A neural networks approach to changes in European corporate communications in the wake of Fridays for Future

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# Statement of authorship

I declare that I have used no other sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are indicated as such, i.e. cited or attributed. This Thesis was not submitted in any form for another degree or diploma at any university or other institution of tertiary education.

Fabio Keller, <date>

# Acknowledgments

# Abstract

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# Introduction

Various large corporations worldwide claim to reduce greenhouse gas emissions, advance gender equality or implement effective risk management. According to Fleming and Jones (Fleming 2012), companies take environmental, social, and governance measures to attain legitimacy. Legitimacy is a general perception that an entity and its actions are good and right (Suchman 1995). Companies care about perception and corresponding legitimacy because it increases acceptance and recognition (Bergek, Jacobsson, and Björn A. Sandén 2008), contributes to economic success and helps to establish new products (Kwak, Zhang, and Yu 2019).

In recent years, the system of norms and values within which legitimacy is fulfilled has changed. Societal values have shifted towards environmental protection and low-emissions economic activity. The 2015 Paris Agreement, various national legislations and other institutional frameworks enshrined these principles. The shift accelerated when Swedish activist Greta Thunberg launched the global movement Fridays for Future - FFF - in late 2018. The movement brought climate change to the forefront of the political agenda. It sparked debates about the role of the individual, businesses' responsibilities, and the importance of the state to tackle climate change (Marquardt 2020).

From the perspective of Institutional Theory, such a change in societal values leads to external pressure and corresponding new demands on the legitimacy of firms. Suppose companies want to preserve or improve their recognition among stakeholders in such a situation. If so, they need to improve environmental legitimacy by taking measures that align the perception of their activity with society's shifting priorities (Berrone, Fosfuri, and Gelabert 2017).

According to (Alrazi, de Villiers, and van Staden 2015), "environmental legitimacy is conditional upon the public evaluation of corporate environmental performance and environmental reporting." Thus environmental legitimacy is only indirectly related to the actual environmental performance of the company. In between is the influenceable public evaluation. Legitimacy is, therefore, also achievable when the public positively re-evaluates a company even though its true impacts did not change or only changed marginally (Berrone, Gelabert, and Fosfuri 2009). Institutional theory suggests that "the appearance rather than the fact of conformity is often presumed to be sufficient for the attainment of legitimacy (Oliver 1991)." When a company deliberately tries to bring about such an unsubstantiated change in public or consumer perception, it is greenwashing (Lyon and Maxwell 2011). Greenwashing is, at its core, a fundamental conflict between the information a firm communicates and its actual behaviour (Kurpierz and Smith 2020).

Whether increased legitimacy is based on actual underlying changes or just a product of deception, disclosure and communication are crucial for legitimacy building (Prado-Roman, Diez-Martin, and Blanco-Gonzalez 2020). Communication is the fundamental vehicle that brings mutual sense-making and sense-giving amongst stakeholders. It is an essential instrument for corporations to advance legitimacy. Social media are particularly well-suited channels for communication because they enhance stakeholder engagement, enable a more direct dialogue and democratise access to information. Communication on social media is a fast way of managing public expectations (Nwagbara and Reid 2013).

When FFF protests grew in size and frequency in 2018 and 2019, how did Europe's largest companies' communication change? Did they communicate more about sustainability? Did communication become more subjective, which would indicate greenwashing?

Missing: Contribution of this paper and setting the agenda.

# Background

## Legitimacy theory

## Major social incidents

### Greta Thunberg

### Fridays for Future

### Spatial proximity

## Impression and corporate image management

(Hooghiemstra 2000) showed that companies whose legitimacy was threatened by social upheavals or incidents reacted by increasing their coverage of environmental issues in annual reports. Increasing coverage of environmental issues in such a social context is a kind of impression management. Firms communicate more on a given "hot" topic to influence public opinion and to prevent or contain damage to their general perception, which can indeed benefit legitimacy, at least in the short term (Berrone, Gelabert, and Fosfuri 2009).

*H1: As FFF protests grew larger from late 2018 until mid-2019, the largest European companies communicated relatively more about environmental issues than in the year preceding the protests.*

In situations of social upheaval, companies need to react immediately to societal crises. Therefore, reactive communication is often short-term oriented and more symbolic than substantive, which is decoupled from actual underlying changes in corporate activity (Berrone, Gelabert, and Fosfuri 2009). Accordingly, a symbolic short-term increase in environment-related communication tends to be subject to the greenwashing accusation. (Bazillier and Vauday 2013) have shown that greenwashers communicate more soft than hard information, meaning that they express subjective, vague statements rather than verifiable, quantitative facts.

*H2: Following the FFF protests, the largest European companies' communication related to environmental issues became, on average, more subjective and vague.*

# Approach

## Data

The Forbes media company publishes an annual list of the world's 2000 largest companies called the "Forbes Global 2000". Companies are screened worldwide according to four metrics: sales, profits, assets and market value (Murphy 2015). [data.world](https://data.world/aroissues/forbes-global-2000-2008-2019/workspace/file?filename=Forbes+Global+2000+-+2019.csv) provides most annual editions of the list to download (dataworld 2021). I choose the 2019 version because of the Twitter data period (see below). From the list, I choose all European companies, which are 434 in total. This set represents Europe's largest companies.

The data for FFF protests are directly obtained from the movement's website. The movement compiled a comprehensive table where the numbers represent protesters at a given location on a given 'climate strike' day for multiple dates starting in late 2018 until recently (Fridays for Future 2021). While it is impossible to assure that the numbers are accurate, it is plausible that they, at least, reflect the protests' size on a given day relative to other days.

I choose the company's tweets as a representation for corporate communications. Twitter has become an important channel to express global and political opinions (Merle, Reese, and Drews 2019). Its range of users, from individuals to corporations, media, NGOs and governments, is uniquely broad (Stieglitz and Krüger 2011). Since large, multinational companies often have multiple Twitter accounts, and since there is no comparable data compilation to my knowledge, I search Twitter for every company's main international account and create a corresponding list. If the company does not have an international account, I choose its national account for the country it is headquartered. If the company is a conglomerate with multiple brands and does not have a "group Twitter" altogether, I choose the account of its largest brand (e.g. Daimler). Dr Gerret von Nordheim, researcher at the University of Hamburg, provides the tweets. He has academic access to the Twitter API and kindly offered to scrape the data. I choose to analyse all corporate tweets from approximately one year before and after the first large FFF protests on November 30th 2018. The period is 1.12.2017 to 30.11.2019.

## Preprocess

To process and model the tweets' topics, I rely on a recent paper published by researchers at the University of Hamburg. (Stanik, Pietz, and Maalej 2021) represent tweets with high-dimensional vectors using a deep bidirectional natural language processing algorithm. Then, they reduce dimensionality and cluster the vectors to find human-understandable topics in the tweets. Their approach does not require predefined critical parameters like the number of clusters, and it achieves an agreement level of up to 98% with human coders which is especially remarkable for short texts. Therefore, Stanik et al.'s approach is in many respects superior to similar, more traditional topic modeling algorithms like bag-of-words, TF-IDF or LDA. The methodology is largely transferable to my problem, but since I use different data and there are already more advanced models, I adapt the approach in some respects.

### Types of tweets

I start by filtering out non-organic tweets. Twitter differentiates four types: First, organic tweets are messages originally created by a given user. Second, retweets are messages taken from another user and posted on a given user's profile. Third, quotes are retweets that a given user adds further content to. Fourth, replies are messages that directly respond to another user's tweet. For logical and economic reasons, I only examine organic tweets. Replies are largely irrelevant in the context of studying high-level corporate communications because many companies use them as a customer services tool to handle particular inquiries. Also, replies account for about 75% of all tweets in my dataset, so excluding them saves a lot of resources. I exclude retweets and quotes because these formats echo other users more than they carry a given user's genuine message.

### Multiple languages

Unlike Stanik et al. I include non-English tweets for a more representative and inclusive outcome. This means translating roughly 180'000 tweets with an average of 179 characters. Fulfilling this task at December 2021 rates would cost roughly EUR 600 with leading service providers DeepL and Google Translate. If one were to translate the tweets with open source software and one's own code instead, one would have to download almost as many models as the dataset has non-English languages, i.e. around forty. I choose a compromise, where tweets in the rarest languages are translated using the [DeepL API](https://www.deepl.com/pro-api?cta=header-pro-api/) to save bandwidth and the more common, non-English languages are translated using models from the [University of Helsinki](https://huggingface.co/Helsinki-NLP).

### Noise and hashtags

Next I remove redundant information and process hashtags. Like Stanik et al. I remove Twitter accounts a given tweet addresses with expressions like "@OtherAccount", and I mask URLs and numbers. Stanik et al. do not mention whether and how they deal with hashtags in tweets. However, this is important because hashtags tend to contain crucial information. For contextualisation and stylistic reasons keywords are often summarised as hashtags, e.g. "We are committed to a #sustainablefuture." The fact that sometimes several words are combined into one hashtag makes it difficult to deal with. I handle this difficulty with a word separator trained on tweets.

## Embedding and clustering

I use the “all-mpnet-base-v2” model instead of the “bert-base-nli-mean-tokens” checkpoint of BERT to create sentence embeddings of the tweets because the latter, which Stanik et al. used, is, as of December 2021, out of date according to the [package's documentation](https://huggingface.co/sentence-transformers/bert-base-nli-mean-tokens). The newer model is supposed to achieve better results, but the principle remains the same. Given an input text, the model outputs a 768-dimensional vector that captures its semantic information. The cosine distance between two vectors is analogous to the semantic similarity between two texts. A topic is thus represented by an accumulation of data points in multidimensional space.

It would be possible to calculate the distances between hundreds of thousands of vectors in high-dimensional space, but that would cost computing power and add little value. Many of the 768 data points are redundant when trying to find human understandable topics. For this reason I use the UMAP algorithm to reduce dimensionality to twenty, with 100 neighbors considered and 0 minimum distance. All hyperparameters are proposed by Stanik et al.

The final step involves the HDBSCAN algorithm, a clustering technique that does not require a predefined number of topics, does not force data points into clusters, does not assume a cluster shape and can find clusters with different point densities. Consistent with Stanik et al., I choose 30 as the smallest cluster size and the "leaf" selection strategy, which favours smaller clusters.

## Analysis

For the analysis, I aggregate the variables obtained from the individual tweets for each company and each month. This results in panel data consisting of tables of all the companies for every month of the period analysed. A single table corresponds to the "Forbes Global 2000" list with additional information: The topic distribution of tweets for the given month and the number of FFF protesters that took to the streets in a given month in the country the company is headquartered.

Then, I descriptively and graphically show how the share of sustainability-related tweets developed during the period overall, per economic sector or country. It may not be possible to analyse the conditions causally because SUTVA is not satisfied. However, it is possible to contrast countries that experienced many protests with countries with hardly any protests and hint at a differences-in-differences approach. It is also possible to calculate various correlation coefficients.

# Results and discussion

As of December 2021 I have advanced to the point of finding a single sustainability cluster among roughly 40 topics identified by HDBSCAN. Using TF-IDF matrices I was able to identify the most relevant words for every topic. The sustainability cluster's top words indeed correspond to: sustainability, sustainable, climate, carbon, emissions, etc.

I expect both hypotheses to be accurate, which means a jump in the share of sustainability-related tweets and a rise in average tweet-subjectivity when FFF protests occur. I expect these changes to be particularly evident when the most significant protests were held in spring 2019. Also, a reverberation effect is expected, meaning that the share of sustainability-related tweets abates slowly and probably does not return to pre-FFF levels.

# Conclusion

# Bibliography