**Supplement**

What drives anti-immigrant sentiments online? A novel approach using Twitter

1. List of immigration-related search terms (only singular forms are listed).

|  |  |  |
| --- | --- | --- |
| 1. General categories:   immigrant immigration migrant migration refugee foreigner Muslim Islam Islamist asylum seeker illegal alien ethnic minority | 1. Origin-group categories:   Polish Romanian Indian Pakistani Bangladeshi Nepali African Nigerian Kenyan Somali Jamaican Chinese Asian Filipino Syrian Afghani Iraqi Eritrean Kurdish Kurdi Gypsy Poles Eastern European non-EU Sri Lanka |  |

2. List of places used for data collection

|  |  |
| --- | --- |
| Name of a place | Region |
| Watford | Bedfordshire and Hertfordshire |
| Luton | Bedfordshire and Hertfordshire |
| Bedford | Bedfordshire and Hertfordshire |
| Stevenage | Bedfordshire and Hertfordshire |
| Oxford | Berkshire, Buckinghamshire, and Oxfordshire |
| Slough | Berkshire, Buckinghamshire, and Oxfordshire |
| Keynes | Berkshire, Buckinghamshire, and Oxfordshire |
| Reading | Berkshire, Buckinghamshire, and Oxfordshire |
| Aylesbury | Berkshire, Buckinghamshire, and Oxfordshire |
| Bracknell | Berkshire, Buckinghamshire, and Oxfordshire |
| Maidenhead | Berkshire, Buckinghamshire, and Oxfordshire |
| Warrington | Cheshire |
| Chester | Cheshire |
| Crewe | Cheshire |
| Carlisle | Cumbria |
| Derby | Derbyshire and Nottinghamshire |
| Nottingham | Derbyshire and Nottinghamshire |
| Chesterfield | Derbyshire and Nottinghamshire |
| Mansfield | Derbyshire and Nottinghamshire |
| Beeston | Derbyshire and Nottinghamshire |
| Carlton | Derbyshire and Nottinghamshire |
| Exeter | Devon |
| Plymouth | Devon |
| Paignton | Devon |
| Torquay | Devon |
| Bournemouth | Dorset and Somerset |
| Poole | Dorset and Somerset |
| Taunton | Dorset and Somerset |
| Christchurch | Dorset and Somerset |
| Weymouth | Dorset and Somerset |
| Norwich | East Anglia |
| Peterborough | East Anglia |
| Cambridge | East Anglia |
| Ipswich | East Anglia |
| Lowestoft | East Anglia |
| Grimsby | East Riding and North Lincolnshire |
| Scunthorpe | East Riding and North Lincolnshire |
| Swansea | East Wales |
| Bangor | East Wales |
| Neath | East Wales |
| Edinburgh | Eastern Scotland |
| Dundee | Eastern Scotland |
| Livingston | Eastern Scotland |
| Dunfermline | Eastern Scotland |
| Kirkcaldy | Eastern Scotland |
| Southend-On-Sea | Essex |
| Chelmsford | Essex |
| Colchester | Essex |
| Basildon | Essex |
| Raleigh | Essex |
| Harlow | Essex |
| Grays | Essex |
| Brentwood | Essex |
| Clacton-On-Sea | Essex |
| Swindon | Gloucestershire, Wiltshire and Bristol/Bath area |
| Bristol | Gloucestershire, Wiltshire and Bristol/Bath area |
| Gloucester | Gloucestershire, Wiltshire and Bristol/Bath area |
| Cheltenham | Gloucestershire, Wiltshire and Bristol/Bath area |
| Bath | Gloucestershire, Wiltshire and Bristol/Bath area |
| Weston-Super-Mare | Gloucestershire, Wiltshire and Bristol/Bath area |
| Filton | Gloucestershire, Wiltshire and Bristol/Bath area |
| Manchester | Greater Manchester |
| Sale | Greater Manchester |
| Bolton | Greater Manchester |
| Rochdale | Greater Manchester |
| Salford | Greater Manchester |
| Stockport | Greater Manchester |
| Oldham | Greater Manchester |
| Wigan | Greater Manchester |
| Bury | Greater Manchester |
| Atherton | Greater Manchester |
| Altrincham | Greater Manchester |
| Portsmouth | Hampshire and Isle of Wight |
| Southampton | Hampshire and Isle of Wight |
| Newport | Hampshire and Isle of Wight |
| Eastleigh | Hampshire and Isle of Wight |
| Gosport | Hampshire and Isle of Wight |
| Farnborough | Hampshire and Isle of Wight |
| Aldershot | Hampshire and Isle of Wight |
| Worcester | Herefordshire, Worcestershire and Warwickshire |
| Nuneaton | Herefordshire, Worcestershire and Warwickshire |
| Redditch | Herefordshire, Worcestershire and Warwickshire |
| Rugby | Herefordshire, Worcestershire and Warwickshire |
| Hereford | Herefordshire, Worcestershire and Warwickshire |
| Kidderminster | Herefordshire, Worcestershire and Warwickshire |
| London | Inner London - West |
| Maidstone | Kent |
| Basingstoke | Kent |
| Gillingham | Kent |
| Chatham | Kent |
| Ashford | Kent |
| Canterbury | Kent |
| Margate | Kent |
| Gravesend | Kent |
| Rochester | Kent |
| Folkestone | Kent |
| Sittingbourne | Kent |
| Blackpool | Lancashire |
| Blackburn | Lancashire |
| Preston | Lancashire |
| Burnley | Lancashire |
| Lancaster | Lancashire |
| Leicester | Leicestershire, Rutland and Northamptonshire |
| Northampton | Leicestershire, Rutland and Northamptonshire |
| Loughborough | Leicestershire, Rutland and Northamptonshire |
| Corby | Leicestershire, Rutland and Northamptonshire |
| Kettering | Leicestershire, Rutland and Northamptonshire |
| Wellingborough | Leicestershire, Rutland and Northamptonshire |
| Liverpool | Merseyside |
| Birkenhead | Merseyside |
| Southport | Merseyside |
| Widnes | Merseyside |
| Runcorn | Merseyside |
| Wallasey | Merseyside |
| Bebington | Merseyside |
| Bootle | Merseyside |
| Crosby | Merseyside |
| Aberdeen | North Eastern Scotland |
| York | North Yorkshire |
| Harrogate | North Yorkshire |
| Scarborough | North Yorkshire |
| Belfast | Northern Ireland |
| Londonderry | Northern Ireland |
| Craigavon | Northern Ireland |
| Newtownabbey | Northern Ireland |
| Sunderland | Northumberland and Tyne and Wear |
| Gateshead | Northumberland and Tyne and Wear |
| Tynemouth | Northumberland and Tyne and Wear |
| Stoke-On-Trent | Shropshire and Staffordshire |
| Telford | Shropshire and Staffordshire |
| Newcastle-Under-Lyme | Shropshire and Staffordshire |
| Shrewsbury | Shropshire and Staffordshire |
| Tamworth | Shropshire and Staffordshire |
| Cannock | Shropshire and Staffordshire |
| Stafford | Shropshire and Staffordshire |
| Glasgow | South Western Scotland |
| Paisley | South Western Scotland |
| Hamilton | South Western Scotland |
| Cumbernauld | South Western Scotland |
| Sheffield | South Yorkshire |
| Doncaster | South Yorkshire |
| Rotherham | South Yorkshire |
| Barnsley | South Yorkshire |
| Brighton | Surrey, East and West Sussex |
| Crawley | Surrey, East and West Sussex |
| Eastbourne | Surrey, East and West Sussex |
| Worthing | Surrey, East and West Sussex |
| Woking | Surrey, East and West Sussex |
| Hastings | Surrey, East and West Sussex |
| Guildford | Surrey, East and West Sussex |
| Littlehampton | Surrey, East and West Sussex |
| Walton-On-Thames | Surrey, East and West Sussex |
| Ewell | Surrey, East and West Sussex |
| Esher | Surrey, East and West Sussex |
| Smethwick | Surrey, East and West Sussex |
| Horsham | Surrey, East and West Sussex |
| Shoreham-By-Sea | Surrey, East and West Sussex |
| Middlesbrough | Tees Valley and Durham |
| Darling | Tees Valley and Durham |
| Hartlepool | Tees Valley and Durham |
| Stockton-On-Tees | Tees Valley and Durham |
| Durham | Tees Valley and Durham |
| Birmingham | West Midlands |
| Coventry | West Midlands |
| Solihull | West Midlands |
| Wolverhampton | West Midlands |
| Dudley | West Midlands |
| Walsall | West Midlands |
| Stourbridge | West Midlands |
| Halesowen | West Midlands |
| Bloxwich | West Midlands |
| Willenhall | West Midlands |
| Kingswinford | West Midlands |
| Cardiff | West Wales and The Valleys |
| Wrexham | West Wales and The Valleys |
| Barry | West Wales and The Valleys |
| Huddersfield | West Yorkshire |
| Leeds | West Yorkshire |
| Bradford | West Yorkshire |
| Wakefield | West Yorkshire |
| Halifax | West Yorkshire |
| Batley | West Yorkshire |
| Dewsbury | West Yorkshire |
| Keighley | West Yorkshire |

3. List of Twitter accounts of news pages

|  |  |  |  |
| --- | --- | --- | --- |
| dailystar | BBCBreaking | politico | essexlive |
| businesslive | BBCNews | PinkNews | JewishChron |
| birmingham\_live | BBCWorld | ConversationUK | The\_Gazette |
| BelTel | CNN | SkyUK | LloydsList |
| BristolLive | nytimes | BBCLondonNews | FarmersGuardian |
| DailyMirror | TheEconomist | BBCNWT | WMNNews |
| Daily\_Record | Reuters | EveningStandard | SunderlandEcho |
| MailOnline | FoxNews | STVNews | TheJournalNews |
| DailyMailUK | TIME | Londonist | shftelegraph |
| EDP24 | ABC | northwaleslive | Bradford\_TandA |
| edinburghpaper | washingtonpost | getreading | ScottishSun |
| standardnews | XHNews | lancstelegraph | M\_Star\_Online |
| ExpressandStar | HuffPost | Bournemouthecho | News\_Letter |
| FinancialTimes | cnni | ShropshireStar | mayhillmatt |
| FT | BreakingNews | Cambslive | thesundaysport |
| theipaper | NewYorker | live\_coventry | swindonadver |
| leicslive | CBSNews | portsmouthnews | ChurchTimes |
| LivEchonews | NBCNews | hulllive | Essex\_Echo |
| MENnewsdesk | BuzzFeed | NewsShopper | IBTimesUK |
| MetroUK | SkyNews | ChronandEcho | TheBoltonNews |
| nottslive | SkyNewsBreak | TeessideLive | EveningExpress |
| RacingPost | Channel4News | Sotlive | NewJournal |
| SheffieldStar | Independent | irish\_news | newsandstar |
| WalesOnline | cnnbrk | derbyshire\_live | SthLondonPress |
| surreylive | guardiannews | southwalesargus | hackneygazette |
| Telegraph | haveigotnews | CatholicHerald | peterboroughtel |
| brightonargus | BBCPolitics | TheOxfordMail | WigToday |
| TheArtNewspaper | BBCr4today | SwanseaOnline10 | CornishGuardian |
| ChronicleLive | PrivateEyeNews | leponline | peckhampeculiar |
| heraldscotland | itvnews | TheNewEuropean | worcesternews |
| TheScotsman | BBCNewsnight | TheEveningTimes | Southwark\_News |
| TheStage | BBCRadio4 | yorkpress | Sunday\_Post |
| TheSun | BBCR1 | TheNorthernEcho | leaderlive |
| thetimes | BBCOne | TheTLS | ipswichstar24 |
| timeshighered | ITV | thecourieruk | coopnews |
| Observer\_Owl | BBCBreakfast | EveningNews | thesundaypeople |
| LeedsNews | BBCRadio2 | Dorsetecho | HertsMercury |
| yorkshirepost | mediaguardian | Examiner | DevonLiveNews |
| guardian | HuffPostUK | CheshireLive | surreymirror |
| BBC | TelegraphNews | CityAM | pressjournal |

4. Proportion of non-western immigrants (NUTS-2 regions) and number of Twitter users in the panel

|  |  |  |
| --- | --- | --- |
| *Region* | *% non-western immigrants* | *N Twitter*  *users in the panel* |
| Bedfordshire and Hertfordshire | 16,17 | 416 |
| Berkshire, Buckinghamshire, and Oxfordshire | 11,64 | 690 |
| Cheshire | 5,13 | 232 |
| Cornwall and Isles of Scilly | 2,69 | 21 |
| Cumbria | 2,93 | 61 |
| Derbyshire and Nottinghamshire | 8,03 | 708 |
| Devon | 6,13 | 212 |
| Dorset and Somerset | 8,79 | 508 |
| East Anglia | 8,17 | 446 |
| East Riding and North Lincolnshire | 7,11 | 94 |
| East Wales | 3,72 | 197 |
| Eastern Scotland | 6,35 | 934 |
| Essex | 8,72 | 992 |
| Gloucestershire, Wiltshire and Bristol/Bath area | 9,20 | 867 |
| Greater Manchester | 10,75 | 2362 |
| Hampshire and Isle of Wight | 8,01 | 611 |
| Herefordshire, Worcestershire and Warwickshire | 7,26 | 285 |
| Highlands and Islands | 3,09 | 4 |
| London\* | 31,21 | 7873 |
| Kent | 8,02 | 646 |
| Lancashire | 8,27 | 417 |
| Leicestershire, Rutland and Northamptonshire | 14,28 | 647 |
| Lincolnshire | 9,43 | 29 |
| Merseyside | 4,68 | 788 |
| North Eastern Scotland | 11,07 | 92 |
| North Yorkshire | 4,98 | 187 |
| Northern Ireland | 5,28 | 430 |
| Northumberland and Tyne and Wear | 5,02 | 579 |
| Outer London - East and North East | 26,66 | 150 |
| Outer London - South | 24,69 | 163 |
| Outer London - West and North West | 34,76 | 116 |
| Shropshire and Staffordshire | 6,80 | 336 |
| South Western Scotland | 4,19 | 1135 |
| South Yorkshire | 7,26 | 586 |
| Surrey, East and West Sussex | 10,95 | 1618 |
| Tees Valley and Durham | 5,01 | 464 |
| West Midlands | 14,40 | 1666 |
| West Wales and The Valleys | 5,46 | 495 |
| West Yorkshire | 9,82 | 1066 |

\*We combined *Inner London West* and *Inner London East*, since many users indicated ‘London’ in their bio and distinguishing between these two was impossible.

5. Data cleaning process

The data we obtained needed to be cleaned, because it contained irrelevant users and tweets. We carefully documented this filtering process for reasons of transparency and reproducibility, so that scholars can check this process, but also use it for their own work (code will be made available after manuscript acceptance). We filtered out irrelevant *users* based on the following criteria:

(1) The user posted less than two tweets during the year.

(2) All the tweets of the user were posted within one day.

(3) The location of the user returned by the Twitter API was non-identifiable or irrelevant. We excluded users who resided in the USA (many settlements in the USA are called after the UK’s settlements); users who indicated a location which is broader than a NUTS-2 region (for instance, ‘GB’, ‘Scotland’, ‘Nord West’ etc.); users with an empty location field in their Twitter profile; users with multiple locations specified; users with non-existent locations (e.g., ‘the Moon’).

(4) The user had too many Twitter connections. To automatically filter out organisations, celebrities or other influential people, we removed from the dataset those users who had too many outgoing (following) or incoming (followers) ties on Twitter. We excluded users who follow more than 5000 Twitter pages, and users with more than 9361 followers (i.e., highest 10%).

Next, we also excluded irrelevant posts from the corpus of *tweets:*

(1) We removed all the entries from the users who were detected as non-relevant based on the criteria described above.

(2) Then we filtered out the tweets with irrelevant content, such as posts mentioning national cuisine of other countries, political figures, and events in other countries.

(3) Lastly, we removed tweets posted by the same users repeatedly.

6. Ethnicity detection

We used the Twitter account names to infer the ethnicity of users and their connections. For this, we relied on the ethnicity-recognition algorithm ‘ethnicolr’ in Python. Ethnicolr detects ethnic origin based on the sequence of letters in the first and last name; it returns the list of probabilities of belonging to one of 13 ethnic groups, the options are listed below. The groups considered as ‘Western’ in the analysis are marked with a plus sign.

|  |  |
| --- | --- |
| Ethnicity Group | Included as  ‘Western’ |
| Asian, GreaterEastAsian, EastAsian |  |
| Asian, GreaterEastAsian, Japanese |  |
| Asian, IndianSubContinent |  |
| GreaterAfrican, Africans |  |
| GreaterAfrican, Muslim |  |
| GreaterEuropean, British | + |
| GreaterEuropean, EastEuropean |  |
| GreaterEuropean, Jewish |  |
| GreaterEuropean, WestEuropean, French | + |
| GreaterEuropean, WestEuropean, Germanic | + |
| GreaterEuropean, WestEuropean, Hispanic | + |
| GreaterEuropean, WestEuropean, Italian | + |
| GreaterEuropean, WestEuropean, Nordic | + |

7. Results additional analyses

We performed several robustness checks. Overall, findings from these sensitivity checks strongly mirror the results of the main analyses (Table 2 manuscript).

A) SenticNet

The main analyses presented in the paper are based on SentiStrength. A key advantage of that algorithm is accuracy. However, coverage (i.e., the proportion of sentences the method can classify as positive or negative) is lower than some of the other sentiment algorithms. To inspect whether the results are sensitive to the algorithm we used for the quantification of sentiments (i.e., SentiStrength), we performed an additional analysis using SenticNet. SenticNet outperforms other sentiment analyses methods with respect to coverage (Ribeiro et al. 2016). The SenticNet sentiment lexicon contains over 100,000 of words and phrases, annotated by sentiment scores on a continuous scale from -1 to 1. We used the Python package ‘sentic’ for sentiment extraction (Liu, 2018); it also performs necessary pre-processing, including negation handling. For the convenience of interpretation, the original scale of the sentiment score (-1 to 1) was (1) multiplied by 100 and (2) multiplied by -1 to get a reversed scale, because our focus is on anti-immigrant sentiments. Thus, anti-immigrant attitudes on Twitter are measured on a scale from -100 to 100, with larger values indicating stronger negativity*.* S1 Table presents the results.

**S1 Table.** Multilevel hierarchical linear regression analysis of anti-immigrant sentiments on Twitter (using SenticNet)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | **Model 1** |  | **Model 2** |  | **Model 3** |
| ***Fixed Part*** | | | | | | |
| Intercept |  | -13.2504\*\*\* |  | -13.2714\*\*\* |  | -12.3976\*\*\* |
|  |  | (.4194) |  | (.4213) |  | (.5330) |
| Salience immigration |  | .1078\*\* |  | *.1080\*\** |  | .0552 |
| in national news, one week |  | (.0479) |  | .0479 |  | (.0582) |
|  |  |  |  |  |  |  |
| Salience immigration |  |  |  |  |  | .0761\*\*\* |
| in personalised news, one week |  |  |  |  |  | (.0192) |
|  |  |  |  |  |  |  |
| Non-western immigrants in region (%) |  | -.0831\*\*\* |  | -.0840\*\*\* |  | -.1137\*\*\* |
|  |  | (.0308) |  | (.0308) |  | (.0350) |
|  |  |  |  |  |  |  |
| Salience immigration in national news, |  | .0005 |  | .0005 |  | .0015 |
| one week × non-western im. in region (%) |  | (.0045) |  | (.0045) |  | (.0055) |
|  |  |  |  |  |  |  |
| Salience immigration in personalized news, |  |  |  |  |  | -.0009 |
| one week × non-western im. in region (%) |  |  |  |  |  | (.0018) |
|  |  |  |  |  |  |  |
| Non-western ties on Twitter (%) |  |  |  | .0018 |  | -.0147\*\*\* |
|  |  |  |  | (.0037) |  | (.0046) |
|  |  |  |  |  |  |  |
| ***Sample size*** |  |  |  |  |  |  |
| N user-timepoints |  | 314589 |  | 314589 |  | 223685 |
| N users |  | 28161 |  | 28161 |  | 19611 |
| N regions |  | 39 |  | 39 |  | 38 |
| ***Random Part*** | | | | | | |
| *σ2e ij* |  | 512.353438 |  | 512.353438 |  | 499.583762 |
| *σ 2u0 (individual)* |  | 33.968645 |  | 33.968645 |  | 30.458972 |
| *σ 2v0 (region)* |  | 0.146954 |  | 0.146954 |  | 0.159380 |
| ***Model Fit*** | | | | | | |
| *AIC* |  | 2867709 |  | 2867720 |  | 2032939 |
| *BIC* |  | 2867768 |  | 2867768 |  | 2033002 |

*\*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05 (Two-tailed test).Controls: population density region, number of followers on Twitter (log), number of connections on Twitter (log). Model 3 is based on the subsample of those who follow news outlets on Twitter.*

B) Negative sentiment scores

In the main analysis the values for negative words (ranging from -5 to -1) are subtracted from the values for the positive words (range 1-5). The result is the ‘overall’ sentiment of the tweet. Another way to assess the robustness of the findings, is to focus on negative words only and to ignore positive words. The results of this analysis are presented in S2 Table.

**S2 Table.** Multilevel hierarchical linear regression analysis of anti-immigrant sentiments on Twitter   
(SentiStrength, using only negative sentiment scores)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | **Model 1** |  | **Model 2** |  | **Model 3** |
| ***Fixed Part*** | | | | | | |
| Intercept |  | 1.6980\*\*\* |  | 1.7212\*\*\* |  | 1.8349\*\*\* |
|  |  | (.0243) |  | (.0245) |  | (.0304) |
| Salience immigration |  | .0249\*\* |  | .0247\*\*\* |  | .0215\*\*\* |
| in national news, one week |  | (.0020) |  | (.0020) |  | (.0025) |
|  |  |  |  |  |  |  |
| Salience immigration |  |  |  |  |  | .0057\*\*\* |
| in personalised news, one week |  |  |  |  |  | (.0009) |
|  |  |  |  |  |  |  |
| Non-western immigrants in region (%) |  | - .0025 |  | -.0016 |  | -.0014 |
|  |  | (.0021) |  | (.0021) |  | (.0022) |
|  |  |  |  |  |  |  |
| Salience immigration in national news, |  | .0000 |  | -.0000 |  | .0001 |
| one week × non-western im. in region (%) |  | (.0002) |  | (0.0002) |  | (.0002) |
|  |  |  |  |  |  |  |
| Salience immigration in personalised news, |  |  |  |  |  | -.0001 |
| one week × non-western im. in region (%) |  |  |  |  |  | (.0001) |
|  |  |  |  |  |  |  |
| Non-western ties on Twitter (%) |  |  |  | -.0023\*\*\* |  | -.0025\*\*\* |
|  |  |  |  | (.0002) |  | (.0003) |
|  |  |  |  |  |  |  |
| ***Sample size*** |  |  |  |  |  |  |
| N user-timepoints |  | 314589 |  | 314589 |  | 223685 |
| N users |  | 28161 |  | 28161 |  | 19611 |
| N regions |  | 39 |  | 39 |  | 38 |
| ***Random Part*** | | | | | | |
| *σ2e ij* |  | .844665 |  | .844708 |  | .866745 |
| *σ 2u0 (individual)* |  | .164252 |  | .162625 |  | .163021 |
| *σ 2v0 (region)* |  | .001372 |  | .001463 |  | .001155 |
| ***Model Fit*** | | | | | | |
| *AIC* |  | 864209 |  | 864083 |  | 619841 |
| *BIC* |  | 864315 |  | 864200 |  | 619975 |

*\*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05 (Two-tailed test). Controls: population density region, number of followers on Twitter (log), number of connections on Twitter (log).   
Model 3 is based on the subsample of those who follow news outlets on Twitter*

C) More-refined geographical units

In the main analysis, we measured the share of non-western immigrants at the level of NUTS-2 regions in the UK (N=39). Because these regions are rather broad, we also identified the geolocation of a subsample of the Twitter users in our panel at the Local Authority Districts level (LAD), which consists of 379 districts (Office for National Statistics, 2018). Findings are reported in S3 Table. Note that the number of users for whom we were able to define geolocation at the level of LAD is considerably smaller, compared to the size of the main sample, and that’s why we do not present these results in our main analysis.

**S3 Table**. Multilevel hierarchical linear regression analysis of anti-immigrant sentiments on Twitter   
(SentiStrength, using LAD instead of NUTS-2 as level 3)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | ***Model 1*** |  | ***Model 2*** |  | ***Model 3*** |
| ***Fixed Part*** | | | | | | |
| Intercept |  | -.0287 |  | -0.0155 |  | .1100\*\*\* |
|  |  | (.0343) |  | (.0344) |  | (.0465) |
| Salience immigration |  | .0299\*\*\* |  | .0298\*\*\* |  | .0243\*\*\* |
| in national news, one week |  | (.0031) |  | (.0031) |  | (.0039) |
|  |  |  |  |  |  |  |
| Salience immigration |  |  |  |  |  | .0091\*\* |
| in personalised news, one week |  |  |  |  |  | (.0013) |
|  |  |  |  |  |  |  |
| Non-western immigrants in region (%) |  | -.0039\*\* |  | -.0030 |  | -.0035 |
|  |  | (.0016) |  | (.0016) |  | .0019 |
|  |  |  |  |  |  |  |
| Salience immigration in national news, |  | -.0005 |  | .0005 |  | -0.0005 |
| one week × non-western im. in region (%) |  | (.0004) |  | (.0045) |  | (.0005) |
|  |  |  |  |  |  |  |
| Salience immigration in personalised news, |  |  |  |  |  | -.0000 |
| one week × non-western im. in region (%) |  |  |  |  |  | (.0002) |
|  |  |  |  |  |  |  |
| Non-western ties on Twitter (%) |  |  |  | -.0018\*\*\* |  | -.0026\*\*\* |
|  |  |  |  | (.0003) |  | (.0004) |
|  |  |  |  |  |  |  |
| ***Sample size*** |  |  |  |  |  |  |
| N user-timepoints |  | 212549 |  | 212549 |  | 150588 |
| N users |  | 18971 |  | 18971 |  | 13114 |
| N regions |  | *213* |  | *213* |  | 205 |
| ***Random Part*** | | | | | | |
| *σ2e ij* |  | 1.431639 |  | 1.431648 |  | 1.460438 |
| *σ 2u0 (individual)* |  | 0.303247 |  | 0.302281 |  | 0.309640 |
| *σ 2v0 (region)* |  | 0.001524 |  | 0.001648 |  | 0.001903 |
| ***Model Fit*** | | | | | | |
| *AIC* |  | 696946 |  | 696860 |  | 496768 |
| *BIC* |  | 696966 |  | 696983 |  | 496776 |

*\*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05 (Two-tailed test). Controls: population density region, number of followers on Twitter (log), number of connections on Twitter (log). Model 3 is based on the subsample of those who follow news outlets on Twitter.*

8. Measurement additional analyses

Inferring gender of Twitter users

In order to enrich our knowledge about Twitter users in the sample, we applied the Python algorithm *genderComputer* to infer gender (Vasilescu et al., 2014). The procedure assigns a category (female/male/None) to an input consisting of a first name, last name and a name of a country of origin. Accordingly, we passed to the algorithm names of the Twitter users along with the country of origin we assume to be the most probable given the set of locations employed for data collection, which is the United Kingdom. As Twitter users often do not use real names for their Twitter identity, for 30% of the sample we were not able to identify their gender. We classified these cases as ‘unknown’, and kept them in the analyses. The rest of our sample was identified as male (50%) or female (20%).

Measurement of personalised news that include Twitter pages of journalists

We also constructed an alternative measure of personalised media exposure, which includes exposure to tweets from journalists. To detect journalist accounts, we largely relied on the procedure suggested by Spierings et al. (2019). First, we detected all the accounts followed by more than 100 users from our sample. Next, we examined if the Twitter bio of those users have the following words: journalist, journo, reporter, correspondent, editor. We found 1265 accounts with at least one of these keywords. Next, we collected the tweets posted by these journalist/reporter accounts during the period of our main data collection (November 1, 2018 – October 31, 2019) and measured the percentage of immigration-related tweets on a daily level. We then combined these values with the values from the measure capturing exposure towards tweets from news accounts.

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