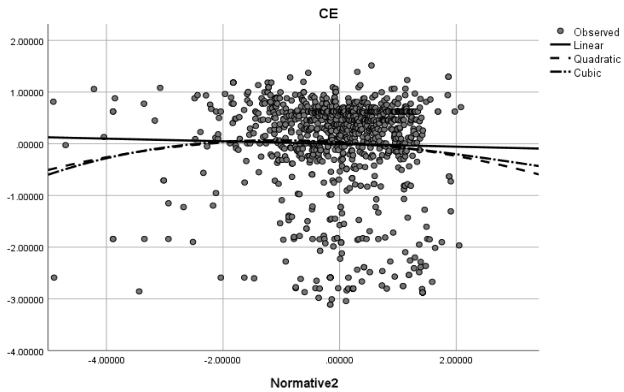


Figure 2.3. The fit of different regression models.

Concerning the results, Hypotheses 1a and 1b indicate how coercive institutional pressure affects the development of CE (Table 2.7). In Model 6, the results show that coercive institutional pressure on product development (ß = 0.372, p <0.001), and process development (ß = 0.238, p <0.001), have a significant and positive effect, corroborating the two hypotheses. Regarding Hypothesis 2a which explores the effect that normative institutional pressure, derived from sector associations and with voluntary basis, has on the development of CE. The hypothesis is not corroborated since it was argued that it had no effect (Table 2.7; Models 6). The results suggest that the effect is significant but negative (ß = -0.088, p <0.05). Finally, Hypothesis 2b is supported since the results do not show a significant effect of the normative pressure in the form of collaboration and professionalisation (Table 2.7; Model 6).

Table 2.7. Regression and Multicollinearity Analysis.

	Model 1 Estimated	Model 2 Estimated	Model 3 Estimated	Model 4 Estimated	Model 5 Estimated	Model 6 Estimated	VIF
Coercive 1		.501***				.372***	1.023
Coercive 2			.452***			.238**	1.049
Normative 1				-.045**		-.088*	1.520
Normative 2					-.028	-.016	1.558
Sector	.174**	.156**	.167**	.176**	.172**	.142*	1.333
Environmental Management	-.141*	-.127*	-.054	-.140*	-.137*	-.087	1.320
Adjusted R2	.045	.295	.238	.044	.039	.322	
R2	.053	.304	.247	.056	.052	.340	
Durbin-Watson	1.787	1.848	1.712	1.867	1.710	1.869	

*p<0.05, **p<0.01, *** p<0.001

Hypothesis 3 refers to normative institutional pressures in interaction with coercive institutional pressures. This hypothesis is analysed using an ANN. Following Cavalieri et al. (2004) and Ciurana et al. (2008), two types of tests were performed: the robustness of the ANN architecture and the robustness of the simulation. The robustness and reliability of the ANN are high, reflected by the level of error (training stage: 0.573, testing stage: 0.507) and the level of correlation between the ANN's predicted output and the observed output (correlation: 0.650). Moreover, Figure 2.4 shows the response of the network to the variation of each input variable (institutional pressures) and its effect on the output of the real variables and the predicted output of the ANN. In the graphs, a similar response to the real variable output and predicted output can be seen. This enables us to confirm, in accordance with previous studies, that the ANNs' fit is better compared to that of regression models, explaining the effect between independent variables and the dependent variable more adequately (see Table 2.7). To construct the ANN model, a *trial and error* approach was followed. The data was adjusted to a 4-1-1 configuration (Figure 2.5), which corresponds to 4 input variables, 1 node in the hidden layer, and 1 variable in the output. In this case, a hyperbolic activation function and an identity function are used for the hidden layer and the output layer, respectively. Figure 2.6 shows the interaction of the two institutional pressures and the normalised importance of the effect of each institutional pressure type on the output variable (*CE*)[28]. It is

[28] For an explanation on obtaining the relative importance of input variables on output variables, see Ibrahim (2013). Specifically, we obtained the coefficients following Garson's (1991) work.

observed that both *Coercive 1* (0.484; 100% normalised value) and *Coercive 2* (0.288; 59.5% normalised value) have a positive effect on the output variable, which is in accordance with the results of the regression analysis. However, the effect is more significant when the variable affects product development (*Coercive 1*). This can be explained either because the specific measures on the product (for example, designs of environmental products) are more concrete, or because the measures on the CE process are more ambiguous. Additionally, as Lewandowski (2016) points out, the latter (CE process – *Coercive 2*) involves third parties for the establishment of cooperation agreements. On the other hand, both normative pressures *(Normative 1 and 2)* have a significant and positive effect on the development of CE when interacting with coercive pressures, supporting Hypothesis 4. As shown in the table, *Normative1* (0.162; 33.4% normalised value) and *Normative 2* (0.066; 13.7% normalised value) have a positive impact on the adoption of CE in companies. It is worth noting that *Normative1* is more important in the contribution towards the development of CE in firms. This can be explained, as before, because *Normative2* involves cooperation as well.

Figure 2.4. Representation of the output and predicted output for different institutional pressures.

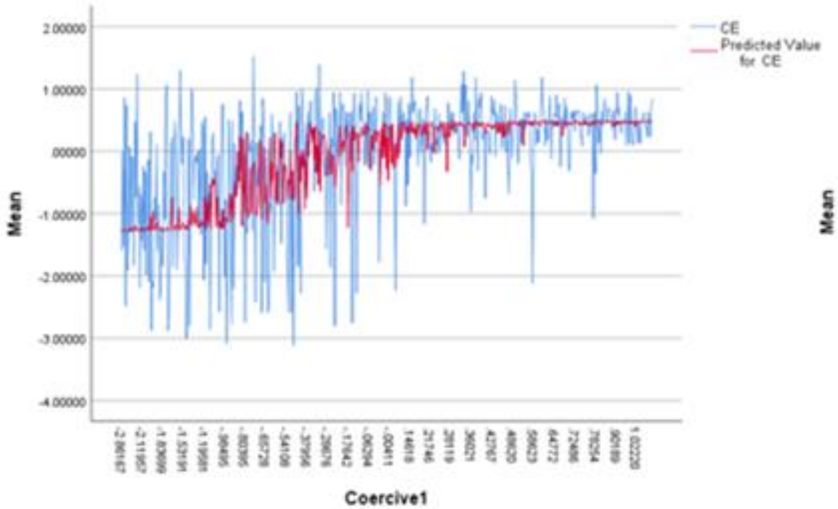


Figure 4a. Representation of the output and predicted output for *Coercive1*.

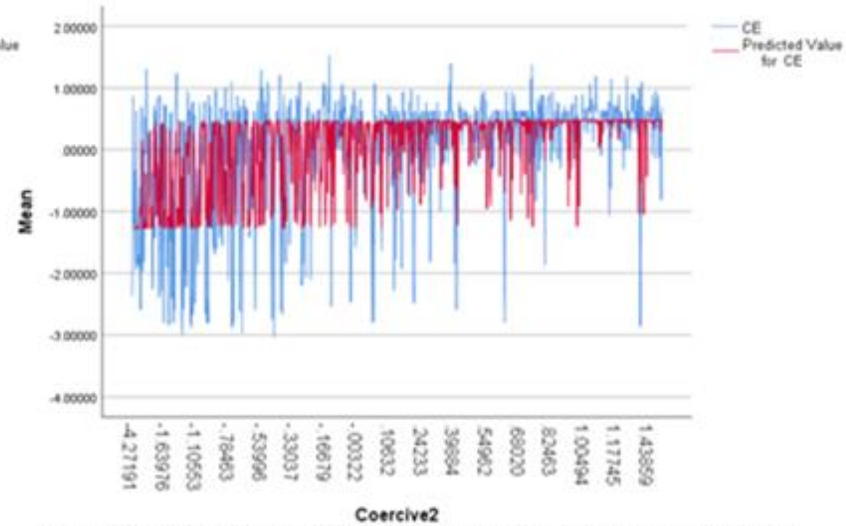


Figure 4b. Representation of the output and predicted output for *Coercive2*.

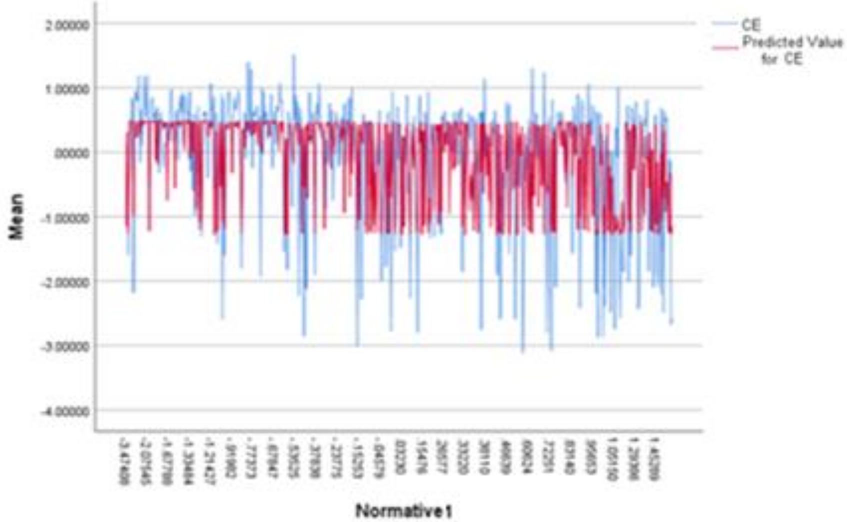


Figure 4c. Representation of the output and predicted output for *Normative1*.

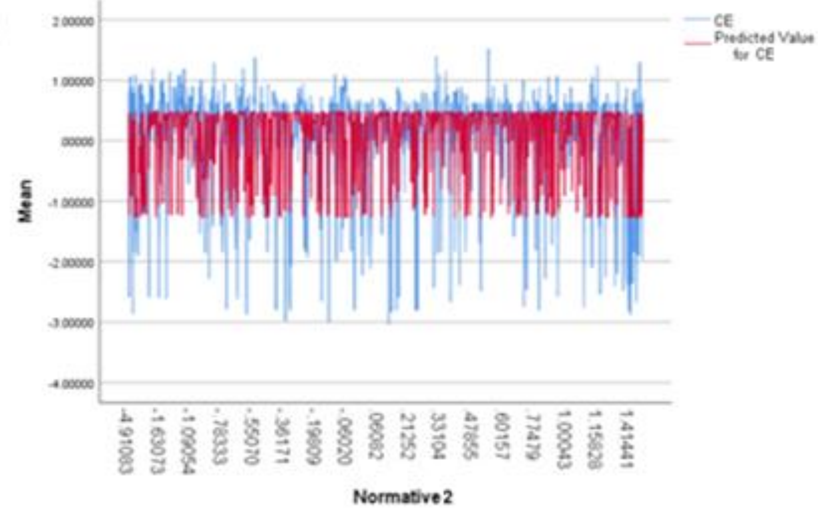


Figure 4d. Representation of the output and predicted output for *Normative2*.

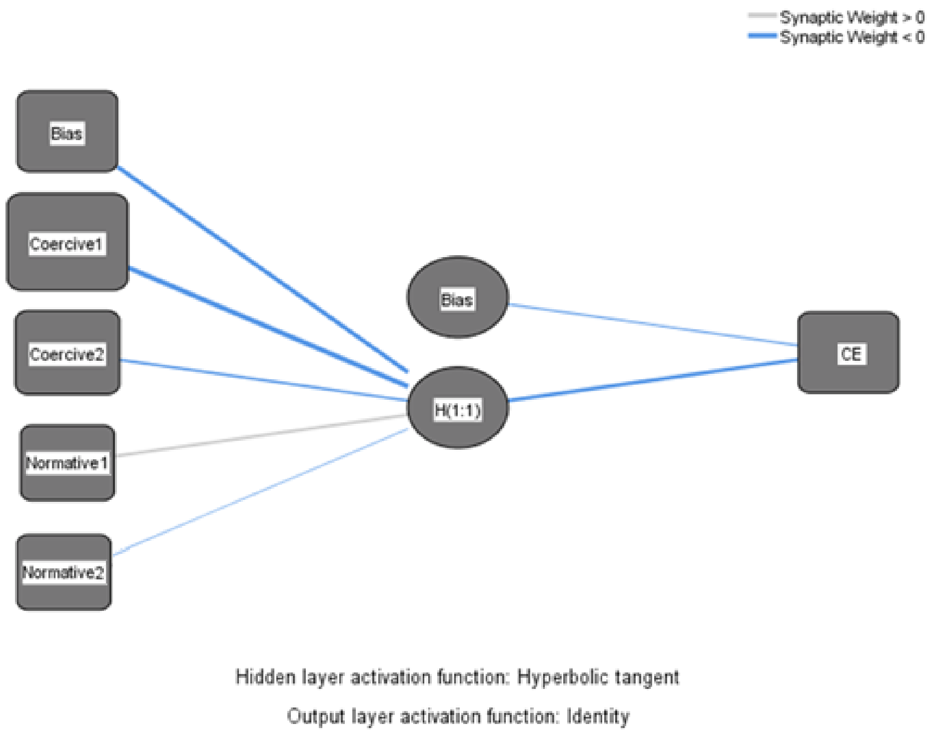


Figure 2.5. ANN-MLP architecture.

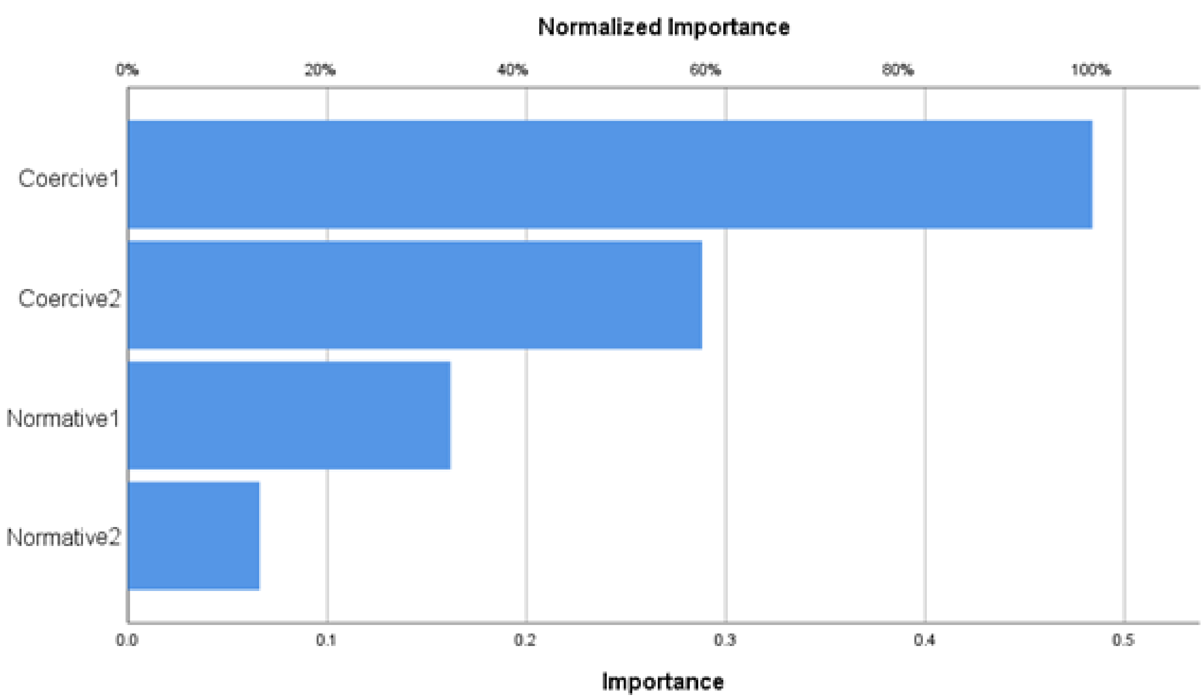


Figure 2.6. Diagram of normalised importance of input variables to the output variable.

2.8 Discussion and Conclusion

This paper studies the effect of institutional pressures on the development of CE in firms. This research distinguishes between various types and levels of institutional pressure (coercive and normative), examining how these institutional pressures affect the development of CE in companies, but also explaining how these pressures act.

This study is framed in the context of the EU, a supranational institution, which, following Battilana et al. (2009) and Alonso-Almeida et al. (2021), meets the conditions of being an institutional entrepreneur. Thus, first, the role of institutional entrepreneur that this institution exercises is confirmed, as it has the ability to influence companies. The results demonstrate that the pressures or power exerted by the EU makes it possible to achieve a greater degree of acceptance and contribution to the change towards the CE, corroborating previous studies (De Jesus and Mendoça, 2018; Alonso-Almeida et al., 2021). Thus, the results show that the EU uses both coercive and normative pressures, which allow for promoting change through technical and economic means, modifying values and practices, and shaping attitudes and preferences for the implementation of CE in firms (Alonso-Almeida et al., 2021; Elliot, 2016; Covaleski et al., 2013; Battilana et al., 2009; DiMaggio, 1988).

Regarding Hypotheses 1a and 1b, which indicate that coercive institutional pressures affect the development of CE. The results of the analysis are in accordance with DiMaggio and Powell (1983), coercive pressure utilised by governments and institutions compels organisations to obey them. These results confirm previous literature, which suggested that compulsory institutional pressure or incentives for the promotion of CE have a significant impact on CE adoption in companies (Alonso-Almeida et al., 2021; Rodriguez-Anton et al., 2019). This is either because companies would be castigated if they infringe the rules and regulations (Wang et al., 2019; Li, 2014; Roxas and Coetzer, 2012), or because the incentives (tax deductions, subsidies, and a low bank financing rate) encourage companies to solve the obstacles and difficulties in developing CE in the firm (Latan et al., 2018; Jabbour et al., 2020). More specifically, the results extend previous research (Haque and Ntim, 2018; Hazen et al., 2017), showing that coercive institutional pressures designed to develop the 3Rs, 6Rs, or 9Rs products, or the coercive pressure aimed at the development of CE processes (through financing for collaborative projects or facilitating the search for partners through digital platforms and databases) are an approach for the development of CE in firms.

Regarding Hypothesis 2a and 2b, which explore the effect that normative institutional pressures, derived from sector associations and with a voluntary basis, have on the development of CE, the results partly support and contradict, which indicate that normative pressures either have a positive effect or have no effect on the development of environmental products (Wang et al., 2019; Alonso-Almeida et al., 2021). That is, because the results of Hypothesis 2a oppose findings from previous research (see, for example, Wang et al., 2019), while Hypothesis 2b finds no significant direct effect on the development of CE, in line with prior research (Palmer and Truong, 2017). This paper argues that it does not have a positive effect, framing it in the so-called double externality effect, which relates to the lack of incentives faced by companies when investing in eco-innovation (De Marchi, 2012). Moreover, the results indicate that the development of CE by firms, unlike previous studies on eco-innovation, is a reactive attitude of companies to a voluntarily increase in eco-innovation practices from sectoral associations and the professional sector, without the firm having a clear motivation for its development. This can be explained since the CE model not only involves developing new products, but also a change in the production system, involving other organisations, which is an addition to the complexity of tasks to be carried out in an eco-innovation context.

Concerning Hypothesis 3, the results note that the interaction of normative pressures with coercive pressures changes the effect on firms in the development of CE. Thus, this research concludes that normative pressures have an ambiguous effect by themselves, only in interaction with coercive pressures, they have a clear positive effect on the development of CE in firms. These findings reinforce the conclusions of previous research, such as Alonso-Almeida et al. (2021), providing further evidence that a broad portfolio of actions and policies is critical for the implementation of the CE model. Moreover, a slight difference in the impact of normative pressures is observed, where normative pressures, as regulations and standards from sectoral associations (*Normative1*), have greater normalised importance than normative pressures, as praxis and methods of work and collaboration (*Normative2*), given interaction with coercive pressures. As a consequence, the results extend the literature, indicating that in interaction the pressures of sectoral associations are more effective for CE implementation than, for example, praxis and methods of work and collaboration, derived from the discretionary nature and experience of companies.

The paper makes two key contributions, firstly, it contributes theoretically to the field of institutional theory and environmental sustainability literature, and secondly, it contributes methodologically. Moreover, it provides some interesting implications for environmental policy and managers.

The *first contribution is theoretical*. Prior institutional theory research assumes there is a relationship between institutional pressures for the implementation of environmental activities and the organisation's strategies. In line with DiMaggio and Powell's (1983) and Scott's (2005) seminal work, which classifies institutional pressure both in its intensity and in its diversity, the literature has analysed its effect on the environmental strategies of organisations. However, when the institutional pressure varies or decreases, as in the case of normative, the results are not conclusive. These contradictory results have generated a debate about the effect of institutional pressures on environmental development in companies. The theoretical contribution is framed in this debate, clarifying the results. While coercive pressures have a compulsory effect or incentive for the development of CE in firms, normative pressures have an ambiguous effect by themselves. However, this research observes that the interaction of coercive and normative pressures changes the effect on companies for CE development. This can be argued due to the importance of norms and compulsory rules, or the existence of an incentive in environmental development, for the implantation of CE models in firms. Therefore, normative pressures have an ambiguous effect by themselves, but change their effect in interaction with coercive pressures. These results provide further evidence that a broad portfolio of actions and policies is critical for the implementation of the CE model.

The *second contribution is methodological*. Previous studies have used regression methods and considered exclusively the direct effect of each type of institutional pressure on the organisation, therefore, generating contradictory results. As shown in this study, both the low explanatory power of the regression models, in terms of explained variance, and the low significance of the explanatory variables, are a problem for the analysis with regression models, generating these conflicting results. In contrast, the empirical framework in this paper considers the possible interactions between different institutional pressures, which means, that each type of institutional pressure is due, not only to itself, but rather is conditioned by the rest of the institutional pressures.

To overcome the methodological concerns, an ANN was used, which is a type of ML method that allows analysing the interaction among variables. The use of an ANN allows not only to analyse the interaction of variables, but also to consider the existence of non-linearities in this process, obtaining an explanatory power much higher than that obtained with regression analysis. Therefore, given the results, this research clarifies the debate about discrepancies in the effect of institutional pressures and concludes that it is a methodological problem.

Lastly, the study findings provide a range of *governmental and managerial implications* for the development of CE in firms. From the point of view of governments, this research provides an important contribution, especially from the perspective of environmental policy, since it suggests that a comprehensive policy is required for the development of CE, which implies the coexistence or interaction of the two types of pressures. This is also an interesting finding for policymakers, as in the face of a comprehensive policy, interaction is feasible and may lead to a decentralisation of institutional pressure, comprising either coercive or normative measures.

Regarding managers, despite the compulsory effect of coercive pressures, they should not underestimate the effectiveness of normative measures for the promotion of CE in the company. Hence, based on the findings, this paper provides some guidelines for managers and decision-makers, when a circular environmental regulatory framework (i.e. coercive pressures) is in place:

First, managers and decision-makers should prioritise the adhesion to frameworks, standard measures for voluntary use, or industry-led initiatives, for example, at the sectoral level (normative pressures). This means that normative pressures are an effective measure in the company for the development of CE when there are established coercive pressures.

Second, if there are enough resources and capacity, then managers and decision-makers should also pursue strategies to adapt the praxis and methods of work in the form of professionalisation and the streams of collaboration to facilitate the development of CE in the firm. That is, when coercive and other types of normative pressures are in place, organisations can benefit from the implementation of these second types of measures because they would lead to the successful development of CE. The combination of all the types of pressures will help adopt CE in the firm most effectively.

Chapter 3: The effect of Consumption and Production policies on Circular Economy Business Models - A Machine Learning Approach

3.1 Abstract

The CE is attracting increasing interest, as it can bring environmental, social, and economic benefits. However, policymakers and scholars appear to concentrate more on the production side of CE, while consumption, and particularly, policies that affect consumption have received less attention and their effect is ambiguous. This paper investigates the effect of CE consumption policies on CEBMs in firms, but also examines the interplay this type of policies have with CE production policies, to have a broader picture of the circular economy policy framework, and the relevance of each type of policy on firms. While previous studies assume rational and passive consumer behaviour, this paper borrows from stakeholder theory, arguing that consumers have a proactive attitude towards the consumption of environmentally friendly products. Moreover, we use institutional theory as an analytical framework, for modelling the effects of a particular policy framework on the CEBM. Our analysis combines classical econometric methods with machine learning approaches, employing data from the EU. The results show that CE policies aimed at promoting consumption have a direct and positive effect on CEBMs. This paper also confirms that a wide portfolio of CE policies on production and consumption has a greater effect on the development of CEBMs, due to the complementarity of CE consumption and production policies. Moreover, we show that in interaction with CE production policies, CE policies on consumption have an even greater effect on CEBMs in firms than would have been anticipated.

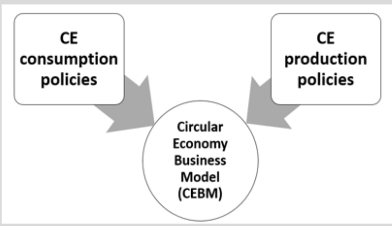
Keywords: *Circular Economy; Circular Business Model; Consumption Policy; Machine learning; ANN; K-means Cluster.*

3.2 Graphical Abstract

The effect of consumption and production policies on circular economy business models: A Machine Learning Approach

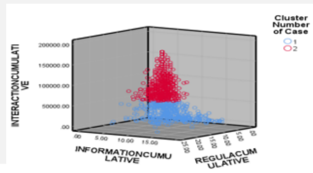
Conceptualisation

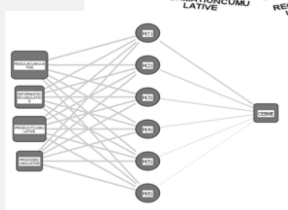
- This paper investigates the effect of CE consumption policies on circular economy business models (CEBMs).
- Also examines the interplay this type of policies have with CE production policies.
- Theoretical framework → Institutional and stakeholder theory.



Analysis

- The analysis combines regression methods with Machine learning (i.e. Artificial Neural Networks and K-means cluster).





Conclusions

- CE policies aimed at promoting consumption have a direct and positive effect on CEBMs.
- A wide portfolio of CE policies on production and consumption has a greater effect on the development of CEBMs, due to the complementarity of CE consumption and production policies.
- In **interaction** with CE production policies → **CE policies on consumption** have an even **greater effect on CEBMs** in firms than would have been anticipated

3.3 Introduction

Addressing the most pressing environmental concerns for society will necessarily involve radical adjustments to global production and consumption of energy, water, and natural resources. In this context, the CE is attracting increasing interest from governments, businesses, society, and academia. This is reflected, for instance, in the European Circular Economy Action Plan and the Chinese Circular Economy Promotion Law (European Commission, 2015; Lieder and Rashid, 2016), or the initiatives by major companies, such as Google or Renault (Esposito et al., 2016; Bocken et al., 2017), or in the significant growth in the number of scholarly publications and journals covering this issue (Geissdoerfer et al., 2017). This is because switching from a linear economy model to a circular one is widely recognised for bringing environmental, social, and financial benefits (Lewandowski, 2016). The use and reuse of resources, as well as the consequent decreased total resource inputs, energy, emissions, and waste leaks, might lessen the detrimental effects on the environment while maintaining prosperity and growth, at the same time striking a more beneficial balance between the environment, economy, and society (Geissdoerfer et al., 2018; Manninen et al., 2018). Implementing circular economy ideas frequently necessitates new visions, strategies, and policies, as well as a profound rethinking of product conceptions, service offerings, and channels for long-term solutions (Bocken et al., 2016; Lewandowski, 2016).

The prominent role that institutions and governments have undertaken in the introduction of CEBMs reflects the growing importance of CE initiatives in firms (Bocken et al., 2016; Lewandowski, 2016; Katz-Gerro and López Sintas, 2019; Kristoffersen et al., 2021). [29] Authors have highlighted that governments and institutions develop a portfolio of policies, both aimed at the production system and consumption (Ariti et al., 2019; Levänen et al., 2018; Milios, 2018; Kosow et al., 2022). While policies that directly affect the productive drive have been shown to have a positive effect on organisations in the implementation of CE models (Wang et al., 2019; Merli, 2018; Phan and Baird, 2015), policies that affect consumption have received less attention and the results are ambiguous (Liobikienė and Dagiliūtė, 2016; Milios, 2018; Pollex and Lenschow, 2020). First, there is a considerable lack of studies on circular economy relating to consumption, only 19% of the literature describing the circular economy examined topics related to consumption (Kirchherr et al., 2017a). Second, it is not sufficiently clear whether consumers would engage in the circular economy or not, this is, due to cultural barriers or lack of consumer acceptance that create certain inertia that can hinder policies of institutions aimed at the diffusion of circular business models (Abbey et al., 2015; Hobson and Lynch, 2016; Kirchherr et al., 2017b). Third, unlike production policies that directly support companies in the development of circular economy business models, consumption policies are oriented towards consumers, and it is not clear, according to Mont and Heiskanen (2015) and Milios (2018), whether this type of policies implies a direct or indirect effect on companies, producing a weak situation or certain controversy in the effect of consumption policies on the implementation of sustainable policies. Ferasso et al. (2020) emphasise the importance of further investigating the interplay between institutions and circular business model transformations and the role of government policies in promoting "green" and sustainable societies.

[29] The World Economic Forum, for example, has developed the Platform of Accelerating the Circular Economy (PACE), a collaborative effort that brings together over 40 partners, including the United Nations Environment Programme (UNEP), the World Resources Institute, the Ellen MacArthur Foundation, or Philips, among others (World Economic Forum, 2019).

It is in this context where this paper lies, by examining how CE consumption government policies affect business model activities related to circularity. This study not only examines CE consumption policies and their effect on CEBMs, but also investigates the interplay this type of policies have with CE production oriented-polices on the CEBMs in firms, to have a broader picture of the circular economy policy framework, and the relevance of each type of policy on firms. Departing from stakeholder theory, which highlights the role of external drivers for sustainability, indicating that firms' interaction with the natural environment leads to pressures exerted by customers, regulators, suppliers, and competitors, which act as drivers for more sustainable practices. Moreover, we use institutional theory, which indicates how policies push organisations to adopt shared notions and routines (Scott, 2005; DiMaggio and Powell, 1983). Institutional theory has been frequently employed to explain firm adoption of organisational practices (Liang et al., 2007; Ariti et al., 2017; Berrone et al., 2013), particularly, in the environmental literature (Gao et al., 2019; Wang et al., 2019). Furthermore, to study the effect of CE policies, this paper focuses on the CE policies of the European Union (EU). Particularly, the Circular Economy Action Plan (CEAP) adopted by the European Commission, which aims to help the EU in the transition toward a circular economy while decreasing the reliance on natural resources and creating long-term sustainable growth and employment. Despite the EU's efforts for the progressive incorporation of important policies for the development of a circular economy, these policies have not been evaluated in detail. The case of the EU policies is interesting because it introduces initiatives throughout the whole product life cycle, both legislative and non-legislative measures, focusing on areas where EU intervention delivers real added value. These areas include how products are designed, the promotion of circular economy processes, stimulation of sustainable consumption, and waste prevention. This paper employs data from the EU survey on Public Consultation on the Circular Economy database composed of 870 companies.

Therefore, the first question raised in this paper examines how the EU's CE consumption policies affect the implementation of CEBMs in firms. Then, since the effect of CE consumption policies cannot be analysed in isolation, we raise a second question to study how the combination of CE consumption policies in interaction with CE production policies affects the development of CEBMs in firms. From a methodological point of view, we address these questions using a combination of classical econometric methods with approaches of machine learning (i.e., Artificial

Neural Networks and K-mean clusters), which allows a greater degree of understanding and explanatory power of how CE consumption policies affect the development CEBM in firms.

3.4 Literature Review

3.4.1 Circular Economy

The circular economy is a cyclical system that seeks to minimise waste by converting end-of-life goods into resources for new products (Stahel, 2016; Kirchherr et al., 2017a). Closing material and product loops can lead to a process of continuous utilisation of resources. This can be accomplished by long-lasting design, proactive maintenance, reusing, recycling, repairing, refurbishing, remanufacturing, and recovering instead of discarding, if not directly reducing the input of resources (Geissdoerfer et al., 2017; Reike et al., 2018). This paper follows the definition of Kirchherr et al. (2017a), which highlights the role of businesses and consumers as enablers[30].

The literature on CE appears to concentrate more on the production side, from investigating circular business models (Rizos et al., 2017; Chauhan et al., 2022), to the development of circular value propositions strategies (Lewandowski, 2016), the examination of the advantages of these CE models (Geissdoerfer, 2017), and waste management (Ghisellini et al., 2016, McDowall et al., 2017). It seems that less attention has been paid to how the CE may influence consumption and consumers (Kirchherr et al., 2017a). The circular economy could translate into substantial changes in the daily lives of people and companies, as indicated by Hobson and Lynch (2016), nevertheless the current scientific literature seems to lack sufficient understanding of such changes and the policies that support the circular economy (Repo et al., 2018). Some of these changes require engaging in behaviours such as restoring and returning goods, by means of giving up the notion of ownership and newness (Schor, 2016; Tunn et al., 2019). Thus, these changes have raised some consumption problems, notably consumer adoption and acceptance, deterring the diffusion of circular business models. After examining companies in Europe, Kirchherr et al. (2017b)

[30] Although this definition has certain flaws, such as neglecting the involvement of other players besides firms and customers or restricting the role of citizens to consumers or users, it is nevertheless useful. (Hobson and Lynch, 2016). The transition from the current traditional linear systems (or open production systems), in which natural resources are employed to create finished products and then dispose after consumption, to circular systems (or closed production systems), in which natural resources are reused and retained in a continuous loop of production and consumption, entails significant organisational modifications of the economy and society. (Urbinati et al., 2017).

suggested that the apathy of consumers and the lack of awareness is the “main impediment regarding a transition towards CE” (p. 7). Previously, the same issue was raised by Rizos et al. (2016) from SMEs seeking to develop circular business models and strategies. They suggested that the “lack of support from demand networks” (p.10) discouraged eco-innovations such as circular business models from being introduced. This lack of understanding of consumers and consumption in the CE has deterred the development and implementation of CE policies aimed at consumption, narrowing the environmental scope of CE policies (Liobikienė and Dagiliūtė, 2016; Milios, 2018; Pollex and Lenschow, 2020).

3.4.2 Stakeholder Theory, Institutional Theory and Circular Economy

Regarding the demand and consumers in the circular economy, Ghisellini et al. (2016) concluded that the current CE literature assumes consumers as passive and rational participants who, when making choices, would abide by labels as well as other signalling from the production side. However, contrary to the previous literature on CE, this paper, borrows from the stakeholder theory, arguing that the consumer’s proactive attitude toward the consumption of environmentally friendly goods has served as a motivation for the development of new products (Demirel and Kesidou, 2019). Stakeholder theory emphasises the external drivers of eco-innovation (Sarkis et al., 2010) for CE, indicating that by incorporating stakeholders, proactive firms manage to control their interactions with the natural world. Moreover, the theory has noted that the stakeholder pressure (exercised by customers, as well as by other actors), acts as a driver of eco-innovation for the CE, both in terms of product and process (Horbach, 2008; Rennings and Rammer, 2011; Lin et al., 2014).

Additionally, this paper draws from institutional theory, which has been used widely in the literature to explain firms' adoption of organisational practices (Liang et al., 2007; Berrone et al., 2013; Gao et al., 2019; Wang et al., 2019; Bag et al., 2021). This theory postulates that organisations are not self-contained entities, but rather are shaped by norms, constraints, shared cognitions, structures, and social expectations from relevant parties (Scott, 2005; DiMaggio and Powell, 1983). According to DiMaggio and Powell (1983) and Scott (2005), institutional pressures force organisations to acquire shared conceptions and procedures. More in detail, in this paper, we consider two dimensions of institutional pressures, the first one refers to CE consumption policies, considering both legislative policies, which regulate the market, and non-legislative measures or informative policies (Pollex and Lenschow, 2020; Levänen et al., 2018; Milios, 2018). Fundamentally, these policies are intended to promote the consumption of CE-compatible products, by influencing the consumer from both a compulsory and informative point of view. The second dimension refers to CE production policies that directly support the development of CE models in companies, establishing a distinction between policies that support product development and those that affect the design of the process.

3.4.3 The role of the EU in the sustainable development of society

In this context, the EU has not overlooked the significance of the institutional push to establish a society that is sustainable and competitive within the European Union framework. Therefore, the EU created the CEAP, comprising 54 measures that lay down the framework for implementing CE at an institutional level (European Commission, 2019). Over the years, the EU has invested significant resources through the CEAP to "help stimulate Europe's transition towards a circular economy, boost global competitiveness, foster sustainable economic growth and generate new jobs" (European Commission, 2015). This institutional push of the EU tries to include actions and initiatives across the whole product life cycle, "it targets how products are designed, promotes circular economy processes, encourages sustainable consumption, and aims to ensure that waste is prevented, and the resources used are kept in the EU economy for as long as possible" (Within, 2015). However, there is still present an important dichotomy in the EU's CEAP between the strategy (which is holistic) and the actions taken, while the more developed and well-implemented policies mainly focus on solutions on the production side, consumption policies are relegated or not addressed, despite their important implications for a circularity transition (Friant et al., 2021; Von Homeyer et al., 2021; Geiger et al., 2021; Kosow et al., 2022). Hence, policies such as the "Right to repair" legislation of the EU (Svensson et al. 2021; Hernandez et al., 2020) receive little attention from institutions and legislators. This has led to lax legislation on the consumption side of CE or ambiguous policies, for example, the "Right to repair" legislation has been criticised for the imprecise meaning of the provision of maintenance and reparability necessities in terms of "fair and reasonable conditions", which leads to both business and consumer uncertainty regarding CEBMs (MacAneney, 2018; Svensson et al., 2021).

3.5 Research Model and Hypotheses

3.5.1 Research Model

Based on the theoretical foundations stated above, we construct the analytical framework depicted in Figure 3.1 for modelling the impacts of a specific policy framework on a company's circularity-related business model. The concept behind this analytical framework is that it may be utilised in the modelling of the interplay between consumption and production policies and CEBMs in different contexts.

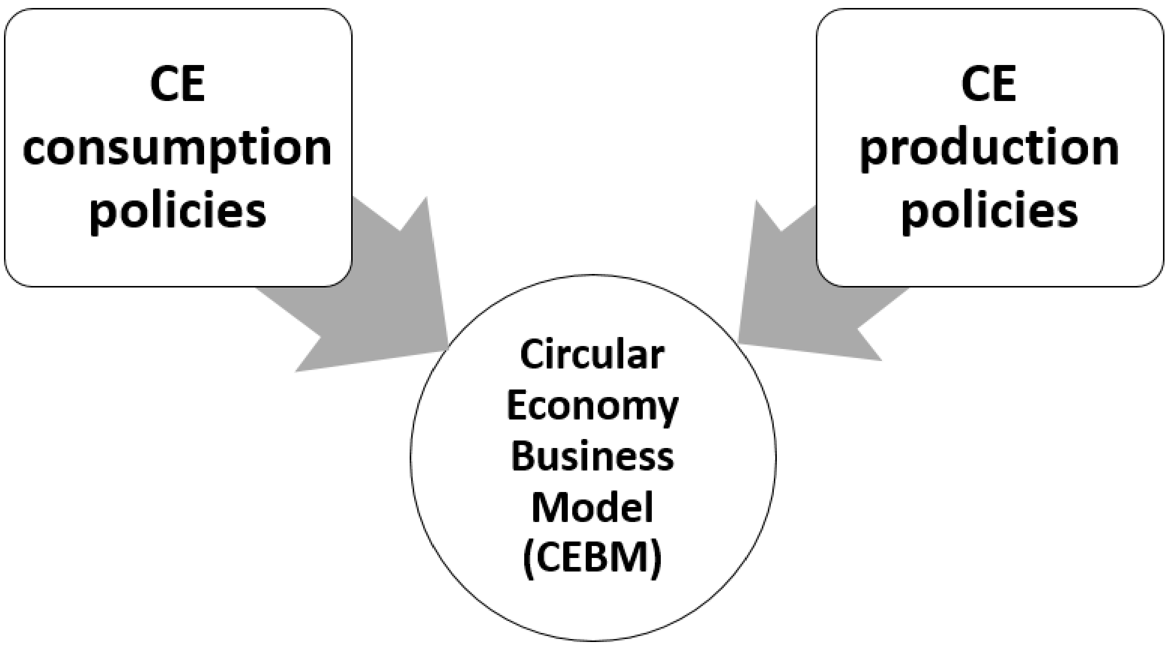


Figure 3.1. Analytical framework for modelling the interplay between policies and the CEBM.

The analytical framework in Figure 3.1 highlights the policies that affect CEBMs in firms in various ways (Baden-Fuller and Morgan, 2010), both CE consumption and production policies. These policies, established by governmental or supra-governmental authorities (such as the EU), are external factors that may facilitate or hamper CEBMs in firms (Levänen et al., 2018). This analytical approach will aid in understanding the complex interactions between firms and the surrounding policy environment by offering a systematic perspective on the interactions between the CEBM and the different institutional policy impulses. Hence, this analytical framework lays the logical rationale for the examination of the effect of these policies and the interplay they have on the CEBM of firms.

3.5.2. Hypotheses

From the analytical framework, it seems clear the way policies, in general, can affect CEBM in firms. In terms, of how consumption policies aimed at promoting or facilitating CE affect a firm's CEBMs, this paper postulates there are two channels: through the demand of consumers, and by a customer/provider duality of firms present in CE frameworks. First, as indicated in the literature review, CE literature assumes consumers as passive and rational participants (Ghisellini et al., 2016). However, this assumption is relaxed by employing stakeholder theory, as other studies have noted (see, for instance, Rave et al., 2011; Albino et al., 2009; Iles, 2008). Therefore, in this paper, we indicate that the environmental consciousness of consumers can act as a driver of environmental demand, or in this case, the demand for CE. Thus, when institutional forces, in the form of policies, are used to influence these consumers, these can, in turn, affect the development of activities related to circularity in firms, through this channel.

Second, regarding the customer/provider duality of firms. This channel stems from the nature of the consumption and production in CE models. As indicated in the literature review, CE encourages the utilisation of under-used assets and the reutilisation of existing goods, by engaging in collaborative consumption and the sharing economy (Belk, 2014). In this context of collaborative consumption, behaviours or activities in which customers serve as both providers and "obtainers" of resources are recognised (Ertz et al., 2016). This is because unlike in traditional linear economy systems, durable products are leased, rented, or shared wherever possible, transforming businesses that traditionally purchased these goods, into customers of other companies, with the incentive to ensure the return of these durable goods for subsequent reuse of the product or its materials and components at their end-of-life primary use period (MacArthur, 2013). Hence, in CE when referring to consumers we are not only looking at particulars but also firms. This duplicity of firms (as customers and producers at the same time) in CE and the interaction of both roles in the company is important to investigate. As suggested by Tukker et al. (2017) firms play a crucial role in the contribution to sustainable consumption and production (SCP). They indicate that at a macro level, businesses are a powerful stakeholder in the national socio-economic systems of consumption and production, and that companies could be viewed as producers in business-to-customer (B2C) or business-to-government (B2G) interactions, but also customers in business-to-business (B2B) markets. This means, that in B2B engagement they also act as a customer and are affected by consumption-oriented policies. This is particularly relevant given the movement of outsourcing parts of the business in a globalised economy, leading to more frequent B2B interactions in today's Business models (Dou and Sarkis, 2010). Given these channels, this paper investigates how CE consumption policies affect firms' CEBM. Hence, we propose:

Hypothesis1: CE consumption policies positively affect CEBMs in firms.

In the previous hypothesis, we have postulated the positive effect that consumption policies as institutional pressures have on the implementation of circular economy in companies. However, CE consumption policies do not work in isolation, there are also CE production-oriented policies that affect firms and their CEBMs. We expected them to interact and/or moderate each other when affecting the development of CEBM in firms, more than consumption policies alone. Wang et al. (2019) and Li and Yu (2011) have pointed out the direct effect that production policies have on the development of circular economy in firms. The development of CEBMs implies two important challenges (Linder and Williander, 2017; Kirchherr, et al., 2018; Katz-Gerro and López Sintas, 2019; Bressanelli et al., 2019). The first challenge refers to the complexity of the design and creation of products congruent with the CE model. The literature on product innovation identifies a set of challenges and barriers that firms must confront, i.e., market complexity, the uncertainty of the process, and the management of organisational resources for innovation. In this sense, an institutional impulse in the form of financial support, with the aim of supporting technical uncertainty (production policy), plus consumption policies that help reduce market uncertainty, can help in the implementation of CE models in firms. Hence, the joint adoption of consumption and production policies is expected to have a greater positive effect on the implementation of CEBM in firms, than acting alone.

The second challenge stems from the closed supply chains, which are a pillar of the CE model (Schaltegger et al., 2016; Lüdeke-Freund et al., 2018; Kirchherr, et al., 2018; Perey et al., 2018). The CE model encompasses not only all tasks involved in the design, production, distribution, and usage of products, but also comprises the maintenance, reuse, recovery, and recycling. In other words, it embraces producer organisations, as well as users and third parties (e.g., organisations devoted to the management of waste or suppliers of raw materials), intending to facilitate the development of CE-compatible products and processes. Lewandowski (2016) noted the importance of collaboration and cooperation among organisations for the implementation of closed-loop systems. However, partnership-building is not without difficulties (see, for example, Arranz et al., 2016). Finding the right partner, coordinating tasks, and preventing and resolving conflicts may inhibit organisations' interest in implementing CE models through cooperation. In this context, institutional support can help mitigate the challenge that cooperation poses in the development of CEBM in firms (see, for example, Ren et al., 2019 or Liao, 2018). Therefore, it is to be expected that a diversified portfolio of institutional impulse CE policies, ranging from production to consumption, will produce synergistic and complementary effects that have a greater effect on firms than only policies aimed at consumption. Hence, we propose:

Hypothesis2: CE consumption policies in interrelation with CE production policies will positively affect CEBMs in firms more than if CE consumption policies acted alone.

3.6 Methodology

3.6.1 Database

As indicated above (section 1.5 of Chapter 1), this thesis employs for the empirical analysis the cross-sectional database from 2015 based on the EU survey on *Public Consultation on the Circular Economy* (European Commission, 2015). This database is used since it is the most recent one done at a European level regarding CE. Although, the total database consists of 1280 organisations and companies. After filtering and eliminating incomplete responses, microenterprises and individuals, the final sample used in this chapter contains 870 organisations. These companies are in different economic sectors and their geographic distribution corresponds to the 27 countries of the EU, Norway, Iceland, Switzerland, and Liechtenstein. The questions and data utilised for the creation of variables, as well as for the analysis, are described below.

3.6.2 Measures

3.6.2.1 Dependent Variable

As a dependent variable, we use the degree of development of the *CEBM*. A CEBM is described as an organisation's or an ecosystem of organisations' rationale for creating, delivering, and capturing value while (i) slowing; (ii) closing; or (iii) narrowing resource flows (i.e., energy or materials) (Pieroni et al., 2021; Bocken et al., 2016; Massa et al., 2017; Osterwalder and Pigneur, 2010)[31]. For this, the questionnaire identifies several elements or characteristics of the circular economy of organisations that narrows or reduces the flow of natural resources both in terms of product creation and in the process. The questionnaire presents the following items displayed in Table 3.1.

Table 3.1. Description of the dependent variable.

Dependent Variable	
CEBM	i) Durability ii) Reparability: Availability of information on product repair (e.g. repair manuals) iii) Reparability: Product design facilitating maintenance and repair activities iv) Reparability: Availability of spare parts v) Upgradability and modularity vi) Reusability vii) Biodegradability and compostability viii) Resource use in the use phase (e.g. water efficiency) ix) Recyclability (e.g. dismantling, separation of components, information on chemical content) x) Increased content of reused parts or recycled materials xi) Increased content of renewable materials xii) Minimising lifecycle environmental impacts.

[31] Slowing the flow of resources entails prolonging or increasing resource utilisation. For example, firms achieve this objective through premium and long-life product sales, providing services that extent product-life, product sharing, or systems of product/service (Bocken et al., 2016; Geissdoerfer et al., 2018). Closing resource flows involves repurposing utilised resources (such as customers-discarded products) for both, sourcing and manufacture. This is done, for example, by valorisating resources that would otherwise be considered as waste, such as multi-flow offers (e.g., industrial symbiosis) or recycling and cascading supplies and products (Bocken et al., 2016; Geissdoerfer et al., 2018). Narrowing resource flows seeks to achieve efficiency in the utilisation of resources, for instance, via minimising the amount of materials used per product (Bocken et al., 2016).

The relevance of each particular item is assessed using a Likert scale, with 4 being "very important," 3 "important", 2 "not very important", and 1 "not important". Following Costantini et al. (2017), the dependent variable *CEBM* is constructed as a cumulative index of the different CEBM elements. This method is used for the creation of the dependent variable since it allows measuring CEBM in all its breadth, while maintaining the typology of the measuring scale and with no loss of variance, as opposed to other methods. Moreover, it is a methodologically sound approach, as there is a high correlation between the variables (Cronbach Alpha: 0.905), and their scales are consistent with each other[32].

3.6.2.2 Independent Variables

In terms of the independent variables, these are represented by the different EU policies on CE aimed at consumption and production. These policies from the questionnaire, arise from the Circular Economy Action Plan adopted by the European Commission (European Commission, 2015). The first group of variables refers to CE policies that directly affect consumption. In line with previous measures, a 4-point Liker scale was used ranging from "very important" (4) to "not important" (1). We construct these variables as a cumulative index in line with the dependent variable. The first variable that measures CE consumption policies refers to legislative measures or measures to regulate the consumption of CE-compatible products to promote the circular economy (*regulation)*. The questionnaire, following Milios (2018), considers the items shown in Table 3.2 (Cronbach's Alpha: .814)[33]. The second variable that measures CE consumption policies refers to non-legislative measures or informative measures to encourage the consumption of products compatible with the circular economy (*information)*. The questionnaire, following Pollex and Lenschow (2020), considers the items illustrated in Table 3.2 (Cronbach's Alpha: .670)[34].

[32] Additionally, we have analysed the robustness of this method comparing it to a variable created using factor analysis with principal components and Varimax rotation (KMO: .908; sig. .000; extracted variance: 50.286). After analysing the correlation between the variable created as cumulative index and the one created with factor analysis, the result is .995. The advantage of the cumulative index is that it does not lose explained variance compared to that obtained by factor analysis.

[33] Furthermore, we have performed a confirmatory factor analysis with these items (KMO: .775; sig .000; explained variance 57.573%).

[34] Additionally, and in line with the previous variable, we have performed a confirmatory factor analysis with these items (KMO: .683; sig .000; explained variance 51.530%).

Table 3.2. Description of independent variables related to CE consumption policies.

Independent Variables (Consumption)	
Regulation	i) Improve/clarify rules and practices affecting consumer protection (e.g., relating to legal and commercial guarantees) ii) Take action on product and material design iii) Encourage financial incentives to consumers at national level (e.g., by differentiated taxation levels depending on products' resource efficiency) iv) Take measures targeting public procurement (e.g., through criteria for Green Public Procurement) v) Encourage new modes of consumption such as shared ownership (e.g. car sharing), collaborative consumption, leasing and the use of internet-based solutions vi) Promote the development of repair and maintenance services
Information	i) Provide more information relevant to the circular economy to consumers, for example, on the expected lifetime of products or availability of spare parts ii) Ensure the clarity, credibility, and relevance of consumer information related to the circular economy (e.g. via labels, advertising, marketing etc.) and protect consumers from false and misleading information in this respect iii) Organise EU-wide awareness campaigns to promote the circular economy iv) Encourage waste prevention (e.g. minimising food waste)

Moreover, we have analysed the robustness of the construction of both variables, examining the correlation between the constructed variable as a cumulative index and the variable constructed with factor analysis, and in both cases the correlation is greater than 0.9 (.943; .921), corroborating the robustness of our constructs.

The next group of variables refers to CE policies that directly affect companies, in terms of production, for the development of CE models. As previously mentioned, these independent variables related to production-oriented EU policies are used to examine hypothesis 2 about the interplay of both, production and consumption policies, on the CEBM. The relevance of each particular item is also assessed on a 4-point Liker scale ranging from "very important" (4) to "not important" (1). We construct these variables as a cumulative index, in line with the dependent variable and the previous independent variable related to consumption. The first variable that measures CE production policies refers to measures that affect the development of CE-compatible products. The questionnaire includes the items listed in Table 3.3 used to create the variable *product* (Cronbach's Alpha: .786)[35]. The second variable that measures CE production policies refers to measures that affect the development of the CE production process. The questionnaire includes the items listed in Table 3.3 used to create the variable *process* (Cronbach's Alpha: .682)[36].

Table 3.3. Description of independent variables related to CE production policies.

Independent Variables (Production)	
Product	i) Establish binding rules on product design (e.g., minimum requirements on 'durability' under Eco-design Directive 2009/125/EC) ii) Promote and/or enable the use of economic incentives for eco-innovation and sustainable product design iii) Review rules on legal and commercial guarantees iv) Encourage the consumption of green products (e.g., via rules on Extended Producer Responsibility schemes)
Process	i) Promote cooperation across value chains (e.g., through encouraging new managerial modes) ii) Support the development of innovative business models (e.g., leasing) iii) Improve the interface between chemicals and waste legislation iv) Promote collaboration between and among private and public sectors, including end-users v) Support the development of digital solutions vi) Identify and promote the exchange of best practice vii) Identify minimum standards for increasing resource-efficient processes (e.g. Best Available Techniques) viii) Provide access to finance for high-risk projects

Furthermore, we have analysed the robustness of the construction of both variables, examining the correlation between the constructed variable as a cumulative index and the variable constructed as factor analysis, and in both cases the correlation is greater than 0.9 (.999; .993), corroborating the robustness of our constructs.

[35] Moreover, we have performed a confirmatory factor analysis with these items (with a single factor KMO .749, sig .000; and explained variance 61.289%).
[36] Additionally, we have performed a confirmatory factor analysis with these items (KMO .764, sig .000; explained variance 61.692%).

3.6.2.3 Control Variables

Moreover, from the questionnaire, we extract two control variables: *Environmentalmanagement and Sector*. The first control variable relates to the utilisation of environmental management schemes at the firm level. The survey proposed the items in Table 3.4, which are used to generate a binary variable that takes the value 1 if the company employs any environmental management scheme (listed in Table 3.4), and 0 otherwise. The second control variable categorises the sector in which the company operates (listed in Table 3.4). This variable takes the value 1 when the company is in the agricultural sector, 2 if it is in the industrial sector, and 3 if it is in the service sector.

Table 3.4. Description of control variables.

Control Variables	
Environmentalmanagement	i) EU eco-label ii) Eco-Management and Audit Scheme (EMAS) iii) Another environmental management scheme iv) No environmental management scheme.
Sector	i) Agricultural sector ii) Industrial sector iii) Service sector

3.6.3 Econometric Models

This paper employs an Ordinal Logistic Regression (OLR), as well as two unsupervised machine learning methods, that is, a K-means Cluster and ANN, to analyse the Hypotheses.

For Hypothesis 1, we use an OLR to determine the direct effect of the different CE consumption policies on CEBMs[37], without considering the interaction with CE production policies variables. For the regression analysis, we have estimated two models, a basic model with the control variables and a complete model with the independent variables related to consumption.

[37] Additionally, we have checked various regression models (linear, quadratic, cubic) to check if another relationship between dependent and independent variables would have better fit. The results show that the different regression models have similar results, both in the contribution to the variability of the model (R^2) and in the significance of the coefficients. Our results do not reveal significant differences between these various types of analysis (see Methodological Appendix III).

Model 1:

$$CEBM = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + e \qquad (3.1)$$

Model 2:

$$CEBM = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) \qquad (3.2)$$

$$+\ ß_3\,(regulation) + ß_4\,(Information) + e$$

For Hypothesis 2, we use a K-means cluster analysis combined with OLR, together with ANN, to examine how the interrelation of CE consumption and production policies has a greater effect on CEBMs than if consumption policies acted alone. First, we analyse the existence of different groups of companies, classifying companies according to the effect of production and consumption policies in interaction, and consumption policies alone. For this, we use the K-means cluster statistical model, which allows us to obtain different groups of companies. The K-means algorithm is a well-known centroid model clustering method (Huang, 1998). Each cluster is represented by a single mean vector, with the algorithms assigning an item to the nearest centroid. This means that K-means clustering uses Euclidean distance to identify reasonably homogenous groups of cases based on selected features (Solorio-Fernández et al., 2020). K-means allows for handling large numbers of cases, which is appropriate for the analysis of this paper. As classification variables, we use CE consumption policies (*regulation* and *information*), and the interaction of CE consumption policies with CE production policies (including *product* and *process*). For the latter, we create a variable named *interaction*.

Second, once the companies have been classified into various groups or clusters, we address Hypothesis 2 by using an OLR model as the econometric model. As a dependent variable, we use the *CEBM* variable. As independent variables, in both cases, we introduce the independent variable, membership in the cluster (i.e., *cluster1 or cluster2),* being coded as a categorical variable. For the analysis of our results, the various regression coefficients must be interpreted as follows. The regression coefficient value 0 reflects the reference category ($cluster_i$), and the rest of the regression coefficients obtained correspond to the various categories ($cluster_j$), which reflect the probability of developing CEBMs with respect to the first category. That is, H0: $ß \leq 0$ means there is a greater probability of developing CEBMs in companies pertaining to $cluster_i$ than $cluster_j$

in, and H1: ß> 0 entails there is a greater probability of $cluster_j$ than $cluster_i$. The models below are estimated to test Hypothesis 2, Model 3 to Model 6 relate to a pre-analysis of the hypothesis, whereas Model 7 corresponds to the regression analysis with clusters[38].

Model 3:

$$CEBM = constant + ß_1 (Environmentalmanagement_m) + ß_2 (Sector_s) + ß_3 (Product) + ß_4 (Process) + e \tag{3.3}$$

Model 4:

$$CEBM = constant + ß_1 (Environmentalmanagement_m) + ß_2 (Sector_s) + ß_3 (Regulation) + ß_4 (Information) + ß_5 (Product) + ß_6 (Process) + e \tag{3.4}$$

Model 5 (OLR – K-means):

$$CEBM = constant + ß_1 (Environmentalmanagement_m) + ß_2 (Sector_s) + ß_3 (Interaction) + e \tag{3.5}$$

Model 6 (OLR – K-means):

$$CEBM = constant + ß_1 (Environmentalmanagement_m) + ß_2 (Sector_s) + ß_3 (Regulation) + ß_4 (Information) + ß_5 (Product) + ß_6 (Process) + ß_7 (Interaction) + e \tag{3.6}$$

Model 7 (OLR – K-means):

$$CEBM = constant + ß_1 (Environmentalmanagement_m) + ß_2 (Sector_s) + ß_3 (Cluster1) + ß_4 (Cluster2) + e \tag{3.7}$$

Additionally, to understand in more detail how the various policies in interaction act, we perform an analysis with ANN[39], to discriminate which policies have the most effect on the implementation

[38] For further information relating the specifics of the K-means cluster analysis performed, see Methodological Appendix III.

[39] This type of analysis is employed since ANNs show greater potential as predictive tools, compared to the performance of regression models (Paruelo and Tomasel, 1997; Gupta et al., 2019) where the interaction of various variables might involve non-linearity, not direct causality, and multi-interactions (for example, Minbashian et al., 2010; Verlinden et al., 2008)

of CEBMs. The ANN typology used in this paper is an RBF. RBFs are meant to approximate multivariable functions through the combination of different terms based on a single univariate function (that is, the radial basis function). This is radialised to allow it to be utilised in several dimensions[40]. Moreover, RBF is employed for the analysis since it is a feedforward[41], supervised learning network[42] with an input layer, a hidden layer (known as the radial basis function layer), and an output layer. Table 3.9 and Figure 3.2 display the architecture of ANN-RBF used for the analysis. This neural network is based on the model below (Model 8) that is developed to examine the interaction of the different policies in more detail[43].

Model 8 (ANN-RBF):

CEBM = f (Regulation; Information; Product; Process) (3.8)

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[40] They are commonly used for the approximation of data or functions that are observable only at a finite number of points (or are too complicated to measure otherwise), with the aim of making evaluations of the approximating function more frequently and efficiently (Cheney 1966; Buhmann, 2003). Among the most significant advantages of this approach is that it may be used in practically any dimension (thus its versatility), as there are few limits on how the data are prescribed.

[41] This means that the data only flows in one direction, from the input neurons via the hidden layer of neurons to the output neurons (Reed and Marks II, 1999).

[42] That is, they map relationships implied by the data, so that the predicted results can be contrasted against the known values of the dependent variable (Mehrotra, 1997; Reed and Marks II, 1999)

[43] Methodological Appendix III cointains further explanation on the ANN-RBF model used for the analysis. More specifically, it describes in detail the specifications of the ANN-RBF model, the basic structure and design, the selection of the different algorithms used, the output of the neural network, and a description of the selected activation functions.

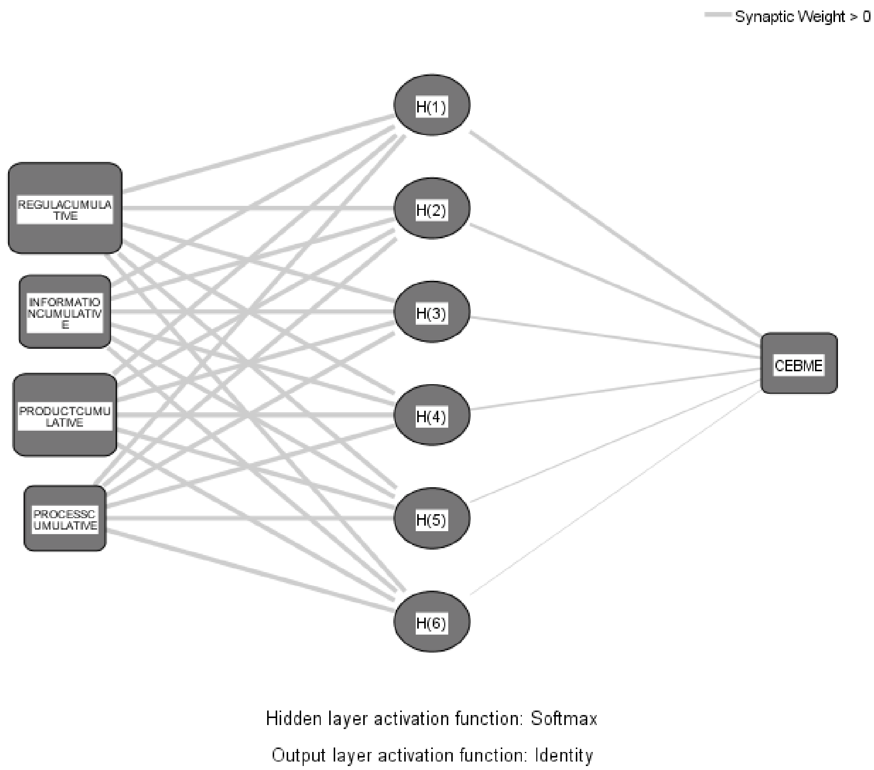


Figure 3.2. ANN-RBF architecture.

3.7 Analysis and Results

Regarding the empirical analysis, the robustness of the questionnaire and results were examined. First, as proposed by Podsakoff et al. (2012) and Spector (2006), the CMB and the CMV were tested. These analyses show the eight constructs that represent 63.072% of the variance. As the first factor is below the recommended threshold of 50% (23.676% of the variance), we can affirm that both CMB and CMV are not a concern in our model. Second, although, there are not many missing values, we tested the data for non-response bias using ANOVA, by comparing non-respondent group characteristics (such as countries, firm size, and knowledge) with respondents (Armstrong and Overton, 1997). We concluded that there are no concerns about the dataset. Third, to examine the statistical robustness of the regression analysis, we have checked the collinearity test (VIF) and autocorrelation test (Durbin-Watson). Table 3.5 displays the reliability and robustness of the results. We obtained values that are acceptable for both the VIF and Durbin-Watson tests (Hair, 2006). Finally, we conducted a reverse causality test, finding no evidence supporting any concerns relating to endogeneity.

Table 3.5 shows the results obtained from measuring the direct effect of the EU consumption policies for the circular economy on CEBM (Hypothesis 1). From the regression analysis, we observe that the model developed for Hypothesis 1 is statistically significant, with a good statistical fit to the model as shown in the table below. Moreover, the pseudo-r-squared values for the model are good (Cox and Snell, 1989; Nagelkerke, 1991; McFadden, 1974). Table 3.5 depicts the parameter estimates of the OLR analysis. The results show that all CE consumption *regulation* policies (β = 2.066; p <.001) and *information* policies (β = 1.231; p <.001), have a positive and significant effect on the development of CEBM in the company[44].

Table 3.5. Ordinal Logistic regression models (analysis Hypothesis 1)

Variables	Model 1	Model 2
Regulation		2.066***
Information		1.231***
Sector	.254*	-.006
Environmental	-.327	-.128
-2 Log Likelihood	464.015	1353.457
Chi-Square	7.751	262.753
Sig.	.021	.000
Cox and Snell	.031	.681
Nagelkerke	.031	.682
McFadden	.004	.162

*p<0.05, **p<0.01, *** p<0.001

Regarding Hypothesis 2, Tables 3.6 and 3.8 display our results. First, we have carried out a pre-analysis, using regression analysis to examine the effect of the various CE policies, both production and consumption, on the development of CEBM, without considering their interaction (see Table 3.6). That is, Model 4 shows the positive effect of the CE policies, both production [*product* (β = .159; p <.001); *process* (β = .060; p <.005)] and consumption [*regulation* (β = .245; p <.001); *information* (β = .203; p <.001)], observing that these variables individually have a

[44] Furthermore, we have checked the robustness of the regression analysis adjustment by comparing the results of linear regression with other non-linear regression models, i.e. quadratic and cubic (please, see Methodological Appendix III). The aim of this robustness test is to check whether any other type of regression model, besides the linear one, would have yielded a better fit for the model. However, as described in the appendix, the results of this robustness check does not reveal significant differences between these various types of regression analysis. Hence, supporting the decision of using a linear model for the analysis of Hypothesis 1.

positive effect on the development of CEBM in companies. Moreover, Model 5 shows the interaction effect of CE production and consumption policies, obtaining a positive and significant effect [*interaction* (β = .000; p <.001)]. Finally, Model 6 shows the moderation analysis, which is inconclusive for our Hypothesis 2. Following Hair (2006), Minbashian et al. (2010), and Asteriou and Hall (2015), this has been explained as the difficulties of using regression models in moderation analysis, either due to the existence of collinearities, due to imbalances in the sample (this is especially critical in the use of OLR), or due to a low value of explained variance. To solve this difficulty, we have carried out a second analysis combining cluster analysis with regression analysis and ANN (Table 3.8).

Table 3.6. Ordinal Logistic regression models (pre-analysis Hypothesis 2)

	Model 3	Model 4	Model 5	Model 6
Regulation		.245***		1.586***
Information		.203***		.949***
Product	1.521***	.159***		.662***
Process	.877***	.060*		.355*
Interaction			0.000E+0***	-.016
Sector	.260*	.073	.149	.071
Environmental	-.438	-.254	-.319	-.286
-2 Log Likelihood	1405.199	1267.046	1313.397	1259.567
Chi-Square	220.011	273.016	212.567	280.494
Sig.	.000	.000	.000	.000
Cox and Snell	.613	.714	.623	.724
Nagelkerke	.613	.715	.623	.724
McFadden	.135	.177	.138	.182

*p<0.05, **p<0.01, *** p<0.001

To corroborate Hypothesis 2, we first explored the behavioural patterns of companies in terms of the CE portfolio of impulse policies that affect them. The results of the K-mean cluster show two groups of companies, the first group consisting of 490 companies (Cluster 1), and the second group of 543 companies (Cluster 2). Moreover, we have performed an ANOVA analysis (see Table 3.7) to verify the robustness of the cluster exploration, using the two institutional impulse policies, consumption (*regulation* and *information),* and the interaction of consumption and production (*interaction*), and as a control variable, the cluster membership (*Cluster1* and *Cluster2*). The results show that there are significant differences in the two types of policies, for each of the clusters, confirming the robustness of the cluster analysis performed.

Table 3.7. ANOVA Analysis

Variables	F	Sig.
Interaction	2311.297	.000
Regulation	1029.174	.000
Information	411.496	.000

Concerning the differences in terms of the portfolio of CE policies of institutional impulse between the two clusters, these are reflected in Figure 3.3. While we observe that the behaviour of the two groups of companies in terms of CE consumption policies is relatively similar, we note that cluster 2 is characterised by being subject to a greater institutional impulse from both consumption and production CE policies in interaction. Figure 3.3 also shows the distribution and density of the distribution of the companies according to the cluster[45].

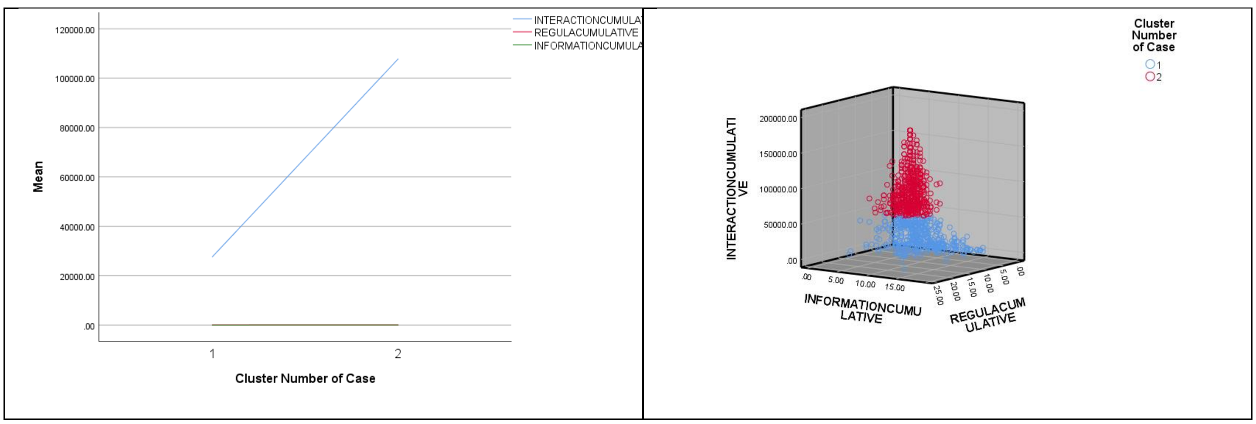


Figure 3.3. The effect of CE policies according to the cluster.

Table 3.8 shows the result of the regression analysis, using cluster membership as categorical variables. We observe that the results confirm our hypothesis (Hypothesis 2) since cluster 1 has a significant but negative coefficient ($\beta = -2.964$; $p <.001$), thereby confirming that the companies that belong to cluster 2, which are the companies affected by the interaction of both consumption and production CE policies, the probability of developing CEBMs is higher than in Cluster 1. Therefore, we can conclude that Hypothesis 2 is corroborated, confirming that a wide portfolio of

[45] Further information an explanation of the k-mean cluster centre selection, distance calculation, and cluster profile can be found in Methodological Appendix III.

CE policies on production (both in terms of product and processes) and consumption (both regulative and informative measures) have a greater effect on the development of CEBM in firms.

Table 3.8. Ordinal Logistic regression models (analysis Hypothesis 2)

Variables	Model 7
Cluster 1	-2.964***
Cluster 2	0
Sector	.120
Environmental	-.296
-2 Log Likelihood	528.861
Chi-Square	108.008
Sig.	.000
Cox and Snell	.391
Nagelkerke	.391
McFadden	.070

*p<0.05, **p<0.01, *** p<0.001

Furthermore, as previously mentioned, we have also performed an ANN-RBF analysis to distinguish which CE policies (that is, consumption or production) when in interaction have the most effect on the implementation of CEBMs in firms. Following Cavalieri et al. (2004) and Ciurana et al. (2008), we have carried out two types of robustness tests for this analysis: the robustness of the ANN architecture and the robustness of the simulation. The robustness of the model is high taking into consideration both the error (.314, in the training stage, and .294 in the testing stage) and the correlation of the ANN's predicted output with the actual output variable (.840). This is shown in Table 3.9 which displays the ANN-RBF architecture for interaction analysis.

Table 3.9. ANN-RBF architecture for interaction analysis

Simulation	ANN architecture	Activation Functions	Sum of Squares Error	Correlation: Output/Predicted Output
Regulation & Information & Product & Process	4-6-1	• Softmax • Identity	• Training: .314 • Testing: .294 • Holdout: .236	.840***

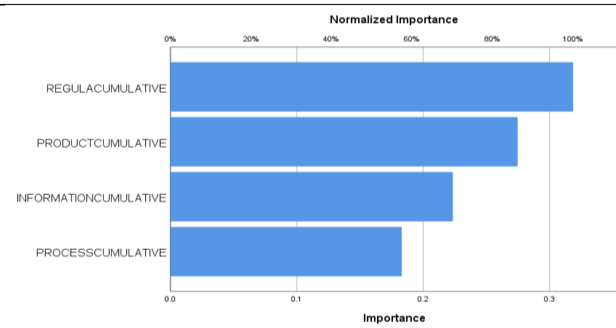
* Error (Cross-entropy)

**Correlation is significant at the 0.01 level (2-tailed).

Focusing on the results of the simulation of the impact of CE policies on the development of CEBMs, Table 3.10 shows the normalised importance[46] of the effect of each policy in the CE models developed by the firm. Firstly, we observe that all policies have a positive and significant impact on the development of CEBMs. It is observed that *regulation* (.319; 100% normalised value), *product* (.275; 86.2% normalised value), *information* (.223; 70.1% normalised value), and *process* (.183; 57.4% normalised value) have a positive effect.

Table 3.10. ANN-RBF simulation for each of the independent variables

Variable	Simulation	
	Importance	**Normalised Importance (%)**
Regulation	.319	100.0%
Information	.223	70.1%
Product	.275	86.2%
Process	.183	57.4%



3.8 Discussion and Conclusion

Our paper is framed in the understanding of how CE institutional impulse policies, particularly consumption policies, affect the development of CEBMs. Highlighted the importance of the implementation of CEBMs, as a source of environmental improvement, we consider the important role that institutional stakeholders have in promoting these models. Thus, we have considered in this paper two dimensions of the institutional impulse, the first one refers to CE consumption policies, considering both legislative policies, which regulate the market, and non-legislative measures, or informative policies. Fundamentally, these policies are intended to promote the consumption of CE-compatible products, by influencing the consumer from both a compulsory

[46] Ibrahim (2013) revises some approaches for determining the relative importance of input variables in ANNs. These approaches are based on Garson's algorithm (1991), which calculates variable contributions using the absolute values of the final connection weights. $RI_x = \sum_{x=1}^{n} \frac{|w_{xy}\, w_{yz}|}{\sum_{y=1}^{m}|w_{xy}\, w_{yz}|}$ (3.9) where RI_x denotes the relative importance of neuron x, while $\sum_{y=1}^{m} w_{xy}\, w_{yz}$ (3.10) represents the sum of the product of the final weights connection from input neurons to hidden neurons and the connnections from hidden neurons to output neurons.

and informative point of view. The second dimension refers to the policies that directly support the development of CE models in companies, establishing a distinction between policies that support product development and those that affect the design of the process. While the CE production policies have been extensively investigated, it has been found that they have a positive effect on supporting CE models, however, there is an important gap in understanding how policies to boost consumption and the market affect the development of CEBMs in firms.

First of all, our results support Hypothesis 1, which highlights the positive impact of consumption policies, both regulatory and informative. These results provide empirical evidence in line with Rave et al. (2011), Albino et al. (2009) and Iles (2008), which consider that consumers' environmental awareness can act as a driver of environmental demand, or in this case, demand for CE. That is, the circular economy literature assumes consumers as passive and rational participants who, when making decisions, would abide by labels and other signals on the production side (Ghisellini et al., 2016). Moreover, our results clarify the role of CE policies to promote green consumption, pointing out that both regulatory and information forces, in the form of policies, are used to influence these consumers, which can, in turn, influence the development of activities related to circularity in companies, through this channel. Therefore, our results are in line with stakeholder theory, which postulates that the institutional pressure exerted on consumption has a positive impact on customers, which in turn translates into, acting as drivers of green products (Horbach, 2008; Rennings and Rammer, 2011; Lin et al., 2014). Additionally, not only does the impulse of institutional policies indirectly affect companies, but our results clarify how institutional momentum can directly affect companies, as customers. Thus, our results provide further evidence to Tukker et al. (2017), which indicate that companies play a crucial role in contributing to sustainable consumption and production. Furthermore, as denoted by Dou and Sarkis (2010) and Belk (2014) companies are important customers, which will be affected by CE consumption-oriented policies. Therefore, our results corroborate that in the CE, companies play a role of customer-producer, together with the CE policy impulse through the consumer channel, which explains that CE policies aimed at consumption have an effect on the development of CE in firms. This is an important finding as it highlights the role of CE consumption policies on the implementation of CEBMs, which have been largely relegated in favour of CE policies aimed at production (Milios, 2018; Friant et al., 2021). Therefore, policies such as the “Right to repair” legislation in the EU (Svensson et al., 2021; Hernandez et al., 2020) or the French “reparability index" on electronics (Maitre-Ekern and Dalhammar, 2016) should receive more attention from institutions, as they affect the development of CEBMs.

Secondly, our results show the importance of developing policies that affect both the company and the consumer, but also as a driver of CEBMs in companies. Our results illustrate that policies aimed at the development of CE products, as well as the implementation of CE processes, have a positive effect, corroborating previous research that indicates the importance of CE production policies for the implementation of CE models (see, for example, Lewandowski, 2016). In addition, our results show the complementarity of CE consumption and production policies aimed at the implementation of CE models in firms, corroborating Hypothesis 2. Thus, unlike previous studies that exclusively examine the effect of CE production policies on CEBMs in firms (see, for example, Wang et al., 2019, and Phan and Baird, 2015), our results highlight that jointly developing CE consumption and production policies reinforce the implementation of CEBMs in companies. This finding is important because it indicates that despite the efforts of governments and institutions, such as the EU, for the progressive incorporation of crucial CE production policies for the development of circular economy in many sectors, on their own, these measures are insufficient to result in a paradigm shift to achieve a transition for a circular economy, as consumption policies are also needed. Therefore, from the environmental policy perspective, our results emphasise the importance of a broad portfolio of CE policies that include both consumption and production-oriented policies, seeking to achieve the synergies and complementarities of them to drive the development of CEBMs in firms.

From a theoretical point of view, our research contributes to the literature on CE, and more specifically, the extant literature on consumption in the CE, improving the understanding of how CE consumption policies work in a CE policy framework, how they interact with CE production-oriented policies, and ultimately how they affect CEBMs in firms. While previous studies assume rational and passive consumer behaviour, this paper borrows from stakeholder theory, arguing that consumers have a proactive attitude towards the consumption of environmentally friendly products (Demirel and Kesidou, 2019). Moreover, we employ institutional theory as an analytical framework, for modelling the effects of a particular policy framework on the business model of a company related to circularity. Based on these assumptions, we postulate two channels for CE consumption-oriented policies, to affect CEBM in firms. These are through the demand of consumers, and by a customer/provider duality of firms present in CE frameworks. The results of our analysis indicate that CE policies aimed at promoting consumption have a direct and positive effect on CEBMs. Moreover, this paper, by means of an OLR and K-means cluster analysis, also confirms that a wide portfolio of CE policies on production (both in terms of product and processes) and consumption (both regulative and informative measures) have a greater effect on the development of CEBM in firms, due to the complementarity of CE consumption and production policies. Moreover, utilising an RBF-ANN, this paper shows that in interaction with CE production policies, CE policies on consumption have an even greater effect on CEBM in firms than would have been anticipated. In fact, they are more important than CE production policies, particularly CE consumption policies of a regulative nature, this means measures that regulate the consumption for a CE, for example, regulating repair and maintenance services, or improving/clarifying consumer protection regulation and procedures. These results not only emphasise the importance of CE consumption policies for building a circular economy, but it has important implications for practitioners and policy development by highlighting the need for a more comprehensive policy approach for achieving a circular economy, which also focuses on the consumption side of CE. Moreover, these results also accentuate the importance of consumption and production policies for CE literature, which is limited and requires further research in the future.

From a methodological point of view, the research contributes to a better understanding of the effect of CE consumption policies on CEBM. Through the use of regression analysis, artificial neural networks, and K-means cluster, this paper studies the direct effect of CE consumption policies, but most importantly, the interplay with CE production policies (in the form of complementarity, interaction, and nonlinearity). The combination of classical econometric methods with approaches from machine learning has allowed us a greater degree of understanding and explanatory power of how CE policies, in particular consumption-oriented CE policies, affect the CEBM in firms.

Lastly, our research provides some important implications for environmental policy and policymakers. Unlike previous research, our paper highlights the importance of complementarity and synergistic effects between CE policies. Thus, policymakers must pursue the application of broad portfolios of measures, which include both consumption and production policies, for a reinforced impulse of the development of CEBMs in firms, seeking both the depth and breadth of these portfolios, considering the circular nature of the CE model, which assumes that the actors play the double role of customer-producer. Hence, more attention to CE consumption policies (particularly regulative measures) by policymakers is needed, which have been relegated in favour of other policies and play a crucial role for an effective policy framework that fosters the development of CEBMs in firms.

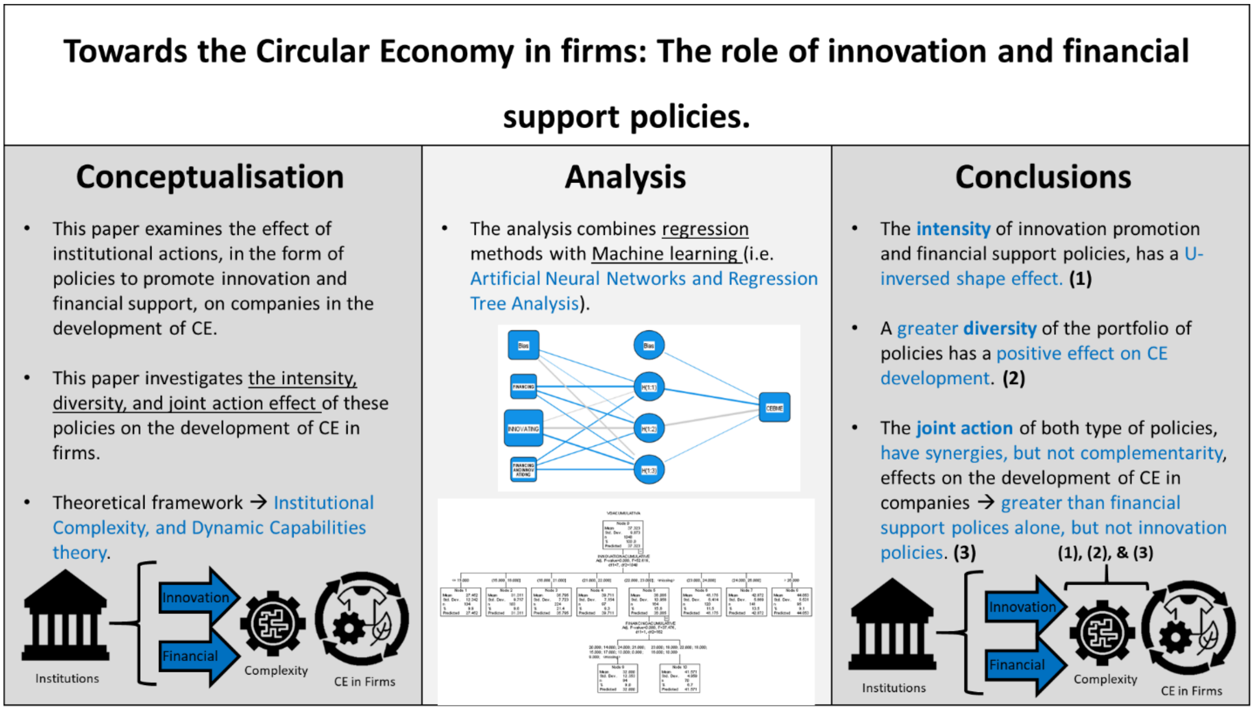
Chapter 4: Towards the Circular Economy in firms - The role of innovation and financial support policies

4.1 Abstract

The implementation of (CE in firms will require new visions, strategies, and policies. However, little research focuses on policies for the transition towards a CE, specifically, on policies to provide financial support or to enable systemic circular innovation, which has yielded discrepant and inconclusive results. This paper examines the effect of institutional pressures, in the form of policies to promote innovation and financial support, on companies developing CE. As a theoretical framework, this paper combines the dynamic capability approach with institutional pressure theories, particularly, institutional complexity. Our methodology jointly employs machine learning (i.e., Regression trees and Artificial Neural Networks) with classical econometric methods, on data from the EU. The results, firstly, show that the intensity of institutional pressures, in the form of innovation promotion and financial support policies, has a U-inversed shape effect, indicating that the development of CE improves as these institutional pressures increase but that there is a threshold point. Any increase in these pressures beyond the threshold point will deteriorate CE development in firms. Secondly, a greater diversity of the portfolio of both innovation and financial support policies has a positive effect on CE development. Finally, the joint action of innovation promotion with financial support policies generates synergistic effects, but not complementarity, on the development of CE in companies, greater than if financial support policies acted alone.

Keywords: *Circular Economy; Innovation; Financial Support; Policy; Machine Learning; ANNs; Decision trees.*

4.2 Graphical Abstract



4.3 Introduction

The CE is gaining traction on the agendas of governments, businesses, and societies around the world. This paradigm change entails transforming production and consumption systems from linear processes to cyclic systems that aim at eliminating waste by turning end-of-life materials and products into resources for new ones (Ferasso et al., 2020; Marrucci et al., 2019). Therefore, closing material loops can create a continual use of resources that leads to efficiency and financial benefits for companies while diminishing the negative environmental impacts, striking an improved balance between the environment, economy, and society (Lewandowski, 2016; Geissdoerfer et al., 2018; Manninen et al., 2018). Given the substantial impact on the environment, the academic literature has not been alien to the circular economy. Many papers have been written in recent years on different aspects of the circular economy (see, for example, Marrucci et al., 2019; Kanda et al., 2021). However, only around 11.55% of the academic literature investigates how to transition toward a CE from a policy perspective at the national and international level

(Millar et al., 2019; Merli et al., 2018; Bigano et al., 2016; McDowall et al., 2017). This is quite problematic, as already argued by Huamao and Fengqi (2007), policy is a fundamental driver in realising a circular economy, and government bodies must play the role of facilitator with regard to overcoming the key lock-ins in the current economic and industrial systems (Genovese et al., 2017).

The extant literature that has studied the effect of policies on the implementation of CE, has done so from different perspectives. DiMaggio and Powell (1983) and Scott (2005), with a broader view, analysed the effect of institutional measures on CE development showing the positive effect of coercive measures and inconclusive results regarding normative and mimetic measures. Another stream of literature has dealt with the effect of public policies on the supply chain analysing how direct actions on the product or the process affect the development of CE in firms (Fischer and Pascucci, 2017; Gao et al., 2019; Liao, 2018). From the resource-based view and dynamic capabilities literature, the focus has been on how these environmental policies act in the adoption of CE (Marrucci et al., 2019). However, the results of the research have been discrepant and inconclusive, either because of the variety of streams and environments studied, or the databases used, or because most of the studies have had a narrow focus, examining only the direct effects. In this regard, as recommended by Milios (2018), it should be investigated not only if such policies affect, but also how they affect, to understand which variables are more significant and if there are synergistic effects between them. Moreover, Milios (2018) pointed out that little research exists on the use of policy to provide financial support or to enable systemic circular innovation to occur. In this context, Su et al. (2013) also identified the shortage of advanced technologies, combined with weak economic incentives, as a key barrier to realising circular economy goals.

This paper analyses how innovation and financial support institutional policy pressures affect the development of CE in the firm. First, as a theoretical framework, we combine the dynamic capability approach with institutional pressure theories, particularly, institutional complexity. Using dynamic capabilities as the theoretical framework, the starting assumption is that when a company implements CE, this implies that its capabilities are oriented towards the development of a proactive innovation process that leads to the adoption of a sustainable growth model (Khan et al., 2020; Scarpellini, 2020; Bag et al., 2019; Russo, 2009; Aragon-Correa and Sharma, 2003). In addition, institutional theory highlights the importance of aligning companies with stakeholders and institutions. In this context, we assume that the institutional impulse consists of a portfolio of promotion policies that facilitate the development of CE in companies. As previously mentioned, this research focuses on two types of policies. On the one hand, institutional policies that are aimed at promoting innovation. As it is well acknowledged in the literature, the implementation of CE models supposes an innovation process where companies develop both product and process innovations, transforming the traditional linear economic model into a model of closed-loop consumption and production (Lüdeke-Freund et al., 2018; Perey et al., 2018; Schaltegger et al., 2016). On the other hand, an important challenge highlighted in the literature is the need for adequate access to financial resources for the CE transition, to avoid detracting them from company resources (Marrucci et al., 2019). In this sense, institutions at national and international levels develop financial support policies for companies, which implies that financing plays a leading role in fulfilling the CE strategy (Scott, 2005).

Focusing on the aforementioned two variables, the goal is to bring new perspectives within the innovation adoptions and financial support literature, with an emphasis on the CE. Firstly, the research question analyses whether institutional pressures in the form of policies to promote innovation and financial support affect companies in the development of CE. Unlike previous studies that examine the drivers that are more relevant for a CE transition, this thesis addresses how the variability of some institutional pressures affects CE development, and therefore, whether an increase in institutional pressures leads to higher levels of CE adoption in firms. Secondly, the research analyses how the diversity of innovation and financial support promotion policies affect the development of CE. Considering that institutions use a portfolio of policies, this chapter analyses if a greater diversity of the portfolio of both innovation and financial support policies positively affects CE adoption in firms. Finally, this research examines the joint action of innovation promotion policies and financial support policies to study if there exists any synergistic and complementary effects on the adoption of CE in companies.

For the analysis, this paper employs the EU survey on *Public Consultation on the Circular Economy* database composed of 870 companies. Our methodology combines the use of machine learning (i.e., Regression trees and Artificial Neural Networks) with classical econometric methods. Thus, the explanatory power of regression analysis together with machine learning techniques allows us to analyse the interaction processes between variables. Unlike previous studies, this combination permits to clarify the complexity of institutional pressures in the development of CE in firms.

4.4. Conceptual Framework

4.4.1. Dynamic Capabilities Theory

Dynamic capabilities are a group of high-level activities that permit companies to refocus their normal operations on high-return ventures (Fainshmidt et al., 2016; Teece, 2014; Faridian and Neubaum, 2020;). In the literature, dynamic capabilities are defined as “the firm’s ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments” (Teece, Pisano, & Shuen, 1997: 516). The dynamic capabilities framework was established to assist managers to organise and prioritise the never-ending stream of competing and contradictory data that comes their way as they try to gain a competitive advantage (Bitencourt et al., 2020). The concept encompasses, on the one hand, the dynamic of entrepreneurial activities throughout the organisation, this includes: (i) environmental scanning, that is, technological possibilities, consumer demand, and other forces that affect the future of the company (Zahra et al., 2006); (ii) evaluate how soon the system can adjust to threats and opportunities (Barreto, 2010); and (iii) keep the company system’s elements in alignment with the strategy and each other (Teece et al., 2007). On the other hand, capabilities establish what the business is able to accomplish and how successfully it can make adjustments in terms of resources and strategies (Cetindamar et al., 2009; Barreto, 2010; Fainshmidt et al., 2016). Resources include equipment, buildings, employees, and intangible assets (Teece, 2015). The strategy helps determine when to enter the market and how to outperform competitors by taking advantage of internal strengths. Firms’ capabilities result from learning, which is an outcome of experimentation and practice (Teece, 2014), and from company resources and histories (Suddaby et al., 2020; Teece, 2014).

4.4.2. Institutional Pressures and Institutional Complexity

Institutional theory (DiMaggio and Powell, 1983; Scott, 2005; Berrone et al., 2013) emphasises the social factors that affect the actions and strategy of organisations. From this perspective, organisations seek approval from their environment and, therefore, are susceptible to social influence. Wang et al. (2019) conclude that organisational practices and behaviours are affected by the institutional and the external environment, that is, by values, norms, laws, cultures, social expectations, and common cognitions. This implies that organisations tend to comply with the institutional and external environment by means of changing their behaviours and structures, and implementing dominant practices, to gain and retain legitimacy independently of business outcomes (DiMaggio and Powell, 1983; Scott, 2005). These aspects have made this theory especially appealing to environmental scholars because ecological investments frequently cannot be justified from a financial point of view (Wahba, 2010; Berrone et al., 2013; Gallego-Alvarez et al., 2017; Liao, 2018; Wang et al., 2019; Gao et al., 2019; Lee and Raschke, 2020). The literature on institutional theory is broad and rich, ranging from institutional logics (see, for example, Thornton and Ocasio, 2008, or Stål, 2015), institutional complexity (Greenwood et al., 2011; Smets and Jarzabkowski, 2013), and institutional entrepreneurship (Alonso-Almeida et al., 2021; Battilana et al., 2009; Elliot, 2016; De Jesús and Mendoça, 2018). This research is contextualised within institutional complexity.

Organisations and businesses encounter institutional complexity when confronted with contradictory prescriptions from different institutional logics (Greenwood et al., 2011). Institutional logics are broad sets of ideas and principles that govern “how to interpret organisational reality, what constitutes appropriate behaviour, and how to succeed” (Thornton, 2004: p. 70). In other words, logics provide instructions and guidelines for reading and acting in social circumstances. Other authors, such as Scott (2005) or Teo et al. (2003), have characterised these institutional logics as institutional pressures or institutional policies. Therefore, companies and organisations adhere to logics or pressures to acquire support from their stakeholders, that is, because logics or pressures give a way of comprehending the social reality and hence provide companies with a structure to operate confidently within the regulatory or policy framework dictated by these logics or pressures (Friedland and Alford, 2012; Greenwood et al., 2017). Organisations are frequently confronted with different logics or pressures that may, or may not, be mutually incompatible (Friedland and Alford, 2012; Kraatz and Block, 2008). When the prescriptions and proscriptions of multiple pressures are contradictory, or appear to be so, they unavoidably create obstacles and conflicts for organisations that are exposed to them. Therefore, institutional complexity arises when multiple institutional pressures are present and can interact and compete for influence in all socioeconomic domains of the organisation (Nigam and Ocasio, 2010). Moreover, institutional pressures are frequently in conflict, which means that their distinct systems of meaning and normative understandings embedded in company practices, create contradictory expectations for companies to adopt and create capabilities to cope with the changing environment (Greenwood et al., 2017). Institutional complexity emerges, unravels, and re-forms over time, resulting in new conditions to which organisations must adapt. This is the case of CE and the different and complex institutional policy framework created around it.

Institutional complexity research has begun to delve into the pattern of linkages between institutional pressures, and it is becoming increasingly aware of the intricacies of those interactions (Battilana and Dorado, 2010). Previous research has indirectly addressed two key aspects of institutional complexity: the number of pressures and the degree of incompatibility between them. The former indicates that the sheer number of institutional pressures at work is a major determinant of complexity. However, the larger number of pressures, the greater the complexity confronting a company (Greenwood et al., 2011; Pache and Santos, 2010). The latter suggests that the disparity and divergence between defined goals and means of different institutional pressures, as well as their relative specificity, increases complexity (Pache and Santos, 2010; Battilana and Dorado, 2010; Tracey et al., 2011).

Nevertheless, while previous studies have revealed the presence of multiple institutional pressures and the degree of incompatibility between those pressures (see, for example, Kraatz and Block, 2008; or Pache and Santos, 2010), more research is needed to have deeper knowledge into how institutional complexity is confronted by businesses as a result of a multiplicity of institutional pressures acting on them. As well as, how they respond to the degree of incompatibility between those institutional pressures. This paper tries to address some of these issues applied to the circular economy.

4.4.3 The firm and the Circular Economy

The circular economy has been defined as a closed-loop economic model that involves production and consumption in which waste is considered a useful resource (Bocken et al., 2016; Kirchherr et al., 2017a). Unlike traditional linear models of production, based on the concept of ‘take, make, dispose’, the circular economy is grounded on the maintenance, remanufacturing, reuse, and recycling of products, which entails changing the ‘end-of-life’ concept in production and consumption for that of restoration (Boons and Lüdeke-Freund, 2013; Zucchella and Previtali, 2019; Salvador et al., 2021). The reuse, recycling, and more efficient use of resources imply a total reduction of inputs (energy, resources, and emissions), as well as a decrease in leakage and waste, all without compromising prosperity and growth, while attaining a more beneficial balance between the environment, the economy, and society (Kiefer et al., 2019; Geissdoerfer et al., 2018;

Manninen et al., 2018). The circular economy model is a cyclical system in which goods that are at the end of their life cycle become resources for new ones (Stahel, 2016; Kirchherr et al., 2017a). This cyclical system can create continuous use of resources by closing material loops in industrial ecosystems through recycling, a durable design, restoration, proactive maintenance, remanufacturing, and repairs (Geissdoerfer et al., 2017).

Urbinati et al. (2017) explain that the CE model implies a change in the way resources are used, transforming open production systems (that is, the existing linear systems, in which resources are employed to generate final goods that are discarded after consumption) in closed production systems (that is, a circular system in which resources are maintained and reused in the cycles of production and consumption). This process of redesigning materials, products, and value creation systems, by maximising the efficient use of resources, should reduce the waste of resources derived from the consumption of physical goods and the negative environmental effects of emissions (Cheng and Shiu, 2012; Rosa et al., 2019). The extension of the useful life of the products, recycling, redistribution/reuse, and remanufacturing can facilitate the CE model (Urbinati et al., 2017). In the scientific literature, the concept of CE has been explored from numerous multidisciplinary angles, including engineering and natural science perspectives, on the one hand, and social science perspectives, on the other (Bocken et al., 2014; Su et al., 2013; Tukker, 2015; Blomsma and Brennan, 2017; Sauvé et al., 2016; Merli et al., 2018; Kirchherr et al., 2017).

4.4.4 Dynamic capabilities, institutional pressures and the CE

Although the theoretical bases of the dynamic capability approach and institutional literature differ, there appears to be agreement on the potentially positive impact of institutional policies on innovation promotion and financial support on the incentives of regulated firms to adopt CE practices.

In this context, the literature emphasises the role of institutional pressures in sustainable development (Sarkis et al., 2010; Hart, 1995; Huamao and Fengqi, 2007), considering the institutional pressures as a key driver for pollution prevention (Ariti et al., 2019; Rosa et al., 2019; Daddi et al., 2016). Therefore, institutional pressures are drivers in the development of CE in firms. The literature has analysed the effect of institutional pressure on various environmental practices. For example, Ren et al. (2019), Liao (2018), and Aragon-Correa and Leyva-de la Hiz (2016) examine the adoption of *green innovation* in firms under the effect of institutional pressures.

Usually, to adjust to the external and institutional environment and to gain legitimacy, companies are prone to modify their organisational configurations and behaviours by adopting the leading strategy (Berrone et al., 2013; Daddi et al., 2016; Liao, 2018; Wang et al., 2019; Wei et al., 2020). Wang et al. (2019) show that if companies do not adapt to the external and institutional environment, they can be isolated. Thus, it could be concluded that it is more likely that firms develop CE under various types of institutional pressures (Arranz et al., 2022), despite the complexity and incompatibility of these pressures. Companies have to navigate this institutional complexity to be able to adopt CE models in the firm. To do so, they have to be able to integrate, foster, and reconfigure their competencies and capabilities, both internal and external, to develop the necessary innovations for implementing CE.

Researchers in the environmental field have categorised institutional pressures from various perspectives (Fischer and Pascucci, 2017; Gallego-Alvarez, 2017). The most common approach has addressed the very nature of the institutional pressures in terms of their implication for companies: from regulatory and coercive pressures, to merely informative (DiMaggio and Powell, 1983; Arranz et al., 2022). Regarding the regulatory and policy forces as drivers for eco-innovation in the adoption of CE practices, the literature centres on the effect that government regulatory forces and subsidies, or financial support, have had on the CE transition (Fischer and Pascucci, 2017). Regulations and subsidies push firms to invest in new or improved socio-technical solutions that lead toward new usage-production closed-loop systems (De Jesus and Mendonça, 2018). Another important dimension approached the study of institutional pressures, considering these as promoting the development of environmental practices, focusing specifically on the acquisition of resources and capacities in companies (Gao et al., 2019; Liao, 2018).

4.5 Hypotheses

4.5.1 The effect of Innovation and Financial Support on CE development

The first research question addresses the role played by innovation and financial support, on the incentives to adopt cleaner technologies. We postulate that these pressures have an inverted U-shape relationship on CE development. The literature on external regulatory and policy forces as drivers for a CE strategy in firms centres on the effect that those factors have on the development of eco-innovations (Fischer and Pascucci, 2017) and the adoption of CE practices (Bocken et al, 2016). Regulations and subsidies push firms to invest in environmental innovation (Aragon-Correa and Leyva-de la Hiz, 2016; Kesidou and Demirel, 2012; Berrone et al., 2013). The evidence on the role of EU measures that affect eco-innovative development and the implementation of CE models in firms shows that they have positive effects (Nover, 2016; Horbach, 2016; Triguero et al., 2013; Kemp et al., 2007). Therefore, in line with previous research, it can be affirmed that the existence of policies to promote environmental innovation, together with financial support should facilitate the process of CE, having a significant impact on companies' decisions to develop them.

However, research often ignores the possible non-linearity of the relationship between institutional pressures that promote environmental innovation and the adoption of CE in companies (Bansal and Roth, 2000; Clemens and Douglas, 2005; Colwell and Joshi, 2013; Delmas and Toffel, 2008). In fact, most environmental and institutional theory research assumes that the nature of the relationship is positive and monotonic (Sharma, 2000; Colwell and Joshi, 2013). Thus, some authors have argued that strict environmental regulation could lead to unproductive investments and higher costs (Walley and Whitehead, 1994), limitations on managerial discretion (Finkelstein and Boyd, 1998), and even fail to stimulate environmental proactivity in companies (Van Leeuwen and Mohnen, 2013). Empirical evidence suggests that strict environmental regulation does not achieve a change in CE adoption and may lead to a reorganisation of R&D towards pollution control (Lanoie et al., 2011; Eiadat and Fernández Castro, 2018). Therefore, the continuous strengthening of environmental regulation may not lead to increases in the responsiveness of companies in the adoption of CE. Following the discussion presented so far, the first hypothesis is as follows:

Hypothesis 1a: The relationship between the policies to promote innovation for the development of CE has an inverse-U shape with the adoption of CE in firms.

Hypothesis 1b: The relationship between policies to promote financial support for the development of CE has an inverse-U shape with the adoption of CE in firms.

4.5.2. The portfolio of Institutional Pressure actions and its effect on CE in firms

As stated in the literature, the implementation of CE skills in companies is an example of dynamic capabilities development (Khan et al., 2020; Scarpellini, 2020; Bag et al., 2019; Amui et al., 2017; Russo, 2009) which, as indicated by Aragon-Correa and Sharma (2003), are linked to practices focused on the product and the process. Both environmental management and CE involve the integration of a series of competencies resources from the organisation such as technical systems, information systems, as well as tacit knowledge. Hence, proactive environmental strategies involve the development of products compatible with CE (Demirel and Kesidou, 2019; Katz-Gerro and López Sintas, 2019; Zucchella and Previtali, 2019; Reike et al., 2018, Bocken et al., 2016; Lewandowski, 2016). Consequently, institutional policies aimed at promoting innovation such as those intended to provide financial support will have a positive effect on the probability that companies adopt CE models.

In general, the CE encourages the use of environmentally friendly materials in the production of consumer products, ensuring that they can be returned to nature after use without damaging the environment. When ecological alternatives are not possible, as in the case of batteries and electronic or metallic components, CE advocates the manufacture of easily removable parts that can be incorporated into new products and thus reused. If this is not feasible, CE models propose to follow an environmentally friendly recycling procedure for non-reusable or non-biodegradable product parts. Therefore, the implementation of CE-related technologies poses important innovation challenges for companies.

Consequently, the CE model, unlike traditional linear economic models, includes not only the phases of design, production, distribution, and use, but also the recycling phases of the product at the end of its useful life. The implementation of the CE model involves not only producer and user organisations but also third parties such as waste management organisations or raw material suppliers. To facilitate the adoption of CE models by companies and the implementation of more radical innovations, specific R&D development methods and/or cooperation with other companies and research institutions may be necessary (Khan, 2020; Fischer and Pascucci, 2017; Witjes and Lozano, 2016). However, the development of collaboration and cooperation agreements also raises important issues for companies, not only in relation to the introduction of innovations in their processes, but also in relation to the new modes of management or the creation of information channels derived from such agreements (Arranz et al., 2016).

These considerations justify the existence of a broad portfolio of institutional support measures for the adoption of CE-related innovation by firms. Among these measures can be pointed: the regulation of the CE process; facilitation of the establishment of collaborations with other companies, providing information on possible partners; dissemination of information on green markets and sustainable environmental practices; and complementary measures such as promoting the development of skills/qualifications and to facilitate the access to financial resources for CE innovation adoptions. This broad portfolio of institutional policies can lead companies to an institutional complexity scenario, where the different policy prescriptions might be incompatible. However, based on the arguments above, it is expected that institutional policies aimed at promoting innovation and financial support will have a positive effect on the probability that companies adopt CE models. These considerations lead us to the second hypothesis:

Hypothesis 2a: The greater diversity or portfolio of policies to foster innovation in firms has a positive effect on the development of CE.

Hypothesis 2b: The greater diversity or portfolio of policies to foster financial support for firms has a positive effect on the development of CE.

4.5.3. Synergistic and Complementary effects of the institutional promotion policies towards CE in firms

Milgrom and Roberts (1995) emphasised the importance of the interaction between variables, pointing out that doing more than one activity increases the returns of doing more of another. Doran (2012) and Hullova et al. (2016) highlight that the interaction between resources and capabilities occurs because of the development of routines and tasks already known or the affinity between them. Moreover, Camisón and Villar-López (2014) and Arranz et al. (2019) conclude that synergic and complementary effects derive from shared routines, skills, and competencies, or through the generation of economies of scale and learning in the development of innovation processes. In general, the literature highlights that the consequence of synergistic effects between dynamic processes is especially important in the study of social and business systems, since the interactions between processes can lead to surprising phenomena in the performance of companies (Arranz et al, 2019).

Hart and Dowell (2011) point out that the migration towards environmental sustainability, a key element of CE, implies many challenges for companies, since it entails important organisational changes (Khan et al., 2020; Strauss et al., 2017). Environmental sustainability depends on the dynamic capabilities of the firm (Wu et al., 2013; Annunziata et al., 2018) that integrate the key functions of the company such as strategic planning, R&D, and product development (Teece, 2014; Arranz et al., 2020).

The implementation of CE practices in the firm requires that it possess a minimum level of competencies that allows it to develop products considering time and budget restrictions. At the same time, the reconfiguration of existing resources and the coordination and integration of routines for the adoption of CE depends on the dynamic capabilities of the company (Teece, 2014). For example, the introduction in the company of standards and regulations compatible with the CE business models implies the development of organisational routines and learning processes that facilitate its implementation. These routines and processes result in efficiencies, for example in routinized waste management, and in the recognition of opportunities for improvement, which allows a suitable response to the audit and monitoring results (Zhu et al., 2013; Russian, 2009).

In addition, the innovations necessary for the adoption of CE in the company may involve collaboration with other organisations and institutions (Bag et al., 2019; Lewandowski, 2016; Bocken et al., 2016). Collaboration is a key micro-foundation of dynamic capabilities and favours the development of innovative activities that allow companies to adapt resources and competencies in response to changing environments (Teece, 2014). Decision-making under uncertainty implies that management, supported by organisational processes, design CE-compatible business models to take advantage of new or changing opportunities in the external environment that allows firms to adapt to these changes (Teece, 2014). In this context, policies to promote innovation can boost the acquisition of skills by companies and organisations in the development of CE strategies, despite the possible complexity generated by the interaction of different institutional policies. However, this process of developing skills and competencies involves a cost for firms, mainly for smaller firms that may experience greater innovation costs due to a lack of financial resources or size to implement CE-related technologies. Therefore, we expect that the joint application of policies to promote the institutional pressure, both in innovation and financial support, will not only have a positive impact on the development of CE, but also produce complementary effects that reinforce or facilitate the development of CE to a greater extent than if these impulse policies acted individually. Hence, the third hypothesis is as follows:

Hypothesis 3a. Policies to promote innovation combined with policies to promote financial support have a greater joint effect on CE development than innovation promotion policies alone.

Hypothesis 3b. Policies to promote innovation combined with policies to promote financial support have a greater joint effect on CE development than financial support policies alone.

4.6 Methodology

As indicated above (section 1.5 of Chapter 1), this thesis employs for the empirical analysis the cross-sectional database from 2015 based on the EU survey on Public Consultation on the Circular Economy (European Commission, 2015). This database is used since it is the most recent one done at a European level regarding CE. Although, the total database consists of 1280 organisations and companies. After filtering and eliminating incomplete responses, microenterprises and individuals, the final sample used in this chapter contains 870 organisations. These companies are in different economic sectors and their geographic distribution corresponds to the 27 countries of the EU, Norway, Iceland, Switzerland, and Liechtenstein. The questions and data utilised for the creation of variables, as well as for the analysis, are described below.

4.6.1 Measures

4.6.1.1 Dependent Variable

The degree of implementation of CE in firms is used as the dependent variable (CE). To do this, the questionnaire identifies several elements or characteristics of CE in organisations that narrow or reduce the flow of natural resources both in terms of product creation and in the process (Pieroni et al., 2021; Bocken et al., 2016; Oghazi and Mostaghel, 2018). This variable consists of twelve items, listed in Table 4.1. The impact of each of these items was assessed on a 3-point Likert scale (where 3 represents very important, 2 represents important, 1 represents not yet significant, and 0 represents not important). Following Costantini et al. (2017), the dependent variable CE is constructed as a cumulative index of the different CE elements. This method is used for the creation of the dependent variable since it allows measuring CE in all its breadth, while maintaining the typology of the measuring scale and with no loss of variance, as opposed to other methods.

Table 4.1. Description of the dependent variable.

Dependent Variable	
CE	i) Durability ii) Reparability: Availability of information on product repair (e.g. repair manuals) iii) Reparability: Product design facilitating maintenance and repair activities iv) Reparability: Availability of spare parts v) Upgradability and modularity vi) Reusability vii) Biodegradability and compostability viii) Resource use in the use phase (e.g. water efficiency) ix) Recyclability (e.g. dismantling, separation of components, information on chemical content) x) Increased content of reused parts or recycled materials xi) Increased content of renewable materials xii) Minimising lifecycle environmental impacts.

4.6.1.2 Independent Variables

In terms of the independent variables, these are represented by the different EU policies to promote innovation and financial support for the adoption of CE. These policies included in the questionnaire, arise from the CE Action Plan adopted by the European Commission in 2015, which aims to "help stimulate Europe's transition towards a CE, boost global competitiveness, foster sustainable economic growth and generate new jobs" (European Commission, 2015).

Innovation. This variable measures the CE-related innovation promotion policies and is measured based on seven items listed in Table 4.2. The relevance of each of these items was assessed on a 3-point Likert scale (where 3 represents very important, 2 represents important, 1 represents not yet significant, and 0 represents not important). (Cronbach Alpha: .750).

Financing. This variable measures the CE-related financial support policies and consists of four items, shown in Table 4.2. The importance of each of these items was assessed on a 3-point Likert scale (where 3 represents very important, 2 represents important, 1 represents not yet significant, and 0 represents not important). (Cronbach Alpha: .707).

Table 4.2. Description of independent variables.

Independent Variables	
Innovation	i) promotion of innovative business models for CE ii) Exchange and promotion of best practices iii) Promoting the development of skills/qualifications relevant to the CE iv) Support for capacity-building in public administrations v) Support for market penetration of innovative projects through labelling vi) Better monitoring the implementation and impact of policies contributing towards the CE agenda vii) Increasing the knowledge base by collecting and providing information and data
Financing	i) Financing innovative projects or technologies relevant to the circular economy ii) Public incentives for private inventors to finance projects conductive to the CE iii) Support for the development of CE projects iv) Support for innovative systemic approaches & cross-sectional cooperation

4.6.1.3 Control Variables

Furthermore, the following two control variables are employed for the analysis to measure the relationship between the dependent and independent variables of the model appropriately.

(i) *Environmental management*, which is a binary variable that takes the value 1 if the company holds any environmental management scheme (listed in Table 4.3), and 0 otherwise. This variable is controlled as environmental management schemes are useful tools for the promotion of CE (see Marrucci et al., 2019).

(ii) *Sector*, which is a binary variable that takes the value 1 if the company belongs to the manufacturing sector and 0 otherwise (see Table 4.3). This variable is used following previous research (see, for example, Rizos et al., 2017) since effects on different sectors are to be expected.

Table 4.3. Description of control variables.

Control Variables	
Environmentalmanagement	i) EU eco-label ii) Eco-Management and Audit Scheme (EMAS) iii) Another environmental management scheme iv) No environmental management scheme.
Sector	i) Industrial sector ii) Service sector

4.6.2. Econometric Models

For the analysis of the hypotheses, this paper employs OLR, as well as two supervised machine learning methods, that is, an ANN and a Tree Regression analysis.

For Hypotheses 1a and b, we use OLR to determine the direct effect of the different CE policies to support the development of CE in firms. We have included, as independent variables, the quadratic value of both institutional policies to analyse the concavity of the relationship between these variables (inverted U-shape). For these hypotheses, the independent variables are obtained as a result of factor analysis to be able to measure the intensity[47].

For the regression analysis, we estimate three models, a basic model only with the control variables and two models with the independent variables.

Model 1:

$$CE = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + e \tag{4.1}$$

Model 2:

$$CE = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + ß_3\,(innovation) + ß_4\,(innovation^2) + e \tag{4.2}$$

Model 3:

$$CE = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + ß_3\,(financing) + ß_4\,(financing^2) + e \tag{4.3}$$

[47] Using factor analysis allow us to create a continuous variable for each independent variable, which is the result of integrating all the individual items from Table 4.2 into one unique variable. Hence, this allows to measure the intensity of the new variable (Hayton, 2004).

For Hypotheses 2a y 2b, we use OLR to examine how the diversity of policies for both innovation promotion and financial support affect the adoption of CE practices in firms. Following the same methodology previously utilised for the dependent variable, we re-recoded the two independent variables, constructing them as a cumulative index of the different elements, allowing us to measure the independent variables in all their breadth (diversity)[48]. First, we tested with OLR the impact of cumulative independent variables on the development of CE in firms. Moreover, as in the previous analysis, we include the quadratic variables to test the existence of concavity in the relationship.

Model 4:

$$CE = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + e \tag{4.4}$$

Model 5:

$$CE = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + ß_3\,(innovation) + ß_4\,(innovation^2) + e \tag{4.5}$$

Model 6:

$$CE = constant + ß_1\,(Environmentalmanagement_m) + ß_2\,(Sector_s) + ß_3\,(financing) + ß_4\,(financing^2) + e \tag{4.6}$$

For the analysis of our results of Hypotheses 2a y 2b, the various regression coefficients must be interpreted as follows. The regression coefficient value 0 reflects the reference category, corresponding to the lowest portfolio diversification value; the rest of the regression coefficients obtained correspond to the various categories (portfolio diversification), which reflect the probability of CE adoption with respect to the first category (the reference category). That is, H0: $ß \leq 0$ means there is a greater probability of CE adoption at that level of diversification of policies; and H1: $ß > 0$ entails there is a greater probability of diversification of policies than in the reference level.

Finally, we have tested Hypotheses 3a and 3b combining ANN with Tree regression analysis to examine the existence of synergistic and complementary effects in the CE adoption of firms. To

[48] Using a cumulative index for the creation of the variables allow us to create a categorical variable, which is the result of adding each individual item of Table 4.2. Thus, this categorical variable has a reference category that corresponds to the lowest portfolio diversification value (0), which when increasing corresponds to higher categories of the portfolio diversification, with respect to the reference category (Hair, 2006).

model the interaction effects, we use an ANN, based on an MLP. This structure is considered feedforward since the connections of the network flow forward from the first layer or input layer (independent variables) to the last layer or output layer (dependent variables). There may be several hidden layers between these two layers, whose role is essential in the generalisation capability of the ANN-MLP. Figure 4.1, below, displays the structure of the ANN-MLP model. The variables *Financing*, *Innovation* and the interaction of both variables (*Financing*Innovation*) are used as input variables, while *CE* is used as output variable. Regarding the structure of the ANN-MLP network, this paper employed the *trial-and-error procedure* (Ciurana et al., 2008), since there are no well-established approaches in the literature for identifying these structures. First, the inputs of the proposed network are determined by the number of independent variables, and the number of neurons in the output layer (i.e., one) by the dependent variable. Second, regarding the number and size of hidden layers, different combinations of the number of hidden layers and the number of neurons were tested to find the right fit (Hornik et al., 1989). Although, as proposed by Ciurana et al. (2008), a two-layer neural network is frequently enough to construct an accurate model. Finally, it is necessary to consider the activation functions. We assessed the same network architecture with three distinct configurations of activation functions (tangential, sigmoid logistic, and linear function) to analyse and determine the best ANN model, following Ciurana et al. (2008). The chosen architecture configuration is shown in Table 4.4 and Figure 4.1, which has been tested against different initial conditions to ensure that the proposed model is the best fit (Wang, 2007)[49].

[49] For further explanation and description of the ANN-MLP model developed in this chapter, please see Methodological Appendix IV, which describes in detail the model and its architecture, the chosen basic structure and design, the selection of the different algorithms used, the output of the neural network model, as well as a description of the selected activation functions.

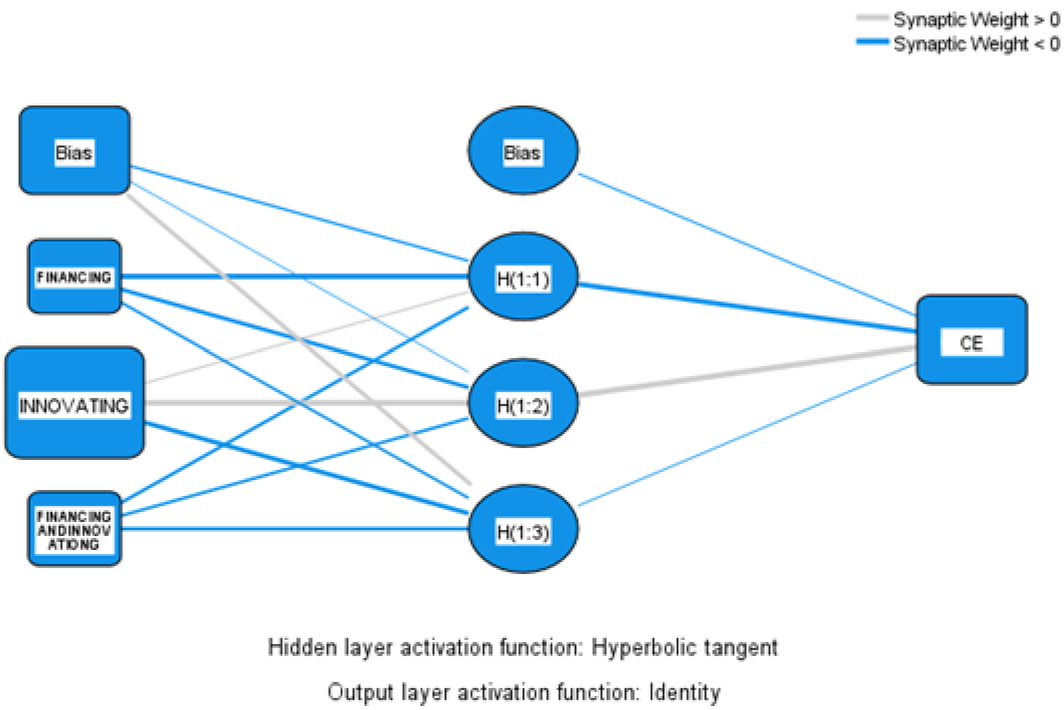


Figure 4.1. ANN-MLP architecture.

Table 4.4. ANN-MLP architecture for interaction analysis

Simulation	ANN architecture	Activation Functions	MSL error	Correlation: Output/Predicted Output
Financing Innovation Financing*Innovation	3-3-1	• Hyperbolic tangent • Identity	• Training: .755 • Testing: .713 • Holdout: .709	.699***

* Error (Cross-entropy)

**Correlation is significant at the 0.01 level (2-tailed).

In addition, to validate the robustness of our results, we have performed a Tree regression analysis. The tree regression analysis allows us to discriminate the value obtained for the dependent variable, considering a combination of values of the independent variables (innovation promotion and financial support policies for CE adoption)[50].

[50] For further explanation and description of the Tree Regression model developed in this chapter, please see Methodological Appendix IV, which describes in detail the process followed for the construction of the Tree Regression model, the method for the adjustment process, the model specifications (including the growing method), as well as an explanation of the output.

Model 7:

$$CE = f\,(Financing;\ Innovation) \tag{4.7}$$

4.7 Analysis and Results

In terms of the empirical analysis, this research tests the robustness of the questionnaire and results. First, as proposed by Podsakoff et al. (2012) and Spector (2006), the CMB and the CMV were tested. These analyses reveal that 63.072% of the variance is represented by six latent constructs. Hence, we can confirm that CMB and CMV are not a concern in our model, as the first factor is below the recommended threshold of 50% (24.772% of the variance). Second, although, there are not many missing values, we tested the data for non-response bias using ANOVA, by comparing non-respondent group characteristics (such as countries, firm size, and knowledge) with respondents (Armstrong and Overton, 1997). We concluded that there are no concerns about the dataset. Third, to examine the statistical robustness of the regression analysis, we have checked the collinearity (VIF) and autocorrelation (Durbin-Watson). Tables 4.5 and 4.6 display the robustness and reliability of the results and show satisfactory values for both the VIF and Durbin-Watson tests (Hair, 2006). Finally, we conducted a reverse causality test, finding no evidence supporting any concerns relating to endogeneity.

Regarding Hypotheses 1a and 1b, which deal with the effect of innovation promotion and financial support policies on CE development, Table 4.5 shows the results. On the one hand, it is observed that both innovation promotion policies [*Innovation* (ß = 1.204; p <0.01)] and financial support [*Financing* (ß = 0.552; p <0.01)], have a positive effect on the development of CE in companies. On the other hand, the results corroborate that the relationship between financial support and innovation promotion policies has an inverted U-shape, as it shows that the squared regression coefficients of both variables have negative and significant values [i.e., $Financing^2$ (ß = -0.008, p <0.01) and $Innovation^2$ (ß = -0.162, p <0.01)]. Therefore, both hypotheses are confirmed[51].

[51] Furthermore, we have checked the robustness of the regression analysis adjustment by comparing the results of quadratic regression with other non-linear regression models (inverse and cubic) and a linear regression model (please, see Methodological Appendix IV). The aim of this robustness test is to check whether any other type of regression model, besides the quadratic one, would have yielded a better fit for the model developed. However, as described in

Table 4.5. Ordinal Logistic regression models (Hypothesis 1a and 1b)

Variables	Model 1	Model 2	Model 3
Financing	.552***		
Innovation		.1,204***	
Financing^2	-.008 ***		
Innovation^2		-.162***	
Financing*Innovation			.167***
Environmental	.096***	.143***	1.03***
Sector	.112***	.118***	1.25***
-2 Log-likelihood	4889.320	4725.902	4099.831
Chi-Square	438.119	421.256	394.830
Sig.	.000	.000	.000
Cox and Snell	.425	.399	.304
Nagelkerke	.425	.385	.302
McFadden	.109	.099	.077

*p<0.05, **p<0.01, *** p<0.001

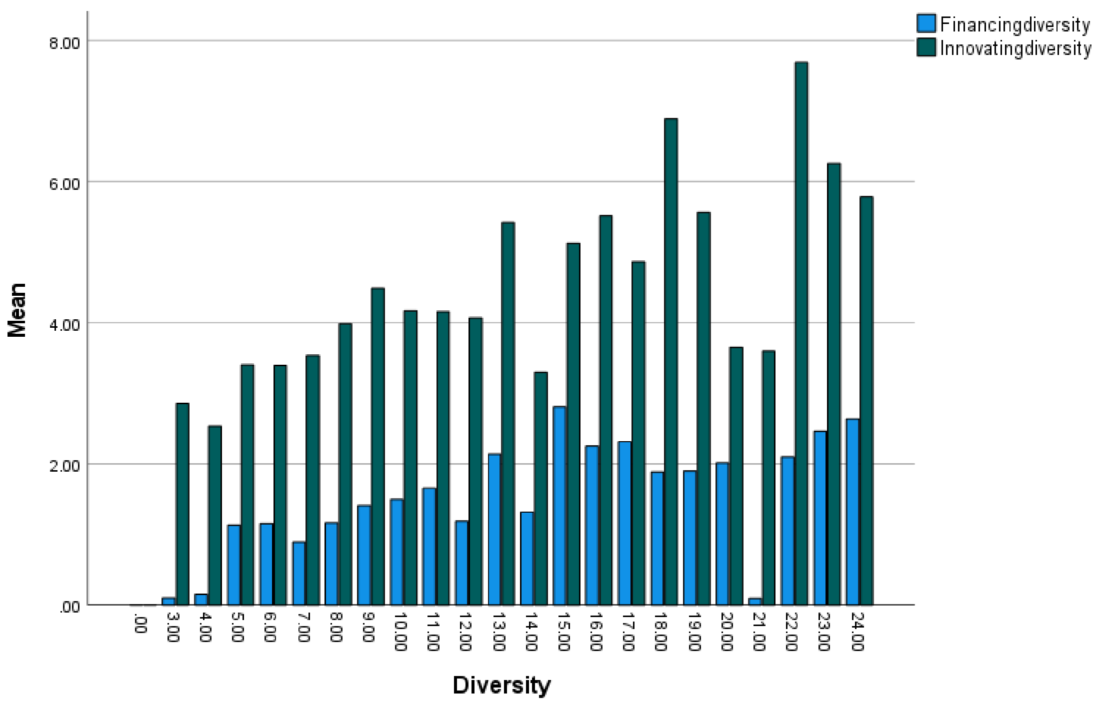
Regarding Hypotheses 2a and 2b, Table 4.6 and Figure 4.2 show the results of the analysis of these hypotheses, which deal with the effect of the diversity of institutional policies to promote innovation and financial support on the development of CE in firms. Firstly, we have carried out a pre-test (shown in Table 4.6), which indicates that the variables *Financing* (ß = 0.134; p <0.01) and *Innovation* (ß = 0.265; p <0.01), have a positive effect on the development of CE, showing that greater diversity in the portfolio of policies increases the probability of developing CE in companies. Moreover, Figure 4.2 shows the results of the regression analysis using categorical variables for the innovation promotion and financial support policies, which displays a positive tendency when the diversity in the portfolio of policies increases. That is, as the portfolio of institutional pressures or policies increases, the value of the regression coefficients grows. The positive values of the regression coefficients indicate that they have a greater effect on the probability of developing CE in firms than the reference value. Therefore, both hypotheses are confirmed.

the appendix, the results of this robustness check does not reveal significant differences between these various types of regression analysis. Hence, supporting the quadratic regression model for the analysis of Hypotheses 1a and 1b.

Table 4.6. Ordinal Logistic regression models (Hypothesis 2a and 2b)

Variables	Model 4	Model 5	Model 6
Financing	.134***		
Innovation		.256***	
Financing^2	-.003		
Innovation^2		-.004	
Financing*Innovation			.007***
Environmental	.133***	.105***	1.09***
Sector	.119***	.127***	1.16***
-2 Log Likelihood	4321.002	4109.341	3278.038
Chi-Square	325.729	310.372	281.392
Sig.	.000	.000	.000
Cox and Snell	.131	.187	.110
Nagelkerke	.129	.186	.105
McFadden	.056	.077	.023

*p<0.05, **p<0.01, *** p<0.001



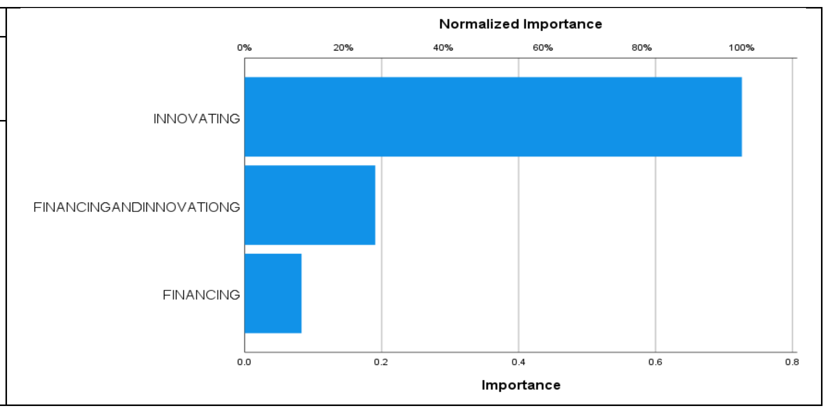
(1) *Financing* Variable: OLR analysis. Pseudo R-Square (Cox and Snell: .122; McFadden: .020). -2 Log-Likelihood: 1655.875; Chi-Square: 132.012; Sig. 0.000.
(2) *Innovation* Variable: OLR analysis. Pseudo R-Square (Cox and Snell:.356; McFadden: .067). -2 Log-Likelihood: 1695.729; Chi-Square: 438.018; Sig. 0.000.

Figure 4.2. Regression coefficients (Hypothesis 2a and 2b)

Regarding Hypotheses 3a and 3b, on the joint action and synergic effects of policies to promote both innovation and financial support in CE developments in firms, the results are shown in Table 4.7 and Figure 4.3. Table 4.7 displays the results of the simulation with ANN-MLP, considering as input variables *Innovation*, *Financing*, and the joint variable *Financing*Innovation*, showing the normalised importance of the effect of each input variable on CE development in the firm[52]. From the analysis, it is observed that all variables have a positive and significant impact on the development of CE, but with different impacts (*Innovation* =.726; 100% normalised value; *Financing*Innovation* =.191; 26.3% normalised value; *Financing* =.083; 11.4% normalised value). Thus, these results show that *Innovation* is the variable with the highest normalised importance, followed by *Financing*Innovation*, and finally *Financing*. This means that innovation promotion policies (*Innovation*) are the policies that have the most weight in the effect on CE adoption in the firm, and therefore the most impact. Hence, Hypothesis 3b is corroborated, showing that the synergistic and complementary effect of the joint action of both innovation promotion policies and financial support policies (*Financing*Innovation)* is greater than financial support policies (*Financing*) alone on the development of CE in firms. However, Hypothesis 3a is not corroborated, since the effect of innovation promotion policies alone (*Innovation*) on CE adoption in firms is greater than the joint effect of financial support and innovation policies (*Financing*Innovation).*

Table 4.7. ANN-MLP simulation for each of the independent variables (Hypothesis 3)

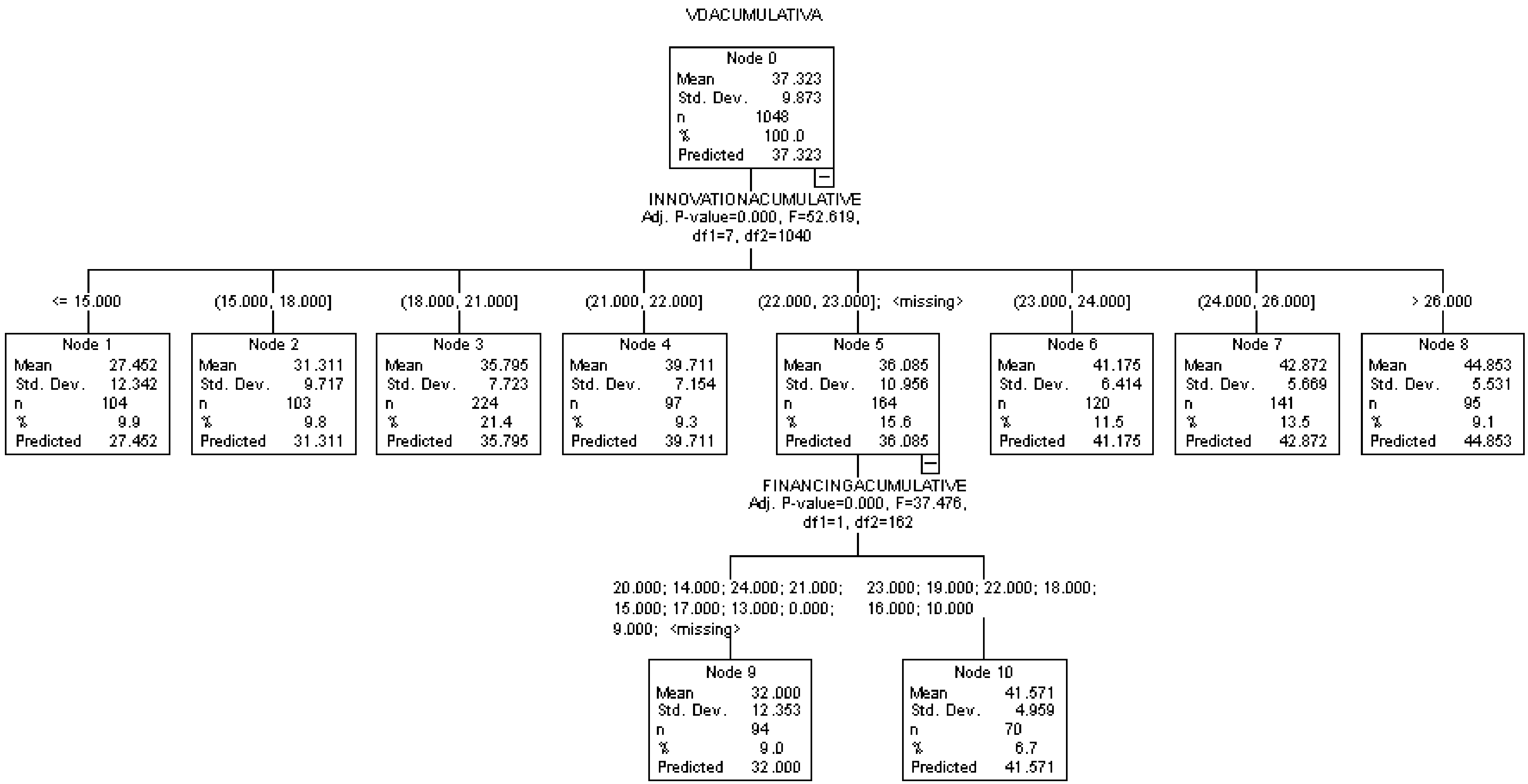
Variable (t-1)	Simulation	
	Importance	Normalised Importance (%)
Financial support	.083	11.4
*Financing*Innovation*	.191	26.3
Innovation	.726	100.0



[52] Ibrahim et al. (2013) revises some methods for assessing the relative importance of input variables in artificial neural networks. These methods are based on Garson's algorithm (1991), which utilises the absolute values of the final connection weights when computing the contribution of the variable. $RI_x = \sum_{x=1}^{n} \frac{|w_{xy}\, w_{yz}|}{\sum_{y=1}^{m} |w_{xy}\, w_{yz}|}$ where RI_x denotes the relative importance of neuron x, while $\sum_{y=1}^{m} w_{xy}\, w_{yz}$ represents the sum of the product of the final weights connection from input neurons to hidden neurons with the connnections from hidden neurons to output neurons.

Additionally, we have tested the robustness of our results by performing a Tree regression analysis. Figure 4.3 shows the results. This analysis corroborates that both innovation promotion and financial support policies affect the probability of developing CE in firms. We obtain 8 models, taking into account that the range of the analysis for the dependent variable is <16 (with a minimum of 0), and more than >26 (with a maximum of 48). Regarding the results, first, it should be noted that there is a positive relationship between the increase in innovation promotion policies and the development of CE. The analysis shows discrimination between the probability of developing CE and the values of the dependent variable. Thus, for example, the values of the dependent variable less than 16, in probabilistic terms, can be obtained with an innovation promotion policy pressure with a mean value of 27,462. However, if the objective is to obtain the maximum value of the dependent variable, which means a greater probability of developing CE, the required value of the innovation variable is 44.853. The only model that contains a combination of innovation promotion policies together with financial support policies is Model 6, which corresponds to a dependent variable value in the range of 22 to 23, which is lower than the maximum. This corroborates the findings from the ANN. Therefore, we can conclude that the combination of financial support and innovation promotion policies has a greater effect on the development of CE than financial support policies alone, corroborating Hypothesis 3b. However, the joint action of the two variables does not produce a greater effect on the probability of developing CE than if the innovation promotion policies acted alone (not corroborating Hypothesis 3a).

Figure 4.3. Tree regression model (Hypothesis 3)



4.8 Discussion and Conclusion

This paper has analysed how innovation and financial policy pressures affect the adoption of CE in the firm. Using as a database the EU survey on *Public Consultation on the Circular Economy* database composed of 870 companies and combining the dynamic capability approach with institutional complexity theories, our starting point is that the adoption of CE practices entails the resources and dynamic capabilities of the firm in the development of environmental innovations. In this process, companies seek the support of stakeholders, especially institutions, whose pressure both in promoting policies for the development of innovations and financial support, although complex in nature, can facilitate the adoption of business processes compatible with CE. We conducted this analysis by employing classical econometric approaches, as well as machine learning methods, that account for the no-linearity of these processes and the interrelation and synergies of institutional policy pressures in the adoption of CE developments in firms.

Our results corroborate the first Hypotheses (1a and 1b), which stated that institutional policies, in the form of innovation promotion and financial support policies, have an inverted U-shaped effect on the development of CE. These results are partly in line with previous literature that indicates that policies to promote environmental innovation together with financial support have a significant impact on company decisions and should facilitate the process of adopting practices compatible with CE (Fischer and Pascucci, 2017; Kesidou and Demirel, 2012; Horbach et al., 2012). Nonetheless, our results extend the existing literature on CE, showing that continuous strengthening of environmental policies can produce a decrease in the probability of developing CE. Hence, the development of CE improves as institutional pressure increases but there is a threshold point. Any increase in these pressures beyond this point will deteriorate CE development in firms. These results provide further empirical evidence to support the findings of other related environmental research literature, see, for example, Colwell and Joshi (2013), Delmas and Toffel (2008) and Van Leeuwen and Mohnen (2013). These authors indicate that excessive institutional pressure through, for example, excessive regulation to encourage innovation and the development of green processes, can be interpreted by companies as an interference in corporate objectives, or cause companies to lose interest in environmental objectives as a consequence of their generalisation to other companies, for which they lose their competitive nature (Van Leeuwen and Mohnen, 2013; Lanoie et al., 2011).

Moreover, our results also suggest that a higher level of diversification of both innovation promotion and financial support policies has a positive impact on the probability of adopting CE practices in the company (Hypotheses 2a and 2b). These results add to previous research that proactive environmental strategies, such as the implementation of CE models, involve the development of a wide range of skills and capabilities in the company, both aimed at product and sustainable processes development that facilitate the transformation of the traditional linear economic models into a closed-loop of production and consumption (Schaltegger et al., 2016; Lüdeke-Freund et al., 2018; Perey et al., 2018). In addition, our results support previous research (Fischer and Pascucci, 2017; Khan, 2020), pointing out how the institutional pressures facilitate the creation of skills and capacities to develop cooperation and collaboration agreements in the adoption of CE models by firms, despite the complexity and incompatibility of these pressures can pose for firms. These findings also help understand better businesses confronting institutional complexity, extending institutional complexity research such as Greenwood et al. (2011) and Pache and Santos (2010). These results show that in the face of institutional complexity scenarios with an increasing number and diversity of institutional pressures, which might create incompatibility between policy prescriptions, companies are able to navigate this institutional complexity by integrating, building, and reconfiguring their competencies and capabilities to develop the necessary innovations for implementing CE.

Finally, our results partially corroborate Hypothesis 3. While our results show a synergistic effect between institutional pressures in the form of financial support and innovation policies compared to exclusively financial support policy pressures. However, this phenomenon of complementarity of the joint action of policies of innovation and financial support does not have a greater effect than the policies promoting environmental innovation alone. Khan et al. (2020), Annunziata et al. (2018), and Strauss et al. (2017) have pointed out that companies have important challenges in the development of CE, not only in the development of skills and capabilities, but also in the need to finance them. Our results suggest that a combination of policies promoting innovation and financial support can boost the development of skills by companies that facilitate the adoption of CE to a greater extent than policies that only tend to finance their development. On the other hand, our findings do not support this synergistic phenomenon between innovation promotion and financial support policies compared to innovation promotion policies alone. In this sense, Daddi et al. (2016) and Fischer and Pascucci (2017) point out that innovation policies are implemented fundamentally through regulations and information, which is more easily assimilated by companies; nevertheless, access to finance can be a complex and administratively tedious process, which turns public financing into a disincentive for companies (Uhrenholt et al., 2022, and Gusmerotti et al., 2019).

The *first contribution* of this research *is theoretical*. First, this research contributes to the extant literature that studies the effect of policies on the implementation of CE, particularly, to the little research that exists on the use of institutional policy pressures to provide financial support or to enable systemic circular innovation to occur. Prior institutional theory research assumes there is a relationship between institutional pressures for the implementation of CE and the organisation's strategies (Fischer and Pascucci, 2017; Gao et al., 2019; Ariti et al, 2019). Our paper advances the discussion by delving into how institutional pressures, in the form of innovation promotion and financial support policies, affect the development of CE in firms. Our results support previous evidence on the positive effects of institutional policies on CE adoption and show that an excess of institutional pressure has a negative effect on the development of CE, which is shown through the marked concavity of the curve that relates both variables. Moreover, our paper extends the previous literature, showing the importance of institutional pressures that contain a broad portfolio of policies. This is particularly relevant for institutional complexity research because it broadens prior literature, explaining that despite the institutional complexity scenario created by a larger and more diverse portfolio of institutional policy pressures, this leads companies to adopt CE models through the reconfiguration of their competencies and capabilities. Finally, our results reinforce previous research by showing the importance that synergistic and complementary effects of innovation promotion and financial support policies have on the development of capacities that favour CE adoption in companies.

Our *second contribution is methodological*. Previous studies have used regression methods and considered exclusively the direct effect of institutional pressures on firms, therefore, generating inconclusive results. The low explanatory power of the regression models, in terms of explained variance, and the low significance of the explanatory variables, are a problem for the analysis, especially when dealing with non-linearity and interaction and synergistic effects. Our empirical framework considers the possible interactions between different institutional policy pressures. This means, that this research does not only study if each type of policy, either innovation promotion or financial support, affects the implementation of CE in firms, but also examines how these institutional policy pressures affect, by allowing them to interact to understand which variables are more significant and if there are synergistic or complementarity effects between them. Hence, to address this objective and overcome these methodological concerns, this research combines regression methods with machine learning methods (i.e.

ANNs and a Tree Regression Analysis). The use of an ANN and a Tree Regression allows not only to analyse the interaction among variables, but also to consider the existence of non-linearities in the processes studied, achieving an explanatory power much higher than that obtained with regression analysis. This methodology contributes to explaining the effect of institutional policies in CE adoption and advances the discussion on the adequacy of linear methods in the analysis of complex relations between variables.

Lastly, the study findings provide a range of *governmental and managerial implications* for the development of CE in firms. From the point of view of governments and policymakers, this research provides an important contribution from the perspective of environmental policy, since it suggests that an integral and wide-raging policy framework, in terms of innovation and financial support, is required for the adoption of CE in firms, which implies understanding how innovation promotion policies and financial support policies affect the company. In this sense, the emerging evidence supports that policymakers should consider three variables in the design of such policies: the intensity of institutional policy pressures, the diversity in the portfolio of policies, and the synergic effect between promotion policies for innovation and financial support. Thus, policymakers have to be aware that in terms of innovation promotion and financial support policies for the adoption of CE in firms, the effect on companies has a U-inversed shape nature, indicating that the development of CE improves as the institutional pressures increase but that there is a threshold point. Therefore, when planning these policies, they have to be careful with the intensity of these pressures not to surpass the threshold point and produce a counterproductive effect on CE adoption. Moreover, the results suggest that policymakers should increase the number and diversity of both innovation promotion and financial support policies as they have a positive impact on the probability of adopting CE practices in the company. Finally, policymakers should be conscious of the synergic effect between promotion policies for innovation and financial support, which have a larger effect on the development of CE models in firms than financial support policies alone. Moreover, in the scenario where policymakers have to choose between innovation promotion and financial support policies, policies for the promotion of innovation should be favour as they have a larger impact on the implementation of CE.

From the point of view of managers, this research indicates that in the face of institutional complexity with increasing number and diversity of institutional pressures and possible incompatibility between policy prescriptions, firm managers have to focus on being able to integrate, foster, and reconfigure their competences and capabilities, both internal and external, develop the necessary innovations for implementing CE. Moreover, this research highlights the relevant role that innovation plays in the adoption of CE, which is another important implication for managers in firms.

Chapter 5: Conclusions (Further Research & Recommendations)

The thesis examines the application of different machine learning tools to the analysis of the implementation of the CE in firms, to be able to better understand and solve the challenges these types of models pose for businesses, governments, and society as a whole. Particularly, this thesis studies how institutional pressures in different policy and business areas affect the development and promotion of CE models in firms, making special emphasis on the interaction of policies and the non-linearity and complementarity of the process. This is done throughout three papers which analyse three different critical dimensions of the institutional environment of the company that have received little attention from scholars, have generated contradictory results, and are essential for the implementation of CE in firms. Hence, this thesis combines regression methods with Machine learning (i.e., Artificial Neural Networks, K-means clusters, and Tree regression analysis) to analyse data from 870 companies in the European Union.

Given that a thesis must significantly advance the corpus of knowledge, the main contributions of this thesis are described below. Moreover, some limitations of the research are presented, together with some future avenues for future research.

This thesis contributes from a *theoretical* point of view to the field of institutional theory and environmental sustainability literature shedding light on the debate of the effects of institutional pressures on the implementation of CE in firms. The thesis contributes within institutional theory, to institutional entrepreneurship theory, by offering a comprehensive understanding of the role that institutions and governments have undertaken (particularly in the European Union) in the introduction of CE models through a portfolio of policies, and the crucial role national and supernational institutions can take to foster CEBMs. Moreover, the thesis contributes to the literature on institutional complexity, clarifying the typology and portfolio of actions that institutions may develop for promoting the development of CEBMs in firms, and at the same time, offering a more nuanced explanation of how the pressures act. Hence, providing further empirical evidence on the interactions and logistics of the various policies and their performance in the development of CE in firms. More in detail, the findings of this thesis serve to provide large-scale empirical evidence as compared to qualitative-based evidence presented by previous studies, and to settle and clarify some of the existing debates within the literature. First, the thesis shows how institutional pressures act, evidencing the importance of the interaction between coercive and normative pressures. Second, the thesis considers consumers as active agents with regard to CE, allowing to provide a more holistic understanding of the implementation of CEBMs, by complementing existing studies that mostly focused on the production side. Therefore, highlighting the role of pressures on consumers, which have an important effect (pull effect) in the development of CE models by firms. Finally, the results of the thesis emphasise that innovation policies are more effective for companies than purely financial support policies, due to the complexity of the administrative processes they involve. Thus, by contributing these three dimensions of the literature on institutional theory, the thesis provides some comprehensive insights into the theory.

The findings of this thesis, also provide important *methodological* contributions. The combination of the three papers in this thesis shows that the application of machine learning tools has an important contribution in solving complex analytical questions involving multivariate non-linear relationships, complementarity, and interaction. Hence, an adequate combination of conventional regression analysis methods with machine learning can serve as an instrumental framework that helps increase the explanatory power of models suitable for the study of the CE.

Finally, the findings of this thesis have value both for managers and policymakers. This research provides an important contribution for government and policymakers, since it suggests that a comprehensive environmental policy is required for the development of CE, which implies the coexistence and interaction of the two types of pressures (i.e., coercive and normative). Moreover, policymakers should pursue the application of broad portfolios of measures -both in depth and breadth-, which include both consumption and production policies, for a reinforced impulse of the development of CEBMs in firms. Therefore, paying more attention to CE consumption policies, particularly regulative measures, because they play a crucial role for an effective policy framework that fosters the development of CEBMs in firms. Lastly, this research shows that an integral and wide-raging policy framework, in terms of innovation and financial support, is required for the adoption of CE in firms. The thesis specifically highlights the need to consider three variables in the design of such policies (the intensity of institutional policy pressures, the diversity in the portfolio of policies, and the synergic effect between promotion policies for innovation and financial support) as well as take into account that the effect on companies of such policies has a U-inversed shape, indicating that the development of CE improves as the institutional policies increase but that there is a threshold point. Moreover, in the scenario where policymakers must choose between innovation promotion and financial support policies, policies for the promotion of innovation should be favour as they have a larger impact on the implementation of CE.

Regarding managers and decision-makers, the thesis provides some guidelines when a CE regulatory framework (i.e., coercive pressures) is in place. First, they should prioritise the adhesion to frameworks, standard measures for voluntary use, or industry-led initiatives (normative pressures) when there are established coercive pressures. Second, decision-makers should not disregard the vital role of customers since they are proactive agents with defined attitudes towards the purchasing and consumption of CE products. Finally, this thesis indicates that managers have to focus on being able to integrate, foster, and reconfigure their competences and capabilities, both internal and external, to develop the necessary innovations, due to the relevant role that innovation plays in the adoption of CE.

As with any research, this thesis has some limitations, which could provide fruitful avenues for future research. This thesis utilises data from companies in the EU. Data from other territories and countries could be collected to further corroborate the hypotheses and conclusions of this research, thus allowing for a more holistic view. Future studies could examine the role of institutional pressures as drivers of CE in firms pertaining to other countries, such as the US, or developing countries, in regions such as Latin America or Africa, where more research is needed. However, it is worth mentioning that the results of this thesis could be generalised to countries such as China, where a large body of research on the effect of institutional pressures exists[53], as well as the implementation of the Circular Economy Promotion Law.

Moreover, this research employs a cross-sectional database, and therefore, is unable to examine how the effect of institutional pressures on the adoption of CE in firms changes over time. Such a line of inquiry could provide insights into the dynamic forces that shape the environmental responsiveness of firms in an institutional environment. Although, this does not diminish the validity of the results and their contribution to the literature. Finally, repeated surveys would help deliver more robust evidence and insights on the role of institutional pressures as drivers of CE in firms, however, official surveys often tend to change circular

[53] See, for example, Zhu and Sarkis (2007), Li and Yu (2011), Chen et al. (2018).

economy questions, or even take many years, undermining the possibility of observing the dynamic path.

References

Abbey, J. D., Meloy, M. G., Guide Jr, V. D. R., & Atalay, S. (2015). Remanufactured products in closed-loop supply chains for consumer goods. *Production and Operations Management*, 24(3), 488-503.

AFNOR (2018). *A practical guide to getting into circular economy*. AFNOR. https://www.afnor.org/en/news/practical-guide-circular-economy/

Ahmad, A., & Dey, L. (2007). A k-mean clustering algorithm for mixed numeric and categorical data. *Data & Knowledge Engineering*, 63(2), 503-527.

Ahrens, T., & Ferry, L. (2018). Institutional entrepreneurship, practice memory, and cultural memory: Choice and creativity in the pursuit of endogenous change of local authority budgeting. *Management Accounting Research*, 38, 12-21.

Alda, M. (2019). Corporate sustainability and institutional shareholders: The pressure of social responsible pension funds on environmental firm practices. *Business Strategy and the Environment*, 28(6), 1060-1071.

Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A. J. (2020). A systematic review on supervised and unsupervised machine learning algorithms for data science. *Supervised and unsupervised learning for data science*, 3-21.

Alpaydın, E. (2014). *Introduction to machine learning*. Cambridge, MA: MIT Press.

Alpaydin, E. (2021). *Machine learning*. MIT Press.

Amui, L., Jabbour, C., Jabbour, A., & Kannan, D. (2017). Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition. *Journal of Cleaner Production*, 142, 308-322.

Annunziata, E., Pucci, T., Frey, M., & Zanni, L. (2018). The role of organizational capabilities in attaining corporate sustainability practices and economic performance: Evidence from Italian wine industry. *Journal of Cleaner Production*, 171, 1300-1311.

Aragon-Correa, J. A., & Leyva-de la Hiz, D. I. (2016). The influence of technology differences on corporate environmental patents: A resource-based versus an institutional view of green innovations. *Business Strategy and the Environment*, 25(6), 421-434.

Aragón-Correa, J. A., & Sharma, S. (2003). A contingent resource-based view of proactive corporate environmental strategy. *Academy of Management Review*, 28(1), 71-88.

Ariti, A. T., van Vliet, J., & Verburg, P. H. (2019). The role of institutional actors and their interactions in the land use policy making process in Ethiopia. *Journal of Environmental Management*, 237, 235-246.

Armstrong, J.S. & Overton, T.S (1977). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing*, 14, 396–402.

Arranz, C. F. A., Sena, V., & Kwong, C. (2022). Institutional pressures as drivers of circular economy in firms: A machine learning approach. *Journal of Cleaner Production*, 131738. https://doi.org/10.1016/j.jclepro.2022.131738.

Arranz, N., Arroyabe, M. F., & Fernandez de Arroyabe, J. C. (2016). Alliance building Process as Inhibiting Factor for SME International Alliances. *British Journal of Management*, 27(3), 497-515.

Arranz, N., Arroyabe, M. F., Molina-García, A., & Fernandez de Arroyabe, J. (2019). Incentives and inhibiting factors of eco-innovation in Spanish firms. *Journal of Cleaner Production*, 220, 167-176.

Arranz, N., Arroyabe, M., Li, J., & Fernandez de Arroyabe, J. C. (2020). Innovation as a driver of eco-innovation in the firm: An approach from the dynamic capabilities theory. *Business Strategy and the Environment*, 29(3), 1494-1503.

Asteriou, D., & Hall, S. G. (2015). *Applied econometrics*. Macmillan International Higher Education.

Baden-Fuller, C., & Morgan, M. S. (2010). Business models as models. *Long Range Planning*, 43(2-3), 156-171.

Bag, S., Gupta, S., & Foropon, C. (2019). Examining the role of dynamic remanufacturing capability on supply chain resilience in circular economy. *Management Decision*, 57(4), 863-885.

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, 163, 120420.

Bansal, P., & Roth, K. (2000). Why companies go green: A model of ecological responsiveness. *Academy of Management Journal*, 43(4), 717-736.

Bansal, A., Sharma, M., & Goel, S. (2017). Improved k-mean clustering algorithm for prediction analysis using classification technique in data mining. *International Journal of Computer Applications*, 157(6), 0975-8887.

Barney, J. B., Ketchen Jr, D. J., & Wright, M. (2011). The future of resource-based theory: revitalization or decline?. *Journal of Management*, 37(5), 1299-1315.

Barreto, I. (2010). Dynamic capabilities: A review of past research and an agenda for the future. *Journal of Management*, 36(1), 256-280.

Battilana, J., Leca, B., & Boxenbaum, E. (2009). 2 how actors change institutions: towards a theory of institutional entrepreneurship. *Academy of Management Annals*, 3(1), 65-107.

Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. *Journal of business research*, 67(8), 1595-1600.

Berrone, P., Fosfuri, A., Gelabert, L., & Gomez-Mejia, L. R. (2013). Necessity as the mother of 'green'inventions: Institutional pressures and environmental innovations. *Strategic Management Journal*, 34(8), 891-909.

Berry, M. W., Mohamed, A., & Yap, B. W. (Eds.). (2020). *Supervised and unsupervised learning for data science*. Springer Nature.

Bigano, A., Śniegocki, A., & Zotti, J. (2016). Policies for a more dematerialized EU economy. Theoretical underpinnings, political context and expected feasibility. *Sustainability*, 8(8), 717.

Bitencourt, C. C., de Oliveira Santini, F., Ladeira, W. J., Santos, A. C., & Teixeira, E. K. (2020). The extended dynamic capabilities model: A meta-analysis. *European Management Journal*, 38(1), 108-120.

Bocken, N. M. P., de Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering*, 33, 308–320.

Bocken, N. M. P., Ritala, P., & Huotari, P. (2017). The circular economy: Exploring the introduction of the concept among S&P 500 firms. *Journal of Industrial Ecology*, 21, 487–49c0.

Bocken, N. M. P., Short, S. W., Rana, P., & Evans, S. (2014). A literature and practice review to develop sustainable business model archetypes. *Journal of Cleaner Production*, 65, 42–56.

Boggia, A., Massei, G., Paolotti, L., Rocchi, L., & Schiavi, F. (2018). A model for measuring the environmental sustainability of events. *Journal of Environmental Management*, 206, 836-845.

Bönte, W., & Dienes, C. (2013). Environmental innovations and strategies for the development of new production technologies: empirical evidence from Europe. *Business Strategy and the Environment*, 22(8), 501-516.

Boons, F., & Lüdeke-Freund, F. (2013). Business models for sustainable innovation: State-of-the-art and steps towards a research agenda. *Journal of Cleaner Production*, 45 (1), 9–19

Bressanelli, G., Perona, M., & Saccani, N. (2019). Challenges in supply chain redesign for the Circular Economy: a literature review and a multiple case study. *International Journal of Production Research*, 57(23), 7395-7422.

Buhmann, Martin (2003). *Radial basis functions: theory and implementations*. Cambridge University Press, Cambridge. ISBN 978-0-521-10133-2.

Camisón, C., & Villar-López, A. (2014). Organizational innovation as an enabler of technological innovation capabilities and firm performance. *Journal of Business Research*, 67(1), 2891-2902.

Cavalieri, S., Maccarrone, P., & Pinto, R. (2004). Parametric vs. neural network models for the estimation of production costs: A case study in the automotive industry. *International Journal of Production Economics*, 91(2), 165-177.

Cetindamar, D., Phaal, R., & Probert, D. (2009). Understanding technology management as a dynamic capability: A framework for technology management activities. *Technovation*, 29(4), 237-246.

Chang, L., Li, W., & Lu, X. (2015). Government engagement, environmental policy, and environmental performance: Evidence from the most polluting Chinese listed firms. *Business Strategy and the Environment*, 24(1), 1-19.

Chauhan, C., Parida, V., & Dhir, A. (2022). Linking circular economy and digitalisation technologies: A systematic literature review of past achievements and future promises. *Technological Forecasting and Social Change*, 177, 121508.

Cheney, E W (1966). *Introduction to Approximation Theory.* McGraw-Hill, New York.

Cheng, C. C., & Shiu, E. C. (2012). Validation of a proposed instrument for measuring eco-innovation: An implementation perspective. *Technovation*, 32(6), 329-344.

Choi, Y., Bone, C., & Zhang, N. (2016). Sustainable policies and strategies in Asia: Challenges for green growth. *Technological Forecasting and Social Change*, 112, 134-137

Ciurana, J., Quintana, G., & Garcia-Romeu, M. L. (2008). Estimating the cost of vertical high-speed machining centres, a comparison between multiple regression analysis and the neural networks approach. *International Journal of Production Economics*, 115(1), 171-178.

Clemens, B., & Douglas, T. J. (2006). Does coercion drive firms to adopt 'voluntary'green initiatives? Relationships among coercion, superior firm resources, and voluntary green initiatives. *Journal of Business Research*, 59(4), 483-491.

Colwell, S. R., & Joshi, A. W. (2013). Corporate ecological responsiveness: Antecedent effects of institutional pressure and top management commitment and their impact on organizational performance. *Business Strategy and the Environmen*t, 22(2), 73-91.

Creswell, J. W. (2002). *Educational research: Planning, conducting, and evaluating quantitative* (Vol. 7). Prentice-Hall Upper Saddle River, NJ.

Costantini, V., Crespi, F., Palma, A., 2017. Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. *Research Policy*, 46(4), 799-819.

Covaleski, M. A., Dirsmith, M. W., & Weiss, J. M. (2013). The social construction, challenge and transformation of a budgetary regime: The endogenization of welfare regulation by institutional entrepreneurs. *Accounting, Organizations and Society*, 38(5), 333-364.

Daddi, T., Bleischwitz, R., Todaro, N. M., Gusmerotti, N. M., & De Giacomo, M. R. (2020). The influence of institutional pressures on climate mitigation and adaptation strategies. *Journal of Cleaner Production*, 244, 118879.

Daddi, T., Testa, F., Frey, M., & Iraldo, F. (2016). Exploring the link between institutional pressures and environmental management systems effectiveness: An empirical study. *Journal of Environmental Management*, 183, 647-656.

Dangelico, R. M. (2016). Green product innovation: Where we are and where we are going. *Business Strategy and the Environment*, 25(8), 560-576.

Dangelico, R. M., Pujari, D., & Pontrandolfo, P. (2017). Green product innovation in manufacturing firms: A sustainability-oriented dynamic capability perspective. *Business Strategy and the Environment*, 26(4), 490-506.

De Jesus, A., & Mendonça, S. (2018). Lost in transition? Drivers and barriers in the eco-innovation road to the circular economy. *Ecological Economics*, 145, 75-89.

De Jesus, A., Antunes, P., Santos, R., & Mendonça, S. (2019). Eco-innovation pathways to a circular economy: Envisioning priorities through a Delphi approach. *Journal of Cleaner Production*, 228, 1494-1513.

De Marchi, V. (2012). Environmental innovation and R&D cooperation: Empirical evidence from Spanish manufacturing firms. *Research Policy*, 41(3), 614-623.

del Mar Alonso-Almeida, M., Rodriguez-Anton, J. M., Bagur-Femenías, L., & Perramon, J. (2021). Institutional entrepreneurship enablers to promote circular economy in the European Union: Impacts on transition towards a more circular economy. *Journal of Cleaner Production*, 281, 124841.

Delmas, M. A., & Toffel, M. W. (2008). Organizational responses to environmental demands: Opening the black box. *Strategic Management Journal*, 29(10), 1027-1055.

Delmas, M., & Toffel, M. W. (2004). Stakeholders and environmental management practices: an institutional framework. *Business Strategy and the Environment*, 13(4), 209-222.

Demirel, P., & Kesidou, E. (2019). Sustainability-oriented capabilities for eco-innovation: Meeting the regulatory, technology, and market demands. *Business Strategy and the Environment*, 28(5), 847-857.

Deepa, N., Pham, Q. V., Nguyen, D. C., Bhattacharya, S., Prabhadevi, B., Gadekallu, T. R., ... & Pathirana, P. N. (2022). A survey on blockchain for big data: approaches, opportunities, and future directions. *Future Generation Computer Systems*.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 147-160.

Domenech, T., & Bahn-Walkowiak, B. (2019). Transition towards a resource efficient circular economy in Europe: policy lessons from the EU and the member states. *Ecological Economics*, 155, 7-19.

Dorado, S. (2005). Institutional entrepreneurship, partaking, and convening. *Organization Studies*, 26(3), 385-414.

Doran, J. (2012). Are differing forms of innovation complements or substitutes? *European Journal of Innovation Management*, 15(3), 351-371.

Dou, Y., & Sarkis, J. (2010). A joint location and outsourcing sustainability analysis for a strategic offshoring decision. *International Journal of Production Research*, 48(2), 567-592.

Dougherty, J., Kohavi, R., & Sahami, M. (1995). Supervised and unsupervised discretization of continuous features. In *Machine learning proceedings* 1995 (pp. 194-202). Morgan Kaufmann.

Elliot, V. H. (2016). Institutional entrepreneurship and change: A contemporary history of the Swedish banking industry and its performance management systems. *Journal of Accounting & Organizational Change*.

Ertz, M., Durif, F., & Arcand, M. (2016). Collaborative consumption: Conceptual snapshot at a buzzword. *Journal of Entrepreneurship Education*, 19(2), 1-23.

Esposito, M., Tse, T., & Soufani, K. (2016). Companies are working with consumers to reduce waste. *Harvard Business Review*.

European Commission (2015). *Public Consultation on the Circular Economy.* EU Data Base. https://ec.europa.eu/environment/consultations/closing_the_loop_en.htm

European Commission (2015). *Public Consultation on the Circular Economy*. EU Data Base. https://ec.europa.eu/environment/consultations/closing_the_loop_en.htm

European Commission (2019). *Circular Economy: Implementation of the Circular Economy Action Plan*. European Union. https://ec.europa.eu/environment/circular-economy/index_en.htm

Evans, S., Vladimirova, D., Holgado, M., Van Fossen, K., Yang, M., Silva, E. A., & Barlow, C. Y. (2017). Business model innovation for sustainability: Towards a unified perspective for creation of sustainable business models. *Business Strategy and the Environment*, 26, 597–608.

Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: a meta-analytic evaluation and extension. *Journal of Management Studies*, 53(8), 1348-1380.

Faridian, P. H., & Neubaum, D. O. (2020). Ambidexterity in the age of asset sharing: Development of dynamic capabilities in open source ecosystems. *Technovation*, 102125. https://doi.org/10.1016/j.technovation.2020.102125.

Ferasso, M., Beliaeva, T., Kraus, S., Clauss, T., & Ribeiro-Soriano, D. (2020). Circular economy business models: The state of research and avenues ahead. *Business Strategy and the Environment*, 29(8), 3006-3024.

Figge, F., Thorpe, A. S., & Good, J. (2021). Us before me: A group level approach to the circular economy. *Ecological Economics*, 179, 106838.

Finkelstein, S., & Boyd, B. K. (1998). How much does the CEO matter? The role of managerial discretion in the setting of CEO compensation. *Academy of Management Journal*, 41(2), 179-199.

Fischer, A., & Pascucci, S. (2017). Institutional incentives in circular economy transition: The case of material use in the Dutch textile industry. *Journal of Cleaner Production*, 155, 17-32.

Fonseca, L. M., Domingues, J. P., Pereira, M. T., Martins, F. F., & Zimon, D. (2018). Assessment of circular economy within Portuguese organizations. *Sustainability*, 10(7), 2521.

Fonseca, L.M. & Domingues, J.P. (2018). Exploratory Research of ISO 14001:2015 Transition among Portuguese Organisations. *Sustainability* 10, 781.

Friant, M. C., Vermeulen, W. J., & Salomone, R. (2021). Analysing European Union circular economy policies: words versus actions. *Sustainable Production and Consumption*, 27, 337-353.

Gallego-Alvarez, I., Ortas, E., Vicente-Villardón, J. L., & Álvarez Etxeberria, I. (2017). Institutional constraints, stakeholder pressure and corporate environmental reporting policies. *Business Strategy and the Environment*, 26(6), 807-825.

Gao, Y., Gu, J., & Liu, H. (2019). Interactive effects of various institutional pressures on corporate environmental responsibility: Institutional theory and multilevel analysis. *Business Strategy and the Environment*, 28(5), 724-736.

Gao, K., Mei, G., Piccialli, F., Cuomo, S., Tu, J., & Huo, Z. (2020). Julia language in machine learning: Algorithms, applications, and open issues. *Computer Science Review*, 37, 100254.

Garbero, A., Carneiro, B., & Resce, G. (2021). Harnessing the power of machine learning analytics to understand food systems dynamics across development projects. *Technological Forecasting and Social Change*, 172, 121012.

Garson, G. D. (1991). A comparison of neural network and expert systems algorithms with common multivariate procedures for analysis of social science data. *Social Science Computer Review*, 9(3), 399-434.

Gedam, V. V., Raut, R. D., de Sousa Jabbour, A. B. L., Tanksale, A. N., & Narkhede, B. E. (2021). Circular economy practices in a developing economy: Barriers to be defeated. *Journal of Cleaner Production*, 311, 127670.

Geiger, N., Swim, J. K., & Benson, L. (2021). Using the three-pillar model of sustainability to understand lay reactions to climate policy: A multilevel approach. *Environmental Science & Policy*, 126, 132-141.

Geissdoerfer, M., Morioka, S. N., de Carvalho, M. M., & Evans, S. (2018). Business models and supply chains for the circular economy. *Journal of Cleaner Production*, 190, 712–721.

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The circular economy—A new sustainability paradigm? *Journal of Cleaner Production*, 143, 757–768.

Genovese, A., Acquaye, A. A., Figueroa, A., & Koh, S. L. (2017). Sustainable supply chain management and the transition towards a circular economy: Evidence and some applications. *Omega*, 66, 344-357

Gevrey, M., Dimopoulos, I., & Lek, S. (2006). Two-way interaction of input variables in the sensitivity analysis of neural network models. *Ecological Modelling*, 195(1-2), 43-50.

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production,* 114, 11–32.

Greenwood, R., & Suddaby, R. (2006). Institutional entrepreneurship in mature fields: The big five accounting firms. *Academy of Management Journal*, 49(1), 27-48.

Greenwood, R., Raynard, M., Kodeih, F., Micelotta, E. R., & Lounsbury, M. (2011). Institutional complexity and organizational responses. *Academy of Management Annals*, 5(1), 317-371.

Gupta, S., Chen, H., Hazen, B. T., Kaur, S., & Gonzalez, E. D. S. (2019). Circular economy and big data analytics: A stakeholder perspective. *Technological Forecasting and Social Change*, 144, 466-474.

Gurney, K. (2018). *An introduction to neural networks*. CRC press.

Gusmerotti, N. M., Testa, F., Corsini, F., Pretner, G., & Iraldo, F. (2019). Drivers and approaches to the circular economy in manufacturing firms. *Journal of Cleaner Production*, 230, 314-327.

Hair, J. F. (2006). *Multivariate data analysis*. Pearson Education.

Haque, F., & Ntim, C. G. (2018). Environmental policy, sustainable development, governance mechanisms and environmental performance. *Business Strategy and the Environment*, 27(3), 415-435.

Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review*, 20(4), 986-1014.

Hart, S. L., & Dowell, G. (2011). Invited editorial: A natural-resource-based view of the firm: Fifteen years after. *Journal of Management*, 37(5), 1464-1479.

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Organizational Research Methods*, 7(2), 191-205.

Hazen, B. T., Mollenkopf, D. A., & Wang, Y. (2017). Remanufacturing for the circular economy: An examination of consumer switching behaviour. *Business Strategy and the Environment*, 26(4), 451-464.

Hernandez, R. J., Miranda, C., & Goñi, J. (2020). Empowering sustainable consumption by giving back to consumers the ‘right to repair’. *Sustainability*, *12*(3), 850.

Hina, M., Chauhan, C., Kaur, P., Kraus, S., & Dhir, A. (2022). Drivers and barriers of circular economy business models: Where we are now, and where we are heading. *Journal of Cleaner Production*, 333, 130049.

Heidari, A.A., Faris, H., Mirjalili, S., Aljarah, I., Mafarja, M. (2020). Ant Lion Optimizer: Theory, Literature Review, and Application in Multi-layer Perceptron Neural Networks. In: Mirjalili, S., Song Dong, J., Lewis, A. (eds) *Nature-Inspired Optimizers. Studies in Computational Intelligence*, 811. Springer, Cham.

Hobson, K., & Lynch, N. (2016). Diversifying and de-growing the circular economy: Radical social transformation in a resource-scarce world. *Futures*, 82, 15-25.

Hofmann, T. (2001). Unsupervised learning by probabilistic latent semantic analysis. *Machine Learning*, 42, 177–196.

Hopkinson, P., Zils, M., Hawkins, P., & Roper, S. (2018). Managing a complex global circular economy business model: opportunities and challenges. *California Management Review*, 60(3), 71-94.

Horbach, J. (2016). Empirical determinants of eco-innovation in European countries using the community innovation survey. *Environmental Innovation and Societal Transitions*, 19, 1-14.

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural networks*, 2(5), 359-366.

Huamao, X., & Fengqi, W. (2007). Circular economy development mode based on system theory. *Chinese Journal of Population Resources and Environment*, 5(4), 92-96.

Hullova, D., Trott, P., & Simms, C. D. (2016). Uncovering the reciprocal complementarity between product and process innovation. *Research Policy*, 45(5), 929-940.

Ibrahim, O. M. (2013). A comparison of methods for assessing the relative importance of input variables in artificial neural networks. *Journal of Applied Sciences Research*, 9(11), 5692-5700.

Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Sarkis, J., & Godinho Filho, M. (2019). Unlocking the circular economy through new business models based on large-scale data: an integrative framework and research agenda. *Technological Forecasting and Social Change*, 144, 546-552.

Jabbour, C. J. C., Seuring, S., de Sousa Jabbour, A. B. L., Jugend, D., Fiorini, P. D. C., Latan, H., & Izeppi, W. C. (2020). Stakeholders, innovative business models for the circular economy and sustainable performance of firms in an emerging economy facing institutional voids. *Journal of Environmental Management*, 264, 110416.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255-260.

Kalra, M., Lal, N., & Qamar, S. (2018). K-mean clustering algorithm approach for data mining of heterogeneous data. In *Information and Communication Technology for Sustainable Development*, 61-70. Springer, Singapore.

Kanda, W., Geissdoerfer, M., & Hjelm, O. (2021). From circular business models to circular business ecosystems. *Business Strategy and the Environment*, 30(6), 2814-2829.

Katz-Gerro, T., & López Sintas, J. (2019). Mapping circular economy activities in the European Union: Patterns of implementation and their correlates in small and medium-sized enterprises. *Business Strategy and the Environment*, 28(4), 485-496.

Kemp, R., & Foxon, T.J. (2007). Tipology of eco-innovation. In: *MEI Project: Measuring Eco-Innovation.* European Commission.

Kesidou, E., & Demirel, P. (2012). On the drivers of eco-innovations: Empirical evidence from the UK. *Research Policy*, 41(5), 862-870.

Khan, O., Daddi, T., & Iraldo, F. (2020). Microfoundations of dynamic capabilities: Insights from circular economy business cases. *Business Strategy and the Environment*, 29(3), 1479-1493.

Kiefer, Ch.P., Del Rio, P., Carrillo-Hermosilla, J. (2019). Drivers and barriers of eco-innovation types for sustainable transitions: A quantitative perspective. *Business Strategy and the Environment*, 28(1), 155-172.

Kirchherr, J. W., Hekkert, M. P., Bour, R., Huijbrechtse-Truijens, A., Kostense-Smit, E., & Muller, J. (2017b). Breaking the barriers to the circular economy. https://circulareconomy.europa.eu/platform/sites/default/files/171106_white_paper_breaking_the_barriers_to_the_circular_economy_white_paper_vweb-14021.pdf

Kirchherr, J., Piscicelli, L., Bour, R., Kostense-Smit, E., Muller, J., Huibrechtse-Truijens, A., & Hekkert, M. (2018). Barriers to the circular economy: evidence from the European Union (EU). *Ecological Economics*, 150, 264-272.

Kirchherr, J., Reike, D., & Hekkert, M. (2017a). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, conservation and recycling*, 127, 221-232.

Kosow, H., Weimer-Jehle, W., León, C. D., & Minn, F. (2022). Designing synergetic and sustainable policy mixes-a methodology to address conflictive environmental issues. *Environmental Science & Policy*, 130, 36-46.

Kotsiantis, S. B. (2007). Supervised machine learning: A review of classification techniques. *Informatica*, 31, 249–268.

Kristoffersen, E., Mikalef, P., Blomsma, F., & Li, J. (2021). Towards a business analytics capability for the circular economy. *Technological Forecasting and Social Change*, 171, 120957.

Kumar, N., Upadhyay, G., & Kumar, P. (2017). Comparative Performance of Multiple Linear Regression and Artificial Neural Network Based Models in Estimation of Evaporation. *Advances in Research*, 11(5): 1-11.

Lakatos, E.S., Dan, V., Cioca, L.I., Bacali, L., & Ciobanuet, A.M. (2016). How Supportive Are Romanian Consumers of the Circular Economy Concept: A Survey. *Sustainability* 8, 789-806.

Lanoie, P., Laurent-Lucchetti, J., Johnstone, N., & Ambec, S. (2011). Environmental policy, innovation and performance: new insights on the Porter hypothesis. *Journal of Economics & Management Strategy,* 20(3), 803-842.

Latan, H., Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Wamba, S. F., & Shahbaz, M. (2018). Effects of environmental strategy, environmental uncertainty and top management's commitment on corporate environmental performance: The role of environmental management accounting. *Journal of Cleaner Production*, 180, 297-306.

Lee, M. T., & Raschke, R. L. (2020). Innovative sustainability and stakeholders' shared understanding: The secret sauce to "performance with a purpose". *Journal of Business Research*, 108, 20-28.

Levänen, J., Lyytinen, T., & Gatica, S. (2018). Modelling the interplay between institutions and circular economy business models: A case study of battery recycling in Finland and Chile. *Ecological Economic*s, 154, 373-382.

Lewandowski, M. (2016). Designing the business models for circular economy—Towards the conceptual framework. *Sustainability*, 8, 43.

Li, J., & Yu, K. (2011). A study on legislative and policy tools for promoting the circular economic model for waste management in China. *Journal of Material Cycles and Waste Management*, 13(2), 103.

Li, J., Zhang, Y., Hu, Y., Tao, X., Jiang, W., & Qi, L. (2018). Developed market or developing market?: A perspective of institutional theory on multinational enterprises' diversification and sustainable development with environmental protection. *Business Strategy and the Environment*, 27(7), 858-871.

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *MIS Quarterly*, 31(1), 59-87.

Liao, Z. (2018). Institutional pressure, knowledge acquisition and a firm's environmental innovation. *Business Strategy and the Environment*, 27(7), 849-857.

Libbrecht, M. W., & Noble, W. S. (2015). Machine learning applications in genetics and genomics. *Nature Reviews Genetics,* 16(6), 321–332.

Lieder, M., & Rashid, A. (2016). Towards circular economy implementation: a comprehensive review in context of manufacturing industry. *Journal of Cleaner Production*, *115*, 36-51.

Linder, M., & Williander, M. (2017). Circular business model innovation: inherent uncertainties. *Business Strategy and the Environment*, 26(2), 182-196.

Liobikienė, G., & Dagiliūtė, R. (2016). The relationship between economic and carbon footprint changes in EU: the achievements of the EU sustainable consumption and production policy implementation. *Environmental Science & Policy*, 61, 204-211.

Lüdeke-Freund, F., Carroux, S., Joyce, A., Massa, L., & Breuer, H. (2018). The sustainable business model pattern taxonomy—45 patterns to support sustainability-oriented business model innovation. *Sustainable Production and Consumption*, 15, 145–162.

Lüdeke-Freund, F., Gold, S., & Bocken, N. M. P. (2019). A review and typology of circular economy business model patterns. *Journal of Industrial Ecology*, 23(1), 36–61.

MacAneney, M. (2018). If it is broken, you should not fix it: the threat fair repair legislation poses to the manufacturer and the consumer. *John's L. Rev*., 92, 331.

MacArthur, E. (2013). Towards the circular economy. *Journal of Industrial Ecology*, 2, 23-44.

Madhiarasan, M., & Deepa, S. N. (2017). Comparative analysis on hidden neurons estimation in multi-layer perceptron neural networks for wind speed forecasting. *Artificial Intelligence Review*, 48(4), 449-471.

Maitre-Ekern, E., & Dalhammar, C. (2016). Regulating planned obsolescence: a review of legal approaches to increase product durability and reparability in Europe. *Review of European, Comparative & International Environmental Law*, *25*(3), 378-394.

Manninen, K., Koskela, S., Antikainen, R., Bocken, N., Dahlbo, H., & Aminoff, A. (2018). Do circular economy business models capture intended environmental value propositions?. *Journal of Cleaner Production*, 171, 413-422.

Manninen, K., Koskela, S., Antikainen, R., Bocken, N., Dahlbo, H., & Aminoff, A. (2018). Do circular economy business models capture intended environmental value propositions? *Journal of Cleaner Production*, 171, 413–422.

Marrucci, L., Daddi, T., & Iraldo, F. (2019). The integration of circular economy with sustainable consumption and production tools: Systematic review and future research agenda. *Journal of Cleaner Production*, 240, 118268.

Marshland, S. (2015). *Machine learning: An algorithm perspective*. Boca Raton, FL: CRC Press.

Martinelli, E., Mencattini, A., Daprati, E., & Di Natale, C. (2016). Strength is in numbers: Can concordant artificial listeners improve prediction of emotion from speech? *PLoS One*, 11(8), e0161752.

Martins, N. O. (2018). The classical circular economy, sraffian ecological economics and the capabilities approach. *Ecological Economics*, 145, 38-45.

Marzucchi, A., & Montresor, S. (2017). Forms of knowledge and eco-innovation modes: Evidence from Spanish manufacturing firms. *Ecological Economics*, 131, 208-221.

Massa, L., Tucci, C. L., & Afuah, A. (2017). A critical assessment of business model research. *Academy of Management Annals*, 11(1), 73-104.

McDowall, W., Geng, Y., Huang, B., Barteková, E., Bleischwitz, R., Türkeli, S., & Doménech, T. (2017). Circular economy policies in China and Europe. *Journal of Industrial Ecology*, 21(3), 651-661.

Merli, R., Preziosi, M., & Acampora, A. (2018). How do scholars approach the circular economy? A systematic literature review. *Journal of Cleaner Production*, 178, 703-722.

Milgrom, P., & Roberts, J. (1995). Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics*, 19(2), 179-208.

Milios, L. (2018). Advancing to a Circular Economy: three essential ingredients for a comprehensive policy mix. *Sustainability Science*, 13(3), 861-878.

Millar, N., McLaughlin, E., & Börger, T. (2019). The circular economy: swings and roundabouts? *Ecological Economics*, 158, 11-19.

Minbashian, A., Bright, J. E., & Bird, K. D. (2010). A comparison of artificial neural networks and multiple regression in the context of research on personality and work performance. *Organizational Research Methods*, 13, 540-561.

Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). *Foundations of machine learning*. MIT press.

Mehrotra, K., 1997. *Elements of artificial neural networks*. Cambridge, MA: MIT Press.

Mont, O., & Heiskanen, E. (2015). *Breaking the stalemate of sustainable consumption with industrial ecology and a circular economy*. In Handbook of research on sustainable consumption. Edward Elgar Publishing.

Müller, B., Reinhardt, J. & Strickland, M. T. (1995). *Neural networks: an introduction*. Springer Science & Business Media.

Munther, A., Razif, R., AbuAlhaj, M., Anbar, M., & Nizam, S. (2016). A preliminary performance evaluation of K-means, KNN and em unsupervised machine learning methods for network flow classification. *International Journal of Electrical and Computer Engineering*, 6(2), 778–784.

Nisbet, R., Elder, J., & Miner, G. (2009). *Handbook of statistical analysis and data mining applications*. Academic Press.

North, D. C. (1991). Institutions. *The Journal of Economic Perspectives*, 5(1), 97–112. http://www.jstor.org/stable/1942704

Nover, C., 2016. *Drivers and Obstacles towards Eco-Innovation of European Entrepreneurs* (Doctoral Dissertation), Universidade Católica Portuguesa.

Olden, J. D., Joy, M. K., & Death, R. G. (2004). An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling*, 178(3-4), 389-397.

Orhan, U., Hekim, M., & Ozer, M. (2011). EEG signals classification using the K-means clustering and a multilayer perceptron neural network model. *Expert Systems with Applications*, 38(10), 13475-13481.

Osterwalder, A., & Pigneur, Y. (2010). *Business model generation: a handbook for visionaries, game changers, and challengers*. John Wiley & Sons.

Paliwal, M., & Kumar, U. A. (2009). Neural networks and statistical techniques: A review of applications. *Expert Systems with Applications*, 36(1), 2-17.

Palmer, K., Oates, W. E., & Portney, P. R. (1995). Tightening environmental standards: the benefit-cost or the no-cost paradigm?. *Journal of Economic Perspectives*, 9(4), 119-132.

Palmer, M., & Truong, Y. (2017). The impact of technological green new product introductions on firm profitability. *Ecological Economics*, 136, 86-93.

Park, Y. S. & Lek, S. (2016). Artificial neural networks: Multilayer perceptron for ecological modeling. In *Developments in environmental modelling*, 28, 123-140. Elsevier.

Paruelo, J., & Tomasel, F. (1997). Prediction of functional characteristics of ecosystems: a comparison of artificial neural networks and regression models. *Ecological Modelling*, *98*(2-3), 173-186.

Perey, R., Benn, S., Agarwal, R., & Edwards, M. (2018). The place of waste: Changing business value for the circular economy. *Business Strategy and the Environment*, 27(5), 631-642.

Phan, T. N., & Baird, K. (2015). The comprehensiveness of environmental management systems: The influence of institutional pressures and the impact on environmental performance. *Journal of Environmental Management*, 160, 45-56.

Pieroni, M. P., McAloone, T. C., & Pigosso, D. C. (2021). Circular Economy business model innovation: sectorial patterns within manufacturing companies. *Journal of Cleaner Production*, 286, 124921.

Pieroni, Marina P. P.; McAloone, Tim C.; Pigosso, Daniela C. A. (2019). Business model innovation for circular economy and sustainability: A review of approaches. *Journal of Cleaner Production*, 215: 198-216.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63, 539-569.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology,* 88(5), 879-903.

Pollex, J., & Lenschow, A. (2020). Many faces of dismantling: Hiding policy change in non-legislative acts in EU environmental policy. *Journal of European Public Policy*, 27(1), 20-40.

Porter, M. E., & Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, 9(4), 97-118.

Rana, A., Rawat, A. S., Bijalwan, A., & Bahuguna, H. (2018). Application of multi-layer (perceptron) artificial neural network in the diagnosis system: a systematic review. *IAES International Journal of Artificial Intelligence*, 7(30), 138~142.

Reed, R., & Marks II, R. J. (1999). *Neural smithing: supervised learning in feedforward artificial neural networks*. MIT Press.

Reichert, P., & Omlin, M. (1997). On the usefulness of overparameterized ecological models. *Ecological Modelling*, 95(2-3), 289-299.

Reike, D., Vermeulen, W. J., & Witjes, S. (2018). The circular economy: New or refurbished as CE 3.0?—Exploring controversies in the conceptualization of the circular economy through a focus on history and resource value retention options. *Resources, Conservation and Recycling*, 135, 246-264.

Ren, S., He, D., Zhang, T., & Chen, X. (2019). Symbolic reactions or substantive pro-environmental behaviour? An empirical study of corporate environmental performance under the government's environmental subsidy scheme. *Business Strategy and the Environment*, 28(6), 1148-1165.

Repo, P., Anttonen, M., Mykkänen, J., & Lammi, M. (2018). Lack of congruence between European citizen perspectives and policies on circular economy. *European Journal of Sustainable Development*, 7(1), 249-249.

Rizos, V., Behrens, A., Van der Gaast, W., Hofman, E., Ioannou, A., Kafyeke, T., & Topi, C. (2016). Implementation of circular economy business models by small and medium-sized enterprises (SMEs): Barriers and enablers. *Sustainability*, 8(11), 1212-1230.

Rizos, V., Tuokko, K., & Behrens, A. (2017). The Circular Economy: A review of definitions, processes and impacts. *CEPS Papers*, (12440).

Rojas, R. (1996). *The backpropagation algorithm. In Neural networks*. Springer, Berlin, Heidelberg.

Rosa, P., Sassanelli, C., & Terzi, S. (2019). Towards circular business models: A systematic literature review on classification frameworks and archetypes. *Journal of Cleaner Production*, 236, 117696. https://doi.org/10.1016/j.jclepro.2019.117696.

Russo, M. V. (2009). Explaining the impact of ISO 14001 on emission performance: a dynamic capabilities perspective on process and learning. *Business Strategy and the Environment*, 18(5), 307-319.

Salvador, R., Barros, M. V., Freire, F., Halog, A., Piekarski, C. M., & Antonio, C. (2021). Circular economy strategies on business modelling: Identifying the greatest influences. *Journal of Cleaner Production*, 299, 126918.

Sammut, C., & Webb, G. I. (Eds.). (2011). *Encyclopedia of machine learning*. Springer Science & Business Media.

Sandhu, T. H. (2018). Machine learning and natural language processing—A review. *International Journal of Advanced Research in Computer Science*, 9(2), 582–584.

Sarkis, J., Gonzalez-Torre, P., & Adenso-Diaz, B. (2010). Stakeholder pressure and the adoption of environmental practices: The mediating effect of training. *Journal of Operations Management*, 28(2), 163-176.

Scarpellini, S., Valero-Gil, J., Moneva, J. M., & Andreaus, M. (2020). Environmental management capabilities for a “circular eco-innovation”. *Business Strategy and the Environment*, 29(5), 1850-1864.

Schaltegger, S., Hansen, E. G., & Lüdeke-Freund, F. (2016). Business models for sustainability: Origins, present research, and future avenues. *Organization & Environment*, 29, 3–10.

Schor, J. (2016). Debating the sharing economy. *Journal of Self-Governance and Management Economics*, 4(3), 7-22.

Schumacher, E. F. (1973). *Small is beautiful: economics as if people mattered*. New York: Harper & Row.

Scott, W. R. (2005). *Institutional theory: Contributing to a theoretical research program*. In Great minds in management: The process of theory development, Chapter 22, 460-484.

SIGNUS (2020). *SIGNUS transforma en nuevos materiales: Cerca de 200.000 toneladas de neumáticos recogidas en España*. Retrieved February 05, 2021, from https://www.signus.es/en/signus-transforma-nuevos-materiales-cerca-200-000-toneladas-neumaticos-recogidas-espana-2019/

Smets, M., & Jarzabkowski, P. (2013). Reconstructing institutional complexity in practice: A relational model of institutional work and complexity. *Human Relations*, 66(10), 1279-1309.

Somers, M. J., & Casal, J. C. (2009). Using artificial neural networks to model nonlinearity: The case of the job satisfaction—job performance relationship. *Organizational Research Methods*, 12, 403-417.

Song, Y. Y., & Ying, L. U. (2015). Decision tree methods: applications for classification and prediction. *Shanghai archives of psychiatry*, 27(2), 130–135.

Spector, P. E. (2006). Method variance in organizational research: truth or urban legend?. *Organizational research methods*, 9(2), 221-232.

Stahel, W. R. (2016). The circular economy. *Nature*, 531(7595), 435–438.

Stål, H. I. (2015). Inertia and change related to sustainability–An institutional approach. *Journal of Cleaner Production*, 99, 354-365.

Strauss, K., Lepoutre, J., & Wood, G. (2017). Fifty shades of green: How microfoundations of sustainability dynamic capabilities vary across organizational contexts. *Journal of Organizational Behavior*, 38(9), 1338-1355.

Suddaby, R., Coraiola, D., Harvey, C., & Foster, W. (2020). History and the micro-foundations of dynamic capabilities. *Strategic Management Journal*, 41(3), 530-556.

Svensson-Hoglund, S., Richter, J. L., Maitre-Ekern, E., Russell, J. D., Pihlajarinne, T., & Dalhammar, C. (2021). Barriers, enablers and market governance: A review of the policy landscape for repair of consumer electronics in the EU and the US. *Journal of Cleaner Production*, 288, 125488.

Tang, M., Walsh, G., Lerner, D., Fitza, M. A., & Li, Q. (2018). Green Innovation, Managerial Concern and Firm Performance: An Empirical Study. *Business Strategy and the Environment*, *27*(1), 39-51.

Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives*, 28(4), 328-352.

Teece, D. J. (2015). Intangible assets and a theory of heterogeneous firms. In A. Bounfour, & T. Miyagawa (Eds.), Intangibles, market failure and innovation performance (pp. 217–239). New York: Springer.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533

Teo, H. H., Wei, K. K., & Benbasat, I. (2003). Predicting intention to adopt interorganizational linkages: An institutional perspective. *MIS Quarterly*, 19-49.

Thornton, P. H., & Ocasio, W. (2008). Institutional logics. *The Sage handbook of organizational institutionalism*, 840(2008), 99-128.

Tukker, A., Charter, M., Vezzoli, C., Stø, E., & Andersen, M. M. (Eds.). (2017). *System innovation for sustainability 1: Perspectives on radical changes to sustainable consumption and production*. Routledge.

Tunn, V. S. C., Bocken, N. M. P., van den Hende, E. A., & Schoormans, J. P. L. (2019). Business models for sustainable consumption in the circular economy: An expert study. *Journal of cleaner production*, 212, 324-333.

Urbinati, A., Chiaroni, D., & Chiesa, V. (2017). Towards a new taxonomy of circular economy business models. *Journal of Cleaner Production*, 168, 487–498.

Van Capelleveen, G., Amrit, C., Zijm, H., Yazan, D. M., & Abdi, A. (2020). Toward building recommender systems for the circular economy: Exploring the perils of the European Waste Catalogue. *Journal of Environmental Management*, 277, 111430.

Van Leeuwen, G. & Mohnen, P. (2013). Revisting The Porter Hypothesis, An Empirical Analysis of Green Innovation For The Netherlands. *UNU-MERIT Working Paper* 2013-02, UNU-MERIT, Maastricht.

Verlinden, B., Duflou, J. R., Collin, P., & Cattrysse, D. (2008). Cost estimation for sheet metal parts using multiple regression and artificial neural networks: A case study. *International Journal of Production Economics*, 111(2), 484-492.

Von Homeyer, I., Oberthür, S., & Jordan, A. J. (2021). EU climate and energy governance in times of crisis: Towards a new agenda. *Journal of European Public Policy*, 28(7), 959-979.

Wahba, H. (2010). How do institutional shareholders manipulate corporate environmental strategy to protect their equity value? A study of the adoption of ISO 14001 by Egyptian firms. *Business Strategy and the Environment*, 19(8), 495-511.

Wahyudin, I., Djatna, T., & Kusuma, W. A. (2016). Cluster analysis for SME risk analysis documents based on pillar K-means. *TELKOMNIKA*, 14(2), 674.

Walley, N., & Whitehead, B. 1994. It's not easy being green. *Harvard Business Review*, 72(3), 46-52.

Wang, Q. (2007). Artificial neural networks as cost engineering methods in a collaborative manufacturing environment. *International Journal of Production Economics*, 109, 53-64.

Wang, S., Wang, H., & Wang, J. (2019). Exploring the effects of institutional pressures on the implementation of environmental management accounting: Do top management support and perceived benefit work? *Business Strategy and the Environment*, 28(1), 233-243.

Wei, P., Mao, X., & Chen, X. (2020). Institutional investors' attention to environmental information, trading strategies, and market impacts: Evidence from China. *Business Strategy and the Environment*, 29(2), 566-591.

Within, G. (2015). A circular economy vision for a competitive Europe. *Ellen Macarthur Foundation*, 1-98.

Witjes, S., & Lozano, R. (2016). Towards a more Circular Economy: Proposing a framework linking sustainable public procurement and sustainable business models. *Resources, Conservation and Recycling*, 112, 37-44.

Wu, Q., He, Q., & Duan, Y. (2013). Explicating dynamic capabilities for corporate sustainability. *EuroMed Journal of Business*, 8(3), 255–272.

Yadav, J., & Sharma, M. (2013). A Review of K-mean Algorithm. International Journal Engineering Trends Technology, 4(7), 2972-2976.

Yegnanarayana, B. (2009). *Artificial neural networks*. PHI Learning Pvt. Ltd.

Yuan, Z., Bi, J., & Moriguichi, Y. (2006). The circular economy: A new development strategy in China. *Journal of Industrial Ecology*, 10(1-2), 4-8.

Zahra, S. A., Sapienza, H. J., & Davidsson, P. (2006). Entrepreneurship and dynamic capabilities: A review, model and research agenda. *Journal of Management Studies*, 43(4), 917-955.

Zapata, P., & Zapata Campos, M. J. (2019). Cities, institutional entrepreneurship and the emergence of new environmental policies: The organizing of waste prevention in the City of Gothenburg, Sweden. *Environment and Planning C: Politics and Space*, 37(2), 339-359.

Zeng, H., Chen, X., Xiao, X., & Zhou, Z. (2017). Institutional pressures, sustainable supply chain management, and circular economy capability: Empirical evidence from Chinese eco-industrial park firms. *Journal of Cleaner Production*, 155, 54-65.

Zhang, J. A., & Walton, S. (2017). Eco-innovation and business performance: the moderating effects of environmental orientation and resource commitment in green-oriented SMEs. *R&D Management*, 47(5), E26-E39.

Zhao, Z., Xu, S., Kang, B. H., Kabir, M. M. J., Liu, Y. & Wasinger, R. (2015). Investigation and improvement of multi-layer perceptron neural networks for credit scoring. *Expert Systems with Applications*, 42(7), 3508-3516.

Zucchella, A., & Previtali, P. (2019). Circular business models for sustainable development: A “waste is food” restorative ecosystem. *Business Strategy and the Environment*, 28(2), 274-285. Dietterich, Thomas G. "Machine-learning research." AI Magazine 18.4 (1997): 97-97.

Methodological Appendix I

Methodological Appendix I relates to the database and sample used in this thesis. This appendix presents some descriptive statistics and representations of the data, as well as some further clarification on the methodological approach utilised for the creation of the different measures and variables in the respective chapters of the thesis.

1. DATABASE AND SAMPLE

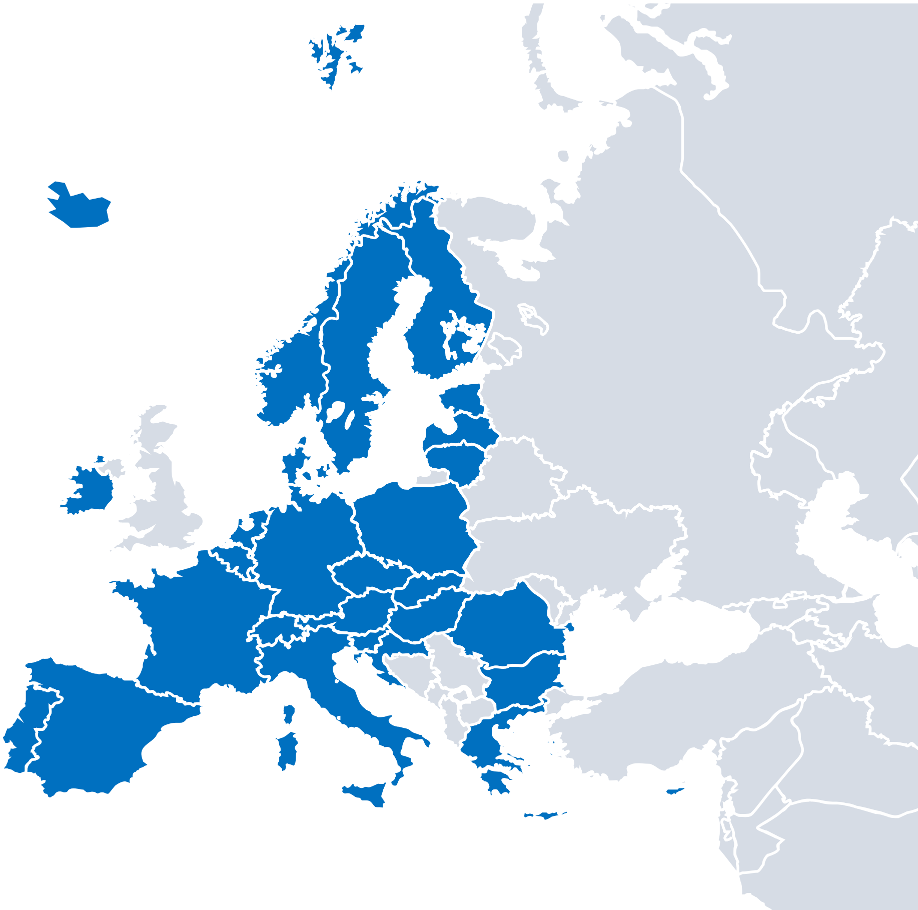
The database used for this thesis is based on the EU survey on the *Public Consultation on the Circular Economy* from European Commission. The objective of this public consultation was to help the Commission to pinpoint and define the main barriers to the development of a more circular economy and to gather views regarding which measures could be taken at the EU level to overcome such barriers.

Through a comprehensive, coherent approach the questionnaire aims to fully reflect interactions and interdependence along the whole value chain, rather than focusing exclusively on one part of the economic cycle. The survey contains six sections.

- The first one collects general information about respondents.
- The second section seeks the views on actions that respondents think the EU should take to promote the circular economy in the production stage, including product design, production, and sourcing of materials.
- The third section collects the consumers' perspective as an essential part of the circular economy, seeking their views on the best way to promote the circular economy in the consumption phase.
- The fourth section aims to identify the barriers to the development of markets for secondary raw materials.
- The fifth section seeks the views on which sector(s) should be considered a priority for EU action, and which relevant measures or actions should be taken.
- Finally, the sixth section collects the views on the role of enabling factors (supporting the development, dissemination, and uptake of innovative solutions, investing in technology and infrastructure, etc.) in the development of the circular economy.

Although, the total database consists of 1280 organisations and companies. After filtering and eliminating incomplete responses, microenterprises and individuals, the final sample used in the analysis contains 870 firms. The survey contains data from the 27 EU Member States, including Norway, Iceland, Switzerland, and Liechtenstein. Figure A-1.1 shows the countries comprised by the database used.

Figure A-1.1. Map of countries covered by the database.



(1) The survey comprised the 27 EU Member States.
(2) It also includes non-members, such as Norway, Iceland, Switzerland, and Liechtenstein.

Moreover, Figures A-1.2 and A-1.3 display the graphical representation of some descriptive statistics relating to the companies present in the database. These are the size of the companies in the database (Figure A-1.2) and the percentage of environmental certifications or schemes implemented by the companies in the database (Figure A-1.3).

Figure A-1.2. Company size representation of the database.

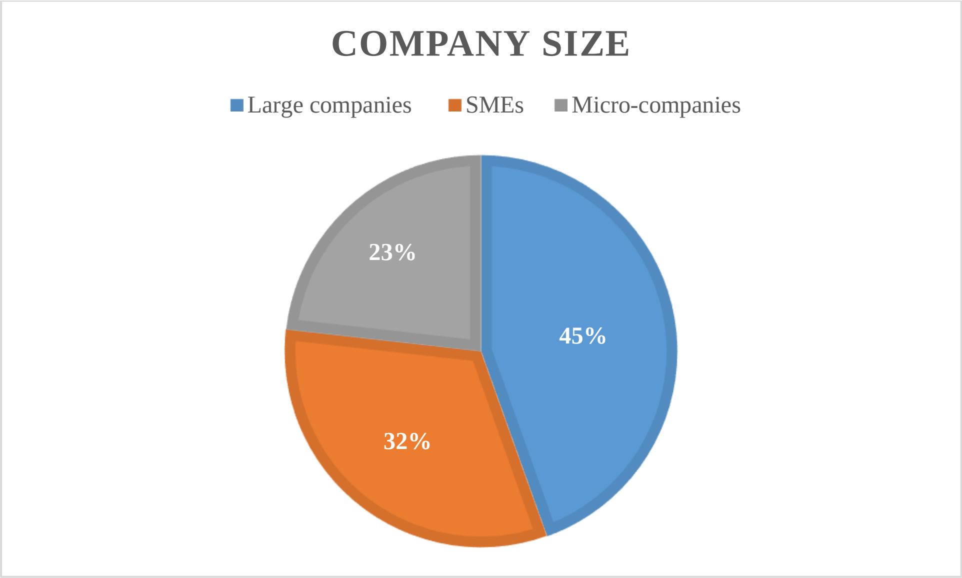
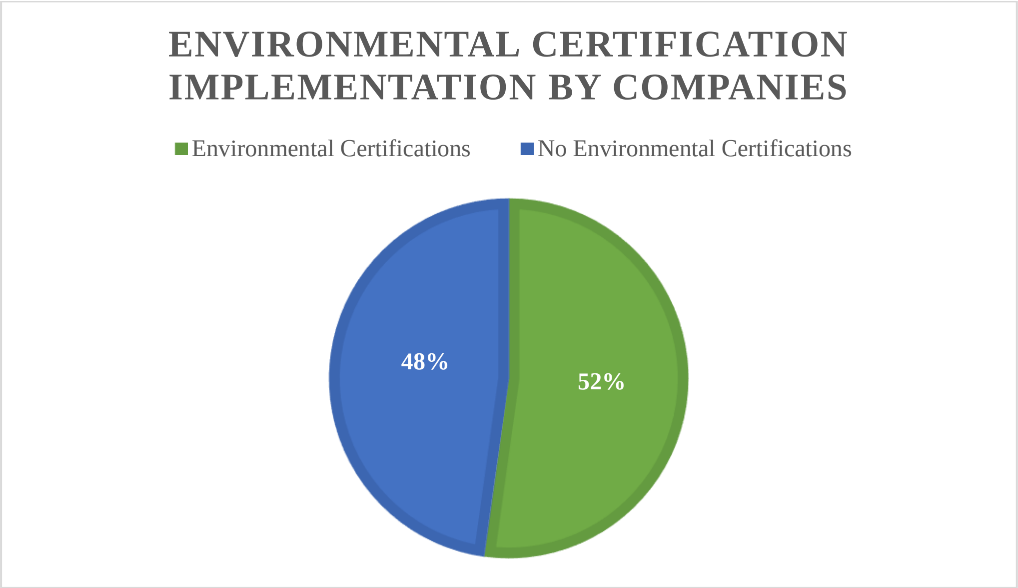


Figure A-1.3. Environmental certifications implemented by companies in the database.



2. FACTOR ANALYSIS

Throughout the different chapters in the thesis, and their respective analysis, we use Factor Analysis for the creation of some of the variables, in line with previous studies (see, for example, Wang et al., 2007). Factor analysis is a technique for considering a large number of variables and reducing them into a smaller number of factors (Hayton et al., 2004). It is worth noting that a “factor”, therefore, represents a collection of variables or dimensions with comparable response patterns. Thus, this methodology of variable creation extracts the largest possible common variance from all the variables in the analysis and converts them into a single score (Hayton et al., 2004).

In order to confirm the internal consistency of the variables or measures created with factor analysis, this thesis provides next to each new measure the value for its Cronbach’s alpha. Hence, the Cronbach's alpha is a method of assessing the internal consistency or trustworthiness of a measure or variable, by comparing the amount of shared variance, or covariance, among the components that conform the variable with respect to the overall amount of variation (Asteriou and Hall, 2015). The rationale behind Cronbach's alpha is that if the variable or measure is reliable, the covariance between the components that conforms the variable is high, in terms of variation (Creswell, 2002). It is generally agreed in the literature that a value for the Cronbach's alpha above 0.6 is considered to be acceptable because it provides high reliability and internal consistency to the variable created with factor analysis (see, for example, Creswell, 2002). All the variables created throughout the thesis have a value above 0.6, see chapters 2, 3, and 4, as well as Methodological Appendices II, III, and IV. The formula for the Cronbach's alpha is shown below:

$$\alpha = \frac{N\overline{c}}{\overline{v} + (N-1)\overline{c}} \tag{A-1.1}$$

The Cronbach’s alpha formula displayed above is expressed as a function of the number of components that conforms the main variable and their mean covariance. In this case, N represents the number of components, the mean covariance among the components is represented by $\overline{c}$, and the average variance is equal to $\overline{v}$.

Methodological Appendix II

Methodological Appendix II relates to the methodology and analyses employed in Chapter 2 of this thesis. This appendix places particular emphasis on the Artificial Neural Network model developed in this chapter, describing the model and its architecture, the basic structure and design, the selection of the different algorithms used, and the output of the neural network model, as well as a description of the selected activation functions.

1. ARTIFICIAL NEURAL NETWORK (ANN-MLP).

1.1. Model

The neural network is based on the model represented in Formula 2.9 (Model 7, Chapter 2), which is represented below:

CE = f (Coercive1; Coercive2; Normative1; Normative2)

All further analyses, graphs, and tables in this methodological appendix are related to this model.

Table A-2.1 describes the different steps for the procedure to develop de artificial neural network (ANN) model. This table shows a summary of the procedure that has been used throughout this thesis to build the different ANN models used. However, Table A-2.1 is customised for the ANN model employed in Chapter 2 of this thesis.

Table A-2.1. Steps of the ANN procedure

1. Choice of the ANN typology	• We choose the ANN architecture with Multilayer Perceptron (MLP)
2. Design of architecture of ANN-MLP	• The network accuracy and the efficiency are dependent on various parameters: hidden nodes, activation functions, training algorithm parameters and characteristics such as normalisation and generalisation. • The number of inputs and outputs is given by the number of available input and output variables. • The number and size of hidden layers is determined by testing several combinations of the number of hidden layers and the number of neurons • For the types of activation functions, for the hidden layer, we used a hyperbolic tangent (-1 to 1), and an Identity function for the activation function of the output layer.
3. Choice of the learning algorithm	• We are going to use is Backpropagation. This learning algorithm determines the connection weights of each neuron, readjusting the weights and minimizing the error.
4. Learning stage	• To avoid problems of overfitting and consumption of processing time, we divided the sample randomly into three subsamples (training, testing and holdout). • In the training stage, the weights and links between nodes are determined, to minimize the error. In the validation stage, the generalizability of the obtained architecture is checked. Lastly, the holdout data is used to validate the model.
4. Sensitive analysis	• A sensitive analysis is developed to quantify the influence of each input variable on the output variables.

As displayed in Table A-2.1, the learning algorithm used is the backpropagation algorithm. This learning algorithm decides the weight of the connection of each neuron, modifying the weights and minimising the error (Rojas, 1996). The equation for modifying the algorithm weights is shown below:

$$\Delta w_{ji}(n+1)=\mathcal{E}.\mu_{pi}.\ x_{pi}+\beta\Delta w_{ji}(n) \qquad \text{(A-2.1)}$$

Being, w_{ji}= weight neuron i and j
n= number of interactions
$\mathcal{E}$= learning rate
μ_{pi}= neuron j error for pattern p
x_{pi}= output of neuron i for pattern p
β=momentum

From equation (A-2.1), we can see that there are three critical variables: the number of interactions, the learning rate, and the moment. Regarding the number of interactions (n), we have used 10,000[54]. As for the value of the learning rate (β), it controls the size of the change

[54] Normally the number of iterations ranges from 1000 to 10,000, and a trial and error process is recommended (Cabaneros et al., 2019; Yegnanarayana, 2009).

of the weights in each iteration[55], the learning rate usually has a value of between 0.05 and 0.5. Finally, the moment factor (α) accelerates the convergence of the weights. Hassoun (1995) and Yegnanarayana (2009) point out that a value close to 1, for example, 0.9, is a good value.

The analytical equation of our simulation with ANN-MLP takes the following form:

$$CE = h\left[\sum_{k=1}^{6} \alpha_k \cdot g\left(\sum_{j=1}^{6} \beta_{jk} \cdot X_j\right)\right] \tag{A-2.2}$$

with X_j being the input variables;
j the number of input variables;
$h(.)$ and $g(.)$ the hyperbolic tangent and identity activation functions;
α_k and β_{jk} the input and hidden network weights, respectively;
k the number of hidden layers.

1.2. ANN-MLP Output

Regarding the output of the ANN-MLP, Table A-1.2 shows the distribution of the sample in the training, testing, and holdout steps of the ANN design. The sample is randomly divided into these three subsamples, to avoid overfitting problems, as well as high consumption of processing time.

Table A-2.2. Summary of ANN processing

		N	Percent
Sample	Training	622	63.2%
	Testing	266	27.0%
	Holdout	96	9.8%
Valid		965	100%
Excluded		354	
Total		1319	

As shown in Table A-2.2 the dataset was divided into a 7, 2, 1 configuration (this is because the relative proportions of the training, testing, and holdout samples relate roughly to 70%, 20%, and 10%). This type of partition of the dataset follows the configuration of other studies,

[55] Two extremes should be avoided: too little of a learning rate can cause a significant decrease in the speed of convergence and the possibility of ending up trapped in a local minimum; instead, too high of a learning rate can lead to instabilities in the error function, which will prevent convergence from occurring because jumps around the minimum will be made without reaching it. Therefore, it is recommended to choose a learning rate as large as possible without causing large oscillations (Hassoun, 1995).

such as Ciurana et al. (2008) and Cavalieri et al. (2004). Moreover, as observed by Alloghani (2020), a training subset of around 60% is logical and aids in attaining the intended outcome without requiring more processing effort. The training sample consists of a set of data points from the dataset that is utilised to train the ANN model. The testing sample consists of a separate set of data points that are utilised to monitor the errors during the training stage to avoid overtraining. Generally, network training works best when the testing sample is smaller than the training sample. Finally, the holdout sample entails an additional separate set of data points utilised to evaluate the final ANN model. The error obtained for the holdout sample provides an "honest" assessment of the predictive capability of the model since the holdout cases are not utilised to develop the ANN model.

Tables A-2.3 and A-2.4, and Figure A-2.1 show ANN-MLP architecture, using as output a cumulative variable.

Table A-2.3. ANN-MLP structure

Input Layer	Covariates	1	COERCIVE1
		2	NORMATIVE1
		3	COERCIVE2
		4	NORMATIVE 2
	Number of Units[a]		4
	Rescaling Method for Covariates [b]		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		2
	Activation Function [c]		Hyperbolic tangent
Output Layer	Dependent Variables	1	CEFACTOR
	Number of Units		1
	Rescaling Method for Scale Dependents [d]		Standardized
	Activation Function [e]		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Table A-2.3 displays the ANN-MLP structure used in the analysis. Regarding the rescaling covariates (independent variables), a standardised method (*SM*)[(b)] was used, as shown in the table. This method subtracts the mean and divides it by the standard deviation (sd). This method has the form:

$$SM = \frac{(x - mean)}{sd} \quad \text{(A-2.3)}$$

The same rescaling method was used for the scale of the dependent variable[(d)], that is, a standardised method, as also shown in Table A-2.3.

Moreover, Table A-2.3 displays some of the characteristics selected for the hidden layer. The hidden layer comprises network units (or nodes) that are not observable. In this case, there is 1 hidden layer with 2 hidden units in the hidden layer of our ANN model (see Figure A-2.1, for a graphical representation). Each hidden unit is a function of the sum of the weights of the independent variables (or inputs). This function is known as the activation function, where the estimation algorithm determines the weight of the values. Therefore, the activation function "connects" the values of units (calculated via the weighted sums) of one layer to the unit values in the next layer (Garbero et al., 2021). In terms of the activation function used for the Hidden layer in the ANN-MLP of Chapter 2, a hyperbolic tangent function[(c)] was employed (shown in Table A-2.3). This function has the form:

$$\gamma(c) = tanh(c) = \frac{e^c - e^{-c}}{e^c + e^{-c}} \quad \text{(A-2.4)}$$

This function translates real-valued arguments to the range (–1, 1), as indicated in Table A-2.1. This is the most common type of activation function utilised for the hidden layer when constructing a neural network (see, for example, Garson’s algorithm (1991, 1999; or Wang, 2007). Linking it back to Formula (A-2.2), this activation function is represented there by *h(.)*. Regarding the activation function utilised for the output layer, in this case, the selected one is the identity function [(e)] (shown in Table A-2.3). This function has the form:

$$\gamma(c) = c \quad \text{(A-2.5)}$$

This function returns real-valued arguments unchanged to the next layer. This activation function is commonly used for the output layer when selecting an architecture for the neural network (Minbashian et al., 2010). This is represented by the character and *g(.),* in Formula (A-2.2).

Figure A-2.1 represents the final ANN-MLP architecture of the network utilised in the analysis.

Figure A-2.1. ANN-MLP architecture.

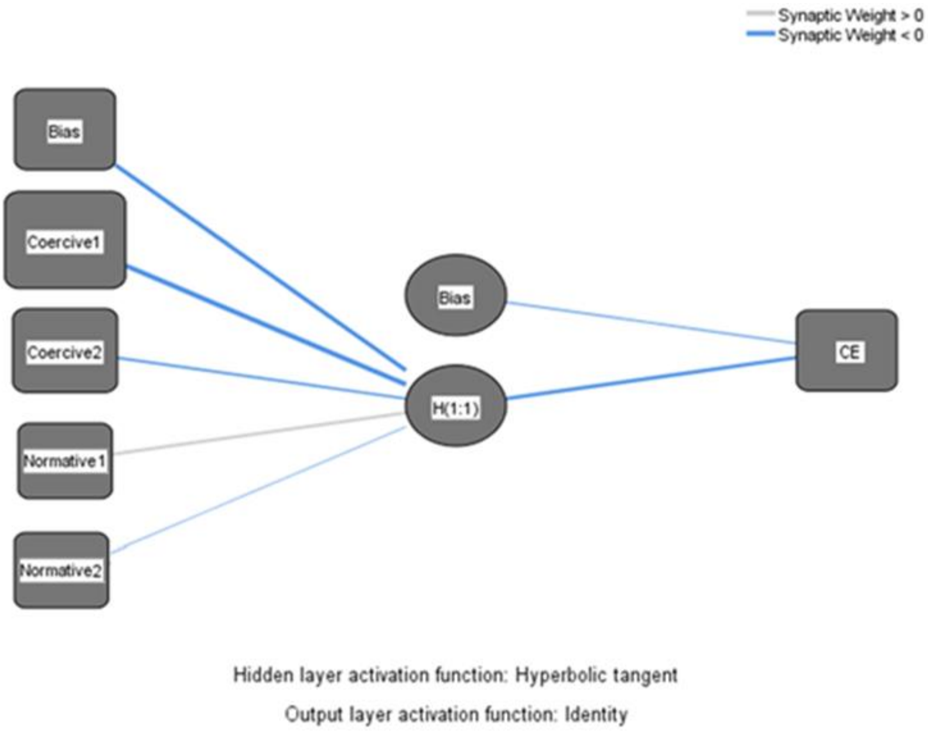


Table A-2.4. ANN-MLP Model Summary

Training	Sum of Squares Error	118.053
	Relative Error	.380
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.47
Testing	Sum of Squares Error	47.983
	Relative Error	.331
Holdout	Relative Error	.563

Dependent Variable: CEFACTOR
a. Error computations are based on the testing sample.

Table A-2.4 displays a summary of the results of the ANN by partition, together with the error, the relative error, the stopping rule used to stop training, and the training time. The error is the SSE when the identity activation function (in this case) is applied to the output layer. As shown in the table, the overall error in the ANN-MLP model used in the analysis is small. Moreover, the stopping rule used is that of one consecutive step with no decrease in error, where the error computations are based on the testing sample. In addition, it is worth noting that the training time is very short, which indicates how efficient neural networks are at computing large amounts of data.

Table A-2.5 (below) shows the simulation results. Table A-2.5 follows the methods based on Garson's algorithm (1991)[56], thus, when computing the variable contributions, the absolute values of the final connection weights are employed. This is RI_x is the relative importance of neuron x:

$$RI_x = \sum_{x=1}^{n} \frac{|w_{xy}\ w_{yz}|}{\sum_{y=1}^{m} |w_{xy}\ w_{yz}|} \tag{A-2.6}$$

Where $\sum_{y=1}^{m} w_{xy}\ w_{yz}$ represents the sum of the product of the final weight connection from input neurons to hidden neurons and the connections from hidden neurons to output neurons.

Table A-2.5. ANN-MLP simulation output (Independent Variable Importance analysis)

Variables	Importance	Normalised Importance
COERCIVE1	.484	100.0%
NORMATIVE1	.066	13.7%
COERCIVE2	.288	59.5%
NORMATIVE 2	.162	33.4%

Thus, Table A-2.5 computes the importance of each predictor in determining the neural network, which is the independent variable importance analysis. The analysis is based on the combined training and testing samples. Accompanying this table there is a diagram displaying the normalised importance of each predictor (shown in Chapter 2, Figure 2.6). Note that sensitivity analysis is computationally expensive and time-consuming if there are large numbers of predictors or cases.

[56] Ibrahim (2013) revises some methods for assessing the relative importance of input variables in artificial neural networks.

1.3 ANN-MLP Simulation

Furthermore, we check the predicted values of the ANN model against the observed values to test the suitability of the model and its fit. This is used as a robustness check of the model. The simulation models are:

CE(Observed) = f (Coercive1; Coercive2; Normative1; Normative2)
CE(Predicted) = f (Coercive1; Coercive2; Normative1; Normative2)

Figures A-2.3 to A-2.6 show the response of the network to the variation of each input variable (institutional pressures) and its effect on the output of the real variables and the predicted output of the ANN. In the graphs, a similar response to the real variable output and predicted output can be seen. For example, Figure A-2.3 shows the variation of the input variable *Coercive1* with respect to the output variable *CE*, maintaining *Coercive2*, *Normative1* and *Normative2* as constant. Hence, as shown in the graph, the light blue line, which corresponds to the predicted value for the output variable (*CE*), and the dark green line, which corresponds to the actual values of the output variable (*CE*), fit each other almost perfectly. Thus, on the one hand, this enables us to confirm, in accordance with previous studies (see, for example, Alpaydin, 2004), that the ANNs' fit is better compared to that of regression models, explaining the effect between independent variables and the dependent variable more adequately. On the other hand, it allows us to graphically determine that the model fitness is good and therefore the predictions of our model are going to be accurate.

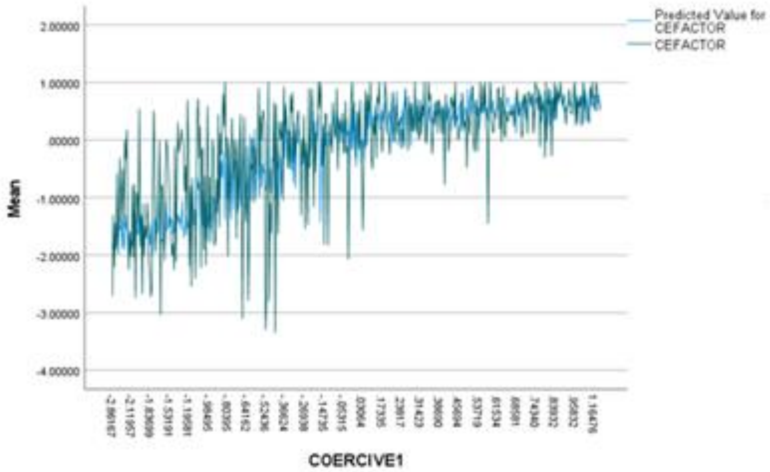


Figure A-2.3. ANN-MLP simulation (constant: Coercive2; Normative1; Normative2).

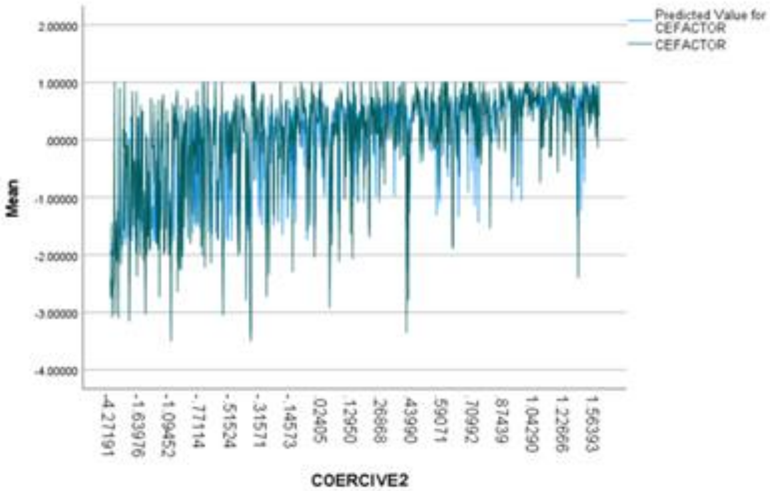


Figure A-2.4. ANN-MLP simulation (constant: Coercive1; Normative1; Normative2).

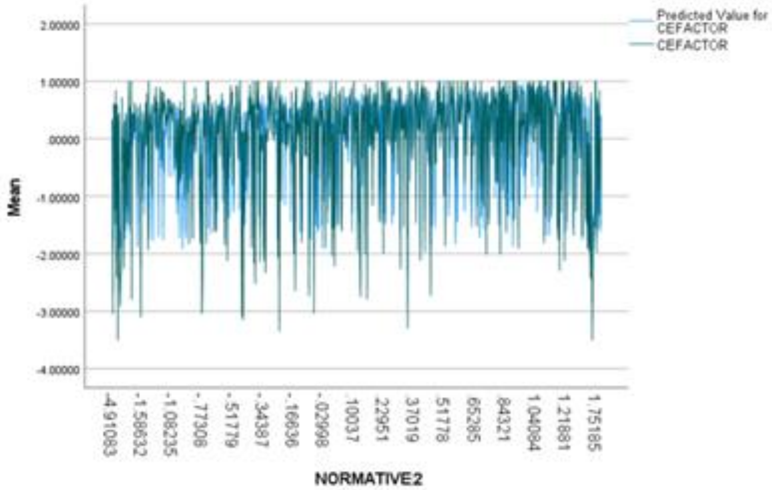


Figure A-2.5. ANN-MLP simulation (constant: Coercive1; Coercive2; Normative1).

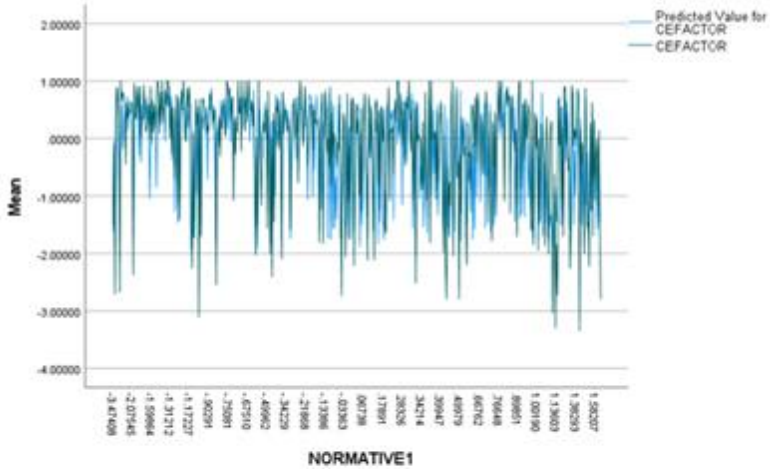


Figure A-2.6. ANN-MLP simulation (constant: Coercive1; Coercive2; Normative2).

2. ARTIFICIAL NEURAL NETWORK (ANN-MLP).

In this section, we reproduce the ANN-MLP used in the analyses in Chapter 2 and explained in the above section of this Methodological Appendix. Unlike the previous analysis, in this case, the input variables have been generated as cumulative variables. This is used to analyse and compare both models to check there are no differences in the results and conclusions arrived at in Chapter 2. Moreover, it serves as a robustness check of the construction of the variables used, and therefore, confirms that variable selection is appropriate for the analysis. As shown in the section, no significant differences can be appreciated between the two ANN with the different variables, hence corroborating the suitability of utilising the factor analysis variables in the main analysis of Chapter 2.

2.1. Model (Cumulative Variables)

CE = f (Coercive1; Coercive2; Normative1; Normative2)

2.2. ANN-MLP Output

Table A-2.6 shows the distribution of the sample in the training, testing, and holdout steps of the ANN design. A similar partition of the sample is used as in the previous ANN model.

Table A-2.6. Summary of ANN processing

		N	Percent
Sample	Training	637	64.7%
	Testing	256	26.0%
	Holdout	91	9.2%
Valid		965	100.0%
Excluded		354	
Total		1319	

Tables A-2.7 and A-2.8, and Figure A-2.7 show ANN-MLP architecture, using as an output variable the cumulative version of the dependent variable.

Table A-2.7. ANN-MLP structure

Input Layer	Covariates	1	COERCIVE1
		2	NORMATIVE1
		3	COERCIVE2
		4	NORMATIVE2
	Number of Units[a]		4
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	VDACUMULATIVE
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

As shown in Table A-2.7, the structure of the ANN-MLP with a cumulative output variable is very similar to the one used in the analysis in Chapter 2. In this case, we also have one hidden layer, but there is a larger number of units in the Hidden layer (7 in this case). Regarding the specificities of the structure, the same rescaling method for the covariates (in the input layer) and the output layer is used as in the previous ANN-MLP (i.e. standardised). This is displayed in Figure A-2.7, which graphically shows the final architecture of the ANN-MLP with a cumulative variable. Moreover, as shown in Table A-2.7, a hyperbolic tangent activation function is utilised in the hidden layer, as well as an identity function as the activation function for the output layer, which is the same type of activation function employed in the previous ANN.

Figure A-2.7. ANN-MLP architecture (cumulative).

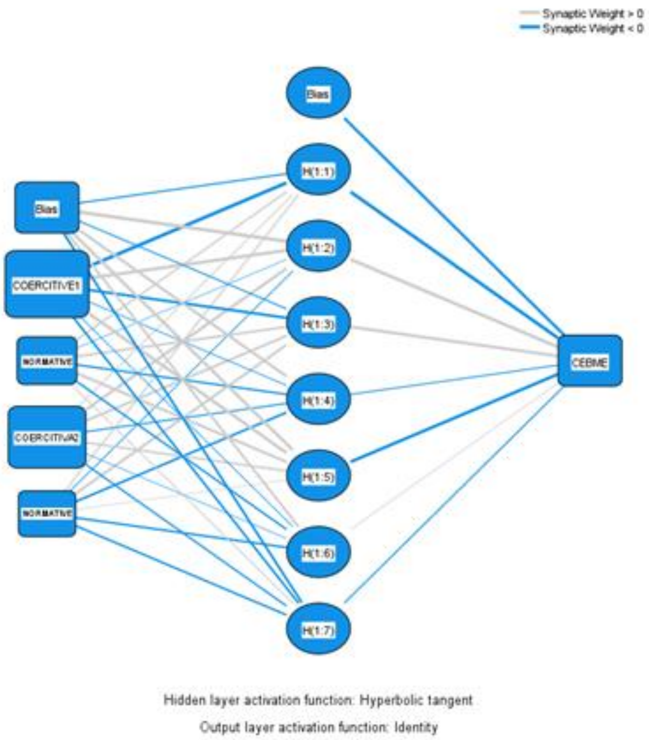


Table A-2.8. ANN-MLP Model Summary

Training	Sum of Squares Error	108.190
	Relative Error	.340
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.55
Testing	Sum of Squares Error	40.898
	Relative Error	.340
Holdout	Relative Error	.305

Dependent Variable: VDACUMULATIVE

a. Error computations are based on the testing sample.

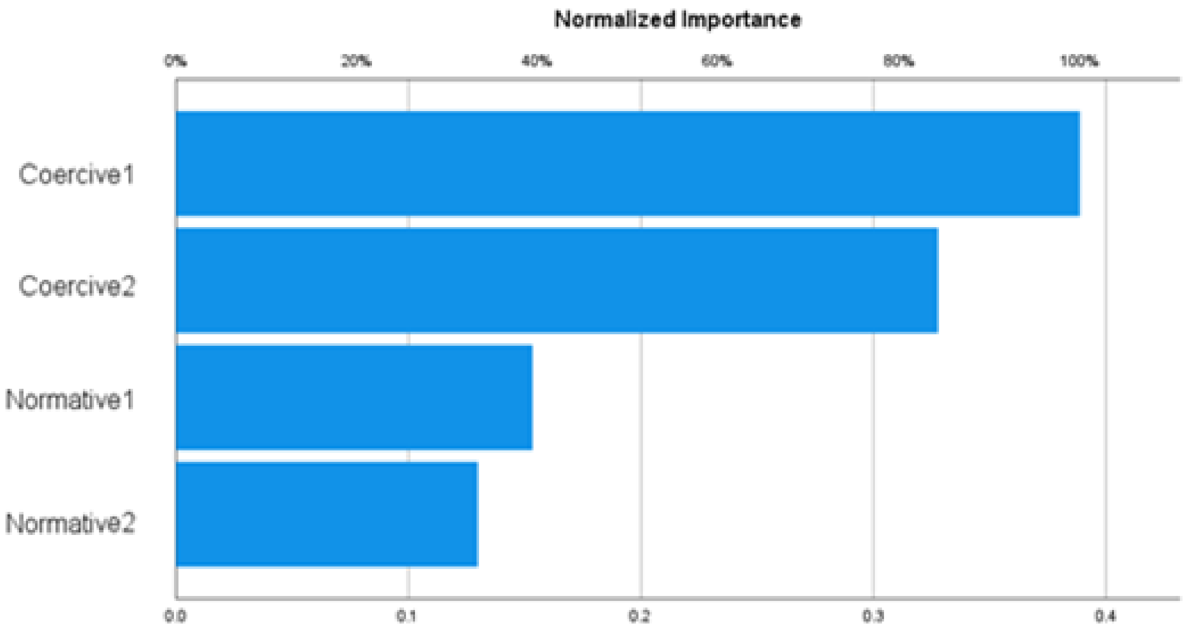
Table A-2.8 displays a summary of the results of the ANN by partition, containing the error, the relative error, the stopping rule used to stop training, and the training time. This table is similar to Table A-2.4, but in this case for the ANN with a cumulative dependent variable. As before, the error is the SSE when the identity activation function is applied to the output layer. As shown in the table, the overall error in ANN-MLP Model used in the analysis is small, which is similar to the one obtained for our previous ANN model.

Table A-2.9 (below) shows the simulation results. Table A-2.9 follows the methods based on Garson's algorithm (1991), as explained in the section above of this Appendix. Therefore, Table A-2.9 displays the importance of each predictor in determining the ANN, which is the independent variable importance analysis. The analysis is based on the combined training and testing samples. Accompanying this table is Figure A-2.9 displaying the normalised importance of each predictor (similar to the Figure 2.6 shown in Chapter 2). As shown both in Table A-2.9 and Figure A-2.8, the results are almost identical to those in the analysis in Chapter 2. There are no significant differences that can be appreciated between the two ANN with the different variables. Hence, this corroborates the suitability of utilising the factor analysis variables in the main analysis of Chapter 2.

Table A-2.9. ANN-MLP simulation output (Independent Variable Importance)

Variables	Importance	Normalised Importance
COERCIVE1	.389	100.0%
NORMATIVE1	.153	39.4%
COERCIVE2	.328	84.3%
NORMATIVE 2	.130	33.4%

Figure A-2.8. ANN-MLP simulation output (Independent Variable Importance)



2.3 ANN-MLP Simulation

As before, we also check the predicted values of the ANN model against the observed values to test the suitability of the model and its fit. This is used as a robustness check of the model The simulation models are:

CE(Observed) = f (Coercive1; Coercive2; Normative1; Normative2)
CE(Predicted) = f (Coercive1; Coercive2; Normative1; Normative2)

Figures A-2.9 to A-2.12 show the response of the network to the variation of each input variable (institutional pressures) and its effect on the output of the real variables and the predicted output of the ANN. In the graphs, a similar response to the real variable output and predicted output can be seen, since for all graphs the light blue line, which corresponds to the predicted value for the output variable (*CEcumulative*), and the dark green line, which corresponds to the actual values of the output variable, fit each other almost perfectly. The results obtained are in line with those from the previous model, where factor analysis variables were used. Once again, we can conclude that, on the one hand, this confirms, in accordance with previous studies (see, for example, Alpaydin, 2004), that the ANNs' fit is better compared to that of regression models, explaining the effect between independent variables and the dependent variable more adequately. On the other hand, it allows us to graphically determine that the model fitness is good and therefore the predictions of our model are going to be accurate.

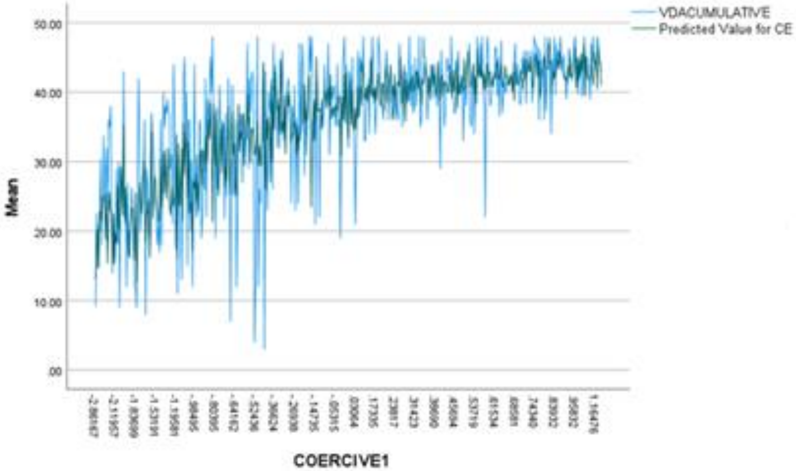


Figure A-2.9. ANN-MLP simulation (constant: Coercive2; Normative1; Normative2).

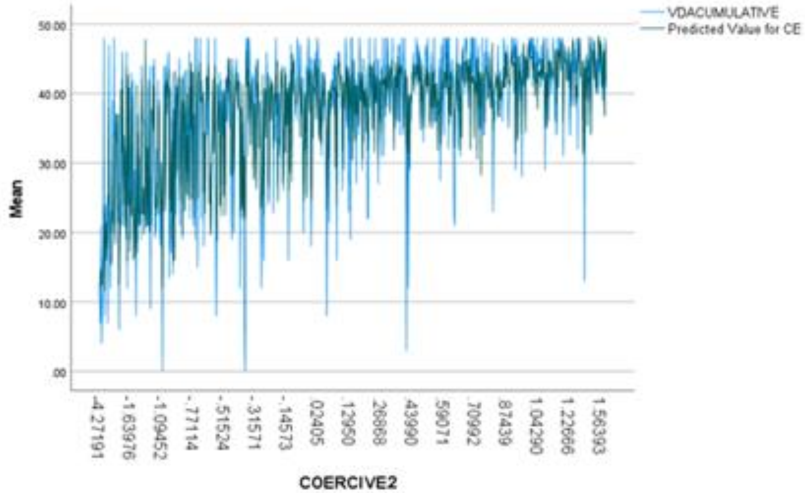


Figure A-2.10. ANN-MLP simulation (constant: Coercive1; Normative1; Normative2).

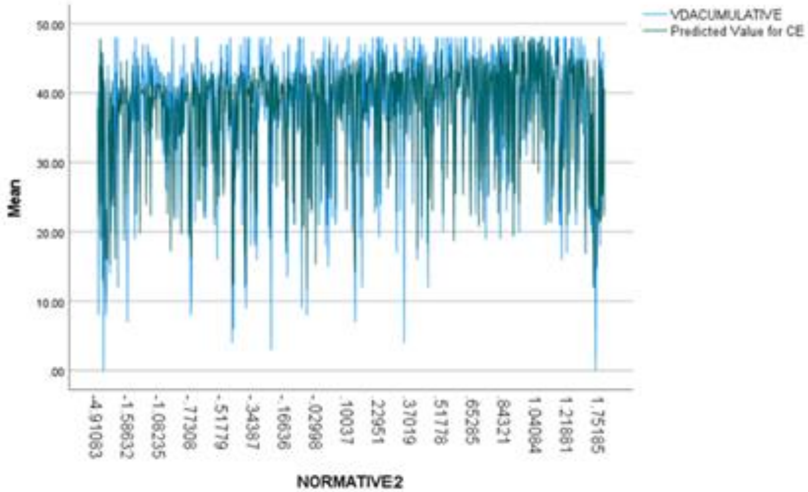


Figure A-2.11. ANN-MLP simulation (constant: Coercive1; Coercive2; Normative1).

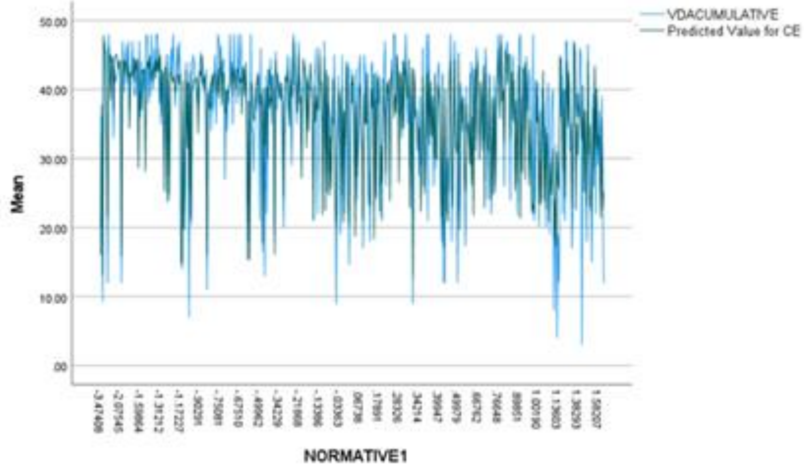


Figure A-2.12. ANN-MLP simulation (constant: Coercive1; Coercive2; Normative2).

Methodological Appendix III

Methodological Appendix III relates to the methodology and analyses employed in Chapter 3 of this thesis. This appendix describes in more detail the K-means cluster analysis and the Radial Basis Function Neural Network model developed in Chapter 3. A particular emphasis is paid to the process and specifications of each model, their basic structure and design, the selection of the different algorithms used, the output of the neural network and the k-means cluster model, as well as a description of the selected activation functions.

1. CLUSTER ANALYSIS (K-means cluster).

In this section, the process for the cluster creation and the output of such cluster is explained in the detail. As mentioned before, the cluster specifications described in this section refer to the K-means cluster developed for the analysis in Chapter 3.

There are two key stages when conducting a k-means cluster analysis. These are the initial cluster centres stage and the final cluster centre stage (Wahyudin et al., 2016). Below, we explain the steps and considerations undertaken in this research for building the cluster for the analysis. As mentioned, the initial stage in k-means clustering is identifying the k centres, which is done through an iteration process. Hence, we began with a set of initial centres, in our case two initial centres, as shown in Table A-3.1. Then, these centres are modified until the difference between the two iterations is small enough. It is worth noting, that K-means clusters are extremely sensitive to outliers because they are generally chosen as initial cluster centres. As a result, outliers will form clusters with a small number of cases (Munther et al., 2016). Therefore, before performing the cluster analysis, we screened the data to check for outliers and to eliminate them from the first analysis.

Table A-3.1. Initial Cluster Centres

	Cluster	
	1	2
INTERACTION	.00	196608.00

Following the selection of the first cluster centres, each case is allocated to the nearest cluster based on its proximity to the cluster centres. The proximity or distance to the cluster centre is measured based on the Euclidian distance (Hofmann, 2001; Wahyudin et al., 2016). After assigning all cases to a cluster, the cluster centres are re-computed using all of the cases in the cluster. Then, cases are assigned to a cluster once more, however, this time with the newly updated cluster centres. This process of assigning cases and re-computing cluster centres is repeated until no cluster centre differs noticeably (Munther et al., 2016). Table A-3.2 illustrates this process for our particular cluster developed in this thesis, displaying the history of iterations used. As can be seen, in each round the difference between the iterations is reduced, until it is small enough. In our particular case, this took ten rounds of iterations, but this process can be longer or shorter depending on the data.

Table A-3.2. Iteration History

	Change in Cluster Centres	
Iteration	1	2
1	46870.097	66880.565
2	6438.259	8999.838
3	4895.730	5431.475
4	3972.055	3892.411
5	1858.961	1692.900
6	1220.493	1104.132
7	572.719	514.580
8	163.607	147.324
9	163.520	147.522
10	.000	.000

a. Convergence achieved due to no or small change in cluster centres. The maximum absolute coordinate change for any centre is .000. The current iteration is 10. The minimum distance between initial centres is 196608.000.

Regarding the Euclidean distance used for the allocation of cases to different clusters, it is worth describing this process in more detail. In our particular case, we utilise the sum of the squared error (SSE), also known as scatter, for our objective function in the cluster analysis. This means that we compute its Euclidean distance to the nearest centroid (i.e. the error of each data point), and then total the SSE. Hence, in our particular analysis scenario, where two sets of clusters are generated by different iterations of K-means, the rationale is that we favour the one with the smaller SSE, as this indicates that the centroids of the cluster represent a closer approximation of the points in their respective cluster. We can express the SSE formula as follows:

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} dist(c_i, x)^2 \qquad \text{(A-3.1)}$$

Where x is an object
c_i represents the i[th] cluster
C is the centroid of cluster c_i
K is the number of clusters

In Formula A-3.1, *dist* represents the standard Euclidean distance among items in the Euclidean space. Moreover, we note that the mean represents the centroid that minimises the sum square error of the cluster. Hence, the centroid of the cluster i[th] can be described as follows:

$$c_i = \frac{1}{m_i} \sum_{x \in C_i} x \qquad \text{(A-3.2)}$$

Where m_i is the number of objects present in the cluster i[th]

The other important stage in the k-means cluster analysis process is the final cluster centre stage. Following the end of the iterations, based on the last set of cluster centres, all cases are allocated to clusters (Wahyudin et al., 2016). Then, one last time, we compute the cluster centres after all of the cases have been clustered. Table A-3.3 shows the final cluster centres. These final cluster centres already can help us characterise the clusters used in the analysis in Chapter 3. As shown in Table A-3.3, cluster 2 has a substantially greater average CEBM implementation than cluster 1. This is in line with the conclusions arrived at in the K-means cluster analysis in Chapter 3.

Table A-3.3. Final Cluster Centres

	Cluster	
	1	2
INTERACTION	27584.75	107797.25

Moreover, we present below Table A-3.4, which displays the distances between the final cluster centres of our two clusters.

Table A-3.4. Distances between Final Cluster Centres

Cluster	1	2
1		80212.499
2	80212.499	

Furthermore, we performed an ANOVA as shown in Table A-3.5, which is significant.

Table A-3.5. ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
INTERACTION	1658994223655.965	1	716046680.362	1032	2316.880	.000

Finally, we produce Table A-3.6, which shows the number of cases in each cluster. This table indicates that cluster 1 has assigned 491 cases or companies, whereas cluster 2 has 543 cases or companies assigned. This shows a well-balanced and distributed clusters which are what is expected, as the opposite does not provide a good basis for the analysis (Wahyudin et al., 2016).

Table A-3.6. Number of Cases in each Cluster

Cluster	1	491.000
	2	543.000
Valid		1034.000
Missing		285.000

Figure A-3.1, Figure A-3.2, Figure A-3.3, and Figure A-3.4 display the clusters graphically. These mimic the ones in Chapter 3 and show the profile of both clusters and the interaction term, as well as the scatter-plot of the distribution of the companies with respect to the variable Regulation and Information.

Figure A-3.1. Profile of cluster (Regulation and Information)

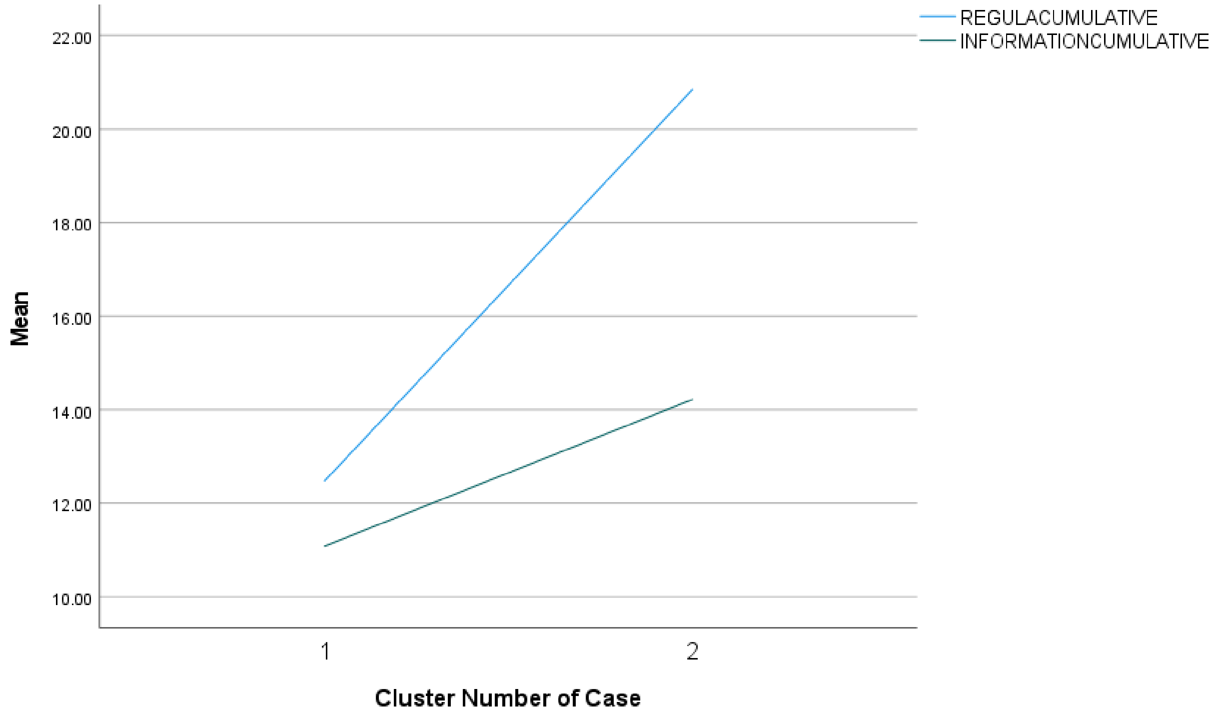


Figure A-3.2. Profile of cluster (Interaction, Regulation and Information)

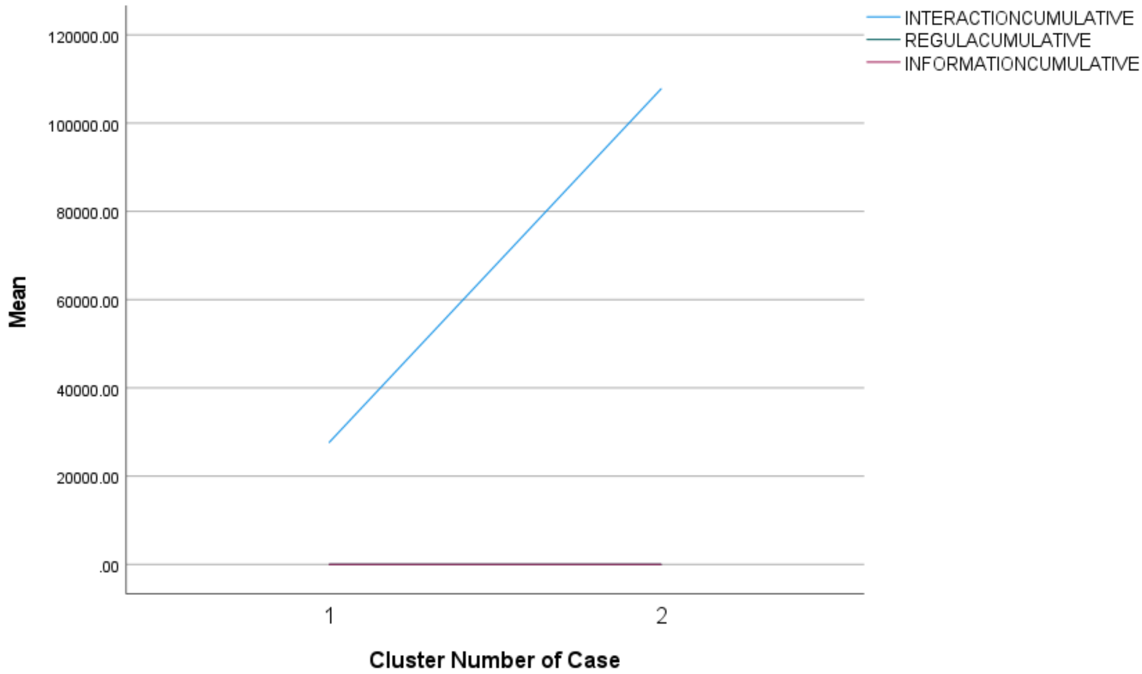


Figure A-3.3. Scatter-plot of the distribution of the companies (Variables: Interaction, Regulation and Information)

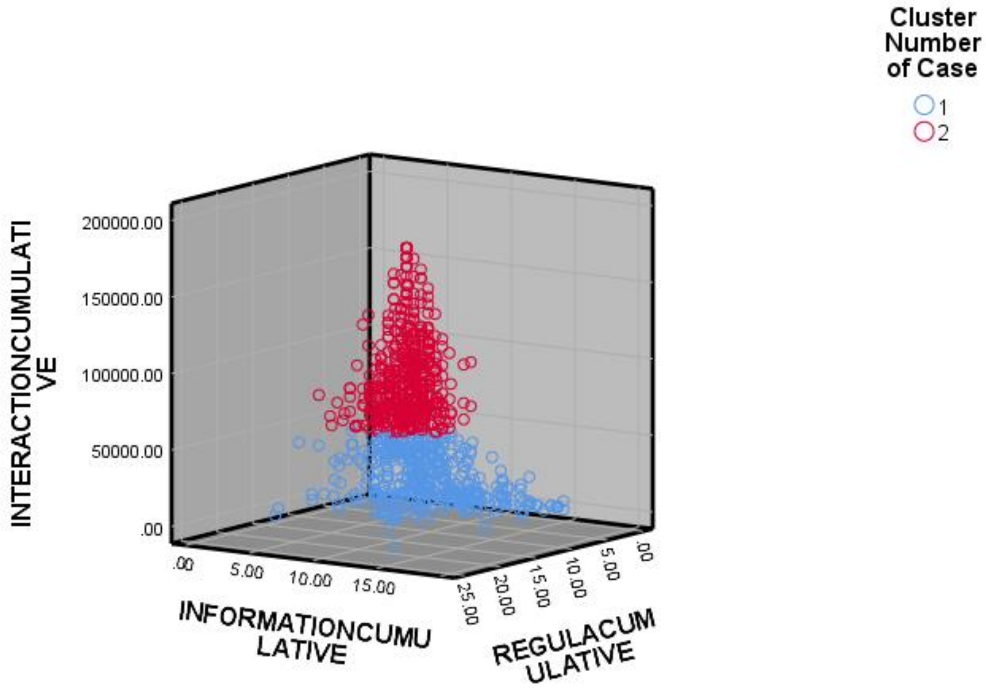
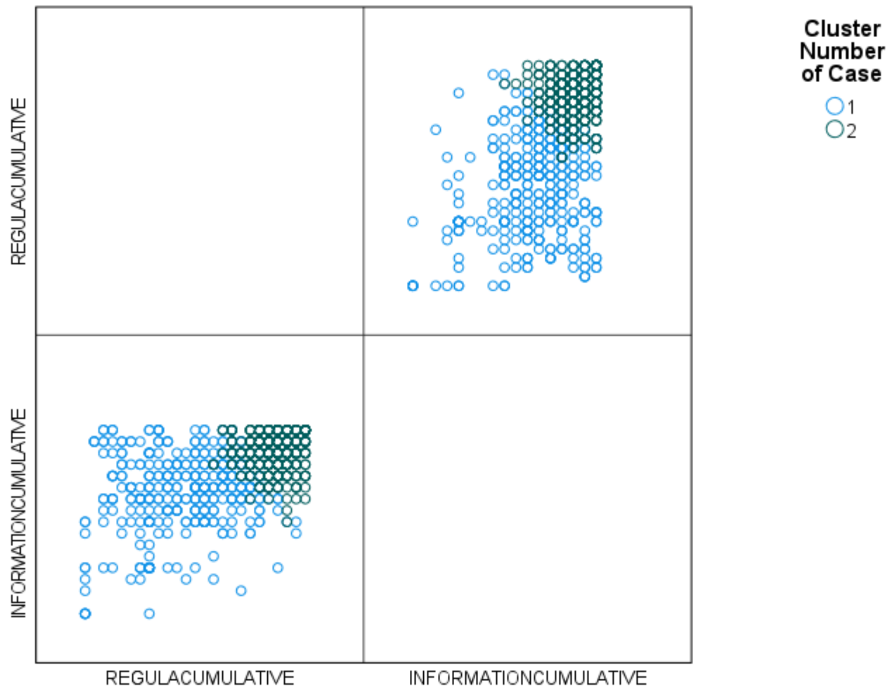


Figure A-3.4. Scatter-plot of the distribution of the companies (Variables: Regulation and Information)



2. ARTIFICIAL NEURAL NETWORK (ANN-RBF)

This section describes in more detail the Radial Basis Function Artificial Neural Network (ANN-RBF) model used in the analysis of the research questions in Chapter 3 of this thesis. Moreover, the model architecture, structure, and design process are explained, as well as the selection of the different algorithms and activation functions used, and the output of the neural network model.

2.1. Model (Cumulative Variables)

The neural network is based on the model represented in Formula 3.8 (Model 8, Chapter 3), which is represented below:

CEBM = f (Regulation; Information; Product; Process)

All further analyses, graphs, and tables in this methodological appendix are related to this model. Table A-3.7 (below) describes the different steps for the procedure to develop de ANN-RBF model. This table is similar to Table A-2.1 (Methodological Appendix II), which presents the steps of the ANN-MLP procedure. However, Table A-3.7 is customised for the ANN-RBF model employed in Chapter 3 of this thesis.

Table A-3.7. Steps of the ANN-RBF procedure

1. Choice of the ANN typology	• We choose the ANN architecture with Radial Basic Function (RBF)
2. Design of architecture of ANN-MLP	• The network accuracy and the efficiency are dependent on various parameters: hidden nodes, activation functions, training algorithm parameters and characteristics such as normalisation and generalisation. • The number of inputs and outputs is given by the number of available input and output variables (4 and 1, respectively) • The number and size of hidden layers is determined by testing several combinations of the number of hidden layers and the number of neurons • For the types of activation functions, for the hidden layer, we used a Softmax, and an Identity function for the activation function of the output layer.
3. Choice of the learning algorithm	• We are going to use is Backpropagation. This learning algorithm determines the connection weights of each neuron, readjusting the weights and minimising the error.
4. Learning stage	• To avoid problems of overfitting and consumption of processing time, we divided the sample randomly into three subsamples (training, testing and holdout). • In the training stage, the weights and links between nodes are determined, to minimise the error. In the validation stage, the generalisability of the obtained architecture is checked. Lastly, the holdout data is used to validate the model.
4. Sensitive analysis	• A sensitive analysis is developed to quantify the influence of each input variable on the output variables.

As displayed in Table A-3.7, the learning algorithm used is the backpropagation algorithm. This learning algorithm decides the weight of the connection of each neuron, modifying the weights and minimising the error (Rojas, 1996).

2.2. ANN-RBF Output

Regarding the output of the ANN-MLP, Table A-3.8 shows the distribution of the sample in the training, testing, and holdout steps of the ANN design. The sample is randomly divided into these three subsamples, to avoid overfitting problems, as well as high consumption of processing time.

Table A-3.8. Case Processing Summary of the ANN-RBF

		N	Percent
Sample	Training	674	69.3%
	Testing	199	20.5%
	Holdout	100	10.3%
Valid		973	100.0%
Excluded		346	
Total		1319	

As shown in Table A-3.8 the dataset is divided into a 7, 2, 1 configuration (this is because the relative proportions of the training, testing, and holdout samples relate roughly to 70%, 20%, and 10%). This type of partition of the dataset follows the configuration of other studies, such as Ciurana et al. (2008) and Cavalieri et al. (2004). Moreover, as observed by Alloghani (2020), a training subset of around 60% is logical and aids in attaining the intended outcome without requiring more processing effort. The training sample consists of a set of data points from the dataset that is utilised to train the ANN model. The testing sample consists of a separate set of data points that are utilised to monitor the errors during the training stage to avoid overtraining. Generally, network training works best when the testing sample is smaller than the training sample. Finally, the holdout sample entails an additional separate set of data points utilised to evaluate the final ANN model. The error obtained for the holdout sample provides an "honest" assessment of the predictive capability of the model since the holdout cases are not utilised to develop the ANN model.

Tables A-3.9 and A-3.10, and Figure A-3.5 show the ANN-RBF architecture, using as output a cumulative variable, which is the one used in the analysis in Chapter 3.

Table A-3.9. RBF-Network Information

Input Layer	Covariates	1	REGULATION	
		2	INFORMATION	
		3	PRODUCT	
		4	PROCESS	
	Number of Units			4
	Rescaling Method for Covariates		Normalized [b]	
Hidden Layer	Number of Units			6[a]
	Activation Function		Softmax[c]	
Output Layer	Dependent Variables	1	CEBM	
	Number of Units			1
	Rescaling Method for Scale Dependents		Normalized[d]	
	Activation Function		Identity[e]	
	Error Function		Sum of Squares	

a. Determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

Table A-3.9 displays the ANN-RBF structure used in the analysis in Chapter 3. Regarding the rescaling covariates (independent variables), a normalised method (*NM*) [b] was utilised, as shown in the table. This method subtracts the minimum and divides it by the range. This method has the form:

$$NM = \frac{(x - min)}{(max - min)} \tag{A-3.3}$$

The same rescaling method was used for the scale of the dependent variable [d], that is, a normalised method, as also shown in Table A-3.9.

Moreover, Table A-3.9 displays some of the characteristics selected for the hidden layer. The hidden layer comprises network units (or nodes) that are not observable. In this case, there is 1 hidden layer with 6 hidden units in the hidden layer of our ANN model (see Figure A-3.5, for a graphical representation). Each hidden unit is a function of the sum of the weights of the independent variables (or inputs). This function is known as the activation function, where the estimation algorithm determines the weight of the values. Therefore, the activation function "connects" the values of units (calculated via the weighted sums) of one layer to the unit values in the next layer (Garbero et al., 2021). In terms of the activation function used for the Hidden layer in the ANN-RBF of chapter 3, a Softmax activation function [c] was employed (shown in Table A-3.9). This function has the form:

$$\gamma(c_k) = \frac{\exp(c_k)}{\sum_j \exp(c_k)} \tag{A-3.4}$$

This function takes real-valued arguments of a vector and converts them into another vector, so that its elements belong within the range (0, 1) and sum to 1. This is a quite common type of activation function utilised for the hidden layer when constructing a neural network (see, for example, Reed and Marks, 1999; or Wang, 2007).

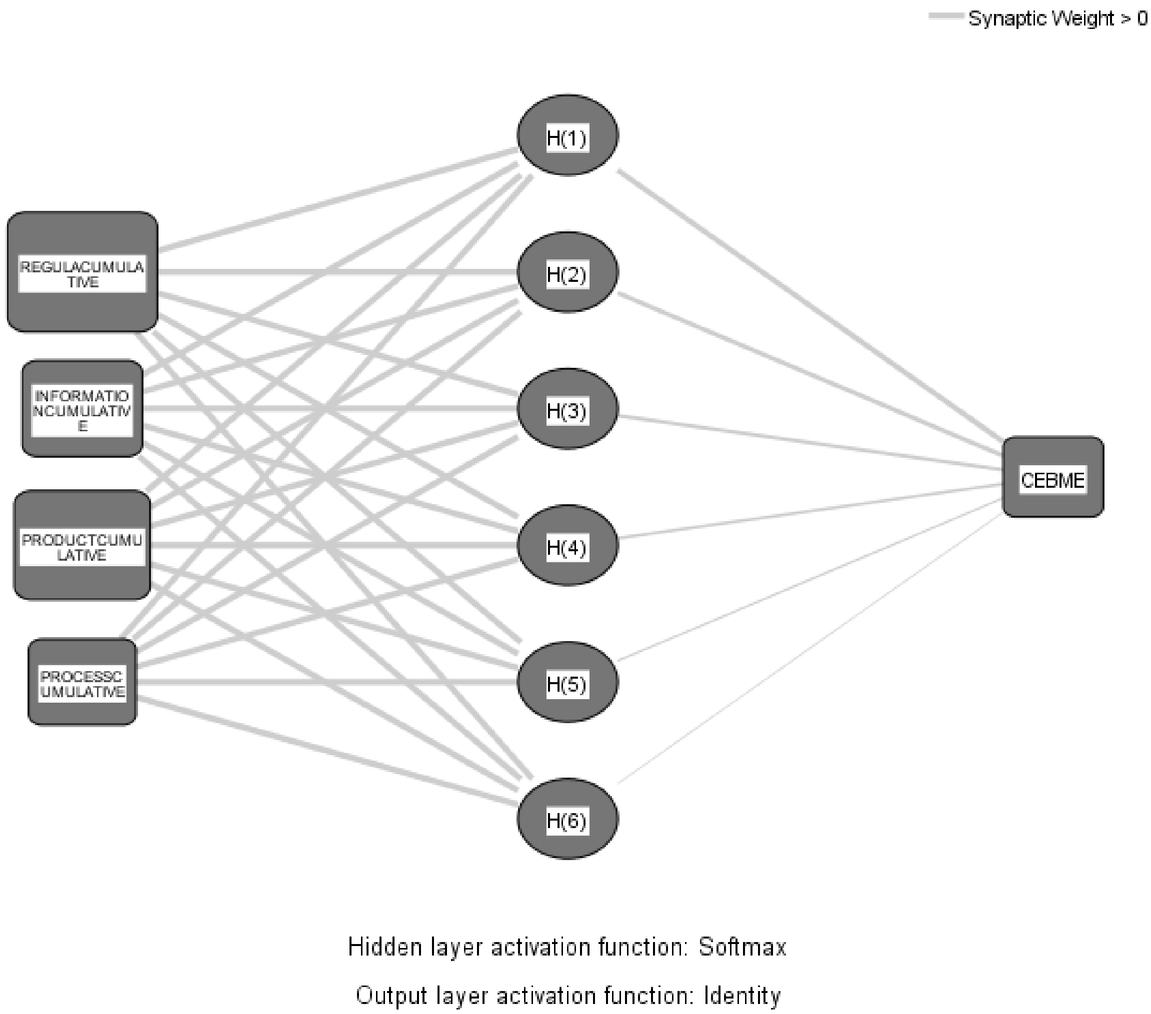
Regarding the activation function utilised for the output layer, in this case, an identity function [e] is employed (shown in Table A-3.9). This function has the form:

$$\gamma(c) = c \tag{A-3.5}$$

This function returns the real-valued arguments unchanged. This activation function for the output layer is commonly used when selecting an architecture for the neural network (Minbashian et al., 2010).

Figure A-3.5 shows the final architecture of the ANN-RBF used. As displayed in the figure there are 4 nodes or neurons in the input layer (given by the independent variables), 1 hidden layer with 6 hidden nodes or neurons, and finally 1 node or neuron in the output layer (given by the dependent variable). This information is also available in Table A-3.9.

Figure A-3.5. ANN-RBF architecture.



Furthermore, we present below Table A-3.10. This table displays a summary of the results of the ANN by partition, containing the error, the relative error, and the training time. The error is the SSE when, in this case, the identity activation function is the one employed for the output layer. As shown in the table, the overall error in the ANN-RBF model used in the analysis is small. Moreover, the stopping rule used is that of one consecutive step with no decrease in error, where the error computations are based on the testing sample.

Table A-3.10. ANN-RBF Model Summary

Training	Sum of Squares Error	4.409
	Relative Error	.314
	Training Time	0:00:00.61
Testing	Sum of Squares Error	1.372[a]
	Relative Error	.294
Holdout	Relative Error	.236

Dependent Variable: CEBM
a. The number of hidden units is determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

Table A-3.11 (below) shows the simulation results of the ANN-RBF. The simulation results shown in the table follow the methods based on Garson's algorithm (1991), which is explained in Methodological Appendix II, Formula A-2.6. Thus, Table A-3.11 shows the importance of each predictor in determining the ANN, which is the independent variable importance analysis. The analysis is based on the joint samples of training and testing. This table, with its accompanying diagram, displays the normalised importance of each predictor shown in Chapter 3, Table 3.10.

Table A-3.11. ANN-RBF simulation output **(**Independent Variable Importance analysis)

Variables	Importance	Normalised Importance
REGULATION	.319	100.0%
INFORMATION	.223	70.1%
PRODUCT	.275	86.2%
PROCESS	.183	57.4%

2.3 ANN-RBF Simulation

Additionally, and in a similar fashion to the previous appendix (Methodological Appendix II), we check the predicted values of the ANN model against the observed values to test the suitability of the model and its fit. This is used as a robustness check of the model. The simulation models are:

CEBM(Observed) = f (Regulation; Information; Product; Process; Interaction)

CEBM(Predicted) = f (Regulation; Information; Product; Process; Interaction)

Figures A-3.6 to A-3.10 show the response of the network to the variation of each input variable (i.e. *Regulation*, *Information*, *Product*, *Process*, and *Interaction*) and its effect on the output of the real variables and the predicted output of the ANN-RBF. In the graphs, a similar response to the real variable output and predicted output can be observed. For example, Figure A-3.6 shows the variation of the input variable *Regulation* with respect to the output variable *CEBM*, maintaining *Information*, *Product*, *Process*, and *Interaction* as constant. Hence, as shown in the graph, the light blue line, which corresponds to the predicted value for the output variable (*CEBM*), and the dark green line, which corresponds to the actual values of the output variable (*CEBM*), trace each other almost perfectly. Thus, on the one hand, this enables us to confirm, in accordance with previous studies (see, for example, Alpaydin, 2004), that the ANNs' fit is better compared to that of regression models, explaining the effect between independent variables and the dependent variable more adequately. On the other hand, it allows us to graphically determine that the model fitness is good and therefore the predictions of our model are going to be accurate.

Figure A-3.6. ANN-RBF simulation (constant: Information; Product; Process; Interaction).

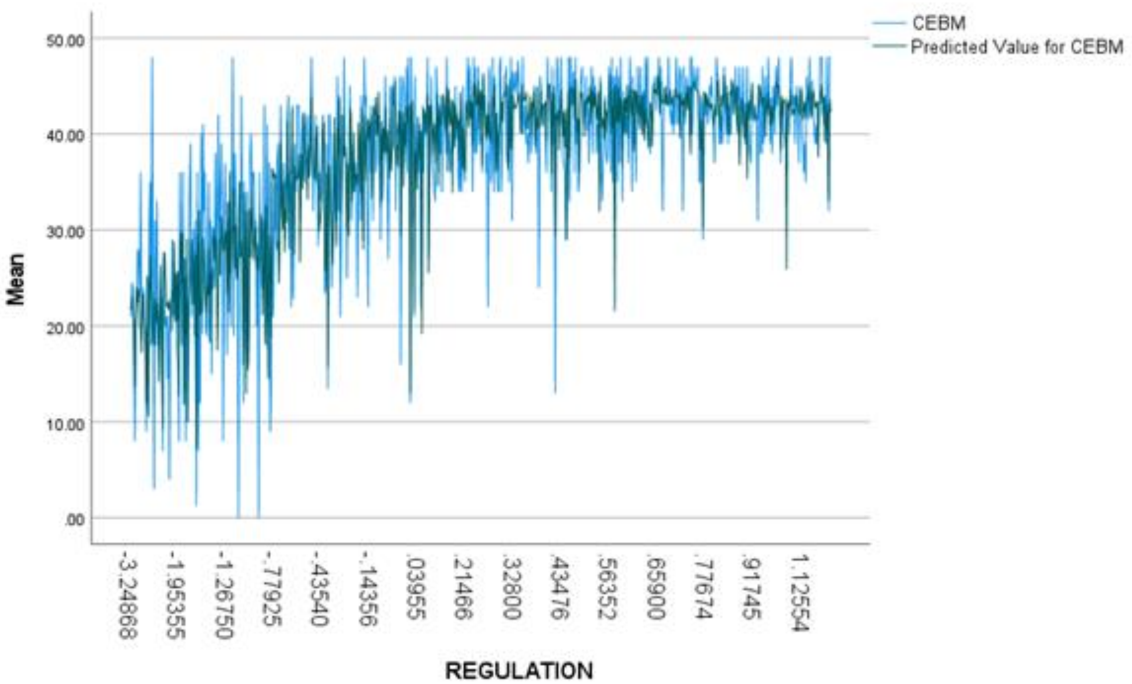


Figure A-3.7. ANN-RBF simulation (constant: Regulation; Product; Process; Interaction).

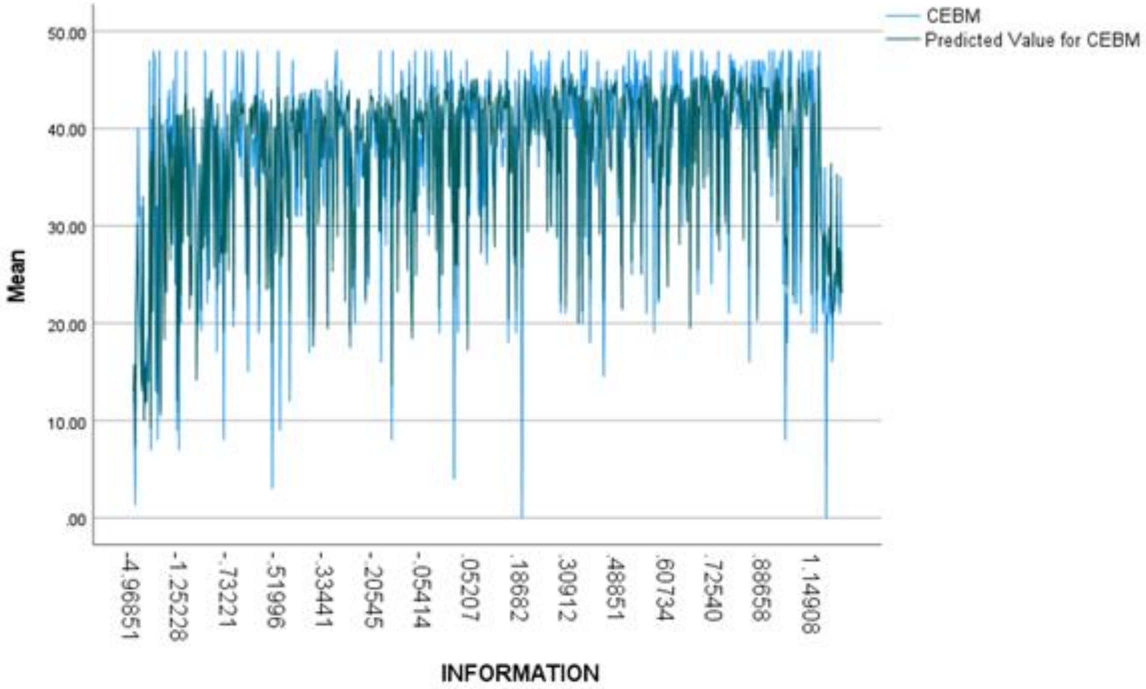


Figure A-3.8. ANN-RBF simulation (constant: Information; Regulation; Process; Interaction).

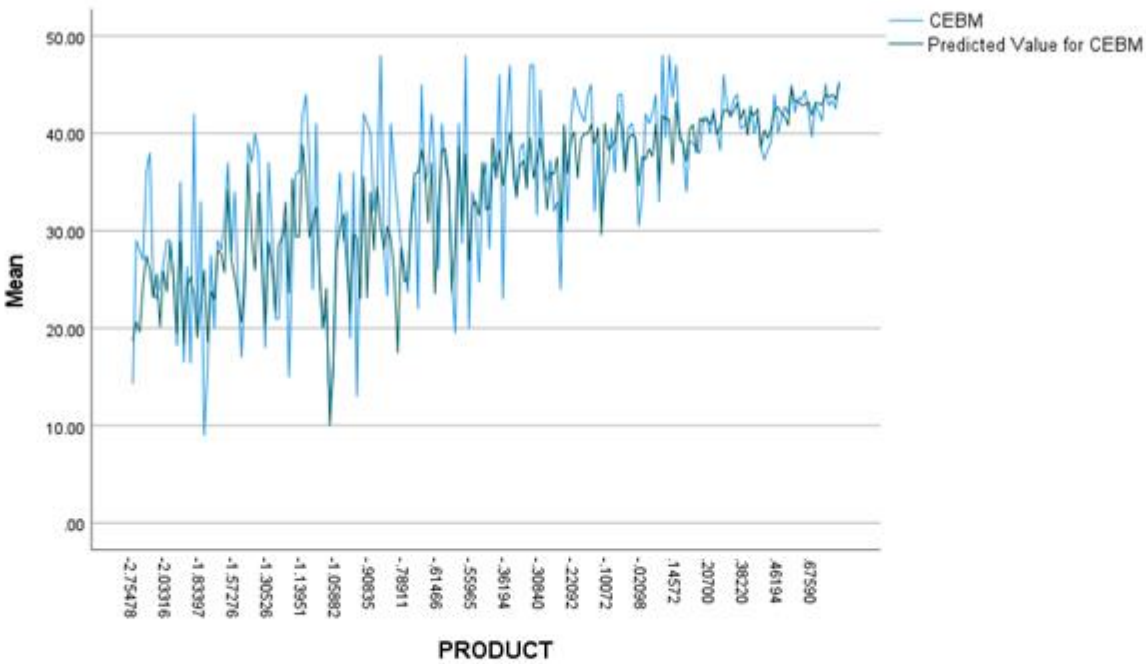


Figure A-3.9. ANN-RBF simulation (constant: Information; Regulation; Product; Interaction).

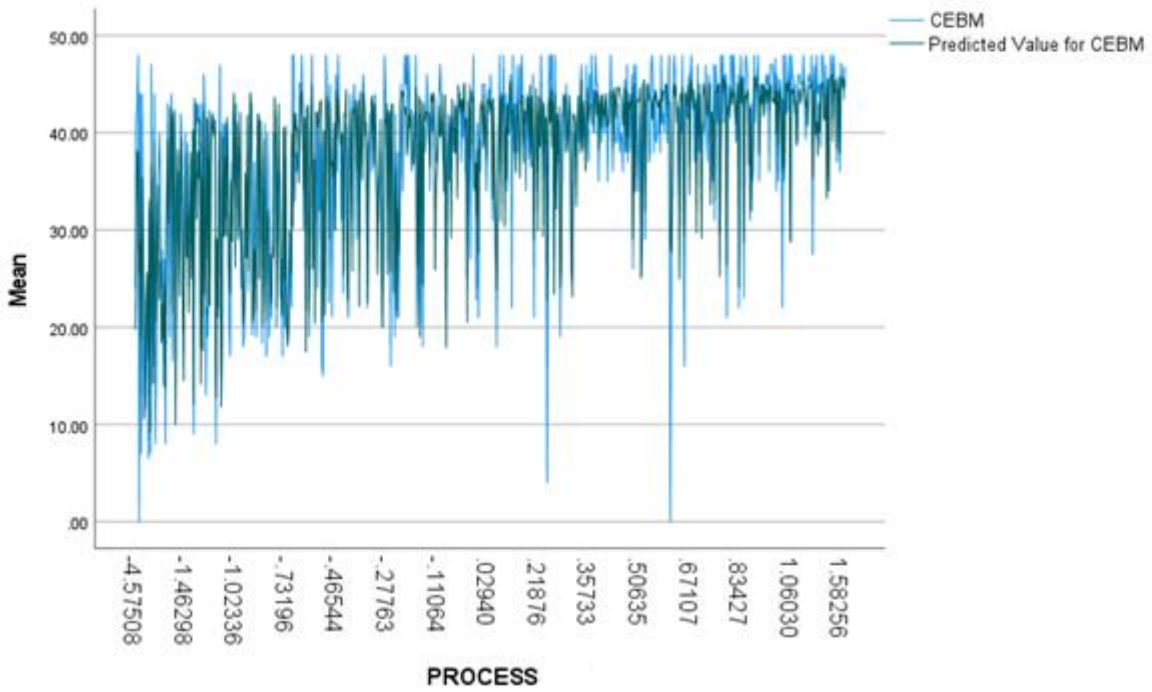
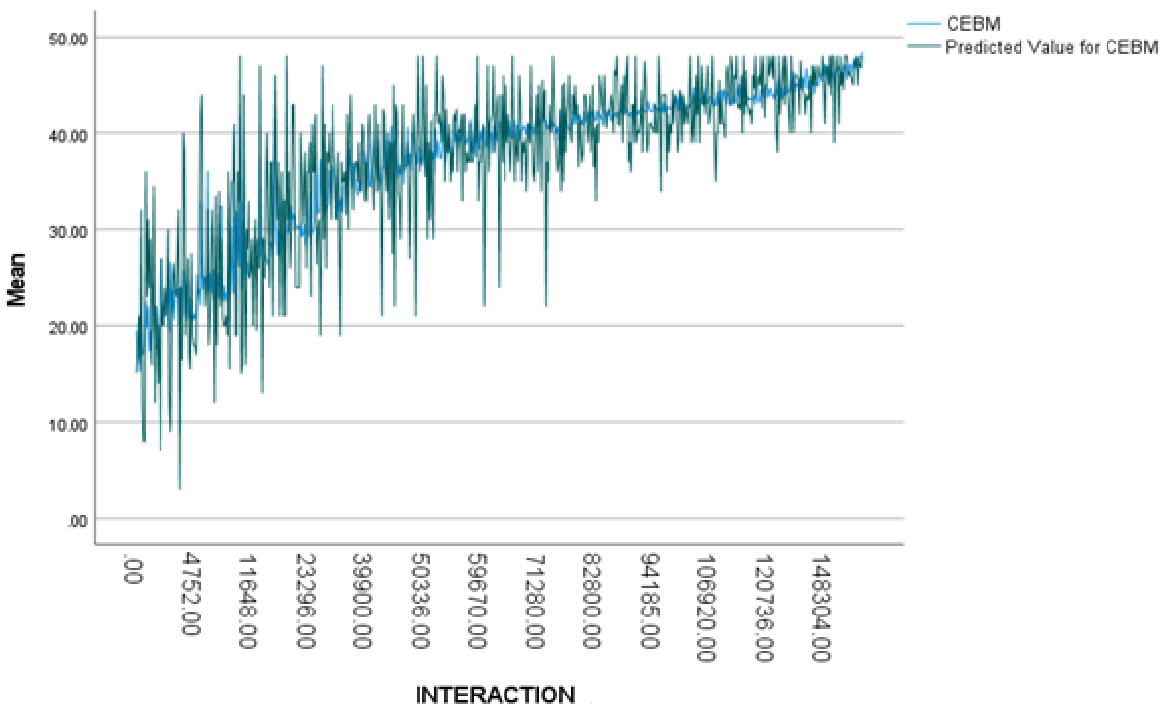


Figure A-3.10. ANN-RBF simulation (constant: Information; Regulation; Product; Process).



3. REGRESSION ANALYSIS

This section of Methodological Appendix III is dedicated to checking the robustness of the regression analysis adjustment by comparing the results of linear regression with other non-linear regression models (quadratic and cubic). This refers to the regression analysis performed in Chapter 3 to test Hypothesis 1 about the effect of CE consumption policies on CEBMs in firms (see Formula 3.2: Econometric Model 2 – OLR and Table 3.5: Ordinal Logistic regression models). The aim of this robustness test is to check whether any other type of regression model, besides the linear one, would have yielded a better fit for the model. However, as described below the results of these robustness checks do not reveal significant differences between these various types of analysis. Hence, the linear model was used for the analysis of Hypothesis 1 in Chapter 3.

3.1. Model I

First, we check the independent variable *Regulation* against the dependent variable *CEBM* used in the analysis in Chapter 3. This is represented below:

CEBM = f (Regulation)

All the further analyses, graphs, and tables in this subsection are related to this model. The first table that we present is Table A-3.12, which shows a summary of the case processing for the regression analysis. As displayed in the table, there is a small number of excluded cases and the number of total cases used for the analysis is high, which is a good indication regarding the regression analysis carried out in this robustness check.

Table A-3.12. Regression Analysis: Case Processing Summary (Regulation)

	N
Total Cases	1319
Excluded Cases[a]	273
Forecasted Cases	0
Newly Created Cases	0

a. Cases with a missing value in any variable are excluded from the analysis.

Table A-3.13 shows the model summary and parameter estimates for the regression analysis regarding the variable *Regulation*. As can be observed, the different regression models have similar results, both in the contribution to the variability of the model (R^2) and in the significance of the coefficients. The results do not reveal significant differences between these various types of analysis. Hence, this provides justification for the use of the linear regression model for the analysis of Hypothesis 1 in Chapter 3.

Table A-3.13. Regression Analysis: Model Summary and Parameter Estimates (Regulation)

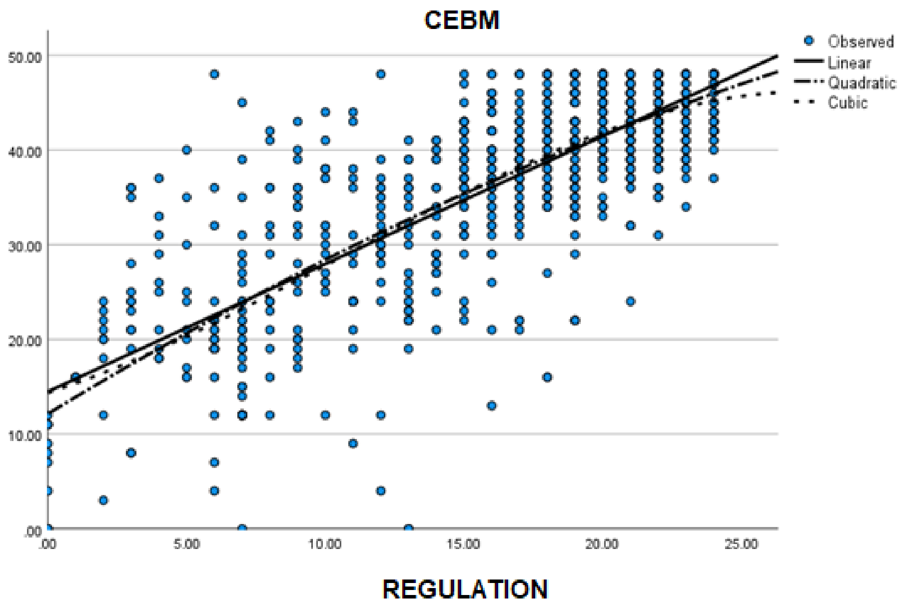
Dependent Variable: CEBM

	Model Summary					Parameter Estimates			
Equation	R^2	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.624	1734.919	1	1044	.000	14.485	1.348		
Quadratic	.627	878.193	2	1043	.000	12.144	1.782	-.016	
Cubic	.629	590.009	3	1042	.000	14.372	.941	.059	-.002

The independent variable is REGULATION.
a. The independent variable (REGULATION) contains non-positive values. The minimum value is .00. The Logarithmic and Power models cannot be calculated.
b. The independent variable (REGULATION) contains values of zero. The Inverse and S models cannot be calculated.
c. The dependent variable (CEBM) contains non-positive values. The minimum value is .00. Log transform cannot be applied. The Compound, Power, S, Growth, Exponential, and Logistic models cannot be calculated for this variable.

Moreover, Figure A-3.11 illustrates the fit of the various regression models proposed in Table A-3.13 (linear, quadratic, and cubic regression). Further corroborating the conclusions derived from Table A-3.13.

Figure A-3.11. Regression Analysis Regulation



3.2. Model II

Second, we repeat the robustness check performed in the previous subsection, but this time the independent variable used is *Information*, which is the other variable used in the analysis of Hypothesis 1 in Chapter 3. Following the methodology previously employed, we regress the independent variable against the dependent variable *CEBM* used in the analysis in Chapter 3. This is represented below:

CEBM = f (Information)

All the further analyses, graphs, and tables in this subsection are related to this model. The first table that we present is Table A-3.14, which shows a summary of the case processing for the regression analysis. As displayed in the table, there is a small number of excluded cases and the number of total cases used for the analysis is high, which is a good indication regarding the regression analysis carried out in this robustness check.

Table A-3.14. Regression Analysis: Case Processing Summary (Information)

	N
Total Cases	1319
Excluded Cases[a]	245
Forecasted Cases	0
Newly Created Cases	0

a. Cases with a missing value in any variable are excluded from the analysis.

Table A-3.15 shows the model summary and parameter estimates for the regression analysis regarding the variable *Information*. As can be observed, the different regression models have similar results, both in the contribution to the variability of the model (R^2) and in the significance of the coefficients. The results do not reveal significant differences between these various types of analysis. Hence, this provides justification for the use of the linear regression model for the analysis of Hypothesis 1 in Chapter 3.

Table A-3.15. Regression Analysis: Model Summary and Parameter Estimates (Information)

Dependent Variable: CEBM

	Model Summary					Parameter Estimates			
Equation	R^2	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.370	628.968	1	1072	.000	10.962	2.073		
Quadratic	.376	322.005	2	1071	.000	5.517	3.248	-.056	
Cubic	.377	216.073	3	1070	.000	9.152	1.474	.156	-.007

The independent variable is INFORMATION.

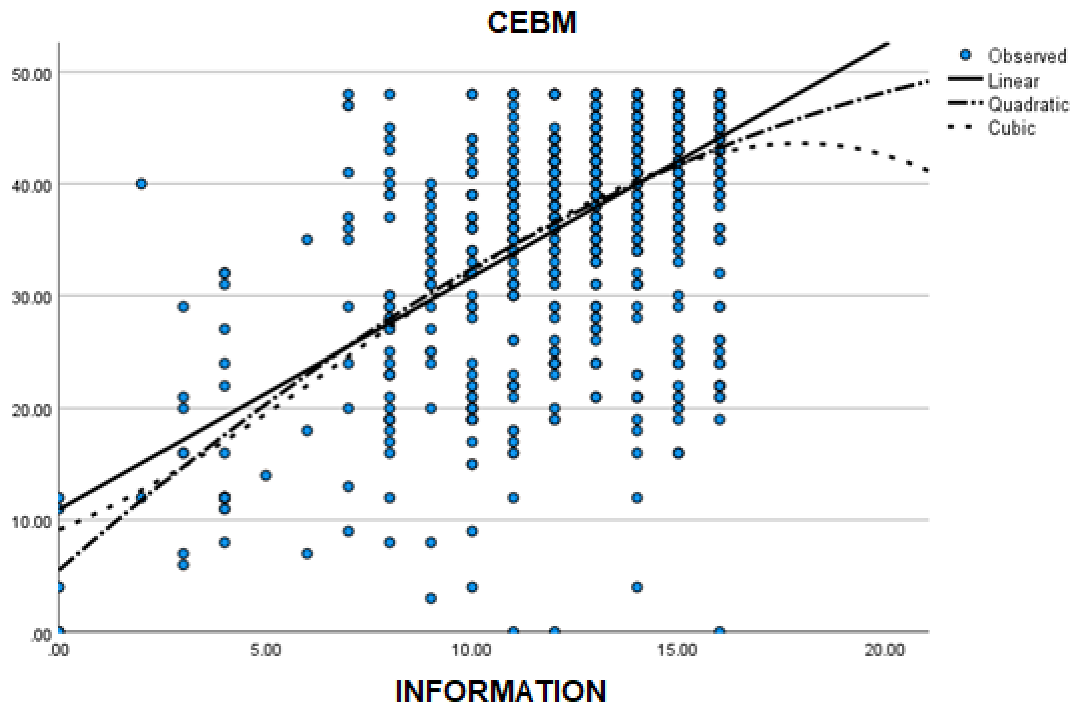
a. The independent variable (INFORMATION) contains non-positive values. The minimum value is .00. The Logarithmic and Power models cannot be calculated.

b. The independent variable (INFORMATION) contains values of zero. The Inverse and S models cannot be calculated.

c. The dependent variable (CEBM) contains non-positive values. The minimum value is .00. Log transform cannot be applied. The Compound, Power, S, Growth, Exponential, and Logistic models cannot be calculated for this variable.

Moreover, Figure A-3.12 illustrates the fit of the various regression models proposed in Table A-3.15 (linear, quadratic, and cubic regression). Further corroborating the conclusions derived from Table A-3.15.

Figure A-3.12. Regression Analysis Information



Methodological Appendix IV

Methodological Appendix IV relates to the methodology and analyses employed in Chapter 4 of this thesis. This appendix places particular emphasis on the Artificial Neural Network model and Decision Tree developed in this chapter, describing the model and its architecture, the basic structure and design, the selection of the different algorithms used, the output of the neural network and decision tree model, as well as a description of the selected activation functions. Furthermore, the appendix presents and describes a robustness check regarding the linear regression model utilised in Chapter 4.

1. ARTIFICIAL NEURAL NETWORK (ANN-MLP) (Cumulative Variables).

This section describes in more detail the Multilayer Perceptron Artificial Neural Network (ANN-MLP) model used in the analysis of the research questions in Chapter 4 of this thesis. Moreover, the model architecture, structure, and design process are explained, as well as the selection of the different algorithms and activation functions used, and the output of the neural network model.

1.1. Model (Cumulative Variables)

The neural network is based on the model represented in Formula 3.8 (Model 8, Chapter 4), which is represented below:

*CE = f (Financing; Innovation; Financing*Innovation)*

All the further analyses, graphs, and tables in this methodological appendix are related to this model.

First and following the structure of the previous methodological appendices, Table A-4.1 describes the different steps for the procedure to develop de artificial neural network (ANN) model. This table shows a summary of the procedure that has been used throughout this thesis to build the different ANN models used. However, Table A-4.1 is customised for the ANN-MLP model employed in Chapter 4 of this thesis.

Table A-4.1. Steps of the ANN-MLP procedure

1. Choice of the ANN typology	• We choose the ANN architecture with Multilayer Perceptron (MLP)
2. Design of architecture of ANN-MLP	• The network accuracy and the efficiency are dependent on various parameters: hidden nodes, activation functions, training algorithm parameters and characteristics such as normalisation and generalisation. • The number of inputs and outputs is given by the number of available input and output variables. • The number and size of hidden layers is determined by testing several combinations of the number of hidden layers and the number of neurons • For the types of activation functions, for the hidden layer, we used a hyperbolic tangent function (-1 to 1), and an Identity function for the activation function of the output layer.
3. Choice of the learning algorithm	• We are going to use is Backpropagation. This learning algorithm determines the connection weights of each neuron, readjusting the weights and minimising the error.
4. Learning stage	• To avoid problems of overfitting and consumption of processing time, we divided the sample randomly into three subsamples (training, testing and holdout). • In the training stage, the weights and links between nodes are determined, to minimise the error. In the validation stage, the generalisability of the obtained architecture is checked. Lastly, the holdout data is used to validate the model.
4. Sensitive analysis	• A sensitive analysis is developed to quantify the influence of each input variable on the output variables.

As displayed in Table A-4.1, the learning algorithm used is the backpropagation algorithm. This learning algorithm decides the weight of the connection for each neuron, modifying the weights and minimising the error (Rojas, 1996). This is the same learning algorithm used for all the ANN models in this thesis.

1.2. ANN-MLP Output

Regarding the output of the ANN-MLP, Table A-4.2 shows the distribution of the sample in the training, testing, and holdout steps of the ANN design. The sample is randomly divided into these three subsamples, to avoid overfitting problems, as well as high consumption of processing time.

Table A-4.2. Summary of ANN processing

Case Processing Summary			
		N	Percent
Sample	Training	625	64.8%
	Testing	250	25.9%
	Holdout	90	9.3%
Valid		965	100.0%
Excluded		354	
Total		1319	

As shown in Table A-4.2 the dataset is divided into a 7, 2, 1 configuration (this is because the relative proportions of the training, testing, and holdout samples relate roughly to 70%, 20%, and 10%). This type of partition of the dataset follows the configuration of other studies, such as Ciurana et al. (2008) and Cavalieri et al. (2004). Moreover, as observed by Alloghani (2020), a training subset of around 60% is logical and aids in attaining the intended outcome without requiring more processing effort. This partition configuration is the same one used in chapters 2 and 3 for their corresponding ANN models.

Tables A-4.3 and A-4.4, and Figure A-4.1 show ANN-MLP architecture, using cumulative variables, which is the one used for hypotheses 2a, 2b, 3a and 3b in Chapter 4.

Table A-4.3. ANN-MLP structure

Input Layer	Covariates	1	FINANCING
		2	INNOVATION
		3	FINANCING*INNOVATION
	Number of Units[a]		3
	Rescaling Method for Covariates		Standardized (b)
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1		3 (a)
	Activation Function		Hyperbolic tangent (c)
Output Layer	Dependent Variables	1	CE
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized (d)
	Activation Function		Identity (e)
	Error Function		Sum of Squares

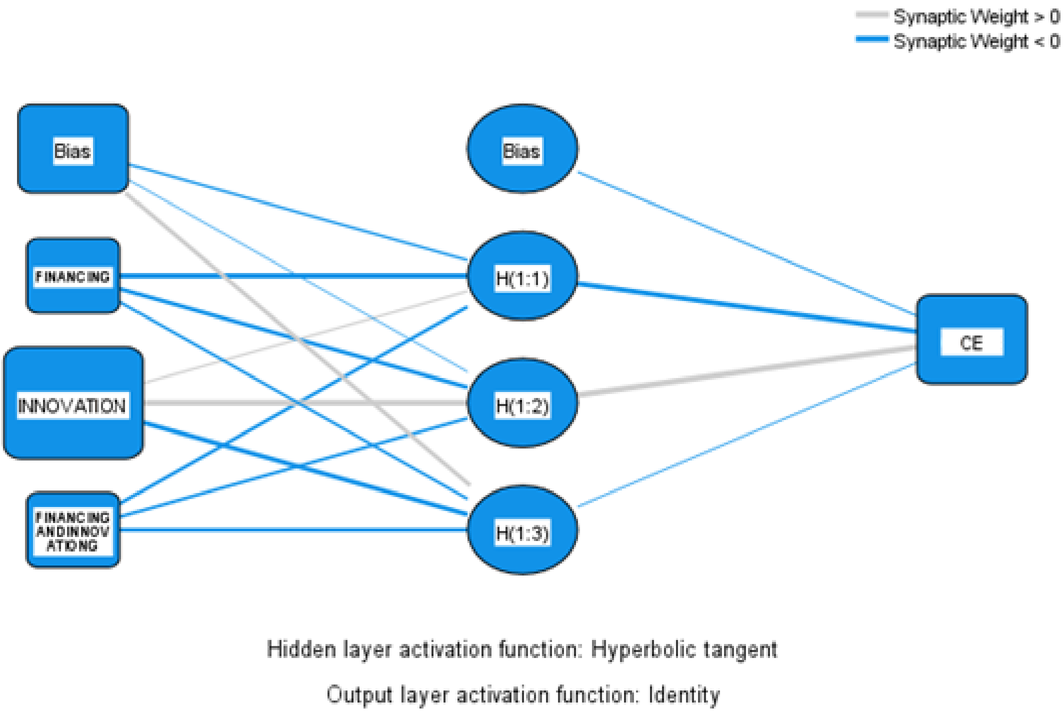
Table A-4.3 displays the ANN-MLP structure used in the analysis of Chapter 4, which follows a similar structure to the ANN-MLP used in Chapter 2. Regarding the rescaling covariates (independent variables), a standardised method [(b)]. The same rescaling method was used for the scale of the dependent variable, as shown in Table A-4.3 [57]. Furthermore, Table A-4.3 displays some of the characteristics selected for the hidden layer. The hidden layer contains unobservable network nodes (units). In this case, there is 1 hidden layer with 3 hidden units in the hidden layer of our ANN model (see Figure A-4.1, for a graphical representation). In terms of the activation function used for the Hidden layer in the ANN of Chapter 4, a hyperbolic tangent function [(c)] was employed (shown in Table A-4.3). This is the most common type of activation function used for the hidden layer when constructing a neural network (see, for example, Reed and Marks, 1999; or Wang, 2007)[58]. Moreover, regarding the activation function utilised for the output layer, in this case, an identity function [(e)] is employed (shown in Table A-2.3). This activation function is commonly employed for the output layer when selecting an architecture for the ANN (Minbashian et al., 2010).

Figure A-4.1 shows the final architecture of the ANN-MLP used. As displayed in the figure there are 3 nodes or neurons in the input layer (given by the independent variables), 1 hidden layer with 3 hidden nodes or neurons, and finally 1 node or neuron in the output layer (given by the dependent variable). This information is also available in Table A-4.3.

[57] For more details on these rescaling methods, please see Methodological Appendix II.

[58] For more details on the hidden layer and the activation function used (hyperbolic tangent), please see Methodological Appendix II, where a detail explanation is provided with the meaning behind these concepts and the formulas utilised.

Figure A-4.1. ANN-MLP architecture.



Furthermore, we include below Table A-4.4, which shows a summary of the results of the ANN by partition, containing the error, the relative error, the stopping rule used to stop training, and the training time. The error is the SSE when, in this case, an identity activation function is utilised for the output layer. As shown in the table, the overall error in the ANN-MLP model used in the analysis is small. Moreover, the stopping rule used is that of one consecutive step with no decrease in error, where the error computations are based on the testing sample. In addition, it is worth highlighting the training time that is very short, which indicates how efficient neural networks are at computing large amounts of data.

Table A-4.4. ANN-MLP Model Summary

Training	Sum of Squares Error	240.700
	Relative Error	.755
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.14
Testing	Sum of Squares Error	76.882
	Relative Error	.713
Holdout	Relative Error	.709

Dependent Variable: CE
a. Error computations are based on the testing sample.

Table A-4.5 (below) shows the simulation results of the ANN-MLP. The simulation results shown in the table follow the methods based on Garson's algorithm (1991), which is explained in Methodological Appendix II, Formula A-2.6. Thus, Table A-4.5 shows the importance of each predictor in determining the ANN, which is the independent variable importance analysis. The analysis is based on the joint sample from training and testing. This table with its accompanying diagram displays the normalised importance of each predictor shown in Chapter 4, Table 4.7.

Table A-4.5. ANN-MLP simulation output (Independent Variable Importance)

Variables	Importance	Normalised Importance
FINANCING	.083	11.4%
INNOVATION	.726	100.0%
FINANCING*INNOVATION	.191	26.3%

1.3 ANN-MLP Simulation

Moreover, we check the predicted values of the ANN model against the observed values to test the suitability of the model and its fit. This is used as a robustness check of the model. This follows the test performed in Methodological Appendix II and Methodological Appendix III. The simulation models are:

*CE(Observed) = f (Financing; Innovation; Financing*Innovation)*

*CE(Predicted) = f (Financing; Innovation; Financing*Innovation)*

Therefore, Figures A-4.2 to A-4.4 show the response of the network to the variation of each input variable (i.e. *Financing, Innovation, and Financing*Innovation*) and its effect on the output of the real variables and the predicted output of the ANN-MLP. In the graphs, a similar response to the real variable output and predicted output can be observed. Thus, on the one hand, this enables us to confirm, in accordance with previous studies (see, for example, Alpaydin, 2004), that the ANNs' fit is better compared to that of regression models, explaining the effect between independent variables and the dependent variable more adequately. On the other hand, it allows us to graphically determine that the model fitness is good and therefore the predictions of our model are going to be accurate.

Figure A-4.2. ANN-MLP simulation (constant: Innovation, and Financing*Innovation).

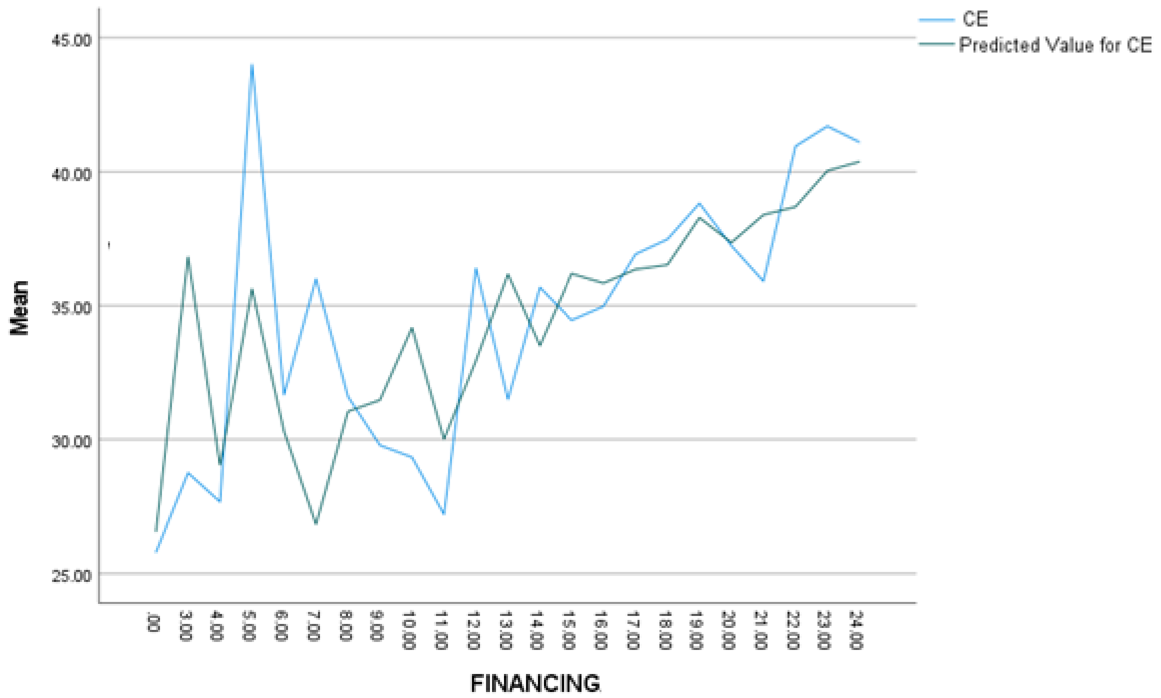


Figure A-4.3. ANN-MLP simulation (constant: Financing, and Financing*Innovation).

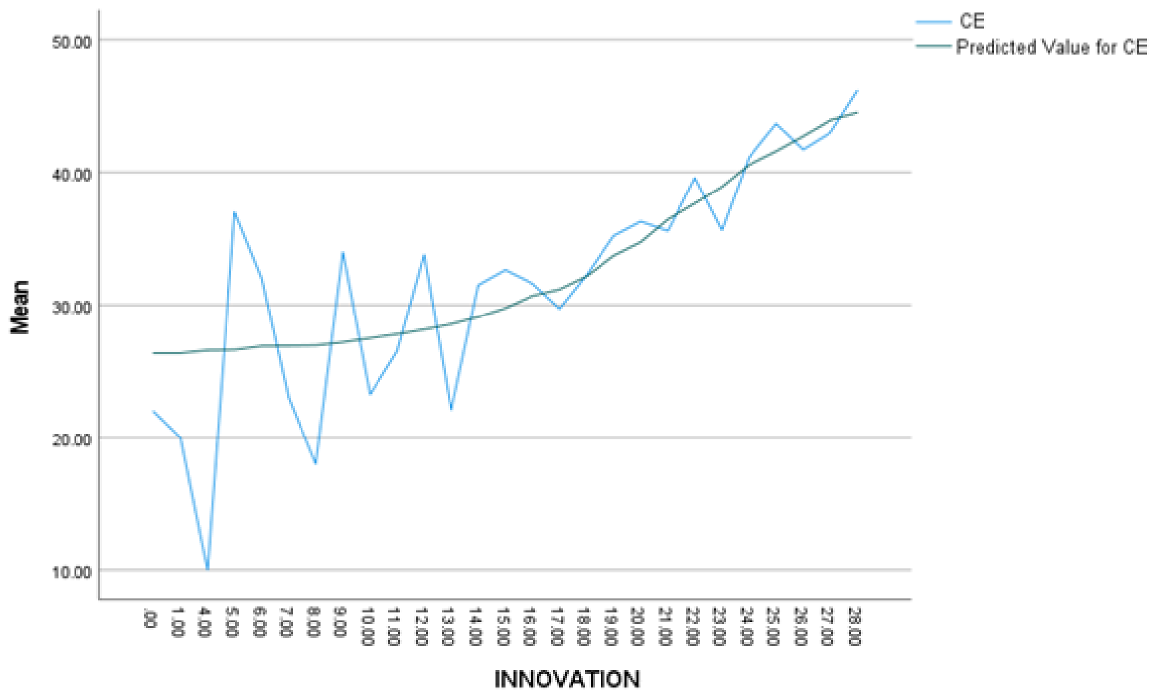
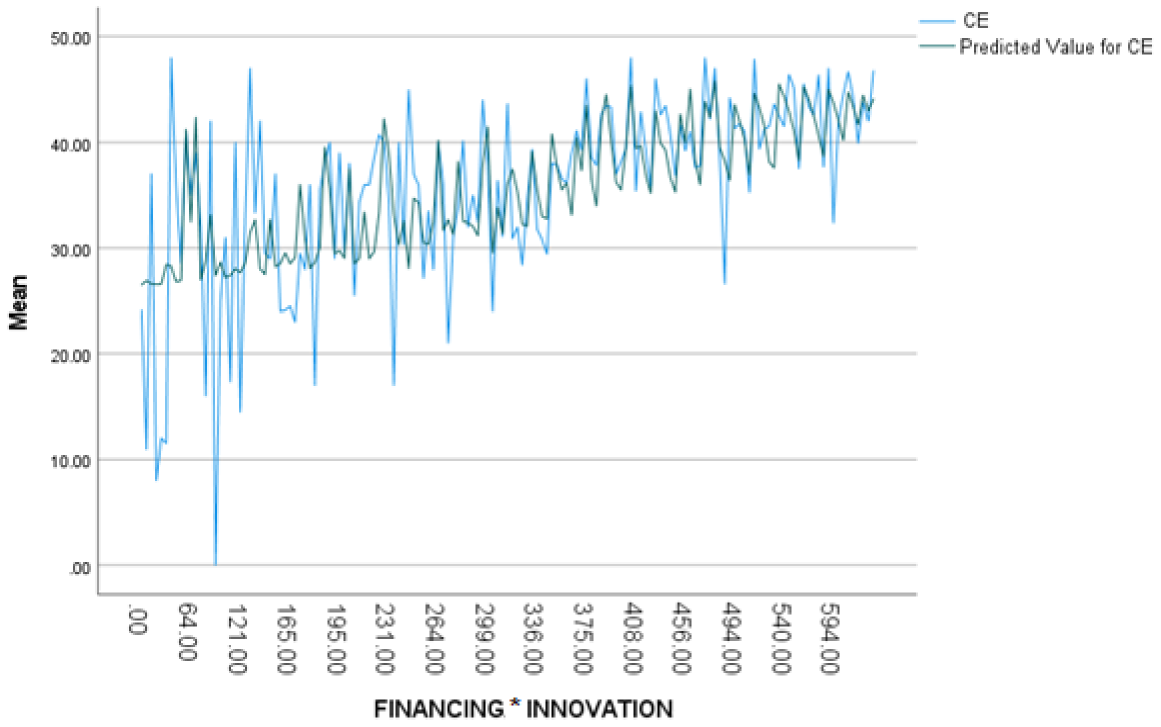


Figure A-4.4. ANN-MLP simulation (constant: Financing, and Innovation).



2. ARTIFICIAL NEURAL NETWORK (ANN-MLP)

In this section, we reproduce the ANN-MLP used in the analysis in Chapter 4 and explained in the above section of this appendix (Methodological Appendix IV). Unlike the previous analysis, in this case, the input variables have been obtained with Factor Analysis. This is used because for the analysis performed in Chapter 4, both types of variables are used. Therefore, we need to analyse and compare the models with both types of variables to check there are no differences in the results and conclusion arrived at in Chapter 4.

2.1. Model

The neural network model used stays the same and as mentioned before, the only difference is that the input variables have been obtained with Factor Analysis. The is represented below:

*CE = f (Financing; Innovation; Financing*Innovation)*

2.2. ANN-MLP Output

Table A-4.6 shows the distribution of the sample in the training, testing, and holdout steps of the ANN design. The same partition configuration of the sample is used as in the previous ANN model with accumulative variables.

Table A-4.6. Summary of ANN processing

Case Processing Summary			
		N	Percent
Sample	Training	590	61.1%
	Testing	281	29.1%
	Holdout	94	9.7%
Valid		965	100.0%
Excluded		354	
Total		1319	

Tables A-4.7 and A-4.8, and Figure A-4.5 show the architecture of the ANN-MLP.

Table A-4.7. ANN-MLP structure

Input Layer	Covariates	1	FINANCING
		2	INNOVATION
		3	FINANCING*INNOVATION
	Number of Units[a]		3
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		2
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	CE
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

As shown in Table A-4.7, the structure of the ANN-MLP with factor analysis variables is very similar to the previous ANN-MLP with accumulative variables. In this case, we also have one hidden layer, but there are a smaller number of units in the hidden layer (2 in this case). Regarding the specificities of the structure, the same rescaling method for the covariates (in the input layer) and the output layer is used as in the previous ANN-MLP (i.e. standardised). This is also displayed in Figure A-4.5, which graphically shows the final architecture of the ANN-MLP with factor analysis variables. Moreover, as shown in Table A-4.7, a hyperbolic tangent activation function is utilised in the hidden layer, as well as an identity function as the activation function for the output layer, which are the same types of activation functions employed in the ANN-MLP with cumulative variables.

Figure A-4.5. ANN-MLP architecture.

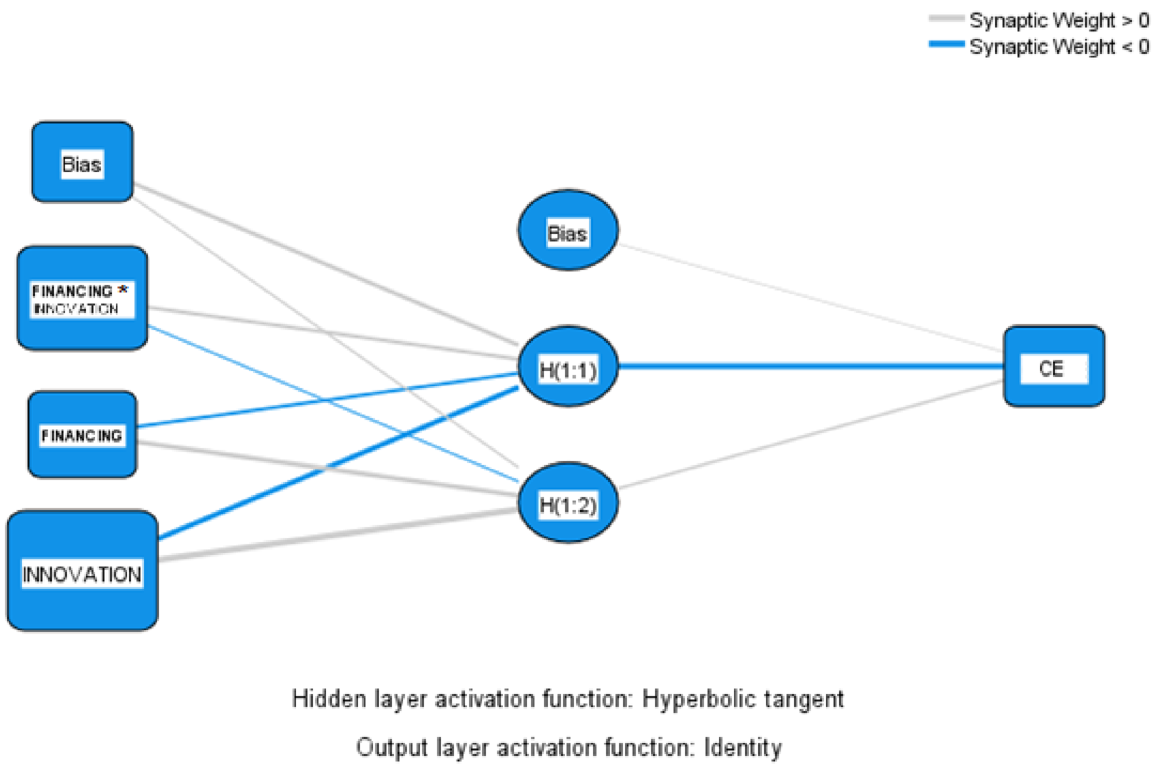


Table A-4.8 displays a summary of the results of the ANN by partition, containing the error, the relative error, the stopping rule used to stop training, and the training time. This table is similar to Table A-4.4, but in this case for the ANN-MLP with factor analysis variables. As before, the error is the SSE when an identity activation function is utilised for the output layer.

Table A-4.8. ANN-MLP Model Summary

Training	Sum of Squares Error	.761
	Relative Error	1 consecutive step(s) with no decrease in error[a]
	Stopping Rule Used	0:00:00.14
	Training Time	96.822
Testing	Sum of Squares Error	.751
	Relative Error	.806
Holdout	Relative Error	.761

Dependent Variable: CE
a. Error computations are based on the testing sample.

Table A-4.9 (below) shows the simulation results. Table A-4.9 follows the methods based on Garson's algorithm (1991)[59]. Therefore, Table A-4.9 shows the importance of each predictor in determining the ANN, also known as, independent variable importance analysis. The analysis is based on the joint sample from training and testing. The results from this analysis are similar to those in the analysis in Chapter 4 and the section above of this appendix (Methodological Appendix IV). There are no significant differences that can be appreciated between the two ANN with the different variables. Hence, this corroborates the suitability of utilising the factor analysis or accumulative variables in the analysis of Chapter 4.

Table A-4.9. ANN-MLP simulation output (Independent Variable Importance)

Variables	Importance	Normalised Importance
FINANCING*INNOVATION	.335	79.4%
FINANCING	.244	57.8%
INNOVATION	.421	100.0%

2.3 ANN-MLP Simulation

As before, we also check the predicted values of the ANN model against the observed values to test the suitability of the model and its fit. This is used as a robustness check of the model The simulation models are:

*CE(Observed) = f (Financing; Innovation; Financing*Innovation)*
*CE(Predicted) = f (Financing; Innovation; Financing*Innovation)*

Therefore, Figures A-4.6 to A-4.8 show the response of the network to the variation of each input variable (*Financing, Innovation, Financing*Innovation*) and its effect on the output of the real variables and the predicted output of the ANN-MLP. In the graphs, a similar response to the real variable output and predicted output can be seen, since for all graphs the light blue line, which corresponds to the predicted value for the output variable (*CE*), and the dark green line, which corresponds to the actual values of the output variable, fit each other almost

[59] For further and more detailed explanation about this algorithm, please see Methodological Appendix II, Formula A-2.6.

perfectly. The results obtained are in line with those from the previous model, where cumulative variables were used. Once again, we can conclude that the ANNs' fit is better compared to that of regression models, explaining the effect between independent variables and the dependent variable more adequately. Moreover, it allows us to graphically determine that the model fitness is good and therefore the predictions of our model are going to be accurate.

Figure A-4.6. ANN-MLP simulation (constant: Innovation, and Financing).

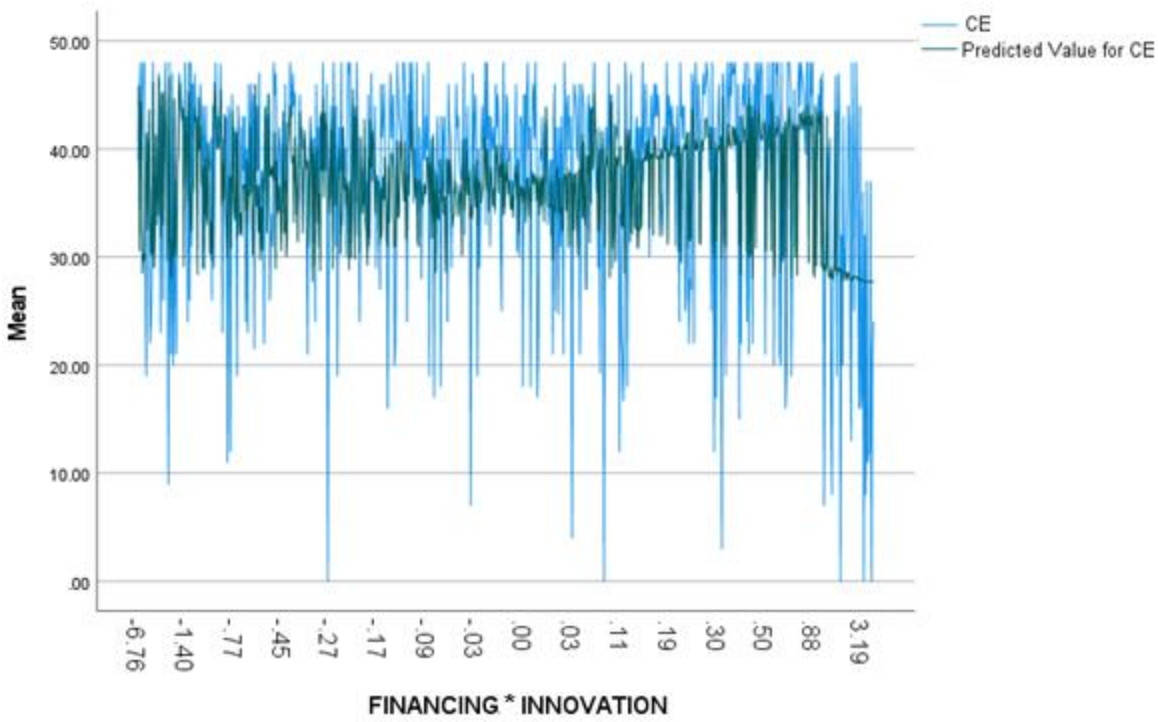


Figure A-4.7. ANN-MLP simulation (constant: Innovation, and Financing*Innovation).

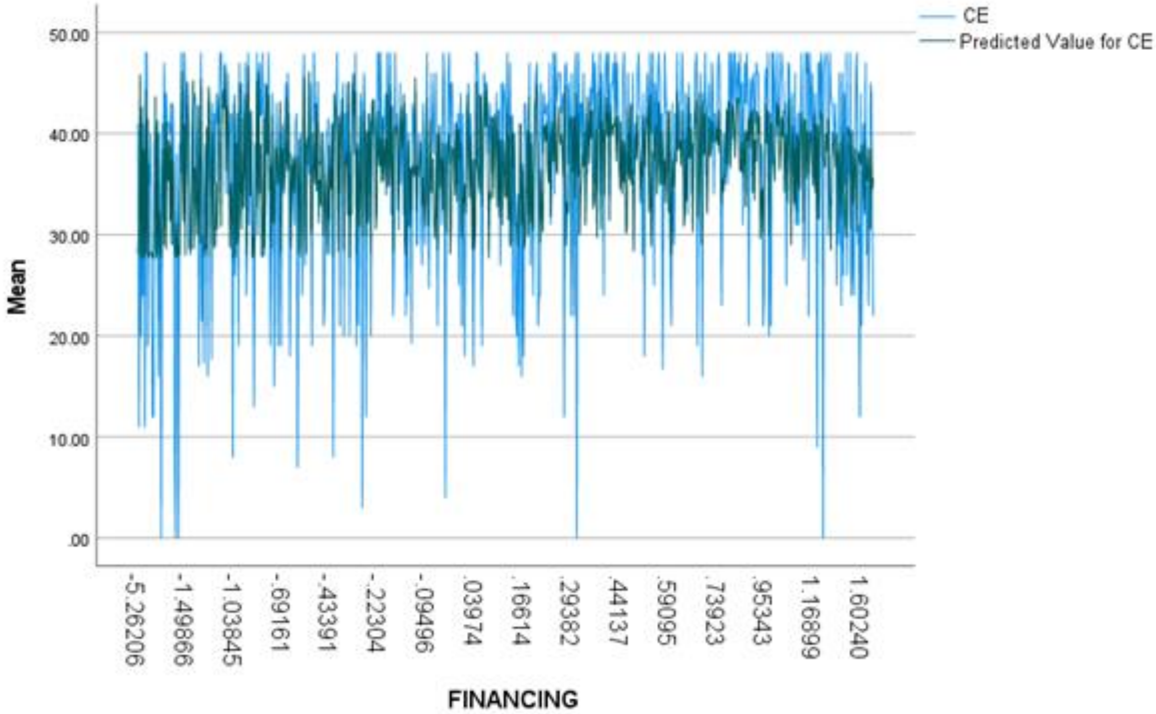
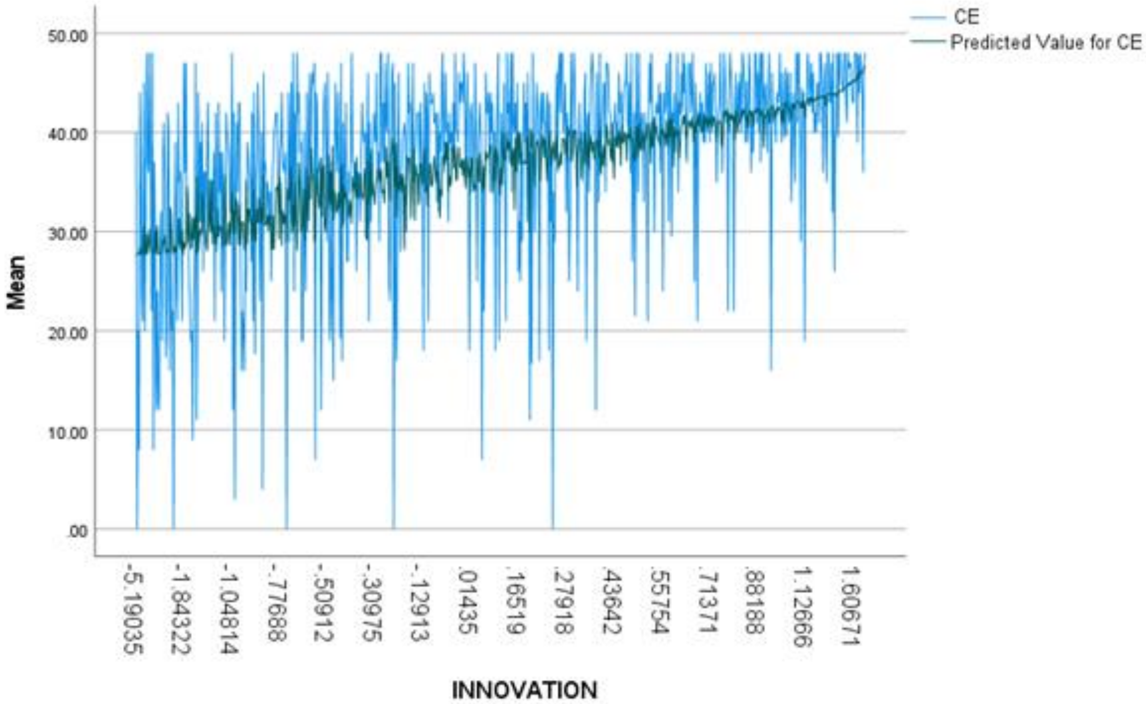


Figure A-4.8. ANN-MLP simulation (constant: Financing, and Financing* Innovation).



3. TREE REGRESSION ANALYSIS

In this section, the process for the Decision Tree Regression, the adjustment process method, the specifications (including the growing method and design parametrisation) and the output of such tree are explained in the detail. This relates to the tree regression used in Chapter 4 for the analysis of Hypotheses 3a and 3b.

3.1. Model

The Tree regression is based on the model represented in Formula 4.7 (Model 7, Chapter 4), which is represented below:

*CE = f (Financing; Innovation; Financing*Innovation)*

3.2. Tree Regression Output

Table A-4.10 provides a summary of the structure of the Tree Regression Analysis. The table shows the main specifications, from the method to the variables included, and the results of the analysis.

Table A-4.10. Summary of Tree Regression Analysis

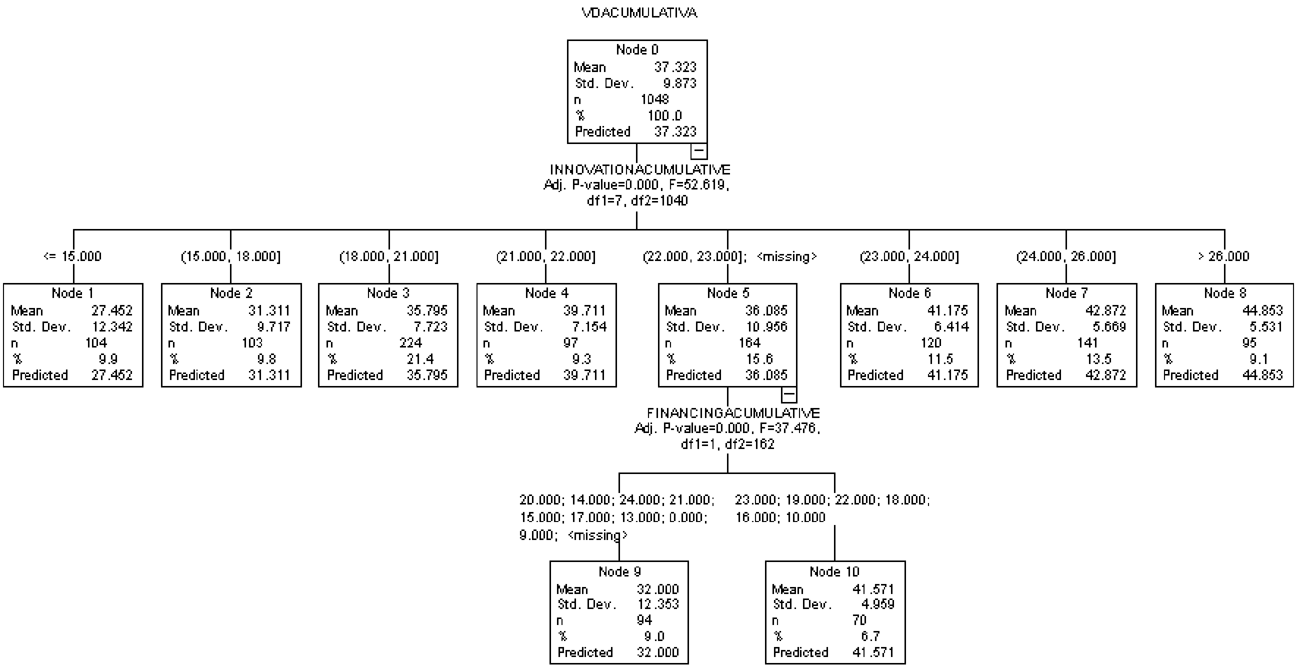
Specifications	Growing Method	CHAID
	Dependent Variable	CE
	Independent Variables	FINANCING, INNOVATION
	Validation	Cross Validation
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	INNOVATION, FINANCING
	Number of Nodes	11
	Number of Terminal Nodes	9
	Depth	2

Regarding the specifications of the model section of Table A-4.10, the most important feature is the growing method. In this case, the method selected is the Chi-squared Automatic Interaction Detection (CHAID). There are different growing methods for Decision trees: CHAID, Exhaustive CHAID, CRT and Quest. Although the most commonly utilised growing method is CHAID. Some of the advantages of using this method are that CHAID allows for multiway node splitting, influences variables, and permits for fast calculation. Hence, due to the characteristics above, and following Song and Ying (2015) and Alpaydin, (2021), we employ CHAID as the growing method for the decision tree regression model (Model 7) developed to analyse Hypothesis 3 in Chapter 4. Moreover, in terms of the CHAID criteria, we establish the significance value for splitting nodes and merging categories to 0.05. Regarding the chi-square statistics, the likelihood-ratio approach is utilised to compute the chi-square in order to determine node splitting and category merging. Although it takes longer to compute, this approach is more robust than the Pearson method (Song and Ying, 2015). Furthermore, as shown in Table A-4.10, we set the maximum tree depth to 3, the minimum cases in the parent node to 100, and the minimum cases in the child node to 50. These are parametrisations commonly used when designing a tree regression analysis (see, for example, Song and Ying, 2015).

Based on these specifications, the resulting tree regression has the structure illustrated in Figure A-4.9[60]. In this tree, the dependent variable is *CE*, and *Innovation* and *Financing* are the independent variables included, which are the same variables used throughout Chapter 4. As shown in the figure below, the resulting tree has 11 nodes and 9 terminal nodes, with a depth of 2.

[60] Figure A-4.9 replicates the tree regression model displayed in Figure 4.3 (Chapter 4)

Figure A-4.9. Tree Regression Structure.



Moreover, we produce Table A-4.11, which shows the Tree decision regression in table format. This table provides a summary of the key features of the tree regression diagram and information on each node in the tree, comprising the number of the relating parent node, the independent variable value and its statistic for the node, as well as other statistics relating to each node, such as the mean and the standard deviation. It is worth noting that the Bonferroni method is utilised in the adjustment process of significance values for splitting and merging nodes.

Hence, as shown in Table A-4.11and Figure A-4.9, the only node where there is a combination of innovation promotion and financial support institutional policies is node 5, which is not the maximum value for CE adoption. This finding is explained in more detail in the results and discussion sections of Chapter 4.

Table A-4.11. Tree Regression Simulation

Node	Mean	Std. Deviation	N	Percent	Predicted Mean	Parent Node	Primary Independent Variable: Variable	Sig.[a]	F	df1	df2	Split Values
0	37.3235	9.87328	1048	100.0%	37.3235							
1	27.4519	12.34211	104	9.9%	27.4519	0	INNOVATION	.000	52.619	7	1040	<= 15.000
2	31.3107	9.71660	103	9.8%	31.3107	0	INNOVATION	.000	52.619	7	1040	(15.000, 18.000]
3	35.7946	7.72294	224	21.4%	35.7946	0	INNOVATION	.000	52.619	7	1040	(18.000, 21.000]
4	39.7113	7.15448	97	9.3%	39.7113	0	INNOVATION	.000	52.619	7	1040	(21.000, 22.000]
5	36.0854	10.95580	164	15.6%	36.0854	0	INNOVATION	.000	52.619	7	1040	(22.000, 23.000];
6	41.1750	6.41383	120	11.5%	41.1750	0	INNOVATION	.000	52.619	7	1040	(23.000, 24.000]
7	42.8723	5.66928	141	13.5%	42.8723	0	INNOVATION	.000	52.619	7	1040	(24.000, 26.000]
8	44.8526	5.53128	95	9.1%	44.8526	0	INNOVATION A	.000	52.619	7	1040	> 26.000
9	32.0000	12.35322	94	9.0%	32.0000	5	FINANCING	.000	37.476	1	162	20.000; 14.000; 24.000; 21.000; 15.000; 17.000; 13.000; .000; 9.000,
10	41.5714	4.95946	70	6.7%	41.5714	5	FINANCING	.000	37.476	1	162	23.000; 19.000; 22.000; 18.000; 16.000; 10.000

Growing Method: CHAID
Dependent Variable: CE
a. Bonferroni adjusted

Moreover, we construct Table A-4.12, which shows the Gain Summary for Nodes of the Tree Regression Simulation. The Gain summary is a way of representing the results of the tree regression simulation analysis, which arranges all, or a portion, of the nodes from best performing to worst, and offers predictive percentage cumulative results based on the best node. Therefore, Table A-4.12 corroborates the findings and conclusions arrived at in Chapter 4. The table shows that the best performing nodes, or the ones that yield a higher probability of CE adoption in companies, are nodes 8 and 7, which are the ones that take only innovation promotion policies, whereas node 10, which includes the combination of innovation promotion and financial support policies, has a poorer performance.

Table A-4.12. Tree Regression Simulation (Gain Summary for Nodes)

Node	N	Percent	Mean
8	95	9.1%	44.8526
7	141	13.5%	42.8723
10	70	6.7%	41.5714
6	120	11.5%	41.1750
4	97	9.3%	39.7113
3	224	21.4%	35.7946
9	94	9.0%	32.0000
2	103	9.8%	31.3107
1	104	9.9%	27.4519

Growing Method: CHAID

Dependent Variable: CE

Additionally, we provide a measure for the predictive accuracy of the tree. That is, the risk of the estimate and its standard error. The risk refers to the number of wrong classifications that the tree regression can incur. Table A-4.13 displays these results, which are good for our model.

Table A-4.13. Tree Regression Simulation (Risk)

Method	Estimate	Std. Error
Resubstitution	68.411	4.018
Cross-Validation	71.350	4.333

Growing Method: CHAID

Dependent Variable: CE

Moreover, and in a similar fashion to the previous appendices, we check the predicted values of the tree regression model against the observed values to test the suitability of the model and its fit.

Figures A-4.10 and A-4.11 show the response of the tree to the variation of each input variable (i.e. *Innovation* and *Financing*) and its effect on the output of the real variables and the predicted output of the tree regression. Comparatively with the robustness checks performed in the previous models used to test Hypothesis 3, the figures show a similar response between the real variable output and predicted output. Thus, this enables us to corroborate that the tree regression used in the analysis has a good predictive capacity.

Figure A-4.10. Tree Regression simulation (constant: Innovation, and Financing* Innovation).

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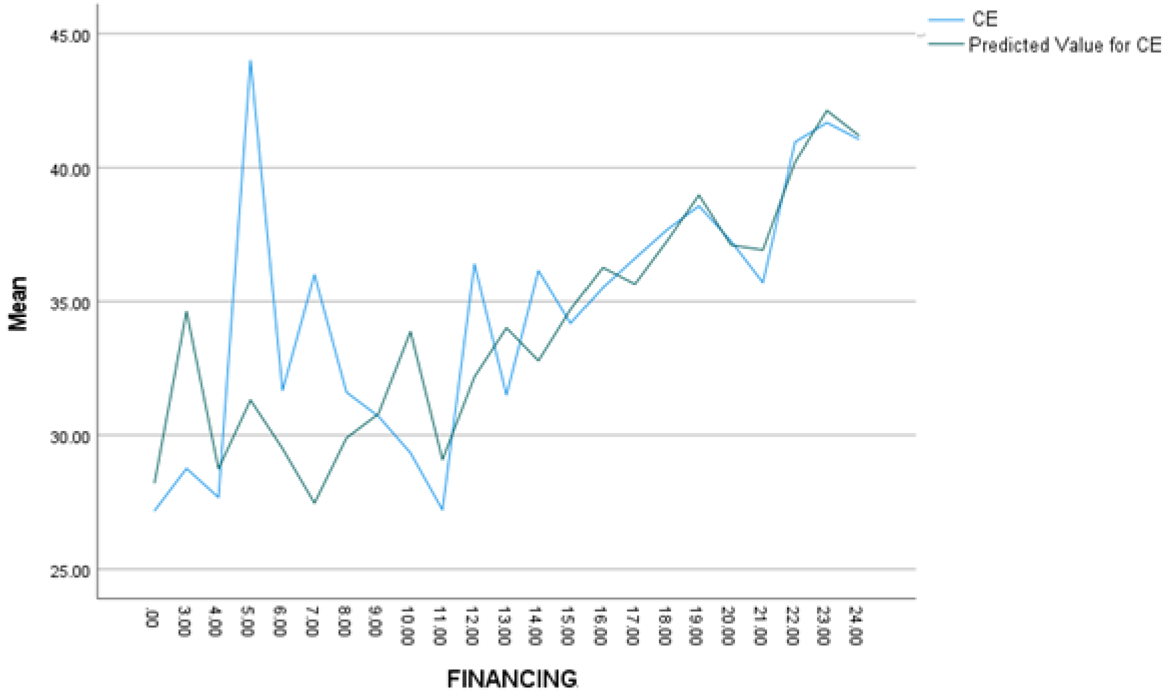
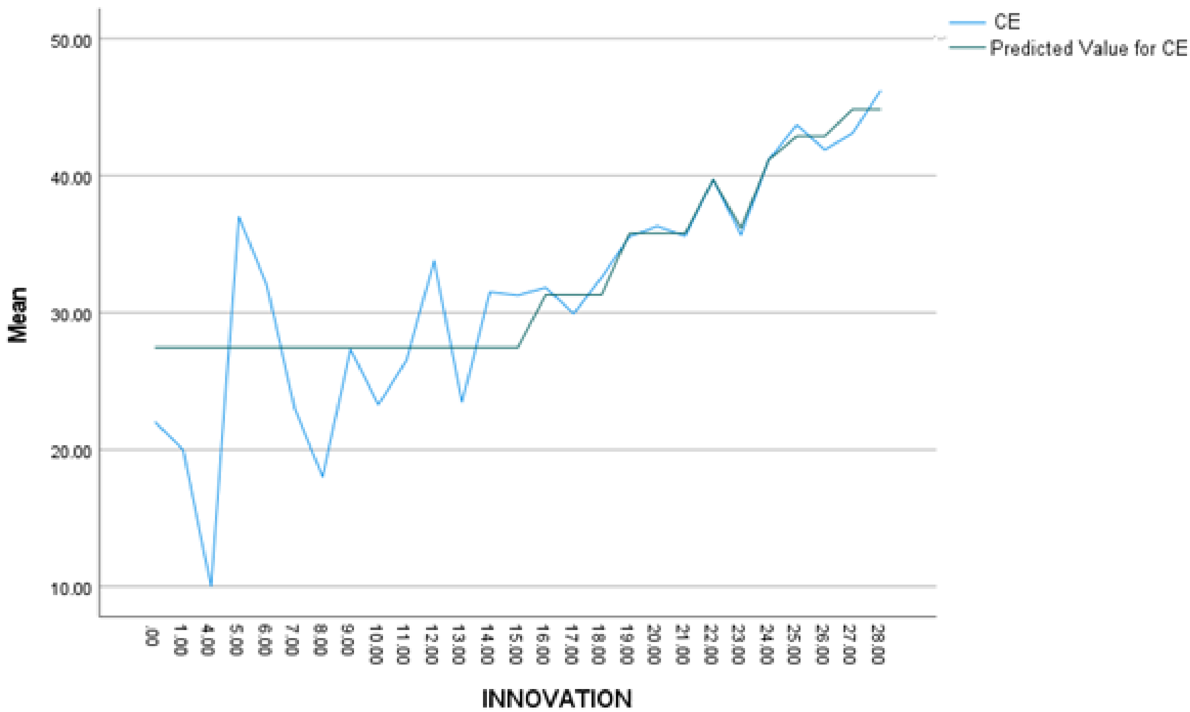


Figure A-4.11. Tree Regression simulation (constant: Financing, and Financing*Innovation).



4. REGRESSION ANALYSIS

This section of Methodological Appendix IV is dedicated to checking the robustness of the regression analysis adjustment by comparing the results of quadratic regression with other non-linear regression models (inverse and cubic) and a linear regression model. This refers to the regression analysis performed in Chapter 4 to test Hypothesis 1. The aim of this robustness test is to check whether any other type of regression model, besides the quadratic one, would have yielded a better fit for the model. However, as described below the results of these robustness checks do not reveal significant differences or improvements between these various types of analysis. Hence, the quadratic model was used for the analysis of Hypothesis 1 in Chapter 4.

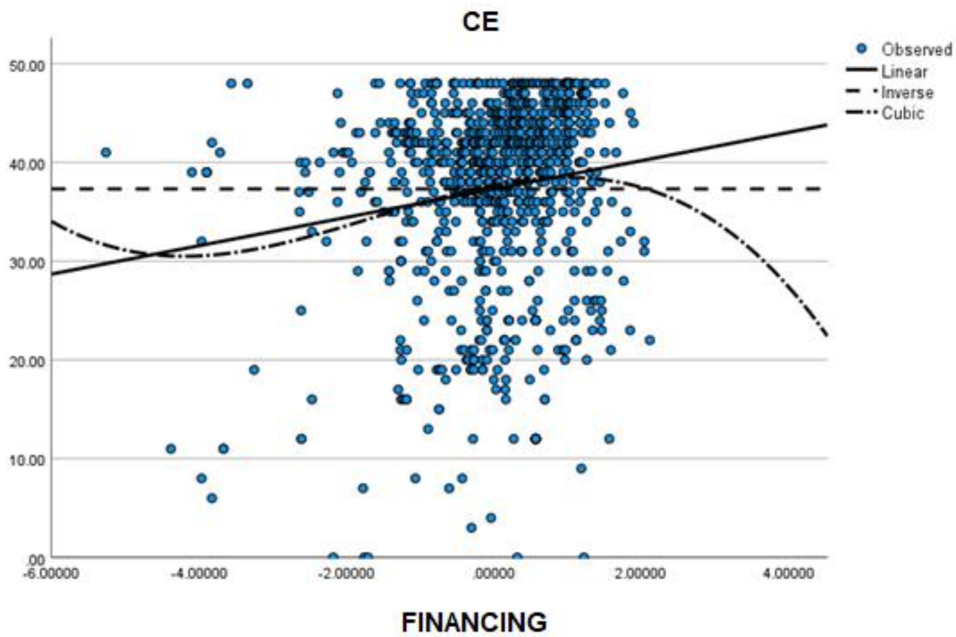
4.1 Model I

First, we check the independent variable *Financing* against the dependent variable *CE* used in the analysis in Chapter 4. This is represented below:

CE = f (Financing)

Figure A-4.12 illustrates the fit of the various regression models proposed (i.e. linear, inverse, and cubic regression). These corroborate further our regression model selection from Chapter 4.

Figure A-4.12. Regression Analysis simulation (Financing).



4.2 Model II

Second, we repeat the robustness check performed in the previous subsection, but this time the independent variable used is *Innovation*, which is the other variable used in the analysis of Hypothesis 1 in Chapter 4. Following the methodology previously employed, we regress the independent variable against the dependent variable *CE* used in the analysis in Chapter 4. This is represented below:

CE = f (Innovation)

Figure A-4.13 illustrates the fit of the various regression models proposed (i.e. linear, inverse, and cubic regression). Further corroborating the conclusions derived from Chapter 4.

Figure A-4.13. Regression Analysis simulation (Innovation).