Supplementary Information: Historical reconstruction of human moralization with word association and text corpora

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Supplementary Information Guide

1 Supplementary Notes

1.1 Additional details on model evaluation

We compared our model performance in reconstructing empirical moral association with alternative model architectures and baselines. As described in *Methods* section of the main text, we designed three distinct architectures—Residual GCN, GCN, and BERT baseline. To train these architectures, we used two BERT-based pre-trained language models: `bert-base-uncased` and `xlm-roberta-large`. The `bert-base-uncased` model [1] was pre-trained on BooksCorpus [2] and English Wikipedia, and has 110M parameters. The `xlm-roberta-large` model [3] is a large multilingual masked language model with 2.5TB parameters, and was pre-trained on CommonCrawl data. We also considered a moral change inference model from related study [4], which uses pre-trained Google Ngrams Word2Vec embeddings [5] to estimate moral relevance and moral polarity of various concepts. To further compare our results with mere lexical features, we collected relative degrees of co-occurrence with moral (MFD) terms for all words in COHA (indirect moralization score, See Methods Section for detail). Table 1 provides the summary of our results, comparing different architectures on the test section of our pipeline. Given the superior performance of the Residual GCN architecture with `bert-base-uncased` embeddings, we use this model for the rest of our analyses.

Moreover, we provide a direct comparison between our best model, the Residual GCN, and the Word2Vec-based approach from [4] to reconstruct moral associations of disease-related terms, following a similar experimental setup as in Figure 2c in the main text. Table 2 presents the results of the permutation test, which compares the moral associations of disease-related terms with randomly generated sets from COHA. Due to the limited availability of political figure names in the Word2Vec-based approach, we were unable to replicate the analysis in Figure 2d (main text) using this method.

Similarly, Table 3 reproduces our the international conflict experiments as shown in Figures 2e and 2f (main text), using the Word2Vec framework. Together, these results indicate that while the Word2Vec-based moral inference method can detect moral signals in major global events and issues, the effects are generally weaker and noisier than those identified by our reconstruction framework.

Table 1 Comparing different architectures and training corpora in reconstructing empirical moral association scores. NA stands for not applicable. Pearson correlation coefficients were calculated and tested for significance using two-sided tests. Except for the last row, all correlation values are statistically significant with $P < 0.0001$.

Data	Association	Size	Architecture	Base embeddings	Pearson's r, 95%CI	R^2
COHA	Moral relevance	937	**Residual GCN**	`bert-base-uncased`	**0.669**, $[0.632, 0.703]^{***}$	**0.445**
			GCN	`bert-base-uncased`	0.657, $[0.619, 0.692]^{***}$	0.429
			BERT baseline	`bert-base-uncased`	0.661, $[0.623, 0.695]^{***}$	0.433
			Residual GCN	`xlm-roberta-large`	0.643, $[0.604, 0.679]^{***}$	0.412
			GCN	`xlm-roberta-large`	0.639, $[0.599, 0.675]^{***}$	0.399
			BERT baseline	`xlm-roberta-large`	0.624, $[0.583, 0.662]^{***}$	0.387
	Moral polarity	843	**Residual GCN**	`bert-base-uncased`	**0.675**, $[0.637, 0.710]^{***}$	**0.447**
			GCN	`bert-base-uncased`	0.651, $[0.610, 0.688]^{***}$	0.407
			BERT baseline	`bert-base-uncased`	0.555, $[0.506, 0.600]^{***}$	0.203
			Residual GCN	`xlm-roberta-large`	0.606, $[0.561, 0.647]^{***}$	0.364
			GCN	`xlm-roberta-large`	0.594, $[0.549, 0.636]^{***}$	0.331
			BERT baseline	`xlm-roberta-large`	0.463, $[0.408, 0.514]^{***}$	-0.071
NYT	Moral relevance	883	**Residual GCN**	`bert-base-uncased`	**0.645**, $[0.604, 0.682]^{***}$	**0.414**
			GCN	`bert-base-uncased`	0.623, $[0.581, 0.662]^{***}$	0.385
			BERT baseline	`bert-base-uncased`	0.632, $[0.590, 0.670]^{***}$	0.398
	Moral polarity	789	**Residual GCN**	`bert-base-uncased`	**0.665**, $[0.624, 0.702]^{***}$	**0.439**
			GCN	`bert-base-uncased`	0.620, $[0.575, 0.661]^{***}$	0.383
			BERT baseline	`bert-base-uncased`	0.625, $[0.580, 0.666]^{***}$	0.306
Google Ngrams	Moral relevance	897	Skipgram	`Word2Vec`	0.426, $[0.371, 0.478]^{***}$	NA
	Moral polarity	795	Skipgram	`Word2Vec`	0.479, $[0.424, 0.531]^{***}$	NA
COHA	Moral relevance	937	MFD Co-occurrence	NA	0.465, $[0.413, 0.514]^{***}$	NA
	Moral polarity	835	MFD Co-occurrence	NA	-0.06, $[-0.13, 0.005]$ ($P = 0.068$)	NA

Table 2 Comparing moral association scores of disease-related terms with randomly selected sets of terms. Each set contains 135 samples, and the random selection is repeated for $1,000$ times. Results show the performance of our reconstruction framework and alternative moral change inference methodology based on Word2Vec embeddings [4]. All values are statistically significant with $P < 0.0001$ using one-sided t-tests.

Category	Association	Method	t-statistic	Cohen's d
Disease terms	Moral relevance	Ours (Residual GCN)	-652.57^{***} (df = 999)	20.63
		Word2Vec [4]	-70.6^{***} (df = 999)	2.23
	Moral polarity	Ours (Residual GCN)	896.32^{***} (df = 999)	28.34
		Word2Vec [4]	749.38^{***} (df = 999)	23.7

Table 3 Comparing the effect of major world conflicts on moral association scores estimated by our reconstruction model and an alternative moral change inference methodology based on Word2Vec embeddings [4]. Top rows compare moral association scores in wartime and peacetime periods. Bottom rows compare moral association scores of the winning and losing sides of world conflicts. The asterisks indicate the significance levels for one-sided t-tests ("*," "**," "***" for $P < 0.05, 0.01, 0.001$ respectively).

Experiment	Association	Method	t-statistic	Cohen's d
Wartime vs. Peacetime	Moral relevance	Ours (Residual GCN)	6.23^{***} (df = 182)	0.15
		Word2Vec [4]	4.15^{***} (df = 247)	0.13
	Moral polarity	Ours (Residual GCN)	-8.65^{***}(df = 182)	0.17
		Word2Vec [4]	0.84 ($P = 0.798$, df = 247)	0.03
Winner vs. Loser	Moral relevance	Ours (Residual GCN)	1.83^{*} ($P = 0.035$, df = 209)	0.20
		Word2Vec [4]	1.38 ($P = 0.08$, df = 221)	0.12
	Moral polarity	Ours (Residual GCN)	-2.48^{**} ($P = 0.002$, df = 209)	0.27
		Word2Vec [4]	-2.53^{**} ($P = 0.006$, df = 221)	0.26

1.2 Additional details on systematic moralization

We evaluated the effectiveness of our model in reconstructing human moral judgment toward conceptual categories. We do so by using our model to compute the moral relevance scores for all of these categories based on the concepts within those categories (e.g., *cholera* and *cancer* are two concepts within the "disease" category) and validating them against empirical human data. As described in *Methods*, the empirical data is collected from moral relevance scores derived from word association network of Small World of Words (SWOW) [6, 7]. We collected these empirical scores for individual concepts within each category, and then averaged these scores to estimate category-level scores. A Spearman correlation test indicates that our reconstruction model correlates strongly with the empirical moral relevance associations with $\rho = 0.744$ (95% CI $= [0.65, 0.82]$, $P < 0.0001$, sample size = 117 categories).

Similarly, we prompted GPT-4o, a state-of-the-art large language model developed by OpenAI, to generate moral relevance scores for individual concepts within the categories. Using GPT-4o we were able to reconstruct empirical scores with $\rho = 0.565$ (95% CI $= [0.43, 0.68]$, $P < 0.0001$, sample size = 117 categories). The prompt used for this experiment is as follows:

```
You will be given a word that represents a particular concept. Provide a number from 0 to
1 that represents the proportion of people in North America who think morally about this
concept. For example, if the word is "murder", the score should be very close to 1, since
the majority of people believe "murder" is morally wrong. However, if the given word is
"desk" your score should be close to 0 since "desk" is morally irrelevant.
Word: [The query is inserted here]
Score:
```

Table 4 details the number of concepts per category (excluding words with no mentions in COHA). Figure 1 shows sample time courses of moral relevance (estimated by our reconstruction model) and log frequencies for the categories "disease", "science", and "supernatural being". The estimated degrees of moral relevance and frequencies (y-axis) represent the average values from all concepts in each category across different time points.

To further investigate systematicity in moralization, we tried to predict category membership based on our estimated moral association scores. Figure 2 shows that category membership can be predicted from concepts' moral relevance and polarity scores. For this analysis, each concept ($1,559$ in total) was represented in a two-dimensional space defined by its average moral relevance and polarity across all time points (1850s to 1990s). The moral relevance and polarity scores were generated by our reconstruction model. Category membership was then predicted based on the k-nearest neighbors algorithm with a euclidean metric applied to this 2-dimensional moral space, with no other semantic information. Results, as compared to a baseline model that predicts the most frequent category (i.e., "animal"), further support the systematic nature of moral associations across categories. In other words, concepts that have similar moral association profiles belong to the same conceptual category.

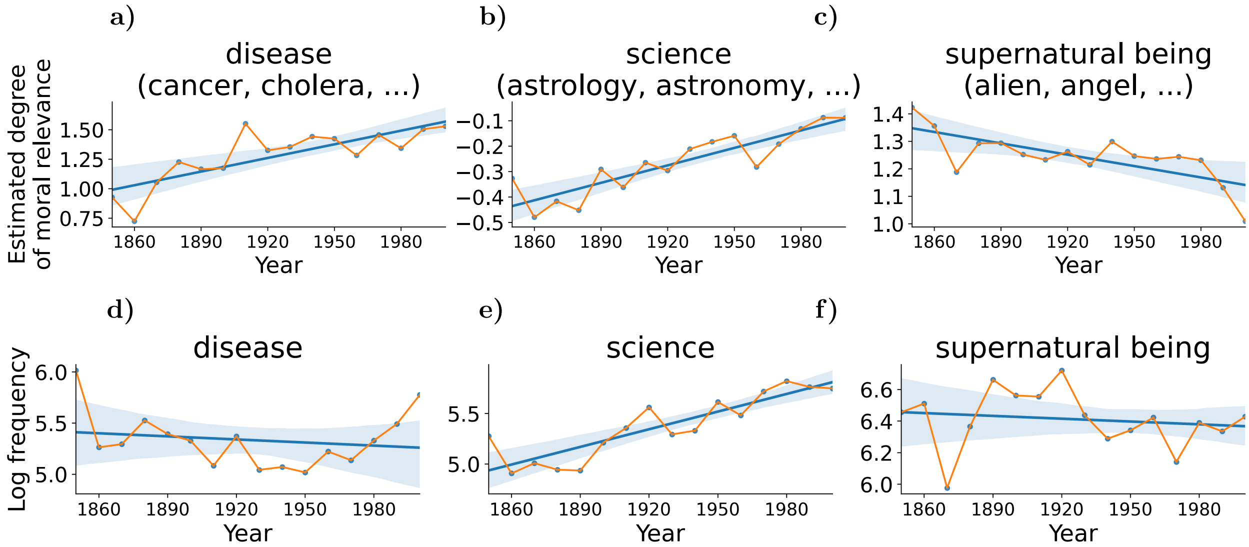

Fig. 1 Time courses of moral relevance and log frequencies for the categories of "disease," "science," and "supernatural being." Sample concepts from each category are shown in the plot titles.

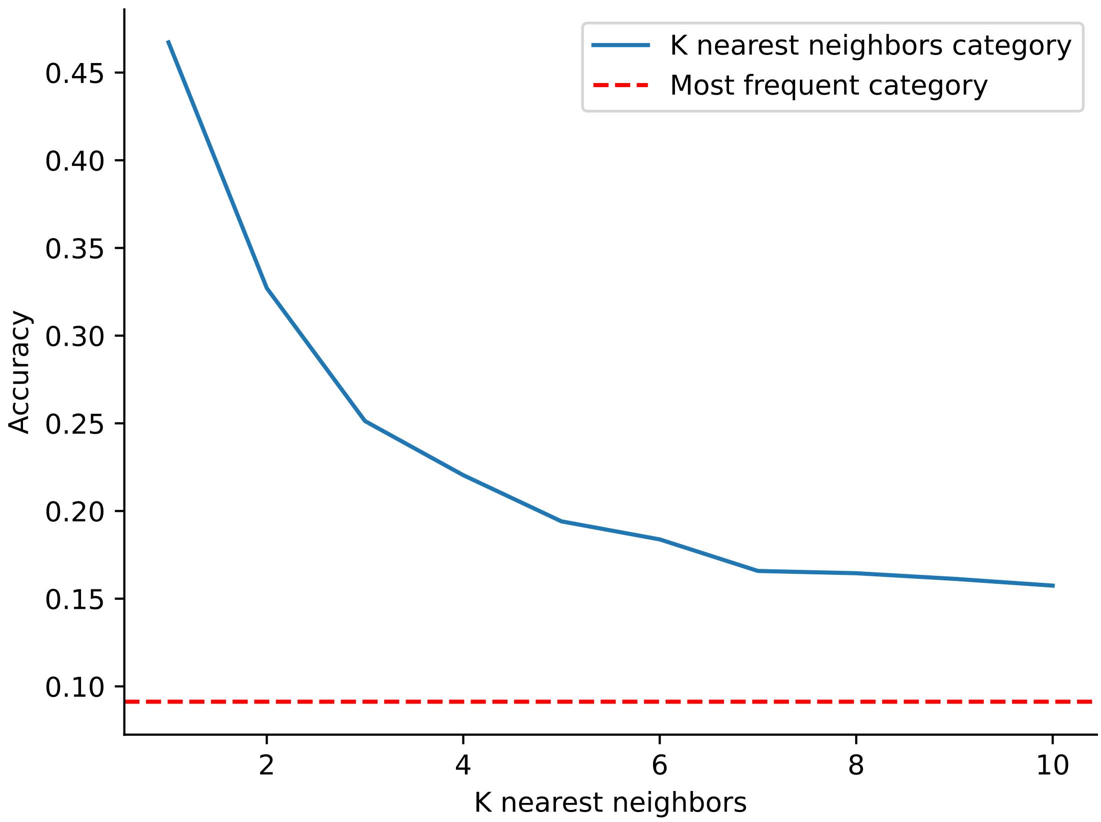

Fig. 2 Accuracy on predicting category membership based on k-nearest neighbors in the moral space. The horizontal line shows the baseline from always predicting the category with the most members (i.e., "animal").

Table 4: Conceptual categories with their sizes and a sample set of representative members.

Category	Size	Sample concept members
academic subject	24	art, biology, chemistry, drama, economics
alcoholic drink	16	ale, beer, brandy, champagne, cider
animal	64	ant, antelope, ape, badger, bat
art form	14	architecture, dance, drawing, model, music
artistic movement	4	abstract, dance, gymnastics, realism
bathroom fixture	13	bath, blind, cabinet, cupboard, door
bird	29	blackbird, canary, chicken, crow, dove
bird of prey	8	buzzard, eagle, falcon, hawk, kite
boat	6	canoe, ferry, kayak, motorboat, ship
body of water	12	bath, canal, lake, ocean, pond
book genre	19	action, adventure, autobiography, biography, comedy
breed of dog	9	beagle, boxer, bulldog, husky, labrador
building	26	apartment, bungalow, castle, cathedral, church
building material	14	bamboo, cement, concrete, glass, hammer
camping equipment	9	blanket, caravan, fire, food, hammer
carpenter's tool	10	chainsaw, chisel, drill, file, hammer
chemical element	24	arsenic, bromine, calcium, carbon, chlorine
citrus fruit	8	clementine, grapefruit, lemon, lime, mandarin
clothing	22	belt, blouse, bra, cap, cardigan
colour	23	amber, beige, black, blue, brown
cosmetic	11	conditioner, contour, cream, foundation, lipstick
crime	9	assault, burglary, fraud, kidnap, murder
dairy product	7	butter, cheese, chocolate, cream, ice cream
day of the week	7	friday, monday, saturday, sunday, thursday
disease	13	cancer, cholera, cold, diabetes, flu
drug	13	alcohol, caffeine, cocaine, ecstasy, heroin
emotion	22	angry, anxious, content, depressed, disappointment
fabric	12	cloth, cotton, denim, fur, leather
family relationship	17	auntie, brother, cousin, daughter, father
farm animal	15	bull, cat, chicken, cow, dog
fish	14	bass, carp, catfish, cod, goldfish
flower	10	daffodil, daisy, dandelion, lavender, lily
four-legged animal	34	antelope, bear, bison, cat, cheetah
four-wheeled vehicle	9	bus, car, coach, jeep, lorry
fraction	11	eighth, fifth, half, ninth, piece
fruit	24	apple, apricot, avocado, banana, clementine
fuel	10	coal, diesel, electricity, food, gas
furniture	16	armchair, bed, bookcase, bookshelf, cabinet
gardening tool	11	brush, bucket, chainsaw, fork, hoe
gemstone	9	amber, diamond, emerald, opal, pearl
geometric shape	8	circle, cube, diamond, kite, pentagon
green vegetable	8	broccoli, cabbage, celery, cucumber, leek
hair colour	15	auburn, black, blonde, blue, brown
hat	5	beret, cap, fedora, sombrero, top hat
healthcare profession	9	consultant, dentist, doctor, nurse, pharmacist
herb	13	basil, cinnamon, dill, garlic, lavender
human dwelling	15	apartment, attic, bungalow, caravan, castle
infectious disease	7	cholera, cold, flu, hiv, malaria
injury	12	blister, bruise, burn, cut, fall
insect	15	ant, bee, beetle, butterfly, caterpillar
jewellery	5	bracelet, necklace, ring, tiara, watch
kitchen appliance	22	blender, bowl, dishwasher, fork, freezer

kitchen utensil	14	blender, bowl, fork, frying pan, kettle
legal profession	8	clerk, judge, jury, lawyer, magistrate
living room furniture	18	armchair, bookcase, bookshelf, carpet, chair
meat	24	bacon, beef, chicken, crocodile, deer
medical specialty	7	cardiac, dentist, doctor, nurse, psychiatrist
metal	13	brass, bronze, copper, gold, iron
military title	13	captain, chief, colonel, commander, corporal
month	11	april, august, december, february, january
musical instrument	20	bass, bassoon, cello, clarinet, flute
natural landform	10	cave, cliff, desert, hill, island
negative emotion	18	anger, annoyed, anxiety, depressed, despair
negative personal quality	18	abrupt, aggressive, angry, annoying, anxious
non-violent crime	3	fraud, robbery, theft
nut	5	acorn, chestnut, hazelnut, peanut, walnut
part of a boat	18	anchor, bow, cabin, deck, engine
part of a building	18	attic, bathroom, carpet, ceiling, corridor
part of a tree	7	bark, branch, fruit, sap, stem
part of the body	27	ankle, arm, back, blood, brain
part of the face	14	beard, cheek, chin, earlobe, forehead
personal quality	28	academic, annoying, brave, bubbly, charismatic
political system	9	communism, conservative, democracy, democrat, dictatorship
positive emotion	10	calm, cheerful, confident, content, ecstatic
positive personal quality	26	cheerful, confident, dedication, empathy, friendly
prime number	9	eleven, five, nine, nineteen, seven
profession	39	actor, actress, babysitter, baker, bartender
psychological illness	6	anxiety, autism, dementia, depression, psychosis
racket sport	2	squash, tennis
reading material	20	article, blog, book, comic, diary
religion	7	atheism, buddhism, catholicism, christianity, islam
religious building	8	cathedral, chapel, church, monastery, mosque
rodent	8	cockroach, ferret, guinea pig, hamster, mouse
room in a house	19	attic, basement, bathroom, bedroom, conservatory
royal title	13	baron, baroness, dame, duchess, duke
science	9	astrology, astronomy, biology, chemistry, engineering
season	7	autumn, dry, fall, monsoon, spring
snake	4	cobra, python, rattlesnake, viper
social gathering	12	birthday, christmas, club, dance, dinner
social relationship	22	acquaintance, boyfriend, brother, child, colleague
spice	10	basil, cinnamon, cumin, ginger, mint
sport	20	athletics, baseball, basketball, cricket, dance
statistical term	12	algebra, average, correlation, data, graph
stinging insect	6	bee, hornet, mosquito, scorpion, spider
string instrument	10	banjo, bass, cello, guitar, harp
supernatural being	12	alien, angel, demon, devil, fairy
symptom of illness	11	aching, cold, fever, headache, nausea
team sport	11	baseball, basketball, cricket, football, hockey
three-dimensional shape	6	cone, cube, cylinder, prism, pyramid
time of day	13	afternoon, bedtime, breakfast, dawn, daytime
tool	12	axe, chainsaw, chisel, crowbar, drill
tree	16	ash, birch, cedar, cherry, chestnut
two-dimensional shape	5	circle, pentagon, rectangle, square, triangle
two-wheeled vehicle	2	bicycle, scooter
type of word	4	adjective, noun, pronoun, verb
unit of length	4	foot, kilometre, mile, yard
unit of time	3	century, epoch, fortnight
unit of weight	7	gram, kilogram, milligram, ounce, pound
vegetable	17	asparagus, broccoli, cabbage, carrot, cauliflower

vehicle	17	ambulance, bicycle, boat, bus, car
violent crime	10	assault, battery, genocide, kidnapping, murder
water bird	10	duck, flamingo, goose, gull, heron
water sport	1	rowing
weapon	16	arrow, axe, bomb, crossbow, crowbar
weather	26	breezy, bright, cloudy, cold, drizzle
wind instrument	7	bassoon, clarinet, flute, oboe, recorder
winter sport	2	hockey, skiing

1.3 Quantifying moral change based on economic-political shifts

In a series of analyses, we investigate the relationship between moral associations and social events.

1.4 Moral associations and price dynamics

We study the dynamic relationship between moral associations and consumer price index in the United States. We hypothesize that when retail prices of common products (e.g., bread) undergo dramatic shifts, these shifts should be reflected in people's moral associations.

To investigate this relationship, we used average retail prices reported by the U.S. Bureau of Labor Statistics from 1987 to 2007. This database offers monthly price statistics for various categories of food items, utility gas, fuel oil, electricity, and automotive fuels. To quantify the total annual change in product prices, we compared monthly prices to those from the same month in the previous year, and calculated the average relative price change over the 12-month period. To estimate moral association scores of products, we matched each product item to a corresponding token that best represents it; for instance, the product "Apples, Red Delicious, per lb. (453.6 gm)" is mapped to the token *apple*. Table 5 provides the list of products in this database along with their simplified names used in our analyses. To test our hypothesis, we used an Ordinary Least Squares (OLS) that estimates annual changes in retail prices based on the annual changes in products' moral polarity scores, while controlling for the year of change, the previous year's price, and the specific product of interest. We only included example where moral relevance of the product increased over the span of a year, in order to focus our investigation on items with sufficient moral relevance signals. Formally, we used the following equation for the OLS model

$$\Delta\text{price}_{(t-1\to t)} \sim \Delta\text{mp}_{(t-1\to t)} + \Delta s_{(t-1\to t)} + t + \text{price}_{(t-1)} + p \tag{1}$$

where *price* represents the price of a product (time-dependent), *mp* represents the moral polarity score of the product (time-dependent), s represent the sentiment score, t represents the time-point (i.e., a year from 1987 to 2007), and p represents the product. To ensure the robustness of our results, we excluded product items with fewer than 10 years of available price data. This resulted in 335 examples.

The inclusion of moral polarity and sentiment scores resulted in an increase in the explained variance, with an R-squared value of 0.180 compared to 0.140 when excluded. Results further show that that annual changes in moral polarity significantly contribute to the variability in products' annual price changes with $\beta = -0.147$, 95% CI=$[-0.266, -0.027]$, $t(335) = -2.419$, $P = 0.016$, suggesting that products that undergo greater moral polarity change, typically experience decreases in their price change (deflation). We did not find a significant effect for moral relevance and sentiments on retail prices. Figure 3 shows the relationship between moral polarity and average retail prices for three product items in "Gasoline," "Bread," and "Beef" categories.

Table 5: List of products for consumer price index estimation and their simplified names used for our price reconstruction analysis.

Product	Simplified name
Apples, Red Delicious, per lb. (453.6 gm)	apple
Bacon, sliced, per lb. (453.6 gm)	bacon
Bananas, per lb. (453.6 gm)	banana
Beans, dried, any type, all sizes, per lb. (453.6 gm)	bean
Chuck roast, USDA Choice, bone-in, per lb. (453.6 gm)	beef
Ground beef, 100% beef, per lb. (453.6 gm)	beef
Ground chuck, 100% beef, per lb. (453.6 gm)	beef
Rib roast, USDA Choice, bone-in, per lb. (453.6 gm)	beef

Round roast, USDA Choice, boneless, per lb. (453.6 gm)	beef
Steak, T-Bone, USDA Choice, bone-in, per lb. (453.6 gm)	steak
Steak, round, USDA Choice, boneless, per lb. (453.6 gm)	steak
Steak, sirloin, USDA Choice, bone-in, per lb. (453.6 gm)	steak
Chuck roast, USDA Choice, boneless, per lb. (453.6 gm)	beef
Steak, sirloin, USDA Choice, boneless, per lb. (453.6 gm)	steak
Chuck roast, graded and ungraded, per lb. (453.6 gm)	beef
Ground beef, lean and extra lean, per lb. (453.6 gm)	beef
Round roast, graded and ungraded, per lb. (453.6 gm)	beef
Steak, rib eye, USDA Choice, boneless, per lb. (453.6 gm)	steak
Steak, round, graded and ungraded, per lb. (453.6 gm)	steak
Steak, sirloin, graded and ungraded, per lb. (453.6 gm)	steak
All Uncooked Beef Roasts, per lb. (453.6 gm)	beef
All Uncooked Beef Steaks, per lb. (453.6 gm)	beef
All Uncooked Other Beef (Excluding Veal), per lb. (453.6 gm)	beef
All uncooked ground beef, per lb. (453.6 gm)	beef
Bologna, all beef or mixed, per lb. (453.6 gm)	bologna
Bread, French, per lb. (453.6 gm)	bread
Bread, white, pan, per lb. (453.6 gm)	bread
Bread, whole wheat, pan, per lb. (453.6 gm)	bread
Broccoli, per lb. (453.6 gm)	broccoli
Butter, salted, grade AA, stick, per lb. (453.6 gm)	butter
Cabbage, per lb. (453.6 gm)	cabbage
Carrots, short trimmed and topped, per lb. (453.6 gm)	carrot
Celery, per lb. (453.6 gm)	celery
American processed cheese, per lb. (453.6 gm)	cheese
Cheddar cheese, natural, per lb. (453.6 gm)	cheese
Cherries, per lb. (453.6 gm)	cherry
Chicken breast, bone-in, per lb. (453.6 gm)	chicken
Chicken legs, bone-in, per lb. (453.6 gm)	chicken
Chicken, fresh, whole, per lb. (453.6 gm)	chicken
Chicken breast, boneless, per lb. (453.6 gm)	chicken
Coffee, 100%, ground roast, 13.1-20 oz. can, per lb. (453.6 gm)	coffee
Coffee, 100%, ground roast, all sizes, per lb. (453.6 gm)	coffee
Coffee, instant, plain, regular, all sizes, per lb. (453.6 gm)	coffee
Cola, nondiet, cans, 72 oz. 6 pk., per 16 oz. (473.2 ml)	cola
Cola, nondiet, per 2 liters (67.6 oz)	cola
Cookies, chocolate chip, per lb. (453.6 gm)	cookie
Corn on the cob, per lb. (453.6 gm)	corn
Corn, canned, any style, all sizes, per lb. (453.6 gm)	corn
Cucumbers, per lb. (453.6 gm)	cucumber
Eggs, grade A, large, per doz.	egg
Electricity per KWH	electricity
Flour, white, all purpose, per lb. (453.6 gm)	flour
Gasoline, all types, per gallon/3.785 liters	gasoline
Gasoline, leaded regular (cost per gallon/3.8 liters)	gasoline
Gasoline, unleaded premium, per gallon/3.785 liters	gasoline
Gasoline, unleaded regular, per gallon/3.785 liters	gasoline
Gasoline, unleaded midgrade, per gallon/3.785 liters	gasoline
Grapes, Thompson Seedless, per lb. (453.6 gm)	grape
Grapefruit, per lb. (453.6 gm)	grapefruit
Ham, canned, 3 or 5 lbs, per lb. (453.6 gm)	ham
Ham, rump or shank half, bone-in, smoked,per lb. (453.6 gm)	ham
Ham, boneless, excluding canned, per lb. (453.6 gm)	ham
All Ham (Excluding Canned Ham and Luncheon Slices), per lb. (453.6 gm)	ham
Ice cream, prepackaged, bulk, regular, per 1/2 gal. (1.9 lit)	ice cream
Lamb and mutton, bone-in, per lb. (453.6 gm)	lamb
Lemons, per lb. (453.6 gm)	lemon
Lettuce, iceberg, per lb. (453.6 gm)	lettuce
Lettuce, romaine, per lb. (453.6 gm)	lettuce
Margarine, soft, tubs, per lb. (453.6 gm)	margarine
Margarine, stick, per lb. (453.6 gm)	margarine
Milk, fresh, low fat, per 1/2 gal. (1.9 lit)	milk

Milk, fresh, whole, fortified, per 1/2 gal. (1.9 lit)	milk
Milk, fresh, low fat, per gal. (3.8 lit)	milk
Milk, fresh, whole, fortified, per gal. (3.8 lit)	milk
Onions, dry yellow, per lb. (453.6 gm)	onion
Oranges, Navel, per lb. (453.6 gm)	orange
Oranges, Valencia, per lb. (453.6 gm)	orange
Orange juice, frozen concentrate, 12 oz. can, per 16 oz. (473.2 ml)	orange juice
Peaches, per lb. (453.6 gm)	peach
Peaches, any variety, all sizes, per lb. (453.6 gm)	peach
Peanut butter, creamy, all sizes, per lb. (453.6 gm)	peanut butter
Pears, Anjou, per lb. (453.6 gm)	pear
Peppers, sweet, per lb. (453.6 gm)	pepper
Chops, center cut, bone-in, per lb. (453.6 gm)	pork
Shoulder picnic, bone-in, smoked, per lb. (453.6 gm)	pork
Chops, boneless, per lb. (453.6 gm)	pork
All Other Pork (Excluding Canned Ham and Luncheon Slices), per lb. (453.6 gm)	pork
All Pork Chops, per lb. (453.6 gm)	pork
Rice, white, long grain, uncooked, per lb. (453.6 gm)	rice
Sausage, fresh, loose, per lb. (453.6 gm)	sausage
Strawberries, dry pint, per 12 oz. (340.2 gm)	strawberry
Sugar, white, 33-80 oz. pkg, per lb. (453.6 gm)	sugar
Sugar, white, all sizes, per lb. (453.6 gm)	sugar
Tuna, light, chunk, per lb. (453.6 gm)	tuna
Turkey, frozen, whole, per lb. (453.6 gm)	turkey
Vodka, all types, all sizes, any origin, per 1 liter (33.8 oz)	vodka
Wine, red and white table, all sizes, any origin, per 1 liter (33.8 oz)	wine
Yogurt, natural, fruit flavored, per 8 oz. (226.8 gm)	yogurt

1.5 Moral associations in political speech

Next, we investigated the interplay between moral associations and political discourse. Specifically, we hypothesize that concepts gaining prominence in political discourse would also evoke stronger moral reactions, thereby gaining moral associations. For instance, if *taxes* become a central political issue, we expect that paying taxes will similarly become morally relevant for many individuals. To test our hypothesis, we used the Congressional Record for the 43rd-114th Congresses, as collected by Gentzkow et al. [8]. This database contains transcripts of speeches delivered on the floors of the United States House of Representatives and Senate from the 43rd to the 114th Congress. Additionally, it provides key words and phrases manually classified into 22 substantive political topics.

Using the Congressional Speech Record database, we extracted the annual frequencies of 174 politically significant words across each Congress from 1987 to 2007. After normalizing each word's frequency relative to the total number of words spoken each year, we employed an Ordinary Least Squares (OLS) model to predict yearly changes in words' frequency as a function of shifts in moral association scores, while controlling for the words' frequency in the prior year and individual word effects. Formally, the model is defined as follows:

$$\Delta f_{(t-1\to t)} \sim \Delta \mathrm{mp}_{(t-1\to t)} + \Delta \mathrm{mr}_{(t-1\to t)} + \Delta s_{(t-1\to t)} + f_{(t-1)} + w. \tag{2}$$

In this equation, f stands for the log-normalized frequency of the word w, mp and mr represent moral polarity and moral relevance scores of w respectively, s represents the sentiment scores, and t represents the time point (i.e., a year from 1987 to 2007). Training the OLS model on $3,257$ examples (R-squared = 0.249) suggests a positive correspondence between annual changes in words' moral relevance scores and the annual changes in their congressional frequencies ($\beta = 0.499$, 95% CI = $[0.378, 0.621]$, $t(3,257) = 8.079$, $P < 0.0001$). We also find a negative correspondence between annual changes in words' moral polarity scores and annual changes in congressional frequencies ($\beta = -0.141$, 95% CI = $[-0.261, -0.021]$, $t(3,257) = -2.300$, $P = 0.022$). Our findings suggest that when a word's moral relevance score increases, it becomes more used in political discussions. Similarly, when a word's moral polarity decreases (i.e., it becomes associated with negative moral concepts), it becomes more used in political discussions.

We further investigate the effect of presidential elections in the United States on moral relevance scores of political concepts. To do so, we run a linear mixed-effect model with random intercepts for each year to

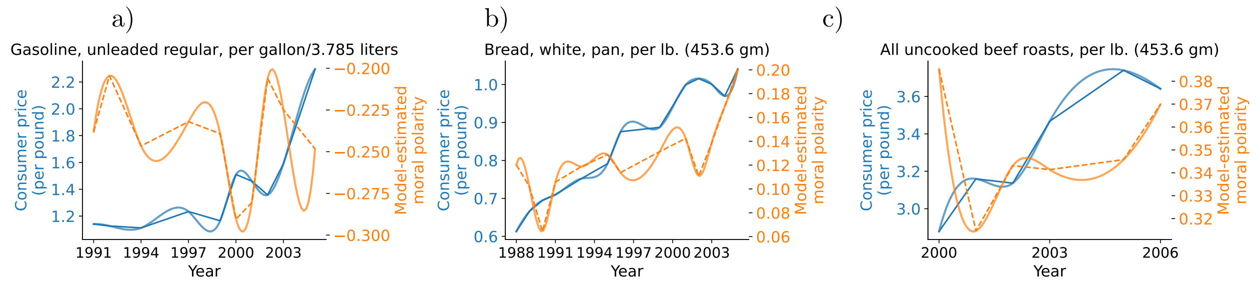

Fig. 3 Time course of model-estimated moral polarity (orange dashed lines) and ground-truth consumer prices (solid blue lines) for individual product items of a) gasoline, b) bread, and c) beef roasts. Moral scores are shown after z-score standardization, and the time courses are smoothed using a cubic spline for visualization.

predict the changes in moral relevance scores in first years after the elections. Formally, we have

$$\Delta\mathrm{mr}_{(t-1\to t)} \sim \mathrm{mr}_{(t-1)} + \mathbf{1}(\text{Republican victory}) + C + \mathbf{1}(\text{Republican victory}) \times C + (1|t) \tag{3}$$

where mr is moral relevance score of a word w from category C, $t-1$ is the year of a presidential election, and Democratic victory is the reference election outcome. Table 11 summarizes the results of training this model on $43,042$ observations.

1.6 Model prediction of empirical moral ratings

Using data from Gallup's Moral Issues series, we investigated whether shifts in moral associations reflect broader population-level concerns as captured by national surveys. To test this hypothesis, we collected empirical measures of moral concerns from Gallup's "Values and Beliefs" survey series. This series samples approximately 1,000 adult participants from the United States annually, and participants are asked whether issues like "abortion" and "death penalty" are 1) morally acceptable, 2) not a moral issue, or 3) morally wrong. [1] From this series, we selected 10 issues with token-level representations compatible with our framework. Table 6 lists each issue alongside its corresponding query concept. To quantify empirical estimates of moral concerns, we mapped survey responses to a scale of -1, 0, 1, where 1 represents morally acceptable, 0 represents no moral stance, and -1 represents morally unacceptable. We averaged responses across participants to obtain a mean rating of moral acceptability for each concept by year. We then used an Ordinary Least Squares (OLS) regression with the following formalization:

$$\Delta r_{(t-1\to t)} \sim \Delta\mathrm{mp}_{(t-1\to t)} + \Delta\mathrm{mr}_{(t-1\to t)} + r_{(t-1)} + w + t. \tag{4}$$

In the equation above, the variable r represents annual human moral acceptability ratings for the topic w (e.g., "abortion"), t represents the time point, while mp and mr represent annual moral polarity and moral relevance scores respectively. Our model was trained on 54 observations and achieved an R-squared of 0.485, suggesting that nearly half of the variability in public moral acceptability ratings can be explained by our formulation. Furthermore, we find a significant relationship between changes in moral polarity (Δmp) and shifts in public moral opinions (Δr) with a coefficient $\beta = 0.12$ (95% CI $= [0.010, 0.229]$, $t(54) = 2.215$, $P = 0.033$). This finding suggests that as an issue becomes associated with more positive moral concepts, it is more likely to be viewed as morally acceptable or morally permissible and vice versa. However, we found no significant effect for changes in moral relevance, possibly because the topics already held high moral importance for most participants.

1.7 Bottom-up discovery of historical moralization

Our framework enables us to identify terms and concepts with the most prominent shifts in moralization over time. To quantify these shifts, we calculated the moral relevance score for each term at a given time point T, and compared it to its historical average moral relevance using the formula:

$$\text{Moral relevance}(T) - \frac{1}{|T-1|}\sum_{t<T}\text{Moral relevance}(t). \tag{5}$$

[1] More information available at https://news.gallup.com/poll/1681/Moral-Issues.aspx.

Table 6 Moral topics in Gallup's Moral Issues series and their representative query concepts.

Topic	Query concepts
Abortion	abortion
Sex before marriage	sex
Death Penalty	death penalty
Divorce	divorce
Same-sex marriage and relationship	homosexuality, homosexual
Using the fur of animals	fur
Stem cell research	stem cell
Committing suicide	suicide
Gambling	gambling
Having an affair	affair

Tables 7 and 8 list the top 20 words with the largest significant increases in moral relevance ($\alpha = 0.01$) for each time point within COHA and NYT datasets.

Table 7 Top 20 words with significant ($\alpha = 0.01$) increases in moral relevance in the indicated decade compared to their historical average. Words are retrieved using the Corpus of Historical American English (COHA).

Decade	Retrieved words
1860	grey, theater, breach, staff, normal, digest, bureau, hannah, par,witch, bedside, butler, martial, commanding, reservation, luke, harvey, neutral, rib, queen
1870	killing, bos, eliot, fried, stolen, lincoln, corp, saloon, commander, murray, riot, disturbing, tramp, receiver, battalion, roger, mortgage, von, immigration, mason
1880	intent, discrimination, league, discriminate, circuit, liability, dot, punch, assault, michael, bribe, leslie, beverage, conjunction, manor, primary, prior, turk, marshal, cleveland
1890	headquarters, pike, privacy, crater, trench, corruption, consumption, grub, raymond, pierre, liquor, flora, spill, mosaic, attitude, department, warren, alleged, fleet, paul
1900	buck, orient, courtroom, mentally, china, fray, partnership, homeless, jeff, graveyard, chinese, opium, lynch, casket, let go, lieutenant, arrest, widespread, wilson, trance
1910	bud, crook, bunch, triple, german, germ, spar, shell, ally, safeguard, contagious, swollen, bleeding, confession, crooked, handle, con, mighty, rust, intervention
1920	battlefield, friction, clash, unrest, fair, drug, rotten, disarm, ax, sophie, aggression, claw
1930	spade, board, peg, thorn, purge, representation, relief, cologne, ransom, repulsive, celestial, palestine, legion, inquiry, ambush, italy, groom, iii, bank, delicious
1940	axis, zone, pearl, marshall, japanese, occupation, hemisphere, canon, underground, termination, armed, harbor, concentration, objective, psychological,chaos, wonderful, activity, medal, obstruct
1950	beating, intervene, marine, east, western, berlin, aye, west, contempt, deter, rude, bout, spy, germany, deficiency, security, needy, overthrow, tension, invoke
1960	mortar, pastoral, screw, implement, stitch, transplant, wallace, incident, foundation, owen, artillery, kin, bounty, scrutiny, troop, infantry, meditate, defect, recipient, heed
1970	panther, intelligence, asia, hazard, prick, involved, former, withdrawal, mental, arab, investigation, hamlet, oppress, ban, meditation, ireland, terrific, involuntary, comprehensive, deceased
1980	bush, turf, obstruction, chemical, abuse, africa, apprehend, squad, guinea, brutality, pageant, toll, group, stroke, affirmative, alcohol, enforcement, exposure, sandy, lash
1990	coach, hazardous, counterfeit, harass, waste, renewal, persian, repress, gang, violence, confidential, dispose, survey, amendment, center, deadly, speech, definitely, accidental, erection
2000	laden, bin, ex, terror, outbreak, dignity, substance, supplement, gore (al gore), hack, detain, chapter, complication, rogue, ministry, violent, attack, bodily, dispatch, tragedy

Table 8 Top 20 words with significant ($\alpha = 0.01$) increases in moral relevance in the indicated decade compared to their historical average. Words are retrieved from the New York Time Corpus (NYT).

Decade	Retrieved words
1988	temptation, occupied, stab, cobra, panama, antonio, cruiser, funnel, guardian, fencing, burnt, stoned, symmetry, platoon, heavenly, horrifying, apache, bonding, crack, chemical weapon
1989	verse, rouge, generic, edward, alpha, vile, prague, prickly, dna, forum, cache, ambulance, qualifying, unsolved, microbe, lincoln, oliver, clique, fang, gateway
1990	weld, stray, covenant, lithuania, purposeful, gulf, lust, township, nightingale, hussein, crook, nelson, aggression, wailing, vampire, apocalypse, brazen, samurai, bulgaria, protector
1991	snare, serial, crescent, stagger, cholera, clarence, cloister, persian, allied, anita, stump, piercing, infidelity, foreman, tel, naughty, compulsion, inclusive, boris, peru
1992	irregular, shining, rodney, clinton, ross, sling, bleed, maiden, cradle, mutter, beating, path, riley, sap, unnatural, nintendo, nanny, obituary, venom, x
1993	cult, stimulus, graft, slaughter, compound, partition, reef, clan, ferret, nation, shield, christopher, omar, stalking, janet, stomp, muck, probe, baton, bleach
1994	patriotic, cleansing, shear, fusion, den, digest, perry, colonial, throbbing, settler, father, evelyn, pierced, folklore, stain, handle, hut, normandy, korean, oneill
1995	simpson, buck, sect, kiwi, cone, frivolous, loot, abrasive, managed, visiting, rogue, hooker, badge, stitch, spree, orlando, plotting, mariner, lord, bullock
1996	briefing, freeman, dew, bologna, fellowship, genocide, sherry, duncan, martini, forgiveness, frontier, host, crooked, hawking, forbes, centre, mate, neglect, conformity, reform
1997	devoted, blair, mass, grandmother, jaguar, conception, dear, immaculate, marlin, grandfather, switzerland, mother, keeper, bun, tutu, pot (pol pot), shin, adored, blade, southeast
1998	bin, monica, obstruction, intern, hyde, misconduct, privilege, grand, stepmother, lad, oral, splinter, saint, eliot, formerly, neediest, zombie, paula, volleyball, offense
1999	gong, pew, ceo, shepherd, loss, stearns, incense, bronco, payback, lauren, indonesia, alcoholic, perjury, valentine, subdue, maverick, burning, wrestler, systematic, gentle
2000	nile, sierra, ambiance, portal, postseason, rapture, aptitude, dedication, venus, rocker, hacker, healthcare, avoidance, warmth, spray, quake, deceptive, concede, mosquito, prescription
2001	laden, raven, comb, cyclone, humanity, mole, terror, ecstasy, xray, scare, retarded, wrench, gloria, aided, bless, goodness, body part, redemption, generous, suspicious
2002	bomber, clerical, canon, cardinal, screw, axis, neptune, pry, parish, align, moose, incest, bud, involuntary, pitt, rash, pastoral, thorn, operation, injure
2003	reconstruction, matrix, recall, biological, acute, charred, drone, donaldson, rebuilding, chemical, donald, mustard, captured, goodwill, advancing, dating, iii, mutant, abel, rebuild
2004	fahrenheit, halo, mortar, marine, interim, martyr, masked, swing, usa, reuters, fighter, geneva, exploded, worm, security, dick, elderly, left wing, bombing, underage
2005	apex, apprentice, randolph, domain, suicide, ping, unconditional, merry, doctrine, ledger, hurricane, ex, rice, infect, oconnor, affected, devil, dignified, insecure, steroid
2006	nepal, rocket, anatomy, appendix, stroke, bond, nativity, lay, morale, rosemary, excel, artillery, casualty, turf, torso, negatively, apparition, surveillance, havoc, impaired
2007	paisley, friar, steward, galaxy, pawn, shady, habitat, latex, insure, chlorine, squad, rag, idol, mae, cricket, catholicism, traumatic, gracious, frost, dale

Table 9: Total number of concepts (unigrams and bigrams) extracted from Corpus of Historical American English (COHA) and New York Times corpus (NYT) across time points.

Data	Time point	Unigram count	bigram count
COHA	1850	9597	161
	1860	9789	185
	1870	9835	197
	1880	9994	219
	1890	10046	235
	1900	10304	270
	1910	10392	290
	1920	10819	366
	1930	10734	403
	1940	10740	436
	1950	10933	483
	1960	10963	490
	1970	11078	533
	1980	11334	570
	1990	11638	583
	2000	11754	612
NYT	1987	13207	341
	1988	13181	351
	1989	13168	346
	1990	13141	352
	1991	12937	345
	1992	12930	346
	1993	12963	343
	1994	12944	343
	1995	13066	337
	1996	13116	353
	1997	13193	346
	1998	13447	354
	1999	13503	352
	2000	13504	360
	2001	13417	360
	2002	13456	358
	2003	13411	349
	2004	13393	351
	2005	13458	352
	2006	13475	350
	2007	12191	332

Table 10 World leaders and query terms used to locate them in the Corpus of Historical American English (COHA).

Political leader	**Query term**
Zachary Taylor	president taylor
Franklin Pierce	president pierce
James Buchanan	president buchanan
Abraham Lincoln	president lincoln
Andrew Johnson	president johnson
Ulysses S. Grant	president grant
Rutherford B. Hayes	president hayes
James A. Garfield	president garfield
Chester A. Arthur	president arthur
Grover Cleveland	president cleveland
Benjamin Harrison	president harrison
William McKinley	president mckinley
Theodore Roosevelt	president roosevelt
William H. Taft	president taft
Woodrow Wilson	president wilson
Warren G. Harding	president harding
Calvin Coolidge	president coolidge
Herbert Hoover	president hoover
Franklin D. Roosevelt	president roosevelt
Harry S. Truman	president truman
Dwight D. Eisenhower	president eisenhower
John F. Kennedy	president kennedy
Lyndon B. Johnson	president johnson
Richard M. Nixon	president nixon
Gerald R. Ford	president ford
Jimmy Carter	president carter
Ronald Reagan	president reagan
George H. W. Bush	president bush
William J. Clinton	president clinton
George W. Bush	president bush
Mao Zedong	mao zedong
Joseph Stalin	stalin, joseph stalin
Adolf Hitler	hitler, adolf hitler
Chiang Kai-Shek	chiang, kai-shek, kaishek, kai-shek
Hirohito	hirohito
Vladimir Lenin	lenin, vladimir lenin
Pol Pot	pol pot
Suharto	suharto
Mengistu Haile Mariam	mengistu, haile mariam
Saddam Hussein	saddam hussein
Ho Chi Minh	chi minh
Viet Cong	viet cong
Benito Mussolini	mussolini, benito mussolini
Francisco Franco	francisco franco
Ahmed Sékou Touré	ahmed toure, toure
Rafael Trujillo	trujillo, rafael trujillo
François Duvalier	duvalier
Ferdinand Marcos	ferdinand marcos
Queen Victoria	queen victoria
King George VI	king geroge, george sixth, george vi
King Edward VIII	king edward, edward vii, edward seventh
King George VI	king george, george v, george fifth
Nelson Mandela	nelson mandela
Martin Luther King Jr	marthin luther, luther king
Tsar Nicholas II	tscar nicholas, nicholas ii
Winston Churchill	winston churchill
Margaret Thatcher	margaret thatcher
Mikhail Gorbachev	mikhail gorbachev, gorbachev
Georgy Malenkov	georgy malenkov, malenkov
Nikita Khrushchev	nikita khrushchev, khrushchev
Leonid Brezhnev	leonid brezhnev, brezhnev
Yuri Andropov	yuri andropov, andropov
Konstantin Chernenko	konstantin chernenko, chernenko

Variable	β **Coefficient**	P	**95% CI**
Main Effects			
Intercept	0.005	0.707	[-0.023, 0.034]
Election result (Republicans)	−0.002	0.900	[-0.040, 0.035]
Budget	−0.030*	0.042	[-0.059, -0.001]
Business	−0.018	0.197	[-0.046, 0.010]
Crime	−0.026	0.074	[-0.055, 0.003]
Defense	−0.013	0.352	[-0.041, 0.015]
Economy	−0.029*	0.046	[-0.057, -0.000]
Education	−0.040**	0.005	[-0.068, -0.012]
Elections	−0.053***	$\leq$ 0.001	[-0.082, -0.024]
Environment	−0.047**	0.001	[-0.076, -0.018]
Federalism	−0.031*	0.028	[-0.059, -0.003]
Foreign	−0.003	0.862	[-0.031, 0.026]
Government	−0.007	0.608	[-0.035, 0.021]
Health	0.001	0.952	[-0.027, 0.029]
Immigration	−0.010	0.526	[-0.040, 0.020]
Justice	−0.003	0.825	[-0.031, 0.025]
Labor	−0.025	0.075	[-0.053, 0.003]
Mail	−0.005	0.763	[-0.036, 0.027]
Minorities	−0.004	0.800	[-0.032, 0.025]
Money	0.006	0.693	[-0.023, 0.034]
Religion	−0.022	0.155	[-0.051, 0.008]
Tax	0.007	0.629	[-0.021, 0.035]
Trade	−0.032*	0.025	[-0.061, -0.004]
Moral relevance (in the previous year)	−0.007***	$\leq$ 0.001	[-0.009, -0.006]
Interaction Effects			
Election result (Republicans):Budget	0.035	0.066	[-0.002, 0.073]
Election result (Republicans):Business	0.037*	0.043	[0.001, 0.074]
Election result (Republicans):Crime	0.015	0.441	[-0.023, 0.052]
Election result (Republicans):Defense	0.006	0.750	[-0.030, 0.042]
Election result (Republicans):Economy	0.034	0.072	[-0.003, 0.070]
Election result (Republicans):Education	0.038*	0.042	[0.001, 0.074]
Election result (Republicans):Elections	0.000	0.993	[-0.038, 0.037]
Election result (Republicans):Environment	0.051**	0.007	[0.014, 0.089]
Election result (Republicans):Federalism	0.055**	0.003	[0.019, 0.092]
Election result (Republicans):Foreign	0.012	0.525	[-0.025, 0.049]
Election result (Republicans):Government	0.026	0.159	[-0.010, 0.062]
Election result (Republicans):Health	0.002	0.918	[-0.034, 0.038]
Election result (Republicans):Immigration	0.031	0.119	[-0.008, 0.070]
Election result (Republicans):Justice	0.061**	0.001	[0.025, 0.098]
Election result (Republicans):Labor	0.030	0.105	[-0.006, 0.066]
Election result (Republicans):Mail	−0.006	0.763	[-0.047, 0.035]
Election result (Republicans):Minorities	0.010	0.592	[-0.027, 0.047]
Election result (Republicans):Money	−0.004	0.826	[-0.041, 0.033]
Election result (Republicans):Religion	0.025	0.205	[-0.014, 0.064]
Election result (Republicans):Tax	−0.009	0.614	[-0.046, 0.027]
Election result (Republicans):Trade	−0.019	0.319	[-0.056, 0.018]

Table 11 Results of a mixed-effects linear regression model predicting change in moral relevance immediately after election years. Democratic victory serves as the reference category for the election outcome. Year was included as a random intercept. Coefficients (β) are presented with 95% Wald confidence intervals. Statistical significance was assessed using two-sided Wald z-tests, as implemented in `statsmodels` package. No adjustments were made for multiple comparisons. Asterisks indicate significance levels: "*" for $P < 0.05$, "**" for $P < 0.01$, and "***" for $P < 0.001$.

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