Master Thesis – Innovation Sciences

The relationship between firm characteristics and greenwashing in the European energy sector;

An NLP approach

by

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Abstract

Greenwashing is an increasing problem in our society as it is hard to detect due to increasingly sophisticated greenwashing techniques and an asymmetry of information between firms and the general public. Firms make claims regarding their corporate sustainability in their CSR reports, which might be genuine or could be greenwashed. When firms engage in greenwashing their symbolic actions (“the green talk”) do not align with their substantive actions on environmental issues (“the green walk”). These substantive actions are measured by examining patents which are an indicator of technological innovations. We examine 134 firms in the European energy sector to determine if they are “walking the talk”. To get a better understanding of which firms are more likely to engage in greenwashing this master thesis investigates which firm characteristics influence the extent of greenwashing in CSR reports. We obtain this objective using three steps. First, we define *the extent of greenwashing* as a discrepancy between symbolic and substantive actions. Second, we find three theoretically informed firm characteristics, which were described as important determinants of greenwashing and we formulate corresponding hypotheses for them. Third, we propose a new measurement approach to test these hypotheses based on the discrepancy between symbolic and substantive actions using state-of-the-art machine learning techniques.

This thesis demonstrates that the measurement approach manages to detect discrepancies between the symbolic and substantive actions for firms operating in the European Energy sector. We find that neither of the three formulated firm characteristics directly relate to *the extent of greenwashing*, indicating that greenwashing does not seem to be a systematic phenomenon for our dataset. We also find that firms mainly engage in technological innovation with regards to solar energy, wind energy, and the reduction of emissions and toxic gasses. Moreover, we discover that the majority of energy firms are “walking the talk” with some outliers, indicating that greenwashing can be seen as an exception instead of the norm. Lastly, we find that electricity firms engage less in technological innovation on the topics wind and solar energy in comparison to oil & gas firms that seem to engage in a diversification strategy. Altogether, this research demonstrates that measuring greenwashing determinants is feasible in an empirical setting, by presenting a proof-of-concept, which hopefully will inspire other researchers to apply machine learning techniques more often to innovation sciences problems and test more determinants of greenwashing in an empirical setting.

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List of abbreviations

BERT	Bidirectional Encoder Repetitions from Transforms
BoW	Bag-of-Words
CPC	Cooperative Patent Classification
CSR	Corporate Social Responsibility
EPO	European Patent Office
EU	European Union (27 member countries)
IP	Intellectual Property
NLP	Natural Language Processing
OLS	Ordinary Least Squares
R&D	Research and Development
TBL	Triple Bottom Line

1. Introduction

Greenwashing is an increasing problem and challenge for our current society in which environmental concerns are gaining interest. Firms are increasingly pressured to change their business practices towards a more sustainable approach. Changing this approach is not without risk because transitioning towards sustainable innovation tends to be non-incremental and therefore could have adverse effects on business interests (Smink et al., 2015). Firms can decide to take this risk or try to procrastinate their change and engage in defensive institutional work (Maguire & Hardy, 2009). While engaging in this institutional work, these firms try to maintain a positive image towards the public. Maintaining this image can be done through greenwashing, which is "the act of misleading the public regarding the environmental practices of a company or the environmental gains of a product or service" (Delmas & Burbano, 2011 p. 66).

This phenomenon is especially prevalent in the energy sector, as scholars have identified several situations in which firms in the energy sector are engaging in extensive greenwashing practices (e.g. Parafiniuk & Smith, 2019; Cherry & Sneirson, 2010; Plec & Pettenger, 2012; Seele & Gatti, 2017). Within this sector, firms create sustainability reports, talk about sustainability on their webpages, spend funds on projects that make them appear green, while at the same time, spending a significantly higher amount of money on lobbying against environmental regulations (Parafiniuk & Smith, 2019). These firms have a strong focus on disclosing sustainability information in an advanced and extended way to convince the general public of their sustainability efforts (Carini et al., 2018). In this way, energy firms can sustain their current business practices, which traditionally rely on non-sustainable energy sources, while pretending to be "green".

For the general public, it is hard to detect greenwashing as the methods of greenwashing become increasingly sophisticated (Carini et al., 2018). For instance, the overuse of green marketing campaigns, that might be greenwashed, has created confusion among the general public (Gallicano, 2011). Furthermore, the general public has limited information regarding the firm's operations and to what degree sustainable business practices are adopted. Because of this lack of information, firms are able to portray themselves as environmentally friendly even though this does not align with their actual efforts (Lyon & Maxwell, 2011). For some firms, there is no clear benefit to voluntarily releasing information about their environmental impact, especially when this performance is low, and the impact can be criticized. They prefer to maintain the information asymmetry between the firm and the general public (Seele & Gatti, 2017).

To detect greenwashing, only a few studies exist that propose integrated frameworks to analyse greenwashing based on different measurement approaches, ranging from measuring selective environmental disclosure (Marquis & Toffel, 2012b; Marquis et al., 2016), over-applying greenwashing criteria (Alves, 2009; Gallicano, 2011; Gräuler & Teuteberg, 2014), to single-case studies (Cherry & Sneirson, 2011; Siano et al., 2017). However, these approaches stay at the general level of analysing CSR texts and meta-data but cannot capture details on different greenwashing topics and are designed for single-firm evaluations rather than systematic empirical investigations. Therefore, literature currently lacks empirical investigations of factors that influence the likeliness of firms to engage in greenwashing. This is problematic, as insights on these factors are needed to understand which firms are more likely to greenwash in an empirically setting, to develop more targeted regulations to effectively reduce the extent of greenwashing.

Consequently, this study aims at exploring the relationship between firm characteristics and the extent of greenwashing in CSR reports of firms operating in the European energy sector. Which leads to the following research question:

What is the relationship between firm characteristics and the extent of greenwashing of firms operating in the European energy sector?

This research question is going to be addressed in three steps; Firstly, by defining *the extent of greenwashing* as a discrepancy between symbolic and substantive actions with regards to technological innovations. Secondly, by identifying three theoretically informed firm characteristics, such as *firm size*, *firm profitability* and *organizational inertia*, which are described as prominent organization determinants of greenwashing in literature (Delmas & Burbano, 2011; Reverte, 2009; Seele & Gatti, 2017; Shahudin et al., 2015). For these firm characteristics, hypotheses are formulated to test their relationship to *the extent of greenwashing*. Thirdly, by proposing a new approach to measure greenwashing based on discrepancies between symbolic and substantive actions. Whereas symbolic actions are defined by claims made in the CSR reports and substantive actions as technological innovations that are measured using patents.

This new measurement approach will be based on the patent portfolio and CSR reports of energy firms. This because the patent portfolio provides insights into the (non-)sustainable technological innovations an energy firm pursues to transition towards more sustainable business practices. These technological innovations are important to look at as they are seen as important strategic options for energy firms to make this transition (Shaw & Donovan, 2019). These technological innovations are considered as the substantive actions of a firm, as the firm has conducted R&D research in specific (non-)sustainable innovations. Whereas the CSR reports provide insights in the symbolic actions of the firm, which might or might not be substantiated with the actual innovation actions. When the symbolic actions do not align with the substantive actions, discrepancies can be detected. These discrepancies will be identified using a Natural Language Processing (NLP) method, which can extract topics from both the symbolic and substantive actions and compare if they align. This will serve as a measurement to detect to what extent a firm engages in greenwashing in its CSR report. As such, greenwashing will be defined in this study as a discrepancy between symbolic and substantive actions.

Altogether, the aim of this thesis is to empirically investigate the relationship between firm characteristics and the extent of greenwashing in CSR reports of energy firms. As such, this thesis contributes to a better understanding regarding specific characteristics, which make a firm more likely to engage in greenwashing. Understanding these characteristics regarding greenwashing, contributes to developing environmental assessment methods and policy particularly targeted to specific types of firms that are more likely to greenwash. In the end, this could result in more effective greenwashing regulations which help to reduce greenwashing in firm communication and induce substantive environmental change.

The remainder of this thesis is organized as follows. Firstly, the theoretical and conceptual background will be explained and hypotheses regarding the firm characteristics will be formulated (chapter 2). Afterwards, the method regarding data collection and model development will be presented and validated (chapter 3). Then, we will perform a descriptive-, correlation- and regression-analysis and discuss its findings (chapter 4). Subsequently, conclusions will be drawn regarding the research question (chapter 5). We close by discussing the limitations of this research, its contributions, and providing suggestions regarding future research (chapter 6).

2. Theoretical and conceptual background

In the next section (2.1) the environmental challenges and technological innovations in the energy sector are formulated to gain insights into the sector specifics. Afterwards, in section 2.2, several theories will be outlined to get a better understanding of the phenomenon of greenwashing and the reasons for firms to engage in it. This leads to section 2.3, in which the discrepancies between symbolic and substantive actions will be discussed. We argue that CSR reports can be seen as a form of symbolic actions, and technological innovations as substantive actions. Subsequently, we argue that both actions can be combined into a discrepancy framework. At last, in section 2.4 we look into the influence of firm characteristics on the extent of greenwashing and formulate corresponding hypotheses.

2.1. Environmental challenges and technological innovations in the energy sector

The energy sector consists of firms that are involved in the production and sale of energy. This includes firms that engage in oil and gas extraction, refining, electricity generation, energy distribution, and selling this energy. Currently, oil & gas firms provide the primary resources in today's world energy mix and despite the availability of renewable energy sources, it is expected that these firms will maintain this role in the future (IEA, 2019). The increasing demand for oil & gas in developing countries will especially contribute to a steady upwards trend of these unstainable energy sources (IEA, 2019). This results in a sector that is under strong environmental pressure by the general public, NGOs and regulations, but at the same time still observes a financial future for their unsustainable business practices. A rapid transition towards sustainable energy would impose significant challenges for existing business models of these firms (Caldecott et al., 2018).

The R&D intensity (R&D expenditure as share of net income) of oil & gas firms (0.30%) and electricity firms (0.74%) are traditionally characterized as "low R&D intensity", as they both invested less than 1% of their net income into R&D (Moncada-Paternò-Castello et al., 2010). However, this tendency seems to be changing, as more firms indicate that technological innovations are considered as strategic priorities, and R&D spending has increased significantly (Alemán et al., 2010). This trend is also observed in the patent output of these firms, as for example, the number of patents in the oil & gas sector have significantly increased in comparison to the overall number of patents in other sectors (Deloitte, 2015). Altogether, it can be observed that the energy sector has become more technology and intellectual property (IP) focussed as they are under environmental pressure to develop more sustainable energy solutions.

To cope with these current pressures and challenges to become more sustainable, energy firms have several strategic options available to make this transition (Shaw & Donovan, 2019). These options are; 1) portfolio adjustment; moving away from high-carbon assets while increasing low-carbon assets, 2) adjusting the focus of R&D; focusing on developing low-carbon technologies, 3) diversification; pursuing a new low-carbon line of business, 4) extension of the value chain; pursuing business opportunities along low-carbon value chain and 5) partnership & venturing; investing in partnerships with low-carbon innovators. Options one to three are related to changes a firm could make regarding technological innovations, while the others are related to changes in their strategic and operational business practices. Thus, when energy firms employ one of these technological innovation strategies, we can assume that they become more focused on environmental-related technologies and innovations, visible in their patent portfolio.

2.2. Theories for understanding the phenomenon of greenwashing

The balancing act of corporate sustainability

When firms tackle these sustainability challenges, they engage in *corporate sustainability* which can be defined as "meeting the needs of a firm's direct and indirect stakeholders [...], without compromising its ability to meet the needs of future stakeholders as well" (Dyllick & Hockerts, 2002, p 131). Currently, firms seek to overemphasize short-term gains as they are directly evaluated by stakeholders and in particular shareholders. These practices may be in contradiction with sustainability in the long run and ignore the needs of future stakeholders. When evaluating future needs, merely looking at the economic sustainability is not a sufficient condition to gain corporate sustainability (Gladwin et al., 1995). The Triple Bottom Line (TBL) approach (Elkington, 1998) argues that a firm needs to distinguish between economic, environmental and social dimensions. When a firm wants to achieve corporate sustainability, it needs to balance the performance of these three dimensions to stratify a diverse set of stakeholders in both the short and long term.

Balancing these economic, environmental and social dimensions of sustainability may be especially hard for firms in the energy sector as they often face opposing interests on the different dimensions by different stakeholders. For example; the interest of using non-renewable energy sources is often good for the economic dimension (good for the shareholders), while this is less favourable on the environmental and social dimensions (the general public, NGOs). Because of these opposing interests, they might be more likely to engage in societally unwanted or environmentally harmful practices to spread misleading claims (Lane, 2012; Mills, 2009) or to selectively disclose information in their communication to their stakeholders and the general public (Kim & Lyon, 2011; Lyon & Maxwell, 2011; Marquis & Toffel, 2012a).

Defining greenwashing

Firms can greenwash by misleading customers regarding the environmental actions of the firm (firm-level greenwashing) or the environmental benefits of a product or service (product-level greenwashing) (Delmas & Burbano, 2011). For this thesis we consider firm-level greenwashing as we want to determine the influence of firm-level characteristics on the extent of greenwashing. In scientific literature there is no clear consensus on the definition of greenwashing among scholars that research the phenomenon of greenwashing. The definitions used in greenwashing literature are different and sometimes contradictory[1].

Altogether, this research conforms to the following firm-level greenwashing definition "the act of misleading consumers regarding the environmental practices of a company" (Delmas & Burbano, 2011, p. 66). Whereas "misleading" in our research is not defined as a deliberate misleading act from the firm, as we cannot assess the intentions of the firm and we do not want to rely on third-party accusations. In contrast, "misleading" is defined as a discrepancy between the symbolic and substantive actions of a firm. As such, we can make a risk assessment if claims from a specific firm are greenwashed by looking at the actions. How we will detect these discrepancies and define symbolic and substantive actions will be elaborated on in section 2.3.

Reasons why firms engage in greenwashing

Signalling theory can be used to describe how a firm communicates and how stakeholders choose to interpret the signal when both have access to different information (Connelly et al., 2011). Using this theory two main reasons of greenwashing are provided by Seele & Gatti (2017). The first reason is, in terms of costs, firms performing low on sustainability perceive a high incentive to engage in greenwashing. Mainly because signalling green values is easier than actually changing business processes. The second reason is, that corporate communication is based on an asymmetry of information between the firm and the general public. This creates the possibility for the use of false green communication as a signal of CSR activities. This asymmetry makes it hard for the general public to verify CSR claims with regard to the actual environmental performance of a firm.

Greenwashing can also be assessed through the locus of *legitimacy theory*, as it recognizes that firms are bound by social contracts, where their objectives are only approved when they adhere to socially desired actions (Reverte, 2009). Greenwashing can be seen as a legitimacy strategy where a firm voluntarily releases CSR reports to enhance the impression of committing to environmental values, which may or may not be substantiated (Neu et al., 1998). This strategy enables a firm to gain legitimacy as it is perceived as caring about sustainability, but actually it is willing to incur the costs

[1] As claimed by Gatti et al. (2019) the majority of academics (61%) consider greenwashing as exclusively dealing with environmental issues, while other academics (38%) also include social issues. The "degree of falsehood" of greenwashing claims also varies among scholars. Some scholars argue that greenwashing is spreading misleading claims (Lane, 2012; Mills, 2009). While others (Kim & Lyon, 2011; Lyon & Maxwell, 2011; Marquis & Toffel, 2012a) argue that it is not necessary about spreading misleading claims, but that it concerns the selective disclosure of positive environmental communication, while ignoring the negative information. Other authors argue that greenwashing can only be assessed using third-party accusation and it only exists in the eye of the beholder (Seele & Gatti, 2017).

of voluntarily disclosing misleading information. By doing so, a positive impression about the firm is created, but the CSR disclosure does not correspond with the actual environmental performance (Cho & Patten, 2007).

Differentiate greenwashing firms from non-greenwashing firms using typologies

To distinguish between firms that greenwash and those which do not, Delmas & Burbano (2011) have developed firm typologies based on environmental performance and communication as depicted in Figure 1. Firms can have a “bad performance” (brown firms) or a “good performance” (green firms). For simplicity, firms are divided into one of those two classes, but in reality, it is represented by a spectrum. Firms can either choose to have “no communication” or a “positive communication” about their environmental performance. Based on these variables, four quadrants are formulated. Especially interesting are firms that are in quadrant I, which are greenwashing firms. These firms have a bad environmental performance but communicate positively about their environmental performance. Delmas & Burbano (2011) do not describe what indicators could be used to identify firms into one of these four quadrants. Instead, they provide arguments based on case studies to put firms into a specific quadrant. This study is specifically focussing on quadrants I and II on the spectrum of environmental performance vs. positive communication. Where positive communication is seen as a symbolic action and environmental performance is seen as substantive action.

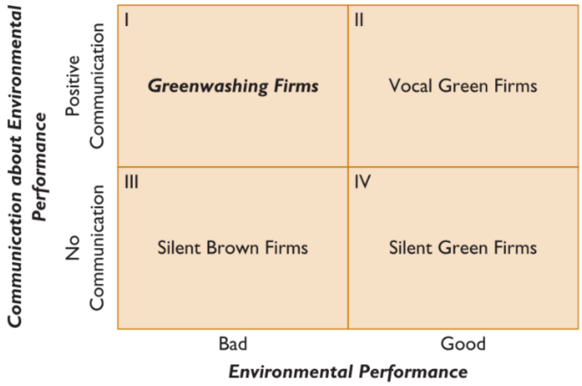


Figure 1: Firm typologies based on Environmental Performance and Communication about Environmental Performance (Delmas & Burbano, 2011)

2.3. Discrepancy between symbolic and substantive actions

The difference between symbolic and substantive actions is described in environmental literature as a difference between the degree of implementation and goal alignment (Iatridis & Kesidou, 2018; Marquis et al., 2016; Shabana & Ravlin, 2016). Symbolic actions are intended to merely signal conformity to stakeholders, without changing day-to-day activities or strategic goals. These actions are used to shape stakeholder perception to ensure the firm conforms to environmental expectations (Westphal & Graebner, 2010). In this process, they decouple their business routines from the claims they make. This could be a risky process, as stakeholders could observe these symbolic actions and scrutinize the firm (Marquis et al., 2016). On the opposite, the costs for appearing to conform are significantly lower than actual conformity while still obtaining the benefits from legitimacy (Suchman, 1995). As such, symbolic actions without substantive actions could be a rewarding strategy for firms.

In contrast, substantive actions induce higher costs and change the day-to-day activities and strategic goals of the firm with the aim to minimize the firm's environmental impact (Berrone et al., 2017; Delmas & Burbano, 2011). It often requires significant changes in business practices which imposes high risks, but these risks could be rewarding when they result in real improvements in the environmental performance and environmental legitimacy of the firm (Berrone et al., 2009). Environmental management literature has identified at least two important substantive actions: pollution prevention and environmental innovation (Berrone et al., 2009). Pollution prevention is used to minimize the amount of toxic or greenhouse gases. This requires structural investments in cleaner technologies and applying them in the production processes (Bowen & Aragon-Correa, 2014). Environmental innovation strives to improve and produce new products that enhance environmental performance. They are often associated with costly R&D, which requires substantive commitment regarding resources and time (Truong et al., 2020). Thus, engaging in substantive actions is more costly, but results in conforming to stakeholder pressures and improved environmental legitimacy.

CSR reports as a form of symbolic action

Symbolic actions of a firm often manifest themselves in the form of environmental reporting. Environmental reporting provides the means for a firm to disclose and signal their CSR activities to stakeholders. Whereas CSR at an organizational level is generally understood as a private firm policy towards operating their business in a sustainable matter. The term suffers from a clear definition within the scientific community (Castka et al., 2004), but for this research, it is formulated as the process that aims to embrace responsibility for the firm's actions and encourages a positive impact through its activities on the environment and stakeholders (Sia, 2015).

CSR reporting is increasingly recognized as an important driver for firms to engage more with sustainable business practices (Lozano & Huisingh, 2011). CSR reporting generally serves two purposes; 1) to evaluate the current state of a firm's economic, environmental and social dimensions, and 2) to communicate a firm's efforts and sustainability progress to its stakeholders (Dalal-Clayton et al., 2003; Hamann & Kapelus, 2004). As can be observed, the first purpose is directly related to the earlier introduced TBL dimensions and the second one to *signalling theory*. Thus, firms are trying to use CSR reporting to signal to their stakeholders that they are sustainable on all the TBL dimensions. These signals might be substantiated with evidence, but because firms face opposing interests on the TBL dimensions they might be tempted to engage in greenwashing and spread misleading claims (Lane, 2012; Mills, 2009).

The disclosure of CSR activities of a firm can be significantly influenced by stakeholder groups like; NGOs, governments, scholars and consumers (Huang & Kung, 2010). Firms will be more willing to undertake voluntary CSR disclosure when the benefits of providing a CSR report outweigh the associated costs (Li et al., 1997). Particularly, firms with superior CSR performance are more likely to voluntarily disclose CSR information as they seek to obtain a competitive advantage (Prado-Lorenzo & Garcia-Sanchez, 2010). Therefore, firms with a bad CSR performance are less likely to disclose their CSR information as it could adversely affect the public perception about the firm, or they seek to engage in greenwashing to portray themselves more positively.

Technological innovation as a form of substantive action

As described above, environmental innovation is an important strategy for a firm to engage in substantive actions. It is based on technological innovations that strive to improve the toxic burden of production processes and engage in climate change mitigation (Berrone et al., 2009). For energy firms, technological innovations are increasingly considered as strategic priorities (Alemán et al., 2010) especially regarding transitioning towards more sustainable business practices under strong environmental pressures (Shaw & Donovan, 2019). As such, these technological innovations are a product of a costly R&D process (Migotto & Haščič, 2015), which is a good indication of the (non-)sustainable direction of the innovations conducted. When a firm engages in environmental innovation this could signal commitment to stakeholders that the firm acts on environmental pressures. Despite these substantive actions taken, it could be hard to notice for stakeholders, as they do not have the knowledge and time to assess the technological output of a firm. Thus, these substantive actions need to be joined with symbolic actions to actively signal conformity (Berrone et al., 2009). Altogether, substantive and symbolic actions need to be coupled and aligned to obtain environmental legitimacy.

Discrepancy framework

When the symbolic and substantive actions do not align, discrepancies occur, and greenwashing might be suspected. Walker & Wan (2012) describe these discrepancies as "not walking the talk" in which the substantive actions of environmental issues ("the green walk") do not align with symbolic actions ("the green talk"). As such, greenwashing is a discrepancy between words and deeds (Seele & Gatti, 2017), in which poor environmental performance is combined with positive communication about that performance (Delmas & Burbano, 2011; Guo et al., 2017). Altogether, these discrepancies can be observed when the symbolic claims regarding technological innovation topics in the CSR report of a firm are not substantiated with technological innovations. This approach is summarized in a discrepancy framework in Figure 2.

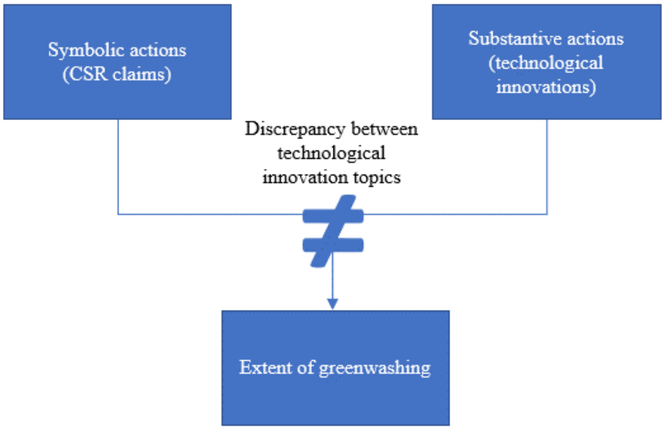


Figure 2: Discrepancy Framework

Measuring discrepancies between symbolic and substantive actions is done in a similar matter in the studies of Walker & Wan (2012) and Schons & Steinmeier (2016). The biggest difference is that Walker & Wan (2012) measured substantive actions using a research assistant that coded CSR claims based on "how substantive they are". Using this approach there is a risk of detecting claims which are still greenwashed but "look substantive". Whereas Schons & Steinmeier (2016) measured substantive actions using resource allocation or organizational change. This approach is preferred as it measures actual firm change instead of claims. For this study, we strive to also measure actual firm change but take a different metric to measure substantive actions by using technological innovations as an indicator.

To observe discrepancies between symbolic and substantive actions one could simply count how often a firm is “not walking the talk”. For example; when an energy utility firm claims in its CSR report that they engage actively in the R&D of solar panels (symbolic), but in reality, their technological output does not contain any solar panel technologies (substantive), this could be counted as a discrepancy. This is a useful approach as we are able to measure if “the talk” about a specific technological innovation is substantiated in the R&D process (Migotto & Haščič, 2015).

The advantage of taking this approach is that we can detect firm strategies based on the level of technological innovations. As such, using this framework, we can focus on which technological innovation topics are suspected of greenwashing, instead of completely marking a firm as engaging in greenwashing or not. On the other side, the disadvantage of this approach is that we assume that firms should be able to substantiate these claims with technological innovations. For example, this approach does not capture a firm that engages in environmental actions by “building a solar farm” but is not actively engaged in the R&D process of this technology.

2.4. The influence of firm characteristics

To further investigate the likelihood of different types of firms to be “not walking the talk”, this thesis discusses prominent possible determinants of greenwashing as identified in the CSR and greenwashing literature. Literature affirms the role of *firm size* (Delmas & Burbano, 2011; Reverte, 2009; Seele & Gatti, 2017; Shahudin et al., 2015), *firm profitability* (Delmas & Burbano, 2011; Reverte, 2009; Shahudin et al., 2015) and *organizational inertia* (Delmas & Burbano, 2011; Maxwell et al., 1997; Shahudin et al., 2015) as possible determinants of greenwashing[2]. These characteristics have not yet been systematically evaluated in an empirical setting, as they were mostly derived on theoretical grounds.

Firm size

Several studies have empirically found a positive relationship between firm size and CSR disclosure (Cowen et al., 1987; Reverte, 2009). These studies showed that larger firms are more likely to disclose CSR information, but it does not necessarily mean that the information provided is correct

[2] These characteristics are by no means exclusive, as possible other firm characteristics also might influence the probability of greenwashing like; ownership structure, listed on stock exchange, male/female leadership, lifecycle stage, incentive culture, intra-firm communication, number of shareholders.

and not greenwashed. Because these firms are more engaged in CSR reporting, their CSR reports become more sophisticated and extensive (Carini et al., 2018). This could mean that they try to be good corporate citizens and try to create as much environmental transparency as possible or they strategically try to influence stakeholder perceptions in a sophisticated way (Seele & Gatti, 2017).

As introduced in the theoretical background, *legitimacy theory* describes firms being bound by social contracts. These contracts are enforced by the general public and stakeholders. When firms are larger, they are more visible and get more attention from the general public and stakeholders, which means they are bound by more social contracts. This is in line with the political cost hypothesis (Watts & Zimmerman, 2006), which states that larger firms are more visible to the public, have more market power, and are more newsworthy. Hence, they are more prone to consumer hostility, public resentment, militant employees and government regulations (Reverte, 2009). This applies especially to greenwashing accusations as it is a phenomenon that exists in "the eye of the beholder" and is based on stakeholders' accusations (Seele & Gatti, 2017). Moreover, larger firms have generally a larger effect on the community and therefore have inherently more stakeholders that influence the firm (Knox et al., 2005). Thus, having more stakeholders inherently means more risks of being accused of greenwashing. For example; NGOs (like Greenpeace) pay more attention to Shell in comparison to smaller unknown oil & gas firms, as Shell is well known by the general public and has a large effect on the community. This implies that larger firms are more "under threat of audit" (Lyon & Maxwell, 2011) by NGOs than smaller ones. In general, being under the threat of audit will prevent firms with poor environmental performance to engage in greenwashing (Huang & Kung, 2010). Thus, we expect that larger firms are less likely to engage in greenwashing.

H1: There is a significant negative relationship between firm size and the extent of greenwashing in CSR reports.

Firm profitability

Several studies have empirically found a positive relationship between profitability and CSR disclosure (Haniffa & Cooke, 2005; Wang et al., 2008). Firms with higher profitability are more likely to distinguish themselves from other firms by releasing more information that positively distinguishes them (Dye, 1985). Hughey & Sulkowski (2012) observed that firms in the oil & gas sector that release more information have a better CSR reputation. Again, this perspective only considers the availability of the data and not the quality of the content, as the CSR reputation was measured by aggregating the presence of CSR information. It could be argued that profitable firms have more financial resources, the so-called organizational slack (Cowen et al., 1987), to develop an extensive CSR report. Whereas firms with lower profitability can put fewer financial resources in developing a CSR report.

It could be argued that profitable firms have more financial resources to cope with temporarily reduced profits from reputational damage when begin accused of greenwashing by NGOs in comparison with lower profitable firms with less financial resources (Delmas & Burbano, 2011). Moreover, they are able to create extensive and sophisticated CSR reports in which they have the resources to hide the fact they are greenwashing. In the unlikely case that they are accused of greenwashing, they can cope more easily with fines that might be imposed on them and whenever needed, can hire legal teams to defend them against these fines. This means that they observe the potential consequences of getting caught are smaller, as they are able to cope with them. Thus, when making a risk assessment more profitable firms might be more likely to assess greenwashing as a financially beneficial strategy.

H2: There is a significant positive relationship between firm profitability and the extent of greenwashing in CSR reports.

Organizational inertia

Organizational inertia is well accepted within the management literature as a factor that explains and influences firm behaviour (Rumelt, 1995). Organizational inertia can be described as a strong persistence of existing forms and functions within a firm that hampers strategic change. Firms seek by nature to perpetuate stability (DiMaggio, 2009), as they resist change and employees generally prefer certainty in structure and routines. This phenomenon is especially prevalent in older firms in comparison to newer firms (Hannan & Freeman, 1984). As the structures and routines are carved out deeply within older firms, due to the fact that they grew over a longer period of time. Thus, organizational inertia is able to explain the lag between a firm manager's green intent and the actual implementation of this intent by the firm itself (Maxwell et al., 1997). For example; when a CEO has a genuine intent to increase corporate sustainability, the "talk" is easily done by putting this statement in a CSR report, while the "walk" takes a lot more time and resistance because of organizational inertia within the firm. This time-lag poses a high risk of getting involved in greenwashing as the "walk" and "talk" are not aligned. This risk is higher for firms with a stronger organisational inertia and thus we expect them to engage more in greenwashing.

H3: There is a significant positive relationship between organizational inertia and the extent of greenwashing in CSR reports.

3. Methods

In the next section (3.1) the general research design will be outlined and justified. Following, we will explain how the firm sample is defined using a firm selection funnel (section 3.2). Afterwards, the operationalization of the dependent variable (*extent of greenwashing)* using a machine learning pipeline will be explained in Section 3.3. The operationalization of the different steps of this pipeline will be discussed and argued for. Subsequently, the independent variables *firm size, profitability* and *organizational inertia* are operationalized in section 3.4. At last, in section 3.5 we will go into detail regarding the regression analysis which is used to test the hypotheses and analyse how the independent variables are related to the dependent variable.

3.1. General research design

The research design of this thesis differs from other approaches in literature to detect greenwashing, which are mainly based on applying greenwashing criteria (Alves, 2009; Gallicano, 2011; Gräuler & Teuteberg, 2014) and single-case studies (Cherry & Sneirson, 2011; Siano et al., 2017). Literature makes use of greenwashing criteria as it helps to detect different sorts of greenwashing using different data sources. The downside of this approach is that it is based on the actions of the firm which are judged by the researcher or third parties (NGO's, media, etc.) which is hard to do in an objective and systematic way. The single-case study approach helps in obtaining highly specific qualitative information on specific occurrences of greenwashing. The main disadvantage of using single-case studies is that it does not help in empirically testing determinants of greenwashing as it is unable to obtain significant statistical results due to fact that this approach does not scale due to a large amount of time and resources needed to analyse firms.

Opposed to current literature, this thesis uses a quantitative approach to provide systematic insights that could be used to statically test determinants of greenwashing. This will be done using a machine learning pipeline to measure the *extent of greenwashing* combined with a statistical regression analysis to gain a better understanding of what firm characteristics could explain greenwashing. Measuring greenwashing will be done based on the discrepancy framework, for which symbolic actions are operationalized using CSR reports and substantive actions using patents (Figure 3). *The extent of greenwashing* score (also referred to as "greenwashing score") for each firm will be calculated based on the discrepancies between these symbolic and substantive actions. When many discrepancies occur, the greenwashing score will be high, and a firm is suspected of greenwashing. Afterwards, the greenwashing scores, calculated by the pipeline, will be used to perform a statistical analysis with regards to the firm characteristics. This enables us to find statistical evidence into the possible relationships and get a better understanding of the characteristics which explain why specific firms might be more likely to engage in greenwashing.

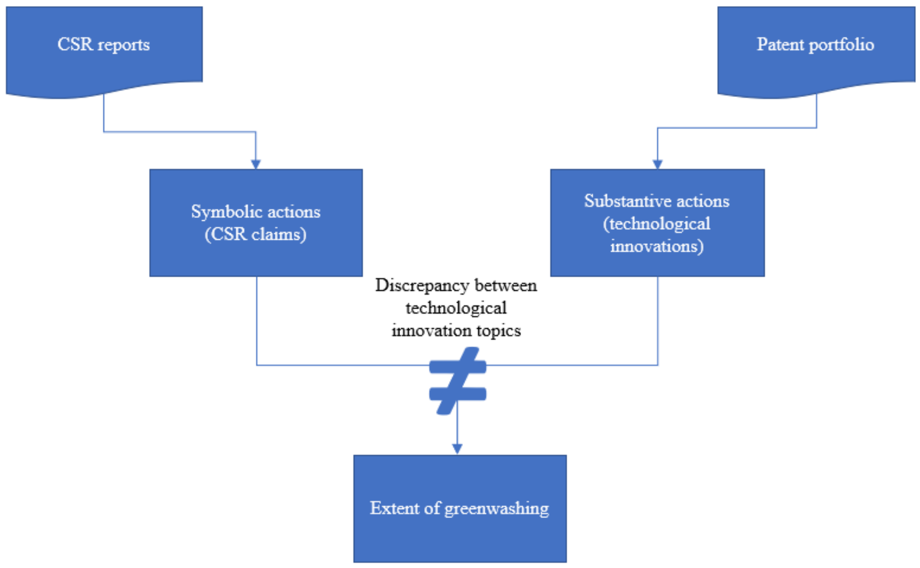


Figure 3: Operationalization of discrepancy framework

By choosing this quantitative approach we are able to assess a set of 134 firms, consisting out of 55.328 patent- and CSR sentences. By doing so, we can cope with the limitations of single-case studies as we are capable of assessing a large set of firms and perform a multiple regression analysis to empirically test the relationship between firm characteristics and *the extent of greenwashing*. The main disadvantage of this approach is that some firm specifics are missed in the analysis which would normally be found using a greenwashing criteria or case-study approach. For example, an energy utility firm that mainly buys solar panels from external parties, without participating in any R&D themselves. We assume that these firm specifics do not significantly influence the overall result and these cases could be detected as outliers that require a manual assessment. As such, the results of this method should be considered as a suspicion of greenwashing which should be confirmed on a firm-by-firm basis in further qualitative analysis.

3.2. Firm sample based on firm selection funnel

The firm sample for this thesis is obtained using a firm selection funnel (see Appendix A. which is based on the following criteria:

1) Firms need to operate within the EU, to make a fair comparison within the same European jurisdiction.
2) Firms need to engage in technological innovation, as patents provide insights in the direction of knowledge development of a firm (Archibugi & Pianta, 1996). Firms are filtered based on a threshold of 10 patents in the Orbis- (Bureau van Dijk, n.d.) and Espacenet-database (Espacenet, n.d.).
3) Firms need to operate within the energy sector, this because merely looking at the broader scope of technology firms will suffer from different firm patenting strategies that vary significantly between sectors. The filtering is done based on the SIC industry codes (13, 29, 491, 492, 493) as this set of codes represents firms active in the energy sector.
4) Firms need to be merged if they are registered in multiple European countries, as they generally only publish a single CSR report for the merged firm.
5) Firms need to publish a single CSR report.

After applying the funnel, the firm sample consists of 134 firms distributed over 25 EU countries. For this research, it is especially interesting to investigate how criteria two (patents) and five (CSR reports) influence the selection process and check if it introduces biases regarding our independent variables[3]. When a firm adheres to these criteria it is labelled as "correct" and is included in the analysis as can be seen in the following figures.

There seems to be a strong bias towards smaller firms not being included in this research (Figure 4), as these firms are less likely to have at least 10 patents and/or publishing a CSR report. This makes sense, as they have fewer resources to engage in filing patents or writing a CSR report. Moreover, it could be observed that the distribution of firms included in the research is strongly positively skewed, so smaller firms are overly represented in our dataset.

[3] Note that the independent variables will be fully operationalized in section 3.5, here they are merely used to illustrate possible selection biases.

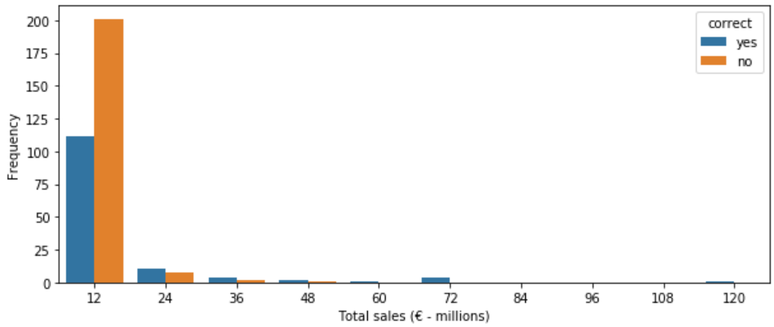


Figure 4: Histogram for including firms regarding firm size measured in terms of total sales

For profitability (Figure 5) it could be observed that slightly profitable firms are less likely to be included, as they might publish fewer patents and/or CSR reports. For organizational inertia (Figure 6) it could be observed that no strong bias occurs. The distribution of included firms regarding organizational inertia is positively skewed. When drawing conclusions, these biases and distributions should be considered.

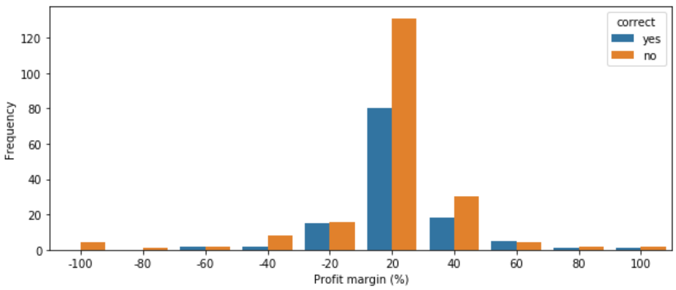


Figure 5: Histogram for including firms regarding profitability measured in terms of profit margin

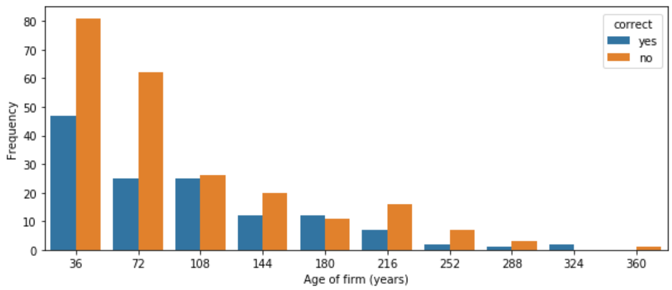


Figure 6: Histogram for including firms regarding organizational inertia in terms of age of a firm

3.3. Measuring the extent of greenwashing based on CSR reports and patent portfolio

The dependent variable, *the extent of greenwashing*, was calculated using a data science pipeline which is visualized in Figure 7. The starting point of the pipeline is our set of energy firms, for which the greenwashing score is unknown. In the subsequent steps, the discrepancy between the CSR texts and patents is calculated based on sentences embeddings and clustering. In the end, these discrepancies can be used to calculate the greenwashing score and assign them to all the individual firms in our set. The different steps of this pipeline will be elaborated on in the coming paragraphs.

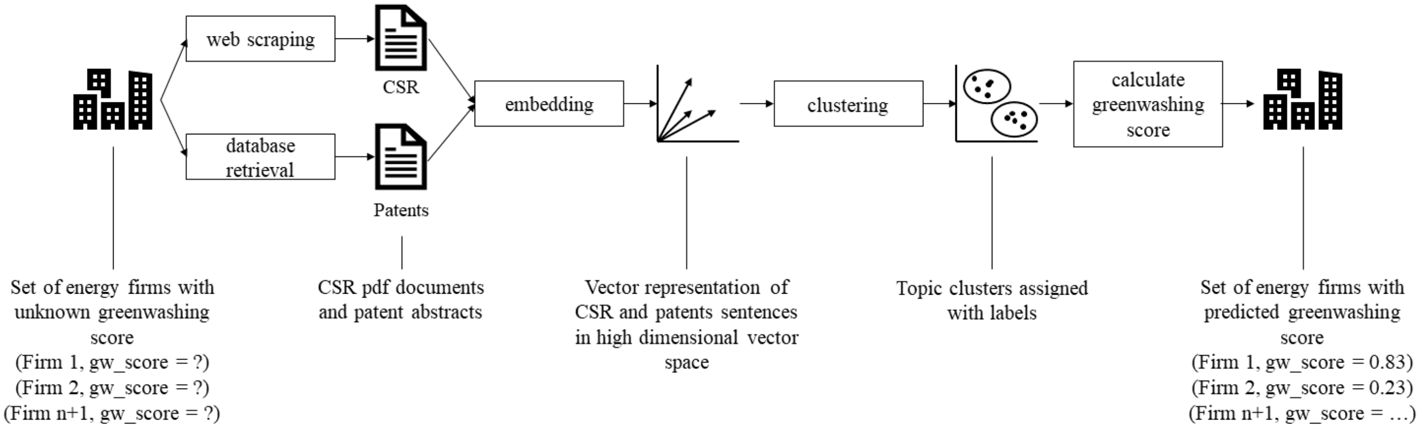


Figure 7: Machine learning pipeline to calculate firm greenwashing scores (See Appendix B. for enlargement)

Gathering CSR reports using web scraping

As described in the theory section, CSR data can be used to detect sustainable business practices. Clarkson et al. (2019) demonstrated that currently 98 percent of stock registered firms engage in CSR reporting. CSR reporting is done using a wide variety of sources, like; media releases, web pages, annual reports, websites, supplemental disclosures, and standalone CSR reports (Mahoney et al., 2013). For this research, we only focussed on one source, namely CSR reports, as most firms publish these reports on a yearly base and reflect on their sustainability efforts. The firms themselves can decide which topics to include in their CSR efforts which results in an extensive range of topics (Kolk, 2003). Moreover, sustainability reports do not have a fixed format and are not prescribed by mandatory reporting criteria. To cope with this extensive range of topics and unfixed format NLP techniques were used to extract relevant technological innovation topics and ignore other irrelevant topics.

The CSR data has been obtained using a web scraper (Scrapy-WebCrawler, n.d.) that performs a search query on Google, it finds the CSR report and saves it in a database. The advantage of using this method is that there is no need to crawl the complete website of a firm. By specifying a search query, we were able to filter directly on CSR reports. Table 1 provides the template of a search query that was used to obtain the CSR report of a specific firm in PDF-format for the year 2017. To validate that for every firm the relevant CSR report is found, the obtained PDF-file has been assessed by the researcher, to verify it was the correct CSR report. When this was not the case, the researcher manually searched for the correct CSR report on the firm website and stored it in the database. By doing so, sample size reduction due to scraping errors is reduced to a minimum. For every firm per year, there is inherently only one CSR report which can be found. This in the end, reduces Type II errors, as the sample size is as big as possible, to detect if empirical differences truly exist.

Table 1: Search query to gather CSR reports

Search query
"corporate sustainability report" OR "sustainability report" OR "CSR" AND "2017" site:*domain-of-firm.com* filetype:pdf

Gathering patent data using database retrieval

As described earlier, patents can be used to measure technological innovation as patents contain far more information than only the actual inventions patented. It provides insights in the technological innovations of a firm and represents the intermediate outputs of an inventive process (Migotto & Haščič, 2015). It also provides insights into the type of research and technological development the firm conducts (Long, 2002). Patents can be used for technology forecasting and provide insights into possible technological directions of a firm in the future (Chen et al., 2011). More specifically, environmental patents are seen as a strong signal for the environmental actions of a firm (Berrone et al., 2017). This is especially applicable for firms in the energy sector where technological innovations are seen as important strategic options to transition towards more sustainable energy sources (Shaw & Donovan, 2019).

Several studies (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Markatou, 2012; Yin & Wang, 2018) use environmental patents as an indicator of environmental performance. These studies base their assessment on whether a patent is environmentally friendly on the CPC-classes in which they are assigned by patent examiners. The authors themselves decide afterwards if specific classes can be considered as sustainable or if they adhere to a predefined set of classes that are generally considered as sustainable (like; Y02, ENV-TECH). This thesis took a similar approach, as it adheres to the Y02 class distinction[4].

[4] As patents are classified in CPC-classes by patent examiners, the sustainability classification of this method relies on the professional skills of these examiners.

The type of information that is derived by using patents merely provides insights into the (non-)sustainable technological innovations of a firm, it does not provide information regarding other environmental practices of a firm (like; closing a coal-fired power plant and buying PV panels instead). Thus, this data is inherently limited as it only provides insights into the technological innovations of a firm that are patentable. Nevertheless, the proportion between patents in sustainable classes in comparison to all patents could indicate an organizational focus of a firm with regards to its environmental practices.

When using patents as an indicator of technological innovations, special attention should be taken with regard to the publication-lag of these patents, as patents are typically disclosed after 18 months after the filling (Migotto & Haščič, 2015), but some patents could take up to several years because of different procedures. Moreover, it should be considered that patent data provides an imperfect view of the actual innovation efforts, as some firms pursue IP to solely gain a strategic competitive advantage (Nameroff et al., 2004). Filtering out this influence is out the scope of this thesis, but when this strategy is suspected, the author could exclude this firm from the analysis and report on it.

For every firm, patent data from 2015 to 2017 has been gathered to consider the publication lag and account for yearly fluctuations of patents. For each patent, the abstract and CPC-code were retrieved from the Espacenet patent dataset (Espacenet, n.d.) of the European Patent Office (EPO). The abstract provides unstructured textual data regarding the innovation, whereas the CPC-code enables us to differentiate between patents that contribute to mitigation or adaption against climate change by checking if a patent is part of a Y02-class. When patents are assigned to multiple classes and one of these classes is Y02, the full-count method was used, and the patent was classified as Y02.[5]

Embedding of CSR reports and patent data

The next step in the machine learning pipeline is to transform the raw CSR reports and patent abstracts into sentence embeddings. Both datasets can be seen as raw input data consisting out of a large number of sentences, every sentence was transformed into a sentence embedding. This transformation is common in the machine learning field to enable a computer to "understand" the text (Deng & Liu, 2018). Traditionally NLP researchers relied on techniques as TF-IDF and LDA to obtain these embeddings and make the computer understand text. The biggest limitations of these techniques

[5] Weighting patents based on the number of citations is a common practice within the scientific community. This research did explicitly not use this method, as the number of patent citations is an indicator of the economic impact of the patent (Harhoff et al., 1999), as it does not represent the importance with regards to the CSR activities.

are that they are unable to distinguish semantical embeddings and they do not perform well on short texts. This is problematic as the computer is unaware of the context in which words are used, resulting in sometimes interpreting sentences wrong. A newer approach is to use a language representation model which is called Bidirectional Encoder Repetitions from Transforms (BERT) (Devlin et al., 2018). BERT is a state-of-the-art deep neural network which currently achieves one of the highest scores on a wide variety of NLP tasks, generally accepted by the scientific community (Devlin et al., 2018) and is also applied in a large number of scientific studies (e.g. Gao et al., 2019; Liu & Lapata, 2019; Polignano et al., 2019). The BERT model can transform words into high-dimensional vectors ($\mathbb{R}^{1024}$). By doing so, every vector represents a single word in high dimensional vector space. Words that are similar to each other (e.g. "cat" & "dog") will have a short distance between their vectors, while less similar words (e.g. "cat" & "plane") will have a longer distance, this because they are used in different contexts. For this research we used full sentences instead of single words.

This research used different methods to obtain sentences embeddings to see which method performs the best on our dataset. We used the more traditional embedding methods TF-IDF and LDA, as they are widely used in scientific literature in the last decade. We also used BERT as a state-of-the-art method that is only used in literature the last two years. At last, we combined BERT with LDA as a combined version might yield better performance as both methods could benefit from each other (Stveshawn, 2020).

Model performance

The performance of the different embedding methods (TF-IDF, LDA, BERT and LDA-BERT) were tested based on two criteria to check which technique yields the best results for our dataset. The first criterion, visually inspecting the formation of clusters, is used to check how the data points are scattered for the different clusters. The second criterion, the coherence- and silhouette scores, are used to determine how well the chosen embedding method (in combination with clustering algorithm) is able to form coherent clusters. When both scores are high it indicates that proper clusters are formed.

As can be observed in Figure 8 and Table 2, TF-IDF does not seem to form coherent clusters and scores especially low on the silhouette score. This could be explained by the fact that the method is based on the bag-of-words (BoW) model. Therefore, it does not perform well on single sentences and cannot determine co-occurrences with regards to other sentences. LDA does also not form coherent clusters and has an even lower coherence score. The reason for this could be found in the fact that it is also based on BoW and it is not able to capture the single sentences based on the probabilities which are calculated by LDA. On the contrary, the BERT model significantly outperforms TF-IDF and LDA, because it can capture the complex contextualisation. BERT is able to "understand" the sentences instead of counting word frequencies. Moreover, visually more coherent clusters seem to be formed, despite that some of them could end up differently based on the cluster centroid initialization of K-means. The LDA-BERT combination seems to outperform BERT slightly, which could be observed visually by looking at the cluster and in the coherence and silhouette score. This results from the LDA sentence probabilities used in combination with the BERT sentence embeddings. Altogether, the LDA-BERT model achieves the highest performance and thus this embedding method is chosen to determine the greenwashing score for the remainder of this research.

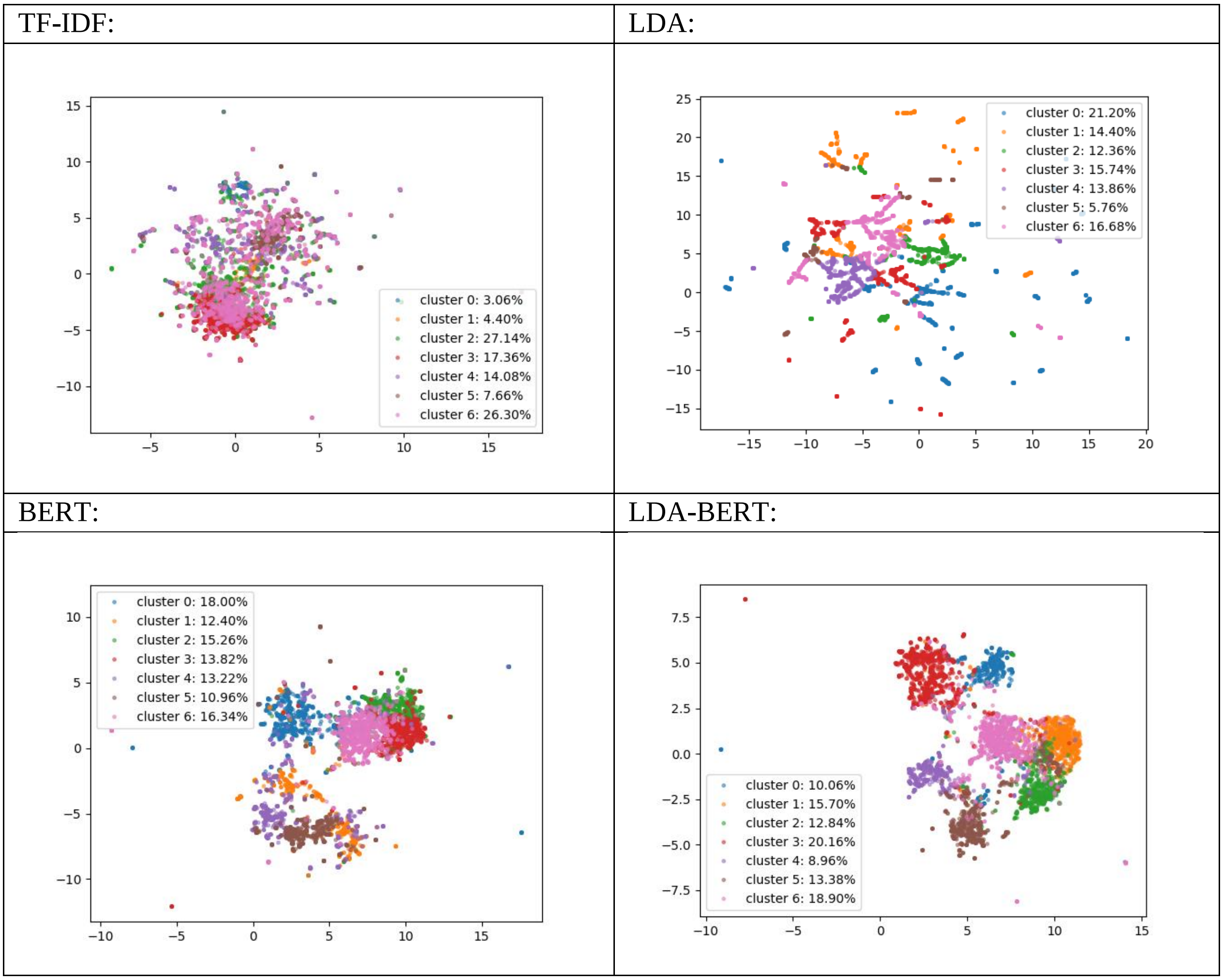


Figure 8: Clustering visualization (UMAP) of four vectorization methods (k=7) (N=5000)

Table 2: Evaluation metrics of four vectorization methods (k=7) (N=5000)

Metric / method	TF-IDF + clustering	LDA	BERT + clustering	LDA-BERT + clustering
Coherence score (should be high)	0.5397	0.4713	0.5466	**0.5992**
Silhouette score (should be high)	0.0074	N/A	0.0554	**0.1301**

Pre-processing data for LDA-BERT

Now that we have established that LDA-BERT yields the best result, we discuss in more detail what pre-processing steps were taken for this model. The CSR data was pre-processed by removing; non-ASCII values, punctuation and numbers[6]. Afterwards, the paragraphs were split up into sentences, as BERT only supports sentences up to 512 characters. As can be observed in Figure 9, limiting the sentence's lengths to 512 characters was only needed for a small set of sentences. Sentences shorter than 20 characters were removed from the dataset, as they mainly contained headers, copyright statements and separate sets of words, that did not resemble interesting data regarding CSR statements.

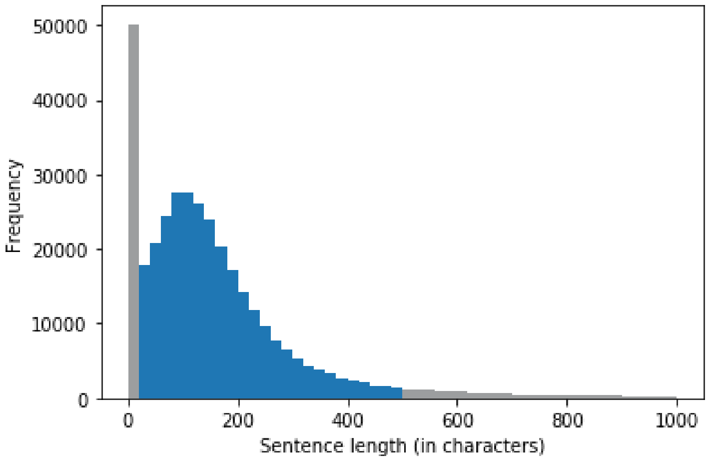


Figure 9: Frequencies of sentence lengths

Afterwards, a distinction was made between CSR sentences which make statements regarding sustainability and sentences which make statements about other topics, as we are only interested in CSR statements which state something regarding sustainability. The sentences were filtered based on a set of sustainability keywords, these keywords were generated using various algorithms to find similar words (Related Words Org, n.d.). As a result, a large set of keywords (provided in the source code) is used, to make the filtering as inclusive as possible, to get all the relevant CSR claims regarding sustainability. The effects of this filtering process are reported on in Figure 10, it provides insight in which keywords were found most often in the filtering process, indicating what kind of

[6] We explicitly did not remove stop words, which is generally a basic pre-processing step in NLP, as our model automatically weights them as less useful but still uses them to obtain the correct semantics of the sentences (Qiao et al., 2019).

sentences are included in the analysis. The filtering process of the patents is rather straightforward, only patents with a Y02 CPC-class are included and are not further pre-processed.

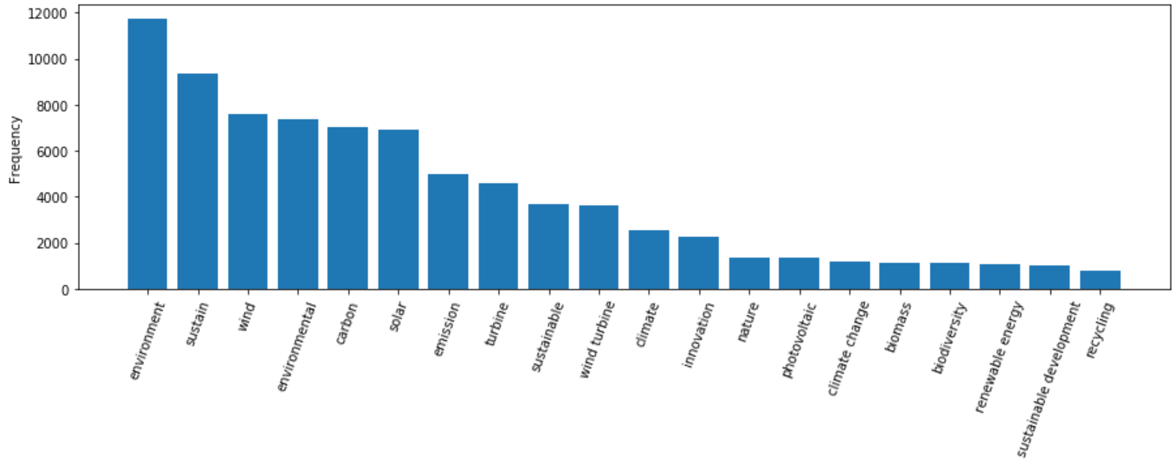


Figure 10: The frequency of the 20 mostly found words during the filtering process

After this filtering process, all the sentences (CSR and patent) were transformed by tokenizing the sentences and adding special tokens to mark the beginning and the end of sentences. The tokenization and adding the special tokens is a pre-requirement for BERT. The minority class, the CSR dataset, was up-sampled such that an equal amount of CSR and patent data points were fed into the embedding method to obtain equal clusters.

The LDA-BERT method was run, and the vector representation of the CSR and patent sentences in (high dimensional) vector space were fetched. Every sentence is represented by a single vector of a specific length, pointing in a specific direction. These vector embeddings were used to determine the similarity of the sentences and cluster them; more information will be provided in the next section.

Clustering

Semantically speaking the patent and CSR sentences are inherently different, patent sentences make use of jargon and technology focussed words, whereas CSR sentences make use of more broadly known words and sometimes buzzwords. When you feed both datasets into an embedding method that is made to detect semantical differences, the biggest signal that will be picked up will be the semantical difference between both datasets. This is something we did not want to measure, as we already know that both datasets are inherently different, we want to find CSR sentences which are similar to patent sentences. To cancel out this unwanted signal, the inherent difference between patent data and CSR data has been calculated in high dimensional vector space and removed from both datasets. To achieve this result, the centroid, which is the arithmetic mean position of all the points, is calculated for the patent data and CSR data (Figure 11). A difference vector can be calculated between both centroids, which represent the semantical differences between both datasets. This is due to the nature of vector embeddings, where the semantical difference between two datasets is captured by the difference vector in high-dimensional space. Deducting this difference vector from one of the two datasets would result in both datasets overlapping and starting to form clusters together.

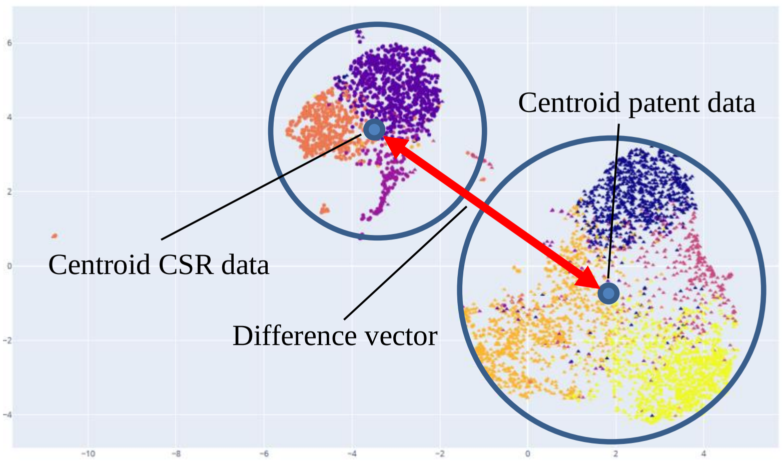


Figure 11: Semantical difference between CSR and patent sentences

Now that the semantical difference between both datasets was accounted for, the K-means clustering algorithm was applied. K-means is a common clustering method in machine learning (Wagstaff et al., 2001), which aims at partitioning *n* observations into *k* clusters, where each observation belongs to the cluster with the closest mean. Consequently, we need to provide the K-means algorithm with a fixed number of clusters (*k*). The "elbow" method (Yellowbrick, n.d.) is a commonly used heuristic in mathematics to determine the point where choosing more clusters results in over-fitting, instead of improving the fit. By plotting the number of clusters against the sum of square distances (which is a measure of distortion) (Figure 12), the optimal *k* can be found by looking at the point where the graph sharply transitions from decreasing quickly (under-fitting region) to decreasing slowly (over-fitting region). As can be observed there is no sharp transition point, but the transition seems to be happening between *k*=5 and *k*=8. Therefore, we choose *k*=7 as the optimal number of topic clusters.

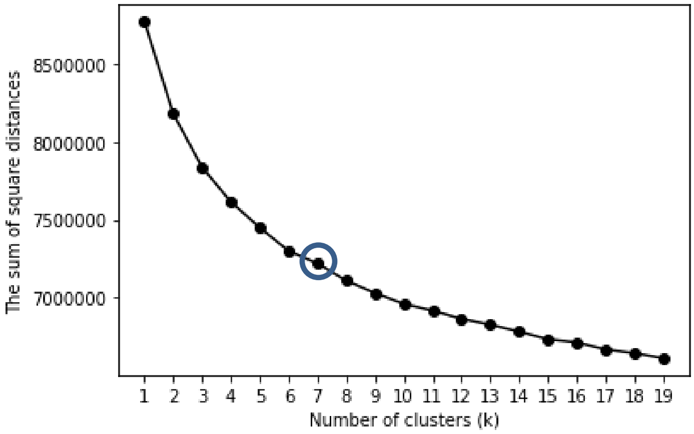


Figure 12: Elbow plot to determine the number of clusters

The seven clusters calculated by K-means are merely clusters of data points, which were not assigned to specific topic clusters yet. Assigning topic clusters was done by the researcher based on systematically assessing word clouds and individual data points. For every cluster, a word cloud was generated to display the commonly used words within this cluster. This provides a good indication regarding the topic of the cluster. Based on the word clouds the researcher wrote down the expected topic and read 20 random patent- and CSR-sentences within this cluster. If the topic discovered in the word cloud describes the meaning of these sentences, the topic was assigned as the label for this cluster. If this was not the case, the above procedure was repeated until a suitable cluster label was found. Besides, for every cluster an assessment was made to determine if it can be considered as a technological innovation. This assessment was done by looking at the percentage of patents in the cluster, when the percentage is high, we could assume that a technological innovation is relevant for this cluster. Moreover, the word clouds were analysed to check if they contain groups of words that refer to technological innovations. For example, the word group “photovoltaic, cell, solar” would refer to the technological innovation of “solar energy”. The possible drawback of using this labelling method is that the researcher is unable to be completely objective, as he is aware of the research goal. This effect is partly reduced since the labelling does not only rely on the word clouds, but also on the individual data points itself.

Calculating the firm specific greenwashing scores

Not all the discovered topic clusters, with their corresponding label, are useful for detecting greenwashing. As this research is focused on detecting greenwashing based on technological innovations, only topic clusters which were encompassing technological innovations were used for further analysis and detecting greenwashing. For each of these technological innovation clusters, the discrepancy between symbolic actions (CSR) and substantive actions (patents) was calculated at the firm level. The discrepancy score was defined by the ratio between the number of symbolic actions and the number of substantive actions. As the proportion of both actions determines if a firm is "walking the talk", when for example a firm talks in 50 sentences about wind turbines ($N_{CSR} = 50$) but only has few wind turbine patent sentences ($N_{patent} = 2$), the ratio is $50:2$. When this ratio is expressed as a fraction, the greenwashing score can be calculated ($GW_{score} = \frac{50}{2} = 25$). The higher the score, the more likely it is that a firm might be engaged in greenwashing.

The exact calculation of the greenwashing score can be formulated as a set of rules which are written down as pseudo-code in Figure 13. The greenwashing score is calculated for every firm with a specific id F_{id} from the total list of firms $[F_{ids}]$. Then, for this firm we loop through every technological innovation cluster $C_i(F_{id})$ which is in the list of all available clusters $[C_n(F_{id})]$. The greenwashing score for each cluster $GW_{score}(C_i)$ is based on the ratio of CSR sentences in a cluster $N_{CSR}(C_l)$ and the number of patent sentences in that cluster $N_{patent}(C_l)$, which are the data points. The cluster importance $C_{importance}(C_l)$ is calculated by taking the data points from merely this cluster and normalizing them by the sum of all data points of all clusters for this specific firm. The greenwashing score for each cluster $GW_{score,w}(C_i)$ is weighted by the cluster importance. The firm specific greenwashing score $GW_{score,firm}(F_{id})$ is calculated by taking the mean of all the weighted greenwashing scores for the clusters $\frac{1}{n}\sum_{i=1}^{n} GW_{score,w}(C_n)$. For every firm, a confidence score $Conf(F_{id})$ is calculated based on the sum of all available data points for this firm. As such, higher data availability results in a more confident greenwashing score. When the confidence score is too low, the firm is not included in the analysis. In the end, a greenwashing score and confidence score is calculated for every firm. Eventually, all the greenwashing scores and confidences were scaled to a value between 0-1, to make them easier to interpret.

Function: **CalculateGreenwashingScores** ($[F_{ids}]$):

Loop for every firm F_{id} in $[F_{ids}]$:

Loop for every tech. inno. cluster $C_i(F_{id})$ in $[C_n(F_{id})]$ where $i \in n$:

If $(N_{CSR}(C_i) + N_{patent}(C_i)) > 0$:

$$GW_{score}(C_i) = \frac{N_{CSR}(C_i)}{N_{patent}(C_i)}$$

$$C_{importance}(C_i) = \frac{N_{CSR}(C_i) + N_{patent}(C_i)}{\sum_{i=1}^{n}(N_{CSR}(C_n) + N_{patent}(C_n))}$$

$$GW_{score,w}(C_i) = GW_{score}(C_i) * C_{importance}(C_i)$$

$$GW_{score,firm}(F_{id}) = \frac{1}{n}\sum_{i=1}^{n} GW_{score,w}(C_n)$$

$$Conf(F_{id}) = \sum_{i=1}^{n}(N_{CSR}(C_n) + N_{patent}(C_n))$$

Return $GW_{score,firm}(F_{id}), Conf(F_{id})$

Figure 13: Pseudo code for calculating greenwashing scores

One could argue that the algorithm needs to be corrected for the fact that larger firms are able to produce more patents in comparison to small firms. This positive correlation between firm size and patent sentences (0.26) has been found (Figure 14). However, a similar positive correlation between firm size and CSR sentences (0.27) has been found too (Figure 15). As they are combined into a ratio, both effects of firm size are cancelled out.

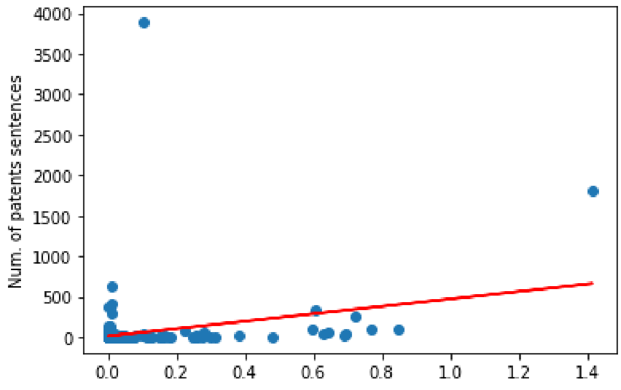


Figure 14: Correlation between 'num. of patent sentences' and 'firm size'

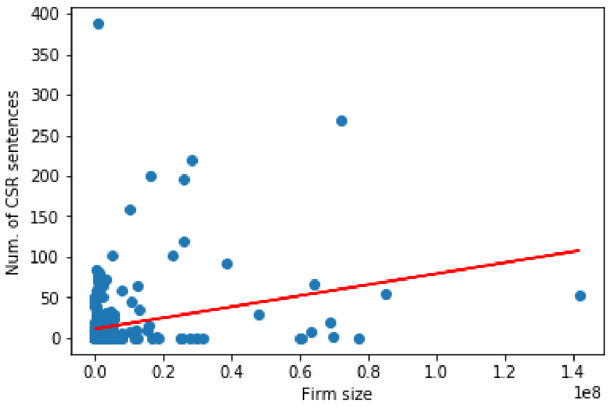


Figure 15: Correlation between 'num. of CSR sentences' and 'firm size'

Validation of machine learning method using dummy firms

To evaluate the validity of the new measurement approach for the variable *the extent of greenwashing*, we need to determine the accuracy of this measurement. Unfortunately, currently no reliable external large-scale dataset exists regarding firm-level greenwashing. Obviously, there are several stakeholders (like; NGOs, newspapers and blogs) that accuse energy firms of greenwashing. However, quantifying these accusations into a reliable data set to verify our approach, is not feasible as it introduces several other unverifiable biases such as; more scrutiny towards specific firms by third-parties, biases towards accusations in specific languages, claims that are hard to verify using substantive actions.

As an alternative, the performance of the model was tested against a manually constructed validation dataset. The validation dataset was used to determine how well the method can measure the discrepancies. This dataset is divided into three subsets which are composed out of 15 dummy firms, which have specific characteristics (Table 3). The patent- and CSR sentences are based on actual firm data but are constructed in such a way that discrepancies do or do not occur. This validation dataset is mixed with the actual dataset to check how the validation dummy firms relate to the actual firms. When the machine learning pipeline performs well, it is expected to see that these three sets of dummy firms will get a greenwashing score which would be respectively, “close to 0”, “close to 1” and “in between 0 and 1”

Table 3: Validation set of dummy firms

Firm subset	Composed out of	Expected greenwashing score
No greenwashing	Dummy firms which make 50 CSR claims which are proven by 50 patent sentences (no discrepancy).	Close to 0
Greenwashing	Dummy firms which make 50 CSR claims which are **not** proven by patent sentences (full discrepancy).	Close to 1
Partly greenwashing	Dummy firms which make 50 CSR claims which are proven by 25 patent sentences (partly discrepancy).	In between 0 and 1

The results of this validation can be seen in Figure 16, the three validation sets ended up at 0.00 (no greenwashing), 0.27 (partly greenwashing) and 0.81 (fully greenwashing), which is in line with our expectation. It is interesting to observe that the "partly greenwashing"-set ended up in the upper quartile instead of near the median. This could be explained by the fact that firms within our sample tend to do have fewer discrepancies than 50%, whereas the validation set was constructed with 50% discrepancies. Altogether, the machine learning algorithm is able to detect the discrepancies and assign appropriate greenwashing scores, which functions well based on the framework of discrepancy.

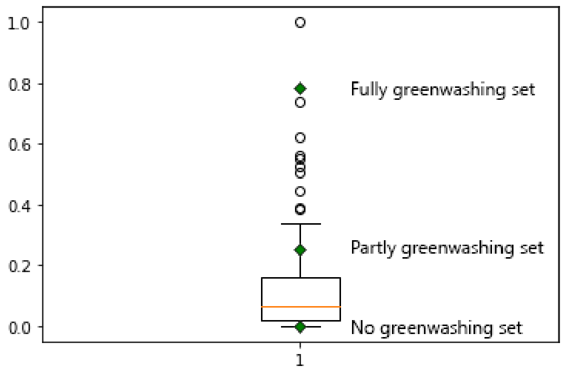


Figure 16: Boxplot of greenwashing scores includig dummy firm validation sets

3.4. Measuring firm characteristics

To be able to determine the relationship between firm characteristics and *the extent of greenwashing*, the firm characteristics *firm size*, *profitability* and *organizational inertia* were operationalized.

The variable, *firm size*, was operationalized by looking at the total sales in euros for the year 2017. This measure has been taken as it is a common proxy for determining firm size in scientific literature and is well representative for firm size (Dang et al., 2018). This information was retrieved from Orbis (Bureau van Dijk, n.d.) and was available for all the firms within the scope.

The variable, *profitability*, was operationalized by looking at the profit margin of the firm for the year 2017, which is determined as the net profit as a percentage of the revenue. This information was retrieved from Orbis (Bureau van Dijk, n.d.) and was available for all the firms within the scope.

The variable, *organizational inertia*, was operationalized by looking at the age of a firm for the year 2017, as the age of a firm is a strong indicator of organizational inertia (Hannan & Freeman, 1984). The age of a firm was calculated by subtracting the founding year from the year of our observations (2017). The information regarding the founding year was obtained from the firms' websites. When this information was not available, it was manually obtained from other sources. When multiple firms were merged into one firm the oldest founding year was taken.

Control variables

The control variable, *country*, was included to account for differences in national environmental legislation, which despite EU efforts, still varies for some countries (Delbard, 2008). To control for these differences, a country dummy was used. This variable was dummy coded for the regression based on country code. "The Netherlands" was set as reference category. Countries with less than 8 firms in our dataset were put in the category "Others".

The control variable, *subsector*, was included to control for the different characteristics of the subsectors that exist within the energy sector. These subsectors were based on the SIC industry codes, to differentiate between "Oil and gas extraction" (SIC: 13), "Petroleum refining and related industries" (SIC: 29), "Electric services" (SIC: 491), "Gas production and distribution" (SIC: 492) and "Combination electric and gas, and other utility services" (SIC: 493). By controlling for these subsectors, we reduced the possible influence of these subsector characteristics. This variable was dummy coded for the regression based on the SIC industry codes as listed above. SIC-code 13 was set as reference category as we want to assess how other sectors relate to oil & gas sector in the regression.

3.5. Analyzing the relationship between firm characteristics and the extent of greenwashing

Regression analysis and correlations were used to test the hypotheses and to analyze which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. The dependent variable – *the extent of greenwashing* – is constrained between zero and one and a significant number of firms were given a score close to zero or zero to indicate "no greenwashing suspected". Having a zero-inflated dependent variable reduces the risk of detecting false positives, to not falsely accuse firms of greenwashing. As such, the dependent variable can be considered as a limited and zero-inflated dependent variable. Using an ordinary least squares (OLS) model would not suffice because it could produce biased and inconsistent estimates of the true regression line in this case. Instead of fitting a continuous line, a logistic regression could be used when we assume that the dependent variable is binary and can be described as "greenwashing" or "not greenwashing". We could also use a multinomial ordered logit model, when we assume greenwashing can be divided into multiple ordered categories. For this research, we did not make this assumption as greenwashing is considered as a continuous phenomenon and when divided into categories the accuracy will be reduced. Instead, this research used the tobit model (Fisher & Goldberger, 1965), which yields the advantage that the data can directly be used as input without having to transform them into categories. Moreover, it makes a regression analysis possible, even though the continuous dependent variable is highly right-skewed as it is zero-inflated. Moreover, it enables us to cope with a limited dependent variable (Kennedy, 2003), as we are able to set a lower limit (zero) and upper limit (one).

4. Results

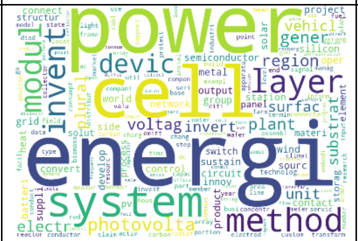
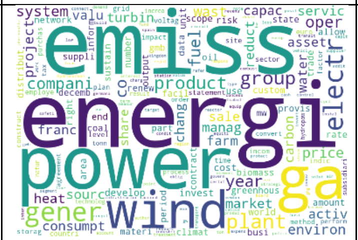
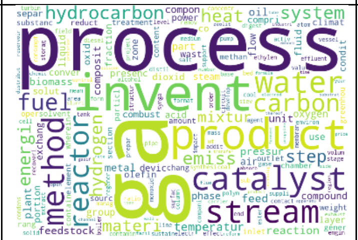
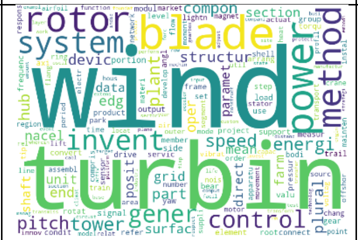
This chapter consists of two main sections. In the comping section (4.1), we will report on the technological innovation topic clusters with their corresponding word clouds and labels. We will interpret why specific technological innovations emerge and what this means for the energy sector. Whereas in the second section (4.2), we will assess the relationship between firm characteristics and *the extent of greenwashing*. This will be done by firstly reporting on some descriptive statistics, secondly by analysing the results of the regression analysis, and lastly by accepting or rejecting the formulated hypotheses.

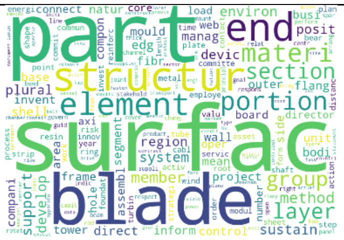
4.1. Technological innovation topic clusters

The clusters that emerged from our method provide useful insights regarding the different technological innovations which were found for the investigated energy firms. Each cluster can be described using a word cloud, which visualizes words that are used most frequently in the cluster, thus providing insights regarding the topic of the cluster. For every cluster, these word clouds are analysed, labelled and when applicable, tagged as technological innovation (see: Table 4). When a cluster gets assigned as a technological innovation and it consists of one coherent topic, this cluster is marked as being suitable for further analysis.

For our sample firms, three technological innovation topics emerged which are suitable for further analysis; solar energy (topic 1), wind energy (topic 5) and reduction of emission and toxic gasses (topic 4). These clusters have a higher percentage of patents in their clusters, which inherently makes sense, as patents always refer to technological innovations and CSR reports do not. The clusters that are referring to more general sustainability terms (topic 2,3 & 7), do have a lower percentage of patents to substantiate these claims. At last, topic 6 refers mainly to technological innovations but does not converge into one specific innovation. This is problematic for further research as mismatches might occur for this cluster, since the CSR sentences might refer to different topics in comparison to the patents.

Table 4: Topic word clouds with labels

Topic num.	**Word cloud**	**Num. patents**	**Num. CSR**	**Perc. patent/ CSR**	**Cluster size**	**Label**	**Tech. inno.**	**Further analysis**
1		**4974**	**3010**	**62%**	**14%**	**Solar energy**	**yes**	**yes**
2		1000	6571	13%	14%	Emissions / general energy	no	no
3		2449	6660	26%	16%	Sustainable management	no	no
4		**7859**	**2607**	**75%**	**19%**	**Reduction of emissions and toxic gasses**	**yes**	**yes**
5		**5209**	**1155**	**81%**	**12%**	**Wind energy**	**yes**	**yes**

6		4668	2218	67%	12%	Separate innovations	yes	no
7		1504	5442	21%	13%	General sustainable business	no	no

The occurrence of the technological innovation topics solar and wind energy are in line with the studies of Shaw & Donovan (2019) and Wen et al. (2018) which found that these technologies are important for energy firms to transition towards more sustainable business practices. Shaw & Donovan (2019) found that renewable energy sources are used by oil & gas firms to engage in new lines of business and re-shape their business models in response to changes in the global energy system. Changing their business models towards solar and wind energy could pose a high risk for these firms, as they traditionally rely on non-sustainable energy sources. As we found in this study, only 26% of the patents of these firms are in solar and wind energy, indicating that on average firms in our set are not solely focussing on these innovations. There are a few exceptions in our dataset in which specific firms mainly tend to focus on developing solar and wind energy, as it is part of their green vision and identity.

The reduction of emission and toxic gasses cluster (topic 4) is interesting as it indicates that some firms are trying to maintain their current business practices and strive to make them greener instead. For these firms, the costs of making their current operations cleaner using technological innovations are lower because they do not have to shift their business practices. Moreover, they can highlight in their CSR reports that they try to lower their emissions and toxic gasses and by doing so signalling that they are good corporate citizens.

Other possible technological innovations that could change their business practices like; geothermal energy, tidal energy, biofuels, and electric vehicles were not found in this analysis. This could be explained by the sensitivity of the algorithm, as we asked it to cluster seven main topics. These other topics are present in our dataset, but they did not surface as they are not large enough to form their own coherent clusters. As such, they become part of larger other clusters like cluster 6.

Adjusting the sensitivity of the algorithm would be interesting for future research to be able to detect these smaller topics as well.

Moreover, it is interesting to observe that within the solar energy cluster only 32% (N=43) of our firms engage in substantive actions, while 78% (N=104) of these firms engage in symbolic CSR communication concerning this field. For wind energy, only 19% (N=26) of the firms engage in substantive actions and 64% (N=86) in symbolic CSR communication. For reduction of emission and toxic gasses this is respectively; 35% (N=47) and 72% (N=96). The percentage of substantive actions with regards to the reduction of emission and toxic gasses is higher than for solar and wind energy. It seems that incremental changes, instead of changing business practices, seems to be an easier and less costly way to become more environmentally friendly for our set of firms. Furthermore, the strong discrepancy between symbolic and substantive actions could be explained by the high costs for a firm to engage in substantive actions, whereas for symbolic actions these costs are relatively small. Looked at from a *signalling theory* perspective, it is more efficient to signal green innovation in their CSR report instead of conducting actual innovation. Stakeholders and specifically shareholders are more likely to read the CSR report of a firm instead of conducting an in-depth investigation if the patents are green. As such, the payoff of writing about technological innovations is higher in comparison to spending it on R&D to develop these innovations.

4.2. The relationship between firm characteristics and the extent of greenwashing

Descriptive statistics

To start with, it is important to look at the distribution of greenwashing scores over the firms in our dataset. The mean of the greenwashing score is 0.13 and the median 0.07, both values are rather low if we would expect that the variable was normally distributed. This indicates that for many firms greenwashing is not or only slightly suspected. This could be explained by the fact that most firms engage in both symbolic and substantive actions with regards to the discovered technological innovation topics. The boxplot in Figure 17, shows that 75% (Q3) of the firms (N = 101) have greenwashing scores below 0.18 and there are several outliers that range between 0.39 and 1.0. When looking at the distribution of the greenwashing score (Figure 18), we observe the same outliers and discover that the data is heavily zero-inflated and the distribution is strongly skewed to the right. These outliers are especially relevant for this research, as they are firms for which the algorithm has found a strong discrepancy between substantive and symbolic actions and greenwashing is suspected. Having such a strongly right-skewed distribution is within the expectations as we would expect that greenwashing is rather an exception than the norm. Moreover, it would be good to be careful in raising suspicion regarding greenwashing as it is a heavy accusation against a firm. Overall, it can be concluded that the majority of the firms are not suspected of greenwashing by the algorithm as they are “walking the talk”. Although for a small set of outlier firms greenwashing is strongly suspected as they are unable to substantiate their symbolic actions with substantive actions.

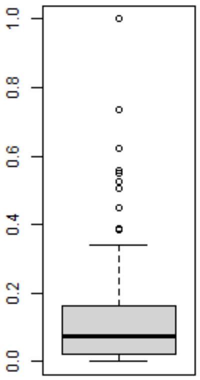


Figure 17: Boxplot of greenwashing score

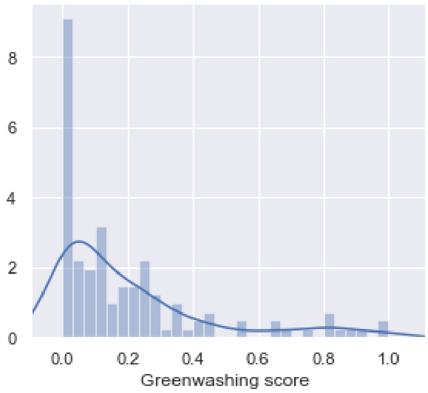


Figure 18: Distribution of greenwashing score

The next step is to determine if firm groups with different characteristics are more suspected of greenwashing. First, we will look at *firm size,* as we divide firms into four different size groups based on the European definitions of SMEs measured in total sales (European Commision, 2014). As can be seen in Figure 19, the median for both micro, small and medium-sized firms are similar, whereas the median for large firms is significantly lower. This lower greenwashing score for large firms (N=7) could be explained by the fact that these firms engage heavily in R&D and have a significantly larger patent output in comparison with SMEs. As large firms only issue one CSR report, which is proportionally only slightly bigger than that for SMEs, they make slightly more claims which can be substantiated by a significantly larger number of patents. As such, the algorithm has a bias towards the seven largest firms but performs well for the other 127 SMEs. Moreover, the variance for the large firm group is also lower than for other SME groups, which could be explained by the fact that the large firm group only contains seven firms.

Secondly, when we look at *profitably,* the dataset is divided into profitable firms (positive profit margin) and non-profitable firms (negative profit margin). Between these groups (Figure 20), no significant difference can be found, as the slightly lower greenwashing score for non-profitable firms is deemed non-significant.

Lastly, when we look at *organisational inertia,* the firms are divided into old firms (older than 50 years) and young firms (younger than 50 years). Between these two groups (Figure 21) no significant differences have been found either.

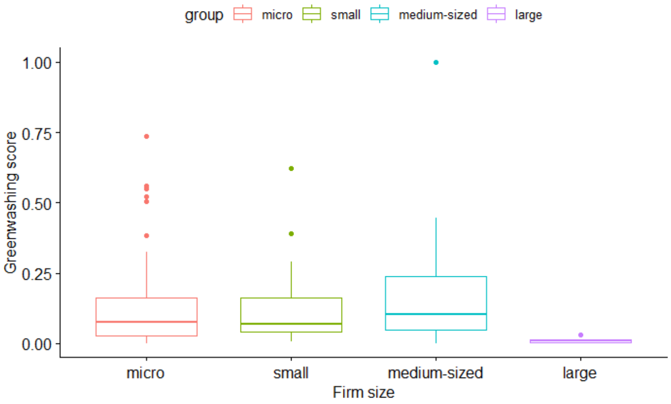


Figure 19: Boxplot of greenwashing score based on firm size

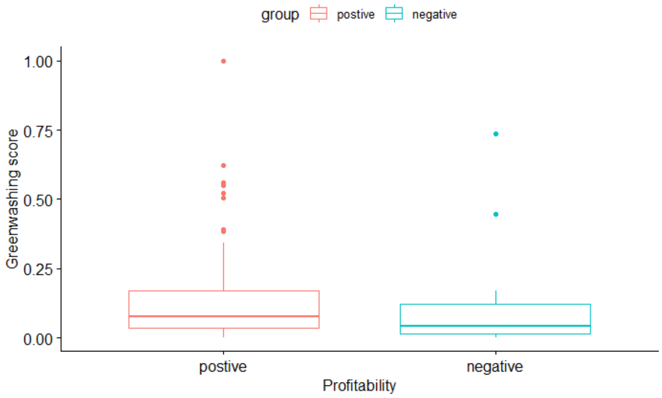


Figure 20: Boxplot of greenwashing score based on profitability

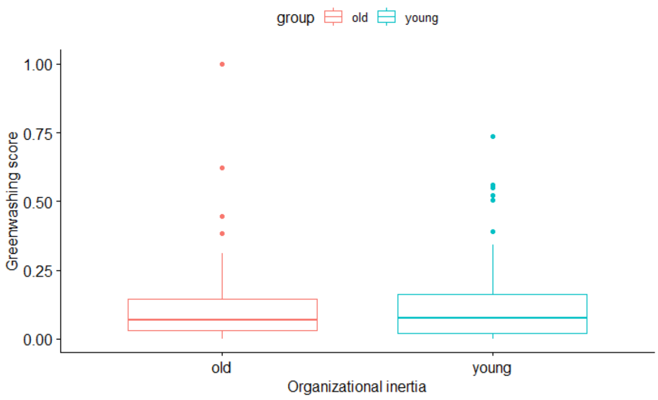


Figure 21: Boxplot of greenwashing score based on organizational inertia

When we make a comparison between sectors (Figure 22), we see that the electric services sector (SIC: 491) has a significantly higher median and more high outliers in comparison to the other groups. When investigating these outliers, we observe that these electric services firms tend to make a large number of CSR claims regarding solar and wind energy but are rarely engaged in technological innovations concerning these topics. When we look at firms in the oil and gas extraction sector (SIC: 13), their greenwashing scores are the lowest and they engage more in technological innovation regarding solar and wind energy. This contrasts with current literature as the R&D intensity of oil & gas firms is found to be lower (0.30%) in comparison to electricity firms (0.74%) (Moncada-Paternò-Castello et al., 2010). It seems that oil & gas firms are engaging in developing technologies that are traditionally not in their fossil focused patent portfolio. They actively engage in the diversification of their fossil-based R&D and possibly enter new sustainable energy markets, whereas electricity firms seem to innovate less on these technologies and maintain a more passive R&D strategy regarding sustainability.

When dividing the firms based on countries (Figure 23), we see that especially The Netherlands and Germany have 75% of their firms assigned with a greenwashing score of 0.15 or less with no outliers. This difference among countries cannot be directly explained by differences in regulations, particularly because the EU has introduced a mix between voluntary and mandatory actions for firms to engage in CSR within the EU (European Commision, 2019). Instead, this difference might be explained by the data sample, namely the fact that Germany and The Netherlands are respectively ranked number three and eight of countries with the most granted patents (EPO, 2019). Whereas other countries are listed lower in this ranking, as such firms in these countries engage inherently less in innovations and thus can provide less evidence with regards to their claims.

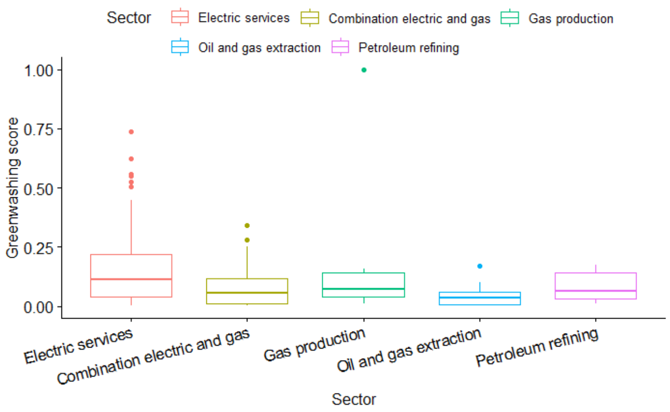


Figure 22: Boxplot of greenwashing score based on SIC industry codes

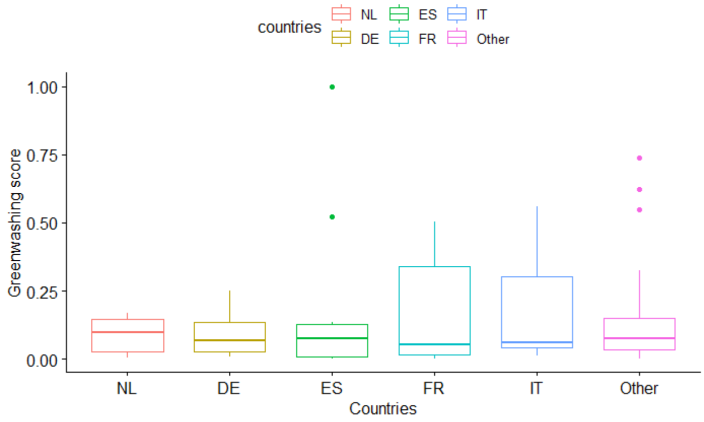


Figure 23: Boxplot of greenwashing score based on countries

In Table 5 we outline some descriptive statistics for the variables and how they correlate. We investigate how the independent variables, relate to the regular greenwashing score and the log of the greenwashing score[7]. The *firm size* negatively correlates (r = -0.12) with the greenwashing score, and negatively (r = -0.36***) with the log of greenwashing score, meaning larger firms tend to engage less in greenwashing. Profitability positively correlates (r = 0.12 and r = 0.03 (log)) with the greenwashing score, but these correlations are deemed insignificant. At last, organizational inertia barely correlates (r = 0.06 and r = -0.01 (log)) with the greenwashing score, meaning that organisational inertia does not seem to relate to the extent of greenwashing.

Table 5: Descriptive statistics and correlations

Variable	Mean	SD	Min.	Max.	1	2	3	4
1. Greenwashing score	0.13	0.17	0	1	1			
2. Greenwashing score (log)	-2.90	1.64	-8.50	0	0.71***	1		
3. Firm size	9.75e6	2.15e7	610	1.42e8	-0.12	-0.36***	1	
4. Profitability	8	22.47	-50	121	0.12	0.03	0.15	1
5. Organisational inertia	48.7	42.5	2	205	0.06	-0.01	0.32***	0.19

Correlations above 0.20 or below -0.20 are significant at 5% level; correlations above 0.25 or below -0.25 at 1% level
N = 134

Regression analysis

To further investigate the relationship between the firm characteristics and *the extent of greenwashing* a regression analysis has been conducted. Table 6 shows the results of the baseline regression with only the control variables and with all the variables added to test H1, H2 and H3. Both results of the tobit model with regular greenwashing score (1a, 1b) and with the log of greenwashing score (2a, 2b) are reported. When looking at the results, only *firm size* shows a very small significant relationship (-2.97e-3 *** (2b)) with the log of greenwashing score. For the other independent variables, none of the coefficients are found significant and have a small estimate, indicating that they do not relate to the greenwashing score. The control variable “Electric services sector” (SIC: 491) is positively related (0.13* (1a) and 0.18** (2a)) to the greenwashing score, indicating that firms operating in the field of electric services have a higher greenwashing score. Finding these results is in line with the results of the descriptive statistics where we also found a higher greenwashing score for this sector.

[7] To improve the model fit, as the greenwashing score variable is strongly skewed to the right. Taking the natural log has been done by adding a small value (0.001) to the zero observations to avoid getting infinite values.

Table 6: Determinants of the extent of greenwashing

Variable	Tobit (1a)	Tobit (1b)	Tobit (2a) (log)	Tobit (2b) (log)
Firm size		-1.62e-3 (0.09) ·		-2.97e-3 (8.25e-4) ***
Profitability		7.09e-4 (0.33)		6.62e-4 (0.35)
Organisational inertia		3.03e-4 (0.46)		3.61e-4 (0.36)
Country (Germany)	-0.01 (0.85)	-0.01 (0.88)	-0.01 (0.92)	-5.30e-3 (0.94)
Country (Spain)	0.08 (0.37)	0.08 (0.32)	-0.02 (0.82)	-3.07e-3 (0.97)
Country (France)	0.07 (0.44)	0.12 (0.21)	0.03 (0.76)	0.12 (0.19)
Country (Italy)	0.07 (0.41)	0.07 (0.42)	0.06 (0.50)	0.05 (0.55)
Other countries	0.02 (0.82)	0.02 (0.83)	0.01 (0.90)	4.89e-4 (0.99)
Petroleum refining (SIC: 29)	0.04 (0.57)	0.03 (0.69)	0.10 (0.12)	0.07 (0.29)
Electric services (SIC: 491)	0.13 (0.02) *	0.11 (0.05) ·	0.18 (1.16e-3) **	0.14 (9.38e-3) **
Gas production (SIC: 492)	0.13 (0.09) ·	0.10 (0.19)	0.17 (0.03) *	0.12 (0.12)
Combination electric and gas (SIC: 493)	0.06 (0.39)	0.04 (0.52)	0.08 (0.24)	0.04 (0.55)
Log-likelihood	38 (201 DF)	44 (198 DF)	36 (201 DF)	44 (198 DF)

Note: For reference purposes, an OLS model has also been run, which resulted in similar coefficients and significance level, which suggests that the estimation bias from using a linear model did barely influence the outcomes (see Appendix C.).

*· $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

$N = 134$

Results with respect to hypotheses

We found some evidence to support hypothesis 1 (*firm size*), but we are not able with the current dataset to fully support or reject the hypothesis suggesting that for our sample *firm size* does not seem to have a systematic relationship concerning *the extent of greenwashing*. When we look at the small evidence, we observe a negative correlation between *firm size* and the log of *the extent of greenwashing*. Furthermore, the tobit model (2b) shows a significant negative relationship between these variables but with a small estimate. Thus, the regression analysis does not allow for any conclusion on rejecting or accepting the hypothesis. As such, the symbolic and substantive actions of larger firms do not seem to align better in this research in comparison to smaller firms. Not finding this relationship could be explained using a contradicting stream of literature based on the phenomenon of *signalling theory*. Which argues that firms that engage in greenwashing prefer to maintain an information asymmetry between the firm and the general public (Seele & Gatti, 2017). As larger firms inherently have a bigger information asymmetry with respect to their stakeholders

(Prencipe, 2004), it could be implied that it is “easier” for larger firms to engage in greenwashing as the asymmetry is already relatively big. This could make greenwashing a more feasible option for these larger firms as they are less prone to being detected. As this stream of literature contradicts with the stream of literature used in the theory section, their effects might cancel out, resulting in not finding significant results for either of the two.

Hypothesis 2 (*profitability*) can neither be supported nor rejected based on our analysis, as no significant results have been found. The correlation analysis showed a small positive correlation between *profitability* and the *extent of greenwashing*, but this correlation is small and deemed as non-significant. This implies that *profitability* does not seem to be a firm characteristic that is systematically related to *the extent of greenwashing.* As such, more empirical research should be done to determine if this relationship does not exist or not finding a relationship is caused by the methods or sample used in this study. A possible reason for not finding such a significant relationship could be that *profitability* measured using the profit margin is a yearly metric that could fluctuate quickly on a yearly base. For example, if a firm decides to buy another firm, their profit margin for that specific year could be very low, whereas the firms itself is still profitable and invests in the long term. In future research, it would be suggested to take a longer time frame to assess, to get a more representative indicator of *profitability*.

For hypothesis 3 (*organisational inertia*) also no significant results have been found that can support or reject the hypothesis suggesting that no systematic relationship exists regarding *the extent of greenwashing*. It seems that the theoretical basis on which this hypothesis was formulated cannot be empirically verified in this research. This basis relies on the structures and routines which are carved out deeply within older firms since they grew over a longer period of time. Measuring this using firm age has been done in previous studies, but there are techniques that might be more reliable to measure *organisational inertia*, for example by using surveys (Roodt et al., 2001). By using this survey technique these structures and routines that might hamper environmental change could be identified more accurately.

5. Conclusion

Greenwashing is an increasing problem in our society as it is hard to detect due to increasingly sophisticated greenwashing techniques and an asymmetry of information between firms and the general public. To understand better which firms are more likely to engage in greenwashing several theoretical determinants for greenwashing have been established in literature. However, these determinants are merely tested in an empirical setting. So far, it has been difficult for researchers to test these relationships as no adequate framework existed to measure greenwashing on a large set of firms. Our objective has been to test some of these determinants at firm level in an empirical setting using a new measurement approach to detect greenwashing. To obtain this objective the following research question was answered:

What is the relationship between firm characteristics and the extent of greenwashing of firms operating in the European energy sector?

To answer this research question, three steps have been conducted. First, we defined *the extent of greenwashing* as a discrepancy between symbolic and substantive actions. Second, we found three theoretically informed firm characteristics, *firm size*, *profitability* and *organisational inertia* which were described as determinants of greenwashing and we formulated corresponding hypotheses for them. Third, we proposed a new measurement approach to test these hypotheses based on the discrepancy between symbolic and substantive actions.

The results showed that neither of the three firm characteristics can be pointed out as having a direct relationship with *the extent of greenwashing* in our dataset. Consequently, based on the investigated firm characteristics in this research, we can state that greenwashing does not seem to be a systematic phenomenon. The effects of the theoretically informed firm characteristics related to *firm size*, *profitability* and *organisational inertia*, do not seem to appear in our research findings. Explanations for missing such a relationship can be found in two theoretical and two methodological factors. The first theoretical factor is that firm characteristics regarding greenwashing have been taken out of theoretical frameworks which list a wide range of different determinants of greenwashing. For example, Delmas & Burbano (2011) list in total twelve determinants of greenwashing spread over the categories “Market External Drivers”, “Nonmarket External Drivers”, “Organizational Drivers” and “Individual Psychological Drivers”. This research only looked at half of the “Organizational Drivers”, proposed in that framework. This means that other determinants, which were not investigated, could play a more dominant role as determinants of greenwashing. Especially, this research highlights that “Market External Drivers” could be more important to explain greenwashing as we found some differences between sectors. This could be explained due to sectors having their own specific characteristics in which firms face different environmental challenges and different environmental pressures. Thus, the extent of greenwashing for an individual firm might be more driven by factors on a sector-level instead of on a firm-level.

The second theoretical factor can be explained due to the fact that a large body of research exists regarding empirically testing CSR disclosure, but not on the validity or truthfulness of this disclosure. Researchers investigate the presence, meta-data or GRI-score of CSR reports, but they merely engage in an in-depth analysis of the content of the reports. As such, theoretically no comprehensive foundation exists on how to determine the truthfulness of the CSR disclosure and by that being able to detect greenwashing.

The first methodological factor can be identified based on the fact that for researchers it is complex to measure greenwashing in a systematic and objective manner. Greenwashing is not a binary phenomenon and can take on different sophisticated forms based on the level of investigation (product level or firm level) and between sectors. Inherently, firms do not want to be identified with greenwashing and as such, they try to hide the fact that they might engage in greenwashing. Furthermore, determining if a specific action can be considered as greenwashing could also depend on the judgment of a third-party. This makes the phenomenon even more complex as the subjective judgment of these third parties might need to be considered. Altogether, these factors make it hard to measure greenwashing in an empirical framework.

The second methodological factor is that this research has chosen to take a specific perspective on greenwashing in which symbolic actions need to be substantiated by substantive actions. Taking this perspective rules out third-party accusations, but inherently relies on measuring substantive actions based on technological innovations. As technological innovations are merely an indicator of the R&D process of a firm, it does not shed light on other processes which might be able to substantiate their symbolic actions. In future research, a more compressive empirical measurement method should be used to provide firms with the opportunity to substantiate their claims using other business processes as well.

Despite not being able to fully accept or reject the hypotheses, several other important findings were found that contribute to a better understanding of the phenomenon of greenwashing. First, we found that European energy firms are engaged in three main technological innovations and several smaller innovations to cope with the current environmental pressures. They mainly engage in solar energy, wind energy and in the reduction of emissions and toxic gasses. Reduction of emissions and toxic gasses was found most prominent, as energy firms prefer to engage in incremental innovations instead of taking the risks of shifting their current business practices. Second, we found that using our method, the majority of firms are assigned a low greenwashing score indicating that they are “walking the talk”. This is interesting as we discovered that greenwashing is rather an exception instead of the norm. Moreover, our method proved to be useful to point out outlier firms that are likely to engage in greenwashing and should be further investigated using a more qualitative approach. Third, we found that electricity firms tend to innovate less with regards to solar and wind energy in comparison to oil & gas firms. This is a new insight as oil & gas firms are engaging in a diversification strategy of their technological assets and might start to compete more against electricity firms. They seem to innovate more on the topics of solar and wind energy which would be expected to be traditionally done by electricity firms.

6. Discussion

6.1. Limitations of this study

In this section, the theoretical, methodological and empirical limitations of this research are discussed. Firstly, it is especially important for this research to consider how well the newly developed method measures *the extent of greenwashing*, as other researchers have not used this method before. In an ideal situation, the validity would be checked using an additional dataset to perform triangulation on the found data. Such a dataset could be obtained from an external data provider or could be constructed within the research itself, by having students manually conduct a greenwashing classification based on a large number of qualitative case-studies for each firm. Having such a dataset would have made it possible to construct training and test datasets on which the algorithm could have been trained and verified. Unfortunately, it does not exist and due to limited time and resources for this thesis, we were unable to construct such a dataset. Thus, this research resorted to including a set of dummy-firms to verify if the algorithm was able to distinguish the discrepancies between symbolic and substantive actions. This seems to be the case, but the biggest limitation of using this method is that the sentences are derived from the actual dataset and this validation assumes that the underlying theoretical framework describes the phenomenon of greenwashing correctly.

Secondly, as described in the last paragraph, we assume that the theoretically formulated framework is correct. This framework, which relies on the discrepancies between substantive and symbolic actions, is directly derived from several scientific studies. Only for these studies, the framework is operationalized with sometimes different indicators. Consequently, we need to critically assess if the discrepancy between CSR claims and technological innovations (measured using patents) is a good measure for *the extent of greenwashing*. This seems to be the case, as statements regarding sustainable technological innovations should be backed up with actual technological innovations. By doing so, we need to take three limitations into account. First, some technological innovations are not patented due to a large set of reasons and because of that they do not appear in our metric. Second, some technological innovations are developed by third parties and are later bought or licensed to firms which are investigated, consequently these firms use the innovations but do not develop them by themselves. Third, measuring technological innovations only reveals a small part of potential greenwashing as it focusses merely on providing evidence for claims with regards to innovations. It has a blind spot for other forms of greenwashing such as hidden trade-offs, vagueness of claims, irrelevant claims, false labels or giving false hopes. Altogether, it can be concluded that the measurement approach has a specific perspective on how to detect greenwashing and because of this, cannot claim to detect all sorts of other forms of greenwashing.

Thirdly, a bias of the researcher could occur when assessing the word clouds and labelling them to specific technological innovations (Section 3.3, Clustering). Within the complete data science pipeline, this is the only moment where manual assessment was needed, which makes it the weakest point regarding subjectivity. To increase the consistency and replicability, the word clouds of the cluster are made available in Table 4, which provides the reader with the opportunity to assess the labelling process. Moreover, the selection of random CSR texts and patents is determined by an algorithm to avoid cherry picking[8].

Fourth, the firm sample was obtained using the Orbis-database (Bureau van Dijk, n.d.) and afterwards filtered based on the criteria if a firm publishes a CSR-report and if it has more than ten patents. This filtering process introduces a strong bias towards smaller firms not being included in this research (Figure 4). This selection bias is unavoidable as these firms are inherently less likely to have at least ten patents and/or publishing a CSR report due to limited resources. When generalizing the results, it should be considered that some small firms cannot be assessed using the developed method and are thus not considered in this research. Moreover, this research only assessed firms operating in the energy sector, which encompasses specific sector characteristics, as this sector traditionally heavily relies on unsustainable energy sources and currently has to face a significant amount of environmental pressure to change business practices. Other sectors might already be more sustainable and face less environmental pressure to change their business practices and thus do not feel the need to engage in greenwashing. Consequently, when generalizing the results to other sectors we should be aware that this research has been focused on a sector where we would expect to find greenwashing, for other sectors we might observe fewer firms that engage in greenwashing.

Fifth, the operationalization of the independent variables could be more accurate, to better approximate the underlying determinants. *Firm size* could be measured using a hybrid variable in which the total sales and number of employees are both considered, instead of just looking at total sales. For *profitability,* a larger range of years could be considered to equal out yearly fluctuations.

[8] Due to possible copyright infringements the raw CSR- and patent-sentences which are randomly selected cannot be included in an appendix to make it available to the reader.

At last, *organisational inertia* could be more accurately measured by conducting surveys instead of merely looking at the age of a firm, as it is a better estimator of the determinant. Besides, other non-firm characteristic variables could be used for further large-scale empirical investigations of the phenomenon of greenwashing as their influence might be more substantial. For example, by investigating the relationship between sectors, different regulations, the amount of scrutiny by third-parties or intra-firm communications.

Sixth, it should be considered that the developed machine learning method of this thesis is a first proof of concept with regard to empirically measuring greenwashing. Consequently, the method should be used in an explorative setting and requires more extensive testing and modifications before it could be used to make definite statements and measurements concerning the *extent of greenwashing*.

6.2. Contributions of this study

In this research, several empirical, theoretical and methodological contributions were made to the existing literature of greenwashing. First empirically, by creating a better understanding with regard to the phenomenon of greenwashing in an empirical setting. This thesis was able to establish that greenwashing does not seem to be a systematic phenomenon based on the selected firm characteristics and greenwashing definition. This indicates for other researchers that greenwashing is a complex phenomenon that is hard to capture in an empirical setting and that other determinants might play a more influential role regarding greenwashing. As such, it might be beneficial to focus on testing other determinants which could yield statistical prove in an empirical setting. For instance, this research found that looking at differences between sectors and countries might be a better indication of greenwashing, as there seems to be a relationship between these variables.

Secondly, these empirical contributions have further theoretical implications because the findings do not align with current literature. The determinants formulated in several theoretical frameworks might need to be assessed more critically as no influences were found in this empirical setting. Greenwashing determinants are mainly formulated in a theoretical setting, their influences are carefully argued for, but largely lack empirical scrutiny. This study shows that more empirical testing of the determinants is needed, and current theoretical frameworks should be critically assessed by challenging their underlying assumptions. Especially, the assumed importance of the investigated firm characteristics does not show in this study, challenging the assumption that “Organizational Drivers” have an important influence on the extent of greenwashing.

Lastly, from a methodological perspective, this study contributes by establishing a method to measure greenwashing in an empirical setting which is more systematic and objective compared to previous approaches, such as applying greenwashing criteria and single-case studies. The thesis developed a first proof of concept of a machine learning pipeline, which can detect greenwashing on a large set of firms. The machine learning method and insights could be used by other researchers who want to statistically test determinants of greenwashing, but who do not have resources to conduct many case studies. Hopefully, this machine learning perspective on tackling an innovation sciences question will help researchers to get a better understanding of the advantages and disadvantages of applying machine learning techniques. For instance, related to how variables can be operationalized using complex state-of-the-art machine learning techniques and how the validity of the outcomes should be critically assessed and compared using more traditional methods. Altogether, this might lead to more innovation sciences researchers that actively benefit from the possibilities that are developed by machine learning researchers.

6.3. Further research

As understanding and measuring the phenomenon of greenwashing is complex, this study leaves room to strengthen further research regarding testing determinants and developing a more comprehensive empirical framework. As such, we suggested the following areas of further research:

To start with, more research could be conducted regarding testing theoretically established determinants of greenwashing in an empirical setting. This research was unable to verify that greenwashing is a systematic phenomenon based on the investigated determinants. Although this does not necessarily mean that such a relationship does not exist, it rather shows that more research is needed to verify if this is the case. Testing these relationships, with possibly other methods, would contribute to a better understanding of these determinants in an empirical setting. This understanding is needed because relying on merely theoretically formulated determinants could either result in counter-productive or ineffective policy implications to reduce greenwashing, as these determinants might not play an important role in the real world.

Secondly, further research could be conducted with regards to other sectors in which the extent of greenwashing might be different due to different sector characteristics. The energy sector can be characterised as a sector in which firms face strong environmental pressures to change their business practices, which might lead to firms engaging in greenwashing. It could be interesting to investigate sectors that face similar pressures like the aviation sector, cement sector or infrastructure sector. Although they might face similar environmental pressures their products are inherently different and as such the extent and form of greenwashing could differ. Investigating these similar sectors provides the opportunity to statically test greenwashing determinants and discover how they might differ between sectors. On the contrary, it could also be interesting to investigate sectors that face less environmental pressures to observe if greenwashing also occurs there. Investigating these sectors makes it harder to statistically prove greenwashing determinants but could provide useful insights on how greenwashing occurs in more subtle instances. Unexpected results could surface in which sectors that are generally considered as not engaging in greenwashing, might become suspected of greenwashing. In the end, having a more comprehensive overview of different sectors helps in developing more targeted policies based on their specific sector characteristics.

At last, the discrepancy framework developed and operationalized in this research can be seen as a first step towards developing a comprehensive empirical framework on how to measure greenwashing. To provide guidance for future research that wants to develop a more compressive framework, we discuss some possible indicators that could be added. Suggestions for these indicators are outlined in Appendix D. and are based on the discrepancy framework between symbolic and substantive actions. For example, future research could try to add “revenue streams” as a substantive action indicator. This leads to a more comprehensive framework as substantive actions could now be measured using technological innovations and using products where a firm obtains revenue from. Consequently, technological innovations that are licensed or bought from other firms can now be used to substantiate symbolic actions. When more of these symbolic and substantive action indicators are integrated into a comprehensive framework, the validity of the greenwashing score increases and more specific details concerning greenwashing could be uncovered. Altogether, striving for such a comprehensive framework would help researchers to better understand the phenomenon of greenwashing and enables them to more accurately test determinants of greenwashing.

7. Supporting information

The complete machine learning pipeline is developed in Python using scikit-learn (scikit-learn, n.d.) and TensorFlow (TensorFlow, n.d.). The source code of this research is available on the private Github repository of Entis BV[9]. After sending a request to Entis BV, the source code can be shared for scientific purposes.

[9] https://github.com/entistech/Greenwashing

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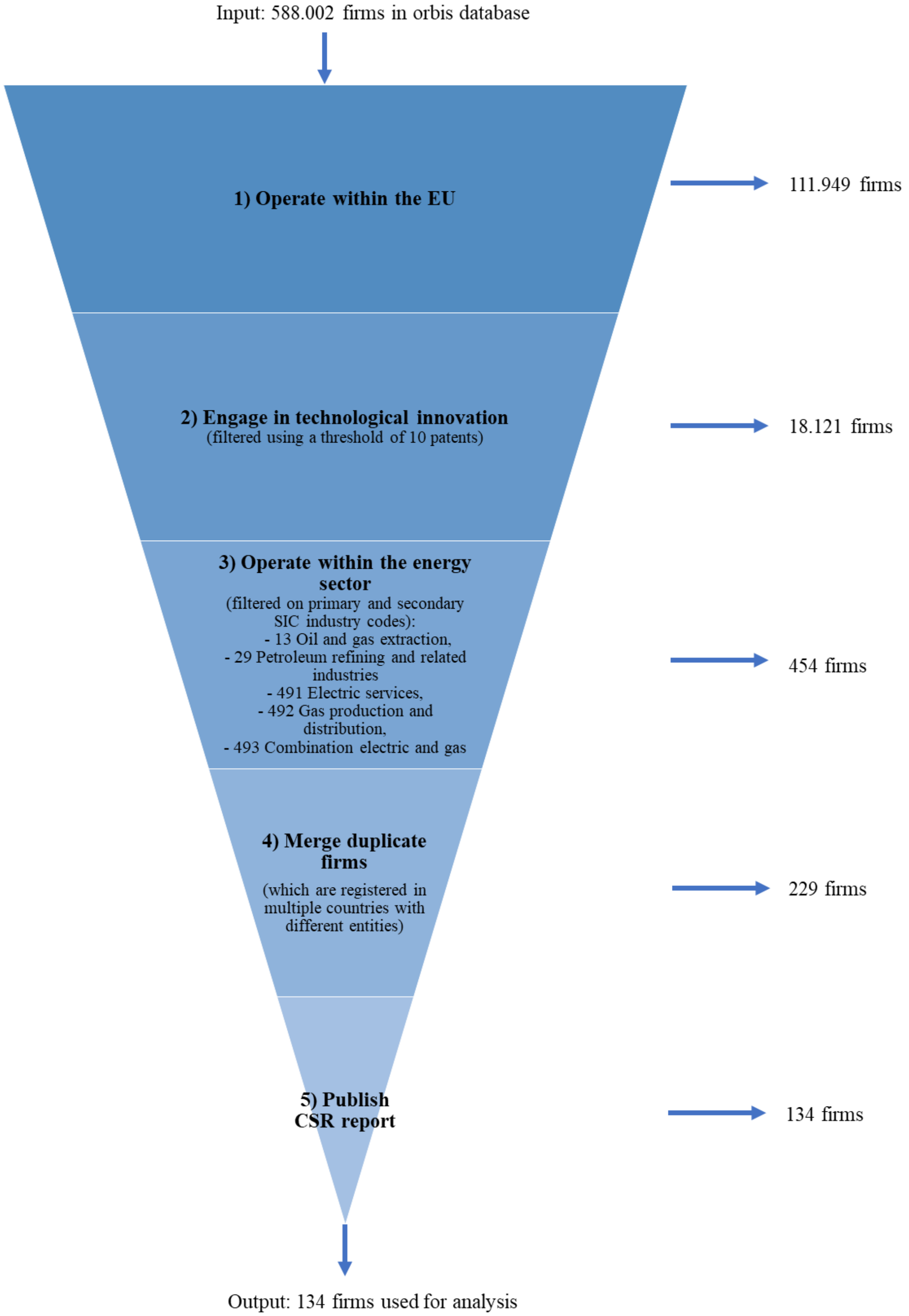
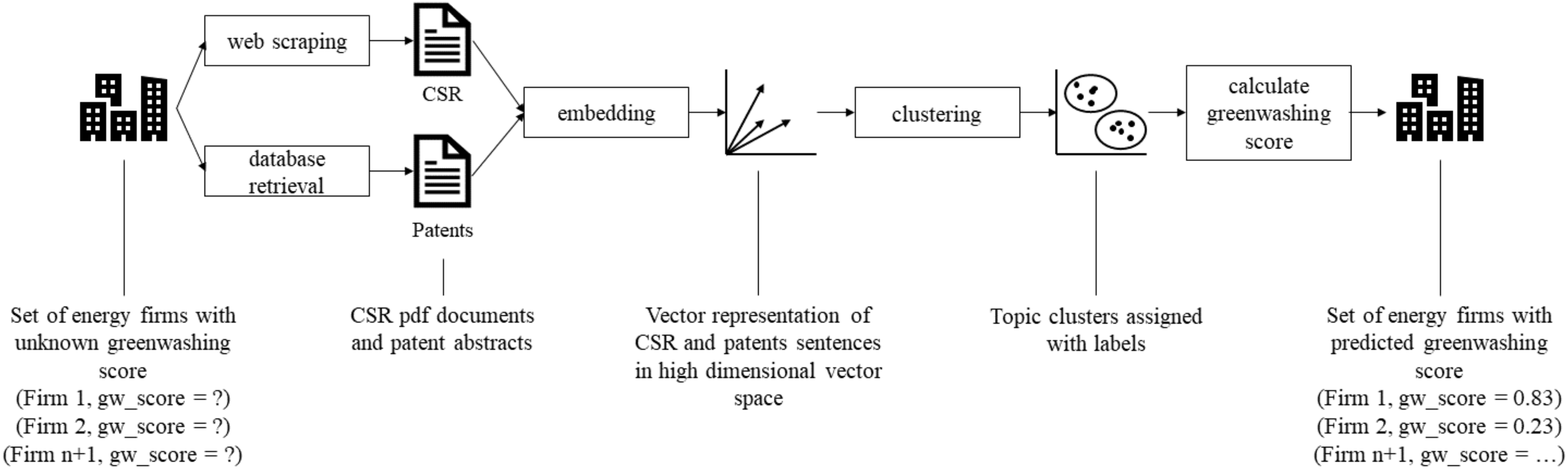
Appendix A. Firm selection funnel



Appendix B. Machine learning pipeline to calculate greenwashing scores



Appendix C. Comparison between OLS and tobit model for the determinants regarding the extent of greenwashing

Variable	Tobit (1a)	Tobit (1b)	OLS (3a)	OLS (3b)
Greenwashing score	0.02 (0.82)	0.02 (0.80)	0.02 (0.82)	0.02 (0.79)
Firm size		-1.62e-3 (0.09) •		-1.62e-3 (0.09) •
Profitability		7.09e-4 (0.33)		7.01e-4 (0.35)
Organisational inertia		3.03e-4 (0.46)		3.00e-4 (0.48)
Country (Germany)	-0.01 (0.85)	-0.01 (0.88)	-0.01 (0.88)	-0.01 (0.91)
Country (Spain)	0.08 (0.37)	0.08 (0.32)	0.08 (0.39)	0.08 (0.34)
Country (France)	0.07 (0.44)	0.12 (0.21)	0.07 (0.44)	0.12 (0.22)
Country (Italy)	0.07 (0.41)	0.07 (0.42)	0.07 (0.41)	0.07 (0.44)
Other countries	0.02 (0.82)	0.02 (0.83)	0.02 (0.82)	0.02 (0.83)
SIC 29	0.04 (0.57)	0.03 (0.69)	0.04 (0.56)	0.03 (0.70)
SIC 491	0.13 (0.02) *	0.11 (0.05) •	0.13 (0.02) *	0.11 (0.05) •
SIC 492	0.13 (0.09) •	0.10 (0.19)	0.13 (0.10)	0.10 (0.20)
SIC 493	0.06 (0.39)	0.04 (0.52)	0.06 (0.34)	0.05 (0.48)
R^2			0.12	0.15

• $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$N = 134$

Appendix D. Proposed symbolic and substantive action indicators for future research

Symbolic action indicator	Reason for investigating indicator
Statements in annual report	The annual report of firms sometimes also contains CSR statements and is bounded to more stricter regulations and is deemed more important to shareholders.
Images used in CSR reports	Several CSR reports contain a large number of "green" images, like windmills and solar panels, which are used to influence the reader with regards to the sustainability of the firm.
Statements made on website	These statements are mostly made for stakeholders which do not perform an in-depth analysis of a firm, as such they are the first statements stakeholders read and can easily be greenwashed due to a minimum of regulations.
CEO statements in written text or interviews	These statements are made by the CEO and thus have a high impact and could be considered as strategic decisions of a firm.

Substantive action indicator	Reason for investigating indicator
Revenue streams	Revenue streams could be used to observe how much revenue a firm makes regarding its (non-)sustainable assets and this information can be found in the annual report.
Installed capacity	For firms in the energy sector; the number of kWh's of electricity generation using renewable energy sources vs. the number of kWh's of non-renewable energy sources.
CO2 emissions	Provide a good indication on what substantive actions a firm takes to reduce CO2 emissions and is bound to strong regulations and often publication obligations.
News reports on the actions of a firm	Using the perspective of third-party accusation, firms could be accused or praised by engaging in (non-)sustainable actions.