Justus-Liebig-Universität Gießen
Institut für Soziologie

Bachelorthesis

„Academic capitalism“ analysed:

Linguistic trends in sociological journals.

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Contents

Abstract

The bachelor thesis examines the change in positive framing in sociological publications against the background of academic capitalism. Based on the theory of increasing self-promotion, it is analyzed whether this is reflected in scientific abstracts through increasingly positive language. The paper conducts a sentiment analysis of 121,789 English-language abstracts of sociological articles from the Web of Science database (1993-2023) with two dictionaries for additional validity. Interval plots, linear regressions and Monte Carlo simulations are used to examine temporal trends in positive and negative sentiment. The results show a very small, statistically insignificant increase in positive sentiment over time, while no clear trend can be identified for negative sentiment. The work reveals methodological challenges in the sentiment analysis of scientific texts, particularly with regard to data distribution and the significance interpretation of large samples. Contrary to the results of previous research, the study provides no evidence for a substantial increase in positive framing.

1 Introduction

In the course of globalization, the economization of communal life has gained new attention. Despite national regulations, the global market reaches the everyday lives of individuals living in society. This is hardly surprising, as Max Weber showed as early as 1904 the logic by which Protestant social norms themselves form the root of capitalism (Weber, 1934). Weber also reflected on the link between science and economics as early as 1919 in the first pages of his essay "Science as a Profession" (Weber, 1919). With its "praxeological turn" from 1980 to 2000, modern science studies began to investigate the interactions of science with politics and economics (Kaldewey, 2023, p. 8). For some years now, bibliometricians and researchers from a wide range of disciplines have been publishing results that show an increase in positive formulations in scientific publications. With a few exceptions, this is happening regardless of the social embedding of science and the resulting interaction between science, economics, politics and society. This thesis aims to contribute to a better understanding of the change in academic language in scientific publications. It examines a change in the framing of sociological publications and relates the results to the increasing economization of science.

First, the work summarizes the theory of academic capitalism. The first chapter presents the causes of academic capitalism based on key works. The chapter then goes on to discuss the consequences of academic capitalism, which affects the individuals conducting research in the academic system. The question is presented and categorized on the basis of the theory described. The second chapter presents the most relevant studies for the investigation of the research question. The third chapter then explains the methodological basis of the study. The method of sentiment and dictionary analyses as well as the operationalization and analytical approach are discussed in more detail. In the penultimate chapter, the results of the analysis of both dictionaries are presented, compared and reflected on using linear regressions. In the last chapter, all results are compared with each other and a conclusion is drawn. The work makes a new contribution by explicitly focusing the analysis of the framing of scientific publications on the discipline of sociology. In addition, this work also introduces new methodological ideas into the researched subject area by using simulations to include distortions of statistical significance due to high case numbers in the interpretation. In order to achieve particularly valid results, a complete survey of all sociological publications from Web of Science is carried out and the measurement of framing is performed with two dictionaries.

2 Theory

2.1 Introduction

The following theory chapter deals with central contents of the theory of “academic capitalism”. The focus is on the works of Slaughter and Leslie (1999) and Münch (2011), due to their fundamental importance for the theory of “academic capitalism”. The chapter begins with a description of the original political decisions that are seen as the cause of academic capitalism. The policies introduced fundamentally changed the academic system. The reactions of corporate universities to the policy changes described above are then presented. To this end, the behavior of companies is made plausible with the help of the garbage can model and the resource dependency theory. It then goes on to discuss how academic capitalism emerges from the behavior of universities as an overlying structure through construction mechanisms and persists through maintenance mechanisms. The second section deals with the consequences of academic capitalism both for the individuals working in the scientific system and for the structure of scientific disciplines. The analysis then focuses on the reactions of individual researchers to the changed circumstances brought about by academic capitalism. In the last thematic section, the consequences of the change in researchers’ actions for scientific disciplines are presented and individual aspects of disciplinary differences are briefly addressed. At the end of the chapter, the research question of this thesis is presented, placed in the context of the chapter and then a summary of the entire chapter is drawn up.

2.2 The background to academic capitalism

The political decisions and their backgrounds, which are considered to be the cause of structural changes in the science system, are presented at the beginning. This is followed by an explanation of the resulting structural changes in the science system. In the first half of the 20th century, academics, especially faculty members, were largely shielded from the market and their work was financed by the state (Slaughter & Leslie, 1999). From the middle of the 20th century, however, professors began to be gradually integrated into the market, which was accelerated by globalization (Slaughter & Leslie, 1999). Weber (1919) already describes “The large institutes of a medical or scientific nature are state capitalist enterprises.”, but nevertheless notes “There is an extraordinarily strong gulf [. . .] between the head of such a large capitalist university enterprise and the ordinary old-style full professor.”. The 1980s marked a turning point for this development (Slaughter & Leslie, 1999). At this time, Ronald Reagan and Margaret Thatcher were instrumental in initiating a market paradigm that led to the global hegemony of New Public Management (Münch, 2011; Slaughter & Leslie, 1999). In particular, “managerialism” should be mentioned here, which legitimized entrepreneurial decision-making logics in political institutions (Münch, 2011). As a result, science was also increasingly evaluated by the state according to market-oriented criteria (Münch, 2011). This evaluation undermined the implicit social contract that had previously legitimized scientific work (Münch, 2011). The previously existing implicit contract is described by Münch (2011) as a kind of "harmonious ideal form". This describes how science enters into a kind of trusteeship with other areas of society. Science provides scientific capital and in return receives social and economic capital as well as legitimization for basic research. The study Slaughter and Leslie (1999) documents the intensification of university competition in the 1980s in the USA, Canada, Great Britain and Australia. A shortage of funding and selective support for successful institutions acted as driving forces. The aim of the policy was to increase national competitiveness and adapt to global market requirements (Slaughter & Leslie, 1999). Similar dynamics can also be observed in Germany (Münch, 2011).

The Bayh-Dole Act of 1980 in the USA (Münch, 2011) was an example of how policy changes were intended to make universities less dependent on state funding and at the same time increase inter-university competition. This allowed universities to patent research results and thus convert them directly into private economic capital (Münch, 2011). Scientific knowledge was thus increasingly transformed from a public to a private good (Münch, 2011). This private knowledge is particularly useful for industry, which increasingly sought new products and pushed for state-funded, commercial research (Slaughter & Leslie, 1999). Bringing universities closer to industry led to the establishment of cooperative research centers, some of which were funded by the state (Slaughter & Leslie, 1999). In addition, increasing student numbers became a political goal, often without taking into account the differences between the education systems of different countries (Münch, 2011). This goal was pursued in the Bologna Process, which aimed to harmonize the education system in order to improve the OECD ranking position (Münch, 2011). Previously, however, German skilled workers outperformed US bachelor's graduates in terms of their qualifications (Münch, 2011).

Universities react as acting institutions to the policies described so far. Two theoretical models can be used to understand university reactions. The garbagecan model offers an explanation for the adaptability of universities in complex and uncertain environments (M. D. Cohen et al., 1972). It describes universities as organized anarchies in which decision-making processes are often random and non-linear (M. D. Cohen et al., 1972). An organization is an organized anarchy if (1) there are problems in setting goals, (2) there is no understanding of internal processes and (3) there is a high variation in the effort expended between the people involved (M. D. Cohen et al., 1972). Under these conditions, which are all present at universities, problems are disconnected from the solutions (M. D. Cohen et al., 1972). Problems are not dealt with directly and solutions already exist for problems that have not yet arisen (M. D. Cohen et al., 1972). Emerging problems can only be solved if the right combination of problem, solution and decision-maker coincides with the necessary sphere of influence and attention (M. D. Cohen et al., 1972). Instead of explicit problem-solving strategies, a garbagecan organization is characterized by high flexibility (M. D. Cohen et al., 1972). "[A Garbagecan Organization] does enable choices to be made and problems resolved, even when the organization is plagued with goal ambiguity and conflict, with poorly understood problems that wander in and out of the system, with variable environment and with decision makers who may have other things on their minds." (M. D. Cohen et al., 1972, p. 16).

In addition to the garbagecan model, there is the resource dependency theory, which is also used by Slaughter and Leslie (1999). According to this theory, the power that donors exert over organizations can be viewed in two dimensions (Slaughter & Leslie, 1999). More power is exercised by the donor who invests more money compared to other donors (Slaughter & Leslie, 1999). In addition, more power is exercised by the funder whose funding is particularly critical to the organization, whereby with the removal of particularly critical funding the organization would no longer function (Slaughter & Leslie, 1999). Organizations strive for stability and create it through autonomy (Slaughter & Leslie, 1999). Imbalances and destabilization of the financial foundations lead to turbulence in the organization, which can damage it (Slaughter & Leslie, 1999). Organizations make additional efforts to restore stability (Slaughter & Leslie, 1999). By reducing critical state funding, universities are destabilized, whereas they try to create stability through industrial donors and changed spending patterns (Slaughter & Leslie, 1999). In return, however, industry places new demands on the university, which is why stability cannot be fully created (Slaughter & Leslie, 1999). Consequently, a reduction of funds on the part of the university requires strategic resource allocation, which is only possible with the help of a more powerful university administration that can control and act deep into the organization (Münch, 2011).

The models presented show that universities are reacting to the new competitive policies. The adaptation processes explained lead to changes in the community of all universities, resulting in an academic system characterized by academic capitalism. Actions of academic actors such as universities, faculties or researchers that aim to generate profit are referred to as "academic capitalism" (Slaughter & Leslie, 1999). Frequent goals are efforts to obtain external funding as well as profit-oriented activities such as patenting, spin-off companies and industrial partnerships with a profit component (Slaughter & Leslie, 1999). Corresponding actions are necessary due to the shift in university funding from block grants to project-related funds (Slaughter & Leslie, 1999). This shift effectively reduces resources for teaching and makes more resources available for research, but also requires the acquisition of third-party funding (Slaughter & Leslie, 1999). Universities have responded with new revenue strategies such as higher tuition fees, contracts and private donations (Slaughter & Leslie, 1999). The triple helix model describes the emergence of entrepreneurial universities as a result of the unification of political, industrial and university requirements (Baumeler, 2009). This development leads to an increased focus on the commercialization of knowledge, whereby core academic tasks such as research and teaching are increasingly permeated by the "spirit of enterprise" (Baumeler, 2009). Entrepreneurial universities legitimize themselves politically by emphasizing their benefits for the knowledge-based industry (Baumeler, 2009).

As a result, the focus of research is shifting from recognition within its own scientific community to solving industrial and social problems. This development stands in contrast to the historical ideal of science described by Münch (2011). This is characterized by the pursuit of recognition by peers and students, the acceptance of failure as part of progress and mutual recognition for participation in the scientific community. In addition, Münch (2011) emphasizes the importance of quality and originality of individual contributions over quantitative performance profiles, which are used to optimize the marketing of one's own person in competition with other scientists (Münch, 2011). Instead of the ideal, communities are divided by competition. In this competition, status hierarchies are constructed through mechanisms of visibility, decisions based on a few criteria and consecutive effects (Münch, 2011). Status hierarchies are maintained through the exchange of resources for recognition, closure effects through oligopolies and the Matthew effect (Münch, 2011). At the expense of the university community, universities of excellence and non-university research centers are being established in Germany as counterparts to the Ivy League universities in order to increase international visibility (Münch, 2011). This happens at the expense of progress in knowledge, which can be facilitated by the exchange of many smaller centers (Münch, 2011).

2.3 Consequences of academic capitalism

The previous section discussed how national policies promote competition among universities to increase visibility, among other things. These changes have affected relationships between universities and increased academic capitalism. The next section looks at the impact of the new system on individuals. The implementation of university goals such as efficiency gains, a higher number of deeper breakthroughs and successful graduates are monitored by a growing control and management apparatus (Münch, 2011). The paradox is that the actual quality of knowledge cannot be measured. Goodhart (1981, p. 116) describes, "[...] that any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes [...]". This applies to the citation metrics and article metadata often used to evaluate science, which are also very selective (Münch, 2011). With these measures, motivated actions of any kind are therefore prone to unintended side effects. The focus on control also neglects education (Münch, 2011). In order to optimize the achievement of the target metrics mentioned at the beginning, only students with already high competencies and researchers with already influential research are hired/recruited. This puts education in the background. The neglect thus manifests itself in the production of degrees that are obtained without subject-specific knowledge and puts teacher-student relationships under pressure (Münch, 2011). Mainly "normal academics" are produced "who are no longer capable of any bold thoughts" (Münch, 2011, p. 146). Increased conformity creates a fear of making mistakes, which leads to a preference for low-risk projects (Münch, 2011). This defensive attitude manifests itself in research practice through the withholding of data sets and the production of minimal publications (Münch, 2011). Such developments jeopardize the innovative strength and quality of science in the long term and reinforce prevailing competitive situations. Industry in particular offers researchers safer alternatives and benefits from collaborations or poaching through specialized expertise.

Universities pass on some of the increased pressure due to more limited resources to their employees. As a result, they have to act as "state-subsidized entrepreneurs" (Slaughter & Leslie, 1999). The increasing importance of third-party funding has a significant influence on publication behavior (Münch, 2011). Strategies are being developed to adapt one's own publishing to the new circumstances. More and more publications are being produced with ever larger groups of authors (Münch, 2011). This means that questions can be dealt with in greater depth and more articles can be added to one's own publication list. Due to the hierarchies between universities and research centers (or clusters of excellence), a middle class is being created at universities that has to concentrate more on teaching and therefore has little time for publications. If you want to do research, you have to go to the research centers in order to be freed from teaching, which leads to a separation of research and teaching (Münch, 2011).

Competition also arises at the individual level. In order to assert themselves in this competition, scientists have to advertise themselves. For this advertising, they act "like marketing persons" (Ylijoki, 2003). One historian describes how money has to be raised through "ome kind of trickery" before the actual research can begin (Ylijoki, 2003). The creation of demonstrators and prototypes as illustrative objects serve to legitimize research funding bodies and the university (Baumeler, 2009). These prototypes are usually only produced in the belief that industry and the rest of society demand practical demonstrations as legitimization. In the project accompanied by Baumeler (2009), demonstrator construction was decoupled from research, as engineering activities are actually an "industrial matter" and resources required for research should not be wasted. The description of the decoupling coincides with statements made by other university employees in Välimaa (2001) and Ylijoki (2003). According to this, inefficient, superficial marketing is finding its way into the academic sector (Välimaa, 2001). This leads to a waste of taxpayers' money for unscientific marketing purposes and a shift in focus from research quality to competitive advantages through visibility (Baumeler, 2009; Ylijoki, 2003). Instead of completely replacing scientific work with market activities, a dualism emerges under which the logic of scientific activity does not change (Ylijoki, 2003). In addition to traditional scientific work, a large amount of time and monetary resources must be invested in measures to increase visibility and legitimize research. Scientific quality suffers from the already scarce resources, but teaching in particular suffers, as it can be made less visible (Münch, 2011; Ylijoki, 2003). In teaching, visibility is also created through marketing, such as with the introduction of new "hybrid degree programs" (Münch, 2011).

Different disciplines and subject groupings have different potential for market actions by faculties and their employees. These differences will now be addressed in the last thematic paragraph. The distinction between applied research and basic research is not taken into account by the growing research management and industry (Slaughter & Leslie, 1999). As a consequence, basic research is often ignored in funding measures, as it has less influence on industry than applied research and therefore has less potential for possible capital transactions. This illustrates the decisive advantage that market-oriented research has over more abstract research (Slaughter & Leslie, 1999). Disciplinary structures are organized in the environment of organizational complexity in and between universities and faculties (Becher, 1989, p. 42). Differences between different disciplines and the boundaries between different disciplines can also be seen in the metadata of the scientific publications produced (Andersen, 2023; Lietz, 2020). In addition to the market-oriented, applied natural sciences, the professional, quantitative sciences that publish in journals are favored by the new funding strategies (Münch, 2011). Thus, within sociology, policy-oriented, public and basic theory sociology are slowly being displaced (Münch, 2011). Corresponding "survival of the fittest" mechanisms accelerate scientific homogenization. External influence is exerted on research topics through funding. These external topic definitions accelerate the standardization of research. A high degree of homogenized practices and theoretical approaches can be observed, particularly in the natural sciences, which are already more strongly adapted to the market (Llanos et al., 2019). In sociology, homogenization can also be observed via publications (citation behaviour, collaborations, ...) (Volle et al., 2024). In German and American sociology, qualitative and quantitative research are gradually forming as independent groups, with both fields becoming less theoretical (Volle et al., 2024). In German sociology in particular, theory plays a stronger role and contributes positively to the stabilization of a research community (Volle et al., 2024).

2.4 Questions

The theoretical considerations raise the question of whether academic capitalism is changing not only publication strategies but also the linguistic expression in scientific publications. Politically motivated competition leads to new logics of action in everyday research. Scientists increasingly have to legitimize their work to donors from industry and politics. Researchers compete for positions in specialized research centers that offer advantages in the acquisition of future projects and promise a more secure market position. For these reasons, the question arises as to whether positive framing in publications is used to optimize one's own research for the self-legitimizing function. This could motivate a better evaluation of one's own research in review processes, readers and industry. On the other hand, academic language style is fundamentally neutral and the excessive evaluation of one's own results could be irritating and appear unprofessional. This paper therefore examines whether there has been an increase in the frequency of positive framing in sociological publications. An increase in the frequency of positive framing occurs when the frequency of words that present research in a more positive light increases over time. To rule out the possibility of a fundamental increase in the emotions expressed in scientific publications, we check whether the frequency of negative formulations has decreased over time or does not show a trend.

RQ: Is there a significant increase in the expression of positive sentiments and only a weak or no significant increase in negative sentiments in sociological publications?

The research question thus explicitly does not address any connection between the previously described theory. It merely examines the existence of linguistic effects in publications and does not establish any connection between the possible occurrence of positive framing and concepts of academic capitalism. The aim of the work and its methods is fundamentally exploratory, and thus inductive. Explorative methods are particularly justified when a phenomenon has not been sufficiently investigated, since a purely deductive analysis cannot expand an existing theory (Stebbins, 2001). The linguistic effects of the discipline of sociology are at the macro level as a concept. Since academic capitalism is also a macrophenomenon, the Coleman boat is suitable for breaking down the relationship in more detail (see appendix .1) (Coleman, 2000). The Coleman boat in Figure 2.1 represents the relationship between academic capitalism and linguistic changes in scientific publications. This scheme is extended with a second Coleman boat, which explains academic capitalism through new competition-promoting policies. The aim of the work is to examine whether linguistic optimization in the form of positive framing exists in sociological publications.

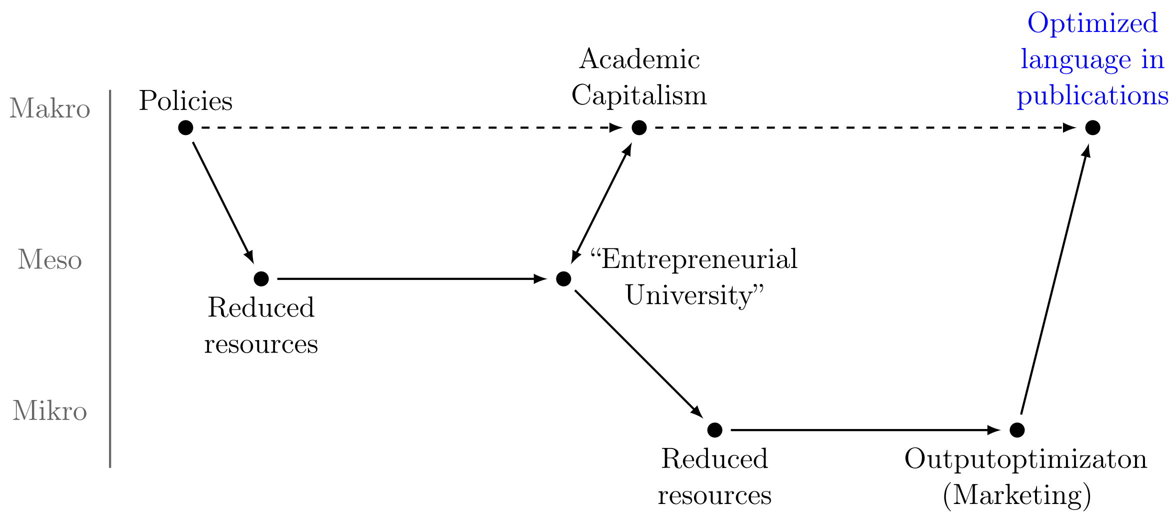

Figure 2.1: Coleman boat of the concepts described in the chapter. Based on the research question, the existence of a positive framing (blue) is examined.

2.5 Summary

This chapter presented the theory of academic capitalism and its impact on research. Finally, the question of the work was presented. In the first section, state goals for competition-promoting laws and individual events with particular historical relevance were briefly presented. Now entrepreneurial universities are reacting to the scarcity of resources by trying to create stability. In doing so, universities market themselves as problem-solving, although they are organized as inefficient garbage-can organizations. In the resulting competition, they have to assert themselves through market-oriented action against other universities and research centers in the fight for visibility. This competition is unfairly distorted by research centers that receive special political funding and leads to less efficient progress in knowledge. The employed individuals are evaluated by university management using ineffective standards. Due to the principles of competition passed on within the university, research on low-risk projects is on the increase. This development results from the increased risk to which researchers are exposed. As a result, researchers assert themselves in research competition with the help of research-legitimizing marketing strategies vis-à-vis sponsors and society. Such practices put additional pressure on already scarce resources, while the actual research must continue unchanged. Disciplines and specialist groups that are closer to the market have a competitive advantage. Applied and empirical research is favored by these competitive advantages, whereby basic research and theory are suppressed. Externally favored topics accelerate the homogenization of science, whereby alternative and classical approaches receive less attention or disappear altogether.

3 State of Research

3.1 Introduction

The aim of the following section is to present previous research in chronological order that is particularly relevant to answering the research question. To this end, a selection of current and classic studies is made in order to highlight particularly innovative approaches within the topic. The section begins with the work of Vinkers et al. (2015), which inspired almost all of the studies that followed it and whose method and in particular the dictionary used were employed in a large number of comparable studies. This is followed by the presentation of the study by Holtz et al. (2017). The topic of the analysis is comparable to the content of Vinkers et al. (2015), but this approach is extended by two new questions. The additional questions allow a closer alignment of the methodology with the theory, which means that the conclusions can be better substantiated (Holtz et al., 2017). In the further course, Lennox et al. (2020) is discussed. This study validates the findings of Vinkers et al. (2015) using an innovative triangulation approach. This is relevant due to its frequent adaptation (Wen & Lei, 2022; Yuan & Yao, 2022). Finally, the section presents the study by Liu and Zhu (2023). This is the only study in which, among other things, a sentiment analysis of abstracts from the discipline of sociology was carried out, which is why the work is relevant to the research question of this thesis not only methodically but also in terms of content (Liu & Zhu, 2023).

3.2 Sentiments in PubMed-Abstracts

The study by Vinkers et al. (2015) examines the frequency of positive, negative and neutral words in scientific abstracts. The study is motivated by past experiences of exaggeration of scientific results (Vinkers et al., 2015). A culture of productivity is considered a possible cause for the use of positive and negative words (Vinkers et al., 2015). The dictionary used was created through discussions among the researchers, analyses of random abstracts and a comparison with thesaurus lists (Vinkers et al., 2015). Additional validation of the dictionary can be achieved by adding words from the study McCarthy (2015). In addition to the dictionary, another word list is used, which consists of 50 randomly drawn adjectives and nouns (Vinkers et al., 2015). The random and neutral words help to increase the validity of the results in comparison to the dictionary (Vinkers et al., 2015). The dictionary is used throughout the process of searching all abstracts in the PubMed database from 1974 to 2014 (Vinkers et al., 2015). The study divides the number of abstracts containing at least one positive, negative or neutral word by the number of published abstracts per year (Vinkers et al., 2015). A graph showing the increase in the individual dictionary words is used to examine the extent to which the results depend on individual words. The result is a discovered increase of 880% for abstracts with at least one positive word (Vinkers et al., 2015). In particular, the words 'robust', 'novel', 'innovative' and 'unprecedented' are responsible for the increase in the frequency of positively tagged abstracts (Vinkers et al., 2015). However, this effect can also be demonstrated without considering the listed words (Vinkers et al., 2015). The frequency also increases over time for the abstracts that contained at least one of the negative words (Vinkers et al., 2015). However, this increase is much weaker compared to the positive abstracts (Vinkers et al., 2015). No increase can be detected for the neutral and random words (Vinkers et al., 2015).

3.3 Crosscultural Psychology and Academic Capitalism

The aim of Holtz et al. (2017) is to determine the extent to which self-marketing has become part of the logic of scientific writing in cross-cultural psychology. The study examines whether there has been a change in positive and negative sentiment and whether the frequency of phrases used to describe marginally significant results has increased (Holtz et al., 2017). In addition, Holtz et al. (2017) analyzes linguistic characteristics of the social science writing style, which are based on the critique of Billig (2013). As a data basis, Holtz et al. (2017) uses full texts and abstracts published between 1974 and 2014 in two journals of cross-cultural psychology (Holtz et al., 2017). For the investigation of positive and negative sentiments, the positive and negative words from the study by Vinkers et al. (2015) are used (Holtz et al., 2017). Additional validation of the results is done by adding the more extensive LIWC dictionary (Holtz et al., 2017). For the second question, a dictionary with phrases was created that was used to publish marginally significant results (Holtz et al., 2017). The analysis of the writing style includes counting words with at least six letters, frequent verbs and nominalizations, as well as counting the phrase "more research is needed" (Holtz et al., 2017).

In the abstracts and full texts of both journals examined, there is an increase in the relative frequency of positive sentiments over time in relation to the total number of words (Holtz et al., 2017). The relative frequencies of negative words show no trend or a downward trend (Holtz et al., 2017). The relative frequency of articles with phrases describing marginally significant results increased over time in both journals examined (Holtz et al., 2017). A, according to Billig (2013), poorer scientific style increased in both journals over time. However, only one of the two journals showed a clear increase in nominalizations (Holtz et al., 2017). Increased academic capitalism could be the common cause of the increase in the measured concepts (Holtz et al., 2017).

3.4 Sentiment analysis in conservation research

The main objective of the study is to investigate temporal trends of sentiments in publications on nature conservation (Lennox et al., 2020). The study examines the assumption of how negative developments in nature conservation are reflected in the form of increased negative sentiments in conservation research (Lennox et al., 2020). To test the hypothesis, abstracts of articles published between 1998 and 2017 in six highly cited journals were analyzed (Lennox et al., 2020). A classification of the articles according to whether endangered animal species were mentioned in the abstracts or titles allowed a more detailed analysis of the sentiment distribution (Lennox et al., 2020). The sentiment analysis was carried out using the sentiment dictionaries Bing, NRC, AFINN and a sentiment algorithm from Jockers (2015) (Lennox et al., 2020). All sentiment values were used as poles of a scale (Lennox et al., 2020). A z-standardization of the respective dictionary results, added with the respective mean value, allows the comparison of the results between the dictionaries (Lennox et al., 2020). The summation of the standardized values per year resulted in a sentiment value informed by all dictionaries (Lennox et al., 2020). Cleaning the dictionaries for domain-specific words such as "shark" or "parasite" further ruled out possible distortions (Lennox et al., 2020). All sentiment dictionaries correlated weakly but significantly with each other. The aggregated sentiment value showed a weak but significant increase with increasing years (Lennox et al., 2020). Abstracts mentioning extinct species had the lowest sentiment values (Lennox et al., 2020). Contrary to the initial expectation, a trend seems to be emerging in optimistic conservation research, in which the focus is on success stories and progress (Lennox et al., 2020).

3.5 Positivity in scientific disciplines

Liu and Zhu (2023) used as a starting point for their study that competitive selection mechanisms make it more important for researchers to advertise their research and that positive language in publications is a tool for doing so. The interdisciplinary comparison of positive framing was novel and closed a research gap that existed at the time (Liu & Zhu, 2023). The change of positive framing over time, between disciplines and the connection between positive framing and research influence are examined independently and together (Liu & Zhu, 2023). The data set used contains abstracts of articles published between 1997 and 2019 on Web of Science in the disciplines of communication, linguistics, political science, sociology, and aerospace, automation and control, software engineering, transportation (Liu & Zhu, 2023). The first four disciplines are representatives of the soft sciences and the last four of the hard sciences (Liu & Zhu, 2023). The positive and negative words from the dictionary by Vinkers et al. (2015) formed the basis of the investigation (Liu & Zhu, 2023). Additionally, sentiment software from Jockers (2015) was used to make the results more reliable (Liu & Zhu, 2023). The normalization of article citations was done using the citation total of all articles of the respective year and the total of all articles in the entire period. In all disciplines, there was a significantly positive increase in positive sentiments, while the results for negative words were more mixed (Liu & Zhu, 2023). The relative frequency of negative words showed a slight significant negative trend only in the discipline of aerospace, linguistics, political science and sociology; in all other disciplines, no trend could be shown (Liu & Zhu, 2023). Overall, the hard sciences received more positive sentiments than the soft sciences (Liu & Zhu, 2023). There was a very small but significant positive correlation between the normalized citation counts and the standardized positive sentiments (Liu

& Zhu, 2023). The negative sentiments did not correlate with the citation counts (Liu & Zhu, 2023).

3.6 Summary

This chapter presented four key studies that are important for the investigation of the increase in positive sentiment in sociological abstracts. Vinkers et al. (2015) developed a basic dictionary for sentiment analysis of scientific abstracts. Their methodology, in particular the dictionary created, was taken up in numerous subsequent studies and also forms the basis for the present thesis. The work of Holtz et al. (2017) demonstrates how the dictionary from Vinkers et al. (2015) can be compared with a more extensive dictionary (LIWC) to increase the validity of the results. This approach uses relative frequencies for both dictionaries and is particularly relevant for the planned investigation of sociological abstracts of this work. An alternative approach to integrating different dictionaries within an analysis is used by Lennox et al. (2020). By calculating the sum of standardized sentiment values from different dictionaries, different sentiment dictionaries can be directly integrated with each other. Their method for standardizing and aggregating sentiment values offers valuable suggestions for analysis with multiple dictionaries. The study by Liu and Zhu (2023) is of particular importance as it is the only one to also examine sociological abstracts. Its results provide important comparative values and methodological approaches for the analysis of positive sentiments in sociology. All the studies presented together form a solid methodological and substantive basis for the planned investigation of the research question.

4 | Method

4.1 Introduction

This chapter is devoted to the data basis and the methodological approaches on which this work is based. The first section describes the practical background of sentiment and dictionary analysis. Both form the core of the analysis later on. Subsequently, the narrowing of the field of sociology is justified and the procedure for data collection is described. This is followed by a detailed examination of the search string and the options for filtering results. The basis of the analysis is the positive framings and the construction of the relative values, which are operationalized in this chapter 4. The approach of the analysis consists centrally of the investigation of the aggregated mean values per year and the comparison of the results of both dictionaries. To answer the central question, the analysis focuses on the peculiarities of the interpretation of statistical significance and the use of inferential statistical methods in the context of the high number of cases. Furthermore, possible trends are examined using linear OLS regressions. Finally, a summary of the chapter follows.

4.2 Sentiment and Dictionary Analysis

Computer-assisted text analysis is based on linguistic concepts. A corpus of texts or documents forms the database (Grimmer & Stewart, 2013). These texts can be tweets, books, chapters or scientific abstracts, for example. The division of texts into tokens as "semantically meaningful units" is the basis of these analyses (Silge & Robinson, 2017). Tokens are usually defined as words, but depending on the research question, they can also be morphemes or paragraphs. Dictionary analysis is a method for classifying text (Grimmer & Stewart, 2013). For classification, the frequencies of occurring tokens in the respective texts are counted. Tokens are first assigned to certain keys that represent categories. Finally, the frequencies of the occurring tokens are grouped by key and assigned to a text document (Ribeiro et al., 2016). Accordingly, the quality of the results depends largely on the quality of the dictionary used. Dictionaries are always created for specific text domains, because the meaning of words changes depending on the text domain. Sentiment analysis aims to identify feelings in texts using computational methods (Thelwall, 2022). The classification approaches vary between dichotomous (e.g., positive/negative) and multi-level scales (e.g., from strongly negative to strongly positive). Polytomic classifications capture a broader range of emotions by also classifying, for example, sadness or surprise as emotions (Mohammad & Turney, 2013).

Dictionary analysis is limited by the lack of consideration of context, such as irony, and the dependence on predefined word lists. Advanced approaches such as classification transformer models based on machine learning attempt to partially compensate for these limitations. The advantage of dictionary classifications over machine learning methods is the higher transparency and traceability of the classification, since the exact keys and frequencies can be viewed for each word. For sentiment analysis, it must be possible to justify why a text should contain expressed sentiments. A special feature of scientific texts is that they are predominantly neutrally formulated. Words that are normally used for sentiment expressions often have different or differently acting meanings in a scientific context. Therefore, the central approach of this study is to capture the authors' evaluation of the respective research. For example, researchers could describe their approaches as "creative". The sentiment analysis thus represents a kind of evaluation analysis. In an evaluation, judgments are made in which researchers interpret a fact and position themselves in relation to it (positively, negatively). The data preparation for a corpus-based analysis differs methodically from the preparation techniques for numerical data. Usually, all tokens are transformed into their lowercase version to also take into account words at the beginning of a sentence. Based on a bag-of-words analysis, stop words are usually removed. In this analysis method, the order of the tokens is not important, and the removed stop words ("a", "an", "be") do not significantly influence the text meaning. In addition, punctuation marks and numbers are often deleted, and hyphenated words are separated. The data preparation technique used in the study is explained in chapter **??**.

4.3 Data

The analysis is based exclusively on data from the Web of Science database (Clarivate Analytics, 2024). In addition to formal metadata such as authors, year of publication, title, place and DOI, Web of Science also provides content-related metadata such as abstracts. The discipline of sociology is narrowed down using the journal categories provided by Web of Science. Accordingly, all articles published in a journal that Web of Science assigns to the journal category "Sociology" are included in the discipline of sociology. All journals in this category are part of the "Social Sciences Citation Index" or the "Emerging Sources Citation Index" (Clarivate Analytics, n.d.-a). Both citation databases are part of the "Web of Science Core Collection" (Clarivate Analytics, n.d.-b). The procedure for categorizing journals by Web of Science is documented (of Science Group, 2019). The categorization comprises four levels in which 28 criteria are tested (of Science Group, 2019). Despite criticism from Milojević (2020) and Norris and Oppenheim (2007), the journal categories provide deep insights into science studies (Boyack et al., 2005; Leydesdorff et al., 2013). Among other things, it is criticized that topic-based classifications are more accurate than journal-based ones and that multidisciplinary research, as well as research published in books, cannot be mapped (Milojević, 2020; Norris & Oppenheim, 2007). Nevertheless, overviews of the scientific landscape can be obtained by classifying topics in journals (Boyack et al., 2005; Leydesdorff & Rafols, 2009). Alternative approaches to determining the boundaries of scientific fields can be found in network research and are based on citation networks (Lietz, 2020; Mejia et al., 2021). Articles published between 1974 and 2023 are downloaded. The basis for this decision was the literature presented in chapter 3. However, a subsequent descriptive analysis of the data set revealed that only publications after 1993 have abstract data. Therefore, only the period 1993-2023 could be considered for the analysis. The following search string was used to search the Web of Science Core Collection via the “Advanced Query” and download all articles:

(WC=(Sociology)) AND DOP=(1974-01-01/2024-01-01)

The “Fast5000” download option via the Web of Science web display allowed the metadata to be saved in sections of 5000 articles. Web of Science blocks manual downloads of more than 100,000 articles per search. To get around this block, the search was divided into four time blocks so that the total number of results per search could be kept below 100,000. The selected time periods were: 1970-1985, 1986-2000, 2001-2014, 2015-2023. In total, metadata for 345,019 articles from a total of 309 journals could be downloaded. Methodologically, the data set represents a complete survey of the article metadata of all articles published between 1993 and 2023 in journals with the Web of Science journal category “Sociology”. The textcat extension for R categorized the stored abstracts by language (Hornik et al., 2023). Subsequent filtering of all non-English articles avoids language-based misclassifications of the English-language dictionaries. It can be assumed that the textcat extension provides reliable results because it uses the same N-gram based classifier from very well-known programs such as LibreOffice (Cavnar & Trenkle, 2001; McNamara et al., 2024).

To test the selection of Web of Science as a database, a test data set was downloaded via OpenAlex. OpenAlex provided access to fewer abstracts with the same disciplinary restrictions despite a larger number of hits. This indicates not only a smaller amount of data, but also a less focused selection of abstracts. The analysis is therefore based on the Web of Science database, as this provided access to a higher absolute number of abstracts with a smaller total number of article hits.

4.4 Operationalization

To capture positive and negative evaluations of the research abstracts, I use the basic approach of dictionary-based sentiment analysis. The analysis is carried out with the positive and negative terms from the dictionary by Vinkers et al. (2015). The results are additionally validated with the open source sentiment software VADER (Hutto & Gilbert, 2014). The dictionary of Vinkers et al. (2015) was created specifically for the analysis of scientific articles, but it only contains 50 words (see appendix .2). The results are therefore susceptible to changes in the frequencies of individual words. Vinkers et al. (2015) themselves note that their detected increase in positive words was largely caused by only four words: ’robust’, ’novel’, ’innovative’ and ’unprecedented’. VADER is one of the most accurate dictionaries in various comparisons with other established sentiment dictionaries (Hutto & Gilbert, 2014; Ribeiro et al., 2016). Although VADER is not a dictionary designed specifically for analyzing scientific texts like Vinkers et al. (2015), VADER can also produce valid results for scientific texts. VADER’s algorithm implements the consideration of full stops and punctuation marks, upper and lower case letters, as well as words that invert, strengthen or weaken sentiments (negations, ”but”, ”very”, etc.) (Edlinger et al., 2023; Hutto & Gilbert, 2014). Validation is carried out by checking inter-rater reliability and then checking annual agreement.

The dictionary analyses are carried out with the text analysis framework quanteda, which was developed for the statistics language R (Benoit et al., 2018; {R Core Team}, 2024). Quanteda allows you to create and apply your own dictionaries. The dictionary from (Vinkers et al., 2015) was integrated into the analysis using this function. VADER also has an interface for use in R (Hutto & Gilbert, 2014). The overview of the frequencies of all words in the dictionary of Vinkers et al. (2015) was created using Julia due to the real-time compiling advantages (Bezanson et al., 2017). All procedures beyond the analysis of the annual mean values of the sentiments are carried out in Python instead of R due to the more memory-efficient environment (Van Rossum et al., 2009) .

When using both dictionaries, each word in an abstract is assigned to one of three category values. The category expressions $K = \{k_1, k_2, k_3\}$ of each sentiment analysis are $K_{\text{vinkers}} = \{\text{positive, negative, unmatched}\}$ and $K_{\text{VADER}} = \{\text{positive, negative, neutral}\}$ (Hutto & Gilbert, 2014; Vinkers et al., 2015). Relative frequencies of the absolute frequencies of each category are calculated for all abstracts.

$$h(k_i) = \frac{H(k_i)}{H(k_1) + H(k_2) + H(k_3)}$$

VADER weights the intensity of the sentiments per word between -4 and +4 (Hutto & Gilbert, 2014). These sentiments are re-weighted based on sentiment-intensity-changing words such as “very,” “but,” “not,” or “!” The final calculated relative frequencies indicate a sentiment’s positivity or negativity for each abstract. The measure, normalized by the number of words in an abstract, allows the comparison of sentiment values aggregated over years.

4.5 Analytical Approach

The presentation of mean values and confidence intervals of the annual sentiment shares in interval plots forms the starting point of the data analysis. This visualization of aggregated data provides a first insight into the development of the sentiment shares over time. In the figures described, the presentation of the confidence interval plays an important role. A significant deviation from the mean indicates a randomness. In the following, it is briefly explained whether inferential statistical methods can be legitimized in the case of almost complete surveys. In contrast to descriptive statistics, inferential statistical models allow an effect to be explained by dividing it into a systematic and a stochastic part (Broscheid & Gschwend, 2005). For example, in a linear regression, the stochastic “random factor” ϵ is interpreted as pure chance or as a collective measure of all unobserved influencing factors (Broscheid & Gschwend, 2005). In the event that the assumptions of the model are violated, two options are available. Either “violations of the assumptions can be considered trivial and statistically corrected" or "diagnosed violations of the model assumptions about the ϵ_i are considered substantially interesting." (Broscheid & Gschwend, 2005, p. 20). Further statistical analysis of the stochastic deviations enables the gain of new insights with which the statistical model and also the theory can be improved. Even though these goals work independently of the sample size, it should be noted that the standard error is artificially reduced when the number of cases is particularly large:

$$\lim_{n\to\infty} \frac{\sigma}{\sqrt{n}} = \sigma \cdot \lim_{n\to\infty} \frac{1}{\sqrt{n}} = \sigma \cdot 0 = 0 \tag{4.1}$$

In the case of particularly large numbers of cases, negligible effects become artificially statistically significant (Tabachnick & Fidell, 2014). The non-interpretability of the statistical significance makes it difficult to assess the actual relevance of the effect.

After considering the aggregated sentiments, the results of both dictionaries are compared. The agreement of the results of both dictionaries is checked with a Pearson correlation. This allows a conclusion to be drawn about the effectiveness of the additional validation by the VADER dictionary. The Pearson correlation, with its properties as an adjusted measure of inter-rater agreement, is well suited for comparison (Lehrstuhl Psychologische Methodenlehre, SS24). Adjusted measures integrate consistency but not the stringency of the evaluations. Both dictionaries evaluate on different scales due to their different sized word lists and different attention to the surrounding terms of a sentence. Therefore, paying attention to stringency would lead to meaningless results. In addition to the correlation, the difference in the z-standardized positive sentiment shares per year and the difference in the z-standardized negative sentiment shares per year are calculated for the direct comparison. However, the positive sentiment shares aggregated per year for both dictionaries are error-prone values. The error propagation according to Gauss (4.2) allows the calculation of the standard error of the difference of both values. The standard errors of the sentiment shares to be compared form the basis of this procedure (Tipler & Mosca, 2015). The theoretical background of the procedure is that statistical errors cancel each other out compared to systematic errors (Tipler & Mosca, 2015).

$$\Delta Y = \sqrt{\sum_{i=1}^{m} \left(\frac{\partial Y}{\partial X_i} \Delta X_i \right)^2} \tag{4.2}$$

Where $\Delta Y = \frac{\sigma}{\sqrt{n}}$ is the standard error. Inserting the sentiment difference into equation 4.2 yields the result 4.3 (see appendix .4). Where s_{vader} and s_{vink} are the sentiment proportions of the abstracts.

$$d_s = s_{\text{vader}} - s_{\text{vink}} \tag{4.3}$$

$$\Delta d_s = \sqrt{\Delta s_{\text{vader}}^2 + \Delta s_{\text{vink}}^2} \tag{4.4}$$

The linear regression according to the OLS procedure enables the specification of possible trends that cannot be reliably determined by simply displaying the mean values. The application of a parametric procedure is legitimized by the formulation of suspected trend progressions following the analysis of the aggregated data. Likewise, the high sample size significantly influences the interpretation of statistical significance in the linear regression analysis. Lin et al. suggested in 2013 to create so-called CPS charts (**C**oefficient/**P**-value/**S**amplesize) using Monte Carlo simulations. In these graphics, the p-value is plotted as a function of the number of cases. To do this, increasing samples are drawn starting at $n = 0$, the linear model is estimated for each, and the p-value is stored (Lin et al., 2013). This allows a transparent representation of the p-value distortions due to the sample size.

4.6 Summary

The first section of the chapter describes the methodological background of a dictionary-based sentiment analysis. This assigns individual tokens to certain categories using dictionaries in order to classify text documents into emotion or evaluation schemes. The quality of the results depends on the quality and congruence of the dictionary used for the text domain. As a data basis for the analysis, 345,019 abstracts were downloaded from publications that appeared in journals in the Web of Science category “Sociology” between 1974 and 2023. The abstracts are filtered by language so that only the English-language abstracts remain. The dictionary from Vinkers et al. (2015) and VADER are used to operationalize positive and negative evaluations. This approach increases the validity of the results. For both dictionaries, the absolute frequencies of the tokens recognized in the texts are converted into relative frequencies based on the number of words in the respective abstract. The sum of the relative sentiments of all abstracts published in one year allows for a comparison between different years. The analysis approach includes the presentation of mean values and confidence intervals of annual sentiment proportions. In the corresponding section, the importance of inferential statistics in the context of large case numbers was also discussed. Particularly large case numbers artificially increase statistical significance, making it more difficult to assess actual relevance. A Pearson correlation of the results of both dictionaries allows an estimation of the validity of the results. In addition, the difference between the positive sentiments of both dictionaries and the negative sentiments of both dictionaries is calculated. The linear regression according to the OLS procedure allows a more precise examination of suspected trends.

5 | Results

5.1 Introduction

The following chapter presents the results of the analysis. First, the data cleansing supported by descriptive analyses is explained and a first impression of the data structure is gained. This is followed by the analysis of the annual mean values of positive and negative sentiment components using interval plots. These already go beyond purely descriptive analyses by displaying confidence intervals. Subsequently, the agreement of the dictionary results is first checked using a Pearson correlation. In addition, the difference between the positive and negative sentiments of the previously calculated annual mean values of both dictionaries is formed and again displayed with confidence intervals. This allows for the identification of over-random distinctions between the dictionaries for individual years. In order to check whether the sentiment trends are non-linear, linear regressions with non-linear terms are then evaluated. The high number of cases in the data set causes distortions in the statistical significance. Simulations in which the regression is calculated for samples of different sizes allow a more precise assessment of the respective effects. Finally, a brief examination of selected assumptions of the linear regression provides an insight into the data structure. Consequently, the legitimacy of the regression results can be critically questioned. At the end of the chapter, a summary of the analysis results is provided.

5.2 Datacleaning and Inspection

To make informed decisions about data cleaning, some exploratory descriptive analyses are carried out first. The figure 5.1 shows that almost all abstracts in the data set were published after 1992. Therefore, the analysis cannot be carried out as planned with abstracts since 1974. The restriction to publications from 1993 serves to exclude distortions due to low annual abstract numbers. Additionally, all articles were removed that either did not contain abstracts or whose abstracts were not written in English. The identification of the non-English articles is explained in Section 4.3. Five abstracts were noticeably extremely long. The removal of all texts with more than 2000 characters, which corresponds to about one page of text, avoids influencing the results with outliers.

The heatmap 5.2 checks whether the almost exponential increase in the number of articles can be attributed to individual journals. The graphic shows each journal on the y-axis over all years recorded on the x-axis. The number of articles published by a journal in a year is color-coded.

The figure 5.2 is characterized by a striking staircase shape. A whole series of journals were added to Web of Science in 1992, both in 2008 and 2019. At the same time, some journals can also be

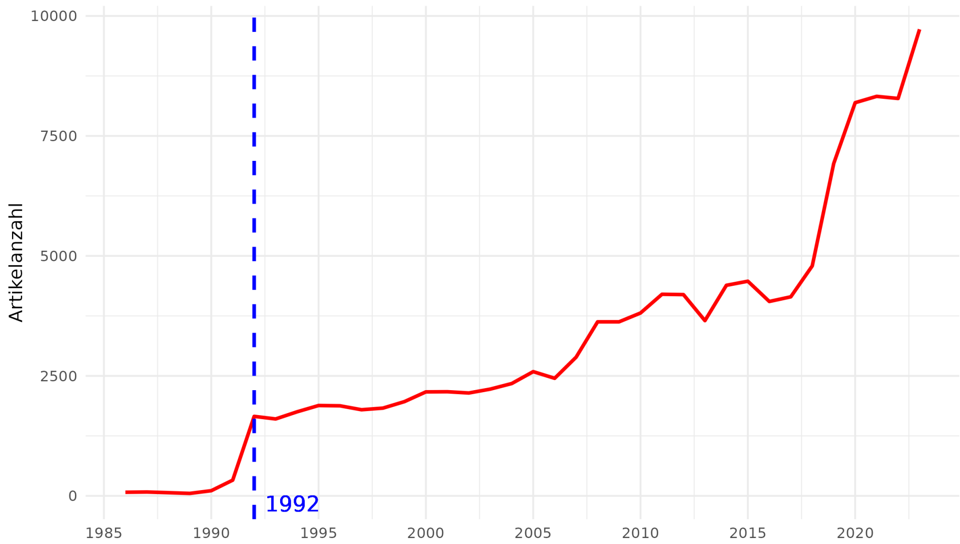

Figure 5.1: Published articles with abstracts contained in the data set per year

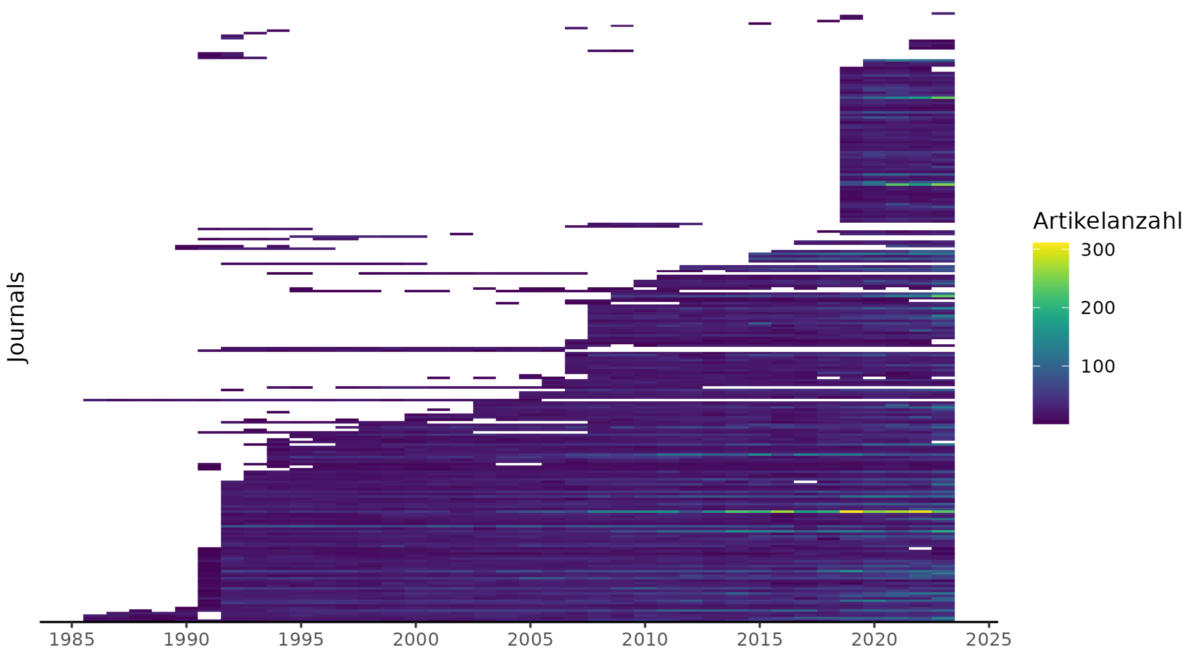

Figure 5.2: Heatmap of the published articles of each journal per year. The lighter the fields, the more articles were published in a year in the respective journal.

identified that have not been represented in Web of Science since these years. The publication frequencies of each journal are in most cases below 100, or even below 50 articles per year. This applies mainly to the earlier years of the data set. In particular, the journals publishing over the longest period of time show a visible increase in the number of articles published per year. The exponential increase in the number of published articles per year shown in Figure 5.1 can be attributed to the journals added in 2008 and 2019. In Figure 5.2, 3–5 journals can be seen that consistently publish a significantly higher number of articles. The journals with the highest number of publications are identified using the frequency table 5.1, which lists the six most frequently publishing journals. This allows the journal that stands out as the “yellow line” in the figure 5.2 to be identified as “Social Indicators Research”.

Journale	**Abstracts**
Social Indicators Research	3900
Ethnic and Racial Studies	2232
Journal of Marriage and Family	2134
Social Science Quarterly	2131
Social Science Research	2014
Society & Natural Resources	1972

Table 5.1: Journals with the largest number of available abstracts

Finally, the question arises as to how seriously the number of published articles in the most influential journals differs from the number of articles in the other journals. Lag measures provide a first insight into the basic distribution of articles published by a journal. A journal published on average 503 articles over the entire period, but the median is only 373.3. Social Indicators Research published more than 10 times as many articles as a journal with a median number of publications. These values also indicate a strong right skew. The figure 5.3 shows a bar chart of the number of articles published per journal.

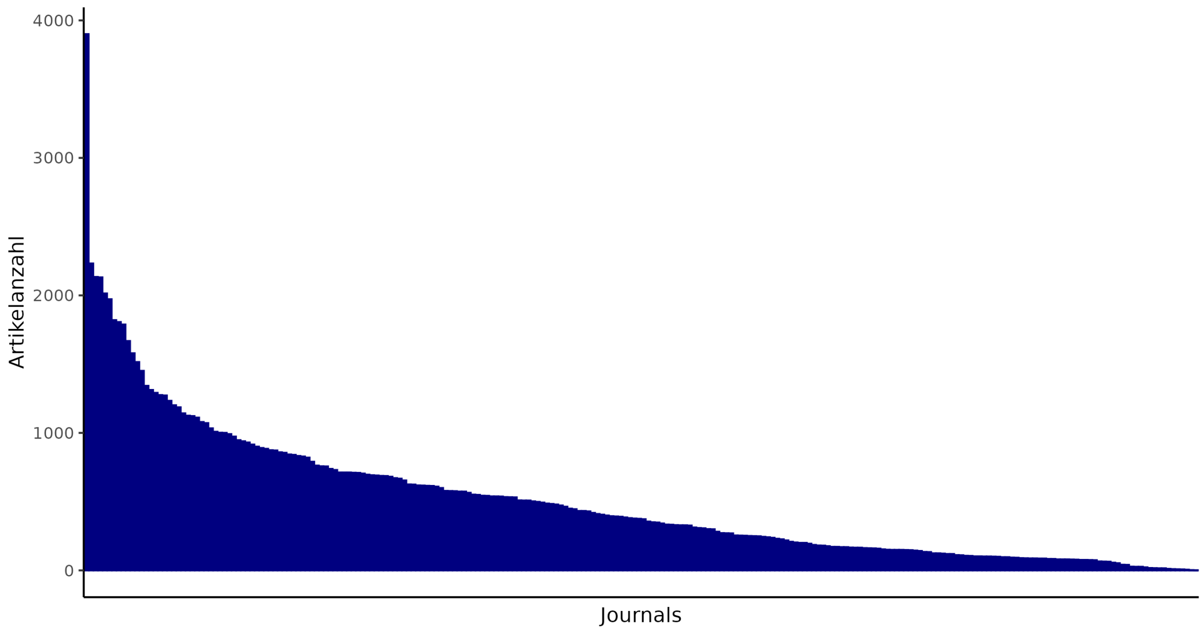

Figure 5.3: Published articles per journal

The sorted distribution of the journals in 5.3 shows the distribution typical of Bradford’s law (Bradford, 1985). Bradford’s law states that when journals are sorted in descending order according to the number of articles they contain, the distribution follows a geometric series $1 : n^2 : n^3$ (Bradford, 1985). Bradford divided the distribution of their increase into zones, which are identified by their increase according to the geometric series. These zones can also be clearly seen in the figure. For example, the core zone, which follows the linear increase, is clearly recognizable after the first two journals. About one-third of all articles are part of this zone and define the core of the field (Bradford, 1985). The data set is not limited to the articles from the core zone for two reasons. Firstly, the order of the journals changes over time. To examine a temporal trend, it is therefore important to include all journals in the analysis, not just those that are relevant by current standards. For the same reason, the journals are not filtered by impact factor. The impact factor is calculated based on the last N years. The information about the impact factors of the journals over the last 30 years is not available. Secondly, Bradford (1985) itself notes that the articles published in the long-tail journals are not part of the core in any discipline. Despite their lack of core relevance, journals and their contributions are considered an integral part of a field, which is why their inclusion in thorough research is essential.

The preparation of the text data is briefly described below. To apply the dictionary of Vinkers et al. (2015) to the abstracts, hyphens were removed. Quanteda automatically recognizes upper and lower case when analyzing dictionaries, so it was not necessary to transform all words into lower case in this step (Benoit et al., 2018). Compared to other computer-assisted text analyses, the application of dictionaries requires less text adaptation because dictionaries are designed to search raw text. The text does not need to be specially prepared for the application of VADER. VADER's algorithm is case sensitive (Hutto & Gilbert, 2014). No sentiments can be formed by VADER for 31 abstracts.

5.3 Annual aggregated sentiment trends

The following analysis of the temporal trends is carried out using interval plots. The years are treated as groups for which the aggregated sentiments are shown with mean values and 95% confidence intervals.

The figure shows that the proportion of positive sentiments in the abstracts increased almost constantly and almost linearly over the entire period. %Die Spearmankorrelation ist positiv und statistisch Signifikant mit einem $\rho = 0.07$ und $p < 0.001$. In the early 1990s, the annual mean values of the proportions of positive words are mostly below 0.07% and have wide confidence intervals. Compared to the remaining years, the mean values of the last five years hardly increase at all. The increased uncertainty in the early years could be due to the smaller number of abstracts (Figure 5.1). The narrowing of the confidence intervals is particularly visible from 2006 and 2017. In these years, the number of articles also increased significantly, as can be seen in the figure 5.1 discussed earlier, which confirms the assumption that the number of articles is the cause. The increased variability of the values between 2000 - 2004 and 2012 - 2018 could perhaps be explained by the figure on journal activity (5.2), although there are no abnormalities

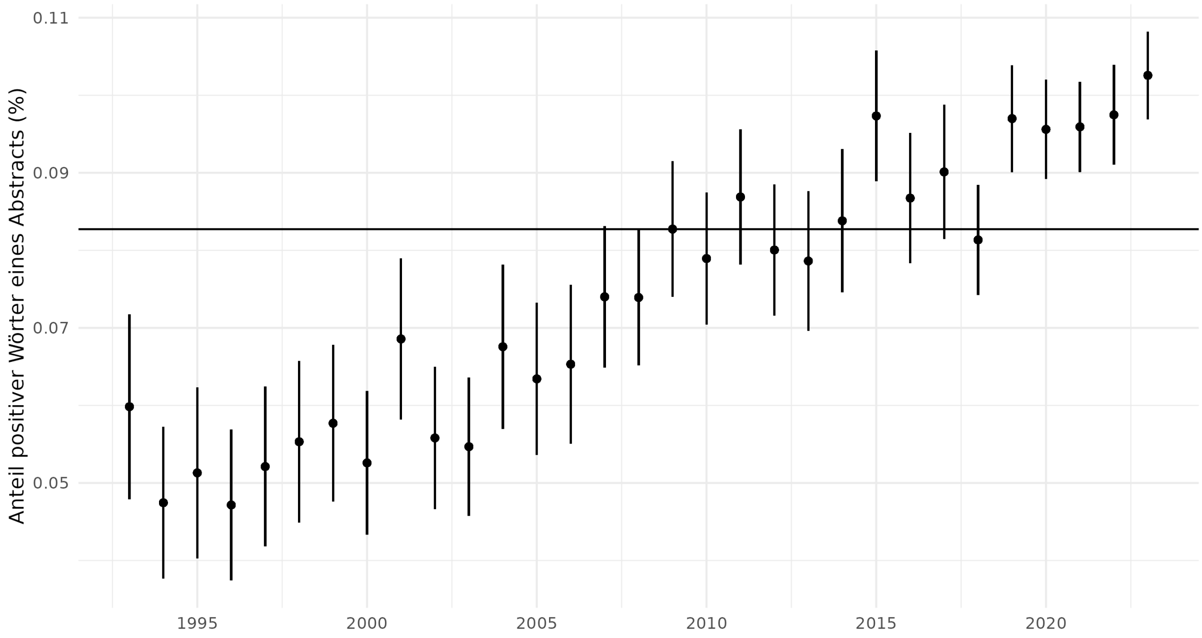

Figure 5.4: Dictionary of Vinkers et al. 2015: annual mean values of the percentage of positive sentiments per abstract with 95% confidence intervals; the horizontal line marks the average sentiment value of the entire period

in both periods in this figure. The irregularities in the increase of positive sentiments would therefore have to be due to content trends.

A closer look at the influence of the individual words (see appendix: .5) reveals that “encouraging”, “innovative”, “novel”, “supportive” and “unique” stand out due to their very different annual mean values in the period from 2000 to 2004. The deviation of the annual mean value of 2000 in appendix .5 is almost entirely due to irregularities in the frequency of the word “supportive”. The frequency of the word “supportive” increased almost constantly in the years before 2000, but dropped abruptly in 2000. Overall, the results are most influenced by the words “unique”, “creative” and “novel”. However, “innovative”, “prominent”, “robust” and “supportive” also have a high influence on the result. Between 2012 and 2018, the otherwise very strong growth of ’novel’ is interrupted. The words ’unique’, ’innovative’ and ’robust’ decrease in frequency, while ’creative’ almost doubles for 4 years before returning to its original value.

No clear trend emerges for the negative sentiments shown in Figure 5.5. In comparison with the proportions of positive sentiments, it can be seen that the mean of the percentages of all positive sentiments is almost three times as high as the mean of the percentages of all negative sentiments. The annual averages between 1993 and 1997 rise steeply in a linear fashion, with the confidence interval of the annual average for 1997 being the only one to lie completely above the average of all sentiment proportions. The following years, up to the annual average for 2001, are again closer to the overall average of the sentiment proportions. Between 2001 and 2007, the annual mean values of the negative sentiment components fluctuate widely around the mean value of all negative sentiments. After that, however, all annual averages up to 2020 are very

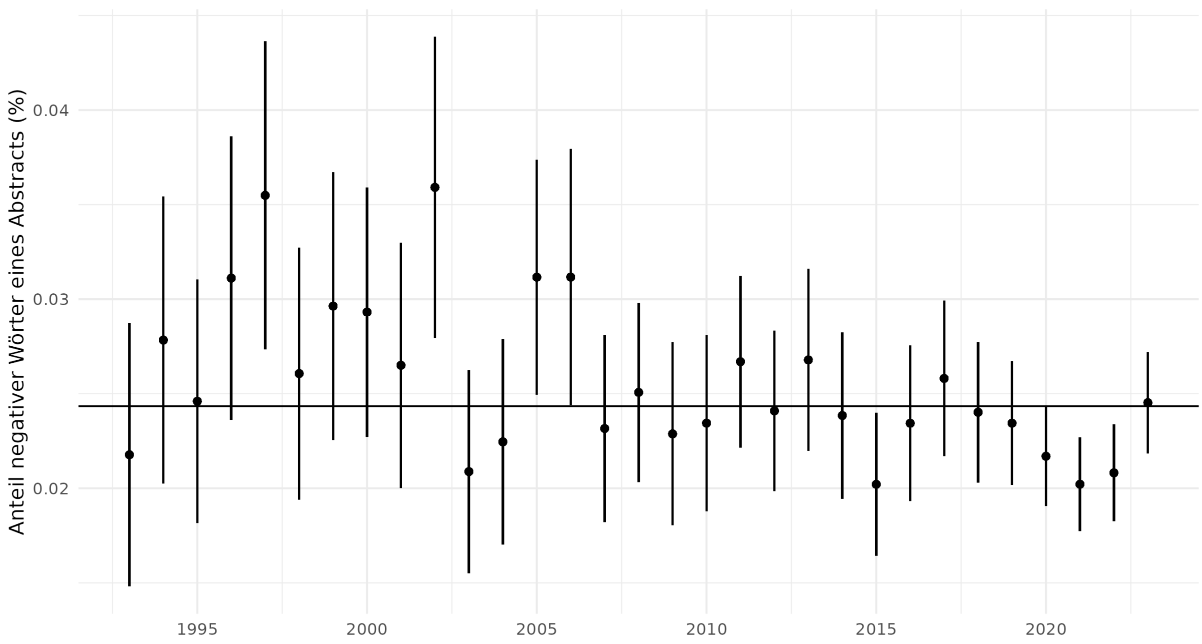

Figure 5.5: Dictionary of Vinkers et al. 2015: annual mean values of the percentage of negative sentiment per abstract with 95% confidence intervals; the horizontal line marks the average sentiment value for the entire period

close to the mean value of all negative sentiments. In particular, a negative trend can be seen from 2017 onwards, which lasts for 6 years but seems to be reversed by an outlier in 2023. The confidence intervals are reduced from 2006 and 2017 as already shown in the figure of the positive sentiments due to the larger sample size.

The annual mean values of the positive sentiments of the VADER dictionary, which are shown in Figure 5.6, all show higher values compared to the sentiments shown in Figure 5.4. The scale differences of the sentiment methods result from the unequal dictionary sizes and VADER's additional rules for token classification. In the early years from 1993 to 2000, no trend emerges for the given values. In the mentioned time interval, the sentiment mean values are around 7.1% and thus below the overall mean (7.6%) of all positive sentiment values. Between 2002 and 2015, the sentiment mean values increased almost linearly to around 7.9% above the overall mean value. The sentiment values of recent years fell abruptly in 2017 and 2018 to just above the mean value. This level was maintained in the following years and showed no clear trend. However, the proportion of positive sentiments rose slightly again in 2023. %Die Korrelation von $\rho = 0.04$ ist statistisch signifikant mit $p < 0.001$. As with the dictionary by Vinkers et al. (2015), the positive sentiments of VADER in the years after 2000, especially 2001, as well as 2016 to 2019, show high irregularities and no clear progression of the positive sentiment values. Parallels can also be seen in the width of the confidence intervals. In Figure 5.6, the confidence intervals also visibly narrow from 2006 and 2017 due to the higher sample size.

The distribution of negative sentiments is shown in Figure 5.7. The average value of the negative sentiments is 5.1. This value corresponds approximately to a quarter of the average value of

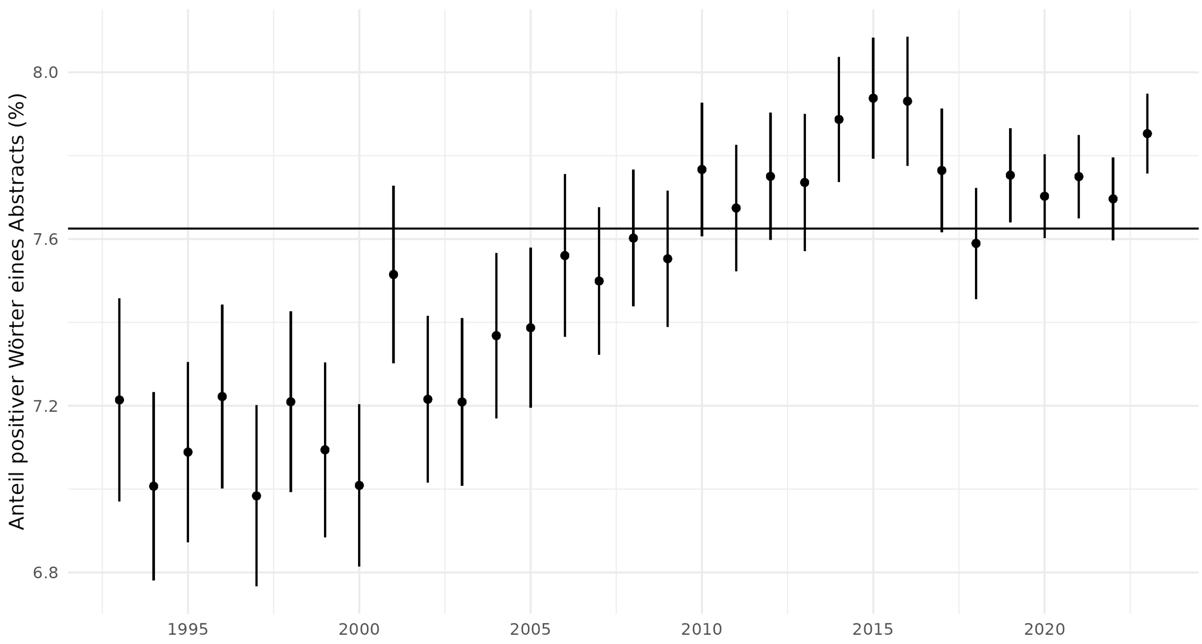

Figure 5.6: VADER: Annual mean values of the percentage of positive sentiments per abstract with 95% confidence intervals; the horizontal line marks the average sentiment value of the entire period.

the positive sentiments. The negative sentiment proportions are on average about four times weaker than the positive sentiments in the analyzed data set. Except for two years (2011, 2014), all confidence intervals intersect the overall mean of the sentiment proportions. Therefore, a statistically significant trend cannot be assumed. Nevertheless, the course of the annual mean values can be recognized more clearly as negative than in the case of the negative sentiments in the dictionary by Vinkers et al. (2015). In the years 1994 to 1999, all annual mean values are above the average of the proportions of all negative sentiments. Between 2000 and 2015, all annual mean values, except for the annual mean value of 2013, are below the total mean value. Between 2005 and 2015, no clear trend can be seen. After that, the mean values rise rapidly until 2017 above the mean value of all sentiment components, only to fall again slightly, but to remain above the overall mean value.

Both dictionaries show a greater overall use of positive language compared to the use of negative language. This effect is already known in research as the Polyanna Hypothesis. The Polyanna Hypothesis has its origins in the study Boucher and Osgood (1969), which lists a series of small studies to show that positive words carry more meaning and are used more diversely. Dodds et al. (2015) showed that the effect demonstrated by Boucher and Osgood (1969) can be confirmed with 24 corpora for 10 languages.

The analysis to date shows a positive trend in the deviations of the annual mean values of positive sentiments in the early and late years based on the confidence intervals. No clear positive trend can be determined for the negative sentiments.

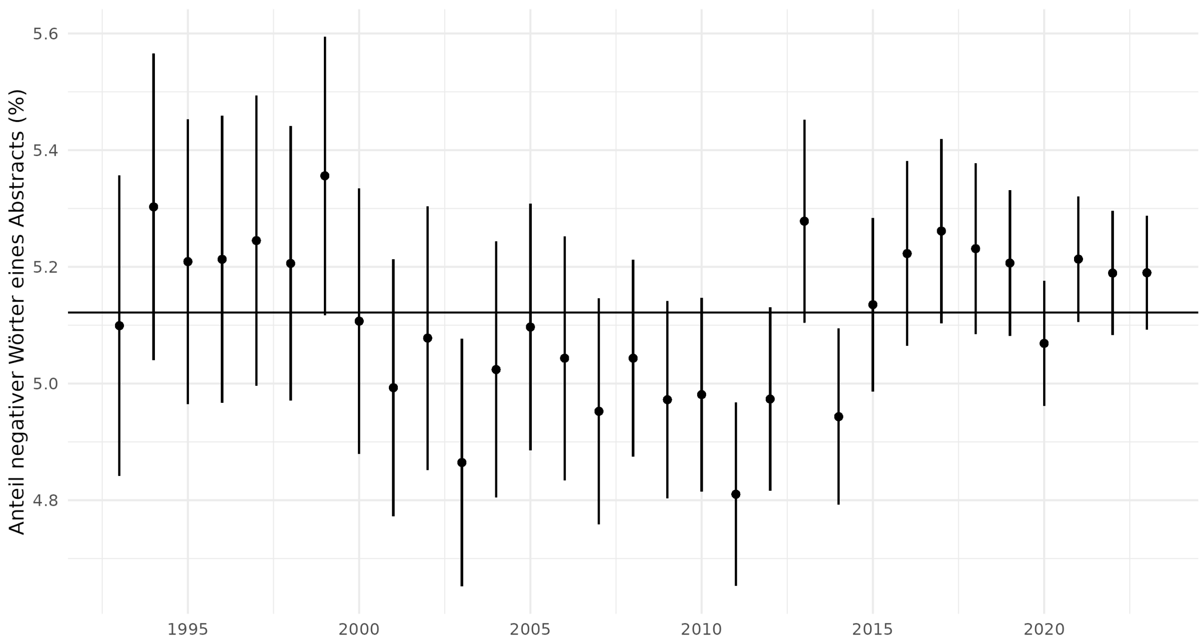

Figure 5.7: VADER: Annual averages of the percentage of negative sentiments per abstract with 95% confidence intervals; the horizontal line marks the average sentiment value for the entire period.

5.4 Comparison of dictionary results

In the following, the results of both dictionaries for positive and negative sentiments are compared. The Pearson correlation of the measured sentiment proportions for the raw values as well as the annual mean values are shown in Table 5.2.

Sentiment	**Individual Abstracts**	**Annual Level**
Positive Sentiments	0.20	0.91
Negative Sentiments	0.15	0.22

Table 5.2: Pearson correlation of sentiment proportions estimated using VADER and Vinkers et al. (2015)'s dictionary.

The evaluation of individual abstracts differs greatly, with only 15% and 20% agreement. The high deviations are plausible because many journals do not contain any of the positive words in the dictionary by Vinkers et al. (2015) due to its small scope. VADER classifies many terms as positive that would rather assign the research to a specific topic than positively evaluate one's own research. For example, VADER classifies the following terms as positive: "trust", "interest", "satisfaction", "ethical", "freedom". On the individual level, VADER's results are therefore less valid than the results of the dictionary by Vinkers et al. (2015). The dictionary of Vinkers et al. (2015) accordingly underestimates the sentiment proportions, while VADER overestimates them. At the annual level, the agreement of positive sentiments is very high at 91%. However, the aggregated negative sentiments only show a correlation of 22% at the annual level. The low correlation of the negative sentiments of both dictionaries at the annual level can be explained by the lack of a clear trend. By the same reasoning, the impression of a positive trend is confirmed by the high correlation of the annual sentiments of both dictionaries.

Figure 5.8: Difference of the z-standardized positive sentiment shares of the sentiment software VADER minus the dictionary from Vinkers et al. (2015) with 95% confidence intervals; the horizontal line marks the average sentiment value of the entire period.

The figure 5.8 shows the difference of the z-standardized annual mean values of the positive sentiment proportions of both dictionaries. The slightly positive overall mean indicates that the z-values of the positive sentiments of VADER are slightly higher than those of Vinkers et al. (2015)'s dictionary. This circumstance could be due to the tokens of VADER. These are charged with topic-indicating meanings rather than research-evaluating meanings. As a result, VADER classifies a higher relative number of words as positive overall. Overall, only in the last 4 years 3 years deviate clearly from the mean. For the previous years, no statistically significant deviation from the mean can be determined.

The figure 5.9 shows the difference in the z-standardized annual mean values of the negative sentiment proportions of both dictionaries. The overall mean of the differences is slightly below zero. VADER therefore assessed the journals less negatively than the dictionary by Vinkers et al. (2015). Only the years 2002, 2015, 2021 and 2022 deviate statistically significantly from the mean. The remaining mean values show no significant deviation. The created figures of the differences show that both dictionaries have a high degree of agreement in the evaluation of positive and negative sentiments at the annual level. The deviations of the last 4 years are excluded from this.

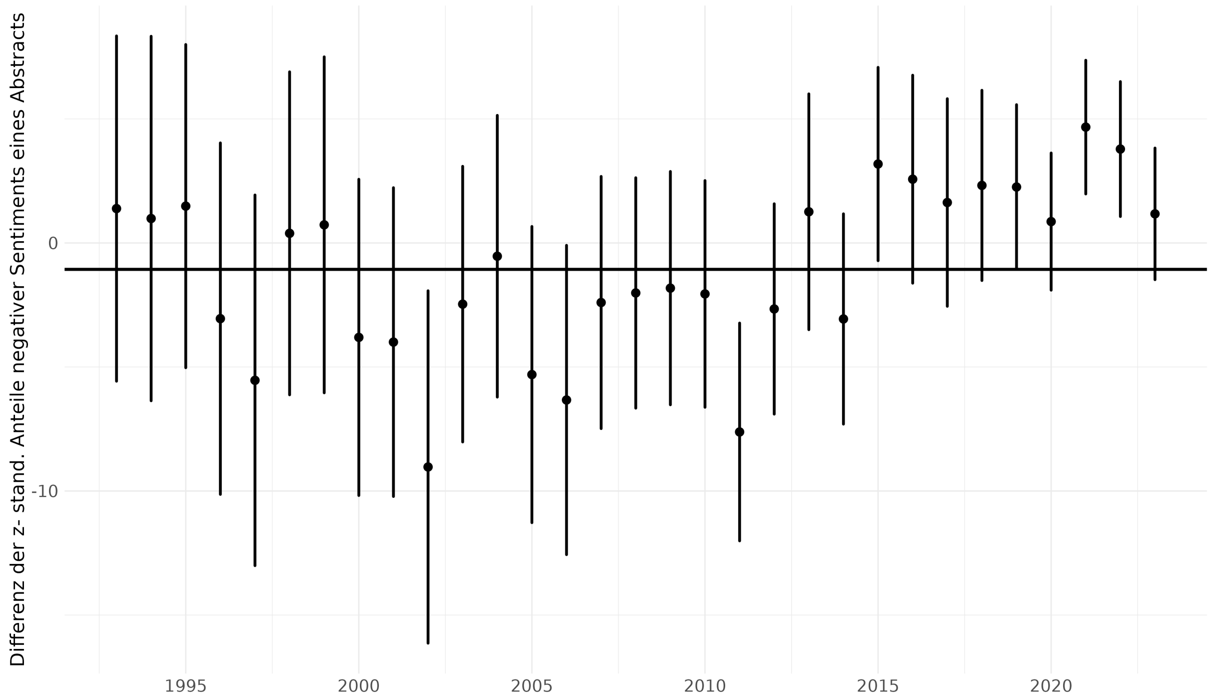

Figure 5.9: Difference of the z-standardized negative sentiment shares of the sentiment software VADER minus the dictionary from Vinkers et al. (2015) with 95% confidence intervals; the horizontal line marks the average sentiment value of the entire period.

$$\text{Vink I:} \qquad s_{\text{vink}_{\text{positiv}}} = \beta_0 + \beta_1 \cdot \text{Year} \tag{5.1}$$
$$\text{Vink II:} \qquad s_{\text{vink}_{\text{positiv}}} = \beta_0 + \beta_1 \cdot \text{Year} + \beta_2 \cdot \text{Year}^2 \tag{5.2}$$
$$\text{Vader I:} \qquad s_{\text{vader}_{\text{positiv}}} = \beta_0 + \beta_1 \cdot \text{Year} \tag{5.3}$$
$$\text{Vader II:} \qquad s_{\text{vader}_{\text{positiv}}} = \beta_0 + \beta_1 \cdot \text{Year} + \beta_2 \cdot \text{Year}^2 \tag{5.4}$$

5.5 Linear Regressions

In the analysis so far, a positive sentiment trend has been identified that is more likely to be positive. However, the methods used so far do not allow any conclusions to be drawn about the type of trend. In the following, the exact trend of the positive sentiment components is examined using linear regression based on the proven OLS method.

In model 1, the years (variable 'year') are used as predictor variables. Subsequently, the model is extended to include the squared form of the years as a predictor variable (variable 'year^2'). This makes it possible to check whether the visually recognizable small deviations of a linear trend of the relative frequencies of positive sentiments should be interpreted as statistically significant. The equations (5.1) - (5.4) explicate the regression equations to be calculated. Unlike in the previous analysis, the regressions do not use data aggregated per year. The reason for this is that the reduced information about the distribution in the data due to the aggregated data could be crucial in identifying correspondingly small deviations when adding a nonlinear term.

	vink I	**vink II**	**vader I**	**vader II**
Intercept	-3.5618***	-6.2191	-41.7167***	-4523.4624***
	(0.1866)	(46.6747)	(3.3142)	(828.7231)
Year	0.0018***	0.0045	0.0245***	4.4841***
	(0.0001)	(0.0464)	(0.0016)	(0.8246)
$Year^2$		-0.0000		-0.0011***
		(0.0000)		(0.0002)
N	121789	121789	121758	121758
R^2	0.003	0.003	0.002	0.002

Table 5.3: Linear regressions of both dictionaries at the abstract level. Standard errors are shown in parentheses.
* p<.1, ** p<.05, ***p<.01

The intercept is not interpretable in any of the models in 5.3, since the start of the time series was chosen arbitrarily according to the availability of the data. Therefore, the year 1993 does not provide a meaningful reference frame for comparing a variable that differs from the intercept. In the "Vink I" model, the coefficient is very small, with an increase of 0.0018 proportions of positive sentiments per year. Converted, the proportions of positive sentiments increase by 1% in about 500 years. The effect is statistically significant at p< 0.01. After adding the quadratic term in the "Vink II" model, the coefficient of the "year" variable increases to 0.0045 sentiment proportions per year. The coefficient of the $year^2$ variable is very small and negative. Both variables are not statistically significant due to high collinearity (J. Cohen et al., 2015, p. 450). In extreme cases, high multicollinearity can lead to changes in the coefficients, which is why the results given should be treated with caution (J. Cohen et al., 2015, p. 450). Both variables are highly correlated by definition, since an increase of "year" by one unit always causes the variable "$year^2$" to increase by a proportionally larger value. The "Vader I" model confirms the very small, statistically significant effect of the "Vink I" model. The coefficient indicates that the positive sentiment components of the abstracts increase by 0.0245% per year. After adding the quadratic term in the "Vader II" model, the coefficient of the "year" variable increases to 4.5% and is statistically significant at $p < 0.01$. The quadratic term is very small at -0.001, but still statistically significant at $p < 0.001$. In this model, too, the influence of the high multicollinearity distorts the predictors. All models have a very small R^2. Accordingly, the average deviation of the measured values from the estimated values exceeds the average deviation of the measured values from the mean by a multiple. The reason for this is the very high standard deviations within the years. The means and standard deviations of the positive sentiments of both dictionaries are shown in Table 5.4. The standard deviation of the positive sentiment proportions of the Vinkers et al. (2015) dictionary is three times as large as the corresponding mean. In contrast, the standard deviation of the positive sentiment proportions of VADER is 35% smaller than the corresponding mean.

positive Sentiments	Mean	Standard deviation
Vinkers et al. (2015)	0,0827	0,2768
VADER	7,6251	4,9120

Table 5.4: Comparison of the location and dispersion of positive sentiment in Vinkers et al. (2015) Dictionary and VADER

Except for the model 'Vinker II', all models were statistically significant with a very small standard error. The following section therefore discusses the simulations presented in chapter 4 and their results. A stepwise, random draw without replacement was used to generate the samples. The resulting sample sizes ranged from 100 to 10,000 data points, with an increase of 100 units each time. For each sample size, 50 random samples were drawn and the linear regression was calculated. The resulting p-values for the coefficient of the variable "year" were stored for each sample size and repetition, and for each sample size a mean p-value of all 50 repetitions of each sample size was calculated. For the "Vader II" model, the sample sizes and the intervals between random draws were varied, starting with a sample of $n = 5000$ and increasing the sample by 5000 cases in the following iteration. The sample sizes of the first exceedances of the typical significance limits are shown in the table 5.5. The CPS plots can be found in the appendix .6.

Compared to the other models, the "Vink I" model requires the smallest sample size to still be significant, with a minimum of 1900 cases. For all variables, very high case numbers are necessary to obtain a statistically significant result. In particular, the quadratic variable in the "Vader II" model, which is intended to represent the nonlinear effect, is only statistically significant from around 30,000 cases. These results show that for usual sample sizes no effect would be statistically significant. Therefore, based on the linear models, no relevant increase in positive sentiments can be assumed. These results suggest that the effect of the variable year on the proportions of positive sentiments is not convincingly statistically significant. When considering this judgment, however, it should be noted that statistical significance does not correspond to the actual significance of an effect (Broscheid & Gschwend, 2005). Since even the actual coefficients are very small, it can be concluded at this point that there is no relevant increase in positive sentiments in sociological publications.

p-Value	Vink I Variable "Year"	Vader I Variable "Year"	Vader II Variable "Year^2"
$p < 0.05$	1900	4100	30000
$p < 0.01$	3100	6300	45000
$p < 0.001$	5300	8700	70000

Table 5.5: Results of Monte Carlo simulations: sample sizes at which typical significance levels are exceeded

5.6 Regression Diagnostics

The last section of the chapter is devoted to a brief regression diagnostics. The aim of the linear regressions was to test the influence of potential nonlinear effects. In the following, the examination of some assumptions of linear regressions will be used to test how much value can be attached to the model results. A violation of the assumptions can lead to distorted standard errors or distorted coefficients (J. Cohen et al., 2015, p. 118) The distribution of the residuals should be homogeneously distributed around the estimator. If the residuals change their distribution depending on the independent variables, heteroscedasticity is present. This circumstance leads to a distortion of the confidence intervals and thus influences the statistical significance (J. Cohen et al., 2015). Figure 5.10 shows the residual diagrams of the four regression models. These show the residuals in relation to the estimated values of the model.

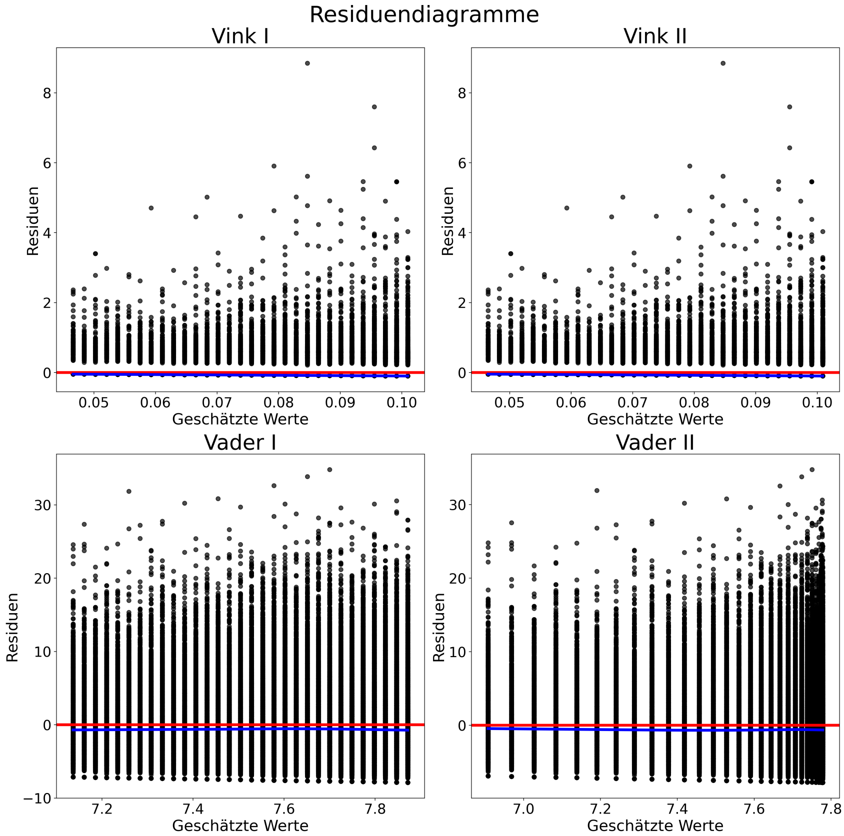

Figure 5.10: Residuals of the four linear regressions. The value zero was marked in red. The locally weighted regression (LOWESS) is shown in blue.

All models show heteroskedastic distributed residuals. Especially for the models "Vink I" and "Vink II" there is a particularly high heteroskedasticity, which is accompanied by strong outliers for the higher estimated values. No model shows the typical distribution of linear distributions, but the LOWESS curve is close to zero. Furthermore, the location of the low measured values of the Vink I & II models is also striking. The value zero seems to occur much more frequently than all the values above it, since the LOWESS curve is almost directly on the zero line. Values above zero only occur again after a "small gap". The "Vader II" model, which already had a slightly higher significant nonlinear term, shows an increase in the density of the estimated values in the higher sentiment proportions. The following section is initially devoted to the increased value density in the higher estimated values of “Vader II”. After that, the distribution of the measured values due to the special small values of Vink I & II is examined. Figure 5.11 shows the regression lines of the four models, together with the annual mean values already known from the interval plots. The nonlinear coefficient of the “Vader II” model is relatively small, but its effect on the trajectory is clearly visible. The last annual means also influence the slope of the straight lines in “Vader I”. The two “Vink I & II” models do not visibly differ from each other. “Vader II”'s nonlinearity is therefore the result of the differences in evaluation of the last years 2019-2023, which have already been identified in the comparison of the differences.

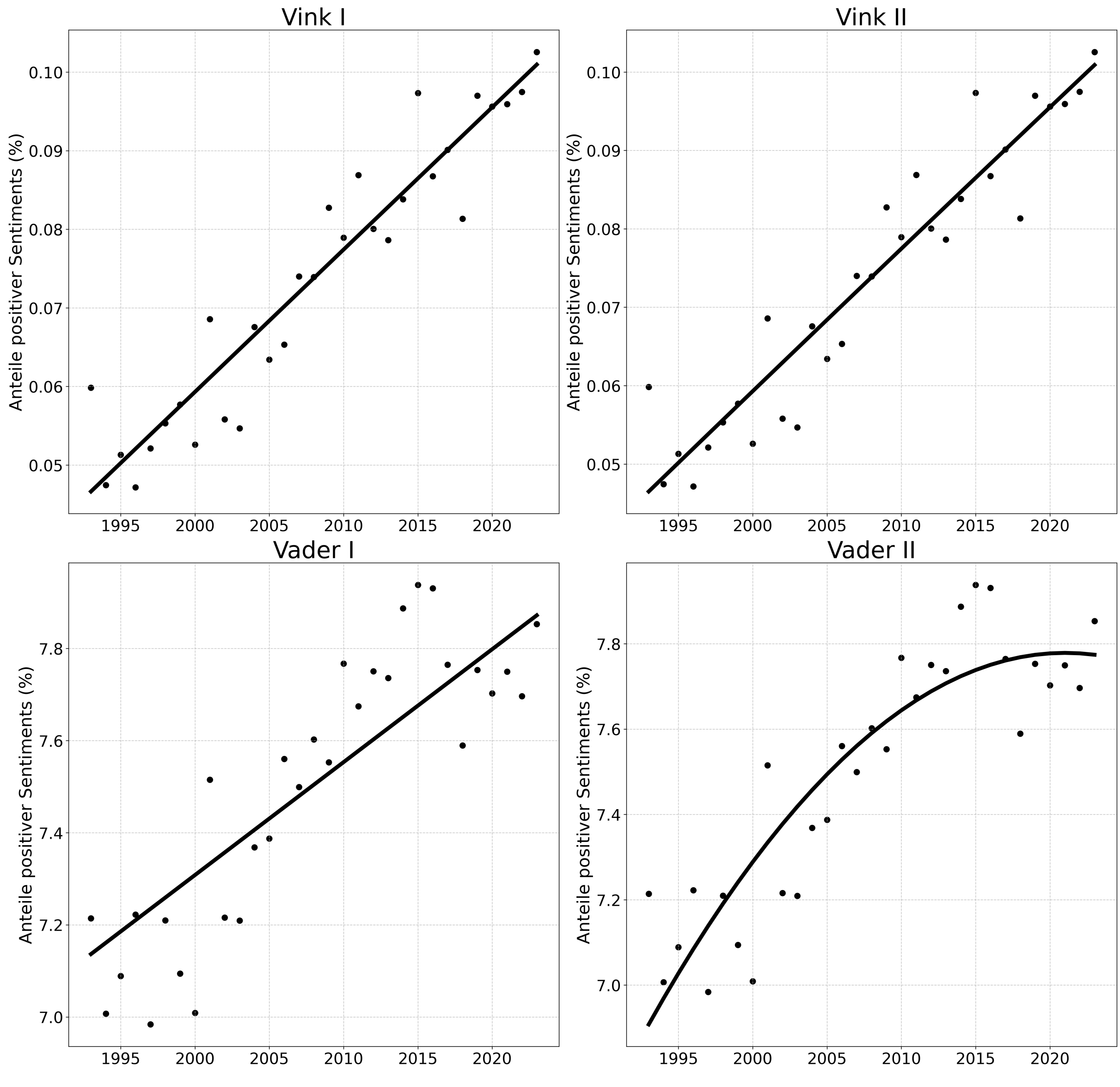

Figure 5.11: Comparison of the estimated trajectories of all four linear regressions. The annual averages, which have already been shown in the interval plots, are also shown.

The figure 5.12 shows the distribution of the positive sentiment proportions of both dictionaries as histograms. The distribution shown in Figure 5.12 is very similar to the residual distributions shown in 5.13. The large number of zeros in the positive sentiment portions of the dictionary from Vinkers et al. (2015) is striking. This is due to the small number of words in the dictionary in the context of scientific texts with predominantly neutral scientific language. The space between zero and the small right-skewed distribution around 0.5 is probably due to the combination of the minimal abstract length and the few words in a dictionary. Most abstracts in which a positive word was found must be at least about two hundred words long. Since Vader categorizes more terms positively overall, the distance between zero and the maximum of the probability distribution is also less pronounced. The strong right skew of both distributions, without the zero values, is reminiscent of a poisson- or logarithmically distributed variable. Since the residuals, in Figure 5.13, are also distributed, the assumption of normally distributed residuals around the estimator is clearly disregarded.

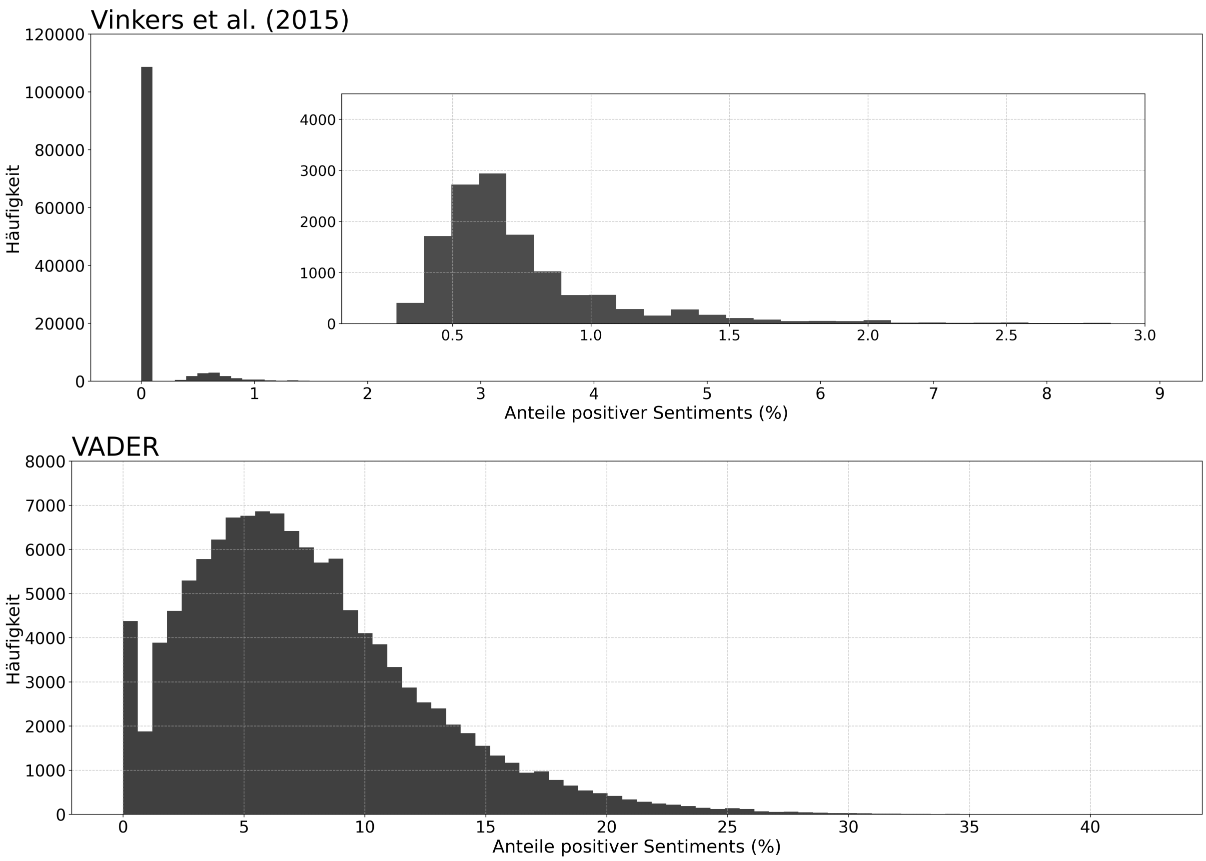

Figure 5.12: Histograms of the measured sentiment proportions of the dictionary from Vinkers et al. (2015) and VADER

Small violations of the assumptions of linear regression do not directly delegitimize the application of linear regression. However, the violations discovered so far are significant. Not only does one of the two dictionaries show a small nonlinear relationship, but there are also major problems with the other dictionary regarding the structure of the measured data. The detected distortions affect not only the standard errors but also the coefficients of the models (J. Cohen et al., 2015, pp. 148–155). According to the diagnoses so far, researchers have several options to choose from, although these are not within the scope of the research question of this paper. While J. Cohen et al. (2015, p. 447) suggests using robust regression to model non-normally

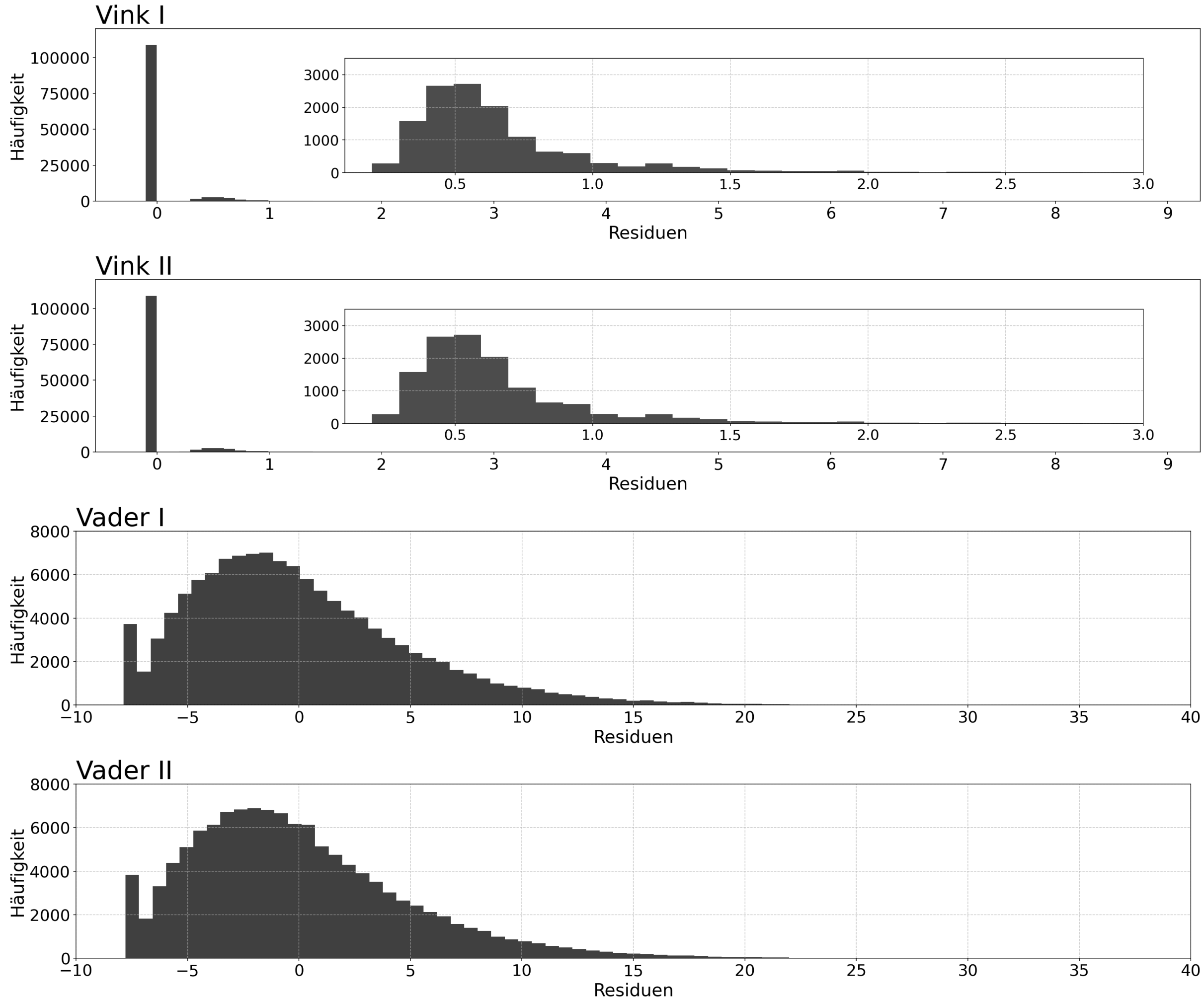

Figure 5.13: Histograms of the residuals of all linear models

distributed data with extreme values, Chatterjee et al. (2000, p. 163) recommends transforming strongly heteroscedastic data with $\sqrt{Y}$. The appendix .7 shows the results of a corresponding transformation.

5.7 Summary

At the beginning of the chapter, descriptive analyses showed that in the years 1993, 2008 and 2019 there was a wave-like increase in journals. The distribution of the numbers of articles published in journals follows Bradford's law. Subsequently, the time series of the sentiment proportions, both positive and negative, are analyzed using annual mean values and interval plots. The annual mean values of positive sentiments increase over time, whereas no clear trend could be observed for negative sentiments. The classification of sentiments in abstracts of both languages correlated very weakly at the abstract level. At the annual level, negative sentiments correlated very weakly, but positive sentiments correlated very highly. The increase in positive sentiments could thus be confirmed, with the exception of the years 2019-2023. The linear regressions show a very small increase in positive sentiments with a very low R^2. Only the VADER dictionary has a small, very small nonlinear effect. The model variables only become statistically significant for samples with several thousand cases. A brief regression diagnostics identifies the heteroscedastic data with nonlinear residuals. As a result, the diagnostics show the complicated structure of the measured data, which raises doubts about the linear model. Finally, suggestions are made for potential solutions to the problems for further analysis.

6 Discussion and Conclusion

6.1 Introduction

The aim of the chapter is to arrive at a conclusion by discussing and interpreting the analysis results. To do this, the results are first summarized and interpreted by establishing links between the various analytical steps and the method used. Subsequently, assumptions are made about possible causes of the identified effects. In particular, the section integrates all the analyses conducted to explain the measured effects. Following this, comments on future research are formulated by reflecting on previous research and the findings of this work. Furthermore, the section discusses the consequences of the results for the theory of academic capitalism. In particular, the dualism of different modes of action is in the foreground. After that, a number of limitations of the research conducted are listed, which particularly focus on the methodology, such as the operationalization of the concepts used. Finally, the conclusion briefly summarizes the entire work and comes to a final judgment.

6.2 Interpretation of Results

The following section is initially devoted to the interpretation of the results. Subsequently, assumptions about the causes of the results are expressed and ideas for future analyses of the topic are presented. In chapter 5, an increase in positive sentiment mean values with both dictionaries was shown, as well as the absence of a clear trend in negative sentiment for the selected database. Consequently, there is a minimal increase in positive framing in articles published between 1993 and 2023 in journals with the Web of Science category ”Sociology”. However, this conclusion only holds if the variability in the raw data is ignored. When the variability is integrated by the standard error, as was done in the interval plots and the linear regression, the increase initially appears to be significant. However, the simulations of the p-values of the regression models show that the significance of the increase is due to the large sample size rather than to a relevant effect. A brief regression diagnostics can show a strong violation of most assumptions of linear regression. In summary, the sentiment values are not linearly and strongly skewed to the right, since no positive sentiments can be found in a particularly large number of abstracts. Furthermore, influential outliers exist in the high value ranges. Given these violations, there are strong doubts about the results of the linear regression and the trend of positive sentiments in the interval plots. The observed mean increases are very small and, based on the simulations and a number of model violations, not statistically significant. Therefore, no significant increase in positive sentiments can be assumed.

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6.3 Implication of Results

On the basis of the interpretation presented in the previous section, methodological and theoretical comments can now be made. Previous studies chose either local or linear regressions for their analysis approach (see chapter 3). The examination of this work of the data structures of sentiment values with scientific texts, as well as the brief regression diagnostics, show the high importance of checking corresponding model assumptions. Local regressions are particularly prone to overfitting, which is favored by strong outliers. Linear regressions are particularly affected by the consequences of inhomogeneous variable distributions. Of course, the complicated data structures of relative sentiment values cannot be transferred to other databases and sentiment scales. Nevertheless, it would be unrealistic to assume that the anomalies are a problem that only affects sociological publications.

On the basis of the results, conclusions can also be drawn for the theory presented in chapter 2. The chapter 2 on the theory of academic capitalism introduced the dualism of market actions and scientific actions (Baumeler, 2009; Ylijoki, 2003). Based on this, the assumption was expressed that marketing actions would also be expressed in the context of positive framing in one's own scientific publications. The results of the analysis of this work contradict this assumption. This work argues that scientific publishing can be seen as a scientific act regardless of the influence of academic capitalism. Nevertheless, the analysis does not represent an all-encompassing study of positive framing in scientific literature. For example, the causes of the outliers and the under- and overestimation of sentiments could not be conclusively explained by the dictionaries used. Furthermore, a simple observation of trends in time series and correlations does not allow any causal conclusions. In addition to the methodological recommendations for future research mentioned at the beginning, a follow-up theoretical possibility can be identified. More precisely, the question arises as to why academic capitalism can influence certain areas of scientific practice and why other aspects remain unaffected.

6.4 Limitations

In addition to the limitations already partially reflected, this section lists the most important limitations of the analysis. At the beginning, general disadvantages of quantitative-explorative methodology become particularly relevant. First of all, it should be noted that the range of exploration is limited by the characteristics of the data set. The data set used for the analysis only represents data available via Web of Science. Furthermore, no relevant variables could be downloaded as control variables. Furthermore, there are many limitations regarding the operationalization. The restriction of the analyzed publications to the discipline of sociology was determined by the journal categories of Web of Science (of Science Group, 2019). The selection processes of the Web of Science Group are not transparently comprehensible for every journal. This lack of transparency was accepted for the analysis based on the procedures communicated by of Science Group (2019). In addition, the data set only includes publications in journals. However, sociology is a highly interdisciplinary field in which a wide variety of publication forms (monographs, anthologies, and journal articles) are common (Becher, 1989, p. 111). Furthermore, the abstract as an unit of analysis is less representative of an article than the entire full text of the article. Furthermore, the usual methods for time series analyses were not used because the coarse time scale made the data structure more reminiscent of a research design with repeated cross-sectional data than of a time series. This data structure, together with the high variances of the sentiment values within the years, makes it difficult to use "lags" and to analyze seasonal trends. Finally, the interpretation of the simulation results is somewhat arbitrary. It should be noted, however, that the problems associated with the frequentist analysis of very large data sets have only been the subject of central discussion since the scientific analysis of social media data. In the past, limited access restricted the dissemination of very large data sets.

6.5 Conclusion

The work was based on the question of whether an increase in positive framing in the form of an increase in positive sentiment and no increase in negative sentiment can be observed in sociological publications. The question was motivated by observed reactions of researchers to structures of academic capitalism. Researchers assert themselves in the intensified scientific competition by promoting their own research with different strategies towards society and funders (Ylijoki, 2003). Previous research shows an increase in positive sentiments and no positive trend in negative sentiments for various scientific disciplines (Holtz et al., 2017; Lennox et al., 2020; Liu & Zhu, 2023; Vinkers et al., 2015). Based on this, the present work analyzes the sentiments of a full survey of Web of Science of all abstracts between 1993 and 2023 from the discipline of sociology using two dictionaries of different sizes. The simulations show that the significance of the supposed increase in positive sentiments is due to the high number of cases. In combination with the low strength of the effect and the problematic distribution of the measured sentiment values, the existence of an increase in positive sentiment cannot be confirmed. The negative sentiments show no clear trend. The results emphasize the importance of carefully checking data for consistency with the model assumptions.

Appendix

.1 Colemanboat Policies

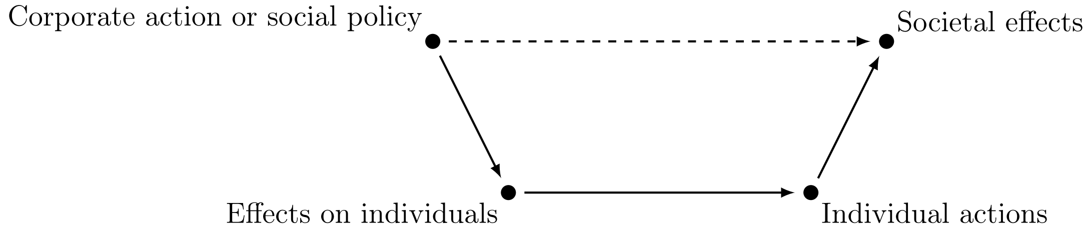

Figure 1: The Coleman boat is introduced in Coleman (2000) on page 572.

.2 Diktionary: Vinkers et al.

positive words:

Amazing, Assuring, Astonishing, Bright, Creative, Encouraging, Enormous, Excellent, Favourable, Groundbreaking, Hopeful, Innovative, Inspiring, Inventive, Novel, Phenomenal, Prominent, Promising, Reassuring, Remarkable, Robust, Spectacular, Supportive, Unique, Unprecedented

negative words:

Detrimental, Disappointing, Disconcerting, Discouraging, Disheartening, Disturbing, Frustrating, Futile, Hopeless, Impossible, Inadequate, Ineffective, Insignificant, Insufficient, Irrelevant, Mediocre, Pessimistic, Substandard, Unacceptable, Unpromising, Unsatisfactory, Unsatisfying, Useless, Weak, Worrisome

.3 Diktionary: Holtz et al.

Marginal significant effects:

marginally significant, $p < .10$, $p < .10$, p.10, marginal significant, marginal significance, trend towards significance, trended towards significance, trending towards significance, approaching significance, approached significance

.4 Calculation of error propagation

$$\Delta Y = \sqrt{\sum_{i=1}^{m} \left(\frac{\partial Y}{\partial X_i} \Delta X_i \right)^2}$$

1. Calculating the partial derivatives

$$\frac{\partial d_s}{\partial s_{\text{vader}}} = \frac{d}{ds_{\text{vader}}}[s_{\text{vader}} - s_{\text{vink}}] = \frac{d}{ds_{\text{vader}}}[s_{\text{vader}}] + \frac{d}{ds_{\text{vader}}}[-s_{vink}] = 1 + 0 = 1$$

$$\frac{\partial d_s}{\partial s_{\text{vink}}} = \frac{d}{ds_{\text{vink}}}[s_{\text{vader}} - s_{\text{vink}}] = \frac{d}{ds_{\text{vink}}}[s_{\text{vader}}] - \frac{d}{ds_{\text{vink}}}[s_{\text{vink}}] = 0 - 1 = -1$$

2. Inserting into the general

Error propagation formula by Gauss

$$\Delta d_s = \sqrt{(1 \cdot \Delta s_{\text{vader}})^2 + (-1 \cdot \Delta s_{\text{vink}})^2} = \sqrt{\Delta s_{\text{vader}}^2 + (-\Delta s_{\text{vink}})^2}$$

$$= \sqrt{\Delta s_{\text{vader}}^2 + \Delta s_{\text{vink}}^2}$$

.5 Wordfrequencies Vinkers et al. (2015)

Figure 2: Vinkers 2015: Percentage of positive sentiment per word in relation to the total number of words in the respective year with 95% confidence intervals.

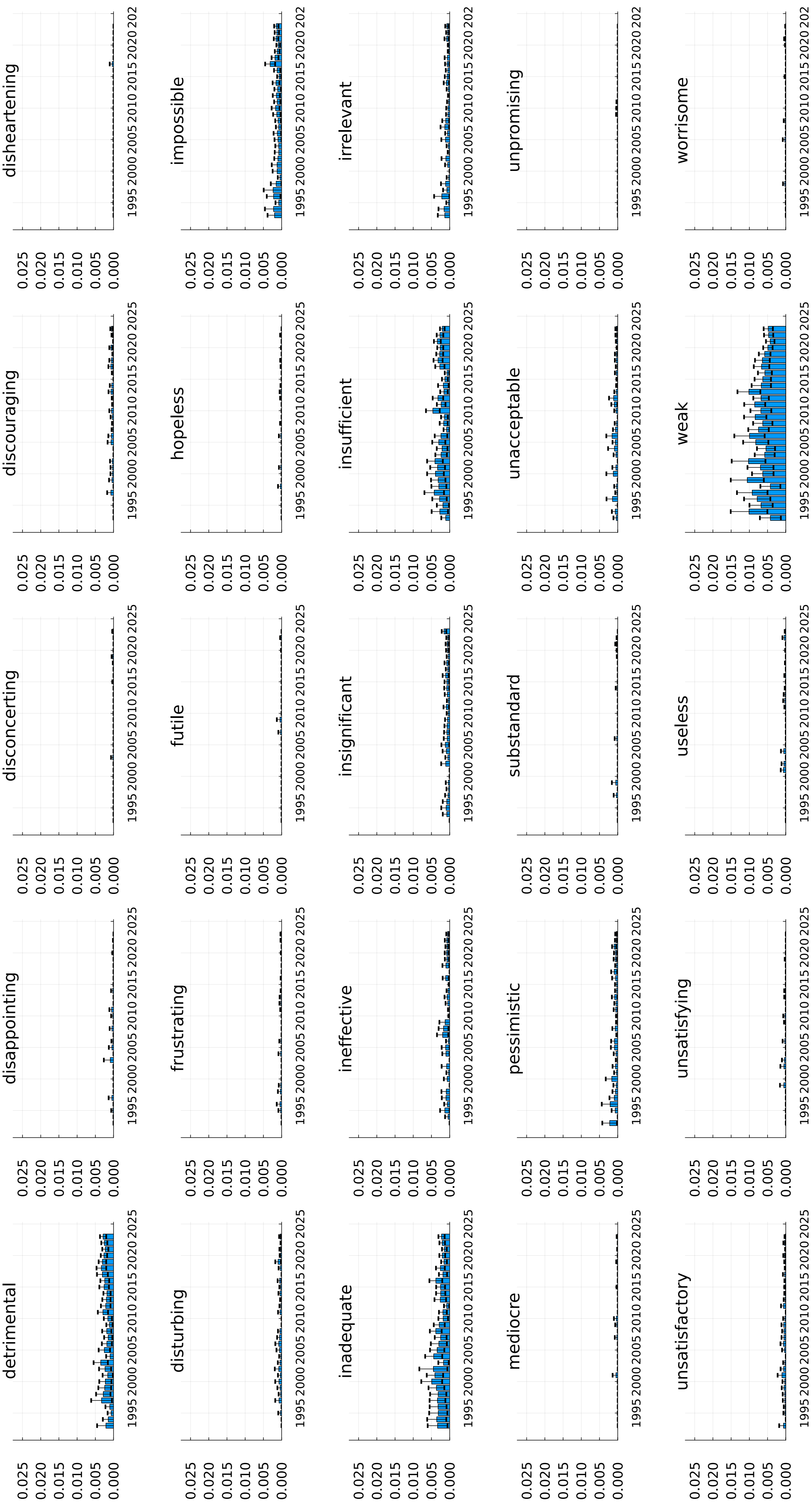

Figure 3: Vinkers 2015: Percentage of negative sentiment per word in relation to the total number of words in the respective year with 95% confidence intervals.

.6 CPS plots of Monte Carlo simulations

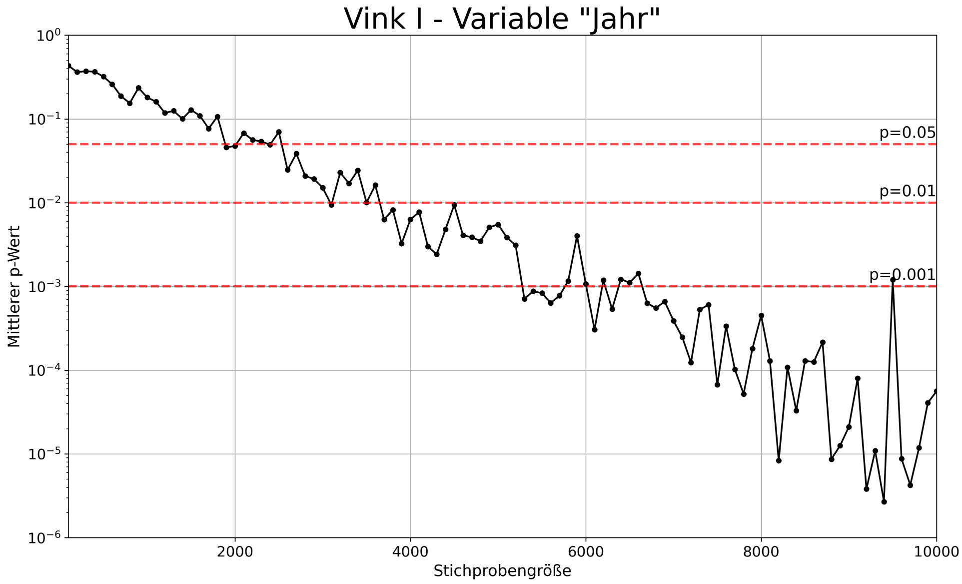

Figure 4: CPS plot of the model “Vink I”;
p-values of the coefficient “year” depending on the sample size

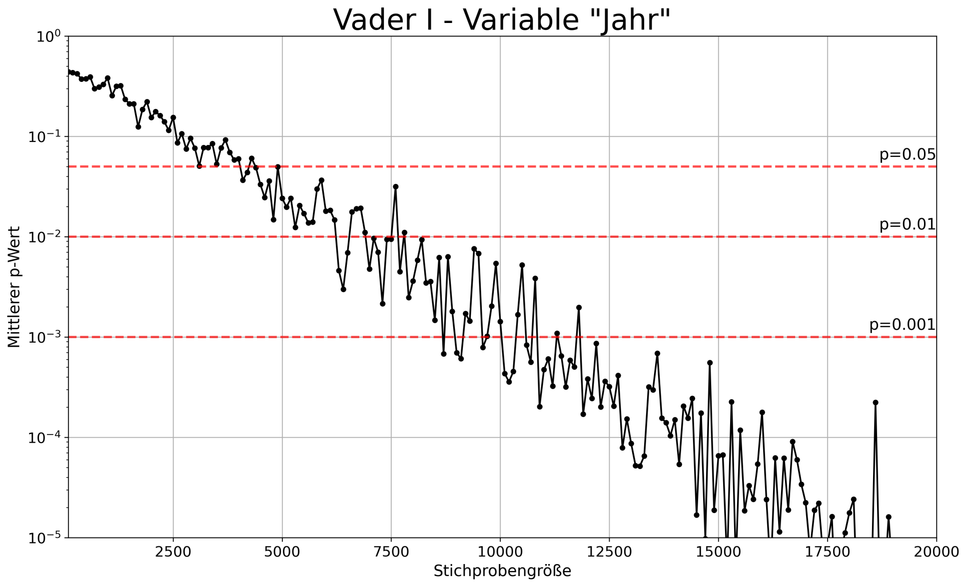

Figure 5: CPS plot of the model “Vader I”;
p-values of the coefficient “year” in relation to the sample size

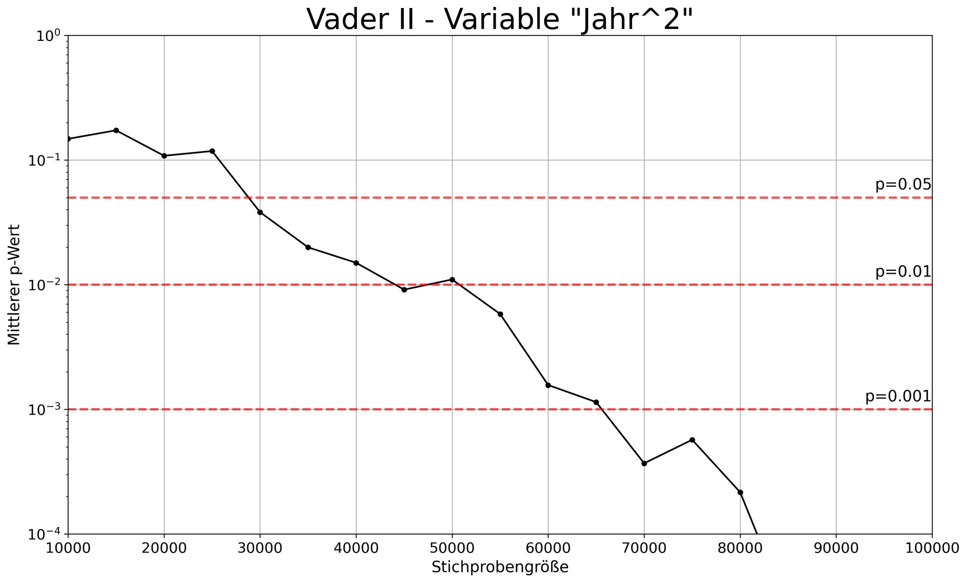

Figure 6: CPS plot of the model "Vader II"; p-values of the coefficient "year^2" as a function of the sample size

.7 Transformation of Variable

	$\sqrt{\text{vink} + 10^{-5}}$ I	$\sqrt{\text{vink} + 10^{-5}}$ II	$\sqrt{\text{vader} + 10^{-5}}$ I	$\sqrt{\text{vader} + 10^{-5}}$ II
Intercept	-4.2054***	13.4408	-8.7060***	-848.3011***
	(0.1829)	(45.7370)	(0.6444)	(161.1437)
Jahr	0.0021***	-0.0154	0.0056***	0.8411***
	(0.0001)	(0.0455)	(0.0003)	(0.1603)
Jahr^2		0.0000		-0.0002***
		(0.0000)		(0.0000)
N	121789	121789	121758	121758
R^2	0.005	0.005	0.003	0.003

Table 1: Linear regressions of both dictionaries with transformed data. Standard errors are shown in parentheses.
* p<.1, ** p<.05, ***p<.01

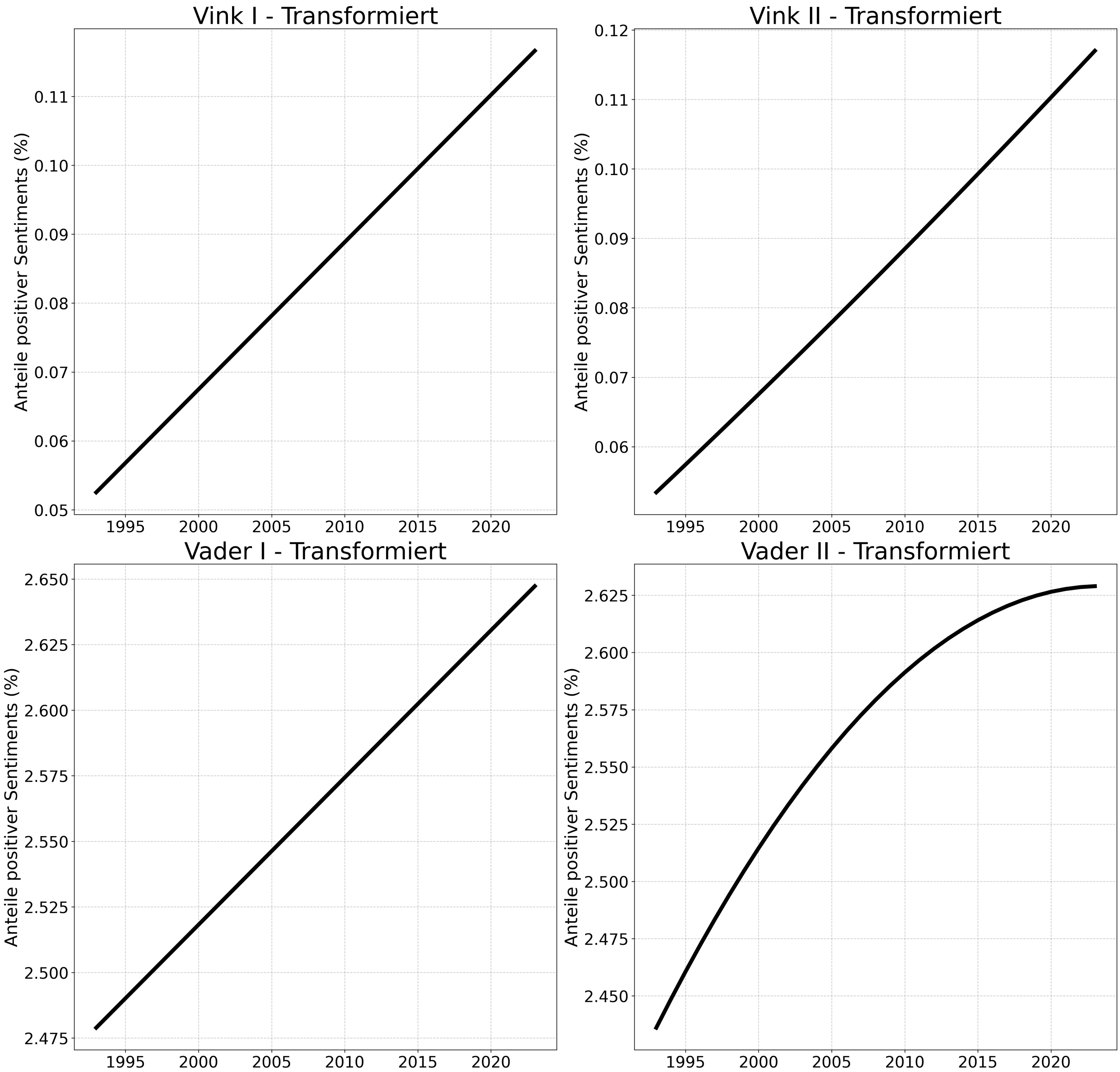

Figure 7: Trajectories of the transformed models

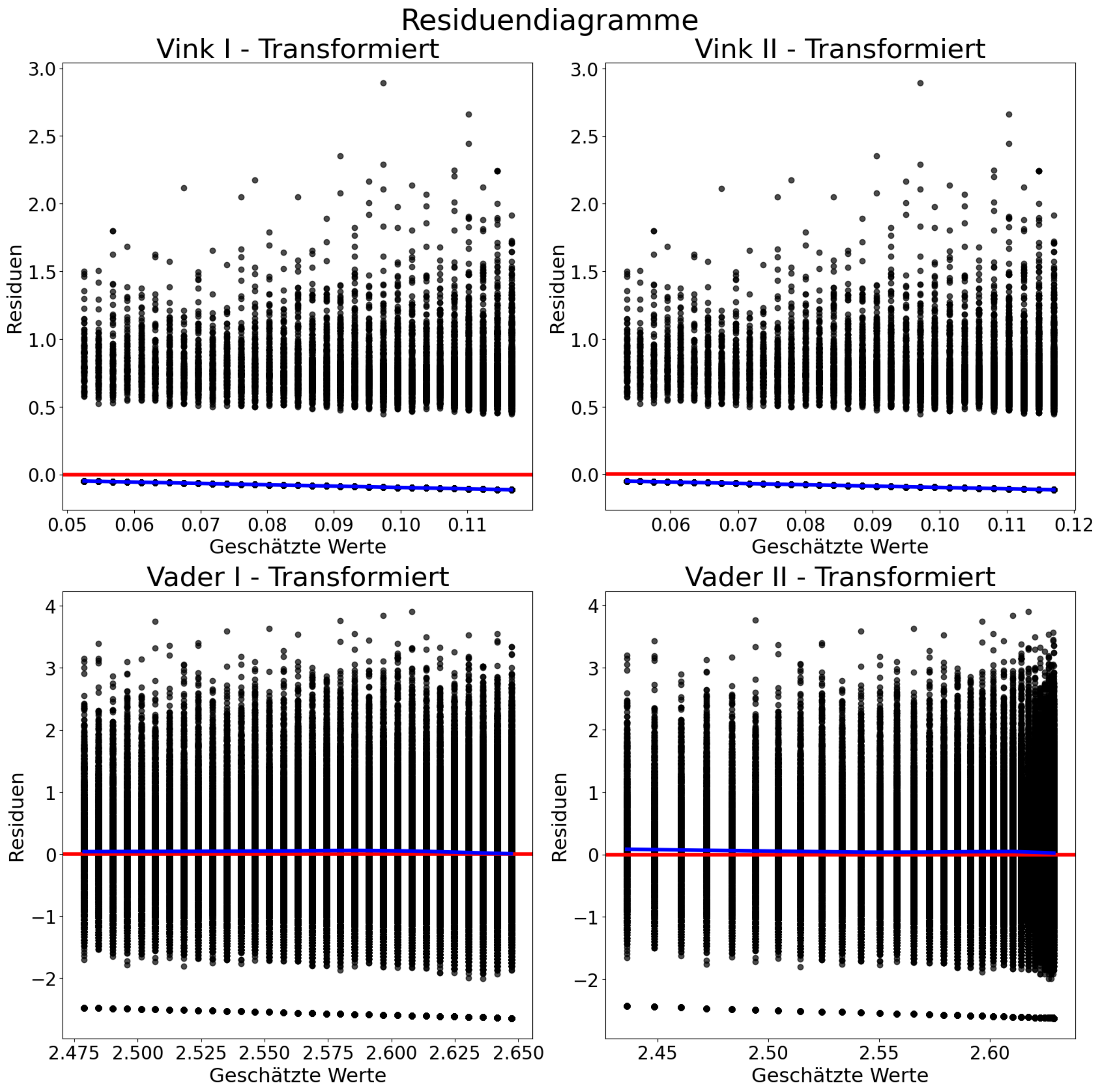

Figure 8: Residual plots of the models with transformed sentiments. Zero is marked by the red line. The LOWESS curve is shown in blue.

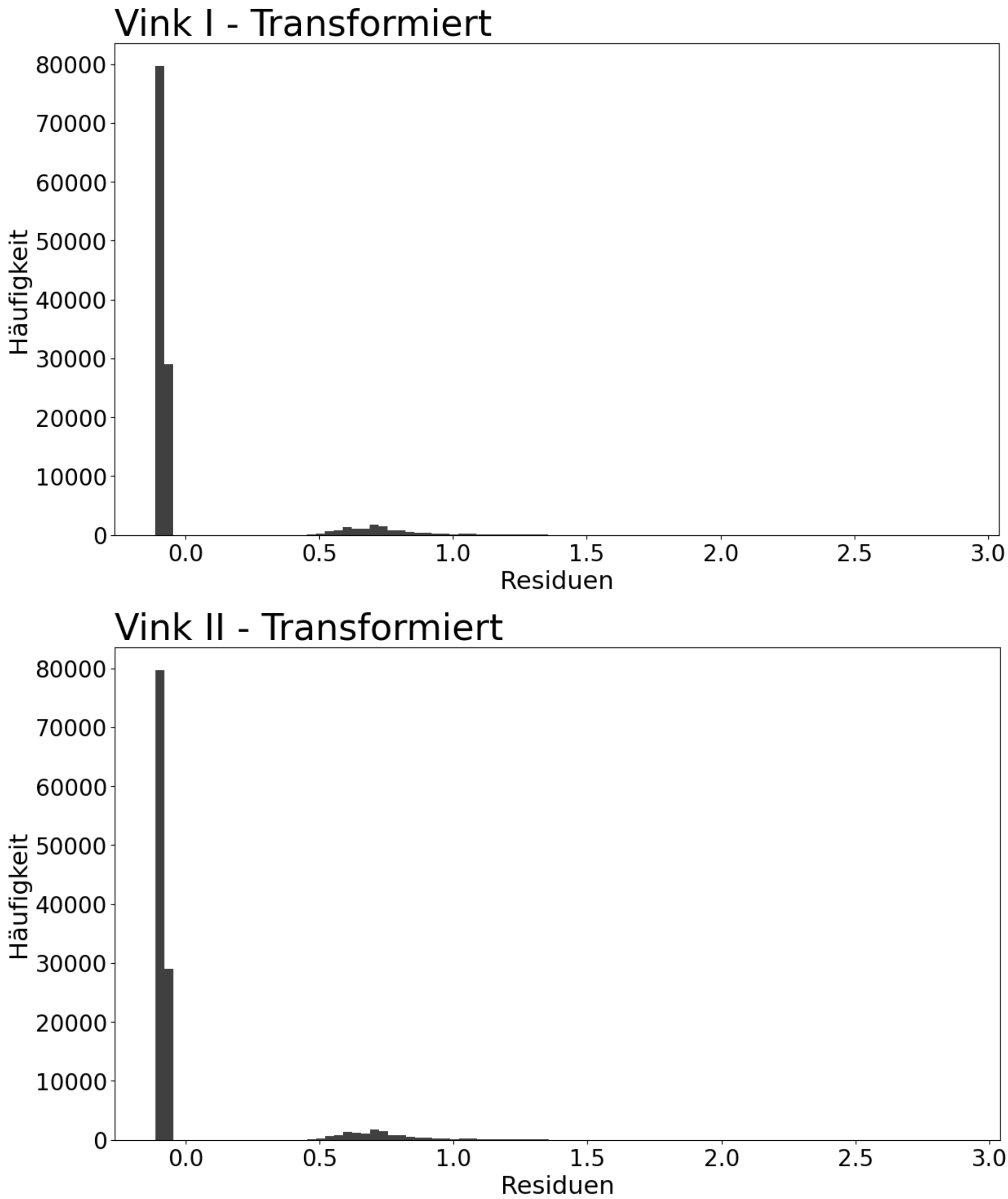

Figure 9: Residual histogram of the models with transformed sentiments

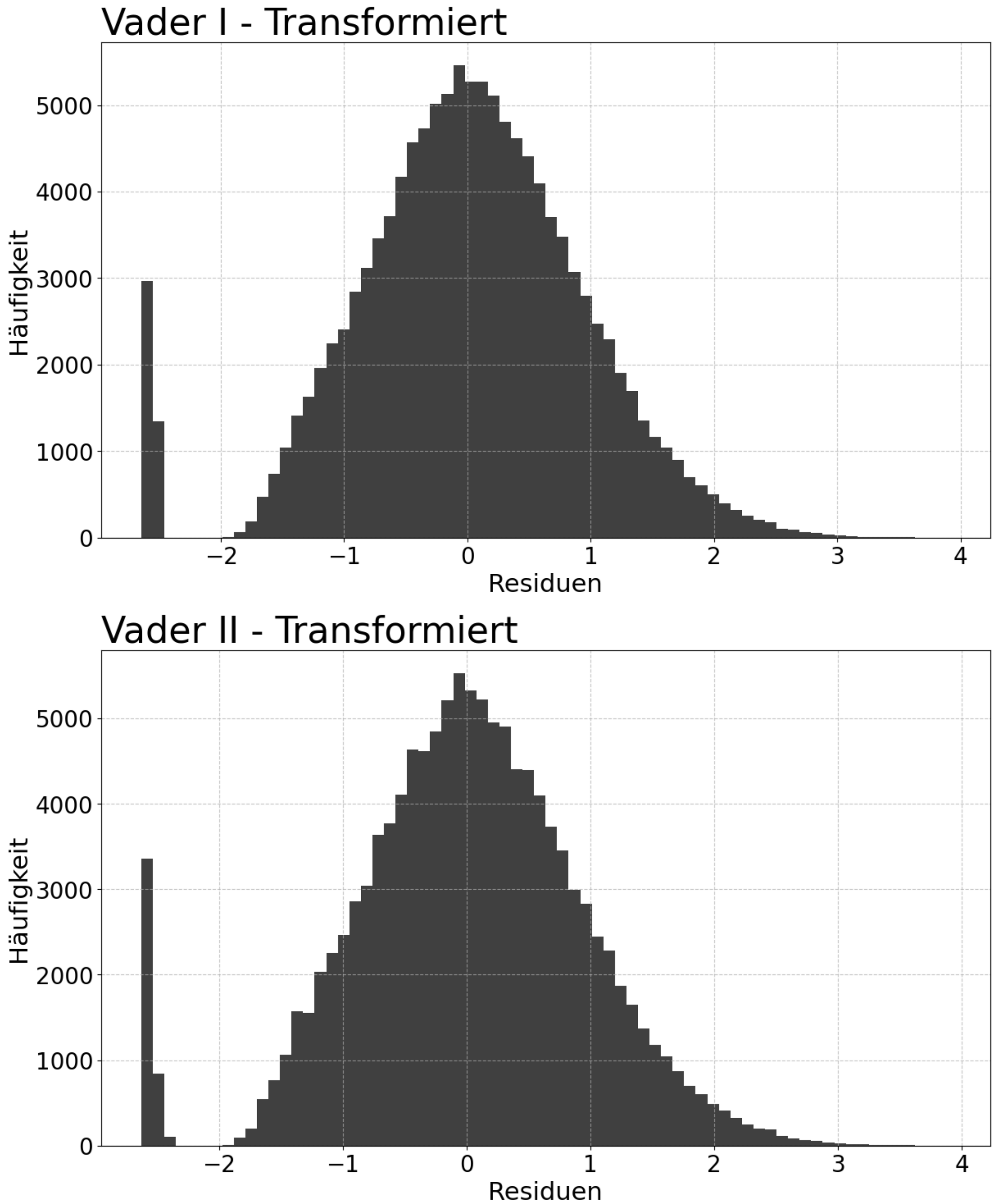

Figure 10: Residual histogram of the models with transformed sentiments

BA Thesis - "Academic capitalism" analysed: Linguistic trends in sociological jo (#175512)

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1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
Can an increase in positive framing, an increase in publications that achieve marginally significant results and an increase in jargon/nominalization be identified in sociological journals as indicators of the increasing influence of academic capitalism?

3) Describe the key dependent variable(s) specifying how they will be measured.
1. The positives framing will be measured through sentimentanalysis of abstracts from sociological journals. Two dictionaires will be used for the analysis. The first consists of a small set of custom positive keywords, the second one will be a large sentiment analysis tool similar to LIWC.
2. The frequency of reported marginal significant results will be measured through a dictionaire containing phrases wich are common to report marginal significant findings.
3. The increase in jargon/nominalization will be measured through counting the use of commonverbs aswell as textreadabilityscores wich measure the complexity of a given text (for example average syllablecount per sentence or Fleschs readbility score)

4) How many and which conditions will participants be assigned to?
-

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
The dataset containing the sociological texts will be split into 3 Parts with equally big time intervals. The average measured values of will be compared through t-tests. At least for the positive framing measurements the smoothed trend will be plotted to gain deeper insights into the result of the dictionaire based analysis.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
-

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
All articles for the yet to be decided time frame of relevant sociological journals will be used.
If data availablilty is given the time frame of 1970-2020 would be optimal, because the results could be compared to the study of Holtz et al. 2017.

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
For exploratory purposes additional analysis of the dataset is going to be made (keyness analysis to compare prominent topics of the described subsets of the data for example).
This thesis tries to replicate the study "Cross-Cultural Psychology and the Rise of Academic Capitalism: Linguistic Changes in CCR and JCCP Articles, 1970-2014" of Holtz, Deutschmann, Dobewall 2017 for sociological articles with minor modifications in the analysis regarding the questions for sentiments and jargon/nominalization.

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