**Online Appendix for**

**“The Distinctive Vocabularies of Right-Wing Populists”**

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**Appendix A – Subcorpora Composition**

**UNITED STATES**

**Table A.1: Donald Trump speeches**

|  |  |  |
| --- | --- | --- |
|  | **Place** | **Date** |
| 1 | Monessen, Pennsylvania  | 28.06.2016 |
| 2 | New York City, New York  | 16.07.2016 |
| 3 | Cleveland, Ohio  | 21.07.2016 |
| 4 | Green Bay, Wisconsin  | 05.08.2016 |
| 5 | Detroit, Michigan  | 08.082016 |
| 6 | Fayetteville, North Carolina  | 09.08.2016 |
| 7 | Youngstown, Ohio  | 15.08.2016 |
| 8 | Dimondale, Michigan  | 19.08.2016 |
| 9 | Akron, Ohio  | 22.08.2016 |
| 10 | Jackson, Mississippi  | 24.08.2016 |
| 11 | Washington DC  | 30.08.2016 |
| 12 | Phoenix, Arizona  | 31.08.2016 |
| 13 | Detroit, Michigan  | 03.09.2016 |
| 14 | Philadelphia, Pennsylvania  | 07.09.2016 |
| 15 | Washington DC  | 09.09.2016 |
| 16 | Miami, Florida  | 16.09.2016 |
| 17 | West Palm Beach, Florida  | 13.10.2016 |
| 18 | Gettysburg, Pennsylvania  | 22.10.2016 |
| 19 | Valley Forge, Pennsylvania  | 01.11.2016 |
| 20 | Eau Claire, Wisconsin  | 01.112016 |
| 21 | Pensacola, Florida  | 02.11.2016 |
| 22 | Raleigh, North Carolina  | 07.11.2016 |

**Table A.2: Hillary Clinton speeches**

|  |  |  |
| --- | --- | --- |
|  | **Place** | **Date** |
| 1 | New York City, New York  | 06.11.2015 |
| 2 | Charlotte, North Carolina  | 07.05.2016 |
| 3 | Hampton, New Hampshire  | 09.05.2016 |
| 4 | Washington DC  | 14.06.2016 |
| 5 | Raleigh, North Carolina  | 23.06.2016 |
| 6 | Atlantic City, New Jersey  | 06.07.2016 |
| 7 | Philadelphia, Pennsylvania  | 11.07.2016 |
| 8 | Portsmouth, New Hampshire  | 12.07.2016 |
| 9 | Springfield, Illinois  | 13.07.2016 |
| 10 | Cincinnati, Ohio  | 18.07.2016 |
| 11 | Washington DC  | 26.07.2016 |
| 12 | Johnstown, Pennsylvania  | 30.07.2016 |
| 13 | Pittsburgh, Pennsylvania  | 30.07.2016 |
| 14 | Youngstown, Ohio  | 30.07.2016 |
| 15 | Columbus, Ohio  | 31.07.2016 |
| 16 | Tampa, Florida  | 22.07.2016 |
| 17 | Philadelphia, Pennsylvania  | 28.07.2016 |
| 18 | Omaha, Nebraska  | 01.08.2016 |
| 19 | Commerce City, Colorado  | 03.08.2016 |
| 20 | Warren, Michigan  | 11.08.2016 |
| 21 | Reno, Nevada  | 25.08.2016 |
| 22 | Greensboro, North Carolina  | 15.09.2016 |
| 23 | Washington DC  | 16.09.2016 |
| 24 | Washington DC  | 18.09.2016 |
| 25 | Philadelphia, Pennsylvania  | 19.09.2016 |
| 26 | Orlando, Florida  | 21.09.2016 |
| 27 | Charlotte, North Carolina  | 02.10.2016 |
| 28 | Akron, Ohio  | 03.10.2016 |
| 29 | Columbus, Ohio  | 10.10.2016 |
| 30 | Miami, Florida  | 11.10.2016 |

**FRANCE**

**Table A.3: Marine Le Pen speeches**

|  |  |  |
| --- | --- | --- |
|  | **Place**  | **Date** |
| 1 | Fréjus  | 18.09.2016 |
| 2 | Paris  | 09.12.2016 |
| 3 | Lyon  | 05.02.2017 |
| 4 | Pierrelatte  | 25.02.2017 |
| 5 | Nantes  | 26.02.2017 |
| 6 | Mont Saint-Michel  | 27.02.2017 |
| 7 | Mirande  | 09.03.2017 |
| 8 | Chateauroux  | 11.03.2017 |
| 9 | Paris  | 13.03.2017 |
| 10 | Metz  | 18.03.2017 |
| 11 | Saint Raphael  | 21.03.2017 |
| 12 | N’Djaména  | 23.03.2017 |
| 13 | Lille  | 27.03.2017 |
| 14 | Bordeaux  | 02.04.2017 |
| 15 | Monswiller  | 05.04.2017 |
| 16 | Ajaccio  | 09.04.2017 |
| 17 | Arcis-sur-Aube  | 11.04.2017 |
| 18 | Pageas  | 13.04.2017 |
| 19 | Henin-Beaumont  | 23.04.2017 |
| 20 | Paris  | 07.05.2017 |

**Table A.4: Emmanuel Macron speeches**

|  |  |  |
| --- | --- | --- |
|  | **Place** | **Date** |
| 1 | Bobigny  | 16.11.2016 |
| 2 | Angers  | 28.02.2017 |
| 3 | Caen  | 04.03.2017 |
| 4 | Talence  | 09.03.2017 |
| 5 | Reims  | 17.03.2017 |
| 6 | Dijon  | 25.03.2017 |
| 7 | Mayotte  | 26.03.2017 |
| 8 | Marseille  | 01.04.2017 |
| 9 | Furiani  | 07.04.2017 |
| 10 | Besançon  | 11.04.2017 |
| 11 | Pau  | 12.04.2017 |
| 12 | Chatellerault  | 18.04.2017 |
| 13 | Nantes  | 19.04.2017 |
| 14 | Victoire  | 23.04.2017 |
| 15 | Arras  | 26.04.2017 |
| 16 | Albi  | 04.05.2017 |

**ITALY**

**Table A.5: Matteo Salvini speeches**

|  |  |  |
| --- | --- | --- |
|  | **Place** | **Date** |
| 1 | Milan | 22.02.2014 |
| 2 | Pontida | 04.04.2014 |
| 3 | Buja | 05.04.2014 |
| 4 | Verona | 06.04.2014 |
| 5 | Bergamo | 13.04.2014 |
| 6 | Treviso | 24.04.2014 |
| 7 | Monza | 30.04.2014 |
| 8 | Cagliari | 02.05.2014 |
| 9 | Genoa | 03.05.2014 |
| 10 | Lamezia Terme | 05.05.2014 |
| 11 | Rome | 11.05.2014 |
| 12 | Padua | 20.07.2014 |
| 13 | Milan | 18.10.2014 |
| 14 | Rome | 19.12.2014 |
| 15 | Bergamo | 28.12.2014 |
| 16 | Rome | 28.02.2015 |
| 17 | Montesilvano | 21.03.2015 |
| 18 | Terni | 14.04.2015 |
| 19 | Reggio Emilia | 25.04.2015 |
| 20 | Catania | 27.05.2015 |
| 21 | Martinengo | 02.06.2015 |
| 22 | Pontida | 21.06.2015 |
| 23 | Milan | 04.07.2015 |
| 24 | Pontida | 18.09.2016 |
| 25 | Florence | 12.11.2016 |

**Table A.6: Matteo Renzi speeches**

|  |  |  |
| --- | --- | --- |
|  | **Place** | **Date** |
| 1 | Rome | 08.12.2013 |
| 2 | Milan | 15.12.2013 |
| 3 | Rome | 13.02.2014 |
| 4 | Palermo | 14.05.2014 |
| 5 | Cesena | 16.05.2014 |
| 6 | Bergamo | 20.05.2014 |
| 7 | Rome | 22.05.2014 |
| 8 | Rome | 14.06.2014 |
| 9 | Rome | 08.12.2014 |
| 10 | Florence | 13.12.2015 |
| 12 | Rome | 14.12.2014 |
| 13 | Rome | 07.02.2016 |
| 14 | Rome | 13.03.2016 |
| 15 | Rome | 04.04.2016 |
| 16 | Milan | 31.05.2016 |
| 17 | Rome | 04.07.2016 |
| 18 | Rome | 23.07.2016 |
| 19 | Rome | 29.10.2016 |
| 20 | Florence | 06.11.2016 |

**Appendix B1 - Analysis excluding stop words**

As explained in the text, we include stop words (i.e. grammar words) in our main analysis since these may contribute to populist style. To ensure that their inclusion does not significantly affect our conclusions regarding the presence of the main pillars of populist ideology, we re-run the analysis excluding stop words. (i.e. words tagged as pronouns, prepositions, determiners, conjunctions, numbers, abbreviations, exclamations by TagAnt: Anthony, L., 2015, TagAnt (1.2.0) [Computer Software]. Tokyo, Japan: Waseda University. Available from https://www.laurenceanthony.net/software ), in addition to all items lemmatized as “unknown”, since their part of speech (POS) classification is likely to be incorrect. In other words, we only leave nouns, proper names, foreign words, adjectives, adverbs, and verbs in our corpus. We then extract the keywords for all leaders again, using the same settings as described in the main text.

The results are reported for each pair of leaders in the figures below.[[1]](#footnote-1) These are consistent with our findings in the paper regarding the distinctive presence of words indicating ‘people’, ‘elite’, and ‘others’ in the speeches of right-wing populists. For example, in Trump’s new list of keywords, only “are” and “is” are not included in our previous keyword list. However, they are not significant in terms of semantic fields. Similarly, while among Clinton’s new keywords, we find “campaign”, “election”, “everything”, “ideas”, and “progress”, this does not change our substantive conclusion that her speeches stressed social inclusion. As regards the French and Italian subcorpora, again we can see no significant changes compared to the analysis reported in the paper that would call into question the conclusions we drew there.

**Figure B1.1: Trump and Clinton Keywords (excluding stop words)**



**Figure B1.2: Le Pen and Macron Keywords (excluding stop words)**



**Figure B1.3: Salvini and Renzi Keywords (excluding stop words)**

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**Appendix B2 – Analysis using chi-square distance**

The chi-square distance was used to check the results obtained with AntConc.

In descending order of chi-square contribution, the top results were selected in order to match the number of keywords produced by AntConc per each leader, and the resulting tables were compared to extract the types which are not included in both lists referring to the same leader.

Differences in rank order were not taken into account, since the corpus analysis conducted in this research considers all the keywords produced by AntConc in their contexts.

The tables below provide all data obtained through the chi-square distance, along with the differences in the types extracted with both methods. These differences are limited in number and do not identify alternative topics or stylistic traits different to those we discuss in the paper.

**Donald Trump**

Four types included in the chi-square list but not in the keyness list: by, percent, the, trillion;

Six types included in the keyness list but not in the chi-square list: american, deficit, destroyed, dishonest, establishment, Libya.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Rank** | **Type** | **Trump Occurrences** | **Clinton Occurrences** | **Chi-Square**  |
| 1 | hillary | 351 | 2 | 0.00357 |
| 2 | clinton | 321 | 9 | 0.00305 |
| 3 | will | 1074 | 427 | 0.00285 |
| 4 | they | 1169 | 493 | 0.00281 |
| 5 | she | 553 | 151 | 0.00236 |
| 6 | very | 361 | 76 | 0.00191 |
| 7 | gonna | 147 | 0 | 0.00152 |
| 8 | it | 1698 | 1181 | 0.00092 |
| 9 | great | 347 | 141 | 0.00089 |
| 10 | isis | 102 | 8 | 0.00083 |
| 11 | folks | 102 | 10 | 0.00078 |
| 12 | going | 781 | 484 | 0.00070 |
| 13 | trade | 152 | 39 | 0.00069 |
| 14 | re | 779 | 487 | 0.00068 |
| 15 | administration | 76 | 4 | 0.00067 |
| 16 | bad | 99 | 16 | 0.00062 |
| 17 | ok | 65 | 2 | 0..00061 |
| 18 | incredible | 66 | 3 | 0..00059 |
| 19 | terrorism | 62 | 2 | 0..00058 |
| 20 | nafta | 56 | 0 | 0..00058 |
| 21 | tremendous | 60 | 2 | 0..00056 |
| 22 | have | 1091 | 771 | 0.00055 |
| 23 | country | 488 | 287 | 0.00053 |
| 24 | massive | 56 | 2 | 0.00052 |
| 25 | illegal | 61 | 4 | 0.00052 |
| 26 | almost | 49 | 0 | 0.00051 |
| 27 | disaster | 72 | 9 | 0.00051 |
| 28 | immigration | 91 | 18 | 0.00050 |
| 29 | total | 51 | 1 | 0.00050 |
| 30 | obamacare | 47 | 0 | 0.00049 |
| 31 | countries | 93 | 20 | 0.00049 |
| 32 | never | 186 | 78 | 0.00045 |
| 33 | border | 49 | 2 | 0.00045 |
| 34 | horrible | 49 | 2 | 0.00045 |
| 35 | borders | 43 | 0 | 0.00045 |
| 36 | happen | 107 | 30 | 0.00044 |
| 37 | crime | 51 | 3 | 0.00044 |
| 38 | number | 74 | 13 | 0.00044 |
| 39 | politicians | 55 | 5 | 0.00043 |
| 40 | totally | 57 | 6 | 0.00043 |
| 41 | iraq | 44 | 1 | 0.00043 |
| 42 | mexico | 74 | 14 | 0.00042 |
| 43 | radical | 49 | 3 | 0.00042 |
| 44 | which | 161 | 65 | 0.00042 |
| 45 | deals | 64 | 10 | 0.00041 |
| 46 | syria | 39 | 0 | 0.00040 |
| 47 | inner | 52 | 5 | 0.00040 |
| 48 | media | 44 | 2 | 0.00040 |
| 49 | east | 41 | 1 | 0.00039 |
| 50 | dollars | 80 | 20 | 0.00037 |
| 51 | foreign | 64 | 12 | 0.00037 |
| 52 | cash | 41 | 2 | 0.00037 |
| 53 | regulations | 41 | 2 | 0.00037 |
| 54 | islamic | 38 | 1 | 0.00036 |
| 55 | wanna | 35 | 0 | 0.00036 |
| 56 | amazing | 55 | 8 | 0.00036 |
| 57 | been | 288 | 162 | 0.00036 |
| 58 | corrupt | 34 | 0 | 0.00035 |
| 59 | cities | 70 | 16 | 0.00035 |
| 60 | look | 176 | 82 | 0.00035 |
| 61 | its | 79 | 21 | 0.00035 |
| 62 | obama | 132 | 53 | 0.00034 |
| 63 | these | 230 | 121 | 0.00034 |
| 64 | immediately | 36 | 1 | 0.00034 |
| 65 | by | 382 | 240 | 0.00033 |
| 66 | emails | 31 | 0 | 0.00032 |
| 67 | iran | 44 | 5 | 0.00032 |
| 68 | unbelievable | 39 | 3 | 0.00032 |
| 69 | government | 90 | 30 | 0.00031 |
| 70 | ever | 131 | 56 | 0.00031 |
| 71 | percent | 123 | 51 | 0.00030 |
| 72 | hispanic | 29 | 0 | 0.00030 |
| 73 | the | 4034 | 3538 | 0.00030 |
| 74 | trillion | 41 | 5 | 0.00029 |

**Hillary Clinton**

Three types included in the chi-square list but not in the keyness one: *about, access, ahead*;

Four types included in the keyness list but not in the chi-square one: *America, com, I, need*.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Rank** | **Type** | **Clinton Occurrences** | **Trump Occurrences** | **Chi-Square**  |
| 1 | he | 929 | 324 | 0.00308 |
| 2 | his | 289 | 49 | 0.00179 |
| 3 | to | 3889 | 3005 | 0.00125 |
| 4 | together | 228 | 55 | 0.00111 |
| 5 | donald | 200 | 48 | 0.00098 |
| 6 | need | 263 | 84 | 0.00097 |
| 7 | economy | 158 | 28 | 0.00095 |
| 8 | women | 153 | 26 | 0.00095 |
| 9 | work | 309 | 116 | 0.00093 |
| 10 | trump | 311 | 119 | 0.00091 |
| 11 | here | 336 | 140 | 0.00085 |
| 12 | kids | 102 | 10 | 0.00079 |
| 13 | sure | 117 | 17 | 0.00078 |
| 14 | families | 154 | 36 | 0.00077 |
| 15 | college | 80 | 6 | 0.00067 |
| 16 | young | 105 | 18 | 0.00065 |
| 17 | help | 130 | 32 | 0.00062 |
| 18 | kind | 76 | 7 | 0.00060 |
| 19 | let | 252 | 110 | 0.00059 |
| 20 | us | 311 | 151 | 0.00059 |
| 21 | who | 558 | 338 | 0.00058 |
| 22 | hard | 137 | 39 | 0.00057 |
| 23 | make | 368 | 195 | 0.00057 |
| 24 | should | 190 | 75 | 0.00053 |
| 25 | when | 340 | 180 | 0.00053 |
| 26 | everyone | 128 | 39 | 0.00050 |
| 27 | too | 138 | 45 | 0.00050 |
| 28 | family | 122 | 36 | 0.00049 |
| 29 | still | 80 | 14 | 0.00049 |
| 30 | someone | 48 | 1 | 0.00047 |
| 31 | can | 523 | 330 | 0.00047 |
| 32 | disabilities | 44 | 0 | 0.00046 |
| 33 | climate | 46 | 1 | 0.00045 |
| 34 | for | 1157 | 870 | 0.00045 |
| 35 | well | 184 | 79 | 0.00044 |
| 36 | how | 235 | 115 | 0.00044 |
| 37 | pay | 154 | 60 | 0.00044 |
| 38 | tim | 55 | 5 | 0.00044 |
| 39 | wage | 44 | 2 | 0.00040 |
| 40 | police | 107 | 34 | 0.00040 |
| 41 | about | 433 | 272 | 0.00040 |
| 42 | dad | 40 | 1 | 0.00039 |
| 43 | businesses | 110 | 37 | 0.00038 |
| 44 | president | 254 | 136 | 0.00038 |
| 45 | challenges | 42 | 2 | 0.00038 |
| 46 | stronger | 60 | 10 | 0.00037 |
| 47 | mother | 43 | 3 | 0.00036 |
| 48 | access | 42 | 3 | 0.00035 |
| 49 | small | 112 | 41 | 0.00035 |
| 50 | ahead | 57 | 10 | 0.00035 |
| 51 | black | 46 | 5 | 0.00035 |
| 52 | every | 271 | 154 | 0.00034 |
| 53 | campaign | 127 | 51 | 0.00034 |
| 54 | election | 99 | 34 | 0.00034 |

**Marine Le pen**

Three types included in the chi-square list but not in the keyness one: *comme, mon, ses*;

Four types included in the keyness list but not in the chi-square one: *à, l, m, s*.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Rank** | **Type** | **Le Pen Occurrences** | **Macron Occurrences** | **Chi-Square**  |
| 1 | français | 575 | 162 | 0.00236 |
| 2 | de | 5190 | 3995 | 0.00145 |
| 3 | fillon | 142 | 6 | 0.00129 |
| 4 | macron | 152 | 11 | 0.00126 |
| 5 | france | 667 | 330 | 0.00114 |
| 6 | etat | 277 | 79 | 0.00112 |
| 7 | peuple | 241 | 60 | 0.00111 |
| 8 | car | 121 | 9 | 0.00099 |
| 9 | immigration | 123 | 11 | 0.00096 |
| 10 | union | 100 | 5 | 0.00089 |
| 11 | son | 267 | 93 | 0.00085 |
| 12 | nationale | 98 | 7 | 0.00081 |
| 13 | leur | 417 | 200 | 0.00077 |
| 14 | nation | 110 | 14 | 0.00076 |
| 15 | européenne | 119 | 19 | 0.00074 |
| 16 | sans | 221 | 79 | 0.00068 |
| 17 | élection | 101 | 17 | 0.00061 |
| 18 | du | 789 | 513 | 0.00057 |
| 19 | leurs | 158 | 50 | 0.00057 |
| 20 | souveraineté | 68 | 5 | 0.00056 |
| 21 | notamment | 57 | 1 | 0.00056 |
| 22 | système | 147 | 48 | 0.00051 |
| 23 | étrangers | 59 | 5 | 0.00047 |
| 24 | compatriotes | 53 | 3 | 0.00046 |
| 25 | peuples | 53 | 3 | 0.00046 |
| 26 | service | 58 | 5 | 0.00046 |
| 27 | les | 2378 | 1914 | 0.00046 |
| 28 | la | 3222 | 2680 | 0.00044 |
| 29 | référendum | 40 | 0 | 0.00041 |
| 30 | intérêts | 89 | 22 | 0.00041 |
| 31 | hollande | 38 | 0 | 0.00039 |
| 32 | réalité | 67 | 12 | 0.00039 |
| 33 | oeuvre | 44 | 3 | 0.00037 |
| 34 | argent | 62 | 11 | 0.00037 |
| 35 | proximité | 40 | 2 | 0.00035 |
| 36 | pourtant | 42 | 3 | 0.00035 |
| 37 | patriotisme | 35 | 1 | 0.00033 |
| 38 | privés | 35 | 1 | 0.00033 |
| 39 | nations | 31 | 0 | 0.00032 |
| 40 | mon | 96 | 33 | 0.00031 |
| 41 | islamisme | 30 | 0 | 0.00031 |
| 42 | ses | 182 | 91 | 0.00030 |
| 43 | comme | 289 | 171 | 0.00030 |
| 44 | des | 1637 | 1329 | 0.00029 |

**Emmanuel Macron**

Five types included in the chi-square list but not in the keyness one: *faire, pas, qui, responsabilité, temps*;

Four types included in the keyness list but not in the chi-square one: *c, profondeur, uns, y*.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Rank** | **Type** | **Macron Occurrences** | **Le Pen Occurrences** | **Chi-Square** |
| 1 | parce | 748 | 177 | 0.00374 |
| 2 | est | 2564 | 1617 | 0.00237 |
| 3 | ça | 305 | 41 | 0.00212 |
| 4 | que | 2113 | 1345 | 0.00188 |
| 5 | ce | 1274 | 692 | 0.00187 |
| 6 | nous | 1743 | 1087 | 0.00168 |
| 7 | donc | 332 | 90 | 0.00147 |
| 8 | cela | 388 | 134 | 0.00132 |
| 9 | europe | 208 | 38 | 0.00124 |
| 10 | soir | 115 | 8 | 0.00098 |
| 11 | on | 714 | 399 | 0.00097 |
| 12 | projet | 318 | 127 | 0.00088 |
| 13 | oui | 229 | 72 | 0.00087 |
| 14 | là | 252 | 87 | 0.00086 |
| 15 | allons | 123 | 25 | 0.00069 |
| 16 | transformation | 70 | 2 | 0.00067 |
| 17 | alors | 235 | 92 | 0.00067 |
| 18 | vous | 819 | 535 | 0.00066 |
| 19 | celles | 103 | 17 | 0.00065 |
| 20 | merci | 105 | 18 | 0.00065 |
| 21 | nôtre | 78 | 7 | 0.00062 |
| 22 | sommes | 208 | 79 | 0.00062 |
| 23 | train | 77 | 7 | 0.00061 |
| 24 | veux | 302 | 143 | 0.00061 |
| 25 | réussir | 71 | 5 | 0.00060 |
| 26 | elle | 391 | 212 | 0.00058 |
| 27 | hui | 283 | 138 | 0.00054 |
| 28 | mais | 552 | 344 | 0.00053 |
| 29 | portons | 64 | 5 | 0.00053 |
| 30 | territoires | 91 | 18 | 0.00052 |
| 31 | ruralité | 62 | 5 | 0.00051 |
| 32 | vraie | 69 | 8 | 0.00051 |
| 33 | va | 130 | 41 | 0.00049 |
| 34 | porter | 92 | 20 | 0.00049 |
| 35 | devons | 145 | 51 | 0.00048 |
| 36 | avez | 118 | 35 | 0.00048 |
| 37 | quelques | 118 | 35 | 0.00048 |
| 38 | investissement | 70 | 10 | 0.00047 |
| 39 | classes | 92 | 21 | 0.00047 |
| 40 | réconcilier | 45 | 0 | 0.00047 |
| 41 | aujourd | 267 | 138 | 0.00045 |
| 42 | avons | 191 | 85 | 0.00044 |
| 43 | ai | 240 | 121 | 0.00042 |
| 44 | société | 108 | 33 | 0.00042 |
| 45 | plan | 68 | 12 | 0.00041 |
| 46 | culture | 115 | 38 | 0.00041 |
| 47 | terrain | 61 | 9 | 0.00041 |
| 48 | travail | 155 | 64 | 0.00041 |
| 49 | celui | 165 | 71 | 0.00040 |
| 50 | numérique | 49 | 4 | 0.00040 |
| 51 | décidé | 56 | 7 | 0.00040 |
| 52 | formation | 51 | 5 | 0.00040 |
| 53 | concitoyens | 59 | 9 | 0.00039 |
| 54 | et | 2906 | 2500 | 0.00038 |
| 55 | moyennes | 83 | 22 | 0.00038 |
| 56 | allez | 48 | 5 | 0.00037 |
| 57 | renouvellement | 43 | 3 | 0.00037 |
| 58 | front | 47 | 5 | 0.00036 |
| 59 | expliquer | 51 | 7 | 0.00035 |
| 60 | vrai | 61 | 12 | 0.00035 |
| 61 | construit | 41 | 3 | 0.00035 |
| 62 | pas | 1046 | 811 | 0.00034 |
| 63 | faire | 355 | 221 | 0.00034 |
| 64 | construire | 68 | 16 | 0.00034 |
| 65 | transformer | 52 | 8 | 0.00034 |
| 66 | chacune | 47 | 6 | 0.00033 |
| 67 | bout | 49 | 7 | 0.00033 |
| 68 | responsabilité | 59 | 12 | 0.00033 |
| 69 | temps | 160 | 76 | 0.00032 |
| 70 | qui | 1919 | 1615 | 0.00032 |

**Matteo Salvini**

Eight types included in the chi-square list but not in the keyness one: *battaglia, idee, migliaia, non, poi, sud, veneto, lavorare*;

Eight types included in the keyness list but not in the chi-square one: *agricoltura, cazzo, e, federale, i, militante, salvini, lavora*.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Rank** | **Type** | **Salvini Occurrences** | **Renzi Occurrences** | **Chi-Square** |
| 1 | lega | 334 | 7 | 0.00349 |
| 2 | quindi | 494 | 76 | 0.00346 |
| 3 | qua | 273 | 21 | 0.00242 |
| 4 | euro | 407 | 91 | 0.00228 |
| 5 | renzi | 196 | 11 | 0.00185 |
| 6 | gente | 245 | 57 | 0.00133 |
| 7 | casa | 269 | 76 | 0.00124 |
| 8 | moneta | 96 | 0 | 0.00107 |
| 9 | papà | 94 | 4 | 0.00092 |
| 10 | fra | 99 | 10 | 0.00082 |
| 11 | perché | 1061 | 725 | 0.00081 |
| 12 | nord | 86 | 5 | 0.00081 |
| 13 | però | 435 | 225 | 0.00080 |
| 14 | mi | 459 | 244 | 0.00079 |
| 15 | bimbi | 64 | 0 | 0.00071 |
| 16 | pontida | 64 | 0 | 0.00071 |
| 17 | galera | 68 | 2 | 0.00069 |
| 18 | se | 855 | 583 | 0.00066 |
| 19 | fornero | 62 | 1 | 0.00066 |
| 20 | palle | 56 | 0 | 0.00062 |
| 21 | coi | 65 | 4 | 0.00060 |
| 22 | tanto | 97 | 19 | 0.00059 |
| 23 | viva | 75 | 9 | 0.00058 |
| 24 | io | 733 | 499 | 0.00057 |
| 25 | là | 72 | 9 | 0.00055 |
| 26 | bruxelles | 71 | 9 | 0.00054 |
| 27 | donna | 54 | 2 | 0.00054 |
| 28 | ringrazio | 68 | 8 | 0.00053 |
| 29 | sono | 819 | 583 | 0.00052 |
| 30 | gli | 432 | 265 | 0.00050 |
| 31 | immigrazione | 69 | 10 | 0.00050 |
| 32 | vado | 65 | 9 | 0.00048 |
| 33 | magari | 124 | 42 | 0.00047 |
| 34 | normale | 77 | 16 | 0.00045 |
| 35 | ti | 167 | 75 | 0.00041 |
| 36 | ne | 174 | 80 | 0.00041 |
| 37 | uomo | 70 | 16 | 0.00039 |
| 38 | non | 2247 | 1932 | 0.00038 |
| 39 | poi | 285 | 167 | 0.00038 |
| 40 | idee | 80 | 22 | 0.00038 |
| 41 | alfano | 34 | 0 | 0.00038 |
| 42 | terra | 65 | 14 | 0.00037 |
| 43 | lavorare | 84 | 25 | 0.00037 |
| 44 | battaglia | 102 | 36 | 0.00037 |
| 45 | clandestina | 32 | 0 | 0.00036 |
| 46 | clandestini | 31 | 0 | 0.00034 |
| 47 | veneto | 41 | 4 | 0.00034 |
| 48 | li | 126 | 54 | 0.00034 |
| 49 | migliaia | 45 | 6 | 0.00034 |
| 50 | ognuno | 35 | 2 | 0.00033 |
| 51 | sud | 60 | 14 | 0.00033 |

**Matteo Renzi**

Seven types included in the chi-square list but not in the keyness one: *cose, cui, diciamo, insieme, prossimi, semplicemente, sia*;

Seven types included in the keyness list but not in the chi-square one: *assemblea, atteggiamento, è, investimenti, molta, ruolo, significa*.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Rank** | **Type** | **Renzi Occurrences** | **Salvini Occurrences** | **Chi-Square**  |
| 1 | soltanto | 183 | 1 | 0.00193 |
| 2 | dire | 414 | 126 | 0.00159 |
| 3 | noi | 984 | 503 | 0.00154 |
| 4 | qui | 174 | 14 | 0.00145 |
| 5 | partito | 246 | 47 | 0.00142 |
| 6 | politica | 243 | 59 | 0.00117 |
| 7 | abbiamo | 564 | 256 | 0.00116 |
| 8 | vorrei | 134 | 10 | 0.00114 |
| 9 | del | 818 | 439 | 0.00112 |
| 10 | che | 3902 | 2993 | 0.00101 |
| 11 | molto | 154 | 26 | 0.00096 |
| 12 | italia | 474 | 219 | 0.00094 |
| 13 | tra | 130 | 17 | 0.00092 |
| 14 | credo | 118 | 12 | 0.00092 |
| 15 | modo | 124 | 15 | 0.00091 |
| 16 | pd | 172 | 38 | 0.00090 |
| 17 | quale | 97 | 7 | 0.00083 |
| 18 | punto | 178 | 46 | 0.00081 |
| 19 | democratico | 83 | 5 | 0.00074 |
| 20 | ciò | 73 | 2 | 0.00072 |
| 21 | questo | 626 | 357 | 0.00071 |
| 22 | semplicemente | 82 | 8 | 0.00065 |
| 23 | idea | 95 | 14 | 0.00064 |
| 24 | luogo | 59 | 0 | 0.00063 |
| 25 | finalmente | 67 | 3 | 0.00063 |
| 26 | nostro | 174 | 56 | 0.00063 |
| 27 | leopolda | 58 | 0 | 0.00062 |
| 28 | grande | 195 | 69 | 0.00062 |
| 29 | nel | 364 | 186 | 0.00057 |
| 30 | tema | 74 | 8 | 0.00056 |
| 31 | di | 3661 | 2970 | 0.00056 |
| 32 | discussione | 72 | 8 | 0.00054 |
| 33 | allora | 144 | 46 | 0.00052 |
| 34 | bellezza | 46 | 0 | 0.00049 |
| 35 | expo | 48 | 1 | 0.00048 |
| 36 | dato | 85 | 18 | 0.00046 |
| 37 | significa | 80 | 16 | 0.00045 |
| 38 | ma | 763 | 517 | 0.00043 |
| 39 | anche | 501 | 312 | 0.00042 |
| 40 | delle | 343 | 192 | 0.00042 |
| 41 | fatto | 343 | 192 | 0.00042 |
| 42 | detto | 208 | 96 | 0.00041 |
| 43 | certo | 63 | 10 | 0.00041 |
| 44 | questione | 46 | 3 | 0.00040 |
| 45 | discutere | 53 | 6 | 0.00040 |
| 46 | possiamo | 84 | 21 | 0.00039 |
| 47 | dell | 293 | 159 | 0.00039 |
| 48 | accaduto | 35 | 0 | 0.00038 |
| 49 | cambiare | 103 | 33 | 0.00037 |
| 50 | questioni | 34 | 0 | 0.00037 |
| 51 | sia | 211 | 104 | 0.00036 |
| 52 | paese | 213 | 106 | 0.00036 |
| 53 | insieme | 121 | 45 | 0.00036 |
| 54 | cui | 227 | 116 | 0.00036 |
| 55 | dirigente | 33 | 0 | 0.00035 |
| 56 | cambiamento | 35 | 1 | 0.00034 |
| 57 | insegnanti | 35 | 1 | 0.00034 |
| 58 | cose | 133 | 55 | 0.00033 |
| 59 | diciamo | 67 | 16 | 0.00033 |
| 60 | scuola | 104 | 37 | 0.00033 |
| 61 | prossimi | 48 | 7 | 0.00032 |

**Appendix C – Sample of concordances analysis**

Although we checked all concordances including keywords, we utilized another tool provided by AntConc to extract clusters (i.e. recurrent word strings), thus helping to automatically define the contexts in which a word occurs. In our research, this tool was used to complement and guide human reading, but its contribution is limited and mostly restricted to content words.

For example, Trump’s first keyword according to rank is “Hillary”, which is preceded 17 times (out of 354) by “crooked”, 9 by “Obama and” and 8 by “Bill and”; whereas it is followed 243 times by “Clinton” (unsurprisingly). Albeit helpful (Hillary Clinton is obviously associated with other “enemies of the people” and, as such, is the object of Trump’s aggressive criticism), this analytical tool is less revealing when used with grammar words such as modal verbs. For example, Trump’s second keyword is “will” (1074 occurrences): apart from the string “make America great again” (12 times), it is followed by verbs which may be significant but need further investigation of their contexts, such as “build”, “end”, “fight”, “fix”, “rebuild”, “stop”, etc.

**Trump corpus**

Clusters pivoting on “Hillary”

Left-oriented

Top results min. 3 occurrences

Rank Freq. Range

1 243 1 hillary clinton

2 25 1 hillary clinton’s

3 21 1 hillary wants

4 20 1 hillary clinton is

5 19 1 hillary clinton has

6 19 1 hillary clinton's

7 19 1 hillary is

8 17 1 hillary clinton wants

9 16 1 hillary wants to

10 14 1 hillary clinton wants to

11 9 1 hillary is the

12 9 1 hillary is the one

13 9 1 hillary is the one who

14 8 1 hillary clinton and

15 6 1 hillary clinton is the

16 5 1 hillary clinton will

17 5 1 hillary clinton's policies

18 5 1 hillary's

19 4 1 hillary clinton said

20 4 1 hillary clinton, who

21 4 1 hillary’s

22 3 1 hillary and

23 3 1 hillary clinton has been

24 3 1 hillary clinton have

25 3 1 hillary clinton is a

26 3 1 hillary clinton wants to double

27 3 1 hillary clinton was

28 3 1 hillary clinton who

29 3 1 hillary clinton's policies than

30 3 1 hillary clinton: death

31 3 1 hillary clinton: death, destruction

32 3 1 hillary clinton’s plan

33 3 1 hillary wants to invade

34 3 1 hillary wants to invade foreign

35 3 1 hillary wants to invade foreign countries

36 3 1 hillary-backed

N-grams pivoting on “Hillary”

Right-oriented

Top results min. 3 occurrences

Rank Freq. Range

1 33 1 and hillary

2 17 1 crooked hillary

3 14 1 by hillary

4 14 1 that hillary

5 12 1 of hillary

6 11 1 for hillary

7 9 1 obama and hillary

8 8 1 bill and hillary

9 6 1 like hillary

10 6 1 under hillary

11 6 1 while hillary

12 5 1 but hillary

13 5 1 president obama and hillary

14 5 1 supported by hillary

15 5 1 yet hillary

16 4 1 about hillary

17 4 1 another bill and hillary

18 4 1 as secretary of state, hillary

19 4 1 if hillary

20 4 1 into hillary

21 4 1 it. hillary

22 4 1 of state, hillary

23 4 1 secretary of state, hillary

24 4 1 state, hillary

25 4 1 the hillary

26 4 1 with hillary

27 3 1 america first. hillary

28 3 1 and by the way, hillary

29 3 1 because hillary

30 3 1 by the way, hillary

31 3 1 first. hillary

32 3 1 from hillary

33 3 1 on hillary

34 3 1 pre-hillary

35 3 1 right? hillary

36 3 1 that. hillary

37 3 1 the way, hillary

38 3 1 think hillary

39 3 1 way, hillary

40 3 1 when hillary

41 3 1 with crooked Hillary

1. The full corpus is available in Harvard Dataverse at: https://doi.org/10.7910/DVN/N5PYXZ. [↑](#footnote-ref-1)