A Appendix

Contents

A.1 Extent of The Sun boycott

We received photos taken by Dr Stuart Wilks-Heeg (University of Liverpool), which illustrate the boycott as of today. Figure A.1 shows two photos: The photo on the left displays a typical taxi cab in the county of Merseyside calling on Liverpudlians not to read and sell The Sun. The photo on the right showcases a shop owner's public rejection of The Sun's apology.

Figure A.1: How Liverpool boycotts The Sun

Source: Stuart Wilks-Heeg.

A.1.1 Internet search activity

One might suggest that even though we show a significant decrease in self-reported Sun readership in Merseyside, respondents might not share their reading behaviour truthfully, for instance due to social desirability bias. They might still access The Sun, for instance via the internet. However, throughout most of the time period under investigation, there was little commercial internet available in the UK. Even in 1998, only 9% of British households had internet access according to the OECD. 2005 was the first year in which half of the population had access to the internet in their homes (OECD 2020). This means that at least until 2000, most people based in Merseyside could not rely on the internet to access The Sun. To get a better understanding of if and how often Liverpudlians access The Sun online after the internet became widely available, from 2004 until today we rely on Googletrends. In the best case scenario we would have access to data on how often The Sun web page has been accessed by IPs stemming from Liverpool. Since we do not have access to such data, Googletrends still allows us to understand how often people from Liverpool search for The Sun on Google – which of course they might do for various reasons. The fact that people might search for The Sun online for reasons other than reading the paper can be understood as providing as an upper bound of how often people seek to read The Sun. In Table A.1 we report the Google search

Table A.1: Googletrend search volume for The Sun by city, 2004-2020

county	searches	county	searches	county	searches	county	searches
Wolverhampton	100	Bolton	73	Croydon	62	Brighton	53
Brentford	93	Derby	73	Bristol	62	Oxford	52
Bletchley	92	Birmingham	69	Leeds	61	Cambridge	50
Thames Ditton	88	Reading	67	Edinburgh	60	London	50
Stoke-on-Trent	85	Manchester	66	Norwich	60	**Liverpool**	**30**
Bradford	80	Nottingham	66	Sheffield	57		
Leicester	79	Northampton	66	Southampton	57		
Milton Keynes	79	Newcastle upon Tyne	65	Belfast	57		
Kingston Upon Hull	74	Coventry	64	Cardiff	56		
Glasgow	74	Portsmouth	64	Aberdeen	55		

volume for the term "The Sun". Googletrends share the relative amount of people searching for a respective term; meaning that we cannot know how many people in Liverpool search for The Sun on Google but only the relative amount in relation to the city where most people searched (Wolverhampton=100%). In Liverpool we find by far the lowest search amount in any British city with a 30% search share. Even in urban, cosmopolitan areas such as London, Oxford or Cambridge the search amount is still at 50%. Overall, this suggests that we have little reason to assume that people from Liverpool bypass the boycott of The Sun or seek access to The Sun via the internet.

A.1.2 Survey of newsagents

In Figure 2 in the manuscript we display the results of a telephone survey we conducted with newsagent and cornershop employees in three English counties, Merseyside, Lancashire and Cheshire between 12 January and 5 February 2021. The telephone survey was reviewed and approved by the Research Ethics Committee at the London School of Economics and Political Science under Ref: 19292. We sampled the entire population of newsagents in these three counties from Yelp and determined if a functioning telephone number could be located either on Yelp or Google Maps. This procedure left us with a sample of 850 newsagents and cornershops, 428 in Merseyside, 264 in Lancashire and 163 in Cheshire. Of these, 344 answered the phone and 212 consented to participate in the survey, which corresponds to a response rate of approximately 25%. Informed consent was obtained verbally on the phone and recorded by interviewers on Qualtrics. 165 newsagents completed the survey and confirmed that they indeed sold newspapers. This is the final sample used for the analysis. Newsagents were interviewed over the phone by two male interviewers who were specifically trained for this study. Both interviewers are native speakers from the North of England. We randomly divided the list of newsagents between the two interviewers. The survey questions are listed below in section A.1.3 and did not prompt respondents to think about Hillsborough or The Sun boycott. Answers were recorded using the Qualtrics online survey software.

A.1.3 Newsagent Survey: Instructions to telephone interviewers

Read out the following text (or paraphrase in your own words conveying all the info in bold below):

Good morning/good afternoon/good evening. My names is Y and I work for the London School of Economics and Political Science. We are researchers conducting an **academic study about the media and political attitudes towards Europe** and would like to **interview you about newspaper sales in your area**. The telephone survey will take approximately **3 minutes**. All information will be **fully anonymised** and neither your name, nor the name of your store will be published. We are only interested in calculating average sales of newspapers per parliamentary constituency, and since you are a newsagent you are **an expert** when it comes to that. You can stop the survey at any point and we would then delete all answers that you have given.

Would you like to participate in this survey? If you answer yes, this indicates that you consent to being interviewed and I will record the answers on my computer.

A. Yes, respondent would like to participate. B. No, respondent would not like to participate.

- Please give me your best guess: How many of the following newspapers would you sell on an average week-day before COVID?

  A The Guardian

  B A local paper

  C The Times

  D The Independent

  E The Daily Mirror

  F The Daily Mail

G The Sun

H The Telegraph

I Refused to answer

- Follow-up: The agent told you that they are selling 0 copies of paper X. Ask the agent: Is this because nobody buys paper X or because they are not selling it?

  A Nobody is buying it

  B Not selling it

  C Both

  D Other

  E Refused to answer

- Follow-up: Ask the agent: Do you remember which year you stopped selling paper X?

- DO NOT READ: Follow up about agents not selling The Sun. Did the agent mention Hillsborough or the boycott unprompted?

  A Yes

  B No

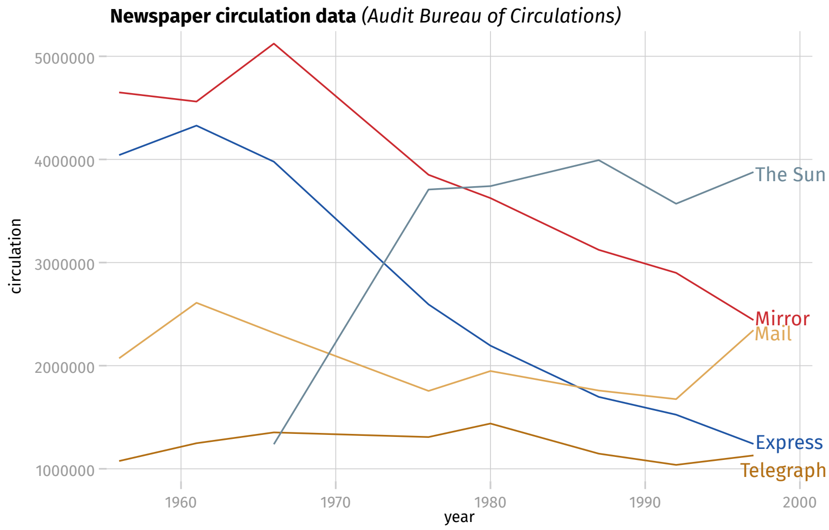
  C Can't remember

A.2 The British media landscape

A.2.1 Newspaper circulation across time

How relevant is the tabloid newspaper The Sun for the British public? Below we report newspaper circulation data for the UK since 1956 stemming from the audit bureau of circulations. As outlined in the main body of our paper we do not have access to circulation data at the constituency or regional level. Yet, at least for some time points (1956, 1961, 1966, 1976, 1980, 1987, 1992, 1997) we do have such information for the entire UK. Figure A.2 reports readership figures for the most relevant newspapers across the UK. Since the 1980s The Sun is the most widely-read newspaper in terms of circulation in the UK. Next to The Mail it also appears to be the only newspaper with growing circulation at the end of the 1990s. Notice that this growing trend continued up until the mid 2000s, when circulation of The Sun slowly started to decrease.

Figure A.2: Newspaper readership in the UK across time



A.2.2 EU coverage in the tabloid media

Figure A.3: Trend of different topics in Mirror

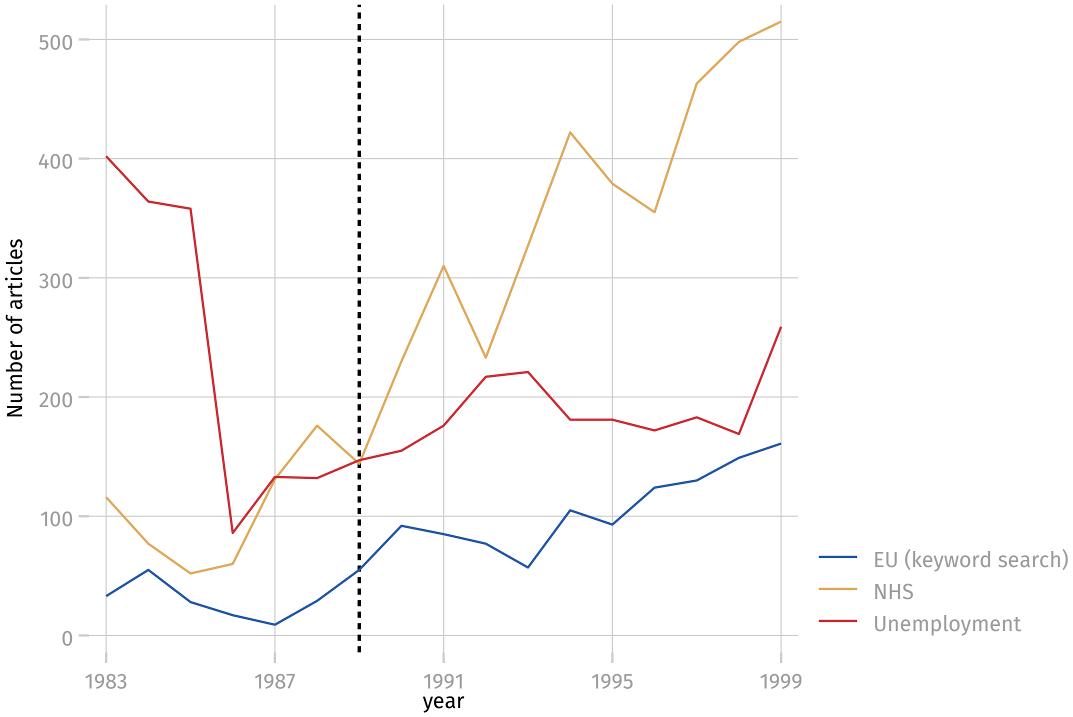


Figure A.4: Trends of EU as topic in Sun and Mirror

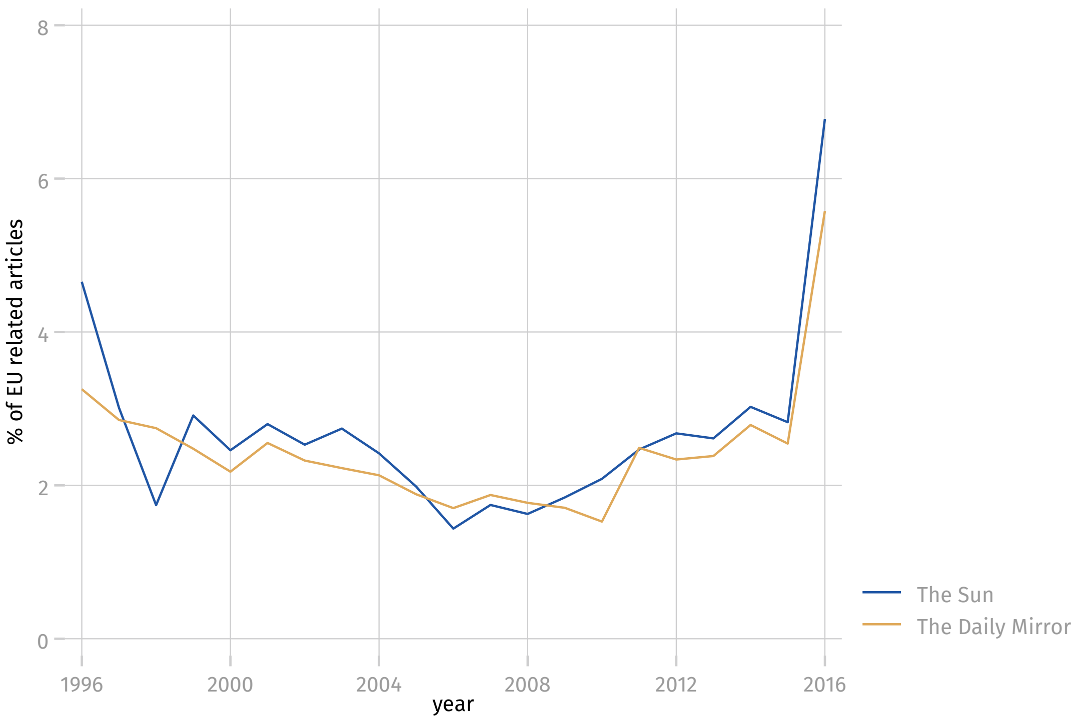


Figure A.5: Trends of EU-related editorials in Sun and Mirror

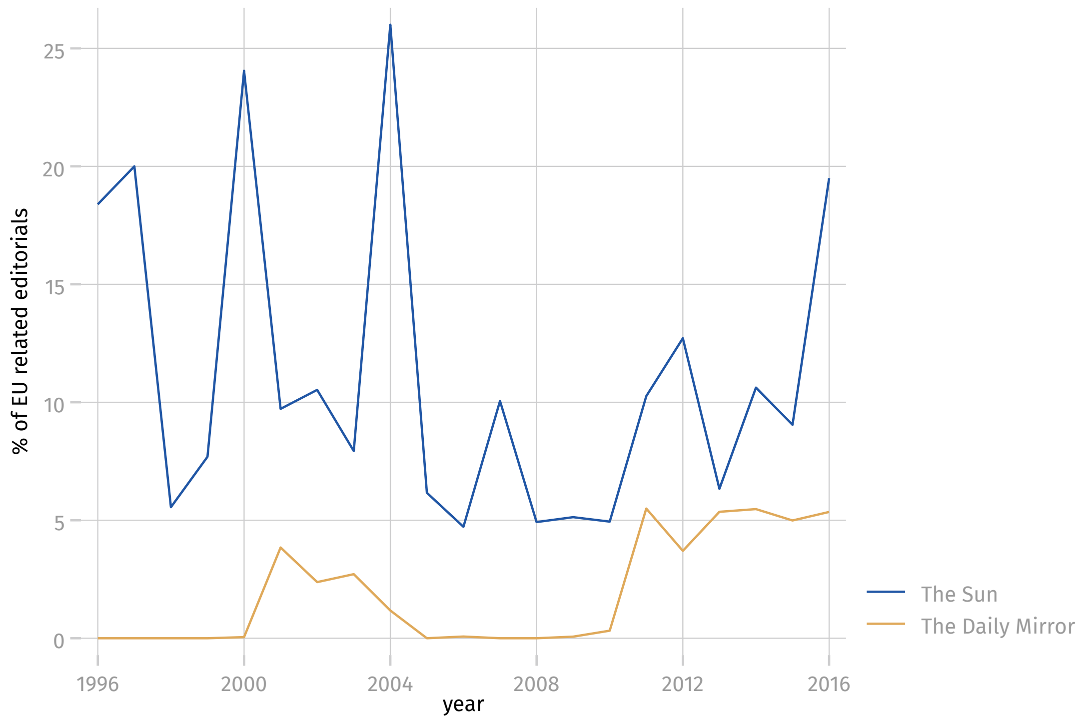
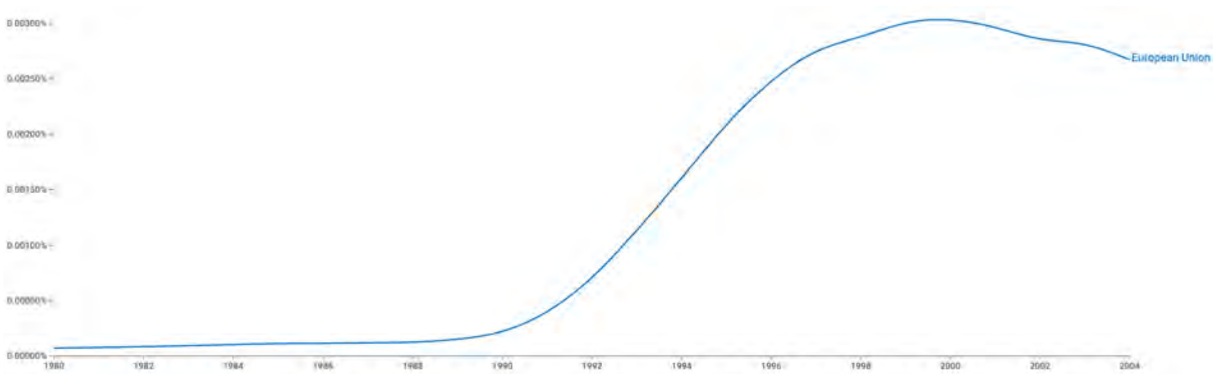


Figure A.6: Trend of EU topic in google ngrams



A.3 EU slant in the tabloid media

A.3.1 Content analysis of The Sun and The Mirror

Based on the Factiva online archive, we randomly sampled 50% of all "Sun" and "Mirror" editorials published between 1 January 1996 and 23 June 2016 based on the following search query: "ns=GCAT and EU or European Union or European Commission or European Community or Europe not football not soccer not rugby not golf not tennis not sports not travel not WBA not footballer not fashion not music OR Brussels not sprouds or Euro and [Pound or Sterling] not European Championships not EURO 1996 not EURO 2000 not EURO 2004 not EURO 2008 not EURO 2012 not EURO 2016". Both samples were hand-coded independently by two research assistants to answer 1) whether the editorial addressed a question about European integration 2) what the tone of the editorial towards the EU was (positive, neutral, negative) 3) How certain the coder was about their judgement (very certain, quite certain, not so certain, not certain at all) 4) How the coder would rate the tone of the editorial on a scale from 0 (very negative) to 100 (very positive) and 5) if the editorial could be categorised as "Eurosceptic" according to the following definition: "the (qualified) rejection of European integration". Coders classified 57% of "Sun" editorials and 49% of "Mirror" editorials in the sample as about Europe. This left us with an overall sample of N=347 observations coded in The Sun and of N=174 observations coded in The Mirror. These editorials constitute the sample for our analysis displayed in Table 1 in the main body of the text.

Inter-coder reliability for the questions was relatively high with % agreement ranging from 77% for the Euroscepticism question to 92% for the question about tone. The corresponding Kappa-statistics which capture inter-coder agreement are displayed in Table 1. A Kappa statistics from 0.21-0.40 is usually considered "fair" agreement, while 0.41-0.60 is considered "moderate" agreement, 0.61-0.80 is considered "substantial" agreement and 0.81-1.0 is considered "almost perfect" agreement. With Kappas of 0.55, 0.67 and 0.83 all three measures of sentiment towards the European Union can be considered reliable.

A.3.2 Qualitative evidence

Figure A.7: The Sun's coverage of the 2016 EU referendum

Sources: left: Woodhouse, Cole, and Pettitt (2016); right: Sutton (2016).

A.4 Validation of BSA data

As discussed in the results section, we find a sharp decrease in Euroscepticism across England in the 1990s in the BSA data. This might raise concerns about data validity and reliability. In this section we address these concerns. We use alternative data to validate the BSA measures we rely on. To do so, we downloaded the Eurobarometer trend file. This data provides us with the most widely used and validated measure of Euroscepticism. Unfortunately, as discussed in the methods section, it does not provide us with regional identifiers before 1990. Nevertheless, we can plot the time trend of Euroscepticism for the entire period covered in the EB trendfile. Figure A.11 reports the time trend for two outcomes.

In the top panel we report the trend for the most similar question to the one we rely on in our analysis, asking respondents if they believe that their country's membership in the EU is a good/bad thing. The trends for these data are remarkably similar to the trend we report for the BSA data. As in our BSA data, public opinion towards the EU is more sceptical in the 70s and early 80s, before Euroscepticism drops to lower levels throughout the 1990s and slightly increases again by the late 90s. The bottom panel then reports the trends for a related out-

Figure A.8: The Sun's (rows 1 and 2) and The Mirror's (row 3) EU coverage in 1989/1990

Sources: British Newspaper Archive (British Library)

come, how much respondents believe the country has benefited from EU membership. Again, we find a similar pattern with strong anti EU opinions in the 80s which decrease during the

Figure A.9: The Sun's Euro-myths in the mid 1990s

NOW THEY'VE REALLY GONE BANANAS

THE SUN CUT OUT AND KEEP GUIDE
This is the official EU minimum size banana.
Cut it out and see how yours measure up. Tell our Banana Hotline about tiddlers, whoppers or very kinky ones.

Euro bosses ban 'too bendy' ones and set minimum shop size of 5½ins

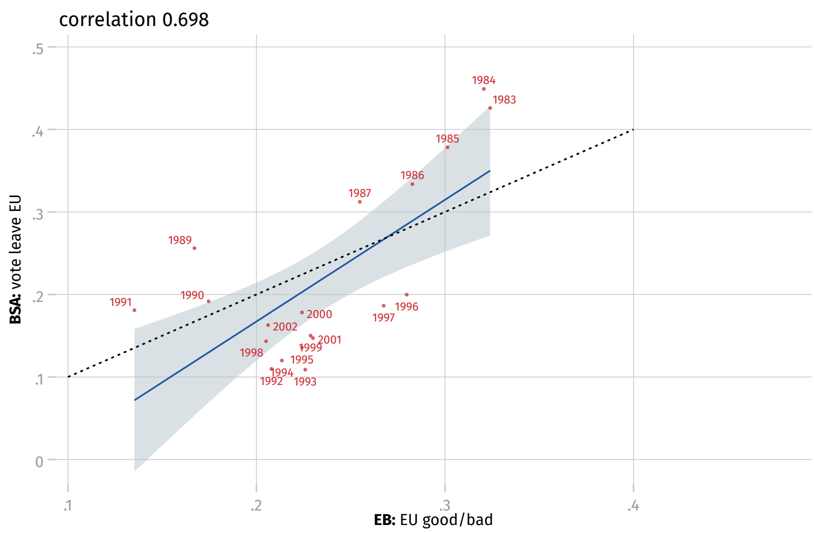
By LUCINDA EVANS

BRUSSELS bureaucrats proved yesterday what a barmy bunch they are – by outlawing curved bananas.

Sources: Evans (2016).

90s. Finally, we merged the BSA data with the EB data on an annual level (annual time series). This allows us to estimate the correlation between both measures. Figure A.10 reports the correlation across years in a scatter plot. We also report the x=y line which is the benchmark for a perfect correlation between both measures; we find a very high correlation of .7 between the two measures, based on two independent data sources. This speaks for the reliability of the measures we use in our study.

Figure A.10: Correlation between Euroscepticism in the Eurobarometer and the British Social Attitudes Data, 1983-2002



Note: based on Eurobarometer Trendfile (1973-2002) and British Social Attitudes data. Both variables return % of population being Eurosceptic.

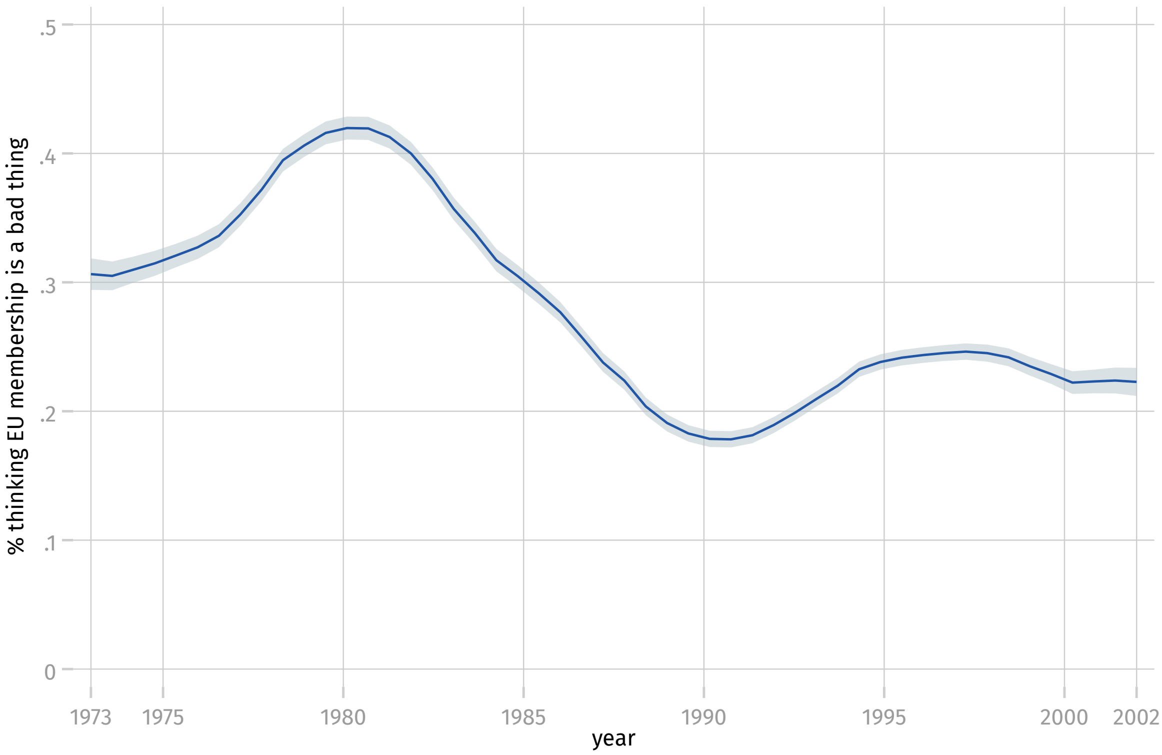
A.5 Effects on 'don't know' responses

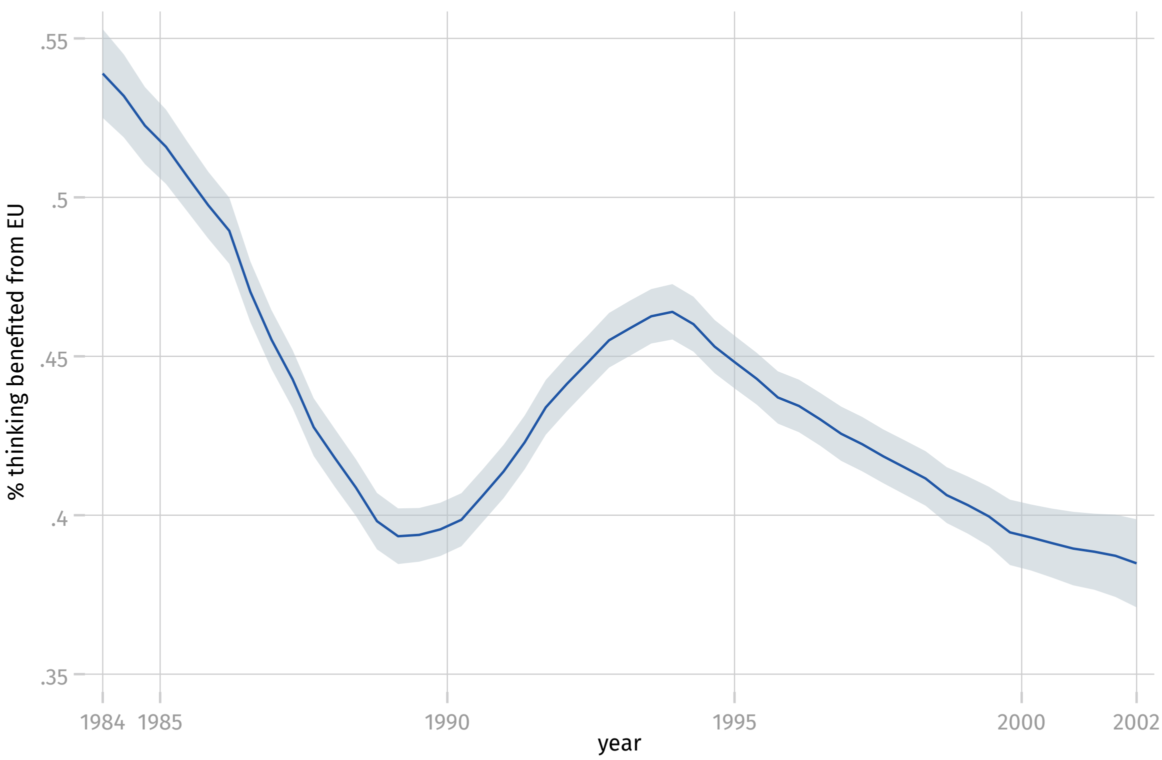
Table A.2: Effect of The Sun boycott on 'don't know' responses

	'don't know' (0,1)					
	(1)	(2)	(3)	(4)	(5)	(6)
δ DiD	0.016	-0.036	-0.035	-0.026	-0.045	-0.046
	(0.020)	(0.039)	(0.041)	(0.040)	(0.037)	(0.037)
Constant	0.080	0.083	0.083	0.166	0.084	0.165
	(0.004)	(0.002)	(0.003)	(0.020)	(0.002)	(0.021)
Constituency FE		✓	✓	✓	✓	✓
Year FE		✓	✓	✓	✓	✓
Quarter FE			✓	✓	✓	✓
Constituency FE × Quarter					✓	✓
Constituency FE × Year					✓	✓
Controls				✓		✓
Obs	10378	10378	10378	10378	10378	10378
$N_{constituencies}$	172	172	172	172	172	172
adj.R^2	0.00	0.02	0.02	0.06	0.03	0.07
adj.R^2 (within)	0.00	0.00	0.00	0.04	0.00	0.04
RMSE	0.27	0.27	0.27	0.27	0.27	0.26

Note: Clustered standard errors by constituency in parentheses. Controls omitted from table (1985-2004): age, gender, education, religion, social class, party-ID. Constituency & time fixed effects omitted from table.

Figure A.11: Euroscepticism in the Eurobarometer for Great Britain, 1973-2002





Note: based on Eurobarometer Trendfile (1973-2002). Reported are local polynomials surrounded by 95% confidence intervals based on annual cross sections of almost 90,000 respondents.

A.6 Including data from 1983 & 1984

Unfortunately, the BSA does not report an important covariate prior to 1985, *education*. Therefore, we include only data from 1985 on-wards in our main analysis. Table A.3 reports the same models as table 2 in the main body of the paper including all available data from the BSA. The major drop in N is due to no information about education existing only for a subset of respondents. Please note that findings are robust to using the entire data. If anything, the point estimate becomes larger in magnitude, suggesting an effect of around 17 percentage points.

Table A.3: Effect of The Sun boycott on Euroscepticism (1983-2004)

	Support leaving the EU					
	(1)	(2)	(3)	(4)	(5)	(6)
δ DiD	-0.083	-0.178	-0.175	-0.173	-0.106	-0.098
	(0.015)	(0.037)	(0.038)	(0.037)	(0.024)	(0.024)
social class (0-5)				0.033		
				(0.002)		
Constant	0.225	0.227	0.227	0.069	0.226	0.151
	(0.004)	(0.001)	(0.001)	(0.010)	(0.000)	(0.015)
Constituency FE		✓	✓	✓	✓	✓
Year FE		✓	✓	✓	✓	✓
Quarter FE			✓	✓	✓	✓
Constituency FE × Quarter					✓	✓
Constituency FE × Year					✓	✓
constant	✓					
Controls				✓		✓
Obs	35204	35203	35201	34060	35201	34060
$N_{constituencies}$	533	532	532	532	532	532
adj.R^2	0.00	0.06	0.06	0.08	0.07	0.09
adj.R^2 (within)	0.00	0.00	0.00	0.02	0.00	0.02
RMSE	0.42	0.40	0.40	0.40	0.40	0.40

Standard errors clustered by constituency in parentheses

A.7 Including respondents from all English constituencies

The figures below are based on the same models reported in the paper, but using all remaining English constituencies as a control.

Figure A.12: Trends in Euroscepticism in Merseyside and control before and after the boycott induced by Hillsborough

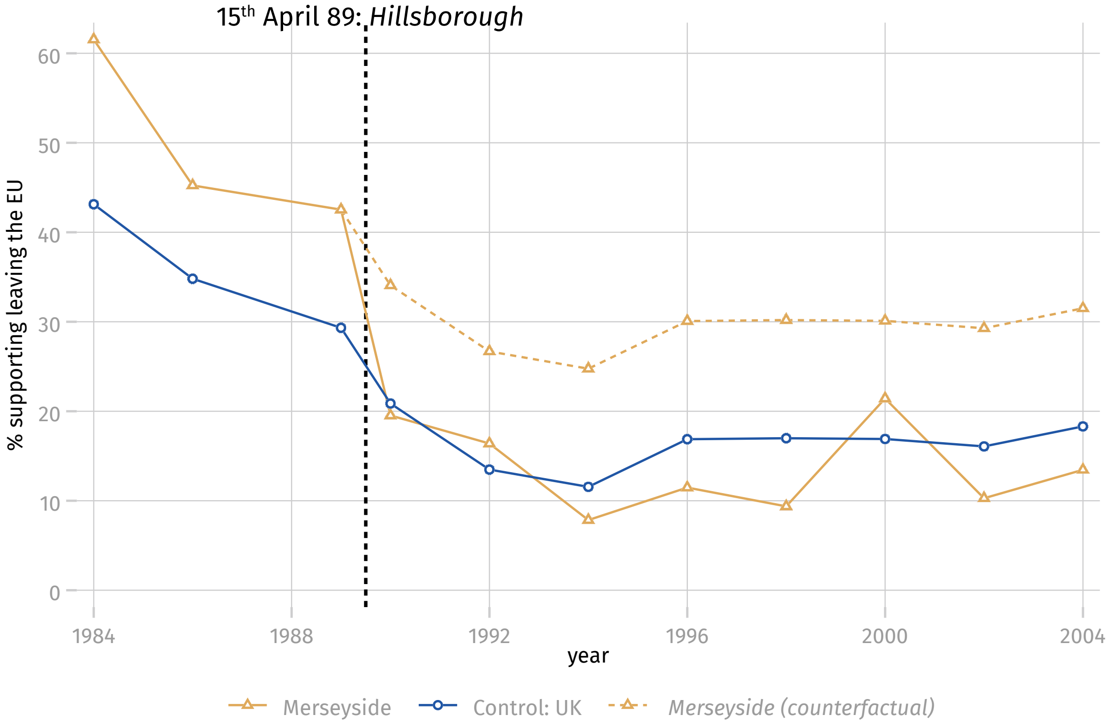


Table A.4: Effect of Hillsborough on Euroscepticism (**All of England**)

	Support leaving the EU					
	(1)	(2)	(3)	(4)	(5)	(6)
δ DiD	-0.064	-0.159	-0.155	-0.160	-0.104	-0.111
	(0.015)	(0.049)	(0.050)	(0.046)	(0.028)	(0.029)
Constant	0.206	0.208	0.208	0.209	0.207	0.208
	(0.004)	(0.001)	(0.001)	(0.016)	(0.001)	(0.016)
Constituency FE		✓	✓	✓	✓	✓
Year FE		✓	✓	✓	✓	✓
Quarter FE			✓	✓	✓	✓
Constituency FE × Year					✓	✓
Constituency FE × Quarter					✓	✓
Controls				✓		✓
Obs	32317	32316	32314	32314	32314	32314
$N_{constituencies}$	532	531	531	531	531	531
adj.R^2	0.00	0.05	0.05	0.07	0.05	0.08
adj.R^2 (within)	0.00	0.00	0.00	0.03	0.00	0.03
RMSE	0.40	0.39	0.39	0.39	0.39	0.39

Standard errors clustered by constituency in parentheses

A.8 Spillover

One potential caveat to our research design is that not only the county of Merseyside, but also adjacent counties might have been affected by The Sun boycott.

Yet, as outlined in the main body of the text, both anecdotal and quantitative evidence based on our newsagents survey suggests that this was not the case. In Figure 2 we show that The Sun boycott is geographically limited to Merseyside and did not spill over to adjacent counties. To go beyond this, we conduct two further robustness tests to investigate if we find evidence consistent with spillover effects.

First, we re-estimate our main models by relying on Merseyside as the treatment group, and three adjacent counties (Cheshire, Lancashire and Greater Manchester) as the control group. Table A.5 reports the findings. Again, our main findings receive support across all models. This suggests that in comparison to adjacent counties – where geographical spillover is most likely – our findings remain unchanged in significance as well as size of the coefficients.

Table A.5: Effect of The Sun boycott on Euroscepticism (**adjacent counties only**)

	Support leaving the EU					
	(1)	(2)	(3)	(4)	(5)	(6)
δ DiD	-0.077	-0.149	-0.143	-0.140	-0.115	-0.109
	(0.019)	(0.048)	(0.048)	(0.044)	(0.037)	(0.039)
Constant	0.219	0.231	0.230	0.174	0.226	0.167
	(0.013)	(0.008)	(0.008)	(0.040)	(0.006)	(0.042)
Constituency FE		✓	✓	✓	✓	✓
Year FE		✓	✓	✓	✓	✓
Quarter FE			✓	✓	✓	✓
Constituency FE × Year					✓	✓
Constituency FE × Quarter					✓	✓
Controls				✓		✓
Obs	3977	3977	3975	3975	3975	3975
$N_{constituencies}$	69	69	69	69	69	69
adj.R^2	0.00	0.07	0.07	0.09	0.07	0.09
adj.R^2 (within)	0.00	0.00	0.00	0.03	0.00	0.03
RMSE	0.40	0.39	0.39	0.39	0.39	0.39

Standard errors clustered by constituency in parentheses

Second, we test if in comparison to the three adjacent counties, readership of The Sun significantly declined in Merseyside. Again, we find a significant decrease of 7 percentage points in Merseyside in comparison to adjacent counties. We report these findings in Table A.6

below. Overall, these two robustness checks as well as the anecdotal evidence we discussed in the main body and the Appendix make us confident that the boycott did not affect adjacent counties.

Table A.6: Effect of The Sun boycott on self-reported Sun readership (**compared to adjacent counties only**)

	Sun reader (0,1)	
	(1)	(2)
δ DiD	-0.072	-0.062
	(0.039)	(0.039)
Constant	0.106	0.246
	(0.006)	(0.033)
Constituency FE	✓	✓
Year FE	✓	✓
Controls		✓
Obs	3926	3926
$N_{constituencies}$	69	69
adj.R^2	0.02	0.05
adj.R^2 (within)	0.00	0.03
RMSE	0.29	0.29

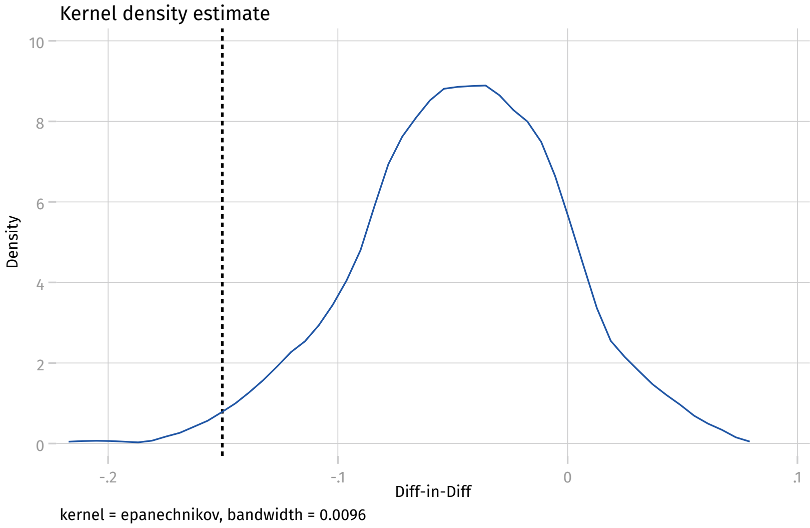
Standard errors clustered by constituency in parentheses

A.9 Permutation test

One might object that the decrease in Euroscepticism was not unique to Merseyside, but driven by a more general trend against Euroscepticism in England in the 1990s. To address this concern, we estimate a placebo test in space. More specifically, we randomly re-assigned the Hillsborough event into constituencies in England that are not located within Merseyside. The upper panel in figure A.13 reports the finding of this permutation test. The vertical line reports the effect we found for Merseyside while the density plot reports the estimated effect for all 1000 permutations we simulated. It becomes strikingly evident that the Hillsborough effect for Merseyside remains distinct and is statistically different from the distribution of placebo effects we estimated across other areas.

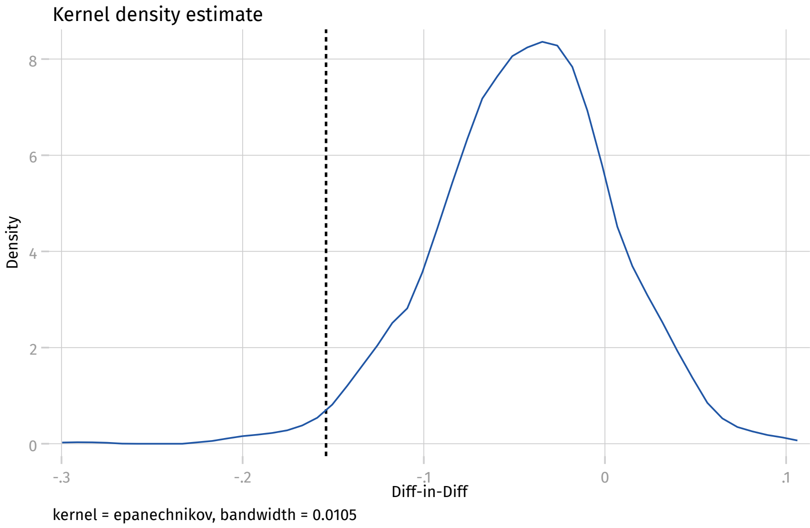
Figure A.14 reports the same permutation test for Northern English constituencies only.

Figure A.13: Placebo in space (**all of England**)



Note: Placebo in space based on 1'000 permutations, reports an ATT=-0.140 with SE(P)=0.0059 and CI: 0.025/0.049

Figure A.14: Placebo in space (**North only**)



Note: Placebo in space based on 1'000 permutations, reports an ATT=-0.130 with SE(P)=0.0057 and CI: 0.024/0.047.

A.10 Matching

Table A.7 reports the DiD findings using matching on observables. We describe the matching procedure in detail in the Online Supplementary Materials in section S.4.

Table A.7: Did Euroscepticism decrease after Hillsborough in Merseyside (**Matching**)? Yes.

	(1)	(2)	(3)	(4)	(5)	(6)
	support leaving the EU (0,1)					
δ DiD	-0.135	-0.118	-0.090	-0.113	-0.098	-0.094
	(0.055)	(0.051)	(0.042)	(0.054)	(0.052)	(0.042)
Constant	0.291	0.287	0.280	0.292	0.288	0.287
	(0.014)	(0.013)	(0.010)	(0.014)	(0.013)	(0.011)
Constituency FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Quarter FE		✓	✓		✓	✓
Constituency FE × Quarter			✓			✓
Constituency FE × Year			✓			✓
Obs	31188	31187	31187	31188	31187	31187
$N_{constituencies}$	531	531	531	531	531	531
adj.R^2	0.08	0.09	0.11	0.10	0.10	0.13
adj.R^2 (within)	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	0.42	0.42	0.41	0.42	0.42	0.41

Note: Clustered standard errors by constituency in parentheses.
Fixed effects omitted from table.

While the ATT decreases to about 9 %-points, the effect of the Hillsborough-induced boycott remains statistically significant and substantive in size. We omit questions on party id in the first three models as they could plausibly be affected by media exposure as shown by Ladd and Lenz (2009). Our findings are not affected by this decision as the results of the remaining 3 models show.

A.11 Clustering by county

Below we report the main analysis clustering at the county level instead of the constituency level. We do this only for the entire sample of England as otherwise we would rely on too few clusters (12 counties in the case of Northern England only, 46 if we include all of England). Merseyside is one county. We also add a set of county-level controls to this analysis – logged population, gdp, employment rate, employment in several sectors (agriculture, construction, industry) – taken from `Cambridge Econometrics`. We then re-estimate the same models with fixed effects at the county level and cluster the standard errors at the county level. Table A.8 reports the findings from the county-level analysis. The first 4 columns subsequently introduce fixed effects and controls. Models (5) - (8) reduce the sample to counties we observe in each and every survey year we can analyze (5 counties are not observed for some years). Model (9) then uses a wild bootstrap approach we discuss below. First, our main findings and

Table A.8: Re-producing main analyses clustering at the county level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				support leaving the EU (0,1)					
δ DiD	-0.154	-0.150	-0.129	-0.117	-0.153	-0.148	-0.124	-0.109	-0.154
	(0.008)	(0.009)	(0.008)	(0.012)	(0.008)	(0.009)	(0.008)	(0.012)	(0.050)
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE		✓	✓	✓		✓	✓	✓	
County FE × Quarter			✓	✓			✓	✓	
County FE × Year			✓	✓			✓	✓	
Controls ID				✓				✓	
Controls RE				✓				✓	
Obs	32317	32315	32315	32189	31009	31007	31007	31007	32317
N $_{counties}$	46	46	46	45	41	41	41	41	41
adj.R^2	0.04	0.04	0.04	0.07	0.04	0.04	0.04	0.07	0.04
adj.R^2 (within)	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.03	
RMSE	0.40	0.40	0.40	0.39	0.40	0.40	0.39	0.39	

Note: Clustered standard errors by county in parentheses. Controls omitted from table, individual level (1985-2004): age, gender, education, religion, social class, party-ID. Regional level: logged population, GDP, employment rate, employed in agriculture, employed in construction, employed in industry. County & time fixed effects omitted from table. Last column uses wild bootstraps, 1000 replications.

conclusions remain unaffected by this change of clustering and fixed effects setting. Second, the standard errors are smaller in size compared to the constituency-level clustering that we report in the main body of the manuscript. Third, one challenge is the fact that we have too few clusters at our disposal for the analysis (below 50). This might bias our standard errors downward (see also: Bertrand, Duflo, and Mullainathan 2004). To address this issue, we follow Esarey and Menger (2019) and use a wild cluster bootstrapped t-statistic (1000 replications) in the final model reported in Table A.8. Even though this increases the reported standard error significantly compared to model (1) in Table A.8, our main findings remain unaffected.

A.12 Robustness: controlling for "offshorability"

Some research indicates that Eurosceptic attitudes can be tied to one's relative level of exposure to globalization. For instance, Colantone and Stanig (2018: 201) show that "support for the Leave option in the Brexit referendum was systematically higher in regions hit harder by economic globalization". Thus, globalization might drive political attitudes differently in Merseyside than in other English regions; the reasoning being that Merseyside might be differently affected by globalization. While we cannot fully incorporate Colantone and Stanig (2018) in our analyses due to lack of suitable data prior to the Hillsborough disaster, we can retrieve information from the British Social Attitudes Survey (BSA) on individuals' occupations. We can merge this data source with information on individual's likelihoods of job "offshorability" (see: Mahutga, Curran, and Roberts 2018). The merged data then provides us with respondents' occupational "routine task intensity" and "offshorability". Table A.9 replicates our main anal-

Table A.9: DiD results, controlling for offshorability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	support leaving the EU (0,1)							
δ DiD	-0.172	-0.165	-0.169	-0.165	-0.170	-0.165	-0.172	-0.167
	(0.058)	(0.055)	(0.058)	(0.054)	(0.059)	(0.055)	(0.058)	(0.057)
offshorability (-0.8-2.6)	-0.013	-0.011			-0.021	-0.009	-0.013	
	(0.005)	(0.005)			(0.006)	(0.006)	(0.006)	
routine task intensity (-1.5-2.4)			0.007	-0.009	0.016	-0.004		0.008
			(0.004)	(0.005)	(0.005)	(0.006)		(0.004)
δ DiD × offshorability							0.007	
							(0.012)	
δ DiD × routine task intensity								-0.010
								(0.017)
Constant	0.225	0.206	0.224	0.192	0.223	0.201	0.225	0.224
	(0.004)	(0.032)	(0.004)	(0.033)	(0.004)	(0.033)	(0.004)	(0.004)
Constituency FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓		
Obs	7490	7490	7490	7490	7490	7490	7490	7490
N $_{constituencies}$	171	171	171	171	171	171	171	171
adj.R^2	0.05	0.08	0.05	0.08	0.05	0.08	0.05	0.05
adj.R^2 (within)	0.00	0.03	0.00	0.03	0.00	0.03	0.00	0.00
RMSE	0.40	0.39	0.40	0.39	0.40	0.39	0.40	0.40

Note: Clustered standard errors by constituency in parentheses. Controls omitted from table (1985-2004): age, gender, education, religion, social class, party-ID. Constituency & time fixed effects omitted from table.

yses controlling for both of these variables as well as their interaction with the DiD estimand. Throughout the models reported above we do not find any effect of including these variables on our main findings. This is evidence that globalization shocks are unlikely to explain away the effect stemming from the Hillsborough disaster.

A.13 Exposure to boycott, replicating DiD and instrumental variable results

Our main analyses rest on the assumption that the exposure to The Sun boycott is equal within Merseyside. Yet, as we discuss in the main body of the text, the extent of the boycott varies within Merseyside. While the newsagent survey shows that some form of boycott applies to the entire county, the city center is more strict and radical in enforcing the boycott. This becomes also strikingly clear when we look at the data we retrieved from "Total Ecplise" reported in Table A.10.

The data on the boycotting shops allow us not only to descriptively estimate how strong

Table A.10: Number of boycotting shops per constituency

1997 constituency	$\sum$ boycotting shops
Liverpool Riverside	64
Liverpool Garston	45
Liverpool Wavertree	43
Knowsley North and Seftone	31
Liverpool Walton	31
Liverpool West Derby	22
Birkenhead	21
Bootle	20
St Helens South	4
Lancashire West*	3
Ellesmereport and Neston*	2
Southport	1
Derbyshire West*	1
St Helens North	1
remaining England	*0*

Note: * = mark consituencies outside of Merseyside.

the boycott is within Merseyside, but also to re-estimate our DiD models using a measure of exposure to the boycott. To do so, we log transformed the number of shops boycotting The Sun for each constituency across England.[15] We then estimate the same DiD models as in the main body of the text with the difference that we use the logged number of boycotting shops as our treatment instead of the binary Merseyside indicator.

Table A.11 reports the findings from this approach. Again we find a significant drop in Sun readers as well as a drop in Euroscepticism. As the estimator is based on a logged number, we can interpret the most conservative test (column (10)) as a 3.5% decrease in Euroscepticism due to one unit increase in boycotting shops.[16] The issue of course with this approach is that we cannot know *when* shops started boycotting. In our telephone survey it also became clear that many shops either changed ownership or opened post treatment. Thus, we should read these results with caution as we need to assume that the distribution of boycotting shops was similar in 1990 as it is today. This is also why we treat this modelling strategy as a robustness test and do not use it as our main analysis. Furthermore, this information on the extent of the boycott allows us to estimate an instrumental variable model. In more detail we estimate

[15] log shop = $\log(N_{shops}+1)$

[16] $(\exp(0.034)-1)\times 100=3.5$

Table A.11: DiD results, using exposure to boycott

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sun reader (0,1)				support leaving the EU (0,1)					
δ DiD(SHOPS)	-0.019	-0.037	-0.037	-0.032	-0.016	-0.058	-0.058	-0.051	-0.038	-0.034
	(0.004)	(0.006)	(0.006)	(0.007)	(0.007)	(0.010)	(0.010)	(0.008)	(0.014)	(0.013)
Constant	0.125	0.127	0.127	0.127	0.210	0.217	0.216	0.228	0.214	0.218
	(0.005)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.001)	(0.028)	(0.002)	(0.028)
Constituency FE		✓	✓	✓		✓	✓	✓	✓	✓
Year FE		✓	✓	✓		✓	✓	✓	✓	✓
Quarter FE			✓	✓			✓	✓	✓	✓
Constituency FE × Year				✓					✓	✓
Constituency FE × Quarter				✓					✓	✓
Controls								✓		✓
Obs	10259	10259	10259	10259	10384	10384	10384	10384	10384	10384
$N_{constituencies}$	172	172	172	172	172	172	172	172	172	172
adj.R^2	0.00	0.02	0.02	0.02	0.00	0.05	0.05	0.08	0.05	0.08
adj.R^2 (within)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.03
RMSE	0.33	0.32	0.32	0.32	0.41	0.40	0.40	0.39	0.39	0.39

Note: Clustered standard errors by constituency in parentheses. Controls omitted from table (1985-2004): age, gender, education, religion, social class, party-ID. Constituency & time fixed effects omitted from table.

models of the following form:

$$\text{leaving EU}_{i,c,t} = \alpha_r + \gamma_t + \widehat{\text{shops}_c} + \text{post Hillsborough} + (\widehat{\text{shops}_c} \times \text{post Hillsborough}) + \epsilon_c \quad (4)$$

$$\widehat{\text{shops}_c} = \psi \text{Merseyside}_c + \epsilon_{c'} \quad (5)$$

We estimate a two stage least squares instrumental variable model in which we instrument the number of shops boycotting "The Sun" with the binary treatment indicator (=Merseyside) in the first stage. We measure the extent of the boycott in two ways. First, we retrieved the number of boycotting shops from the "Total Ecplise" website presented in Table A.10. Second, we rely on our phone survey of newsagents presented in the main body of the text and discussed in section A.1.2. From this survey we extract information on the proportion of newsagents reporting that they sell 0 copies of The Sun. We again introduce time fixed effects along with county fixed effects – we can no longer use constituency-level fixed effects as they are perfectly co-linear with the treatment indicator. England in total has nine regions (North East, North West, Yorkshire and the Humber, West Midlands, East Midlands, South West, South East, East of England, Greater London).

Table A.12 reports the findings from these 2SLS models. First, in order for our instrument to be valid we need a strong first stage. This means that we need to find that the Merseyside indicator is strongly predictive of the number of boycotting shops. We already established this in Table A.11 above. Furthermore, the F-Statistic of this first stage is comparatively strong (>10), as reported at the bottom of Table A.12. Second, we need to establish independence of our instrument. Transferred to our design, a violation of independence would mean that places boycotting The Sun would have been on a different trajectory in the outcome variable than places which did not boycott The Sun. As discussed throughout the the text, the boycott of The Sun occurred due to an exogeneous event and does not appear to be a function of pre-boycott trends. Third, the exclusion restriction needs to be established. In our case, we have to assume that the boycott affects Euroscepticism via the number or proportion of boycotting shops *only*. This assumption could be violated if the boycott triggered other paths to the outcome.

The instrumental variable results further underpin the findings reported in the paper. The first stage returns a strong F-Statistics for all models. Table A.12 also reports a significant and

Table A.12: Instrumental variable results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	support leaving the EU (0,1)							
	IV=self-reported boycott				IV=survey of newsagents			
δ DiD, instrumented	-0.033	-0.033	-0.036	-0.035	-0.400	-0.405	-0.435	-0.413
	(0.013)	(0.013)	(0.013)	(0.010)	(0.157)	(0.159)	(0.155)	(0.129)
Region FE		✓	✓	✓		✓	✓	✓
Year FE			✓	✓			✓	✓
Controls				✓				✓
Obs	10384	10384	10384	10384	10384	10384	10384	10384
RMSE	0.40	0.40	0.40	0.39	0.40	0.40	0.40	0.39
F-Stat.	840.77	750.90	839.48	823.53	22.91	18.40	18.55	18.69

Note: Clustered standard errors by constituency in parentheses. F-Stat is Kleibergen-Papp. Controls omitted from table (1985-2004): age, gender, education, religion, social class, party-ID. Region & time fixed effects omitted from table.

substantial decrease in Euroscepticism due to the boycott. Since the extent of the boycott can be understood as a compliance measure, the estimated effect size will be larger than in the standard DiD model, which presents ITT estimates. Reassuringly, we find similar effect sizes for both measures of the boycott – the list of boycotting shops derived from the Total Eclipse website and the survey responses from our newsagents survey.

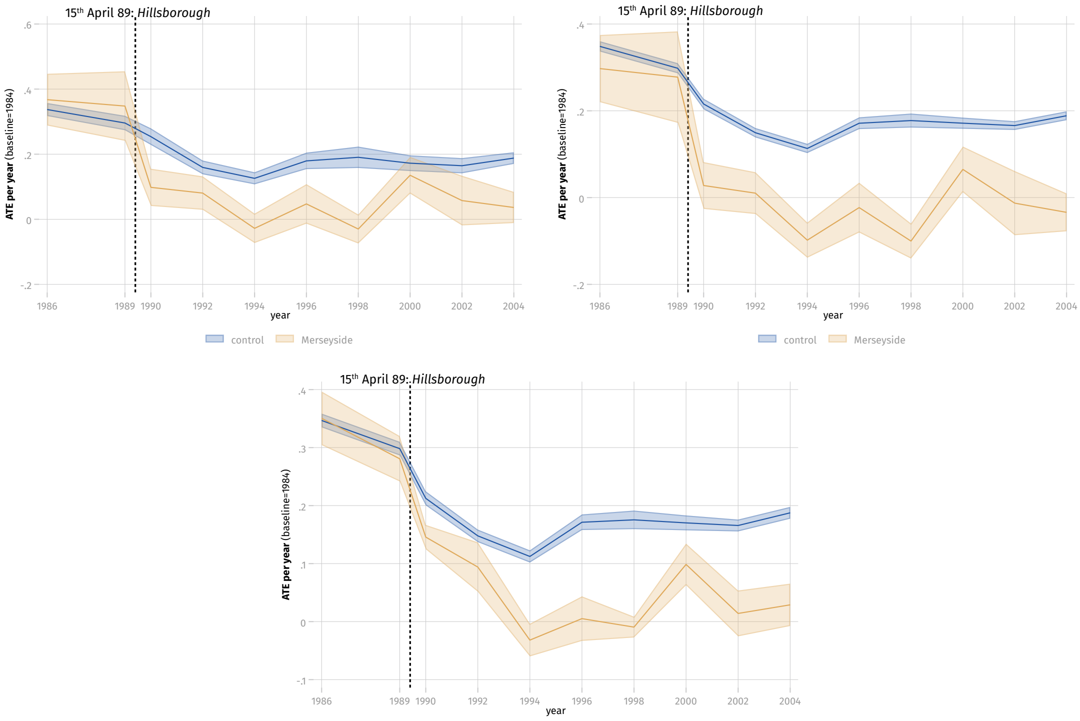
A.14 Parallel trends based on DiD parameter estimates

In the text we relied on the raw data to evaluate if pre-trends are parallel, giving us confidence in the parallel trends assumption underlying the DiD. Here in the Appendix we further substantiate the parallel trends assumption by instead reporting the parameter estimates of our DiD approach in the following form:

$$\text{leaving EU}_{i,c,t} = \alpha_c + \gamma_t + \gamma_{c,t} + \sum_{m=-3}^{8} \delta_{\text{DID}_m} T_{c,t-m} + \varepsilon_{it}, \tag{6}$$

In essence, we estimate the same models with constituency and year fixed effects but interact our treatment indicator with the survey years in our data. We then plot the interaction effects in Figures A.15. We do this for the Northern county sample (our preferred sample), the sample of all English counties, and for the complete sample of all boycotting shops in England that we discuss in detail in section A.1. Given the small sample sizes for some of the years in our data we have to pool two years into a single period. Otherwise we would base our treatment

Figure A.15: Parallel trends based on parameter estimates, Northern counties, all of England and boycotting shops as treatment

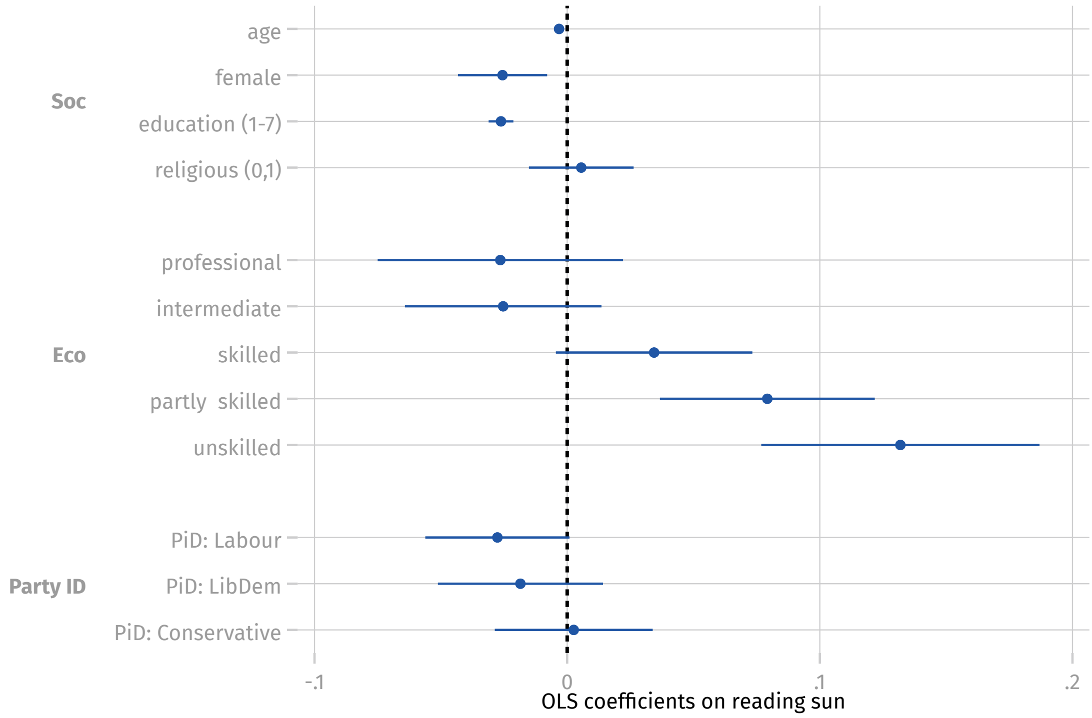


effect estimates in some years on only 30 respondents in Merseyside, which would make them very noisy. Compared to the parallel trends plot we report in the main body of the text, we would expect that the major difference is that the fixed effects should control away the difference in levels between Merseyside and the rest of the country along with common shocks within years. And indeed we do report very similar patterns for the DiD parameters in Figure A.15. As the shop boycott data is a continuous variable we report the effect of a one standard deviation increase in the boycott variable. Again, we find parallel pre-trends and a divergence in trends after the Hillsborough disaster, which continues to persist into the 2000s. Overall, this analysis again gives us confidence in the parallel trends assumption. One outlier post treatment is the year 2000 in which the BSA sampled more respondents in Southport than in any other year. From our shop data we learned that amongst constituencies in Merseyside, Southport has arguably the weakest boycott against The Sun in place. Thus, we would also expect that respondents in this constituency should be more Eurosceptic. This then explains the outlier in the post-treatment trend for the year 2000.

A.15 DiDiD conditional on social class

We estimated an OLS regression on which BSA respondents are most likely to read The Sun in the pre-Hillsborough data. We care about "Sun" readership because the effect of the Hillsborough disaster on Euroscepticism should be strongest for people who would have been plausible "Sun" readers before the disaster and would have continued to read The Sun in the counterfactual world in which Hillsborough would not have happened. However, given that our analyses are based on repeated cross-sections we cannot plausibly know which respondents would have read The Sun in Merseyside if the Hillsborough Disaster had never happened. We only observe respondents in Merseyside post-1989 in the presence of the disaster. Yet, we can approximate this group by relying on the strongest predictor(s) of "Sun" readership in the pre-Hillsborough data. Once we have identified this group we can run a difference-in-difference-in-differences (DiDiD) model as described in the main body of the text.

Figure A.16: Who reads The Sun?



Note: Baseline category for class is “working class”.

The OLS estimates are reported in figure A.16. It becomes clearly visible that university education and social class are the strongest predictors of "Sun" readership in the pre-

Hillsborough data set. The higher respondents' social class, the less likely they are to read The Sun. Unskilled and semi-skilled workers are most likely to read The Sun, followed by the skilled working class. Although we have no data on this question, it appears plausible that working class respondents are also more likely to be Liverpool F.C. supporters. To help with the interpretation of our DiDiD estimates, and to include a large enough number of observations in all cells, we recoded the class variable into three categories, unskilled working class (*"never had job", unskilled workers, semi-skilled workers*), skilled working class (*skilled workers*) and middle class (*intermediate, professionals*). We then use this recoded class variable to estimate the DiDiD model. We do this by interacting the general DiD estimator (Merseyside $\times$ post Hillsborough) with the class variable discussed above.

$$
\begin{aligned}
leavingEU_{i,j,k,c,t,r} &= \alpha + \gamma_1 Merseyside_{i,c} + \lambda_1 post\ Hillsborough_{i,t} \\
&+\beta_1(Merseyside \times post\ Hillsborough_{i,c,t}) + \zeta class_j + \theta class_k + \\
&\gamma_2(class \times Merseyside_{j,c}) + \lambda_2(class \times post\ Hillsborough_{k,t}) + \\
\beta_2(class \times Merseyside \times post\ Hillsborough_{j,c,t}) &+ \lambda_3(class \times post\ Hillsborough_{k,t}) + \\
&\beta_3(class \times Merseyside \times post\ Hillsborough_{k,c,t}) + \varsigma' X_{i,j,k,c} + \tau_t + \rho_r + \epsilon_{i,j,k,c,t}
\end{aligned}
\tag{7}
$$

where subscript $_i$ stands for unskilled working class respondent, subscript $_j$ for skilled working class respondent, and subscript $_k$ for middle class respondent.

A.16 Referendum analysis

The 2016 EU referendum counting areas officially located within Merseyside county are Liverpool, St. Helens, Knowsley, Wirral, Sefton, and Halton. They form the treatment group. The remaining 96 counting areas in North East England and North West England form the control group. The 2016 and 1975 referendums were counted under a different system. Becker and Novy (2017) match 1975 counting areas to 2016 counting areas, and we use their data. We transform the data from wide-format into long-format in order to construct a panel data set with two time periods.

Since covariates for 1975 are unavailable, we use covariate data from 2001 in time period 1. Since our most important control variables are shares of EU and A10 migrants that might have differed between Merseyside counting areas and other Northern areas, the 2001 start date makes sense because it is right before the EU- Eastern enlargement and the ensuing opening of the UK Labour market to migrants from A10 countries in 2004. We hence control for changes in EU and A10 migration at the counting area level from 2001 to 2011, the exact period that saw a large increase in Eastern European migrants to the UK. Table A.13 displays the full model including the estimated coefficients and corresponding standard errors.

Table A.13: DiD: Effect of Hillsborough on 2016 Leave vote share

	(1)	(2)	(3)	(4)	(5)
	leave vote share				
δ DiD	-0.082	-0.083	-0.082	-0.088	-0.088
	(0.031)	(0.032)	(0.031)	(0.025)	(0.026)
share EU migrants				-2.248	-2.248
				(1.721)	(2.138)
share A10 migrants				-0.536	-0.536
				(2.617)	(3.027)
share non-EU migrants				0.027	0.027
				(0.154)	(0.178)
median wage				-0.015	-0.015
				(0.036)	(0.048)
share finance employment				0.838	0.838
				(0.344)	(0.378)
share manufacturing employment				-0.111	-0.111
				(0.103)	(0.113)
share over 60s				0.106	0.106
				(0.113)	(0.117)
share tertiary education				-0.711	-0.711
				(0.164)	(0.180)
Constant	0.453	0.453	0.453	0.601	0.446
	(0.005)	(0.005)	(0.002)	(0.052)	(0.051)
Merseyside FE	✓	✓		✓	✓
region FE	✓			✓	✓
year FE	✓		✓	✓	✓
counting area FE			✓		
region $\times$ year FE		✓			
Obs	102	102	102	102	102

Standard errors in parentheses; model (5) uses bootstrapped standard errors.

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