**Appendix**

**Combining text-as-data approaches and a qualitative in-depth analysis**

The statistical measurement of language comes with challenges and potential pitfalls. Advancements in automated text analysis are significantly progressing this field (e.g. Gilardi et al., 2021), in particular for English-language content. A growing number of scholars claim that the role of qualitative, interpretive and context-specific methodologies must be put to the fore as an integral part of computational methods as they become ever-more elaborated (Grigoropoulou & Small, 2022; Mohr et al., 2015; Nelson, 2020). In particular, researchers are called upon to recognize the significance of social context: The data we capture and formalize by using these techniques is always part of particular social processes that we must reconstruct. In this research, I take up this position: If we seek to answer questions that target political, economic, and social meanings, the close reading of test does not merely serve to validate quantitative models, but must be pursued as an end in itself.

**Selecting and fetching the keywords for construing the corpus**

The fiscal relief programs – the analysis focuses on direct subsidies – studied in this article are identified via their official name (keyword). I fetched the keywords from documents issued by the German Finance Ministry in July and November 2020 (BMF, 2020a, 2020b, 2020c, 2020d), which I downloaded from the ministry’s websites and coded for payments. Six keywords were generated in this way: Corona Assistance (*Coronahilfen)*, Emergency Assistance (*Soforthilfen*), Bridging Assistance(*Überbrückungshilfen*)*,* November Assistance (*Novemberhilfen),* December Assistance(*Dezemberhilfen*)*,* New Start Assistance(*Neustarthilfen*). With the exception of the terms Emergency Assistance and Bridging Assistance, the names of these programs are specific to the pandemic context. As the German government invented the designations Corona Assistance*,* November Assistance*,* December AssistanceandNew Start Assistance only in 2020, these words exclusively capture the discourse on pandemic relief (for the cases of Emergency Assistance and Bridging Assistance, there is a very small number of tweets that use these designations in a context that is not related to the Covid-19 pandemic). The German government consistently used these designations during the pandemic, with no significant new terms emerging later on. This consistency is apparent in a June 2022 report by the Federal Ministry for Economic Affairs and Climate action, which reviews and summarizes the pandemic assistance program’s outcomes using the same terminology as the keywords highlighted in this article (BMWK, 2022).

The study focuses on the direct subsidies to small business and the self-employed. The empirical analysis excludes pandemic relief measures primarily targeting labor, such as the extensive short-time work programs, which were paid or guaranteed to employers (Ebbinghaus & Lehner, 2021). Additionally, it does not cover keywords related to tax credits, reduced interest rates, or the discourse surrounding KfW (development bank) credits and loan guarantees, significant components of the business stabilization programs, particularly for larger firms. While keywords associated with the KfW programs were also initially collected, the discourse on Twitter/X about these keywords is minimal. This discourse was then excluded because the aim of this analysis is to focus on small corporate entities who are not typically the beneficiaries of these larger credit and loan programs.

I analyse a corpus of tweets accessed and downloaded through the Twitter Academic Research track in R (Barrie & Ho, 2021). I fetched all tweets containing four versions of each keyword. For instance, I fetched four variations of Corona Assistance (*Coronahilfe, Coronahilfen, Corona-Hilfe, Corona-Hilfen*) and summarized them into a single keyword. The Twitter/X data was retrieved on Dec 02 and Dec 03, 2021.[[1]](#footnote-1) The data is organized at level of single tweets (each tweet has a unique id number). A single tweet comes with a range of metadata, such as date of creation, number of retweets, likes, mentions, hashtags, associated media content or websites, and information about the author.

**Methodological issues around the use of Twitter/X data**

The use of social media data has become increasingly common in the study of social and economic policies (Gielens et al., 2022; Gilardi et al., 2021; Theiss, 2022). Before the changes to its ownership in October 2022, Twitter/X had a particularly prominent role in policy-related discourse. As more and more government, interest group, corporate, civil society, media and cultural actors engaged with this platform, it had morphed into an important arena of public debate, as well as a key element of a larger media ecology (Tufekci, 2017). Twitter/X is regularly used by social movements and activists to voice their claims, and the platform was also widely used by various social and political groups to make demands on those who were charged with managing the state response in the pandemic crisis situation. In general, political discourse on the site is structured both from the top-down and from the bottom-up.

Twitter/X is a private, profit-driven entity that operates within the wider corporate attention economy, guided by algorithms that prioritize popularity (Davies, 2021). The platform’s algorithmic composition shapes user behaviour. Twitter/X seeks to maximize user traffic, rewarding behaviour that generates attention and increases traffic on the platform. A small number of users produces most content and receives the lion share of the attention, while the majority of Twitter/X users are passive observers (Park & Macy, 2015). Changes in the ownership structure of this platform (as happened in the fall of 2022, after the data for this research was collected) can also significantly affect user behaviour.

Twitter/X is used by certain audiences. While there are increasingly well-founded insights into the demographics and attitudinal profiles of US-American users (e.g., Shugars et al., 2021), less is known about social determinants of the European, and in this case, the German Twitter/X-scape. In Germany, Twitter/X’s user base is relatively small compared to other social media platforms. Data from Frees and Koch (2018) indicate that while Facebook's weekly usage among Germans aged 14 and above was around one-third of the population in 2017, Twitter/X’s usage was approximately 3%. Nonetheless, the gap in usage rates between the two platforms began to narrow by the following year, as reported by Fischer-Preßler et al. (2019). It is likely that the number of active German Twitter/X users has increased during the pandemic. Additional research is needed to determine whether claim-making patterns such as those described in this article can be observed in other media environments, or if there is something unique about this particular platform that influences the findings, such as its alignment with the styles of articulating demands and claims seen in social movements.

Finally, researchers are only beginning to scrutinize the more fine-grained (yet consequential) variation of the meaning of user behaviour on Twitter/X. Different tweet types (authored tweets, retweets, quotes, replies) should not be treated in the same way, as they can have varying functions. A recent study based on a representative sample of the US population on Twitter/X notes that retweets, while by far the most common type of tweets, “have a lower cost of engagement [as the three others], since the retweeting user does not need to expressly articulate their own position” (Shugars et al., 2021, p.26).

**Corpus text analysis: Pre-processing and cleaning the corpus**

I use the R package quanteda for constructing the corpus, cleaning and pre-processing the data (removing duplicates, stopwords, symbols, urls, and numbers) and the statistical analysis of text (Benoit et al., 2018). I removed the terms “Corona”, “Covid”, “Hilfe”, “Hilfen” from the text-field contained in the corpus; they appear so frequently that they are effectively meaningless to the analysis. A few hundred non-German and non-English tweets were discarded (a few thousand tweets labeled, by the Twitter API, as of an “undefined” language were however retained). I did not lowercase the text in order to preserve what are meaningful differences in capitalization in German.

Tweets by Austrian and Swiss accounts were removed. This is a necessary step as some of the keywords are not unique to the German context. For instance, the designation Emergency Assistance (*Soforthilfen*) also exists in the Austrian Covid-19 fiscal relief program and the discourse around it. The best strategy to remove them was by identifying Austrian and Swiss locations in a user’s description (using a computational technique) and dropping the sample of tweets identified in this way from the main corpus. The final corpus contains 357.398 tweets (135.381 without retweets).

**Identifying most active users**

Table A1 provides an overview over the fifteen most active users in the corpus. Three indicators are shown: The number of tweets issued by a single account that contain at least one of the keywords, the number of times a user was mentioned in another tweet that contains at least one of the keywords, and the score generated by multiplying the two. Institutional accounts (by politicians, banks and the media) dominate the conversation. The overview provided by Table A1 is based on the original corpus including retweets (since here, the number of times an account is mentioned, in retweets as well as in other kinds of tweets, is the basis for this measure of influence).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Rank** | **Username**  | **Name**  | **Tweeted**  | **Mentioned**  | **Tweeted\*Mentioned**  |
| 1 | @BMWi\_Bund  | Bundesministerium für Wirtschaft und Energie  | 2305  | 6629  | 15279845  |
| 2 | @BMF\_Bund  | BMF  | 286  | 3797  | 1085942  |
| 3 | @KfW  | KfW Bankengruppe  | 400  | 1442  | 576800  |
| 4 | @peteraltmaier  | Peter Altmaier  | 69  | 7325  | 505425  |
| 5 | @PR\_ibb  | Investitionsbank Berlin  | 211  | 2275  | 480025  |
| 6 | @welt  | WELT  | 200  | 2337  | 467400  |
| 7 | @tagesschau  | tagesschau  | 169  | 2636  | 445484  |
| 8 | @BILD  | BILD  | 170  | 2168  | 368560  |
| 9 | @derspiegel  | DER SPIEGEL  | 113  | 3176  | 358888  |
| 10 | @handelsblatt  | Handelsblatt  | 411  | 854  | 350994  |
| 11 | @Tagesspiegel  | Tagesspiegel  | 242  | 1321  | 319682  |
| 12 | @zeitonline  | ZEIT ONLINE  | 185  | 1494  | 276390  |
| 13 | @WirtschaftNRW  | Wirtschaft.NRW  | 97  | 2746  | 266362  |
| 14 | @hipsterfitness  | Mnemoniker  | 237  | 1104  | 261648  |
| 15 | @Paritaet  | Der Paritätische  | 98  | 2581  | 252938  |

Table A1: Most active user accounts

We may, further, measure the distribution of the popularity of tweets by considering the average number of times a single tweet was liked or retweeted in this corpus. Doing so reveals that a substantial share of tweets does not generate any attention or traffic (which is typical for Twitter/X’s highly unequal attention economy). Of all tweets in this corpus, the mean number of retweets is 1,7 and the median is 0. The mean number of likes is 6,5 and the median is 0. The most-liked tweet captures 12389 likes, the most-retweeted tweet 2280 retweets.

**Identifying Top Hashtags**

We may also consider the most frequently used hashtags. Hashtags can reveal information about thematic foci in a twitter dataset (Puschmann, 2015). Table A2 shows that hashtags related to climate issues (concerning, above all, the issue of contested subsidies to the car industry) are quite prominent. Notably, this issue does not play a role in the debate about state support to small business and the solo-self employed analysed below. The distribution of major hashtags over time (not shown) suggests that climate-related hashtags predominantly appear in the first months of the pandemic.

|  |  |  |
| --- | --- | --- |
| **Rank**  | **Hashtag**  | **Frequency**  |
| 1  | #Berlin  | 1107  |
| 2  | #Soloselbständige  | 840  |
| 3  | #HartzIV  | 822  |
| 4  | #Unternehmen  | 786  |
| 5  | #Künstler  | 784  |
| 6  | #Wirtschaft  | 768  |
| 7  | #NRW  | 737  |
| 8  | #Bundesregierung  | 638  |
| 9  | #Autogipfel  | 615  |
| 10  | #Soloselbststaendige  | 589  |
| 11  | #Klimaschutz  | 579  |
| 12  | #Deutschland  | 575  |
| 13  | #Initiative  | 563  |
| 14  | #Altmaier  | 544  |
| 15  | #Lockdown  | 541  |
| 16  | #EU  | 505  |
| 17  | #Dieselgate  | 454  |
| 18  | #Merkel  | 446  |
| 19  | #lockdown  | 417  |
| 20  | #SPD  | 408  |

Table A2: Most frequent hashtags

**Identifying keywords over time**

As shown in Figure 1 in the main body of the manuscript, discussions about various policies occur at different points in time. The term *Corona Assistance* (Coronahilfen) is used as an umbrella term, and this usage is also adopted by the federal government (BMF, 2020a, 2020b, 2020c, 2020d; BMWK, 2022). *Emergency Assistance* (*Soforthilfen)*, the initial one-time transfer to small businesses and the self-employed (with a maximum of 10 employees), garnered significant attention during the spring and summer of 2020 but gradually diminished in prominence thereafter. *Bridging Assistance* (*Überbrückungshilfen) I-III*, designed to provide subsidies for fixed operating costs, gained significant prominence during the summer of 2020 and once again in early 2021. *November Assistance* (*Novemberhilfen)* and *December Assistance* (*Dezemberhilfen)*, specifically designed for businesses in sectors severely impacted by shutdown regulations, emerged as significant topics in late 2020. Finally, *New Start Assistance* (*Neustarthilfen),* which primarily focuses on freelancers such as artists and was implemented at the start of 2021, generated relatively limited discussion and debate.

**Combining text statistical and qualitative analyses**

The analysis proceeds as follows: First, I map the broad debate around the direct subsidies, considering the distribution of tweets over time. I then condense and dissect the corpus systematically, foregrounding dimensions that reflect the overarching research interest – to understand the construction of meaning around subsidies to small businesses and the self-employed –, combining text statistics and qualitative analyses in this process (Andreotta et al., 2019). As a methodological roadmap, I draw on Laura Nelson’s (2020, p.9) “computational grounded theory”, an inductive, theory-generating approach that combines deep reading and computational approaches. Nelson distinguishes three steps for the analysis: Pattern detection, pattern refinement, and pattern validation. The first is the “the pattern detection step, [which] involves using computational techniques to reduce complicated, messy text into simpler, more interpretable lists or networks of words in order to reveal patterns within the text in an unbiased and reproducible fashion”. It uses “computational methods to reduce messy and complicated text to interpretable groups of words, helping researchers cut through the noise inherent to text-based data.” The initial approximation and classificatory mapping must be complemented by a “pattern refinement” step, in which a deep reading of the text is applied. The second step incorporates holistic interpretation. The third step, finally “involves using computational methods to more reliably test the validity of the inductively identified patterns in the text.” (ibid., pp.4-5, 9).

 In the present study, the process of condensing the main corpus in a systematic, transparent, replicable, and reliable way, is a key element of the pattern detection step (Andreotta et al., 2019). Why not analyse the main corpus as a whole? Since the goal is to inductively discover patterns in the data, an unsupervised computational approach might also produce the desired results. In an earlier stage of this research, I performed a structural topic model (Roberts et al., 2019) on the main corpus (not shown). The model produces meaningful results; however, it generates rather coarse patterns. This is because, as (Isoaho et al., 2021, 308) elaborate, while topic modelling is an excellent tool for distinguishing broad thematic strokes in the data, it is less suited for understanding deeper levels of meaning such as arguments, narratives, or structures of discourse.

 I therefore choose a different approach. It revolves around systematically condensing the main corpus, using both computational and qualitative approaches, in order to enable a qualitative analysis of selected segments. The reproducibility of this procedure is made possible by its transparent design and the availability of the code; the reliability is ensured by an open coding approach that reconstructs meaning from the point of view of the subjects. This approach is also methodologically sound in that it reflects the theoretical scaffolding of this research – it is not based on strong substantive assumptions or hypotheses, but instead on a methodological perspective that proposes to study welfare support as a form of patterned social relationships (Mohr, 1994).

The logic of selection is driven by the following considerations: I condense the corpus by including only the tweets that mention various designations of small businesses and the self-employed. This strategy takes as its point of departure the categories (nouns or noun-phrases) by which particular groups in society, who are the targets of pandemic state assistance, are referred to in public discourse. The language that is used to name specific actors is itself part of the semantic environment of Covid-19 pandemic economic relief. Put differently, in this context, actor designations exist in relation to redistributive policies – these are designations of (potential) recipients of state support (Mohr, 1994). The designation of target groups, the naming and classification of certain social groups in relation to welfare treatments, is itself part of a process of “lumping and splitting” social reality (Fourcade & Healy, 2013; Zerubavel, 1996). Drawing on John Mohr (1994), we may assert that welfare target groups are imaginary designations, “discourse roles” in a network of relationships that are constituted by the structural position of other groups around them. The core question is, then, how the relationship between the state and these groups, as well as the relationships among these groups, are discursively construed in the data.

Other options are available. One approach to narrowing down a large corpus of tweets is to focus solely on a subset of tweets that have garnered significant attention, as evidenced by a high number of likes or retweets, for instance. It is possible to do so, but such a strategy comes with notable downsides: First, it would reflect the logic of popularity that is shaped by a corporate social media platform. This should not be mistaken for a naturally observable form of popularity, as it is influenced by the algorithmic design of the Twitter/X platform. Second, such a strategy would mirror, and hence also foster, the inequalities of attention that typically pervade social media data.

The overall workflow moves from constructing the corpus, to condensing in a way that is informed by the research question (pattern detection), to analysing the data qualitatively (pattern refinement), and finally, to validate the results (pattern validation) (cf. Figure 1 in the main body of the manuscript).

In the following, I illustrate the analytical steps that follow the construction of the corpus in detail. Figure A1 summarizes the key steps in the analytical process, which iteratively goes back and forth between descriptive text statistics and qualitative analyses.

|  |  |
| --- | --- |
| **Analytical Step** | **Rationale behind this step** |
| Using text statistics to identify designations for small businesses and the self-employed (a list of 37 keywords). | *Pattern detection.* Identifying language that is natural to this corpus (using part of speech tagging)  |
| Creating a subset of the main corpus that contains these designations (4543 tweets by 2375 authors)Classifying authors (determining five groups of authors: 1-private/business; 2-political/admin; 3-media; 4-interest groups; 5-legal/tax advisor)Drawing random samples of 50 tweets to compare the language used by different author groups, using text statistics to validate the differences | *Pattern detection*Different author groups talk about state assistance differently |
| Creating the final corpus: a subset of all tweets authored by group 1 (private/businesses) (2359 tweets by 1435 authors)Qualitative coding of the final corpus | *Pattern refinement* Using qualitative content analysis to identifty claims |
| Identifying symbolic boundaries; using deservingness theory (CARIN scheme) to analyse main codes, identifying deservingness discourse in them  | *Pattern refinement* |
| Comparing results to a random sample of 200 tweets from the final corpus coded by a second person (intercoder consistency)Comparing results to a random sample of 100 tweets from the main corpus  | *Pattern validation* |

Figure A1: Steps of the Analysis

1. *Using text statistics to identify designations*

In the first step, the goal is to identify designations that are used to refer to small business and the self-employed in this corpus (i.e., names that are occur naturally in it). This focus on actor designations aligns with the broader theoretical framework.

I employ part of speech (POS) tagging to gather the 500 most-used nouns as well as noun-phrases in the corpus. I use the spacyR package (Benoit & Matsuo, 2018) (integrated with quanteda) and the German language model included in this package (de\_core\_news\_sm) to identify relevant designations for small business and the self-employed. The advantage of doing so – rather than relying on external lists of designations, as in a dictionary approach – is that it enables the discovery and utilization of the language that organically emerges within this corpus for subsequent analysis. I also run quanteda’s textstatistic (including a search for top bigrams and trigrams) to check whether any important expressions are missing from the POS analysis. All in all, this generates a list of 37 words around small businesses and the self-employed:

'selbstständige', 'künstler', 'freiberufler', 'soloselbständige', 'künstler\*innen', 'soloselbstständige', 'solo-selbstständige', 'mittelstand', 'selbständige', 'gastronomie', 'kleinunternehmer', 'gastronomen', 'soloselbststaendige', 'kleinunternehmen', 'einzelhandel', 'hotels', 'solo-selbständige', 'startups', 'kulturschaffende', '\\<Handel\\>', '\\<handel\\>', 'selbständigen', 'kleinstunternehmen', 'restaurants', 'soloselbständigen', 'soloselbstständigen', '\\<Kreative\\>','\\<kreative\\>', 'geschäftsleute', 'kleine unternehmen', 'kleinen unternehmen', 'freie berufe', 'kleine betriebe', 'kleine und mittelständische unternehmen', 'mittlere unternehmen', 'mittelständische unternehmen', 'freie berufe', 'kleine mittlere unternehmen', 'kleine mittelständische unternehmen')

 Using this list, I generate a corpus that contains only tweets that mention these keywords. This generates a corpus of 4543 tweets (authored by 2375 authors).

1. *Classifying authors*

A key goal of the analysis is to capture moral evaluations of pandemic economic relief policies. We can expect participants in this debate to engage in moral evaluations to varying degrees, depending on the capacity in which they present their claims. In the second step, I therefore ask: Who is issuing these tweets, what types of authors can be distinguished in this material? It makes sense to distinguish individual Twitter/X users from institutional accounts (such as politicians, ministries, banks, media, interest groups) for two reasons: first, institutional accounts clearly dominate in terms of the volume of content (see Table A1 above), they produce a lot of content, and consistently, hence only looking at the most active users or the most popular tweets would primarily capture what they are saying. Second, institutional accounts often have a press department and their public communication tends to be scripted; hence we can expect them to be talking about social and economic policies in different ways than individual users.

I classify all 2375 authors manually to make the relevant distinction. For coding author types, I manually analyse author descriptions, or “twitter bios”, which express elements of social identity (Pathak et al., 2021). This kind of data was downloaded as meta-data along with the content of the tweets. Through these self-descriptions, users offer information about themselves (in the case of institutional accounts, these details are often quite straightforward). Based on this broad distinction between individual and institutional accounts, it is possible to identify five distinct groups, as detailed in Table A3.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Type** | **Authors** | **Coding details** | **No. of authors** | **No. of tweets** |
| 1 | Individual accounts: Private and business | Lay Twitter/X users are included in this category, as are entrepreneurs, academics, and financial advisors | 1435 | 2359 |
| 2 | Institutional: Politicians, ministries, and administrative organizations that are charged with implementing the pandemic relief programs | Banks such as KfW (*Kreditanstalt für Wiederaufbau*) are included in this category, since they are entrusted with implementing some of the programs. Organizations for economic support (*Wirtschaftsförderung*) are included as well as they act in the interest of a commune, or federal state, and implement the programs | 245 | 762 |
| 3 | Institutional: News media, journalists, online news platforms | Individual journalists are included if they indicate a permanent affiliation with a newspaper or media organization. Freelancers are included in type 1. | 306 | 632 |
| 4 | Institutional: Interest groups such as trade associations, professional associations, trade unions, civil society organizations, social organizations | News platforms and magazines that target a specific professional audience (for instance, a busdrivers’ magazine) are also included in this category, because the information environment sustained by such media is the result of a professional, interest-based organizing effort | 243 | 593 |
| 5 | Institutional: Tax advisors and auditors | Individuals or firms that specialize in legal and tax matters are included in this category | 146 | 197 |

Table A3: Five author types

Is it accurate to assume that institutional accounts generally refrain from engaging in moral evaluations of pandemic relief? To verify this assumption, additional steps are necessary. I draw a random sample of 50 tweets from groups 2, 3, 4, and 5 for the analysis. Group 2, comprising politicians, ministries, and administrative organizations, focuses on announcing assistance programs, detailing their implementation, advocating for improvements and expansions, summarizing expenditures, creating urgency, and occasionally criticizing policy shortcomings, such as the exclusion of the self-employed from policy formulation and insufficient funding. Overall, politicians and administrative accounts tend to focus on informing about the existence of these programs and adapt a neutral language. While the predominant genre is informational, elements of criticism, particularly from opposition politicians, are also present. The dominant bureaucratic tone, as Rauh (2023) for example notes in the context of EU offices’ political language, is influenced by institutional factors. Group 3, consisting of news media, journalists, and news platforms, primarily reports on various aspects of these programs. Their focus includes the programs’ existence, eligibility criteria, modifications, and expenditure summaries. They also cover issues such as the exclusion of specific groups (like sex workers), insufficient funding, repayment provisions, fraud cases, and inequalities in their distribution. Yet there is a key difference to individual accounts: The analysis of the random sample reveals that these are not direct claims; rather, they predominantly consist of reports on claims. They appear to map out and provide a summary of existing discourse – hence they are not engaged in evaluating the relief programs; they do not take a moral position towards them, but instead in summarize relevant events, actors, processes. Group 4, comprising interest groups and civil society organizations, focuses on keeping their specific audiences (such as brewers or bus drivers) up to date about relevant modifications in the programs. Their tweets call for donations, mobilize for donation campaigns (e.g., for artists), share news about training events, and provide guidance on applying for these programs and meeting eligibility criteria. Additionally, they warn about potential disastrous consequences of insufficient support (e.g. for retailers), offer overviews of existing programs and application procedures, and report on corrections, improvements, deadlines, and extensions of funding. Thus, empowering their specific constituencies through information is a key aspect of their communication. Some tweets from these accounts engage in direct claim-making, advocating for increased funding, the inclusion of more groups, and the recognition of various types of expenses. The language of group 5 (tax lawyers and accountants) is distinctly concerned with legal issues.

While a comprehensive study of, in particular, group 4 (interest groups), as well as the interactions between these different groups, would be valuable, it falls outside the scope of this article. The primary aim of this article is not to assess the effectiveness of small business and self-employed organizations in addressing the shortcomings of these relief programs. Instead, the focus is on understanding and highlighting the prevalent moral perspectives regarding the relief programs. This objective, coupled with the practical limitations in terms of resources for conducting a qualitative analysis, informs the decision to concentrate on individual accounts – which are also by far the largest group – in this study.

In addition to the analysis of the random sample for these groups, I also employ text statistical tools to identify the broad patterns in the language of tweets issued by each of the five author groups and validate the qualitative discussion. One way of doing so is by performing a chi-square comparison (keyness statistics), a tool provided by the quanteda package (Benoit et al., 2018). The results (not shown) corroborate the differences in topical emphases and style discussed here.

Overall, it becomes evident that institutional accounts tend to focus on informing about the existence of these programs and adapt a neutral language. Politicians and organizational accounts avoid divisive language and strive to communicate policies in an inclusive manner. This is not, by itself, surprising, as organizations typically rely on their press department or social media team for these forms of communication. Interest groups aim to mobilize and bring attention to specific policy solutions. Individual accounts, on the other hand, are expected to exhibit significant heterogeneity and a more normative language.

1. *Final corpus for the qualitative analysis*

The final corpus containing tweets by private accounts consists of 2359 tweets issued by 1453 authors.

The qualitative analysis adopts a broad approach to adequately capture the context: What are the subjects of these tweets? How do moral claims surface within them, and what kinds of relational references are expressed in them? This approach aligns with the process-generated nature of the data, necessitating an open and exploratory method. First, it is necessary to gain an overview over the kinds of claims that are being made in this data; second, we can systematically explore how they relate to the CARIN deservingness scheme.

All of the tweets in the final corpus contain three elements that are the formal basis for the qualitative analysis: The name of relief program (for instance, Emergency Assistance (*Soforthilfen)*), the name of the actor (for instance, *Solo-Selbständiger*), and a statement about the relationship between the two. The interpretive approach is key to describing and tracing empirical variations in the third element. Despite the fact that automated tools (such as sentiment analyses) are advanced, only a qualitative analysis allows to interpret the nuanced, context-specific differences that emerge from reading and comparing tweets. A deep reading (Mohr et al., 2015; Nelson, 2020) of the text is necessary in this stage of the research process.

I begin by employing an inductive qualitative content analysis to this end (Krippendorff, 2018; Schreier, 2014). An open approach to coding enhances the reliability, as it allows to reconstruct meaning from the standpoint of the subjects who participate in the social media debate. The unit of analysis are single tweets. As Johannson et al. (2018, p.93) argue, “On Twitter, users express their opinions in micro-posts. Linguistically, opinions are evaluative comments by which social actors engage in a communicative activity that considers an event or an issue, that is, an object of talk.” In tweets, they note, we can identify two genuinely social functions: “stance-taking”, in which social actors “evaluate objects” and “positioning”, in which they “social actors inscribe themselves into situations and determine relationships with others”.

I regard these two elements as integral components of the process of making claims about the relationship between state support and its intended beneficiaries. From a first round of coding 400 tweets, I derive a coding scheme that is then applied to the remaining tweets (this procedure is not exhaustive, however, in the later stage of the process, only minor adjustments are necessary, so the scheme’s validity is ensured). Up to three main codes are allowed per tweet. The coding rule for the main code(s) is as follows: What is the core claim expressed in the tweet? What is the author trying to achieve with it? Using grounded theory practitioners’ recommendations, I formulate main codes as actions (Charmaz, 2006). The coding rule for the sub-code(s) is the following: What specific arguments or bits of evidence are mobilized to support the claim? What is the scope of the argument (what groups are mentioned, what areas and administrative units such as the federal government, federal states, or cities, appear). I record in-vivo-codes wherever possible.

Table A4 summarizes the most frequently recorded main codes. Tweets are coded as “not classifiable” whenever there is no text in the tweet that can be meaningfully interpreted (for example, a tweet that merely consists of a list of hashtags, or of an URL that links to external content. Such a tweet might be relevant, but it cannot be included in the analysis based on the information given). A tweet is coded as “not relevant” if either the actor or the economic relief in fact pertains to a different context. For example, there is still a small number of tweets that relate to the Swiss context. There are also cases where the term Emergency Assistance (*Soforthilfen*) is employed in the context of refugee policies rather than in relation to pandemic state assistance for small businesses and the self-employed.

|  |  |
| --- | --- |
| **Main Code(s)**  | **Freq**  |
| informing about assistances | 514  |
| criticizing exclusionary nature of assistances | 485  |
| criticizing inefficiency  | 140  |
| criticizing unequal distribution (who gets what)  | 122  |
| criticizing delays  | 120  |
| not classifiable  | 108  |
| asking about implementation or eligibility  | 106  |
| criticizing assistances (unspecific)  | 94  |
| criticizing refund demands  | 68  |
| not relevant  | 67  |
| calling for an expansion of assistances | 51  |
| engaging other users  | 51  |
| praising assistances | 48  |
| criticizing complaints by the self-employed  | 30  |
| criticizing delays + warning about economic disaster  | 22  |

Table A4: A selection of main codes (most frequently recorded)

The patterns of variations in the main codes are documented within the sub-codes (not shown). An important code that emerges here that has no discernible relationship to deservingness (and is therefore not discussed in the main body of the manuscript) is *informing about assistances*. A considerable number of tweets revolve around providing information about assistance, including the announcement of specific relief programs, updates on program details and amendments, and sharing information on eligibility criteria and application processes (including programs specific to federal states).

For the final presentation and discussion in the main body of the manuscript, the codes criticising inefficiency and criticising delays are bundled together. As elaborated in the manuscript, the analysis reveals the tension between need and reciprocity as a crucial finding in relation to deservingness theory. *Criticism of inefficiency and delays* serves as a good example of how the principle of need is implied, yet the specific circumstances causing the need are often not elaborated upon in detail. Consequently, the inefficiency of policies is often criticized in a manner that resembles an attack on politics and politicians, labeling them as incompetent and as demonstrating a lack of willingness or abilities to understand the challenges faced by small business owners in their everyday realities. Many applicants faced challenges in navigating these problems. A survey conducted in March 2021 among German entrepreneurs revealed that the majority of respondents criticized the delayed implementation of these programs (Demmelhuber & Wohlrabe, 2021, p.77). For its part, the federal government announced that the first round of cash payments would be distributed “fast” and “non-bureaucratically”, a choice of language that is frequently met with ironic commentary. In one example, “unbureaucratic Emergency Assistance” is referred to as “a rare, mythical creature living in a forbidden forest [alongside] unicorns and fairies”. One person remarks, “I know four solo self-employed individuals whose tax number has been questioned for two months, despite the fact that the ministry of finance has confirmed them, but whose applications haven’t so far been considered”.

Given space constraints, the following aspect is not discussed in the main body of the manuscript: Some individuals also put forth policy solutions, varying from suggestions to implement regular income schemes for entrepreneurs to advocating for a universal basic income for all. These are debates about an entrepreneurial wage (*Unternehmerlohn*) and universal basic income (*Grundeinkommen*). And despite the fact that this is, overall, a contentious debate, it is important to note that the critique of Covid-19 relief programs in this debate does not necessarily equate to a comprehensive criticism of pandemic containment measures. People rarely connect their criticism of these programs to a direct demand for an end to government policies like business closures. The demands primarily revolve around the aspiration to be included within a specific framework of redistribution.

1. *Identifying symbolic boundaries, applying the deservingness scheme*

Theoretical knowledge regarding symbolic and moral classification in welfare support is introduced only at this stage – as part of the pattern refinement – in the analysis. Examining these codes, I look for symbolic boundaries and determine whether deservingness criteria are invoked within them. Identifying symbolic boundaries (Lamont & Molnár, 2002; Wimmer, 2013) – constructions of “us” and “them” – enables the tracing of relational logics at play, the dynamics of relationships between pandemic relief policies and target groups and their subjective construction in the claims expressed in the tweets.

In applying the CARIN scheme, consistent with emerging literature on qualitative approaches to deservingness (Heuer & Zimmermann, 2020; Laenen et al., 2019; Nielsen et al., 2020; Theiss, 2022), I approach these principles not as mutually exclusive entities. Instead, I explore tensions and dynamic negotiations between principles within individual utterances. My focus is on identifying patterns of meaning – recurring themes and nuances in their articulation– rather than drawing conclusions based on the frequency with which these principles appear.

1. *Pattern validation*

Pattern validation is accomplished through two steps: First, a random sample of 200 tweets (approximately 10% of the final corpus) is coded by an independent individual who was not involved in the research process, utilizing the same coding scheme. This is done to ensure intercoder consistency. By comparing the results, the validity of the coding scheme is confirmed. First, a random sample of 200 tweets (approximately 10% of the final corpus) is coded by an independent individual who was not involved in the research process, utilizing the same coding scheme. Second, I draw a random sample of 100 tweets from the main corpus (of 135183 tweets) and perform another round of open coding on it. The results are as follows: A majority of the tweets in the random sample can be classified using the existing coding scheme. The overall salience of certain themes (criticizing delays, criticizing exclusionary nature of assistances, criticizing unequal distribution, and criticizing a one-size-fits all approach of funding) is similar to the one documented earlier. Some additional claims arise from the random sample, including those related to climate change (e.g., the assertion that pandemic state assistance should not support the fossil fuel industry or the car industry), claims concerning the international or EU-level distribution of pandemic assistance (such as the contention that Italy is unjustly receiving a significant portion of EU pandemic support); further allegations of fraud; and broader calls for solidarity (extending beyond the small business community to encompass solidarity for refugees or non-European countries facing economic repercussions from the pandemic).

Overall, the step-by-step analysis reflects the methodological propositions underlying this research: By inductively recording claims about the legitimacy of pandemic state assistance to these groups, I seek to capture fine-grained variation in the public debate about them. Only at a later step, I integrate existing theoretical frameworks into the analysis – these frameworks are also open, as they foreground descriptive, formal features of welfare architectures, such as the logic of state-target group relationships, instead of substantive assumptions about the causes and consequences of particular policies.

**References**

**Andreotta, M., Nugroho, R., Hurlstone, M. J., Boschetti, F., Farrell, S., Walker, I., & Paris, C.** (2019). Analyzing social media data: A mixed-methods framework combining computational and qualitative text analysis. *Behavior Research Methods,* **51**, 1766-1781.

**Barrie, C., & Ho, J. C.** (2021). academictwitteR: an R package to access the Twitter Academic Research Product Track v2 API endpoint. *Journal of Open Source Software,* **6**(62), 3272.

**Benoit, K., & Matsuo, A.** (2018). Spacyr: Wrapper to the ‘spaCy’ ‘NLP’ Library.

**Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., & Matsuo, A.** (2018). quanteda: An R package for the quantitative analysis of textual data, *Journal of Open Source Software,* **3**(30), 774.

**BMF.** (2020a). Außerordentliche Wirtschaftshilfe November, Details der Hilfen stehen. [Press release], *Federal Ministry of Finance*, Retrieved from https://www.bundesfinanzministerium.de/Content/DE/Pressemitteilungen/Finanzpolitik/2020/10/2020-11-05-PM-ausserordentliche-wirtschaftshilfe-november.html

**BMF.** (2020b). Mehr Hilfe für Soloselbständige und die Kultur- und Veranstaltungsbranche, [Press release], *Federal Ministry of Finance*, Retrieved from https://www.bmwi.de/Redaktion/DE/Pressemitteilungen/2020/11/20201113-mehr-hilfe-fuer-soloselbstaendige-und-die-kultur-und-veranstaltungsbranche.html

**BMF.** (2020c). Monatsbericht Juli 2020’, *Federal Ministry of Finance*, Retrieved from https://www.bundesfinanzministerium.de/Content/DE/Downloads/Monatsberichte/2020/07.pdf?\_\_blob=publicationFile&v=10

**BMF.** (2020d). Neue Corona-Hilfe: Stark durch die Krise, [Press release], *Federal Ministry of Finance* Retrieved from https://www.bundesfinanzministerium.de/Content/DE/Pressemitteilungen/Finanzpolitik/2020/10/2020-10-29-PM-neue-corona-hilfe-stark-durch-die-krise.html

**BMWK.** (2022), Überblickspapier Corona-Hilfen. Rückblick – Bilanz- Lessons Learned, *Federal Ministry for Economic Affairs and Climate Action*,Retrieved from https://www.bmwk.de/Redaktion/DE/Downloads/C-D/Corona/ueberblickspapier-corona-hilfen.pdf?\_\_blob=publicationFile&v=8

**Charmaz, K.** (2006). *Constructing Grounded Theory*. Sage.

**Davies, W.** (2021). The politics of recognition in the age of social media. *New Left Review,* **128**, 83–99.

**Demmelhuber, K., & Wohlrabe, K.** (2021). ifo Managerbefragung: Unternehmensfazit nach einem Jahr Coronakrise. *ifo Schnelldienst,* **74**(05), 76­–81.

**Ebbinghaus, B., & Lehner, L.** (2021). Labour hoarding during the pandemic: Assessing the impact of job retention schemes in Europe. *LSE Blogs*, https://blogs.lse.ac.uk/europpblog/2021/06/01/labour-hoarding-during-the-pandemic-assessing-the-impact-of-job-retention-schemes-in-europe/

**Fischer-Preßler, D., Schwemmer, C., & Fischbach, K.** (2019). Collective sense-making in times of crisis: Connecting terror management theory with Twitter user reactions to the Berlin terrorist attack. *Computers in Human Behavior,* **100**, 138–151.

**Fourcade, M., & Healy, K.** (2013). Classification situations: Life-chances in the neoliberal era. *Accounting, Organizations and Society,* **38**(8), 559–572.

**Frees, B., & Koch, W.** (2018). ARD/ZDF-onlinestudie 2018: Zuwachs bei medialer Internetnutzung und Kommunikation. *Media Perspektiven,* **9**, 398–413.

**Gielens, E., Roosma, F., & Achterberg, P.** (2022). More than a Free Lunch: A content analysis of the controversies surrounding Universal Basic Income on Dutch Twitter. *Social Policy and Society*, OnlineFirst.

**Gilardi, F., Gessler, T., Kubli, M., & Müller, S.** (2021). Social media and policy responses to the COVID‐19 pandemic in Switzerland. *Swiss Political Science Review,* **27**(2), 243–256.

**Grigoropoulou, N., & Small, M. L.** (2022). The data revolution in social science needs qualitative research. *Nature Human Behaviour*, **6**(7), 904–906.

**Heuer, J.-O., & Zimmermann, K.** (2020). Unravelling deservingness: Which criteria do people use to judge the relative deservingness of welfare target groups? A vignette-based focus group study. *Journal of European Social Policy,* **30**(4), 389–403.

**Isoaho, K., Gritsenko, D., & Mäkelä, E.** (2021).Topic modeling and text analysis for qualitative policy research. *Policy Studies Journal,* **49**(1), 300–324.

**Johansson, M., Kyröläinen, A.-J., Ginter, F., Lehti, L., Krizsán, A., & Laippala, V.** (2018). Opening up# jesuisCharlie anatomy of a Twitter discussion with mixed methods. *Journal of Pragmatics,* **129**, 90­–101.

**Krippendorff, K.** (2018). *Content Analysis: An Introduction to its Methodology*. Sage.

**Laenen, T., Rossetti, F., & Van Oorschot, W.** (2019). Why deservingness theory needs qualitative research: Comparing focus group discussions on social welfare in three welfare regimes. *International Journal of Comparative Sociology*, **60**(3), 190–216.

**Lamont, M., & Molnár, V.** (2002). The study of boundaries in the social sciences. *Annual Review of Sociology*, **28**, 167–195.

**Mohr, J. W.** (1994). Soldiers, mothers, tramps and others: Discourse roles in the 1907 New York City charity directory. *Poetics,* **22**(4), 327–357.

**Mohr, J. W., Wagner-Pacifici, R., & Breiger, R. L.** (2015). Toward a computational hermeneutics. *Big Data & Society,* **2**(2).

**Nelson, L. K.** (2020). Computational grounded theory: A methodological framework. *Sociological Methods & Research,* **49**(1), 3–42.

**Nielsen, M. H., Frederiksen, M., & Larsen, C. A.** (2020). Deservingness put into practice: Constructing the (un) deservingness of migrants in four European countries *The British Journal of Sociology,* **71**(1), 112­–126.

**Park, P., & Macy, M.** (2015). The paradox of active users. *Big Data & Society,* **2**(2), 2053951715606164.

**Pathak, A., Madani, N., & Joseph, K.** (2021). A method to analyze multiple social identities in twitter bios. *Proceedings of the ACM on Human-Computer Interaction,* **5** (CSCW2), 1–35.

**Puschmann, C.** (2015). The form and function of quoting in digital media. *Discourse, Context & Media,* **7**, 28–36.

**Rauh, C.** (2023). Clear messages to the European public? The language of European Commission press releases 1985–2020. *Journal of European Integration,* **45**(4), 683–701.

**Roberts, M. E., Stewart, B. M., & Tingley, D.** (2019). Stm: An R package for structural topic models. *Journal of Statistical Software,* **91**, 1–40.

**Schreier, M.** (2014). Ways of doing qualitative content analysis: disentangling terms and terminologies. *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research,* **15**(1).

**Shugars, S., et al.** (2021). Pandemics, protests, and publics: Demographic activity and engagement on Twitter in 2020. *Journal of Quantitative Description: Digital Media,* **1**, 1­–68.

**Theiss, M.** (2022). How Does the Content of Deservingness Criteria Differ for More and Less Deserving Target Groups? An Analysis of Polish Online Debates on Refugees and Families with Children. *Journal of Social Policy*, OnlineFirst.

**Tufekci, Z.** (2017). *Twitter and Tear Gas: The Power and Fragility of Networked Protest*. Yale University Press.

**Wimmer, A.** (2013). *Ethnic Boundary Making: Institutions, Power, Networks*. Oxford University Press.

**Zerubavel, E.** (1996). Lumping and Splitting: Notes on Social Classification. *Sociological Forum,* **11**(3), 421–433.

1. The code is available on Github: URL. [↑](#footnote-ref-1)