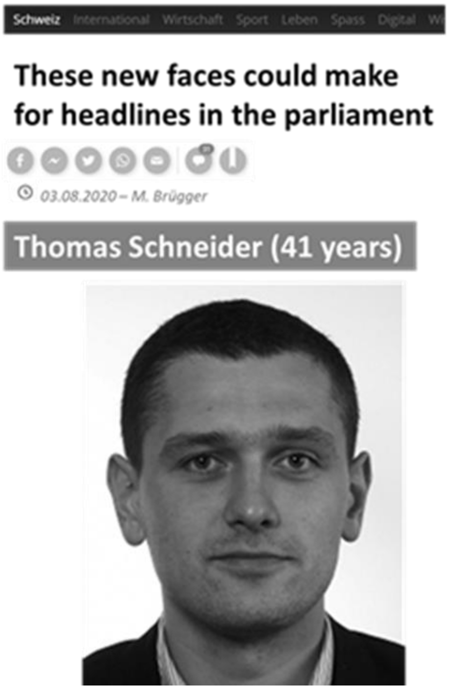
Supplementary Materials

Contents

Stimulus material

Neutral sets (1)

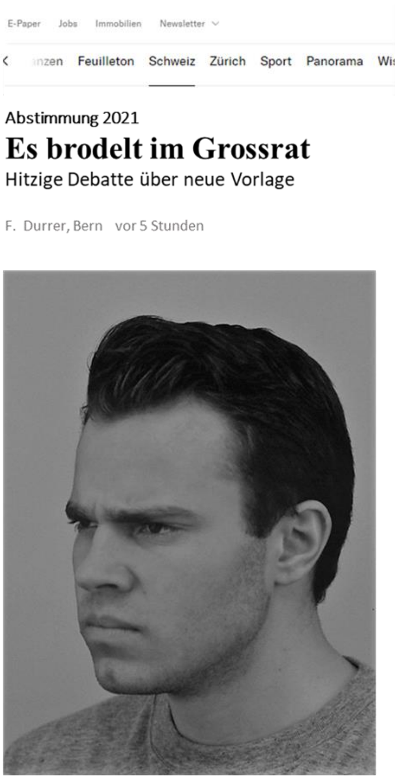


Negative sets (3)

Moral scandal set

Negative campaign set

Anger set



Filler sets (3)

Notes. The filler sets were not considered in the analysis of the present study.

Family set

Gaming set

Selfie set


SRF
News Sport Meteo Kultur DOK
News
Übersicht Coronavirus Abstimmungen Schweiz International Wirtsc
CURIA CONFOEDERATIONIS HELVETICAE
Entscheidung am Wahlsonntag
Ben Keller will ins Parlament
SRF News vom 17.11.2020


SRF
News Sport Meteo Kultur DOK
News
Übersicht Coronavirus Abstimmungen Schweiz International Wirt
Entscheidung am Wahlsonntag
Katja Bauer will ins Parlament
SRF News vom 17.11.2020

Category grid for qualitative Coding

Category	Definition and typical examples from the material
Politics (candidate)	Thoughts related to candidates' *ideology*, party *affiliation*, political *experience* or function, their positions on political *issues*, or the election or political *context*. Examples: He looks like a typical "party soldier"; She is more on the conservative side; Social policy is not her thing; She looks like a teacher, so I'm just assuming she is in the socialist democratic party. His smile looks a bit frozen—those are most likely not his first elections.
Appearance (candidate)	Thoughts about candidates' physical appearance (e.g., *facial features*, biological aspects, such as *age*, height, posture), including aspects of *style and clothing* (make-up, hairstyle, clothing, accessories). Examples: He has a friendly smile; his jaw is clenched tight; she badly needs a new hair cut; his features are rather bland; For a politician, he looks refreshingly young and clear-eyed. He is wearing an informal t-shirt; she only wears little make-up.
Personal (candidate)	All references to candidates' personal life, including their *gender*, *civil status*, *sexuality*, *parenthood* but also their *job*, *hobbies* or non-political attributes and *interests*. Examples: This one is definitely working for a bank; That lady probably has children at home and has not had a good night's sleep in a while; She probably tries to be feminine but not too feminine in the way she dresses; Looks like a fun guy who goes for walks in the park with his two dogs.
Personality Traits: AGENCY (candidate)	Thoughts about the candidates' <u>positive and negative</u> agentic personality traits. Agency comprises characteristics that are aimed at pursuing personal goals and manifesting skills and accomplishments (also referred to as competence, intellectual goodness, or dominance). Agentic traits refer to the question: What can this person do how well? Examples: *<u>Positive</u>:* confident; competent; he knows what he's doing; she wasn't born yesterday and won't be backed into a corner easily; active, experienced etc. <u>Negative</u>: insecure, she is not likely to make an impact if elected; he does not look like he knows what's actually going on; confused etc.
Personality Traits: COMMUNALITY (candidate)	Thoughts about the candidate's <u>positive and negative</u> communal personality traits. Communion comprises characteristics that are related to forming and maintaining social connections (also referred to as warmth, morality, social goodness, or nurturance). Communal traits refer to the questions: What does this person want? Are their intentions well-meaning or not? Examples: <u>Positive:</u> sincere; a good listener; really cares for change; he tries to understand what others are saying; surprisingly patient; polite; friendly; nice; open; warm <u>Negative</u>: cynical; evil; ruthless; cold; he shows up and takes credit for the work that others are doing; he wants to bite off my head; she is definitely a screamer; unpleasant person

Participant-related	All thoughts that are not directed towards the candidate or the image itself but rather encapsulate an aspect of the participant, such as their *attitudes*, *opinions*, *experiences*, *memories*, and *preferences*. Examples: She looks like someone I went to school with; she reminds me of my English teacher; that's not a type of person I would get along with; I really don't like this type of headline; it annoys me that politicians think smiling is the answer to everything
Layout	All references to aspects of stimulus *layout*, including its *color*, *design*, *headline*, *tone*, and *technical details* Examples: The saturation of the photo is very low; it's in black and white; typical broadsheet journalism; the lighting emphasizes his friendly smile; the shot is not frontal but a bit from the side.
Other	All thoughts that cannot be categorized otherwise; if used repeatedly, the the material was re-visited to check whether the observations might form an inductively derived (sub-)category.

Notes. Words in italics were coded as subcategories and then collapsed into larger categories for the analysis (same with agentic and communal traits)

Specification of Bayesian regression models

Choice of prior distributions

Bayesian analysis involves the specification of prior probability distributions for all model parameters. The choice of prior distributions reflects the beliefs about the model parameters before seeing the data and affects both estimation and testing of model parameters from the posterior distributions obtained through updating these beliefs with the observed data (Gelman et al., 2013; Kruschke, 2014).

The literature commonly distinguishes between two general strategies for choosing priors. On the one hand, one can choose a non-informative prior (also called flat or vague prior) that contains (almost) no a priori beliefs about the model parameters. Such priors let the data "speak for itself" by assigning all the weight in the updating process to the observed data. On the other hand, informative priors provide a priori some degree of information relative to the information provided by the observed data. While including prior theoretical knowledge about model parameter is often desirable, it comes at the cost of infusing the analysis with additional sources of subjectivity.

I follow a middle ground and follow current recommendations of using default priors for all regression parameters (Andrew Gelman et al., 2008; Morey & Rouder, 2011; Rouder & Morey, 2012). Specifically, I use a "small to medium wide" (r scale = 0.35) zero-centered Cauchy prior for all regression coefficients. The prior is weakly informative in the sense that it assumes small to medium size effects around zero to be very common and larger or extreme effect sizes to be possible but uncommon. The medium width of the prior distribution is chosen to provide a reasonable a priori assumption for the calculation of Bayes factors whose calculation is susceptible to the choice of priors (Ly et al., 2016; Rouder & Morey, 2012). However, the regularizing effect of this assumption is still rather weak and assigns most of the weight in the updating process to the observed data. Centering the distribution on zero is reasonable given the mixed findings of past studies and because we wish the direction of our results to be influenced only by the observed data.

Model details

All models were run with the *brms* library (Bürkner, 2018) on R 4.1.1. I used 50'000 iterations (with a burn-in of 3000 iterations) for all models. I used the default of the *brms* library of four cores and chains for the Markow-Chain-Monte-Carlo.

Model diagnostics

For all models reported in the manuscript (Models 1 and 2 in Tables 2 and 3), I inspected the following diagnostics:

- *Convergence*: I visually inspected the convergence of MCMC chains by the means of trace plots, which indicated no signs for lacking convergence. Moreover, the Gelman-Rubin statistic does not deviate from 1 for any of the estimates model parameters (see McElreath, 2018).
- *Graphical posterior predictive checks*: I plotted density overlay plots with 150 draws from each estimated models to assess whether the models provide a good representation of the actual data (see Gabry et al., 2019). No concern arises from these checks.
- *Autocorrelation*: An inspection of autocorrelation plots shows signs of autocorrelation only for a small number of lags; this issue is addressed by running a high number of iterations.

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