Online Appendix for Collective Remembrance and Private Choice: German-Greek Conflict and Behavior in Times of Crisis

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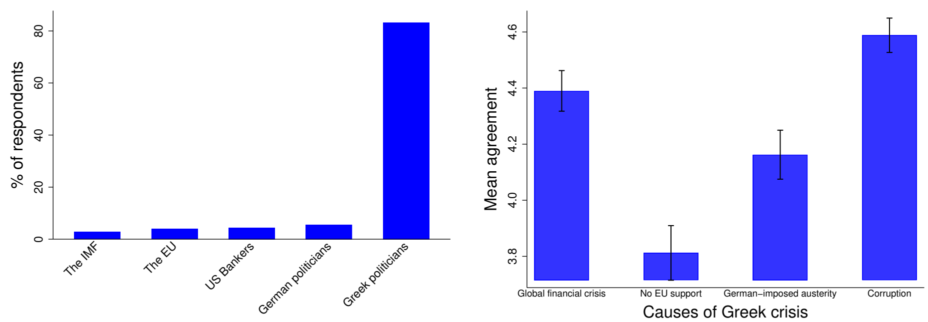
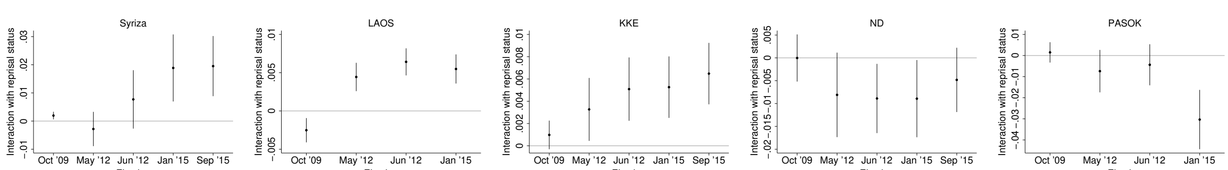
A Additional Figures and Tables

Figure A.1: Blame attribution for Greek crisis



Notes: The plot on the left displays the proportion of survey respondents who indicated each of the actors on the x-axis as primarily responsible for the Greek crisis. The plot on the right displays mean agreement (1-5 Likert scale) and 95% confidence intervals with each of the factors on the x-axis causing the Greek crisis.

Figure A.2: Vote share by party and reprisal status



Notes: The figure displays coefficient estimates of β_τ from equation 2 along with 95% confidence intervals. The dependent variable is the vote share of the party indicated on each subplot title. Standard errors are clustered at the municipal unit level ($N = 1,035$). Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

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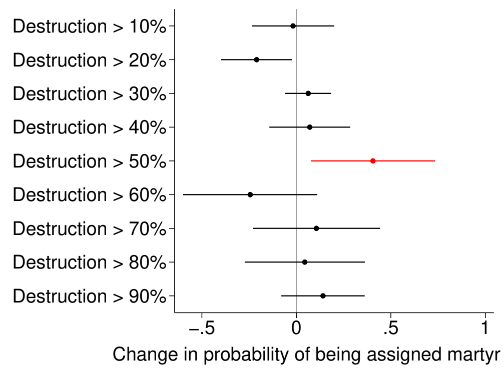
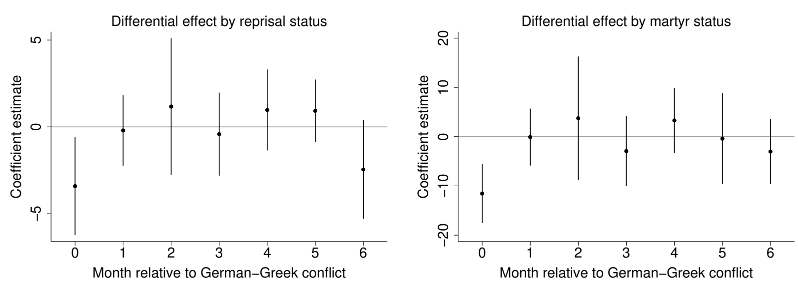
Figure A.3: Probability of being assigned martyr status, by cutoffs of destruction



Notes: The figure plots coefficient estimates and 95% CI from a regression of a martyr status dummy on dummies for destruction above a given cutoff, as indicated on the y-axis. The dataset contains towns suffering reprisals in WWII. Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

Figure A.4: Long-run effect of monthly article share



Notes: The figure displays estimates based on equation 1, but includes interactions of 6 lags of *Article share* with *Share towns* (left) or *Share martyr towns* (right). Point estimates and 90% CI for all interaction coefficients are plotted. Conflict in previous months has no statistically significant differential effect on German market share in a given month. Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

Table A.1: Key events – Greek sovereign debt crisis

Date	Events
Oct 2009	Center-left party PASOK wins parliamentary elections
Oct–Dec 2009	Greek budget deficit reaches 12.5% of GDP
	Consecutive downgrades of Greece's credit ratings
Feb 2010	First austerity package
Mar 2010	Second austerity package
Apr 2010	First bailout; Greece's sovereign debt downgraded to junk bond status
	Greek consumer association calls for boycott of German products
May 2010	Third austerity package passed amidst country-wide riots and strikes
Oct 2010	Brussels EU summit accepts German-inspired new bailout mechanism
Jan 2011	Greek case against Germany for WWII reparations heard in Den Haag
Sep 2011	German finance minister Schäuble suggests Greece may want to leave the Euro
	Germany refuses extension of repayment terms for Greek loan
Oct 2011	Haircut on Greek debt announced
Nov 2011	Prime minister Papandreou resigns
Feb 2012	Second bailout package
May–Jun 2012	Parliamentary elections
Nov 2012	7th austerity package passed; massive protests and unrest outside the parliament
	Den Haag court rules in Germany's favor in reparations case
Jan 2013–Nov 2014	Relative political and economic stability after the EU/IMF bailout and haircut
Dec 2014	Failure to elect new Greek president results in new elections
Jan–Jul 2015	Left-wing party Syriza elected
Jul 2015	Finance minister Varoufakis resigns
	Varoufakis criticizes German-led dominance of the EU
	Continuous conflict between Greece and Germany

Table A.2: Regression discontinuity design – martyr status

Dep. Variable	Granted martyr status		Log population 1940		Applied for martyr status	
	(1)	(2)	(3)	(4)	(5)	(6)
Destruction > 50%	0.401***	0.473***	-0.086	-0.091	0.234	0.353
	(0.108)	(0.160)	(0.390)	(0.608)	(0.184)	(0.381)
Observations	277	277	281	281	280	280
P-value	0.00302	0.0151	0.881	0.254	0.355	0.278
Polynomial	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. P-values are robust p-values, computed by the rdrobust routine, as described in Calonico, Cattaneo and Titiunik (2015). Towns in the 40% to 60% destruction range. MSE-optimal point estimation using a common bandwidth on both sides of the cutoff.

Table A.3: Martyr status predicted by discontinuity, narrow range

Dep. Variable	Share German cars			
	(1)	(2)	(3)	(4)
	Panel A: At least 50% of towns in 0.25-0.75 destruction range			
Article share	0.328	-68.481***	-68.196***	
	(0.249)	(0.293)	(0.316)	
Article share × Mean destruction	-0.128	2.441***	2.413***	-0.532***
	(0.133)	(0.006)	(0.005)	(0.073)
Article share × Predicted martyr status	-0.085	-0.130***	-0.159***	-0.161***
	(0.194)	(0.000)	(0.000)	(0.000)
Observations	831	831	831	831
R-squared	0.180	0.203	0.270	0.367
	Panel B: At least 65% of towns in 0.25-0.75 destruction range			
Article share	0.343	1.410**	1.756**	
	(0.401)	(0.425)	(0.460)	
Article share × Mean destruction	-0.022	-0.871***	-0.890***	-0.868***
	(0.112)	(0.005)	(0.004)	(0.013)
Article share × Predicted martyr status	-0.085	-0.439***	-0.471***	-0.472***
	(0.239)	(0.000)	(0.000)	(0.000)
Observations	495	495	495	495
R-squared	0.150	0.166	0.219	0.355
	Panel C: All towns in 0.25-0.75 destruction range			
Article share	-0.613**	7.287***	7.699***	
	(0.197)	(0.264)	(0.298)	
Article share × Mean destruction	0.718***	0.979***	0.988***	0.988***
	(0.103)	(0.000)	(0.000)	(0.000)
Article share × Predicted martyr status	-0.680**	-0.799***	-0.836***	-0.836***
	(0.212)	(0.000)	(0.000)	(0.000)
Observations	420	420	420	420
R-squared	0.303	0.316	0.373	0.548
Pre-controls × Article share		✓	✓	✓
Prefecture FE × Calendar month FE			✓	✓
Time FE				✓

Notes: Results using the specifications in Panel D of Table 2. Standardized coefficients reported. Samples consist of prefectures with a minimum share of towns in the 0.25-0.75 destruction range, as indicated in the respective title. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Table A.4: Interaction of state recognition and family transmission

Dep. Variable	German car		German ideal car		Blame Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Martyr status, OLS					
Martyr	-0.0114	-0.0020	-0.0899	-0.3136	0.0181	0.0168
	(0.0431)	(0.2579)	(0.0576)	(0.2888)	(0.0203)	(0.0832)
Native	-0.0129	-0.0316	-0.0862	-0.0502	-0.0014	-0.0176
	(0.0499)	(0.0567)	(0.0607)	(0.0748)	(0.0186)	(0.0224)
Martyr × Native	-0.0488	-0.0398	0.0825	0.1039	0.0122	0.0200
	(0.0669)	(0.0719)	(0.0824)	(0.0942)	(0.0333)	(0.0415)
Observations	681	643	581	547	839	794
R-squared	0.0043	0.0820	0.0071	0.1045	0.0028	0.0694
	Panel B: Martyr status, HLM					
Martyr	-0.0114	-0.0020	-0.0899	-0.3136	0.0197	0.0168
	(0.0430)	(0.2472)	(0.0575)	(0.2747)	(0.0207)	(0.0805)
Native	-0.0129	-0.0316	-0.0862	-0.0502	-0.0023	-0.0176
	(0.0498)	(0.0544)	(0.0606)	(0.0712)	(0.0185)	(0.0216)
Martyr X Native	-0.0488	-0.0398	0.0825	0.1039	0.0119	0.0200
	(0.0668)	(0.0689)	(0.0822)	(0.0896)	(0.0331)	(0.0401)
Observations	681	643	581	547	839	794
	Panel C: Destruction, OLS					
% Destruction	-0.0650	-0.0735	-0.1612**	-0.3567	0.0284	0.0292
	(0.0442)	(0.2503)	(0.0662)	(0.3251)	(0.0240)	(0.1087)
Native	-0.0407	-0.0405	-0.0879*	-0.0427	0.0010	-0.0223
	(0.0487)	(0.0523)	(0.0518)	(0.0663)	(0.0200)	(0.0253)
% Destruction × Native	0.0116	-0.0357	0.1331	0.0945	0.0107	0.0489
	(0.0622)	(0.0673)	(0.0982)	(0.1117)	(0.0398)	(0.0484)
Observations	681	643	581	547	839	794
R-squared	0.0058	0.0874	0.0130	0.1083	0.0039	0.0682
	Panel D: Destruction, HLM					
% Destruction	-0.0650	-0.0735	-0.1612**	-0.3567	0.0284	0.0292
	(0.0441)	(0.2399)	(0.0660)	(0.3093)	(0.0240)	(0.1051)
Native	-0.0407	-0.0405	-0.0879*	-0.0427	0.0010	-0.0223
	(0.0486)	(0.0501)	(0.0516)	(0.0630)	(0.0199)	(0.0245)
% Destruction × Native	0.0116	-0.0357	0.1331	0.0945	0.0107	0.0489
	(0.0620)	(0.0645)	(0.0979)	(0.1062)	(0.0397)	(0.0468)
Observations	681	643	581	547	839	794
Controls		✓		✓		✓

Notes: Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1. Panels A and C show OLS results. Panels B and D estimate mixed effects linear models with random effects at the town level (town-specific intercepts). Controls include gender, 6 age categories, 4 educational categories, 7 income categories and prefecture fixed effects, all interacted with martyr status (Panels A and B) or % destruction (Panels B and C). Standard errors clustered at the town level (N= 142) in parentheses.

B Data Appendix

B.1 Details on Variable Construction

B.1.1 Conflict Index

For the construction of the index, we rely on the archive of the newspaper *Kathimerini*, the largest daily newspaper by circulation during the period of our study. All articles are digitized. The database comprises 101,889 articles published in the sections 'Greece', 'Politics', and 'Economy'. We compute the monthly share of articles related to German-Greek conflict following the method of Baker, Bloom and Davis (2016).

First, we sample 10% of articles containing the stem "German-" and manually classify them into relevant and non-relevant to political tension between Germany and Greece. An article classified as relevant must contain a reference, however short, to German–Greek conflicting political interests or political interactions in the context of foreign relations, the Eurozone or the issue of German war reparations. Articles that refer to German-Greek relations in another context – e.g. tourism flows, economic transactions between German and Greek firms etc. – are classified as irrelevant.

We split the audited sample into a training and test set and use the test set to evaluate the classification performance of our algorithm. We start by assigning a frequency score to each term appearing more than twenty times in the articles of the training set. This score captures how frequently the term appears in conflict-related articles relative to non-conflict-related articles. The frequency score for term i is constructed as:

$$\text{Frequency score}_i = \frac{\Pr(\text{i}|\text{c})}{\Pr(\text{i}|\text{c}) + \Pr(\text{i}|\text{nc})} * 100$$

where c is a conflict-related article and nc an unrelated article. The score takes on the value 100 when a term appears only in conflict-related articles and the value 0 when it appears only in unrelated articles. Terms like bankruptcy, memorandum, austerity, but also subtler terms like discipline, painful, tolerance, score above 95 in this index.

We use the 40 highest-scoring terms and form all combinations of 5 to 6 terms from this list. For each combination, we classify an article in our test set as conflict-related if it contains at least one of the terms in the combination. We then compare this classification to the human audit and evaluate each combination of terms based on a compound measure of precision and recall known as the F1-score. Since we are interested in minimizing both false positive and false negative classifications of articles, we put equal weight on the two types of errors and pick the combination that maximizes:

$$F_1 = 2 * \frac{2 * \text{true positive}}{2 * \text{true positive} + \text{false negative} + \text{false positive}}$$

Based on the above procedure, we end up classifying an article as related to German- Greek conflict if it contains the stem "german-" and at least one of the words in the set {haircut, summit, Merkel, troika, Eurozone}. This gives us a monthly count of conflict- related articles, which we normalize by the total number of articles Kathimerini published in the month.

B.1.2 Car Registrations

The Greek Ministry of Transport and Communications collects data on registrations of new passenger vehicles. These are disseminated by the Hellenic Statistical Authority (ELSTAT). We use monthly data on the number of new passenger vehicles registered in each prefecture for the period January 2008 to December 2014, by manufacturing plant, and exclude small manufacturers with less than 10 vehicles sold during the entire period. The raw data from ELSTAT does not contain information on the brand of registered vehicles. However, ELSTAT provides a correspondence list that allows us to match production plants to car manufacturers. This correspondence does not always distinguish between brands produced by the same manufacturer (e.g. Daimler, producing Mercedes and Chrysler). We are nonetheless able to distinguish German from non-German brands in our sample; the former include Volkswagen, Opel, Audi, BMW, Porsche and the brands of the Daimler group. For our purposes, a car's "nationality" is determined by the place of manufacture of (most) cars, and not ownership (i.e. we count Seat as Spanish). If Seat is actually perceived as German, we understate the shift away from German cars, biasing our results downwards.

B.1.3 Anti-German Sentiment in Parliamentary Speeches

To identify parties with a negative stance towards Germany we rely on sentiment in parliamentary speeches. Greek parliamentary proceedings have been digitized in their entirety since 1989 and organized in a dataset by MP and date of parliamentary sitting by Dritsa and Louridas (2018). From this dataset we extract all speeches that contain the stem "German" for the period 2009 to 2015. We code the sentiment of each speech using a dictionary approach. We rely on the GrAFS sentiment lexicon of Tsakalidis et al. (2018), a manually annotated lexicon based on one of the most widely used dictionaries of Modern Greek (Trantafyllides, 1998). GrAFS contains 32,884 unique inflected forms annotated in terms of subjectivity and positive or negative content. We assign a sentiment value to each speech by substracting the number of negative words from the number of positive words and dividing by the total number of words in the speech. We focus on words with values of subjective content higher than 0.5 (in a range of 0 to 1) and label as positive those words with higher positive than negative annotator scores (and vice versa for negative words). We restrict attention to speeches with more than 50 words; shorter speeches are usually brief remarks or procedural interventions.

B.1.4 Martyr Towns

The decision to award martyr status to locations that suffered greatly during the German Occupation was taken after parliamentary debates on the recognition of the victimhood status of the town of Kalavryta. This decision was written into law in 1997. In accordance with Law 2503, a committee composed of professional historians and high-ranking senior officials was established in 1997 to adjudicate applications for martyr status.[1] The Ministry of the Interior at the time stated that

> "the ... Committee was established to examine all the proposals for the characterization of towns and villages as 'martyr' towns and villages and submit relevant proposals to the Ministry. The characterization of 'martyr' was important for the great contribution of towns and villages in the national struggle against the occupied forces in the period 1941–1944, during which the toll in human lives, as well as the material damage, was tragic."

The Presidential Decree that officially awarded martyr status established the following criteria for recognition as a martyred town:

1. The total destruction of houses following a burning, explosion or bombardment.
2. The loss of 10% of the overall population due to collective or individual executions.
3. The destruction of 80% of the total number of dwellings due to burning, explosion or bombardment and the loss of 10% of the population ... also taking into consideration the absolute losses.

The committee did not follow these rules to the letter and used additional sources and supporting evidence. The minutes do not suggest that political considerations played a role in the ultimate decision.

[1] https://www.e-nomothesia.gr/autodioikese-demoi/n-2503-1997.html

For compiling the list of martyr towns we rely on Presidential Decrees no. 2130 (1993), 399 (1998), 99 (2000), 40 (2004) and 140 (2005). The list includes a total of 112 towns, of which 100 experienced reprisals by the German army, 7 by Bulgarian and 5 by Italian forces.

B.2 Variable Descriptions and Summary Statistics

Table B.1: Prefecture-level variables

Variable	Description and source
Share German cars	Monthly share of German-manufactured cars in a prefecture's total new car registrations. Source: Ministry of Transportation and Communications and ELSTAT.
Article share	Monthly *Kathimerini* articles relevant to German–Greek conflict, normalized by the total number of *Kathimerini* articles in the month. For details on the selection of the relevant articles see Appendix B.1.1. Source: *Kathimerini* electronic archive 2008–2014, sections on "Greece", "Politics" and "Economy".
EPU index	Average monthly search volume for the terms "economic", "economy", "policy", "uncertain" and "uncertainty" in the period 2008–2014, for the geographic area of Greece. The index is a normalization of the share of total searches represented by each term in a given time and region and ranges between 0 and 100. Source: Google Trends.
Google Index	Average monthly search volume for the terms "Germans", "German reparations" and "Distomo" in the period 2008–2014, for the geographic area of Greece. The index is a normalization of the share of total searches represented by each term in a given time and region and ranges between 0 and 100. Source: Google Trends.
Share towns	Share of a prefecture's towns in 1940 that experienced reprisals by the German occupying forces during WWII. Original list of towns that experienced reprisals compiled from the following sources: *Destroyed towns and villages owing to the War of 1940-1945*, Ministry of Social Welfare (1946), *Tables of Destruction of Buildings of Greece*, Ministry of Reconstruction (1947), *Report on Atrocities in Crete* (Iraklion, 1983), *Greek Holocausts 1940-1945* (Athens, 2010), Meyer (2002), Hagen (1979), Fotiou (2008). Additional information collected from primary archival work in the Libraries of the Hellenic Parliament and the Archives of the Committee of article 18 of the Law 2508/97 at the Ministry of the Interior in Greece.
Share population	Share of a prefecture's 2011 population in reprisal towns. Source: 2011 Greek census.
Mean destruction	Average destruction in a prefecture during WWII. Estimates of destruction (in %) assigned to each town in our list of reprisal towns from the sources stated above. Towns not in the list are assigned destruction of zero.
Share martyr towns	Share of prefecture's towns awarded martyr status. Sources: Archive of the Committee on martyr towns, Presidential decrees 399(1998), 99(2000), 40(2004), 140(2005), 111(2009), 203(2012)139(2014), 79(2017), Law 2130(1993).

Table B.1: Prefecture-level variables

Variable	Description and source
Share martyr population	Share of prefecture's 2011 population in towns awarded martyr status.
Share towns w/ memorial	Share of a prefecture's towns that commemorate the German occupation, with ceremonies or physical memorials. Original phone survey of mayors' offices for the list of reprisal towns.
Share pop w/ memorial	Share of a prefecture's 2011 population in towns that commemorate the German occupation, with ceremonies or physical memorials.
Share Italian/Bulgarian	Share of a prefecture's towns in 1940 that experienced reprisals by the Italian or Bulgarian occupying forces during WWII. Sources used in the construction of *Share towns*.
Share towns in civil conflict	Share of a prefecture's 1940 towns mentioned as part of major battle in 1943-1944 civil war conflicts. Source: Kalyvas and Marantzidis (2015) and 1940 census.
Population	Source: 2001 Greek census.
Share agriculture	Source: 2001 Greek census.
Share industry	Source: 2001 Greek census.
Share civil servants	Source: 2001 Greek census.
Share secondary education	Source: 2001 Greek census.
Share higher education	Source: 2001 Greek census.
Unemployment rate	Source: 2001 Greek census.
Income p.c.	Source: Eurostat.
Population in 1940	Source: 1940 Greek census.
Share seats to communists	The share of a prefecture's seats allocated to the coalition of the Greek Communist Party and the Greek Agrarian Party (Pallaiko Metopo) in the 1936 parliamentary elections. Source: Hellenic Parliament, Registry of Parliament Members.
Ruggedness	Terrain ruggedness index computed as in Riley et al. (1999) and averaged over each prefecture's surface. The shapefile of prefecture boundaries is from ELSTAT and elevation data from GMTED2010.
Average distance 1940 road	To compute this measure we first compute the distance to the nearest road from the centroid of each 50×50 km grid cell in an equidistant projection and then average over each prefecture's surface. We digitize a physical map of Greece's pre-WWII road network from Doxiadis (1947). The shapefile of prefecture boundaries is from ELSTAT.
Average distance 1940 rail	Similarly to the above measure, we first compute the distance to the nearest railway line from the centroid of each 50×50 km grid cell in an equidistant projection and then average over each prefecture's surface. We digitize a physical map of Greece's pre-WWII railway network from Doxiadis (1947). The shapefile of prefecture boundaries is from ELSTAT.
Nighttime light density	Source: National Centers for Environmental Observation (NOAA).
Predicted resupply	Interaction of average ruggedness and standard deviation of ruggedness, prefecture-level.

Table B.1: Prefecture-level variables

Variable	Description and source
Share dealers who sell German cars	Share of a prefecture's dealers advertising in car.gr who have at least one German car model listed in snapshots of car.gr taken from the Internet Archive's Wayback Machine for select years.

Table B.2: Balancedness

Variable	All	Non-reprisal	Reprisal	Difference	Non-martyr	Martyr	Difference
Log population	12.336	11.989	12.48	-0.491	12.231	12.444	-0.212
	(0.881)	(0.723)	(0.909)	(0.2644)*	(1.003)	(0.738)	(0.2475)
Share agriculture	0.264	0.256	0.267	-0.012	0.264	0.264	0.001
	(0.107)	(0.109)	(0.108)	(0.0332)	(0.113)	(0.103)	(0.0303)
Share industry	0.219	0.208	0.223	-0.015	0.212	0.225	-0.013
	(0.058)	(0.046)	(0.063)	(0.018)	(0.047)	(0.069)	(0.0164)
Share civil servants	0.0136	0.015	0.013	0.002	0.014	0.013	0.001
	(0.0036)	(0.005)	(0.003)	(0.0011)	(0.004)	(0.003)	(0.001)
Share secondary education	0.179	0.17	0.183	-0.012	0.172	0.187	-0.016
	(0.031)	(0.023)	(0.034)	(0.0096)	(0.031)	(0.031)	(0.0086)*
Share higher education	0.110	0.105	0.112	-0.007	0.107	0.112	-0.006
	(0.024)	(0.019)	(0.026)	(0.0074)	(0.025)	(0.022)	(0.0067)
Unemployment rate	0.122	0.127	0.119	0.008	0.123	0.121	0.002
	(0.029)	(0.033)	(0.027)	(0.009)	(0.028)	(0.031)	(0.0082)
Income p.c. (2008-2009)	9.773	9.745	9.785	-0.04	9.756	9.791	-0.035
	(0.224)	(0.196)	(0.237)	(0.0694)	(0.234)	(0.217)	(0.0633)
Income p.c. growth (2008-2009)	-0.054	-0.046	-0.057	0.012	-0.057	-0.05	-0.007
	(0.041)	(0.031)	(0.044)	(0.0125)	(0.045)	(0.037)	(0.0115)
Share German cars	0.260	0.229	0.273	-0.044	0.247	0.274	-0.027
	(0.062)	(0.066)	(0.056)	(0.0182)**	(0.066)	(0.056)	(0.0171)
First diff. share German cars pre-2010	0.003	0.002	0.004	-0.002	0.002	0.004	-0.001
	(0.005)	(0.004)	(0.005)	(0.0014)	(0.005)	(0.004)	(0.0013)
Log population in 1940	11.640	11.431	11.721	-0.291	11.538	11.742	-0.204
	(0.625)	(0.538)	(0.645)	(0.1945)	(0.733)	(0.489)	(0.1762)
Share communist seats 1936	0.029	0.037	0.025	0.012	0.026	0.031	-0.005
	(0.057)	(0.065)	(0.055)	(0.0177)	(0.055)	(0.061)	(0.0162)
Ruggedness	248.925	227.026	258.05	-31.024	235.783	262.592	-26.809
	(77.254)	(95.752)	(67.583)	(23.5696)	(80.059)	(73.319)	(21.5212)
Average distance 1940 road	15.313	33.241	7.843	25.398	25.147	5.085	20.063
	(35.419)	(57.813)	(16.129)	(10.3797)**	(47.94)	(2.426)	(9.6035)**
Average distance 1940 railway	78.167	96.881	70.369	26.512	80.881	75.345	5.536
	(92.127)	(103.936)	(87.127)	(28.3478)	(86.708)	(99.168)	(26.0556)
Observations	51	15	36		26	25	

Notes: Standard errors in parentheses. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table B.3: Summary statistics of main variables for prefecture-level analysis

Variable	Mean	S.D.	Min	Max	N
Cross-section					
Reprisals in prefecture (0/1)	0.706	0.460	0	1	51
Share towns with reprisals	0.052	0.071	0	0.308	51
Share martyr towns	0.015	0.023	0	0.104	51
Share memorials (non-martyr)	0.028	0.044	0	0.2	51
Monthly series					
Article share	0.062	0.040	0.00856	0.182	84
Panel					
Total car sales	211.567	972.944	0	16361	4284
Share German cars	0.259	0.135	0	1	4243

Table B.4: Balancedness, survey

Variable	Control	Reprisal	Difference
Age	52.709	52.435	0.275
	(15.551)	(15.189)	(1.0093)
Female	0.647	0.617	0.03
	(0.478)	(0.487)	(0.0317)
Lost job in last 5 years	0.135	0.132	0.004
	(0.342)	(0.338)	(0.0224)
Year car bought	2005	2005	-0.111
	(6.702)	(7.145)	(0.5517)
Education: high school or higher	0.848	0.846	0.003
	(0.359)	(0.362)	(0.0237)
Education: university or higher	0.291	0.272	0.019
	(0.455)	(0.445)	(0.0295)
Income bracket (1=under 500, 7=over 5000)	2.652	2.64	0.012
	(1.277)	(1.352)	(0.0892)
% Destruction	0	0.658	-0.658
	(0.000)	(0.371)	(0.0171)***
Observations	468	460	

Notes: Standard errors in parentheses. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table B.5: Summary statistics, electoral dataset

Variable	Mean	S.D.	Min	Max	N
Reprisals	0.152	0.359	0	1	1035
Martyr	0.058	0.234	0	1	1035
Memorials	0.079	0.270	0	1	1035
Vote share Syriza	0.188	0.046	0.066	0.704	1035
Vote share LAOS	0.024	0.011	0.001	0.099	1035
Vote share KKE	0.060	0.037	0.005	0.391	1035
Vote share ND	0.321	0.076	0.059	0.603	1035
Vote share PASOK	0.235	0.053	0.039	0.622	1035

C Additional Analyses

C.1 Checks to Account for Economic Effects

C.1.1 Controls

Table C.1: Controlling for differential effects of the debt crisis

Dep. Variable	Share German cars			
	(1)	(2)	(3)	(4)
	Panel A: Monthly unemployment			
Article share	-0.033	-2.286	-1.204	
	(0.105)	(5.818)	(5.901)	
Article share × Share towns	-1.555	-3.053**	-3.121**	-3.131**
	(0.931)	(1.472)	(1.394)	(1.401)
Monthly unemp. rate	0.140	0.142	0.139	
	(0.268)	(0.269)	(0.268)	
Monthly unemp. rate × Share towns	0.035	0.031	0.063	0.086
	(0.589)	(0.592)	(0.609)	(0.609)
Observations	4,243	4,243	4,243	4,243
R-squared	0.258	0.267	0.353	0.391
	Panel B: Nightlight density			
	Panel B1: Baseline regressions for sample with non-missing luminosity data			
Article share	-0.168	-6.703	-6.228	
	(0.139)	(6.560)	(6.340)	
Article share × Share towns	-0.778	-2.544	-2.391	-2.377
	(0.883)	(1.575)	(1.454)	(1.464)
Observations	1,972	1,972	1,922	1,922
R-squared	0.247	0.259	0.373	0.421
	Panel B2: Controlling for monthly prefecture-level luminosity			
Article share	-0.139	-7.337	-7.103	
	(0.137)	(6.605)	(6.376)	
Article share × Share towns	-0.802	-2.582	-2.405	-2.382
	(0.868)	(1.579)	(1.458)	(1.465)
Nighttime light density	-0.004**	-0.004**	-0.005***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,972	1,972	1,922	1,922
R-squared	0.250	0.261	0.376	0.421
	Panel C: EPU index			
EPU index	0.033**	0.033**	0.031**	
	(0.014)	(0.014)	(0.014)	
EPU index × Share towns	-0.185	-0.179	-0.115	-0.122
	(0.187)	(0.187)	(0.227)	(0.229)
Article share × Share towns	-1.724**	-3.096**	-3.110**	-3.135**
	(0.703)	(1.285)	(1.220)	(1.215)
Observations	4,243	4,243	4,243	4,243
R-squared	0.258	0.267	0.353	0.391
Pre-controls × Article share		✓	✓	✓
Prefecture × Calendar month FE			✓	✓
Time FE			✓	✓

Notes: Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

We first use the interaction between monthly unemployment in Greece as a whole and the share of reprisal towns in a prefecture to account for time-varying economic conditions that might have a differential impact across prefectures. Table C.1, Panel A, shows that there is no direct effect of unemployment on the share of German cars in the country as a whole – nor is there a differential effect in prefectures more affected by German massacres. The differential effect of time-varying conflict on prefectures with a reprisal history survives essentially unchanged.

In Panel B, we use nightlight density as an indicator of economic activity. This is computed using luminosity data from NASA at the prefecture level. This data is only available until 2013, and is missing each year between the months of April and August. Due to these limitations, we lose about half of our sample. The basic pattern in the half of the sample with non-missing data is the same as in the rest, but coefficients on the interaction term are not significant at standard levels of confidence (Panel B1). The magnitude of the coefficient in the available sample is unaffected by the inclusion of a control for night-time luminosity (Panels B2 and B3). This indicates that the drop in German car market share we identify is not the result of high-frequency changes in economic activity correlated with the location of reprisals.

As a third alternative, we compile an index of economic uncertainty at the national level. We use Google Trends and extract the monthly volume of searches (in Greek) for "economy" or "economic", "uncertainty" or "uncertain" and "policy" (Baker, Bloom and Davis, 2016). We then control for the interaction of this measure with the share of a prefecture's towns that experienced reprisals. Economic policy uncertainty has no differential effect on reprisal prefectures, but the differential effect of monthly German-Greek conflict remains large and significant. This is further evidence that our baseline measure captures German-Greek animosity specifically, and is not just a proxy for the debt crisis.

C.1.2 Sample Restriction

An alternative to controlling for differential economic performance is to exclude all expensive cars from our sample. This is done in Table C.2. Column 2 only uses sales of cars in the 'Volkswagen category', meaning non-luxury sedans (i.e. excluding Audi, BMW, and Mercedes). The coefficient on the interaction remains similar in magnitude. This indicates that effects are not driven by differential declines in purchasing power across prefectures, causing fewer purchases of luxury items.

Table C.2: Dropping expensive cars

Dep. Variable	Share German cars	
	(1)	(2)
Sample of brands	All cars	VW category
Article share	-1.199	-4.346
	(5.892)	(6.644)
Article share × Share towns	-3.029**	-2.866*
	(1.216)	(1.588)
Observations	4,243	4,220
R-squared	0.353	0.326

Notes: Table replicates the specification in column 4 of Table 1, Panel A. *VW Category* includes the following brands: Volkswagen, Opel, Citroen, Ford, Honda, Hyundai, Nissan, Peugeot, Renault, Seat, Skoda and Toyota. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C.1.3 Survey Evidence

Survey evidence from approximately 900 Greek respondents suggests there was no major additional economic hardship in reprisal areas. As shown in Appendix Table B.4, the share of recently unemployed and the income of respondents are statistically indistinguishable across reprisal and control towns.

We next analyze information on car ownership and buying intentions. Table C.3 displays results at the extensive and the intensive margin, by using both an indicator for reprisals (Panel A) and town-level estimates of destruction provided in publications of the Ministries of Reconstruction and Social Welfare

(Panel B) as proxies of the degree of exposure to reprisals. Destruction is 0 for towns unaffected by reprisals.

Respondents in reprisal towns and towns that experienced a higher level of destruction are less likely to own a German car, though the effect is not significant. Importantly, purchasing intentions differ significantly. German cars are an aspirational good for most respondents – while many people name a German brand as their ideal, few actually own a German car. Columns 3-4 show that respondents in reprisal towns like German cars less, a result that becomes stronger after controlling for individual socioeconomic characteristics and prefecture fixed effects. The difference in taste suggests that differential economic performance is unlikely to drive our main result.

Table C.3: Survey – Main outcomes

Dep. Variable	German car		German ideal car		Blame Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
Reprisal	-0.031	-0.036	-0.058	-0.057*	0.023	0.031**
	(0.031)	(0.030)	(0.040)	(0.033)	(0.017)	(0.014)
Observations	685	646	583	549	844	797
R-squared	0.001	0.050	0.003	0.062	0.002	0.041
			Panel B			
% Destruction	-0.062*	-0.053	-0.106**	-0.131***	0.033	0.041**
	(0.033)	(0.034)	(0.046)	(0.032)	(0.022)	(0.016)
Observations	685	646	583	549	844	797
R-squared	0.004	0.050	0.008	0.069	0.004	0.042
Controls		✓		✓		✓

Notes: Controls include indicators for gender, 6 age categories, 4 educational categories, 7 income categories and prefecture fixed effects. Standard errors clustered at the town level (N= 142) in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Blame attribution also suggests that results are not driven by differential economic conditions. The survey asks directly whether Greeks in reprisal towns hold different beliefs about Germany's role during the Euro debt crisis. In the last two columns of Table C.3, we analyze answers to the question "If you had to blame one actor for the recent debt crisis, who would that be?" The dependent variable is an indicator for respondents who chose Germany as an answer. Residents of reprisal towns and towns that experienced more destruction during the Occupation are markedly more likely to attribute blame for the crisis to Germany, as opposed to Greek politicians, US banks, or international actors like the European Union or the International Monetary Fund.

C.2 Accounting for Unobserved Culture

We can examine directly whether Greeks in reprisal towns are more nationalistic today, or engage in collective action more readily. There is little evidence for either: In our survey, we asked how proud respondents were to be Greek. Table C.4 shows no significant differences in national identity by exposure to destruction. Rates of participation in demonstrations and strikes are higher for reprisal towns, but do not correlate with the extent of destruction.

To provide additional evidence that effects are driven by the memory of reprisals and not latent propensity for activism, we exploit the geography of Greek armed resistance to isolate plausibly exogenous variation in the location of reprisals. No military group can fight for any length of time without substantial supplies. Food, weapons, ammunition, fuel and clothing are everyday necessities. Greek (and other European) partisans during World War II were typically resupplied by the Allies by air, and where feasible, by sea. In Greece, the British dropped supplies by parachute from aircraft flying from Egypt, or landed smaller planes on improvised airstrips; they also used submarines to bring agents and military supplies into occupied Greece.

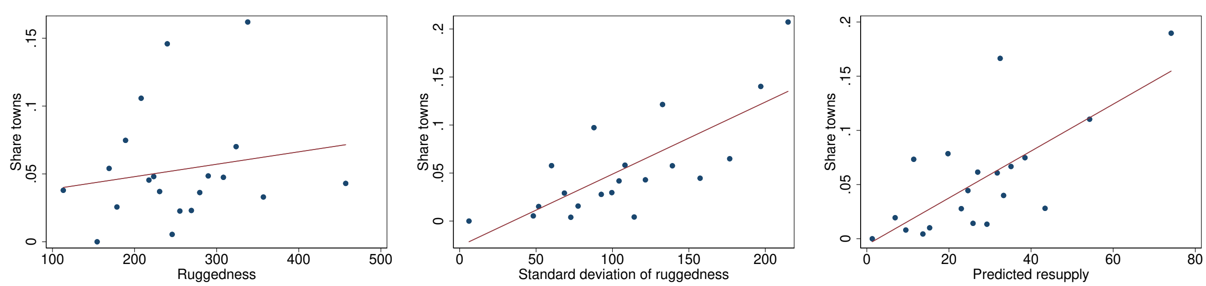
Table C.4: Survey – Placebo outcomes

Dep. Variable	National pride		Lost job		Demonstration		Strike	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A							
Reprisal	0.034	0.060	-0.000	0.002	0.046	0.054^{**}	0.078^{**}	0.087^{***}
	(0.056)	(0.043)	(0.021)	(0.019)	(0.041)	(0.026)	(0.035)	(0.033)
Observations	905	848	904	848	907	849	906	848
R-squared	0.000	0.034	0.000	0.137	0.002	0.120	0.006	0.147
	Panel B							
% Destruction	-0.050	0.014	0.012	0.001	0.014	0.026	0.015	0.059
	(0.054)	(0.053)	(0.025)	(0.024)	(0.048)	(0.029)	(0.044)	(0.054)
Observations	905	848	904	848	907	849	906	848
R-squared	0.001	0.033	0.000	0.137	0.000	0.117	0.000	0.142
Controls		✓		✓		✓		✓

Notes: Controls include indicators for gender, 6 age categories, 4 educational categories, 7 income categories and prefecture fixed effects. Standard errors clustered at the town level (N= 142) in parentheses. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Supply points are important for guerrilla operations. They need to be sufficiently remote for the occupiers to have difficulty in controlling the territory, but accessible enough for Allied aircraft and submarines to reach them. Based on this observation, we construct an instrument for partisan resupply – and, consequently, for reprisal attacks – based on the combination of two terrain characteristics.

Figure C.1: First stage



Notes: Each figure represents a binned scatterplot of the share of reprisal towns in a prefecture against the instrument denoted on the x-axis. *Predicted resupply* is the product of ruggedness and the standard deviation of ruggedness.

The first component is ruggedness. Rugged areas generally provide safe havens to insurgents. Partisans and guerrillas fighting conventional forces are often outgunned, and use asymmetric warfare to even the odds. By retreating to the most inaccessible areas of a country, insurgents can typically deny their foe the use of his strongest assets – armor and heavy artillery. This pattern held in 1940s Greece, where the largest concentrations of partisans were located in inner parts of Central Greece, the Peloponnese, and around the Pindus mountains in Northern Greece. We calculate ruggedness using the method of Nunn and Puga (2012). The left panel of Figure C.1 shows that ruggedness predicts more massacres. A one standard deviation increase in ruggedness increases the likelihood of a prefecture experiencing reprisals by 8%.

The second component of the instrument is variation in the ruggedness of the terrain. Conditional on a location's ruggedness, which would have determined the presence of partisans, it was easier for the Allies to drop supplies from the air in flat locations. Small valleys ringed by rugged mountains allowed the partisans to locate supplies more easily, and at the same time be sufficiently protected from the German army while picking them up. To proxy for this determinant of supply points, we use the standard deviation of ruggedness. The middle panel of Figure C.1 shows that this variable strongly predicts the share of destroyed towns in a prefecture.

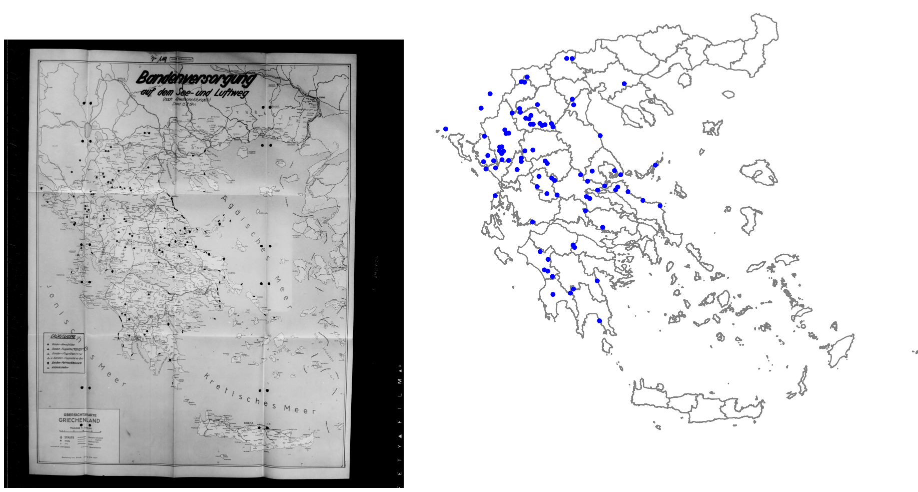
We construct a single instrument (*Predicted resupply*) out of the interaction of these two variables. This variable predicts, albeit weakly, actual proximity to supply points: Table C.5 demonstrates this based on German Army maps of partisan activity and Allied supply points in Greece in 1944, collected from the German federal military archives (Figure C.2). The instrument also strongly predicts the share of reprisal towns in a prefecture, as can be seen in the right panel of Figure C.1.

Table C.5: Pairwise correlations, instrument

	Predicted resupply	Average distance from resupply points	Share towns
Predicted resupply	1.0000		
Log average distance from resupply points	-0.1007	1.0000	
	(0.4822)		
Share towns	0.5059***	0.0993	1.0000
	(0.0002)	(0.4881)	

Notes: P-values in parentheses. *Average distance from resupply points* is the distance from partisan supply points depicted in Figure C.2, averaged over a grid of points for each prefecture. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Figure C.2: Partisan air drop supply points and landing locations



Notes: On the left: original scan of air drop supply points. The German title reads "Resupply of bandit groups by sea and air". Sets of adjacent round holes along the creases are from hole punchers used in the archives, and do not indicate supply points. On the right: digitized version. *Source:* Military maps of Heeresgruppe E (Army Group E), US National Archives.

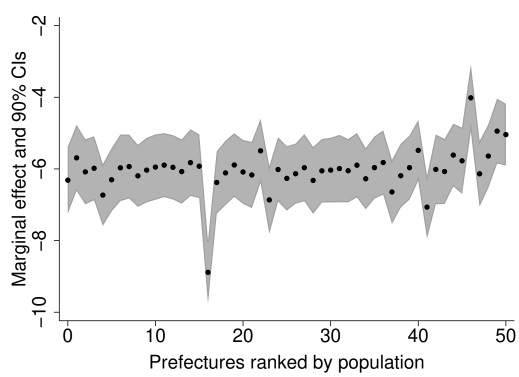
Table C.6 presents the IV-results using predicted resupply as an instrument for a prefecture's share of towns suffering reprisals. Column 2 presents the coefficient from the parsimonious specification of column 4 in Table 1, Panel A. The first stage (column 2) is strong, with the F-statistic of 22.02, being well above the rule-of-thumb cutoff of 10. Columns 3 and 4 present reduced form and 2SLS coefficients, respectively. The estimated differential effect of German-Greek conflict is larger than the OLS estimate, consistent with a higher German market share in reprisal prefectures (Table B.2), which, in the absence of any role for collective memory, may have been less likely to boycott German cars. The downward bias of OLS estimates also speaks against higher activism confounding the effects of collective memory. 2SLS estimates do not appear to be driven by outliers. Figure C.3 plots point estimates and confidence bands after dropping individual prefectures from the sample, one at a time. Effects are always significantly negative.

Table C.6: Predicting reprisals using terrain characteristics

Dep. Variable	Share German cars	Article share × Share towns	Share German cars	Share German cars
	(1)	(2)	(3)	(4)
	OLS	First stage	Reduced form	2SLS
Article share × Share towns	-3.005**			-6.020**
	(1.221)			(2.650)
Article share × Predicted resupply		0.002***	-0.015**	
		(0.001)	(0.006)	
Observations	4,243	4,284	4,243	4,243
R-squared	0.391	0.651	0.016	0.013
F-stat				22.02

Notes: Table replicates the specification in column 4 of Table 1, Panel A. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Figure C.3: IV estimation – Robustness to dropping outliers



Notes: The figure plots coefficient estimates and 90% confidence intervals from the specification in column 4 of Table C.6, dropping one prefecture at a time.

C.3 Ruling Out Other Alternative Explanations

In this section, we rule out three alternative explanations of our main findings: that the civil war during later stages of WWII confounded the effect of reprisal attacks by Germans; that the differential effects we observe in reprisal prefectures reflect differential targeting by consumer groups boycotting German products; and that divergent patterns of car sales are due to differential changes in car dealership networks driven by factors other than anti-German sentiment and its effects on consumer demand.

C.3.1 Civil War Violence

To assess the overlap between early civil war conflict and German war crimes, we rely on Kalyvas and Marantzidis (2015) who list the locations of battles between Communist forces (primarily ELAS) and other military groups during the earliest phase of the Greek civil war in 1943-1944. The list enumerates all major conflicts during the last years of the occupation. Whenever a battle location or date was not precisely specified, we consulted additional sources on the internet.[2] Missing information was straightforward to fill out, as there was never any disagreement in online sources as to the location or date of a conflict.

We compile a list of 74 battles. After excluding 7 battles which took place in mountainous areas away from inhabited locations, and accounting for the fact that some towns were involved in more than one conflict, we end up with 52 distinct battle locations between 1943 and 1944.

There is minimal overlap between civil war battles and reprisals committed by German forces. Out of 52 towns that experienced conflict in the early stages of the civil war, only 3 also experienced reprisals. Importantly, reprisal attacks in these three towns (the town of Kozani, and the hamlets of Triada and Chimarros in the prefecture of Serres) took place in 1941, while civil conflict in the same locations occurred later (in 1943 and 1944). It is thus unlikely that civil conflict in these towns would be attributed to German activity, especially since civil war tensions had not yet erupted in 1941. The majority of German reprisals in Greece took place after 1943, but none of these attacks target towns that were also involved in civil conflict.

To directly test whether civil war violence confounds the effect of memories of German war crimes, we compute the prefecture-level share of towns that participated in early civil conflict and explicitly control for its time-varying effect during the debt crisis. The correlation between a prefecture's share of towns that experienced reprisals and share of towns that experienced civil conflict is 0.16 and not significant. Table C.7 shows that accounting for the time-varying effect of civil war violence does not affect estimates of the time-varying effect of German reprisals. Interaction coefficients for *Article share* × *Share towns* remain significant and even increase in magnitude in the more parsimonious specifications.

Table C.7: Accounting for early civil conflicts

Dep. Variable	Share German cars			
	(1)	(2)	(3)	(4)
Article share	0.005	-0.680	0.332	
	(0.110)	(5.409)	(5.546)	
Article share × Share reprisal towns	-1.298*	-2.422*	-2.465**	-2.435**
	(0.689)	(1.240)	(1.167)	(1.171)
Article share × Share towns in civil conflict	-3.803**	-4.386***	-4.214**	-4.257**
	(1.566)	(1.552)	(1.588)	(1.604)
Observations	4,243	4,243	4,243	4,243
R-squared	0.259	0.267	0.353	0.392
Pre-controls × Article share		✓	✓	✓
Prefecture × Calendar month FE			✓	✓
Time FE × Article share				✓

Notes: Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

[2] Most information was drawn from Wikipedia articles on the Greek civil war, for instance `https://w.wiki/3dxb`.

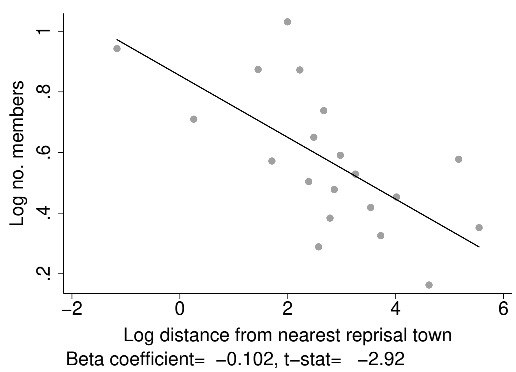
C.3.2 Boycott campaigns

We investigate the connection between grassroots boycott campaigns and exposure to German reprisals by turning to social media.

With minimal penetration of Twitter on the Greek web during 2010-2014, Facebook was the most common platform used to organize consumer boycotts. In 2013, we searched Facebook for mentions of variants of the phrases “boycott German products”, “boycott foreign products” or “boycott Germany” and found around 40 Facebook groups formed during our period of interest and devoted to boycotting of German products. For open groups, we used Facebook’s API to scrape the locations of members who make this information publicly available, by openly listing them in the field “Current city”. We obtained and geocoded locations for 1900 boycott group members, across 225 distinct identifiable towns in Greece. We compute the distance between each location and the nearest town that experienced reprisals by German forces in WWII.

A strong negative correlation (p-value= 0.004) exists between distance to reprisals and membership in Facebook boycott groups, as shown in Figure C.4. Participation in boycott groups is a measure of consumer behavior complementary to that of car purchases and reflective of the same mechanism of associative memory that reactivated latent anti-Germanism. The information available on the Facebook API does not include the date when each member joined, which does not allow us to conduct a time-varying analysis as in the case of cars. Nonetheless, the cross-sectional association is consistent with our baseline results.

Figure C.4: Correlation between membership in Facebook boycott groups and distance to reprisals



Notes: Dots represent bins of locations of members of Facebook groups that call for a German boycott.

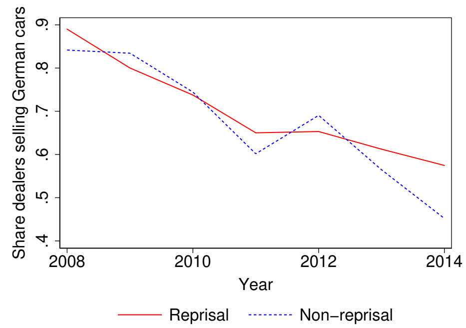
C.3.3 Supply of German Cars

To examine whether the drop in the German car market share is due to changes in the spatial distribution of car dealerships, we use car.gr, the largest online market of vehicles and vehicle parts in Greece during the period under study.[3] Car.gr maintains current lists of car dealers by town and prefecture. To investigate whether the geographic distribution of dealerships changed over time, we access snapshots of historical versions of the webpage using the Wayback Machine, a digital archive of the

[3]Car.gr does not necessarily provide an exhaustive list of car dealerships in Greece, particularly for earlier years. The number of dealers listed increases over time, which could be a result of more dealerships using online markets to sell their products. To our knowledge, this is the most comprehensive online source of car dealerships on the Greek internet. Additionally, our analysis shows no difference between dealers that sell German cars and others across prefectures with different exposure to reprisals. This suggests that, to the extent that dealerships are not included in car.gr, missingness is not systematically correlated with past atrocities or with vehicle manufacturer.

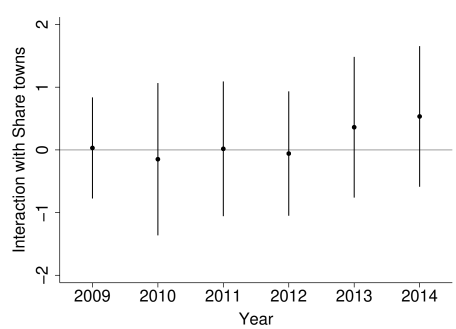
World Wide Web maintained by the nonprofit library Internet Archive. To ensure comparability of the webpage's content over time, we use the most complete snapshot – i.e. the snapshot with the highest share of content captured by the Wayback Machine – taken in the end of each calendar year, between September and December. We are thus able to access lists of dealerships that advertised on car.gr in each end-of-year for all years between 2008 and 2014. We crawl these lists to access snapshots of each dealership's historical listed content, and identify dealers who sell cars, as well as those who have at least one German car listed for sale on their website.

Figure C.5: Share of dealerships that sell German cars by year and reprisal status



Using this approach, we construct a yearly prefecture-level panel of dealerships, by type of car sold (at least one German car or no German car listed).[4] Figure C.5 displays the evolution of the share of dealerships listed on car.gr that sell at least one German car. A declining trend is evident over time, predating the beginning of the debt crisis. However, the raw data provide no evidence of a steeper decline in prefectures with reprisals. Volatility is somewhat higher in non-reprisal prefectures, which are on average smaller in size, but broad trends are very similar across the two types of prefectures.

Figure C.6: Evolution of the share of dealerships selling German cars, by exposure to reprisals



Notes: The figure displays coefficient estimates of β_τ from equation 1 along with 95% confidence intervals. The dependent variable is the prefecture-level share of dealerships that sell at least one German car. Standard errors are clustered at the prefecture level. Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

[4]Some dealerships appear under different names in different years. This could be due to misspellings or other differences in the name string over time. Identifying unique dealers is not entirely straightforward; in several instances, two dealerships in the same town may have the same name (e.g. a person's last name), but they are still listed as different businesses on car.gr. Our findings remain the same regardless of whether or not we standardize strings of business names. Results available upon request.

We provide a more formal analysis of the evolution of dealerships, by estimating the following specification:

$$SD_{it} = c_i + y_t + \sum_{\tau=2008}^{2014} \beta_\tau I_t^\tau \times \text{Share towns}_i + e_{it} \tag{1}$$

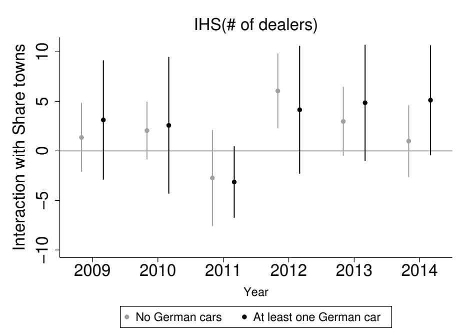
where SD_{it} is the share of dealerships that sell at least one German car, c_i are prefecture fixed effects, y_t are year fixed effects and I_t^τ is an indicator if year t is equal to τ. Figure C.6 displays the estimates of the coefficients β_τ along with 95% confidence intervals. There is no correlation between exposure to reprisals at the prefecture level and the change over time in the share of German car suppliers.

Figure C.7 is an alternative illustration of the same result, which separately displays the evolution of German car suppliers and other dealers. We estimate, separately by nationality of cars supplied:

$$N_{it} = c_i + y_t + \sum_{\tau=2008}^{2014} \beta_\tau I_t^\tau \times \text{Share towns}_i + \sum_{\tau=2008}^{2014} \boldsymbol{\gamma_\tau} I_t^\tau \times \boldsymbol{\Omega_i} + e_{it} \tag{2}$$

where N_{it} is the number of dealerships. To deal with the presence of zeroes we use the inverse hyperbolic sine transformation of the number as dependent variable. We include interactions of a vector of prefecture-level baseline controls (as in column 2 of Table 1) with year fixed effects, to allow prefectures with more reprisals to be on different trajectories depending on baseline economic and social conditions. Figure C.7 reveals a very similar evolution of the number of dealerships over time, regardless of location and type of car sold. Fewer dealers advertise on car.gr in 2011, possibly reflecting the effect of the crisis, but this drop is comparable for all dealerships. Coefficient estimates of the differential effect of crisis years on prefectures with more reprisals are never significantly different by type of vehicle sold. Taken together, the results provide no indication of supply-driven changes in the German car market share.

Figure C.7: Over time change in number of dealerships by exposure to reprisals and type of car sold



Notes: The figure displays coefficient estimates of β_τ from equation 2 along with 95% confidence intervals. The dependent variable is, respectively, the inverse hyperbolic sine transformation of the number of dealerships that do not sell German cars (grey lines) or sell at least one German car (black lines). Standard errors are clustered at the prefecture level. Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

C.4 Additional Robustness and Placebo Exercises

C.4.1 Falsification Tests

We conduct a number of placebo exercises both to support the causal interpretation of our results and to examine the scope conditions of our theoretical mechanism.

Are changes in German car purchases specific to German atrocities and time-varying conflict with Germany? First, we repeat our baseline analysis using the share of towns destroyed by Bulgarian and Italian occupying forces as sources of cross-sectional variation. Second, we replace our main dependent variable with the market share of French and Italian cars and cars in the luxury category, to examine whether time-varying conflict leads to a differential drop in (non-German) luxury cars via economic channels. Finally, we compile an index of articles about disagreements with Italy for the same period, and examine whether it has explanatory power for changes in the German market share.

Column 1 of Table C.8 replicates the parsimonious baseline specification of column 4 in Table 1 (Panel A) for ease of reference. All subsequent columns follow the same specification with alternative dependent variables, and measures of conflict or reprisals.

Column 2 shows that the market share of German cars is not more affected during conflict months in prefectures with a higher share of towns exposed to Italian and Bulgarian reprisals. This speaks against location-specific unobservable cultural differences driving our main results. Locations more prone to conflict or with a stronger national identity might have provoked reprisal attacks from any occupying force, regardless of nationality – and should have reacted to German 'bullying' after 2009 whether the massacres in the early 1940s were committed by Italians, Bulgarians, or Germans. Yet it is atrocities committed specifically by Germans that drive time-varying responses of consumer behavior.

This result is also helpful in understanding when associativity is activated. Reprisals during WWII are not enough to trigger animosity against any occupying force. What is needed is that the actor of past violence and of perceived present aggression is the same.

Table C.8: Falsification tests

Dep. Variable	Share German		Share French & Italian	Share French & Italian luxury	Share luxury	Share German	Share Italian
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
German article share × Share towns	-3.005**		0.428	-0.004	0.339		
	(1.221)		(1.053)	(0.012)	(0.261)		
German article share × Share Italian/Bulgarian		0.036					
		(0.741)					
Italian article share × Share towns						-1.858	5.778*
						(3.099)	(2.964)
Italian article share × Share Italian							24.497
							(22.544)
Observations	4,243	4,243	4,243	3,387	4,223	4,243	4,243
R-squared	0.391	0.389	0.357	0.248	0.302	0.389	0.348

Notes: Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Columns 3 to 5 examine effects on non-German cars and on luxury purchases. No significant differential patterns in car sales of French and Italian cars are found in prefectures with more reprisals. This is true on average (column 3) and for luxury French and Italian cars specifically. Consistent with our results in Table C.2, column 5 shows no significant differential effect on luxury purchases in general. These results suggest two things. First, they speak against economic drivers of differential German car sales in reprisal prefectures; were that the case, luxury purchases, either of non-German cars or on average, would have also displayed a time-varying correlation with reprisal status. Second, there appears to be no immediate substitution between German cars and French or Italian cars, suggesting consumers may be deferring their purchases entirely rather than turning to other car brands in months of German-Greek conflict.[5]

Next, we replicate our baseline analysis with an Italian news index. If our results pick up the effect

[5]Combining French and Italian cars in a single dependent variable may obscure some patterns of substitution. The share of Italian cars shows a significant differential increase in prefectures with more reprisals in conflict months. Results available upon request.

of a Germany-specific news shock, we should not find effects if we use news coverage of another European country. We use the same keywords designed to capture German-Greek conflict during the Euro crisis, but substitute the word stem 'German' with 'Italian' and the German Chancellor Merkel with the Italian Prime Minister Renzi. Despite substantial overlap in the terms composing the Italian placebo index, the estimated differential effect is far from significance, as shown in column 6 Table C.8. This test is additional evidence that generic terms related to the crisis are not enough to drive differential car sales, and thus that the patterns we observe are not due to economic factors.

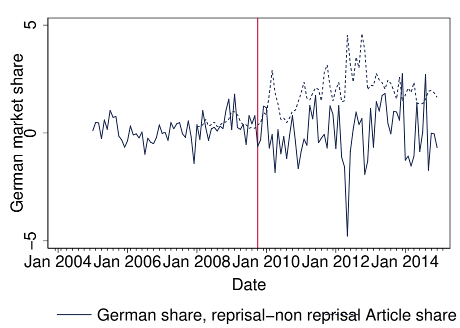
As a final placebo test, we examine patterns of Italian car sales in prefectures with exposure to Italian reprisals. Our theoretical reasoning suggests that areas with a past of Italian atrocities should display changes in purchasing behavior (of Italian cars) only when associative memory is triggered. During the debt crisis, Italy was not associated with foreign-imposed austerity and, if anything, it was perceived to be similarly negatively affected by the global financial crisis as Greece and other countries of Southern Europe. The Italian news index is thus not a measure of conflict and not expected to be associated with anti-Italian sentiment among consumers. Column 7 of Table C.4 confirms these expectations. The Italian car market share is not affected in prefectures with a past of Italian reprisals when the Italian news index is high. They suggest that mere mentions of a perpetrator of past violence are not enough to reactivate memories and affect behavior; an adversarial context that, however remotely, resembles past conflict is crucial.

C.4.2 Baseline Differences in Purchasing Behavior

In this section, we provide evidence that the pattern of car sales was broadly similar across prefectures outside periods of reactivation of latent memories of reprisals. To the extent that there were differences in the immediate pre-crisis period, they do not influence our main findings.

Unfortunately, there is no good data on car registrations for the immediate post-war period. The only available data disaggregated both by geographic location and by car manufacturer (a pre-requisite for our analysis) was compiled by ELSTAT for 1961. This data is not available at the prefecture level, but at the level of the *transport area*, of which there are 11. Only 2 out of 11 transport areas have no experience of reprisals. A t-test suggests no significant difference in German car market share across areas with and without reprisals (p-value= 0.7645), but the number of observations is simply too small to draw valid conclusions.

Figure C.8: Differences in German car sales by reprisal status since 2004



Notes: The solid line is the difference in the seasonally adjusted (expressed as difference of month t from month $t-12$) share of German car registrations in reprisal vs non-reprisal prefectures. The dotted line is the monthly share of *Kathimerini* articles related to German–Greek conflict. Both series are normalized by their standard deviation.

For a more precise comparison of car purchasing behavior across prefectures in periods in which associative memory was not active, we extend our dataset back to 2004, prior to the onset of the debt crisis. Figure C.8 replicates Figure 1 for the entire period 2004-2014. It clearly demonstrates that the

German market share did not differ by reprisal status prior to the fall quarter of 2009. Thereafter, there is a differential decline, tracking the news-based measure of German-Greek conflict closely.

Figure C.8 supports the mechanism of associative memory, as differences in purchasing behavior only kick in after the start of the crisis, and peak during period of heightened conflict. One distinct concern is that the differential drop in the German market share in reprisal prefectures is not driven by memory, but by short-run differences in baseline market shares in the immediate pre-crisis period.[6] To ensure that our results are not driven by floor effects, or a larger capacity of prefectures with reprisals to adjust German car purchases downwards, we present results controlling for lagged shares. Column 1 of Table C.9 replicates the most parsimonious baseline specification (column 4 of Table 1, Panel A). The subsequent three columns include controls for one, three and five lagged values of the dependent variable. As expected, lagged German sales are positive predictors of future market share, but the differential effect of conflict on prefectures with a higher share of towns that experienced reprisals remains large and significant. To additionally address possible bias introduced by controlling for an endogenous regressor, we also estimate a specification in which we interact the average German market share in 2008-2010 with the time-varying measure of conflict. The estimate, presented in column 5, remains close to the original magnitude.

Table C.9: Controlling for baseline differences in German market share

Dep. Variable	Share German cars				
	(1)	(2)	(3)	(4)	(5)
Article share × Share towns	-3.005**	-3.073**	-2.784**	-2.365**	-2.520**
	(1.221)	(1.166)	(1.152)	(1.062)	(1.204)
Share German carst-1		0.095***	0.058**	0.047*	
		(0.022)	(0.028)	(0.028)	
Share German carst-2			0.083***	0.095***	
			(0.031)	(0.026)	
Share German carst-3			0.089***	0.105***	
			(0.025)	(0.026)	
Share German carst-4				0.052	
				(0.034)	
Share German carst-5				0.034	
				(0.026)	
Article share × Share German cars pre-2010					-1.980
					(1.676)
Observations	4,243	4,173	4,047	3,931	4,243
R-squared	0.391	0.415	0.440	0.455	0.392

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column 1 replicates the specification in column 4 of Table 1 Panel A and columns 2-5 include additional controls as indicated in the table.

C.4.3 Famous Massacres

Amongst the litany of bloodshed that marked the German occupation of Greece, a few cases stand out – Kalavrytra, Distomo, and Kommeno. In each of these towns, almost the entire civilian population was killed. We examine the robustness of our findings to dropping these famous cases. In Table C.10, we first drop the three towns when we compile indices of the share of towns affected by reprisals (Panel A), and then exclude the entire prefectures in which they are located (Panel B). Results are almost entirely unaffected.

[6] It is worth pointing out that, though the difference in the German market share between reprisal and non-reprisal prefectures is significant, as shown in Table B.2, there is no significant correlation between our main measure of reprisal exposure (share of affected towns) and the average German market share between 2008–2010 (p-value= 0.447).

Table C.10: Dropping famous reprisals

Dep. Variable	Share German cars			
	(1)	(2)	(3)	(4)
	Panel A: Drop Distomo, Kalavryta, Kommeno			
Article share	-0.018	-2.224	-1.154	
	(0.108)	(5.722)	(5.804)	
Article share × Share towns	-1.561**	-3.139**	-3.171**	-3.147**
	(0.741)	(1.298)	(1.226)	(1.231)
Observations	4,243	4,243	4,243	4,243
R-squared	0.258	0.267	0.353	0.391
	Panel B: Drop entire prefectures			
Article share	-0.035	1.348	2.672	
	(0.113)	(6.165)	(6.192)	
Article share × Share towns	-1.482*	-3.106**	-3.132**	-3.107**
	(0.746)	(1.363)	(1.291)	(1.297)
Observations	3,991	3,991	3,991	3,991
R-squared	0.238	0.247	0.337	0.376
Pre-controls × Article share		✓	✓	✓
Prefecture FE × Calendar month FE			✓	✓
Time FE				✓

Notes: Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

C.4.4 Alternative News Index

As an alternative measure of German-Greek conflict, we use data from Google Trends during the period 2008–2014. The alternative conflict index is based on the following terms: "Germans", "German reparations" and "Distomo" (only searches that were conducted in the Greek language, in Greece). The index value from Google Trends is a normalization of the share of total searches represented by a term in a given time and region. For each of the terms above we compile a monthly search index from Google for the period 2008–2014 and aggregate them into a single measure, ranging from 0 to 100.

Table C.11: Google index

Dep. Variable	Share German cars			
	(1)	(2)	(3)	(4)
Google index	-0.001	-0.001	-0.001	
	(0.000)	(0.000)	(0.000)	
Google index × Share towns	-0.006**	-0.007**	-0.008***	-0.008***
	(0.002)	(0.003)	(0.003)	(0.003)
Observations	4,243	4,243	4,243	4,243
R-squared	0.260	0.269	0.355	0.391
Pre-controls × Article share		✓	✓	✓
Prefecture FE × Calendar month FE			✓	✓
Time FE				✓

Notes: Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

This index has two advantages: it represents a measure of demand, rather than supply of news on German-Greek conflict, and it consists of terms more directly related to the history of the German occupation of Greece during WWII, rather than the debt crisis. Table C.11 shows results using this index as a time-varying measure of conflict. We consistently find negative and significant interactions between the Google index and German massacres. The effect is again large – compared to prefectures without reprisals, the most affected prefectures experience an additional 11 pp. drop in the German car market share when the Google index moves from 0 to its peak value during the crisis period.

C.4.5 Serial Correlation

Our main dependent variable, the share of German cars, is measured at the monthly level and is serially correlated over time. Following Bertrand, Duflo and Mullainathan (2004), we always cluster standard errors at the level of the prefecture, to allow for an arbitrary variance-covariance matrix within the unit of treatment. With a sufficiently large number of clusters, this method is shown to be superior to other approaches of dealing with autocorrelation in the dependent variable, such as parametric modeling.

Table C.12: Wild bootstrap

Dep. Variable	Share German cars			
	(1)	(2)	(3)	(4)
Article share	-0.0203	-2.276	-1.199	
	(0.109)	(5.843)	(6.371)	
Article share × Share towns	-1.505**	-3.009**	-3.029**	-3.005**
	(0.740)	(1.296)	(1.315)	(1.320)
	[0.0521]	[0.0691]	[0.0551]	[0.0551]
Observations	4243	4243	4243	4243
R-squared	0.258	0.267	0.353	0.391
Pre-controls × Article share		✓	✓	✓
Prefecture × Calendar month FE			✓	✓
Time FE × Article share				✓

Notes: Replication of Table 1, Panel A. Numbers in brackets are p-values from the wild bootstrap procedure (Cameron, Gelbach and Miller, 2008) implemented using the command *boottest* in STATA (Roodman et al., 2019). Significance levels based on conventional clustered standard errors: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

In Table C.12, we also estimate standard errors using block bootstrap, an alternative technique shown by Bertrand, Duflo and Mullainathan (2004) to correctly uncover the true variance-covariance matrix in the presence of autocorrelation. To account for the fact that 51 clusters (prefectures) may not be enough to accurately estimate standard errors, we report p-values from the wild bootstrap procedure (Cameron, Gelbach and Miller, 2008). Our estimates do not noticeably lose precision.

C.4.6 Spatial Correlation

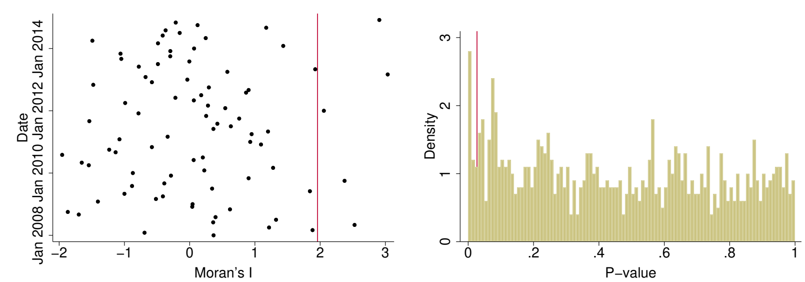
Geographic data usually display a high degree of spatial correlation, and regressions involving geographic data on the left and right hand side may produce artificially inflated t-statistics. Following Kelly (2019), we take a two-step approach to addressing the issue of spatial correlation. First, we assess the degree to which spatial correlation may be a problem in our data. We compute Moran's I for the residuals resulting from column 4 of Table 1 Panel A for every month in our data. The left panel of Figure C.9 plots z-scores by month. Only in about 6% of cases is the z-score larger than 1.96 (the suggestive cutoff for significance at the 5% level). The average value of Moran's I in our data is 0.075, lower than any of the persistence studies analyzed in Kelly (2019). The test based on Moran's statistic thus indicates that our data is not characterized by a high degree of spatial correlation.

We further confirm this by replacing our main explanatory geographic variable (*Share towns*) with spatial noise. We run 1,000 replications of the regression in column 4 of Table 1 Panel A, each time drawing a vector of spatially correlated random values for *Share towns*.[7] The right panel of Figure C.9

[7] Specifically, we draw from the standard normal distribution, but impose a variance covariance matrix based on the Matern

plots p-values resulting from this simulation exercise, alongside the p-value in column 4 of Table 1 (vertical line). The explanatory power of noise is higher than that of Share towns less than 5% of the time. Overall, we conclude that spatial correlation is not an important threat to inference in our context.

Figure C.9: Assessing the degree of spatial correlation in the data



Notes: The left subplot plots Moran's I for the residuals resulting from the specification in column 4 of Table 1 for every month in the dataset. The spatial weighting scheme assigns equal weight on all prefectures. The vertical line is drawn at 1.96. The right subplot plots the distribution of p-values resulting from 1,000 simulations of the specification in Column 4 of Table 1, where *Share towns* has been replaced by generated spatial noise. The vertical line indicates the actual p-value from Column 4 of Table 1. Spatial noise is correlated according to the Matern function, with a variance and shape of 1 and a correlation range of 3 degrees, following Kelly (2019).

C.5 Assessing the Effect of Aggregation on Results

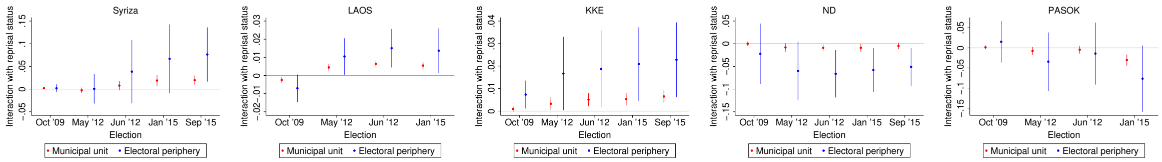
The aggregate nature of car registration data is arguably the greatest empirical challenge in our study. While the treatment unit is the town, the dependent variable is only available at the level of the prefecture. In our main empirical design, we circumvent this problem by constructing an aggregate treatment variable, the share of a prefecture's towns exposed to reprisals. In this section we examine how this aggregation affects the quality of inference and the validity of our results.

We do so by exploiting the dataset of electoral outcomes, in which the unit of analysis is the municipal unit (*dimotiki enotita*), a unit larger than the town but significantly more fine-grained than the prefecture. We examine how results change when we move from a disaggregated analysis at the municipal unit level to an aggregate analysis at the electoral periphery level ($N = 56$) that mirrors the analysis we conduct with car data. Specifically, we re-estimate equation 2 at the electoral periphery level, substituting the indicator for reprisal status with the share of a periphery's municipal units that have experienced reprisals. We control for election period and periphery fixed effects and cluster standard errors at the periphery level. This specification mirrors our main specification in equation 1.

Figure C.10 displays side by side coefficient estimates and 95% confidence intervals for the differential effect of past violence on party vote shares at the municipal unit (in red) and electoral prefecture level (in blue). Three things are evident. First, the direction of the effect is identical in both analyses, suggesting that aggregation does not distort the essence of the results. Second, confidence intervals in the analysis at the periphery level are much larger than at the level of the municipal unit. Aggregation results in an imprecise treatment adding noise to the results. Third, estimated magnitudes for the time-varying effect of reprisals are larger when the analysis is conducted at a more aggregated level. Given the size of standard errors in the aggregate analysis, differences in the estimates are not always significant, but statistically significant differences in magnitude across levels of analysis do emerge in several cases.

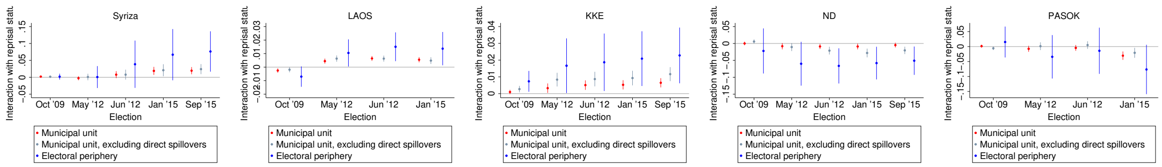
function, as in Kelly (2019). We report results for a correlation range of 2 degrees, but the pattern is similar with different ranges.

Figure C.10: Effect of reprisal status on party vote shares at different levels of aggregation



Notes: In red are coefficient estimates of β_τ from equation 2 along with 95% confidence intervals. In blue are estimates and 95% confidence intervals for interaction coefficients in an equation mirroring 2 at the electoral periphery level, where the indicator of reprisals is replaced with the share of a periphery's municipal units with reprisal status. The dependent variable is the vote share of the party indicated on each subplot title. Standard errors are clustered at the level of the municipal unit or electoral periphery. Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

Figure C.11: Examining the role of spillovers



Notes: Estimates and confidence intervals in red and blue replicate those in Figure C.10. Estimates and confidence intervals in light blue result from estimating equation 2 after dropping untreated municipal units in electoral peripheries with reprisals. The dependent variable is the vote share of the party indicated on each subplot title. Standard errors are clustered at the level of the municipal unit or electoral periphery. Table of full estimation results is provided with supplementary materials on the APSR Dataverse.

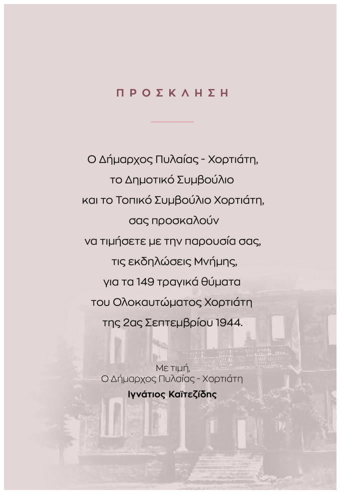
Larger estimated effects at higher levels of aggregation are consistent with the presence of spillovers across affected units. If past reprisals in one town are known and remembered by residents of neighboring towns, then estimated effects are downward biased when neigbors of a reprisal unit are considered to belong to the control group. The analysis of boycott activity in Section C.3.2 showed a significant correlation between distance to reprisal towns and membership in Facebook groups that boycott German products, providing direct evidence for spillovers across locations. In Figure C.11 we provide additional evidence from electoral data. We re-estimate equation 2 at the municipal unit level, but drop all municipal units that did not experience reprisals in electoral peripheries that contain reprisal municipal units. We are then effectively comparing treated municipal units to municipal units in prefectures without reprisals, that can be considered "purer" controls and are less likely to be affected by spillovers.

The results are consistent with the presence of positive spillovers across units. Excluding untreated units in the immediate vicinity of treated ones increases the magnitude of estimated coefficients, which now become statistically indistinguishable from those estimated at the periphery level. Taken together, the results in this section suggest that aggregation does not threaten the validity of our results. If anything, and despite noise induced by aggregation, the presence of spillovers suggests that an aggregated analysis provides meaningful information and may even be more appropriate for understanding the effects of memory than an analysis at the town level.

D Preservation of Memory in Martyr Towns

Blogs and webpages of schools across Greece illustrate the ways in which towns commemorate the experiences of past atrocities. The examples yielded by our internet search almost exclusively come from martyr towns, highlighting the strong correlation between official recognition and memory preservation through education.

Figure D.1: Annual commemoration of the massacre of Chortiatis



(a) Invitation to memorial ceremony for the victims of Chortiatis

(b) Leaflet issued by the martyr town of Chortiatis on the 76th anniversary the massacre

(c) Schedule of activities, involving religious memorial services, a procession to the memorial of victims, and speeches

Many schools of martyr towns educate students on their town's past during WWII on the occasion of Greece's national holiday of October 28, which commemorates the official entry of the country into WWII. For instance, on October 28 of 2018, the blog of the 1st Elementary School of Agria in Volos devoted a post to the reprisal attack on the nearby martyr town of Drakeia. The post, written by two fifth grade students, explicitly refers to Drakeia as a "martyr town" and highlights that it belongs to a group of martyr towns across the country.[8]

Other acts of remembrance reinforce this effect. For instance, schools of the municipality of Pylaia, which contains the martyr town of Chortiatis, organize school visits to the martyr town with the purpose of educating the students on the town's history. Figure D.2 displays a snapshot of the visit from the school's blog. As in the case of Agria above, the blog post accompanying the picture explains to students that Chortiatis is one of the martyr towns of Greece because of reprisals by German occupying forces during WWII.

Other schools encourage even more engagement of students with the past of WWII. The second grade of the Experimental High School of Irakleio participated in the creation of a documentary about the massacres in the towns of Viannos (a cluster of martyr towns in the prefecture of Irakleio, in Crete). As part of the activity, they interviewed older residents of the town with memory of the reprisals.[9]

These examples not only demonstrate how collective memory is preserved through institutionalization, but also have implications for our empirical analysis. Many of the recorded activities do not necessarily take place in martyr towns themselves – many of which are small – but in surrounding areas, usually belonging to the same municipality. This is consistent with our empirical evidence on spillovers in Sections C.3 and C.5 and corroborates the validity of an analysis at the prefecture level, rather than at the level of the individual town.

[8] `https://blogs.sch.gr/1dimagria/2018/10/28/`.

[9] `https://www.neakriti.gr/article/eidiseis/1212104/mathites-ezisan-ti-sfagi-tis-biannoy-mesa-apo-afigiseis/`.

Figure D.2: School visit to massacre memorial

Notes: Students from the 1st Middle School of Pylaia, Thessaloniki, visit the memorial of the massacre of Chortiatis. Source: http://1gym-pylaias.thess.sch.gr/portal/index.php/sxoliko-etos-2018-19/169-sxoliko-etos-2018-19/568-hortiatis2018.

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