Nostalgia in European Party Politics: A Text-Based Measurement Approach

Stefan Müller and Sven-Oliver Proksch

Supporting Information

A Data Availability and Manifesto Length **A2**

B Constructing Text-Based Measures of Nostalgic Rhetoric **A5**

B.1 Method 1: Base Dictionary . . . A5
B.2 Method 2: Base Dictionary + Word Embeddings . . . A6
B.3 Methods 3 and 4: Sentiment . . . A7
B.4 Methods 5 and 6: Supervised Machine Learning . . . A8

C Human Coding and Validation **A9**

C.1 Instructions for Coding of Nostalgic Rhetoric . . . A9
C.2 Inter-coder Agreement and Comparison of Classifiers . . . A11
C.3 Translation Accuracy and Most Frequent Terms by Country . . . A13
C.4 Comparing Parties and Voters . . . A14
C.5 Identifying the Most Frequent Features and Predictive Terms in Nostalgic Sentences . . . A16
C.6 Validating the Measure of Cultural Conservatism . . . A19

D Determining the Best Classifier: Hand-Coding of 50 Manifestos **A22**

E Robustness Tests: Additional Regression Models and Plots **A28**

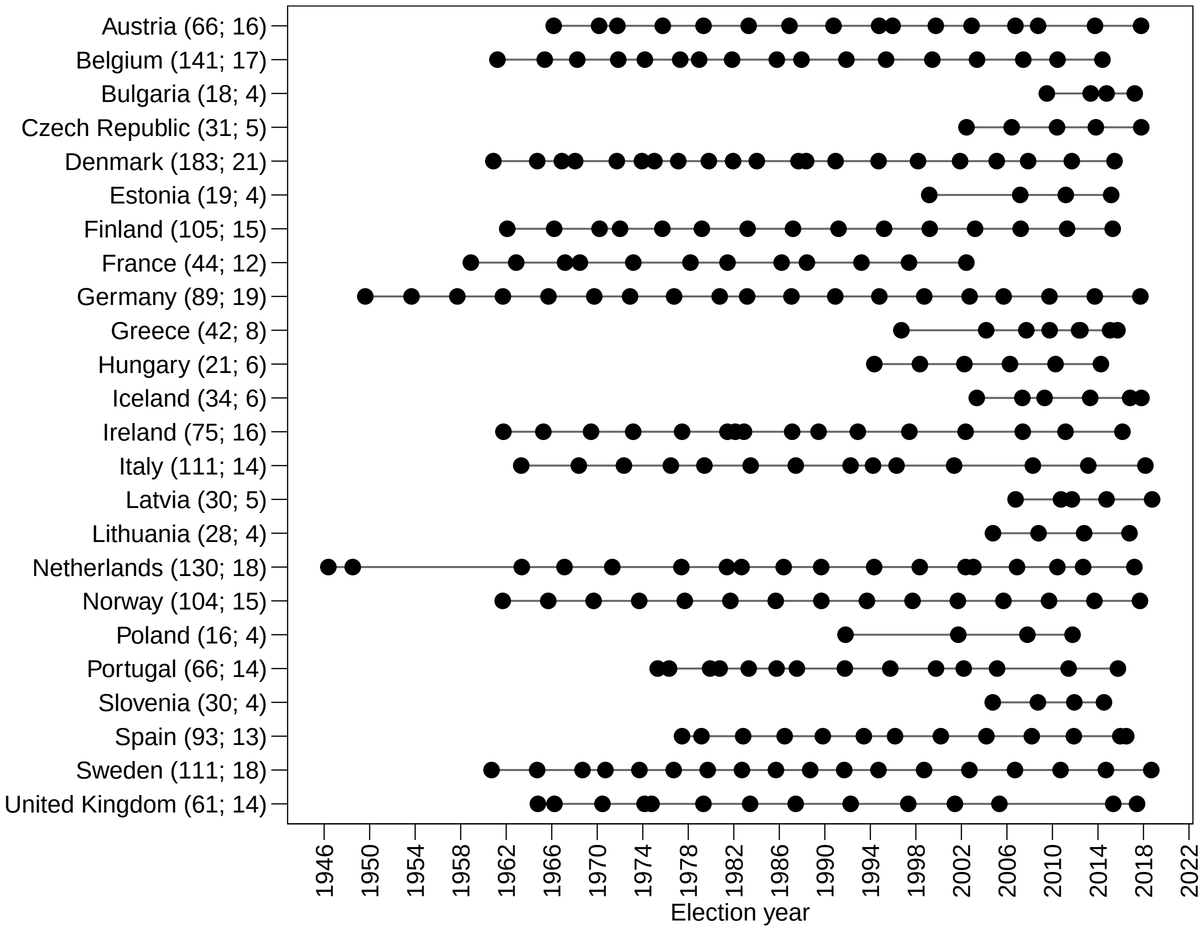
E.1 Different Model Specifications: Fixed Effects, Random Effects, and Exclusion of Control Variables . . . A28
E.2 Differences Across Regions . . . A28
E.3 Different Measures of Party Families . . . A35
E.4 Cultural Conservatism and Economic Left-Right Positions . . . A38

F Cultural and Economic Nostalgia **A40**

A Data Availability and Manifesto Length

Figure A1 shows the manifestos included in our machine-translated corpus used in the analysis. Non-English manifestos are translated to English using Google Translate (De Vries and Hoffmann 2018; Düpont and Rachuj 2022). We limit the sample to European democracies with a clear government-opposition divide, which excludes Switzerland. We only consider countries with available manifestos from at least four elections (based on Krause et al. (2019)) to allow for a sufficiently large number of observations per country and to test for potential changes over time within countries.

Figure A1. Availability of (machine-translated) party manifestos



Note: Numbers beside the country name indicate the frequency of manifestos and elections.

Figure A2 shows the distribution of manifesto lengths in each decade in our sample. The vertical bars show the median values for each decade. The graph shows that manifestos tend to have become longer over time and that manifestos consisting of around 1,000 sentences are not unusual.

Figure A2. The length of party manifestos (x-axis is on log scale to ease interpretability)

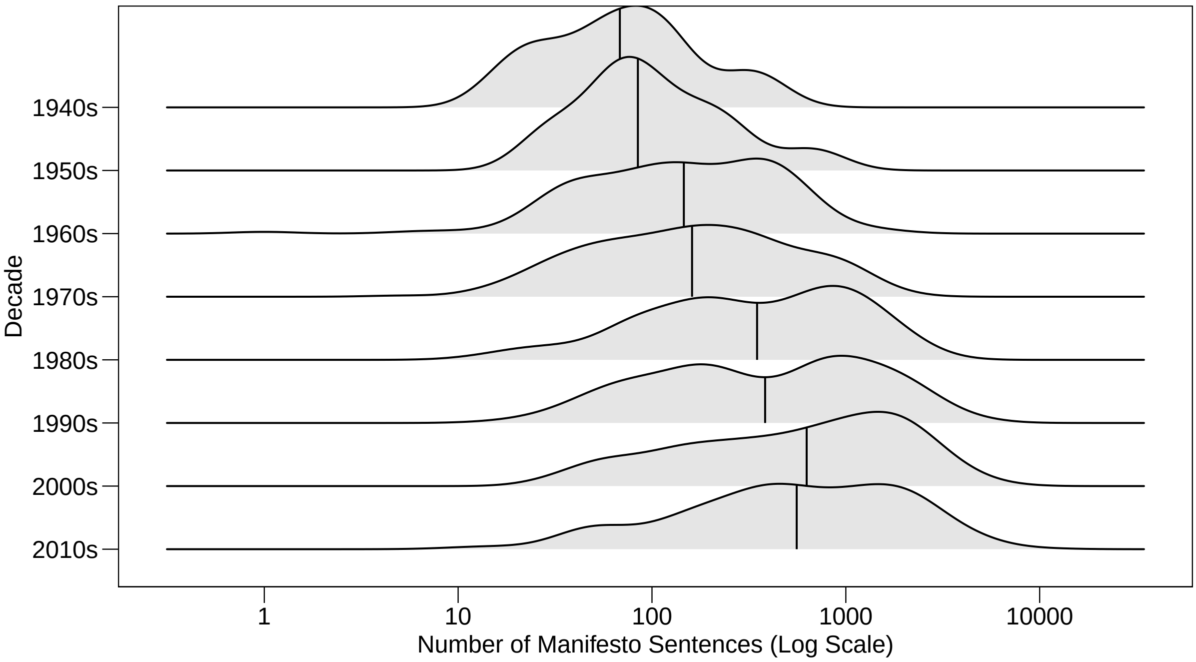


Table A1. List of parties listed in Figure 3.

Country	Party Abbr.	Party	Populist
Austria	FPÖ	Austrian Freedom Party	Pop. Far-right
Austria	BZÖ	Alliance for the Future of Austria	Pop. Far-right
Belgium	CVP	Christian People's Party	Other
Belgium	LDD	List Dedecker	Other
Bulgaria	GERB	Citizens for European Development of Bulgaria	Other
Bulgaria	DPS	Movement for Rights and Freedoms	Other
Czech Republic	ODS	Civic Democratic Party	Other
Czech Republic	SZ	Green Party	Other
Denmark	DF	Danish People's Party	Pop. Far-right
Denmark	VS	Left Socialist Party	Other
Estonia	ERL	Estonian People's Union	Pop. Far-right
Estonia	EER	Estonian Greens	Other
Finland	SKL	Finnish Christian Union	Other
Finland	SMP	Finnish Rural Party	Pop. Far-right
France	FN	National Front	Pop. Far-right
France	MRP	Popular Republican Movement	Other
Germany	DP	German Party	Other
Germany	GP	The Greens	Other
Greece	XA	Golden Dawn	Other
Greece	KKE	Communist Party of Greece	Other
Hungary	MSzDP	Hungarian Social Democratic Party	Other
Hungary	LMP	Politics Can Be Different	Other
Iceland	LibRefP	Reform Party	Other
Iceland	F	Progressive Party	Other
Ireland	WP	Workers' Party	Other
Ireland	SF	We Ourselves	Pop. Far-left
Italy	PPI	Italian Popular Party	Other
Italy	MSI-DN	Italian Social Movement-National Right	Other
Latvia	LNNK	National Alliance 'All For Latvia!' – 'For Fatherland and Freedom - Latvian National Independence Movement'	Other
Latvia	SDPS	Social Democartic Party Harmony	Other
Lithuania	PTT	Order and Justice	Other
Lithuania	DP	Labour Party	Other
Netherlands	CD	Centre Democrats	Pop. Far-right
Netherlands	PPR	Radical Political Party	Other
Norway	SF	Socialist People's Party	Other
Norway	FrP	Progress Party	Pop. Far-right
Poland	MN	German Minority	Other
Poland	PiS	Law and Justice	Pop. Far-right
Portugal	PPM	Popular Monarchist Party	Other
Portugal	UDP	Popular Democratic Union	Other
Slovenia	SNS	Slovenian National Party	Pop. Far-right
Slovenia	DeSUS	Democratic Party of Pensioners of Slovenia	Other
Spain	UCD	Union of the Democratic Centre/Centrist Bloc	Other
Spain	EH Bildu	Basque Country Unite	Other
Sweden	SD	Sweden Democrats	Pop. Far-right
Sweden	SKP	Communist Party of Sweden	Other
United Kingdom	PC	The Party of Wales	Other
United Kingdom	GPEW	Green Party of England and Wales	Other

B Constructing Text-Based Measures of Nostalgic Rhetoric

The following subsections provide detailed information on the construction of our six measures of nostalgia. The main paper summarizes the workflow (see Figure 1). Methods 1–4 rely on a dictionary approach. Methods 5 and 6 are based on machine learning classifiers.

B.1 Method 1: Base Dictionary

We created our first dictionary of nostalgic terms and multiword expressions based on a multi-step approach, involving previous approaches of measuring nostalgia and hand-coding of a random subset of manifesto sentences. In this section, we summarize the process of identifying potentially relevant terms.

We started with the dictionary of nostalgic terms used in Davalos et al. (2015). The following terms and phrases were included in Davalos et al.'s (2015) dictionary: `flashback`, `go back in time`, `good old day*`, `memory lane`, `miss those days`, `nostalgi*`, `recollect*`, `redolent of`, `relive the past`, `remember* when`, `reminiscent`, `those were the days`, `when we were younger`.

We adjusted this dictionary to political text based on published work on nostalgia in politics (Elçi 2022; Lammers and Baldwin 2018), and prominent examples of nostalgic rhetoric. We added the following entries to the dictionary: `back to`, `constant`, `eventful`, `everlasting`, `good time*`, `great time*`, `in retrospection`, `memorable`, `memory`, `not forget`, `past`, `persist*`, `preserve*`, `time ago`, `tradition`, `unforgettable`, `year* ago`.

Third, two coders read 500 sentences from English language party manifestos and extracted sentences that were classified as nostalgic. Based on this coding exercise we added the following entries to the dictionary: `comfortable with * past`, `for * of decades`, `for * of years`, `heritage`, `historic`, `history`, `intellectual roots`, `time-hono* tradition*`.

B.2 Method 2: Base Dictionary + Word Embeddings

We expand the Base Dictionary (Measure 1) by using word embeddings to identify terms potentially expressing nostalgic rhetoric. This procedure is similar to Hargrave and Blumenau's (2022) approach. We proceeded as follows:

We first use the pre-trained GloVe6b word vectors (Pennington, Socher, and Manning 2014). These embeddings are trained based on Wikipedia and Gigaword 5, a comprehensive archive of newswire text data.[1] We follow the workflow in Hvitfeldt and Silge (2021: ch. 5) and identify the "nearest neigbours" of a term. Since the pre-trained embeddings do not allow for the inclusion of multiword expressions, we separate all multiword expressions identified in Methods 1 into unigrams. We remove punctuation characters, English stopwords, and numbers from the data before identifying and storing the 50 nearest neighbours for each term.

In addition to the pre-trained embeddings, we create word embeddings based on our corpus of translated manifesto sentences. We use the corpus of just over 1.4 million sentences as the input. We first compound multiword expressions from the existing dictionary, which allows us to estimate similarities of phrases in the corpus. We create skipgram windows of four tokens which allows us to calculate probabilities of two terms appearing together in this window (see Hvitfeldt and Silge 2021: ch. 5). Afterwards, we calculate the pointwise mutual information of pairs of items to identify words that occur together more often than expected. Based on this dataset we create 100-dimensional word embeddings for the manifesto corpus and identify the 50 nearest neighbors for each term from our dictionary created in SI Section B.1.

Having retrieved similar terms based on pre-trained embedding model and our custom manifesto-based embeddings, we select all unique terms identified through the word embeddings approach. Three human coders assessed which of these terms may poten-

[1] See https://nlp.stanford.edu/projects/glove/ for details. The following newswires are included in Gigaword 5: Agence France-Presse, English Service; Associated Press Worldstream, English Service; Central News Agency of Taiwan, English Service; Los Angeles Times/Washington Post Newswire Service; Washington Post/Bloomberg Newswire Service; New York Times Newswire Service; Xinhua News Agency, English Service.

tially express nostalgic rhetoric. We select terms that all three coders have identified as potentially nostalgic. 59 of 1,769 terms of this set of 'nearest neighbors' fulfill this criterion. The following terms are part of the embeddings-based category in the dictionary: `centuries`, `century`, `cherish`, `chronicles`, `commemoration`, `conserve`, `decade`, `decades`, `era`, `eternal`, `eternity`, `generation`, `generations`, `glorious`, `grandiosity`, `historical`, `historiographic`, `immortality`, `legacy`, `legend`, `memorial`, `memorialize`, `memories`, `monument`, `monuments`, `origins`, `preceded`, `preservation`, `preserving`, `rebuild`, `recreate`, `rediscover`, `regain`, `relics`, `relived`, `relives`, `reliving`, `remembered`, `remembering`, `remembers`, `remembrance`, `restore`, `restoring`, `return`, `returned`, `returning`, `ritual`, `rituals`, `root`, `rooted`, `roots`, `sacred`, `throwback`, `timeless`, `traditional`, `traditionally`, `traditions`.[2]

B.3 Methods 3 and 4: Sentiment

Since nostalgia usually entails "predominantly positive emotion" (Lammers and Baldwin 2018: 599), one could argue to only treat sentences as nostalgic that contain at least one term from the dictionary of nostalgic sentences *and* express positive sentiment. To estimate sentiment on the level of sentences, we follow Proksch et al. (2019). More specifically, we apply the Lexicoder Sentiment Dictionary (Young and Soroka 2012; Benoit et al. 2018) to each sentence and aggregate sentiment as: $log\frac{pos+negated\_neg+0.5}{neg+negated\_pos+0.5}$. Only if a sentence has a sentiment value above 0 (i.e., it contains more positive than negative terms) we consider the sentence as nostalgic. For example, the following sentence (with a negative sentiment score) would *not* be scored as nostalgic:

> "the traditional problems inherited from past decades (long-term unemployment, juvenile delinquency, drug addiction), are added together the unprecedented emergencies aging generalized, widespread insecurity, the difficult coexistence between

[2] The following terms were identified during the human coding exercise of the 'most nearest neighbors', but were scored through the dictionary created in steps 1–3: `historic`, `history`, `memorable`, `memory`, `past`, `persisted`, `persistent`, `persisting`, `persists`, `preserve`, `preserved`, `preserves`, `tradition`, `unforgettable`. We removed these terms from the list since they are already included in the initial categories of nostalgic terms.

> different cultures, the spread of new forms of social exclusion" (Italy, Alleanza Nazionale, 2001)

Even though the sentence relates to the past, it does not frame the past in a positive way. However, the sentence below is scored as nostalgic since it recalls memories of the past using positive emotions (the sentiment score is positive):

> "To protect, conserve, restore and create cultural, artistic, scientific and technological heritage, thereby stimulating for intellectual creativity, artistic and technological" (Spain, Alianza Popular, 1982)

B.4 Methods 5 and 6: Supervised Machine Learning

Methods 1—4 rely on a dictionary approach. Instead of counting keywords that may relate to nostalgia, Methods 5 and 6 combine human coding of manifesto sentences and supervised machine learning.

We created instructions on how to identify nostalgic rhetoric in political text (see SI Section C.1). We trained four research assistants who first conducted two initial coding rounds of 100 sentences each. After these initial intercoder reliability tests, we adjusted the codebook and discussed sentences that had been coded differently.

For each country, we randomly sample 25 sentences labeled as nostalgic (based on Method 2, our broadest dictionary measure of nostalgia) and 25 sentences not labeled as nostalgic, resulting in a stratified sample of 1,200 sentences.

We treat a sentence as nostalgic if at least three out of the four coders assigned the label "nostalgic" to a sentence. We then extract a random sample of 960 sentences (80 per cent of the annotated set of sentences) for our training set. We train a Support Vector Machine (Method 5), which is based on the bag-of-words approach, and a fine-tuned

DistilBERT language model (Sanh et al. 2019) on this set of 960 sentences.[3] We use the remaining 240 sentences as our held-out test set to assess the out-of-sample performance of our supervised classifiers and dictionary-based measures (see SI Section C.2 and Table A3).

C Human Coding and Validation

C.1 Instructions for Coding of Nostalgic Rhetoric

In this research project, we aim to measure and explain nostalgia in parties' campaign communication. Lammers and Baldwin (2018: 599) define nostalgia as "a predominately positive emotion that is associated with recalling memories of important or momentous events, usually experienced with close others."

You will be asked to annotate sentences from party manifestos. The coding proceeds in five steps:

1. You read the 'target' sentence (highlighted in bold), which should be coded along several dimensions. For a better context, we also provide the sentences before and after the target sentence. Make sure to read the context too.

2. You code whether a sentence is nostalgic or not.

3. For non-English text, code if the translation is inaccurate or very inaccurate. Leave the column blank if the sentence is understandable. Some sentences may be very short or so-called quasi sentences. Only code these sentences as inaccurate translations if they are incomprehensible after reading the context too (`text_pre` and `text_post`).

4. If the sentence is *not* nostalgic, proceed to the next sentence.

[3] We use the default parameters for fine-tuning the DistilBERT classifier: `activation "gelu"; architectures: "DistilBertForSequenceClassification"; attention_dropout: 0.1; dim: 768; dropout: 0.1; hidden_dim: 3072; initializer_range: 0.02; max_position_embeddings: 512; model_type: "distilbert"; n_heads: 12; n_layers: 6; pad_token_id: 0; problem_type: "single_label_classification"; qa_dropout: 0.1; seq_classif_dropout: 0.2; sinusoidal_pos_embds: false; tie_weights_: true; torch_dtype: "float32"; transformers_version: "4.20.1"; vocab_size 30522`. The replication materials contain the fine-tuned DistilBERT object.

5. If the sentence is coded as nostalgic, please additionally code whether the sentence mentions cultural aspects, economic aspects, both cultural and economic aspects, or neither of these aspects.

Below, we provide examples for each category.

Nostalgic Sentences

Examples

- "We need to take pride in our country again and claim back our heritage from the 'chattering classes' who have disintegrated our culture, highlighted our failings as a country, rather than celebrating our successes, and tried to make us ashamed to be British."
- "As a small island nation, we need to constantly strive to build international relationships while preserving and nurturing our vibrant heritage."
- "Farmers are, and have been, stewards who for thousands of years have protected and preserved the environment, keeping it alive, clean and productive."

Cultural Nostalgia

Cultural nostalgia mentions aspects such as the cultural plurality or cultural homogeneity within domestic societies. This may include the preservation of the autonomy of religious, and linguistic heritages within the country including special educational provisions.

Examples

- "We recognise Irish as a unique part of our heritage belonging to all and not just the property of one section of the population."
- "We want a Europe that professes its Christian-Western roots and the ideas of the Enlightenment and lives from them."

Economic Nostalgia

Economic nostalgia mentions aspects such as past economic growth, government spending, public services, the welfare state or state benefits, unemployment, investment, pensions, or relations between employers and trade unions.

Example

- "History has shown that the social market economy can best create lasting prosperity."

Economic and Cultural Nostalgia

These sentences include references to both cultural and economic aspects.

- "For hundreds of years, the United Kingdom has determined the rules and formed the environment where new ideas and new technologies prosper – from financial markets to the steam train to human embryology and the code of life itself."

Neither Economic nor Cultural

Example

- "A Conservative Government will be optimistic about Britain's future because we are comfortable with Britain's past."

C.2 Inter-coder Agreement and Comparison of Classifiers

We started our validation by comparing inter-coder agreements between our four research assistants. Recall that the coders annotated a set of 1,200 sentences after two initial coding rounds of 100 sentences each (SI Sections B.4 and C.1). Table A2 reports inter-coder reliability statistics for the set of 1,200 sentences. The percentage agreement amounts to 77.3 per cent, while Krippendorff's Alpha and Fleiss' Kappa, two frequently used measures of inter-coder agreement, are both 0.56. These statistics are in line with similar codings of latent political concepts (e.g., Mikhaylov, Laver, and Benoit 2012; Theocharis et al.

2016). Table A3 shows out-of-sample performance metrics for the held-out test set of 240 sentences. We report the most frequently used performance metrics: accuracy, precision, recall, and the F1 score. As described in the main text, the supervised machine learning methods (DistilBERT and SVM) outperform the dictionary-based approaches. It might be helpful to compare the classification performance with recent studies using similar methods for identifying emotions and latent concepts in political texts. Widmann and Wich (2022) report F1 scores for transfer learning classification of eight discrete emotions ranging from 0.6 to 0.84. Their dictionary classification results in F1 scores between 0.38 and 0.59. Bonikowski, Luo, and Stuhler (2022) use RoBERTa, an advanced transformer-based method, to identify inclusion, exclusion, populism, authoritarianism, and pride. Precision ranges from 0.63 (*High pride*) to 0.85 (*Exclusion*); recall ranges from 0.55 (*Low pride*) to 0.78 (*Exclusion*). Precision and recall for *Populism* are 0.66 and 0.68, respectively (Bonikowski, Luo, and Stuhler 2022: 1751). The classification performance of nostalgic rhetoric is on par with these recent studies seeking to identify – sometimes ambiguous – concepts with low levels of prevalence in political texts.

Figure A3 reports the correlation coefficients between our six nostalgia measures on the level of manifestos. The correlations range from 0.39 to 0.86.

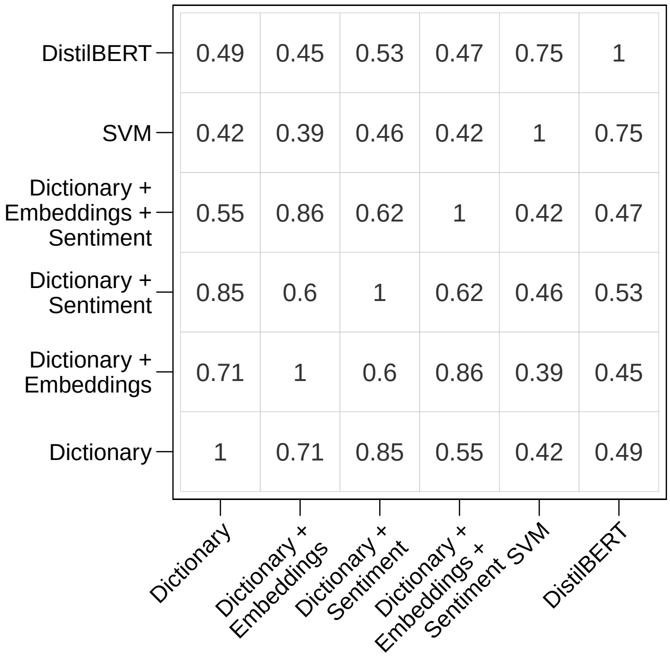
Table A2. Inter-coder reliability

Coders	Sentences	Categories	Agreement	Krippendorff's Alpha	Fleiss' Kappa
4	1200	2	77.3%	0.562	0.561

Table A3. Classification performance of nostalgia for held-out test set

Classifier	Accuracy	F1	Precision	Recall
DistilBERT	0.95	0.81	0.76	0.87
SVM	0.94	0.74	0.83	0.67
Dictionary + Positive Sentiment	0.88	0.48	0.50	0.47
Dictionary	0.81	0.42	0.34	0.57
Dictionary + Embeddings-Based Dictionary + Positive Sentiment	0.75	0.41	0.29	0.70
Dictionary + Embeddings-Based Dictionary	0.60	0.38	0.24	1.00

Figure A3. Manifesto-level correlations between measures of nostalgia



C.3 Translation Accuracy and Most Frequent Terms by Country

Since we are working with a machine-translated corpus, we also validate whether the English translations are comprehensible. The coding instructions for our classification of nostalgic rhetoric (see SI Section C.1) asked the four coders to identify incomprehensibly translated sentences. Overall, only 4 per cent of the 1,100 non-English sentences have been labeled as incomprehensible by at least two of the four coders. Only 1 per cent of sentences was coded as incomprehensible by three or more coders. Table A4 shows the percentages of incomprehensible sentences for each country.

While the machine translation is certainly not without errors (De Vries, Schoonvelde, and Schumacher 2018), we believe that the accuracy is sufficient for identifying nostalgic terms and phrases. To check for systematic differences across countries – potentially as a result of wrong translations – we identify the five most nostalgic terms per country using the base dictionary. Table A7 underscores that the most prevalent terms are similar, suggesting that machine translation does not produce completely different or unexpected patterns.

Table A4. Incomprehensibly translated sentences (threshold: at least two out of four coders labelled translation of sentence as inaccurate)

Country	Not Nostalgic	Nostalgic
Austria	2%	0%
Belgium	0%	0%
Bulgaria	0%	0%
Czech Republic	8%	0%
Denmark	11%	0%
Estonia	10%	11%
Finland	7%	0%
France	2%	0%
Germany	0%	0%
Greece	2%	0%
Hungary	10%	50%
Iceland	9%	0%
Italy	4%	0%
Latvia	3%	0%
Lithuania	2%	0%
Netherlands	2%	0%
Norway	5%	0%
Poland	7%	25%
Portugal	0%	0%
Slovenia	4%	0%
Spain	2%	0%
Sweden	4%	0%

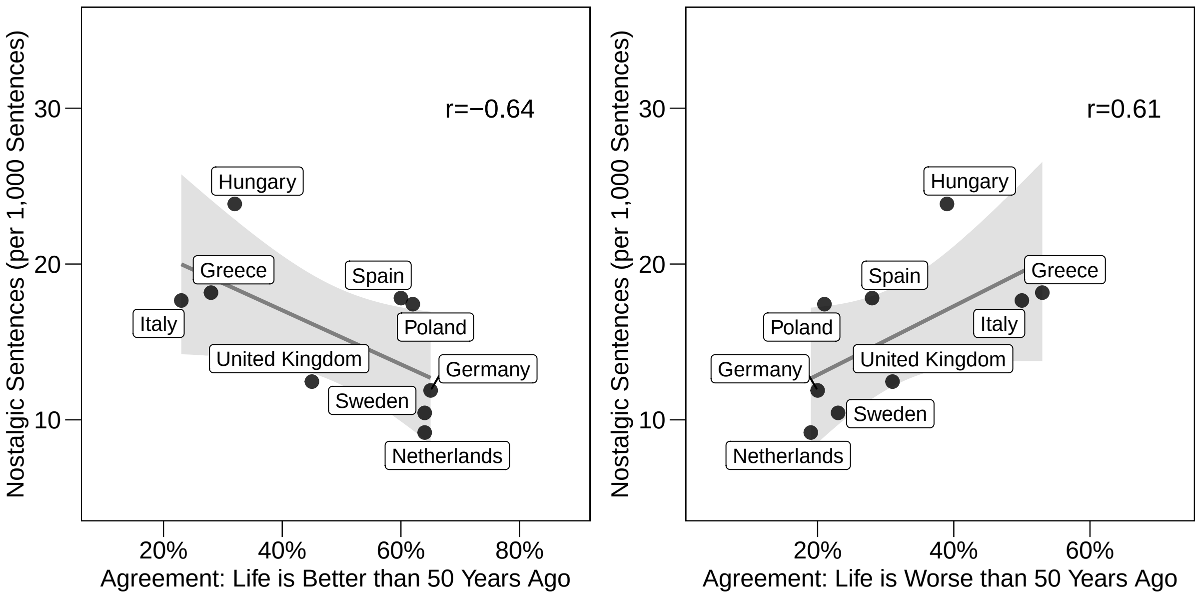
C.4 Comparing Parties and Voters

As an additional validity check, we assess if the national party manifesto averages correspond to general nostalgic emotions in the population. We rely on a survey conducted in 2017 by Pew Research Center (2017) which asked respondents whether they agree with the statement that life is better (worse) than it was 50 years ago. The correlation between our dictionary-based measure for manifestos published between 2010 and 2018 and survey averages is strong: the higher the share of respondents who believe that life is better nowadays, the fewer nostalgic references we find in manifestos overall in those countries ($r = -0.64$). Conversely, the higher the share of respondents who think life is worse than 50 years ago, the more nostalgic references we find in the respective country's manifestos ($r = +0.61$). The comparison of surveys and the text-based measure suggests that our approach captures underlying nostalgic emotions at the country level.

Table A5. Frequencies of dictionary entries (base dictionary) for sentences classified as nostalgic, separately for each country. Frequencies in parentheses. Table lists the five most frequent terms/phrases.

Country	Terms and Phrases
Austria	past (140), history (84), preserve (74), heritage (44), constant (41)
Belgium	past (501), heritage (439), preserve (194), constant (182), history (135)
Bulgaria	heritage (64), past (45), history (29), constant (22), preserve (15)
Czech Republic	heritage (81), past (70), preserve (56), history (39), tradition (20)
Denmark	past (75), history (60), preserve (41), preserved (39), years_ago (31)
Estonia	heritage (75), history (24), preserve (17), memory (16), preservation (15)
Finland	past (38), history (30), tradition (23), heritage (15), preserve (14)
France	past (74), history (72), heritage (58), preserve (47), constant (30)
Germany	past (267), history (226), preserve (199), heritage (99), constant (77), preserved (77)
Greece	heritage (104), history (96), past (80), constant (66), tradition (33)
Hungary	past (234), history (87), preserve (76), heritage (60), historic (47)
Iceland	history (13), heritage (12), past (8), constant (5), memory (4), preserved (4)
Ireland	past (293), heritage (231), history (117), historic (69), tradition (53)
Italy	heritage (402), past (292), history (161), constant (96), tradition (89)
Latvia	heritage (6), history (5), historic (3), traditions (3), constant (2)
Lithuania	heritage (199), history (84), past (80), preserve (73), historical (53)
Netherlands	past (387), history (250), heritage (157), preserve (135), constant (105)
Norway	heritage (650), preserve (400), history (201), tradition (197), preserved (139)
Poland	history (66), past (58), heritage (45), constant (29), years_ago (27)
Portugal	heritage (391), past (201), history (92), constant (87), preserve (51)
Slovenia	heritage (125), past (96), preserve (57), history (55), constant (48)
Spain	heritage (904), history (379), past (272), constant (230), historical (227)
Sweden	heritage (47), past (38), preserve (33), history (30), preserved (27)
United Kingdom	past (210), history (115), heritage (93), historic (74), preserve (62)

Figure A4. Comparing responses in cross-national survey and dictionary-based nostalgic rhetoric (method 1) in party manifestos between 2010 and 2018



C.5 Identifying the Most Frequent Features and Predictive Terms in Nostalgic Sentences

In addition to comparing manifesto-level correlations across our six measures (Figure A3) and calculating performance metrics (Table A3), we also identify terms and phrases that are more likely to appear in sentences classified as nostalgic, relative to sentences not classified as nostalgic. We follow and expand the approach by Goet (2019) and conduct a keyness analysis for each of our six measures (Bondi and Scott 2010). More precisely, we aggregate all sentences classified as nostalgic and all sentences classified as not nostalgic into two groups. We compare the feature frequencies in these two groups using chi-square tests.[4] We conduct this analysis for all six measures of nostalgia.

Table A6 shows the 50 terms with the highest chi-squared values in order to identify predictive terms for nostalgic rhetoric. For all six measures, the terms make intuitive sense. It includes both terms from our dictionary, but also words that did not appear in our list of keywords, for example, `our`, `artistic`, and `twentieth`. These findings suggest that the dictionary terms often co-occur with words that could also be regarded as nostalgic. The keyness terms for our supervised machine learning methods include names of countries, religions, nations (e.g., `estonian`, `finnish`, `christian`, `spanish`, `portugese`), and terms related to arts and culture.

Finally, we retrieve the most frequent dictionary matches for the four dictionary-based methods. Table A7 shows the terms and their frequencies. As expected, the frequencies are lower for Methods 3 and 4 since only sentences with positive sentiment scores are coded as nostalgic.

[4] We use the `textstat_keyness` function which is part of the **quanteda.textstats** package (Benoit et al. 2018).

Table A6. Keyness analysis for sentences classified as nostalgic, separately for each method. Table lists the 50 most important features distinguishing 'nostalgic' sentences (target category) from sentences classified as 'not nostalgic' (reference category).

Measure	Words
Dictionary	heritage, past, history, preserve, constant, tradition, historic, preserved, ago, memory, persistent, cultural, persistence, persist, historical, preserves, years, persists, culture, artistic, persistently, preservation, architectural, monuments, intangible, identity, decade, museums, natural, reminiscent, traditions, nostalgia, museum, decades, archaeological, conservation, biodiversity, centuries, generations, unesco, values, four, nostalgic, persisted, mistakes, geography, landscape, archives, persisting, ancient
Dictionary + Embeddings	return, heritage, past, continued, generation, traditional, generations, history, century, preservation, historical, preserve, decades, restore, continuous, constant, decade, tradition, traditions, historic, ago, preserved, preserving, returned, era, restoring, cultural, roots, regain, monuments, returning, memory, traditionally, 21st, rooted, root, legacy, persistent, rebuild, twenty-first, centuries, cherish, future, xxi, persistence, preceded, twentieth, persist, conserve, origins
Dictionary + Sentiment	heritage, preserve, history, past, tradition, historic, constant, preserved, cultural, memory, ago, historical, artistic, preserves, persistent, culture, preservation, intangible, conservation, architectural, persistence, identity, natural, monuments, museums, years, traditions, enhancement, archaeological, restoration, unique, values, persistently, biodiversity, persist, protection, rich, proud, museum, treasure, decade, arts, achievements, landscape, generations, contemporary, unesco, memorable, national, archives
Dictionary + Embeddings + Sentiment	heritage, return, restore, generations, preservation, generation, continued, preserve, traditional, historical, history, continuous, past, tradition, century, traditions, restoring, historic, preserving, constant, cultural, decades, decade, preserved, monuments, cherish, regain, era, roots, returning, memory, rooted, conserve, traditionally, returned, rebuild, 21st, ago, twenty-first, future, culture, centuries, artistic, natural, xxi, sacred, legacy, younger, confidence, identity
SVM	culture, heritage, cultural, language, history, tradition, identity, traditions, values, sami, preservation, art, historical, preserve, national, christian, lithuanian, important, artistic, monuments, finnish, restoration, dissemination, landscape, arts, museums, nation, part, historic, museum, slovenian, education, intangible, care, rich, society, spiritual, kven, memory, cultures, great, archives, architectural, diversity, folk, music, portuguese, natural, conservation, traditional
DistilBERT	cultural, culture, heritage, language, art, tradition, traditions, history, cultures, artistic, identity, arts, historical, languages, museums, museum, monuments, values, preservation, sami, music, archives, literature, archaeological, artists, historic, christian, dissemination, contemporary, national, portuguese, landscape, diversity, nation, theater, expressions, estonian, dutch, memory, lithuanian, folk, civilization, preserve, architectural, linguistic, ancient, roots, collections, spanish, society

Table A7. Frequencies of dictionary entries for sentences classified as nostalgic, separately for each dictionary. Frequencies in parentheses. Table lists terms and phrases that appear at least five times in sentences classified as nostalgic.

Measure	Terms and Phrases
Dictionary	heritage (4,318), past (3,602), history (2,450), preserve (1,860), constant (1,231), tradition (1,090), historic (710), years_ago (630), preserved (582), historical (490), memory (415), persistent (306), preservation (301), generations (231), decades (200), decade (185), traditions (150), persistence (139), monuments (126), persist (120), traditional (115), century (102), generation (92), return (91), preserves (87), good_times (67), centuries (59), roots (58), persists (56), restore (55), continued (53), preserving (52), good_time (52), legacy (49), persistently (46), back_to (42), rooted (35), continuous (31), reminiscent (24), year_ago (23), nostalgia (21), era (19), memorial (17), cherish (16), time_ago (15), monument (15), not_forget (13), nostalgic (12), traditionally (12), persisted (12), conserve (12), restoring (11), persisting (11), root (8), rebuild (8), everlasting (8), memories (8), returned (7), memorable (7), relics (7), glorious (6), remembrance (6), returning (5), eternal (5), preceded (5)
Dictionary + Emb.	return (4,874), heritage (4,318), past (3,602), continued (3,215), generation (2,964), traditional (2,940), generations (2,758), history (2,450), century (2,017), preservation (1,945), historical (1,879), preserve (1,860), decades (1,760), restore (1,746), continuous (1,709), constant (1,231), decade (1,099), tradition (1,090), traditions (911), historic (710), years_ago (630), preserved (582), preserving (580), returned (564), era (554), restoring (547), roots (458), regain (453), monuments (444), returning (439), memory (415), traditionally (410), rooted (365), root (350), legacy (321), persistent (306), rebuild (287), centuries (243), cherish (203), back_to (149), persistence (139), preceded (129), persist (120), conserve (113), origins (111), remembered (99), preserves (87), memorial (85), monument (84), sacred (75), recreate (71), good_times (67), ritual (57), eternal (56), persists (56), good_time (52), remembrance (47), persistently (46), memories (46), commemoration (45), timeless (27), not_forget (26), reminiscent (24), rediscover (23), year_ago (23), nostalgia (21), remembering (21), rituals (16), time_ago (15), relics (14), remembers (13), glorious (12), nostalgic (12), persisted (12), persisting (11), everlasting (8), throwback (7), memorable (7)
Dictionary + Sent.	heritage (3,081), past (1,484), preserve (1,297), history (1,294), tradition (730), constant (624), historic (485), historical (369), preserved (351), years_ago (243), preservation (227), memory (225), generations (142), traditions (105), persistent (98), decade (85), monuments (82), decades (80), traditional (78), generation (65), century (58), preserves (57), restore (52), persistence (48), good_times (46), good_time (44), return (43), roots (37), preserving (36), persist (29), centuries (29), continued (28), legacy (25), rooted (24), back_to (18), persistently (18), continuous (18), persists (16), cherish (16), conserve (12), monument (11), restoring (10), traditionally (10), year_ago (9), era (8), nostalgia (8), memorial (8), glorious (6), memorable (6), rebuild (6), time_ago (6), memories (6), reminiscent (5)
Dictionary + Emb. + Sent.	heritage (3,081), return (2,688), continued (1,756), generations (1,712), generation (1,694), traditional (1,609), restore (1,552), past (1,484), preservation (1,426), preserve (1,297), history (1,294), historical (1,177), continuous (1,048), century (988), tradition (730), decades (676), constant (624), traditions (620), decade (495), historic (485), restoring (474), preserving (420), preserved (351), monuments (295), era (288), regain (284), roots (246), returned (243), years_ago (243), returning (239), memory (225), traditionally (212), rooted (209), cherish (193), rebuild (169), legacy (124), root (123), centuries (121), conserve (110), persistent (98), back_to (75), preceded (63), sacred (58), preserves (57), monument (56), recreate (50), persistence (48), good_times (46), good_time (44), origins (42), commemoration (38), memorial (37), remembered (35), persist (29), memories (29), remembrance (24), eternal (21), rediscover (18), persistently (18), persists (16), timeless (16), ritual (15), remembering (14), glorious (11), year_ago (9), relics (9), nostalgia (8), rituals (7), memorable (6), remembers (6), time_ago (6), reminiscent (5)

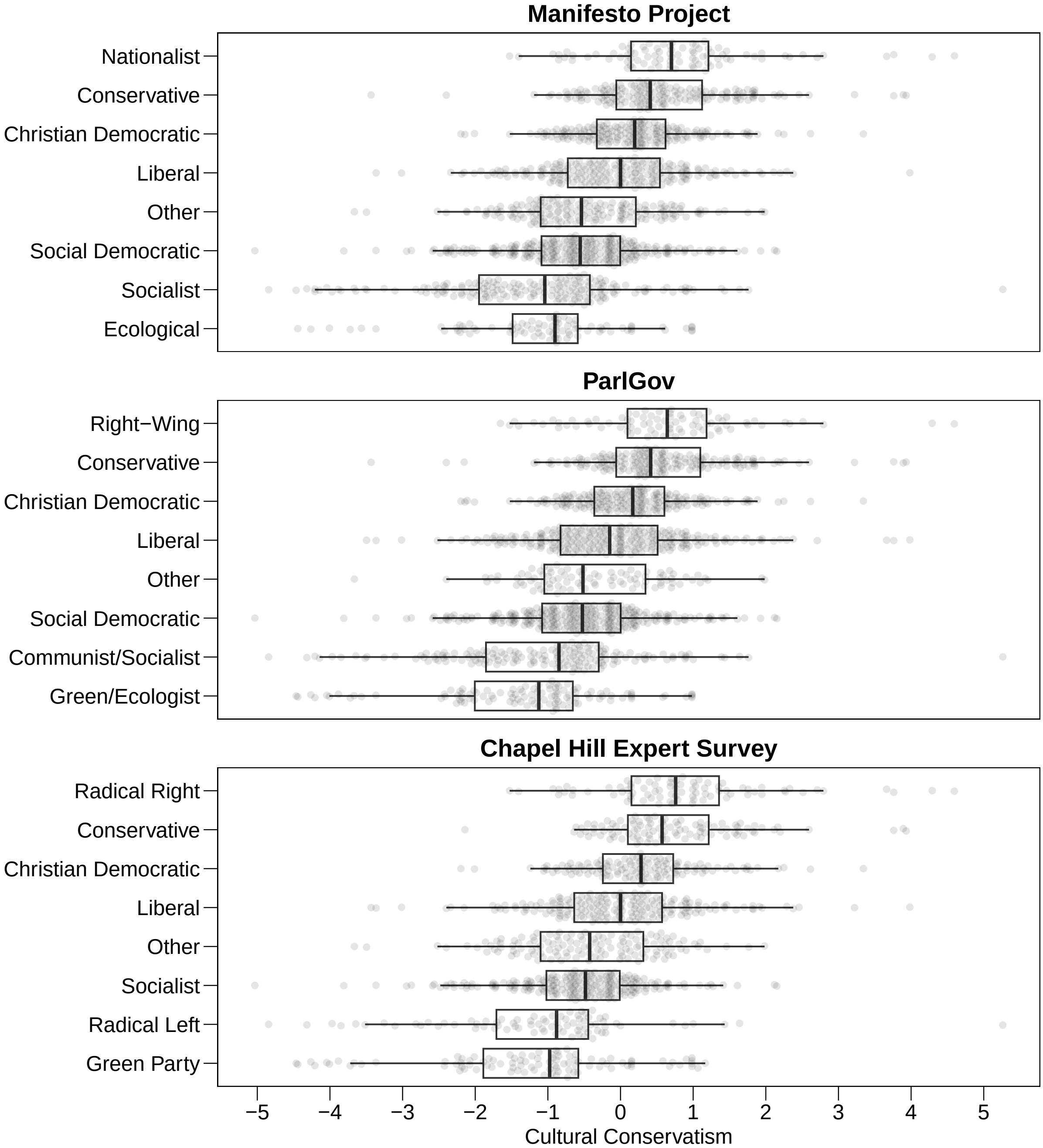
C.6 Validating the Measure of Cultural Conservatism

We construct a measure of *Cultural Conservatism* by contrasting socially liberal and conservative positions of a political party. The measure is based on the qualitative coding of party manifestos (Volkens et al. 2021). More specifically, we extend the policy issues from the social liberal-conservative scale proposed in Lowe et al. (2011). We include additional issues that are typically regarded as socially liberal or conservative positions. The additional items cover socially liberal positions (positive multiculturalism, environmental protection, and equality, and opposition to traditional morality) and socially conservative positions (negative mentions of multiculturalism). We list all issues below. Policy areas printed in italics were not included in Lowe et al.'s (2011) original scale.

- Socially liberal positions:
  1. 103 – Anti-Imperialism: Anti-Colonialism
  2. 105 – Military: Negative
  3. 106 – Peace: Positive
  4. 107 – Internationalism: Positive
  5. 202 – Democracy: Positive
  6. *607 – Multiculturalism: Positive*
  7. *501 – Environmental Protection*
  8. *503 – Equality: Positive*
  9. *604 – Traditional Morality: Negative*
- Socially conservative positions:
  1. 104 – Military: Positive
  2. 201 – Freedom and Human Rights: Positive
  3. 203 – Constitutionalism: Positive
  4. 305 – Political Authority: Positive
  5. 601 – National Way of Life: Positive
  6. 603 – Traditional Morality: Positive
  7. 605 – Law and Order: Positive
  8. 606 – Social Harmony: Positive
  9. *608 – Multiculturalism: Negative*

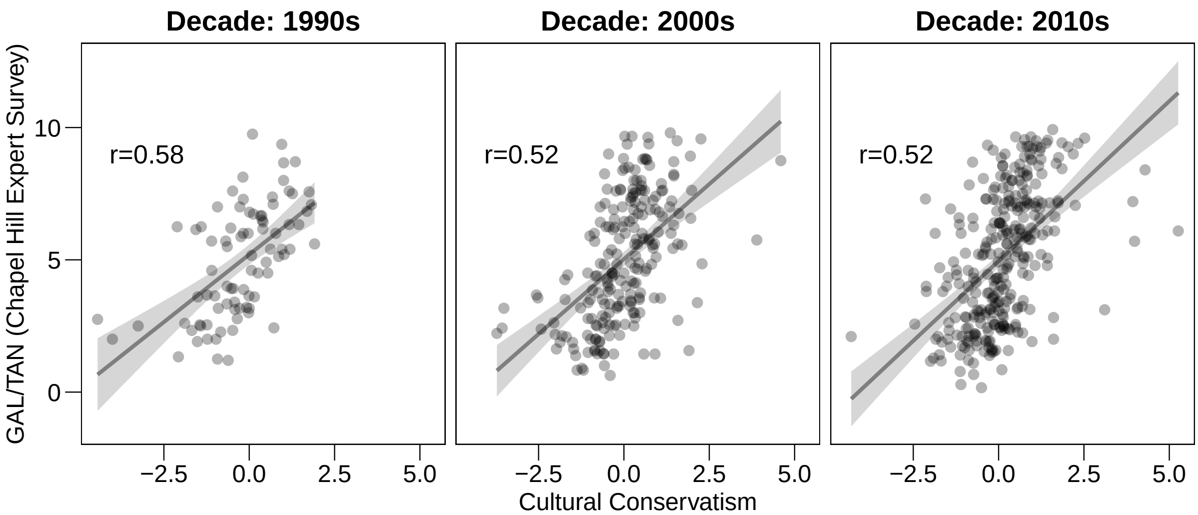
We use the aggregation suggested in Lowe et al. (2011: 131): $log(\frac{Conservative+0.5}{Liberal+0.5})$ Higher values imply more socially conservative positions. Figure A5 shows the distribution of *Cultural Conservatism* across party families. We use the party family codings of the Manifesto Project (Volkens et al. 2021), ParlGov (Döring and Manow 2021), and the Chapel Hill Expert Survey (Bakker et al. 2020). This face validity test shows that Nationalist (based on Manifesto Project coding), Right-Wing (ParlGov), Radical Right (Chapel Hill Expert Survey), Conservative, and Christian Democratic parties have the highest median scores.

Figure A5. Cultural conservatism across party families



We further validate our measure of cultural conservatism positions by comparing it with evidence from expert surveys on parties' positions in terms of their views on social and cultural values, using the GAL/TAN measure (Green-Alternative-Libertarian and Traditional-Authoritarian-Nationalist) from the Chapel Hill Expert Survey (Bakker et al. 2020). We match the average expert survey estimates from 1999, 2002, 2006, 2010, 2014, and 2019 with the election manifesto of the same party with the smallest absolute distance (in years) to an expert survey wave. We could match 603 manifestos with expert survey estimates. The correlation between the GAL/TAN variable and the socially liberal-conservative positions (based on the items from the Manifesto Project) amounts to 0.52 (Figure A6).[5] The correlation decreases considerably ($r = 0.44$) when only considering the policy codes selected by Lowe et al. (2011: Table 3). This further supports expanding the index and includes areas such as multiculturalism, environmental protection, and equality (see list above).

Figure A6. The correlation between the manifesto-based scale of cultural conservatism (x-axis) and the GAL/TAN measure derived from the Chapel Hill Expert Survey (y-axis)



D Determining the Best Classifier: Hand-Coding of 50 Manifestos

Having classified the full corpus based on the six methods presented and validated in Figure 1 and SI Section C, we conducted an additional extensive manual coding exercise. We rely on human codings of 50 party manifestos to determine the best classifier and test whether the substantive conclusions hold when running the regression analysis for manifestos labeled by human coders.

[5] As a point of comparison, for the same set of manifestos the correlation between the RILE variable from the manifestos and the general left-right position based on the expert survey amount to 0.59.

We selected five manifestos from each decile, resulting in a sample of 50 manifestos representing the full range of culturally liberal and conservative parties. Table A8 lists the 50 manifestos. We then extracted all potentially nostalgic sentences from these 50 manifestos. We define a sentence as potentially nostalgic if at least one of the methods treats the sentence as nostalgic. We randomly shuffled the order of sentences and instructed two human coders to annotate whether a sentence is nostalgic. The dataset consists of 3,515 sentences. The coding instructions largely mirror the text from SI Section C.1. All sentences were annotated by two instructed coders. As our main measure, we treat a sentence as nostalgic if both coders identified nostalgia. As a broader measure, we treat a sentence as nostalgic if at least one of the two coders identified nostalgia.

After both coders read and labeled all sentences, we aggregated the observations to the relevant unit of analysis: manifesto-level nostalgia. We proceed in the same way as in the main analysis and calculate the number of nostalgic sentences per 1,000 sentences separately for the six automated methods (Figure 1) and the two aggregations of human codings described in the paragraph above. While we observe differences on the sentence level, the aggregated estimates of nostalgic rhetoric in manifestos are similar.

We also compare our estimates to the Large Language Model (LLM) GPT 3.5 output. LLMs have been introduced as powerful alternatives to human coding and supervised classification (Gilardi, Alizadeh, and Kubli 2023). We provide minimal instructions to the model and ask to position each sentence on a 'nostalgia scale' ranging from 1 to 10. We treat sentences with a value of 5 or higher as nostalgic and aggregate the levels of nostalgia to the manifesto level.[6] We regard the LLM as an alternative validation method of our dictionaries, classifiers, and human annotations. However, we do not classify all sentences using this method due to a lack of transparency about the underlying algorithm, the

[6]After experimenting with various alternatives, we used the following prompt: "You are my research assistant. Please note that the sentences provided are from party manifestos. Please rate the following sentence in terms of nostalgia on a scale from 1 to 10. Then say whether or not the sentence is nostalgic, and provide a one-sentence justification. Use the following structure: 1-10; yes/no; justification. Always separate by semicolon." We used the model `gpt-3.5-turbo` and a temperature of 0. Our workflow follows the approach suggested by Rathje et al. (2023). We decided to use a threshold of 5 rather than the binary classification since the binary classifier tended to be inconsistent. The full prompt and script for classifying sentences using GPT 3.5 are available in the replication materials.

training data, the proprietary nature of OpenAI's models, and the inability to reproduce classification results (Spirling 2023).

The extensive coding exercise speaks to the validity of our main analysis. Culturally conservative parties tend to be more nostalgic than culturally liberal parties. This finding holds with a dictionary, a sophisticated transformer-based transfer learning approach, and hand-coded manifestos. The correlation analysis (Figure 2) reveals that DistilBERT aligns closest with the human coding of over 3,500 potentially nostalgic sentences. We recommend that researchers use the DistilBERT measure if they want to use *PolNos* data and encourage other scholars to test the robustness of their findings with the additional measures.

Table A8. Overview of hand-coded nostalgia and DistilBERT classification for 50 randomly sampled manifestos, stratified by cultural conservatism

Party	Year	Country	Coding (>=1)	Coding (=2)	Nostalgia DistilBERT	Cultural Conser-vatism
Christian Democratic Centre	1996	Italy	166.7	71.4	285.7	1.3
Danish People's Party	2001	Denmark	51.5	19.9	87.5	1.9
Estonian People's Union	2007	Estonia	78.1	7.8	85.9	0.0
Popular Democratic Movement	1979	Portugal	61.9	0.0	82.5	0.6
Coalition of the Radical Left - Unionist Social Front	2012	Greece	47.4	5.4	78.8	-0.4
Democratic Coalition	2014	Hungary	54.2	9.7	66.0	0.1
Left and Democrats	2007	Poland	46.4	11.0	63.0	0.0
Brothers of Italy - National Centre-right	2013	Italy	46.8	2.2	57.9	0.7
Conservative People's Party	2011	Denmark	64.5	24.2	56.5	1.0
Communist Party of Germany	1949	Germany	15.5	7.8	54.3	-0.1
Centre Party	1982	Netherlands	37.5	20.0	52.5	-0.1
Lithuanian Peasant and Green Union	2016	Lithuania	34.5	7.9	43.6	-0.2
Democratic Alliance	1996	Italy	40.1	11.5	43.0	1.1
Alternative for Bulgarian Revival	2014	Bulgaria	36.5	5.2	41.7	0.6
Liberal and Centre Union	2004	Lithuania	32.9	8.2	41.1	0.3
Party of Italian Communists	2001	Italy	33.1	7.8	40.1	-0.2
Democratic Left Party	1992	Ireland	17.2	3.4	37.9	-2.1
Panhellenic Socialist Movement	2009	Greece	28.8	4.9	35.4	-0.6
Christian and Democratic Union - Czech People's Party	2017	Czech Rep.	20.5	2.9	35.2	0.3
Civil Revolution	2013	Italy	39.5	12.3	34.6	-1.0
The Alliance - Social Democratic Party of Iceland	2016	Iceland	20.9	2.5	34.4	-1.2
Progressive Democrats	1989	Ireland	27.0	0.0	31.5	0.2
Social Democratic Party	2005	Portugal	38.8	9.0	31.2	-0.7
Christian People's Party	1973	Norway	31.7	4.5	30.6	-0.3
Alliance of Free Democrats	2002	Hungary	23.9	2.8	30.2	-0.6
Civic Platform	2011	Poland	27.1	5.9	29.6	0.8
Christian Union	2017	Netherlands	24.6	8.6	25.1	0.8
Party of Democratic Socialism	2002	Germany	31.3	1.2	24.1	-0.5
United Kingdom Independence Party	2015	UK	29.5	11.4	23.5	0.8
Swedish People's Party	2003	Finland	19.1	3.8	22.9	-1.7
Czech Social Democratic Party	2010	Czech Rep.	18.2	4.2	22.4	-0.2
Democratic Unionist Party	2015	UK	44.2	17.7	22.1	0.6
More Europe	2018	Italy	16.9	0.0	21.7	-0.7
Francophone Democratic Front of Francophones	1991	Belgium	19.0	0.6	20.7	0.6
Austrian Social Democratic Party	1966	Austria	13.8	0.0	20.7	-0.2
Together 2014 -Dialogue for Hungary Electoral Alliance	2014	Hungary	18.3	4.9	20.4	0.3
Bright Future	2017	Iceland	16.1	3.2	19.3	-0.2
Basque Solidarity	2008	Spain	26.2	3.5	19.2	-0.8
Alliance‘90/Greens	2013	Germany	12.1	1.1	19.0	-1.2
The Left	2009	Germany	18.0	1.4	18.7	-1.2
Left Party	1994	Sweden	24.5	6.1	18.4	-4.0
Liberals	2007	Denmark	14.7	0.0	14.7	0.4
Union, Progress and Democracy	2011	Spain	11.0	0.0	14.2	-1.0
Canarian Coalition	2011	Spain	21.5	4.0	10.7	-1.9
Labour and Freedom List	2013	Italy	21.4	4.3	8.5	-2.3
Party of Liberty and Progress	1968	Belgium	15.3	1.7	8.5	1.2
Social Democratic Party of Germany	1980	Germany	11.3	0.0	8.1	-0.6
Liberal Reformation Party - Francophone Democratic Front	1995	Belgium	12.1	3.0	6.1	0.6
Liberal Party	1966	UK	10.3	0.0	3.4	-0.9
Popular Republican Movement	1958	France	5.9	0.0	1.5	-0.8

The set of 50 coded manifestos also allows us to test whether the main result from the paper holds for human-coded nostalgic rhetoric. Table A9 reports results from linear regression models with nostalgia as the dependent variable. We use five z-standardized measures: nostalgia identified by both coders (Model 1), nostalgic identified by at least one coder (Model 2), DistilBERT (Model 3), the base dictionary (Model 4), and GPT 3.5 (Model 5) and assess whether cultural conservatism predicts nostalgic rhetoric based on these three distinct measures. Due to the smaller number of observations, we only control for the geographic region. Yet, the main focus of this analysis is the direct comparison across methods rather than a fully specified model. The coefficient for *Cultural Conservatism* is positive and statistically significant in all models. A one-unit increase corresponds to increases in standardized nostalgic of 0.37 (Model 1: both coders), 0.4 (Model 2: At least one coder), 0.38 (Model 3: DistilBERT), 0.4 (GPT 3.5) to 0.5 (Dictionary).[7]

[7] These results are stronger than the findings in the main analysis because we only considered manifestos in our sample that included at least 10 sentences classified as nostalgic by Methods 3, 5, and 6. Manifestos with very low levels of nostalgia are not included in this sample.

Table A9. Predicting nostalgic rhetoric (based on human codings) in 50 party manifestos. Dependent variable measures sentences coded as nostalgic by both coders (Model 1), at least one of two coders (Model 2), the DistilBERT approach (Model 3), the Base Dictionary (Model 4), and GPT 3.5 (Model 5) for the same set of sentences. Dependent variables are measured as the number of nostalgic sentences per 1,000 sentences, and z-transformed for comparability. Standard erorrs in parentheses.

	M1 (Coding: =2)	M2 (Coding: >=1)	M3 (DistilBERT)	M4 (Dictionary)	M5 (GPT 3.5)
(Intercept)	-0.10	0.10	0.08	-0.05	-0.05
	(0.29)	(0.26)	(0.27)	(0.24)	(0.27)
Cultural Conservatism	0.37^{**}	0.40^{**}	0.38^{**}	0.50^{***}	0.40^{**}
	(0.13)	(0.12)	(0.13)	(0.11)	(0.13)
Region: Northern E. (ref.: CCE)	0.38	0.05	0.05	-0.29	0.13
	(0.45)	(0.41)	(0.43)	(0.38)	(0.43)
Region: Southern E.	0.51	0.52	0.47	0.79^{*}	0.62
	(0.39)	(0.36)	(0.37)	(0.33)	(0.37)
Region: Western E.	-0.05	-0.49	-0.39	-0.03	-0.15
	(0.37)	(0.34)	(0.35)	(0.31)	(0.35)
R^2	0.18	0.30	0.25	0.41	0.25
Adj. R^2	0.11	0.24	0.18	0.36	0.18
Num. obs.	50	50	50	50	50

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

E Robustness Tests: Additional Regression Models and Plots

E.1 Different Model Specifications: Fixed Effects, Random Effects, and Exclusion of Control Variables

Figure A7 compares country-level nostalgia across our six measures, highlighting that the patterns displayed in Figure 3 do not depend on the measurement of nostalgia. Table A10 compares the results from mixed-effects models (Bates, Mächler, and Walker 2015), reported in the main paper, with linear regression with country fixed-effects and standard errors clustered by party (Blair et al. 2022). The size and direction of the coefficients are very similar, suggesting that our results do not depend on the modeling approach.

Following Lenz and Sahn's (2021) recommendations, Table A13 reports the regression models with and without control variables. The substantive size and levels of statistical significance for *Cultural Conservatism* (Models 1 and 2) and *Party Family* remain very similar. Our findings do not seem to depend on the inclusion or exclusion of control variables.

E.2 Differences Across Regions

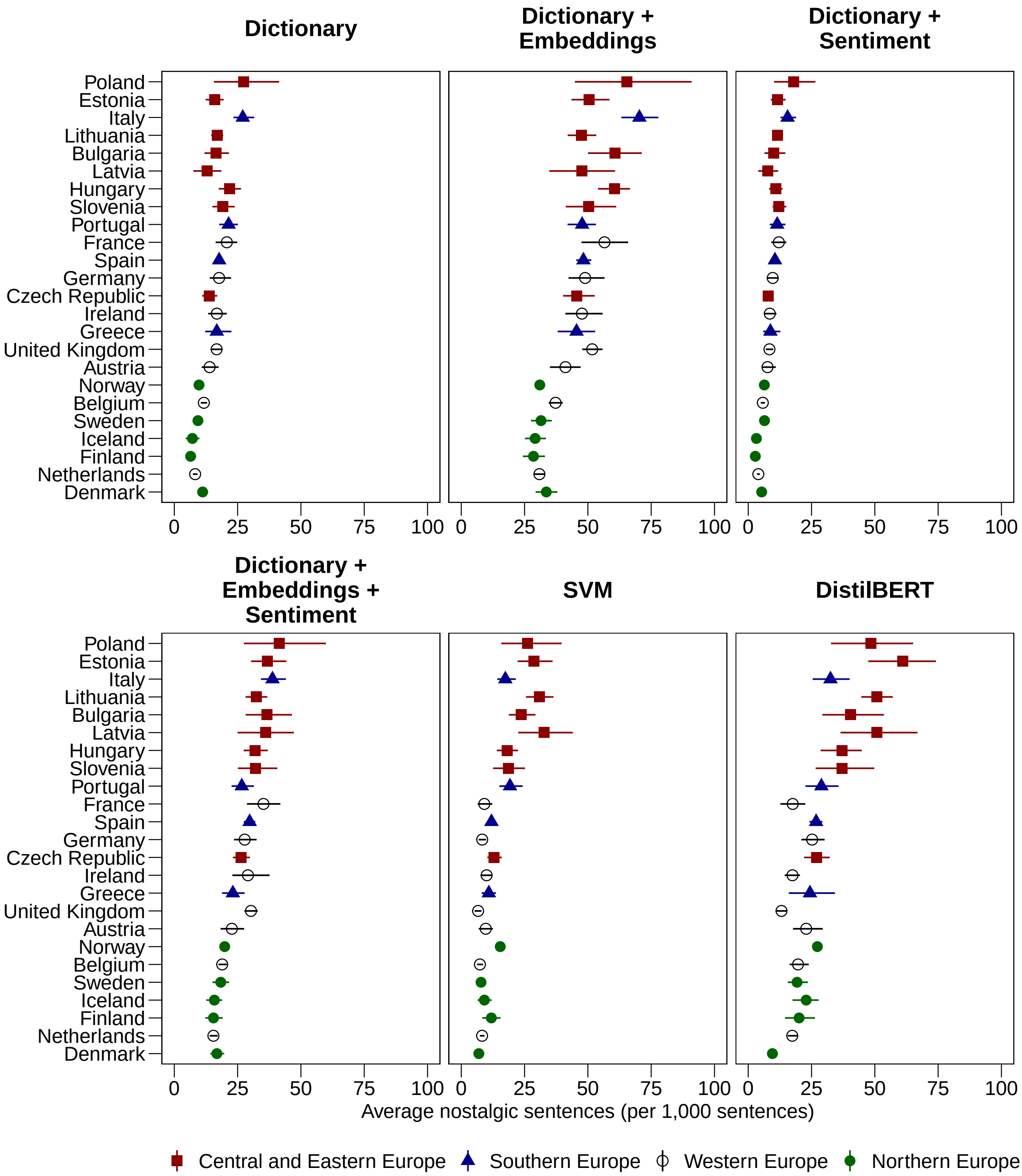
Table A12 reports the regression models for the four regions, largely confirming the results from the main paper. Figure A8 shows the predicted levels of nostalgia over time separately for the four regions. The results suggest that nostalgic rhetoric is not a recent phenomenon.

Table A10. Predicting nostalgia (DistilBERT) using mixed-effects models with random intercepts for countries, parties, and elections (M1 and M3), and a fixed-effects models with country-fixed effects and standard errors clustered by party (M2 and M4). Intercept omitted from table.

	M1 (mixed-effects)	M2 (fixed-effects)	M3 (mixed-effects)	M4 (fixed-effects)
Cultural Conservatism	1.71^{**}	2.32^{**}		
	(0.56)	(0.84)		
Government	1.26	1.72	1.28	1.72
	(1.26)	(1.45)	(1.26)	(1.56)
Vote Share	-0.04	-0.06	-0.07	$-0.11^{\dagger}$
	(0.07)	(0.05)	(0.07)	(0.07)
Unemployment (t-1)	-0.01	0.02	0.03	0.03
	(0.16)	(0.19)	(0.16)	(0.19)
Christ. Dem. (ref.: Nat.)			-14.03^{***}	-6.91
			(3.99)	(5.54)
Conservative			-15.27^{***}	$-10.07^{\dagger}$
			(4.11)	(5.23)
Ecological			-23.19^{***}	-17.91^{***}
			(4.52)	(4.93)
Liberal			-22.13^{***}	-16.98^{***}
			(3.74)	(5.03)
Other			-19.13^{***}	-14.06^{**}
			(3.79)	(5.21)
Social Dem.			-18.22^{***}	-13.24^{*}
			(3.85)	(5.23)
Socialist			-23.31^{***}	-18.02^{***}
			(3.82)	(5.07)
AIC	14281.64		14227.27	
BIC	14324.60		14302.46	
Log Likelihood	-7132.82		-7099.64	
N	1588	1588	1588	1588
N Groups: Parties	365		365	
N Groups: Countries	24		24	
R^2		0.19		0.22
Adj. R^2		0.17		0.20
RMSE		21.75		21.36
N Clusters (Parties)		365		365

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$

Figure A7. Nostalgia across countries based on various measurement approaches



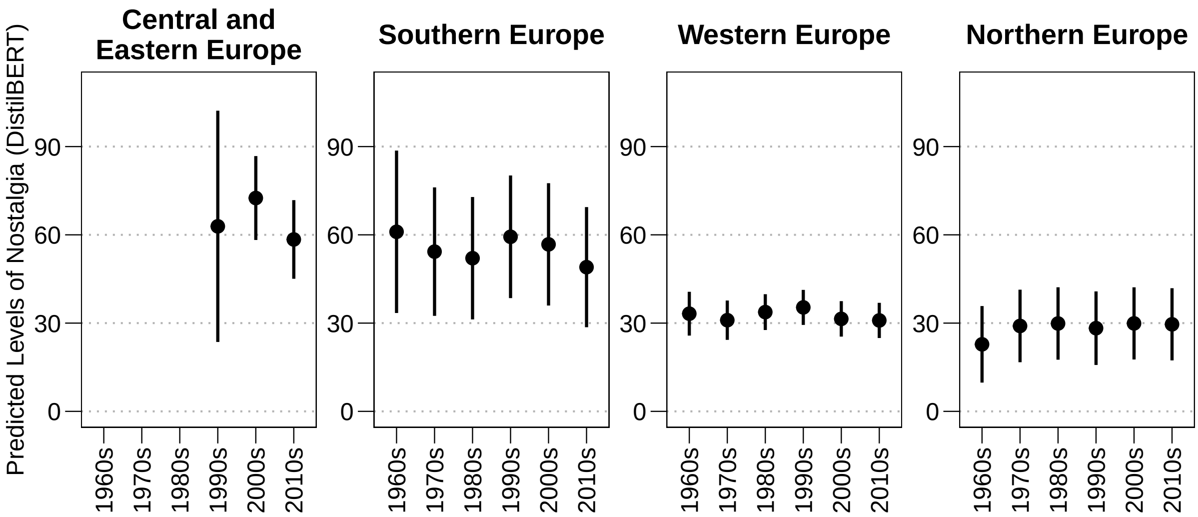
Note: Average levels of nostalgia (per 1,0000 sentences). Horizontal bars show 95 per cent bootstrapped confidence intervals.

Table A11. Predicting nostalgia for various measurements with standardized dependent variables (mean of 0 and standard deviation of 1). Linear mixed-effects models with random intercepts for countries, parties, and elections. Standard errors in parentheses. M1: Base dictionary; M2: Base dictionary + embeddings dictionary; M3: Base dictionary + positive sentiment; M4: Base dictionary + embeddings dictionary + positive sentiment; M5: Bag-of-words classifier (SVM); M6: Transformer-based classifier (DistilBERT).

	Dictionary-Based Methods (M1–M4)				Machine Learning (M5–M6)	
	M1	M2	M3	M4	M5	**M6**
(Intercept)	0.49^{***}	0.39^{**}	0.38^{**}	0.16	0.77^{***}	0.91^{***}
	(0.14)	(0.14)	(0.14)	(0.14)	(0.17)	(0.17)
Christ. Dem. (ref.: Nat.)	-0.41^{**}	-0.47^{***}	-0.29^{*}	-0.18	-0.41^{**}	-0.58^{***}
	(0.13)	(0.13)	(0.14)	(0.13)	(0.16)	(0.16)
Conservative	-0.27^{*}	-0.44^{***}	-0.10	-0.07	-0.57^{***}	-0.62^{***}
	(0.13)	(0.13)	(0.15)	(0.14)	(0.16)	(0.16)
Ecological	-0.57^{***}	-0.48^{***}	-0.58^{***}	-0.37^{*}	-0.81^{***}	-0.94^{***}
	(0.14)	(0.14)	(0.16)	(0.15)	(0.18)	(0.18)
Liberal	-0.57^{***}	-0.65^{***}	-0.45^{***}	-0.37^{**}	-0.78^{***}	-0.89^{***}
	(0.12)	(0.12)	(0.13)	(0.12)	(0.15)	(0.15)
Other	-0.52^{***}	-0.52^{***}	-0.41^{**}	-0.29^{*}	-0.62^{***}	-0.77^{***}
	(0.12)	(0.12)	(0.14)	(0.13)	(0.15)	(0.15)
Social Dem.	-0.46^{***}	-0.57^{***}	-0.29^{*}	-0.25^{*}	-0.66^{***}	-0.72^{***}
	(0.12)	(0.12)	(0.14)	(0.13)	(0.15)	(0.15)
Socialist	-0.73^{***}	-0.78^{***}	-0.66^{***}	-0.61^{***}	-0.79^{***}	-0.94^{***}
	(0.12)	(0.12)	(0.14)	(0.13)	(0.15)	(0.15)
Government	0.12^{*}	$0.08^{\dagger}$	$0.10^{\dagger}$	0.11^{*}	0.08	0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Vote Share	-0.00	0.00	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment (t-1)	0.00	0.02^{**}	0.01	0.02^{**}	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AIC	4161.75	4055.68	4275.04	4189.37	4128.15	4066.74
BIC	4242.31	4136.24	4355.59	4269.93	4208.71	4147.29
Log Likelihood	-2065.88	-2012.84	-2122.52	-2079.69	-2049.08	-2018.37
N	1588	1588	1588	1588	1588	1588
N Groups: Parties	365	365	365	365	365	365
N Groups: Elections	260	260	260	260	260	260
N Groups: Countries	24	24	24	24	24	24

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$

Figure A8. Predicted levels of nostalgia over time



textitNote: Plots show predicted values for nostalgia and 95 per cent confidence intervals, based on Models 1–4 from Table A12. The remaining variables are held constant at the reference level (categorical variables) and average (continuous variables).

Table A12. Predicting nostalgic sentences (per 1,000 sentences; DistilBERT) for each region. Linear mixed-effects models with random intercepts for countries, parties, and election. Standard errors in parentheses.

	M1: East	M2: South	M3: West	M4: North
(Intercept)	53.11*	60.44***	33.67***	25.18***
	(20.66)	(14.09)	(3.61)	(6.86)
Party Family: Christian Dem. (ref.: Nationalist)	−24.70*	−25.33†	−11.19***	3.18
	(10.18)	(13.29)	(3.33)	(8.82)
Party Family: Conservative	−19.67*	−19.77	−14.33***	−8.99
	(8.60)	(13.85)	(4.11)	(8.03)
Party Family: Ecological	−52.24***	−27.68†	−18.80***	−4.43
	(13.55)	(16.48)	(3.47)	(9.27)
Party Family: Liberal	−26.94**	−27.98*	−20.30***	−11.43
	(8.56)	(12.77)	(3.21)	(7.43)
Party Family: Other	−20.22*	−27.99*	−12.73***	−14.63†
	(8.89)	(11.43)	(3.41)	(7.59)
Party Family: Social Dem.	−28.11**	−14.47	−17.42***	−13.48
	(8.90)	(12.30)	(3.32)	(8.68)
Party Family: Socialist	−37.94**	−28.04*	−17.89***	−16.42*
	(12.00)	(11.56)	(3.78)	(7.37)
Vote Share	−0.37†	−0.05	−0.00	0.00
	(0.21)	(0.20)	(0.07)	(0.17)
Unemployment (t-1)	1.56**	0.10	−0.06	−0.50
	(0.53)	(0.44)	(0.28)	(0.38)
Decade: 1970s		−6.74	−2.21	6.24*
		(10.11)	(2.83)	(2.99)
Decade: 1980s		−8.97	0.54	7.08*
		(10.30)	(3.27)	(3.26)
Decade: 1990s		−1.70	2.14	5.48
		(10.61)	(3.16)	(3.88)
Decade: 2000s	9.62	−4.27	−1.76	7.11*
	(19.11)	(10.56)	(3.01)	(3.42)
Decade: 2010s	−4.46	−12.02	−2.29	6.80†
	(18.98)	(11.43)	(3.05)	(3.72)
AIC	1728.90	2744.54	4859.86	4555.91
BIC	1777.52	2811.03	4938.30	4632.65
Log Likelihood	−849.45	−1354.27	−2411.93	−2259.96
N	189	297	577	525
N Groups: Parties	96	98	112	59

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$

Table A13. Predicting nostalgia based on DistilBERT measures with standardized dependent variables (mean of 0 and standard deviation of 1), with and without control variables. Linear mixed-effects models with random intercepts for countries, parties, and elections. Standard errors in parentheses.

	M1	M2	M3	M4
(Intercept)	0.22^{*}	$0.21^{\dagger}$	0.89^{***}	0.91^{***}
	(0.10)	(0.12)	(0.17)	(0.17)
Cultural Conservatism	0.08^{***}	0.08^{**}		
	(0.02)	(0.02)		
Party Family: Christ. Dem. (ref.: Nat.)			-0.46^{*}	-0.58^{***}
			(0.19)	(0.16)
Party Family: Conservative			-0.58^{**}	-0.62^{***}
			(0.19)	(0.16)
Party Family: Ecological			-0.96^{***}	-0.94^{***}
			(0.22)	(0.18)
Party Family: Liberal			-0.88^{***}	-0.89^{***}
			(0.18)	(0.15)
Party Family: Other			-0.69^{***}	-0.77^{***}
			(0.18)	(0.15)
Party Family: Social Dem.			-0.72^{***}	-0.72^{***}
			(0.18)	(0.15)
Party Family: Socialist			-0.95^{***}	-0.94^{***}
			(0.18)	(0.15)
Party Family: Government		0.05		0.05
		(0.05)		(0.05)
Vote Share		−0.00		−0.00
		(0.00)		(0.00)
Unemployment (t-1)		0.00		0.00
		(0.01)		(0.01)
AIC	4321.52	4081.72	4314.98	4066.74
BIC	4353.97	4130.05	4379.87	4147.29
Log Likelihood	−2154.76	−2031.86	−2145.49	−2018.37
N	1648	1588	1648	1588
N Groups: Parties	379	365	379	365
N Groups: Elections	272	260	272	260
N Groups: Countries	24	24	24	24

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$

E.3 Different Measures of Party Families

Table A11 reproduces Table 1 but replaces the continuous measure of cultural conservatism (SI Section C.6) with the party family coding from the Manifesto Project (Volkens et al. 2021). The coefficients for party families are similar for the six measures.

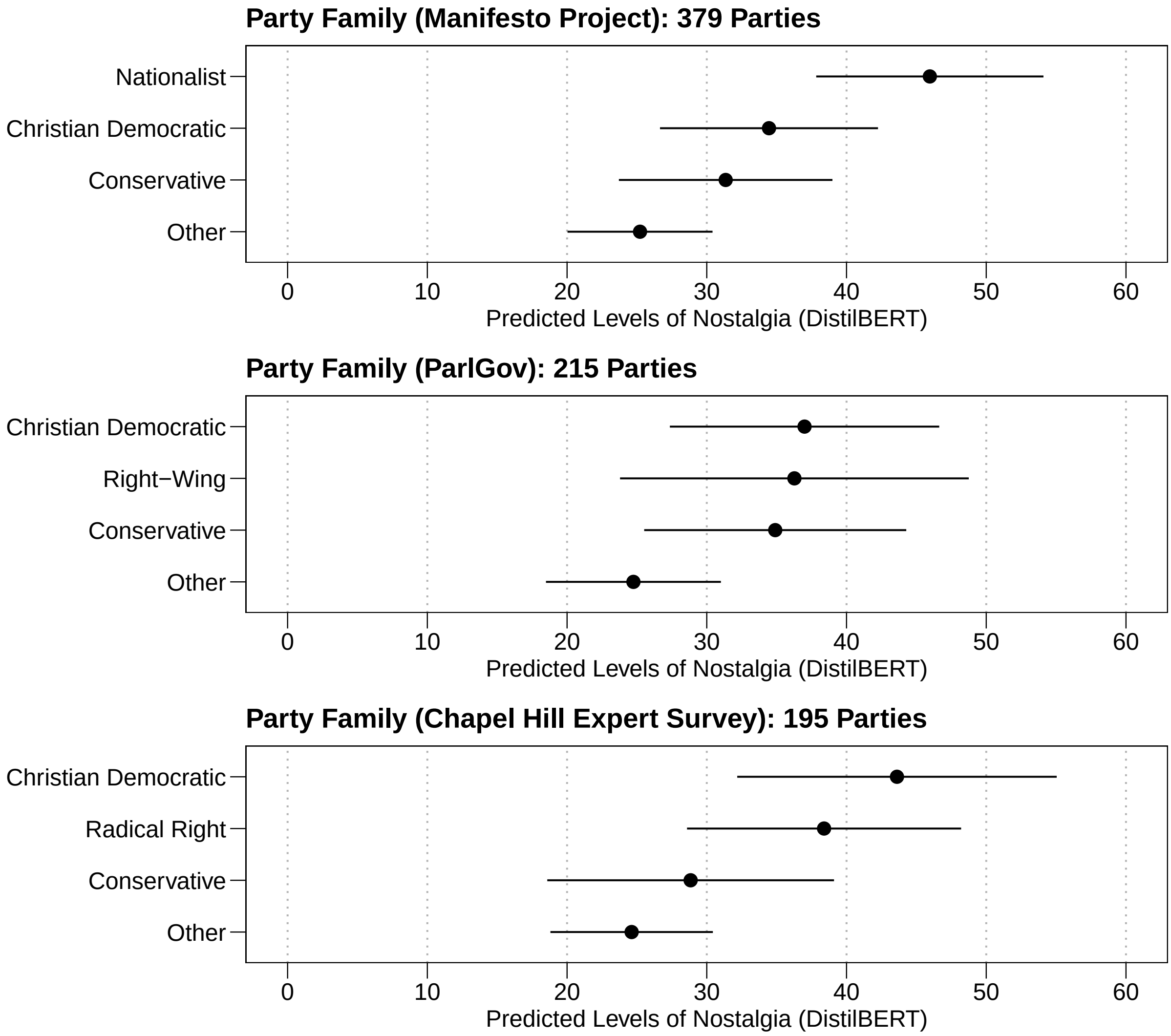
Table A14 compares party family codings from the Manifesto Project (Volkens et al. 2021), ParlGov (Döring and Manow 2021), and the Chapel Hill Expert Survey (Bakker et al. 2020). For the latter two measures not all parties could be classified into families – because ParlGov and the Chapel Hill Expert Survey do not consider all of the parties. If the family assigned to a party changed over time, we use the initial party family coding. Figure A9 shows the predicted levels of nostalgia based on the models in Table A14. The analysis suggests that nationalist (Manifesto Project), right-wing (ParlGov), Radical Right (CHES) Christian Democratic, and Conservative parties are more nostalgic than other parties.

Table A14. Predicting nostalgic sentences (per 1,000 sentences; DistilBERT). Linear mixed-effects models with random intercepts for countries, parties, and election. Standard errors in parentheses.

	M1	M2	M3
(Intercept)	25.22^{***}	24.75^{***}	24.62^{***}
	(2.65)	(3.19)	(2.97)
Party Family (Manifesto Project): Conservative (ref.: Other)	$6.13^{\dagger}$		
	(3.45)		
Party Family (Manifesto Project): Christian Democratic	9.23^{**}		
	(3.48)		
Party Family (Manifesto Project): Nationalist	20.74^{***}		
	(3.71)		
Party Family (ParlGov): Conservative (ref.: Other)		10.15^{*}	
		(4.61)	
Party Family (ParlGov): Christian Democratic		12.25^{**}	
		(4.66)	
Party Family (ParlGov): Right-Wing		$11.52^{\dagger}$	
		(6.18)	
Party Family (CHES): Conservative (ref.: Other)			4.22
			(5.13)
Party Family (CHES): Christian Democratic			18.99^{***}
			(5.68)
Party Family (CHES): Radical Right			13.77^{**}
			(4.87)
AIC	14884.63	12266.85	10528.65
BIC	14927.89	12308.57	10569.16
Log Likelihood	−7434.32	−6125.43	−5256.33
N	1648	1360	1168
N Groups: Parties	379	215	195
N Groups: Elections	272	267	247
N Groups: Countries	24	24	22

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$

Figure A9. Predicted levels of nostalgia across party families derived from three data sources.



Note: Plots show predicted values for nostalgia and 95 per cent confidence intervals, based on Models 1–3 from Table A14. The remaining variables are held constant at the reference level (categorical variables) and average (continuous variables).

E.4 Cultural Conservatism and Economic Left-Right Positions

In the main paper, we predict nostalgia conditional on various measures of party ideology, namely cultural conservatism, the party family, populism, and left-right positions. We find that only party family and cultural conservatism predict levels of nostalgia. We do not use the popular left-right (RILE) scale or the log RILE since it captures both economic and cultural left-right positions.[8] Several Manifesto Project categories appear in the RILE and our scale of cultural conservatism. Instead, we apply Lowe et al.'s (2011) scale of 'State Involvement in the Economy' as a proxy for *economic* left-right positions.

To validate this manifesto-based measure, we again match the average Chapel Hill Expert Survey estimates from 1999, 2002, 2006, 2010, 2014, and 2019 with the election manifesto of the same party with the smallest absolute distance (in years) to an expert survey wave. Figure A10 shows that the scale of State Involvement in the Economy correlates highly with the economic left-right position from the Chapel Hill Expert Survey ($r = 0.70$), which is available for a subset of manifestos. The correlation exceeds the correlation between Log RILE and Economic Left-Right Positions ($r = 0.53$), suggesting that State Involvement in the Economy captures parties' economic left-right positions. Therefore, throughout the paper, we label State Involvement in the Economy as economic left-right positions.

Figure A11 shows the predicted level of nostalgic sentences out of 1,000 sentences conditional on the cultural conservatism (Panel a) and the economic left-right position. We only find a strong and statistically significant relationship for cultural conservatism.

[8] We thank one of the anonymous reviewers for this suggestion.

Figure A10. Manifesto-level correlations between various measures of left-right positions, based on the Manifesto Project coding and the Chapel Hill Expert Survey

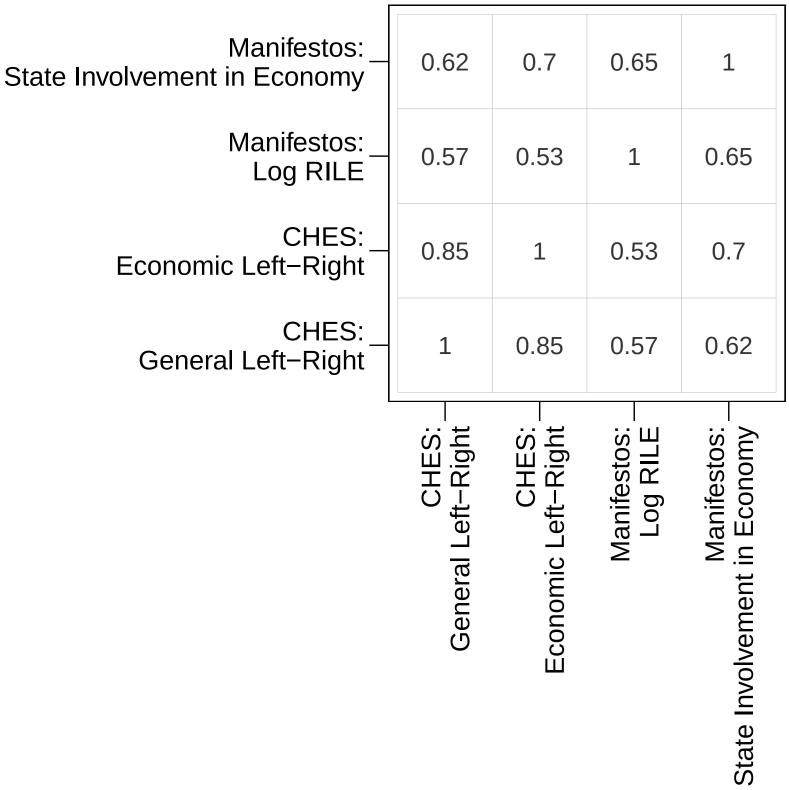
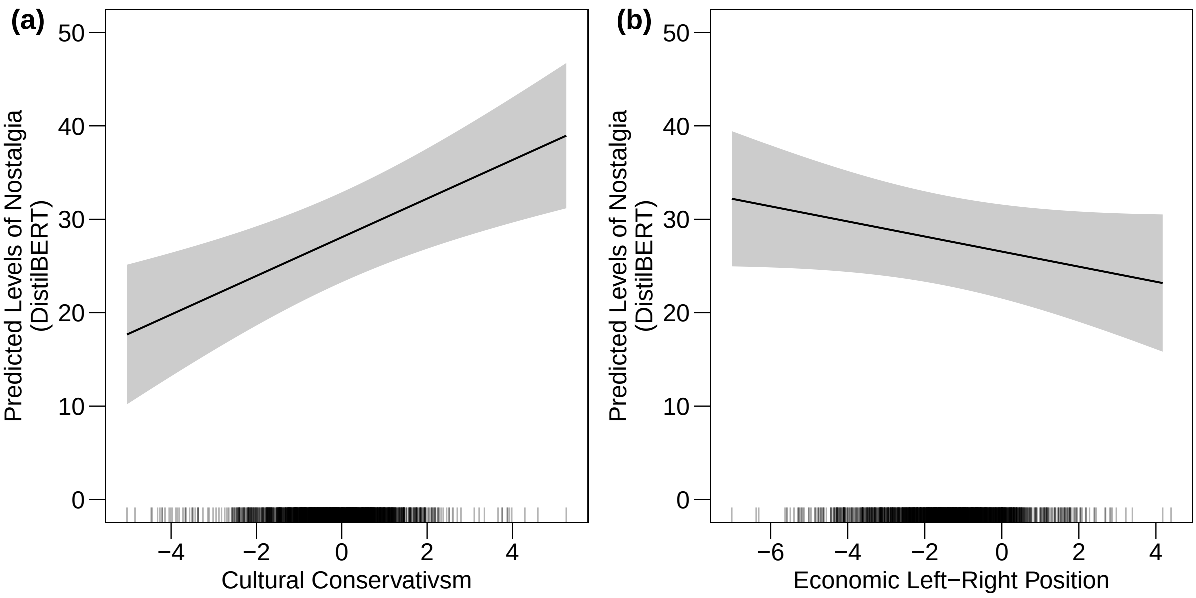


Figure A11. Predicted levels of nostalgia conditional on cultural conservatism (panel a) and economic left-right positions (panel b)



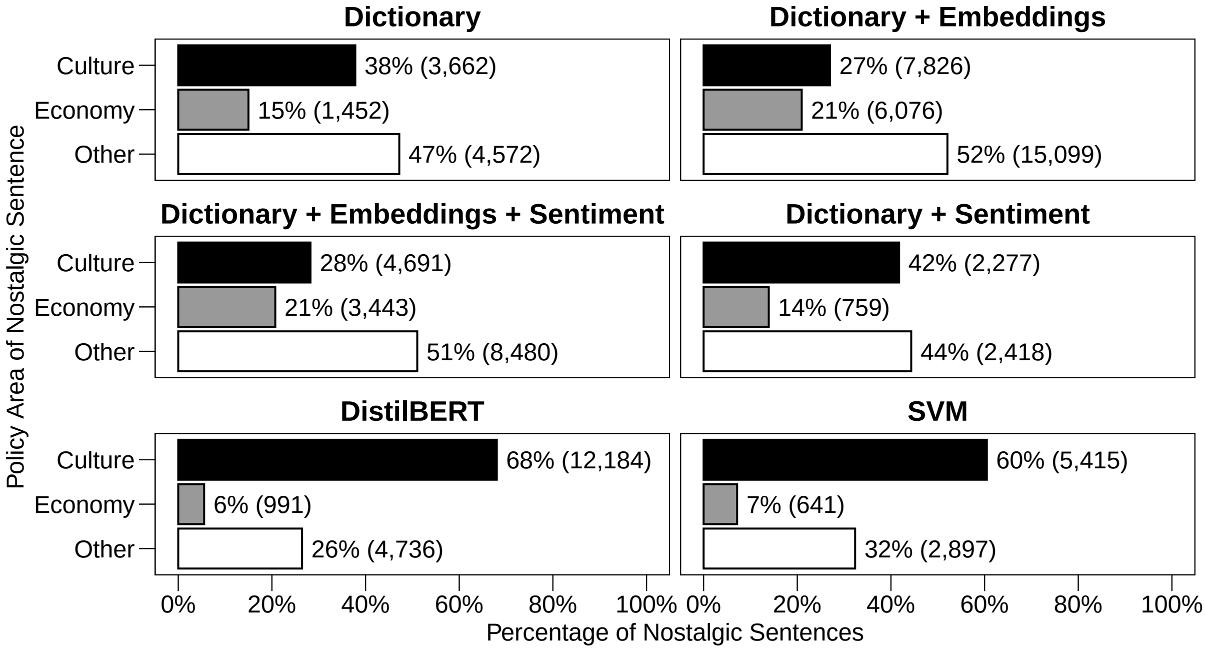
Note: Plots show predicted values for nostalgia and 95 per cent confidence intervals, based on Model 3 from Table 2. The remaining variables are held constant at the reference level (categorical variables) and average (continuous variables).

F Cultural and Economic Nostalgia

We also explore the prevalence of economic and cultural nostalgia. 712 of the 1,648 manifestos in our corpus contain quasi-sentence annotations of policy areas (Krause et al. 2019). We extract the set of nostalgic sentences for each of our six measures and classify them into economic, cultural, and other nostalgic statements. Table A15 shows the detailed policy area (we merge "positive" and "negative" policy codes into one category) and the corresponding aggregated type of nostalgia. We then calculate the proportions of economic, cultural, and "other" nostalgia in the set of nostalgic sentences.[9] Figure A12 reports the percentages for the three main classes for all six methods. Figure A13 calculates the type of nostalgic rhetoric across party families. Table A15 shows the prevalence of the detailed policy areas in our nostalgic sentences. The column *Mean* reports the average prevalence across the six measures. The findings from these analyses are reported in the main paper.

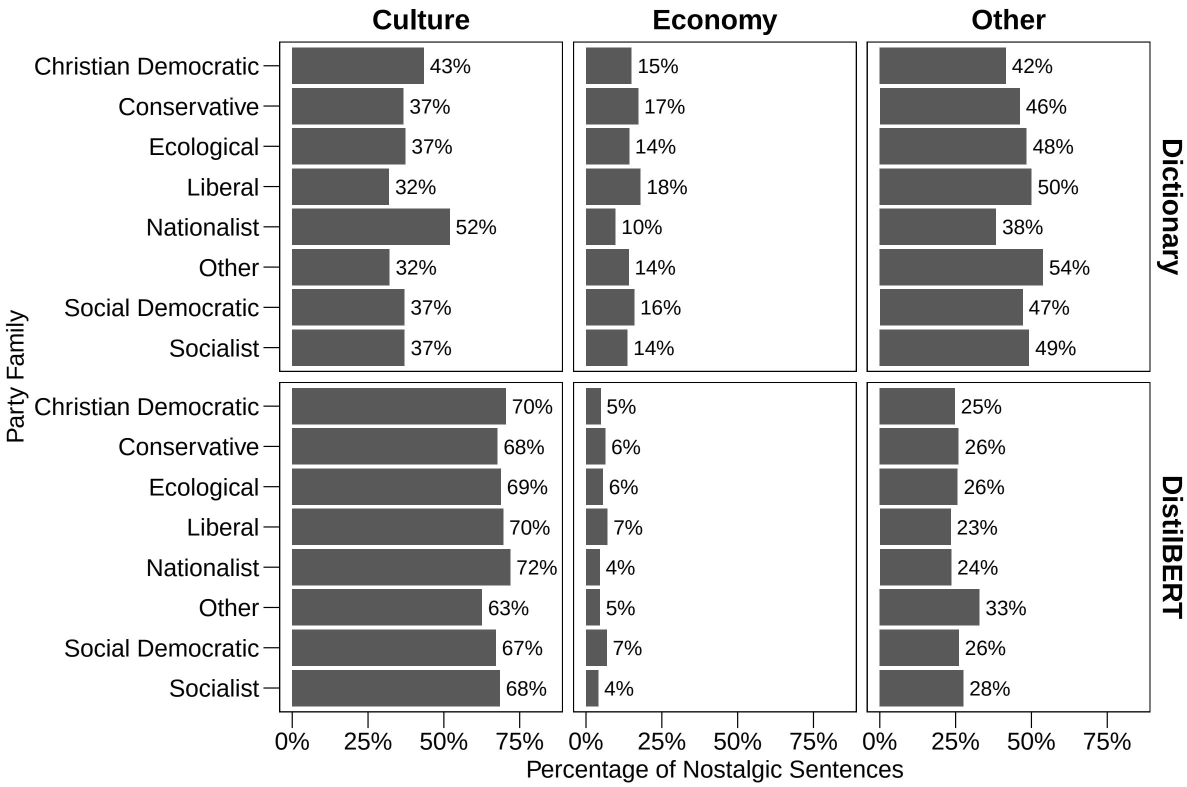
[9]We exclude headings without policy codes and quasi-sentences coded as `000` (no meaningful category applied) before calculating proportions. For more details, see Volkens et al. (2021).

Figure A12. The prevalence of economic policy areas, cultural policy areas, and other policy areas in sentences classified as nostalgic



Note: classification of policy areas based on human codings from the Manifesto Project. Each bar shows the percentages and number of (quasi-)sentences falling into each category. This analysis considers all quasi-sentence annotated manifestos (for more details on the manifesto corpus and codings, see Merz, Regel, and Lewandowski 2016; Däubler et al. 2012). Table A15 lists the prevalence of more fine-grained categories.

Figure A13. The prevalence of economic policy areas, cultural policy areas, and other policy areas in sentences classified as nostalgic



Note: classification of policy areas based on human codings from the Manifesto Project. Each bar shows the percentages of (quasi-)sentences falling into the aggregated policy areas.

Table A15. Prevalance (%) of policy areas in sentences classified as nostalgic

Policy Area	Type	Mean	Dict.	Dict. + Emb.	Dict. + Sent.	Dict. + Emb. + Sent.	SVM	BERT
Culture	Culture	21.7	18.0	9.1	21.9	10.8	31.4	38.9
National Way of Life	Culture	8.3	7.6	5.3	8.3	5.6	11.5	11.7
Environmental Protection	Other	6.3	7.6	7.8	7.8	7.9	3.9	2.9
Multiculturalism	Culture	5.2	3.4	2.8	3.5	2.8	9.1	9.6
Education Expansion	Other	4.0	3.2	3.9	3.6	4.6	5.2	3.6
Welfare State Expansion	Other	3.8	4.2	6.0	3.4	6.0	2.8	0.5
Technology and Infrastructure	Economy	3.6	3.3	5.8	3.4	6.0	1.7	1.5
Traditional Morality	Culture	3.4	3.1	2.8	3.1	2.8	4.1	4.3
Equality	Culture	3.1	3.6	4.5	2.8	3.7	2.0	1.9
Political Authority	Other	2.8	4.4	3.3	3.4	2.5	1.7	1.5
Decentralisation	Other	2.5	2.5	2.5	2.7	2.7	2.3	2.5
Democracy	Other	2.4	2.9	2.4	2.7	2.4	1.9	1.9
Agriculture and Farmers	Other	2.3	2.3	2.7	2.4	3.2	1.5	1.5
Internationalism	Other	2.3	2.2	2.5	2.2	2.7	1.9	2.3
Government Efficiency	Other	2.1	2.3	2.9	2.2	2.7	1.4	1.0
Anti-Growth Economy	Economy	2.0	1.8	3.4	1.9	3.5	1.0	0.5
Civid Mindedness	Culture	1.9	1.6	1.9	1.9	2.1	2.1	1.6
Freedom and Human Rights	Other	1.9	2.2	2.0	2.5	2.2	1.1	1.3
European Union	Other	1.7	2.0	1.8	1.9	1.6	1.2	1.5
Economic Growth	Economy	1.6	2.0	2.0	1.8	2.1	1.0	0.9
Economic Goals	Economy	1.4	1.8	1.9	1.4	1.7	0.7	0.9
Labour Groups	Other	1.4	1.6	2.3	1.3	2.3	0.7	0.3
Law and Order	Other	1.4	2.0	2.4	1.2	1.6	0.8	0.4
Market Regulation	Economy	1.4	1.7	2.1	1.5	2.0	0.6	0.3
Uncoded	Other	1.3	1.4	1.4	1.1	1.1	1.3	1.5
Military	Other	1.2	1.4	1.7	1.4	1.5	0.9	0.4
Economic Orthodoxy	Economy	0.9	1.3	1.7	1.0	1.3	0.3	0.1
Incentives	Economy	0.9	1.0	1.3	1.0	1.3	0.6	0.5
Underprivileged Minority Groups	Other	0.9	0.7	1.1	0.6	1.0	0.9	0.8
Non-economic Demographic Groups	Other	0.8	0.7	1.5	0.6	1.3	0.4	0.3
Foreign Special Relationships	Other	0.7	0.7	0.6	0.7	0.6	0.6	0.7
Constitutionalism	Other	0.6	0.5	0.6	0.6	0.6	0.5	0.5
Free Market Economy	Economy	0.6	0.7	0.9	0.6	0.8	0.4	0.4
Political Corruption	Other	0.5	0.8	0.8	0.4	0.6	0.3	0.2
Nationalism	Culture	0.4	0.5	0.6	0.3	0.5	0.2	0.1
Peace	Other	0.4	0.5	0.4	0.6	0.4	0.3	0.3
Anti-Imperialism	Other	0.3	0.4	0.4	0.3	0.2	0.2	0.2
Controlled Economy	Economy	0.3	0.3	0.4	0.3	0.4	0.2	0.1
Economic Planning	Economy	0.3	0.2	0.4	0.3	0.5	0.2	0.1
Middle Class and Professional Groups	Other	0.3	0.2	0.4	0.3	0.5	0.2	0.2
Protectionism	Economy	0.3	0.3	0.4	0.3	0.4	0.2	0.1
Welfare State Limitation	Other	0.3	0.3	0.5	0.4	0.5	0.2	0.1
Corporatism/Mixed Economy	Economy	0.2	0.2	0.2	0.3	0.3	0.2	0.0
Centralisation	Other	0.1	0.1	0.1	0.0	0.1	0.1	0.1
Keynesian Demand Management	Economy	0.1	0.1	0.3	0.1	0.2	0.0	0.0
Marxist Analysis	Economy	0.1	0.2	0.2	0.1	0.2	0.1	0.1
Education Limitation	Other	0.0	0.0	0.0	0.0	0.0	0.0	0.0

References

Bakker, R. et al. (2020). *1999–2019 Chapel Hill Expert Survey Trend File. Version 1.2*. URL: https://chesdata.eu.

Bates, D. et al. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* 67(1), 1–48.

Benoit, K. et al. (2018). quanteda: An R Package for the Quantitative Analysis of Textual Data. *The Journal of Open Source Software* 3(30), 774.

Blair, G. et al. (2022). *estimatr: Fast Estimators for Design-Based Inference*. R package version 1.0.0. URL: https://CRAN.R-project.org/package=estimatr.

Bondi, M. and M. Scott, eds. (2010). *Keyness in Texts*. Amsterdam: John Benjamins.

Bonikowski, B. et al. (2022). Politics as Usual? Measuring Populism, Nationalism, and Authoritarianism in U.S. Presidential Campaigns (1952–2020) with Neural Language Models. *Sociological Methods & Research* 51(4), 1721–1787.

Däubler, T. et al. (2012). Natural Sentences as Valid Units for Coded Political Texts. *British Journal of Political Science* 41(4), 937–951.

Davalos, S. et al. (2015). 'The Good Old Days': An Examination of Nostalgia in Facebook Posts. *International Journal of Human-Computer Studies* 83, 83–93.

De Vries, C. E. and I. Hoffmann (2018). The Power of the Past: How Nostalgia Shapes European Public Opinion. Gütersloh: Bertelsmann-Stiftung.

De Vries, E. et al. (2018). No Longer Lost in Translation: Evidence that Google Translate Works for Comparative Bag-of-Words Text Applications. *Political Analysis* 26(4), 417–430.

Döring, H. and P. Manow (2021). *Parliaments and Governments Database (ParlGov): Information on Parties, Elections and Cabinets in Modern Democracies. Development Version*. URL: http://parlgov.org.

Düpont, N. and M. Rachuj (2022). The Ties That Bind: Text Similarities and Conditional Diffusion among Parties. *British Journal of Political Science* 52(2), 613–630.

Elçi, E. (2022). Politics of Nostalgia and Populism: Evidence from Turkey. *British Journal of Political Science* 52(2), 697–714.

Gilardi, F. et al. (2023). ChatGPT Outperforms Crowd-Workers for Text-Annotation Tasks. *Proceedings of the National Academy of Sciences of the United States of America* 120(3), e2305016120.

Goet, N. D. (2019). Measuring Polarization with Text Analysis: Evidence from the UK House of Commons, 1811–2015. *Political Analysis* 27(4), 518–539.

Hargrave, L. and J. Blumenau (2022). No Longer Conforming to Stereotypes? Gender, Political Style, and Parliamentary Debate in the UK. *British Journal of Political Science* 52(4), 1584–1601.

Hvitfeldt, E. and J. Silge (2021). Supervised Machine Learning For Text Analysis in R. Boca Raton: CRC Press.

Krause, W. et al. (2019). Manifesto Corpus: Version 2019-2. Berlin: WZB Berlin Social Science Center.

Lammers, J. and M. Baldwin (2018). Past-Focused Temporal Communication Overcomes Conservatives' Resistance to Liberal Political Ideas. *Journal of Personality and Social Psychology* 114(4), 599–619.

Lenz, G. S. and A. Sahn (2021). Achieving Statistical Significance with Covariates and Without Transparency. *Political Analysis* 29(3), 356–360.

Lowe, W. et al. (2011). Scaling Policy Preferences from Coded Political Texts. *Legislative Studies Quarterly* 36(1), 125–155.

Merz, N. et al. (2016). The Manifesto Corpus: A New Resource for Research on Political Parties and Quantitative Text Analysis. *Research and Politics* 3(2), 1–8.

Mikhaylov, S. et al. (2012). Coder Reliability and Misclassification in the Human Coding of Party Manifestos. *Political Analysis* 20(1), 78–91.

Pennington, J. et al. (2014). *GloVe: Global Vectors for Word Representation*. URL: https://nlp.stanford.edu/pubs/glove.pdf.

Pew Research Center (2017). *Spring 2017 Global Attitudes Survey*. URL: https://www.pewresearch.org/global/dataset/spring-2017-survey-data/.

Proksch, S.-O. et al. (2019). Multilingual Sentiment Analysis: A New Approach to Measuring Conflict in Legislative Speeches. *Legislative Studies Quarterly* 44(1), 97–131.

Rathje, S. et al. (2023). *GPT is an Effective Tool for Multilingual Psychological Text Analysis*. PsyArXiv Preprints. URL: https://doi.org/10.31234/osf.io/sekf5.

Sanh, V. et al. (2019). DistilBERT, a Distilled Version of BERT: Smaller, Faster, Cheaper and Lighter. *5th Workshop on Energy Efficient Machine Learning and Cognitive Computing – NeurIPS 2019.*

Spirling, A. (2023). Open Generative AI Models are a Way Forward for Science. *Nature* 616, 413.

Theocharis, Y. et al. (2016). A Bad Workman Blames His Tweets: The Consequences of Citizens' Uncivil Twitter Use When Interacting With Party Candidates. *Journal of Communication* 66(6), 1007–1031.

Volkens, A. et al. (2021). *The Manifesto Data Collection: Manifesto Project (MRG/CMP/MARPOR). Version 2021a*. Berlin: Wissenschaftszentrum Berlin für Sozialforschung. URL: https://doi.org/10.25522/manifesto.mpds.2021a.

Widmann, T. and M. Wich (2022). Creating and Comparing Dictionary, Word Embedding, and Transformer-Based Models to Measure Discrete Emotions in German Political Text. *Political Analysis* FirstView(doi: 10.1017/pan.2022.15).

Young, L. and S. N. Soroka (2012). Affective News: The Automated Coding of Sentiment in Political Texts. *Political Communication* 29(2), 205–231.